Pre-training + Fine-tuning Paradigm 1

Ling 282/482: Deep Learning for Computational Linguistics

C.M. Downey

Fall 2025

Note on Transformer Architecture

Do Transformer Modifications Transfer Across Implementations and Applications?

Sharan Narang* Hyung Won Chung Yi Tay William Fedus
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Nan Ding Jake Marcus Adam Roberts Colin Raffel

Google Research

Abstract

The research community has proposed copious modifications to the Transformer architecture since it was introduced over three years ago, relatively few of which have seen widespread adoption. In this paper, we comprehensively evaluate many of these modifications in a shared experimental setting that covers most of the common uses of the Transformer in natural language processing. Surprisingly, we find that most modifications do not meaningfully improve performance. Furthermore, most of the Transformer

will yield equal-or-better performance on any task that the pipeline is applicable to. For example, residual connections in convolutional networks (He et al., 2016) are designed to ideally improve performance on any task where these models are applicable (image classification, semantic segmentation, etc.). In practice, when proposing a new improvement, it is impossible to test it on every applicable downstream task, so researchers must select a few representative tasks to evaluate it on. However, the proposals that are ultimately adopted by the research community and practitioners tend to be those that reliably improve performance across a wide variety of tasks "in

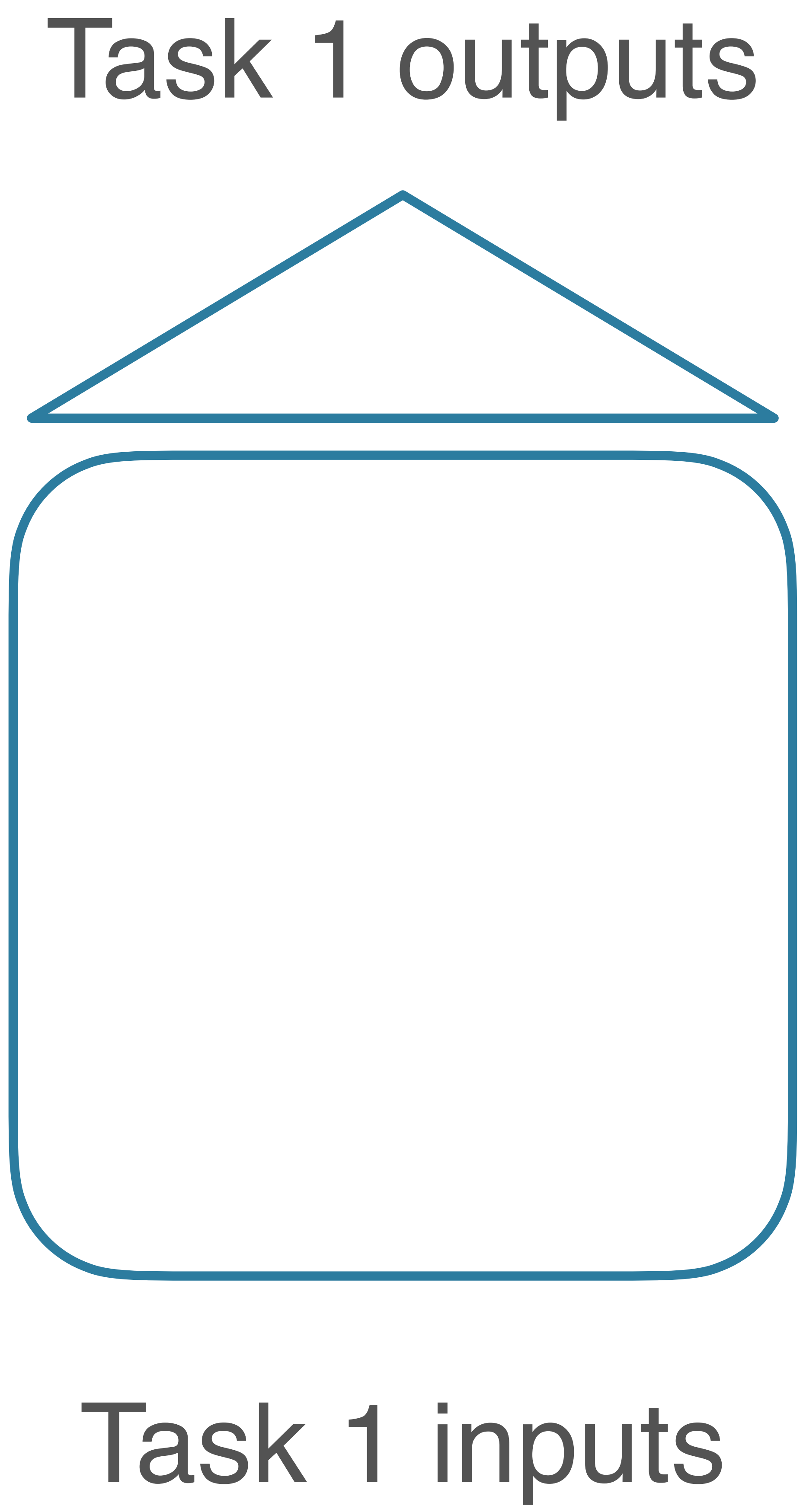
link

Today's Plan

- Transfer learning in general
- Language model pre-training: initial steps
- Transformer-based pre-training
  - Encoder only
  - Decoder only
  - Encoder-Decoder
- Some limitations

Transfer Learning

Traditional Learning



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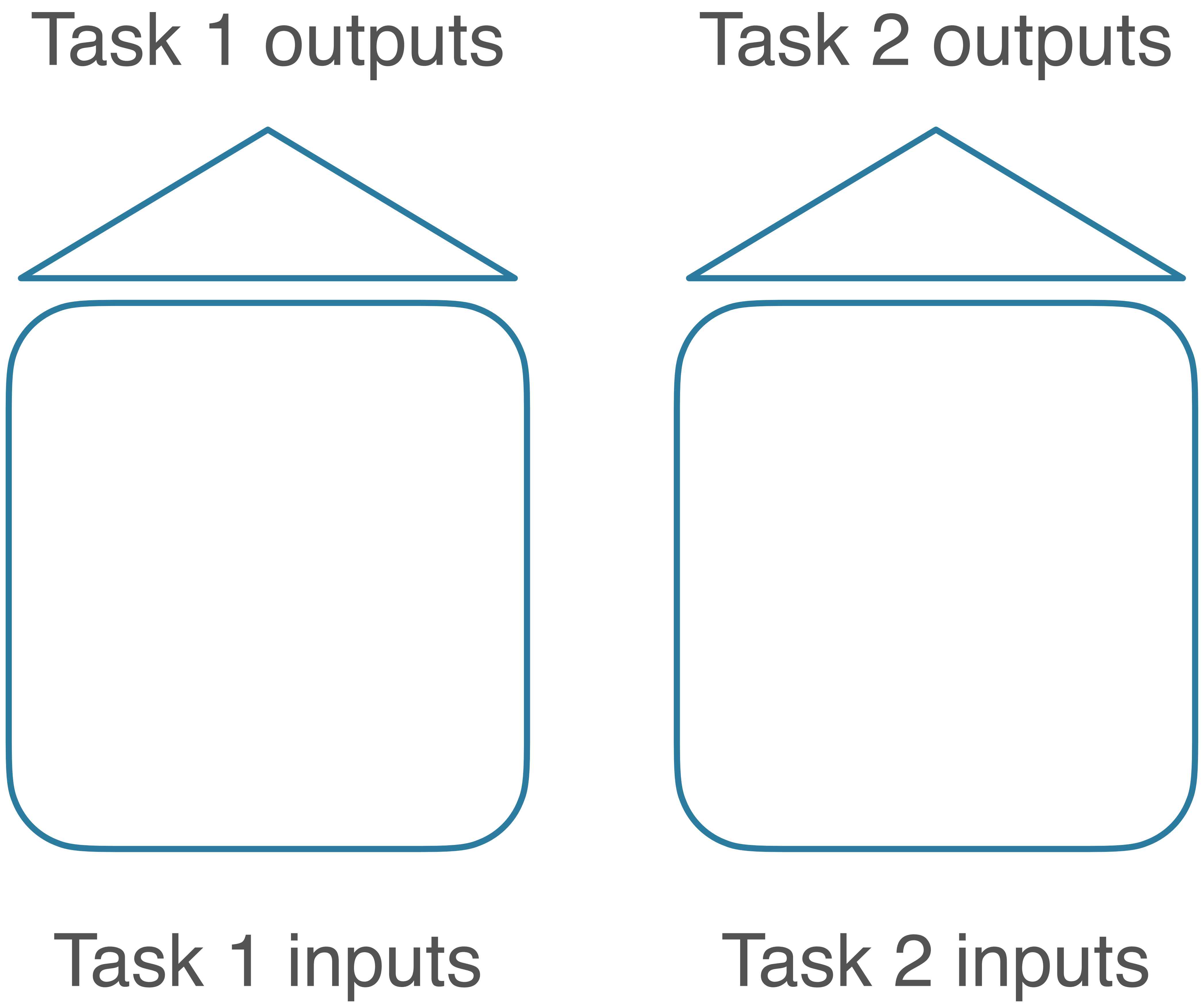

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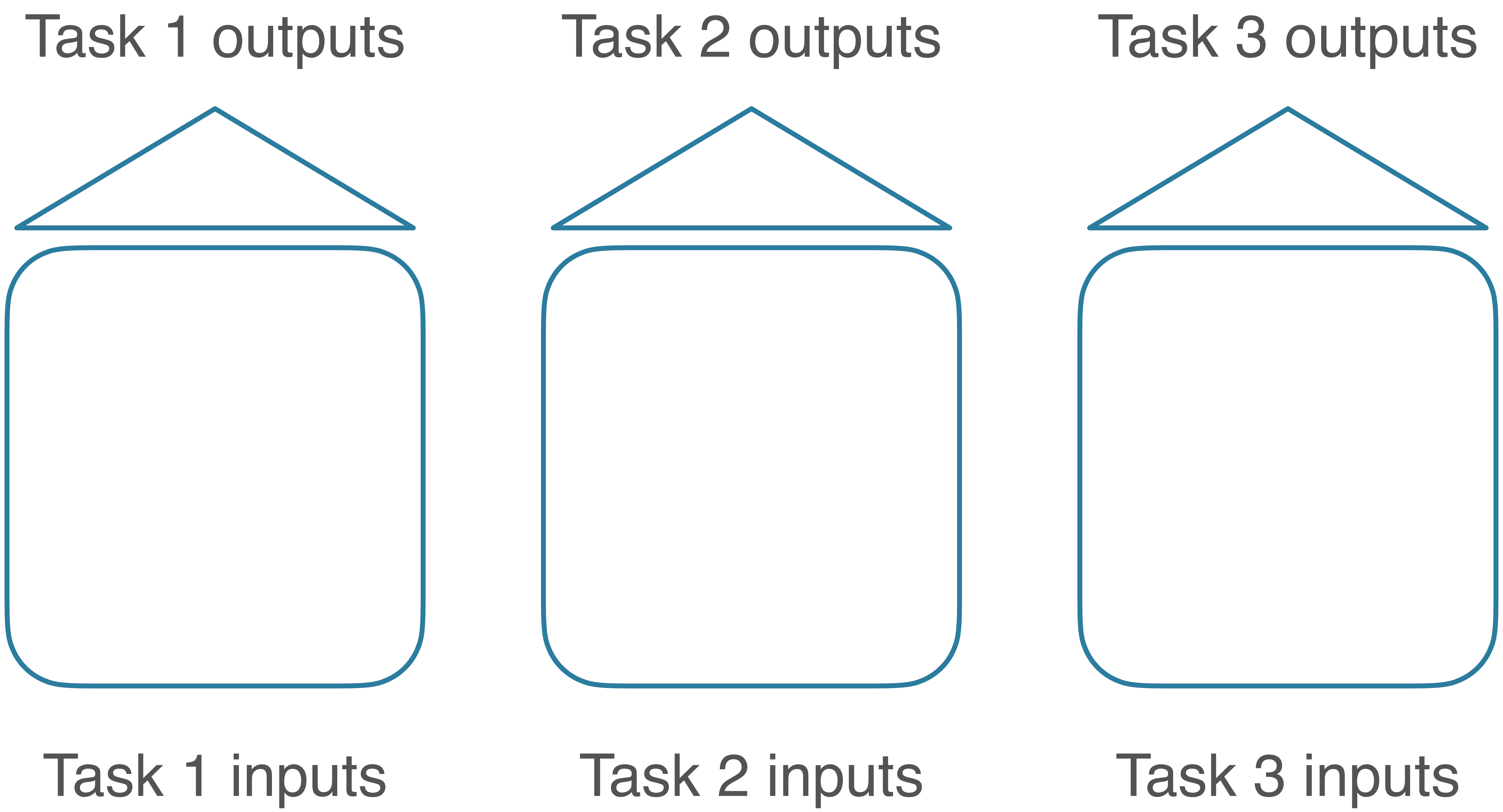

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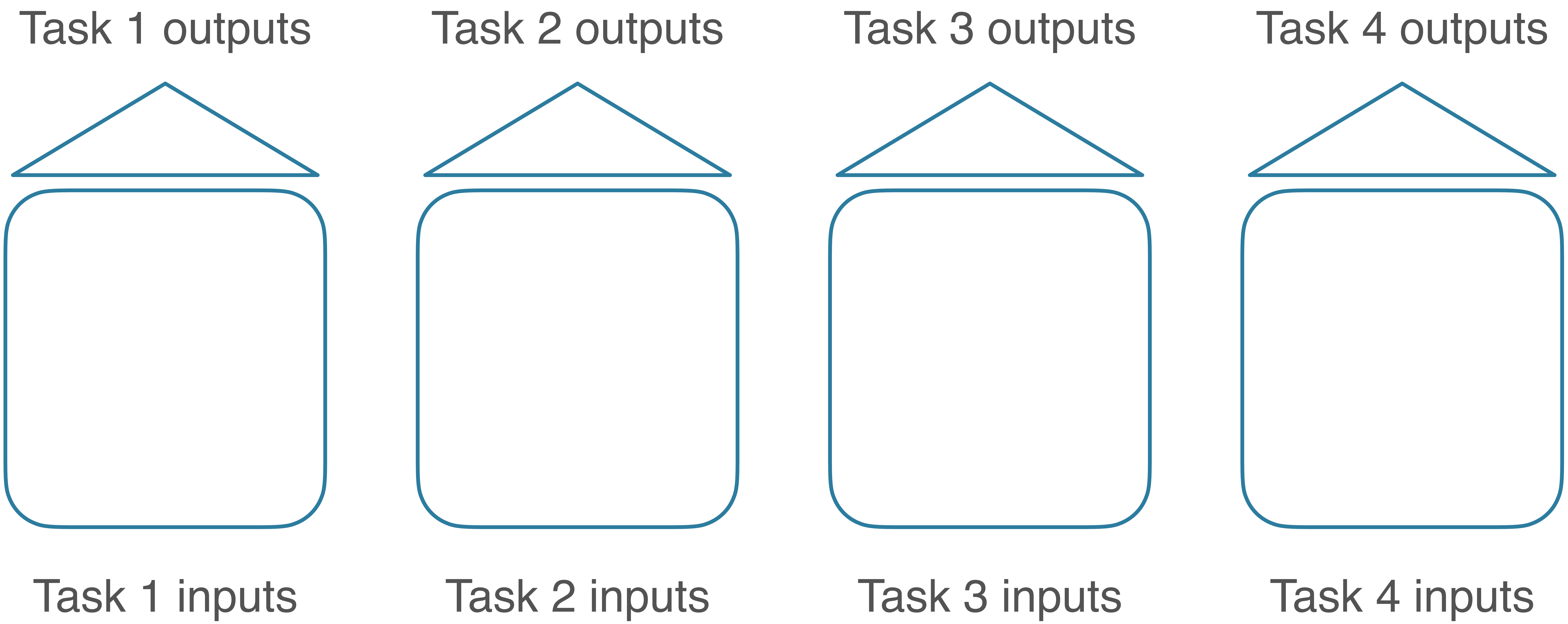
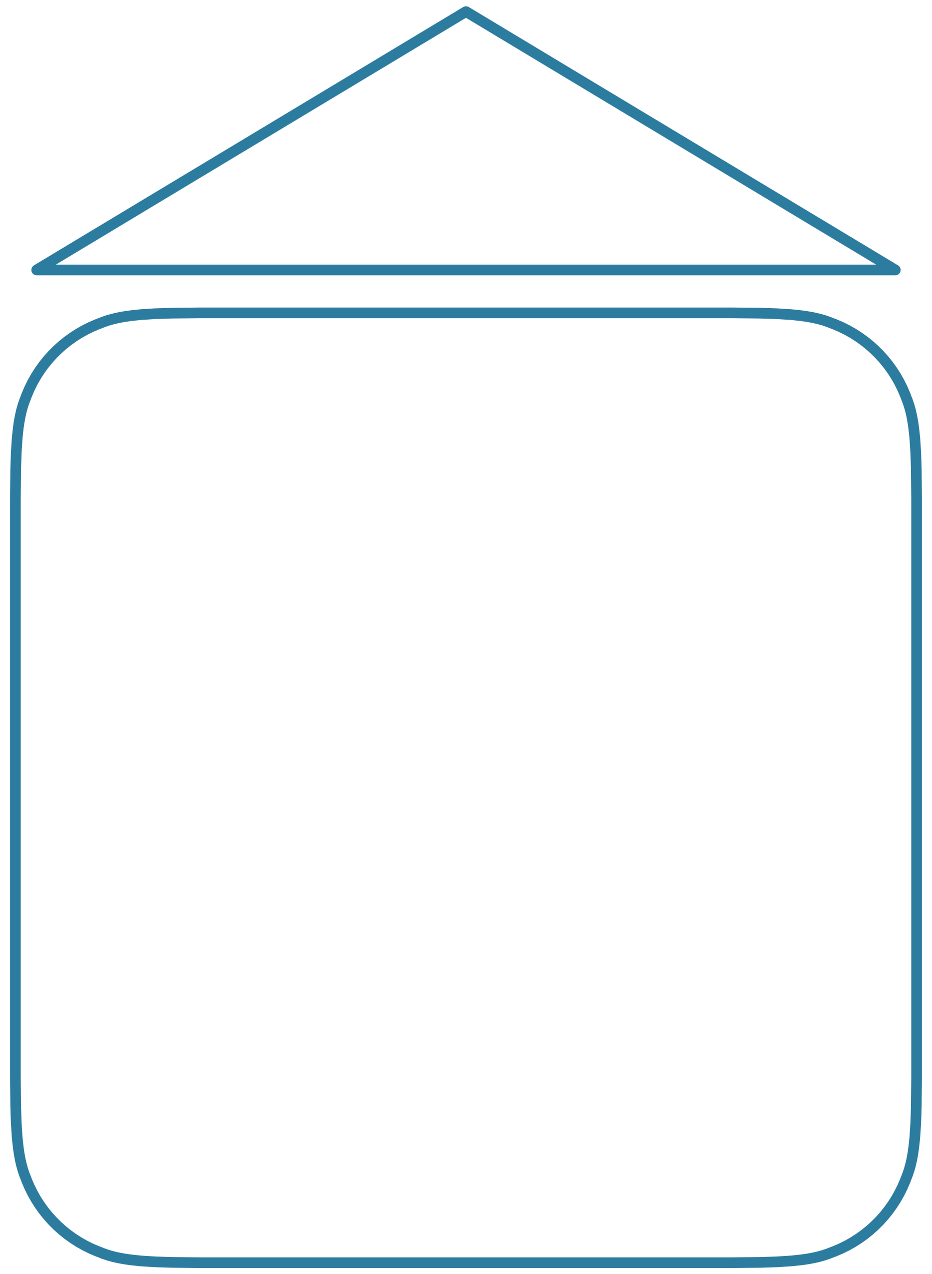


Traditional Learning

- New task = new model
- Expensive!
  - Training time
  - Storage space
  - Data availability
    - Can be impossible in low-data regimes

Transfer Learning

“pre-training” task outputs



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Transfer Learning

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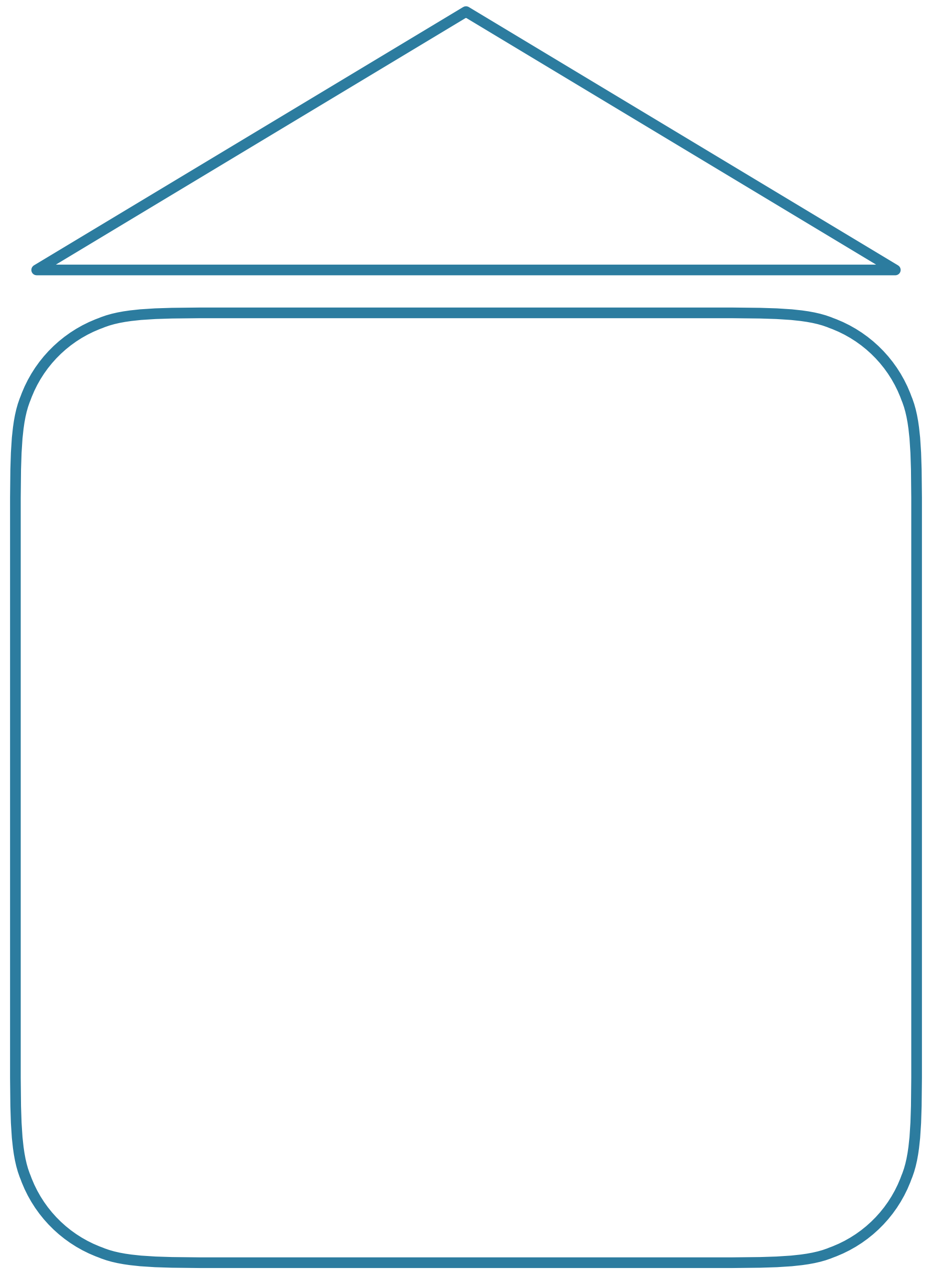

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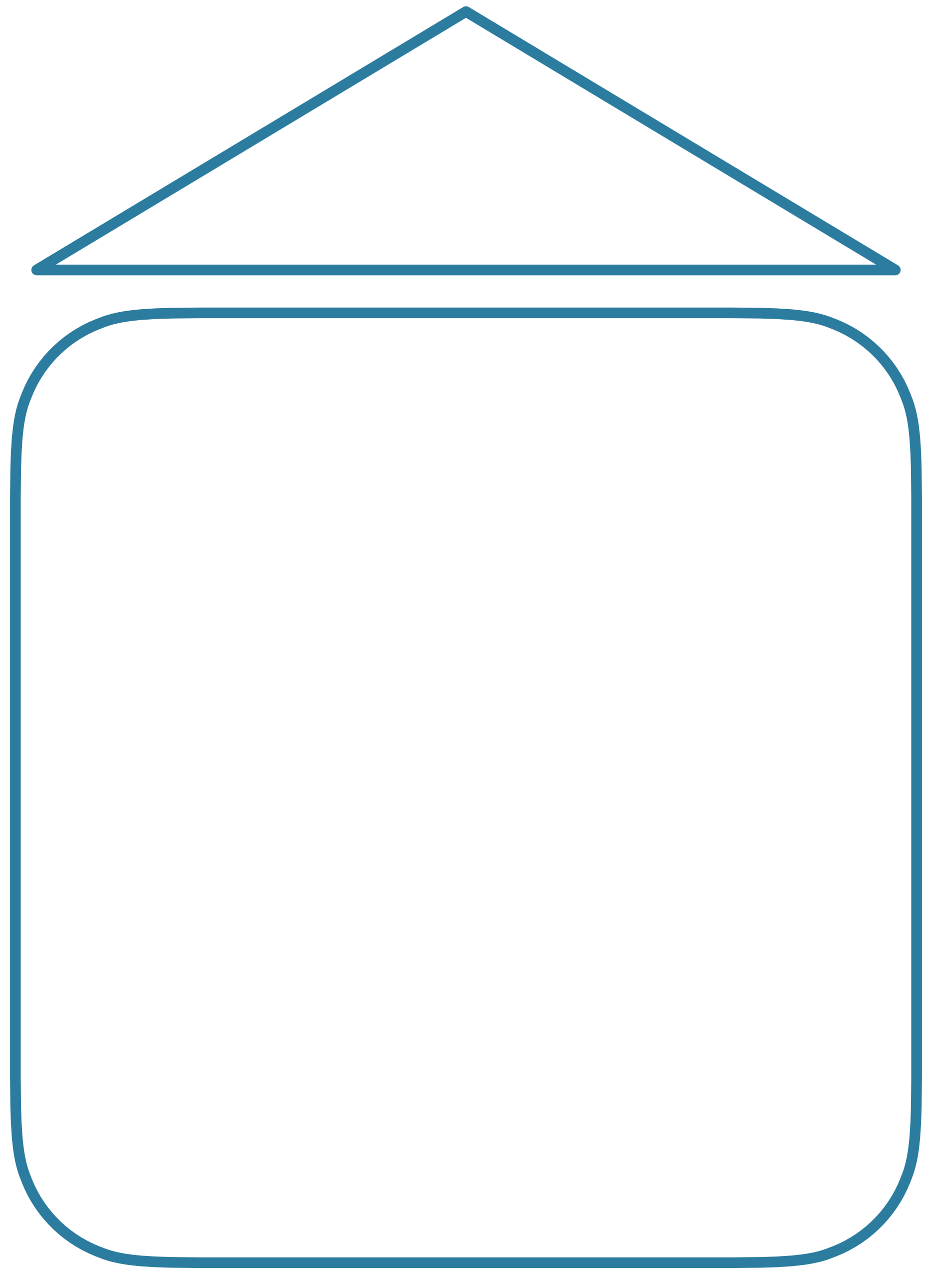
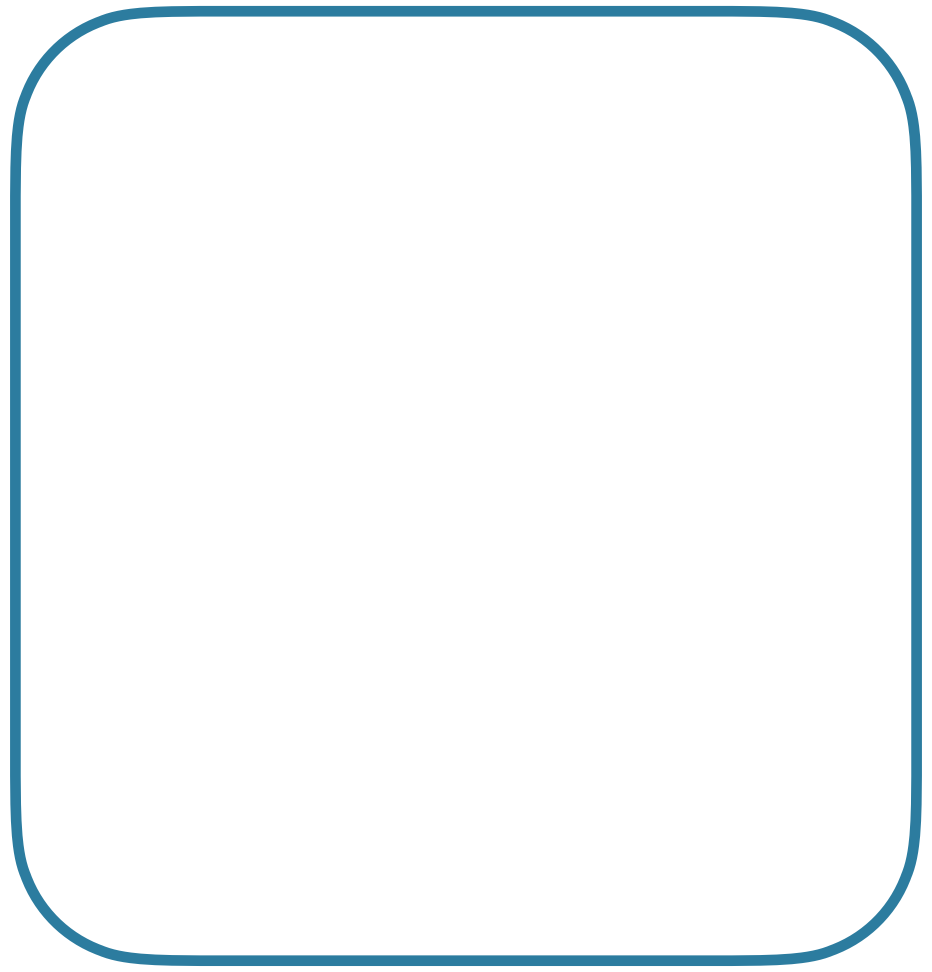


Task 1 inputs

Transfer Learning



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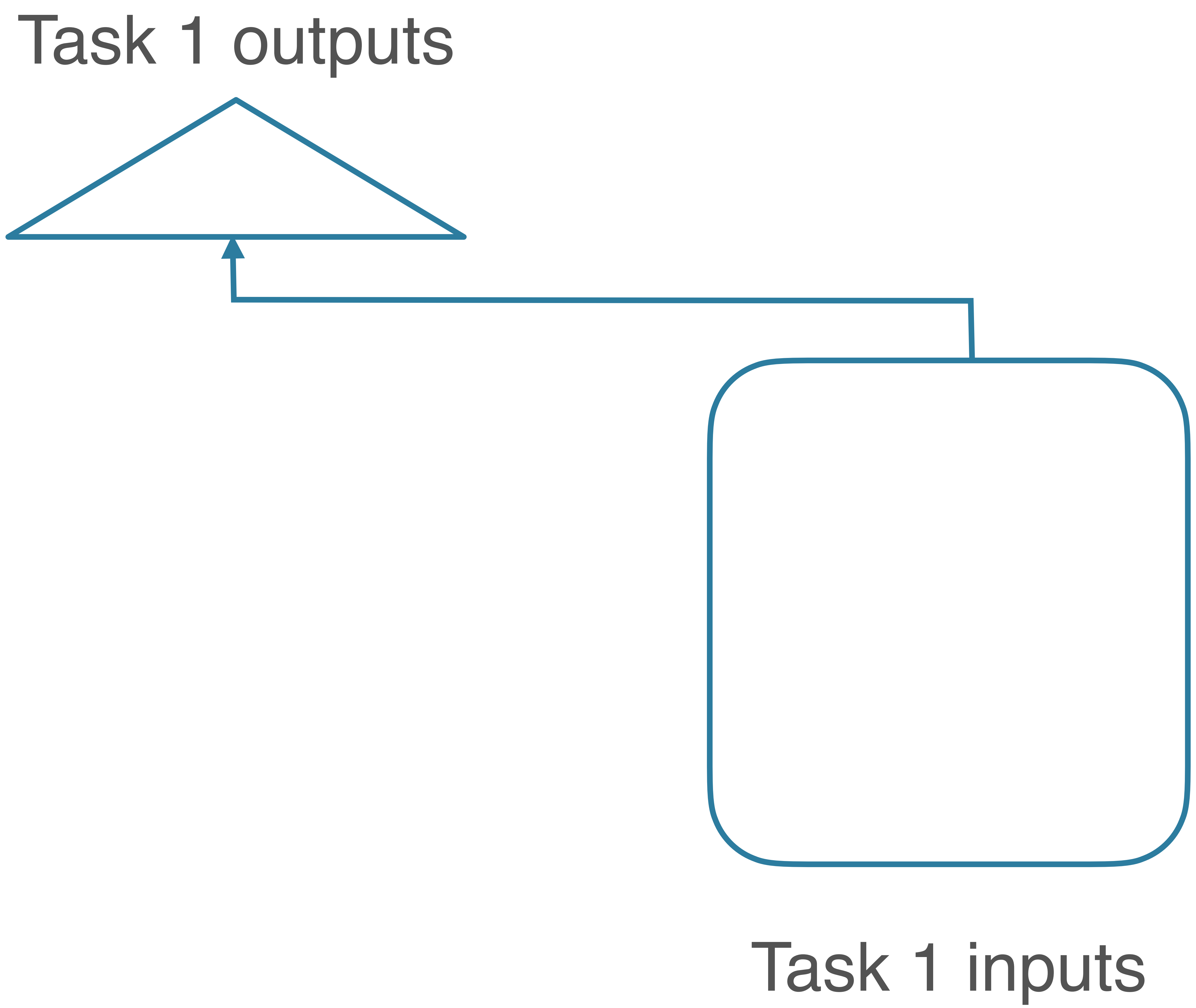
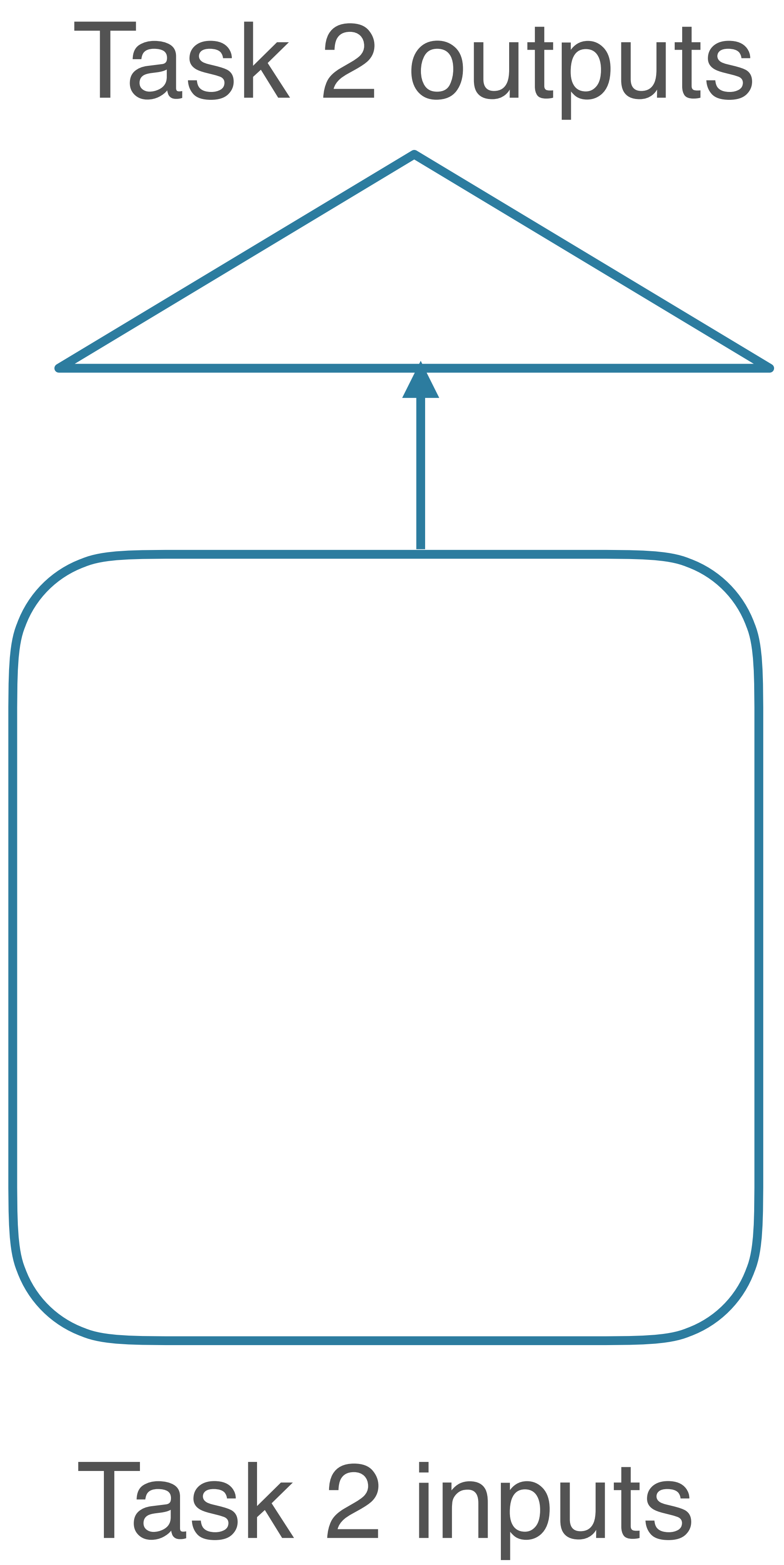


Transfer Learning

Transfer Learning

Task 2 inputs

Transfer Learning



Transfer Learning

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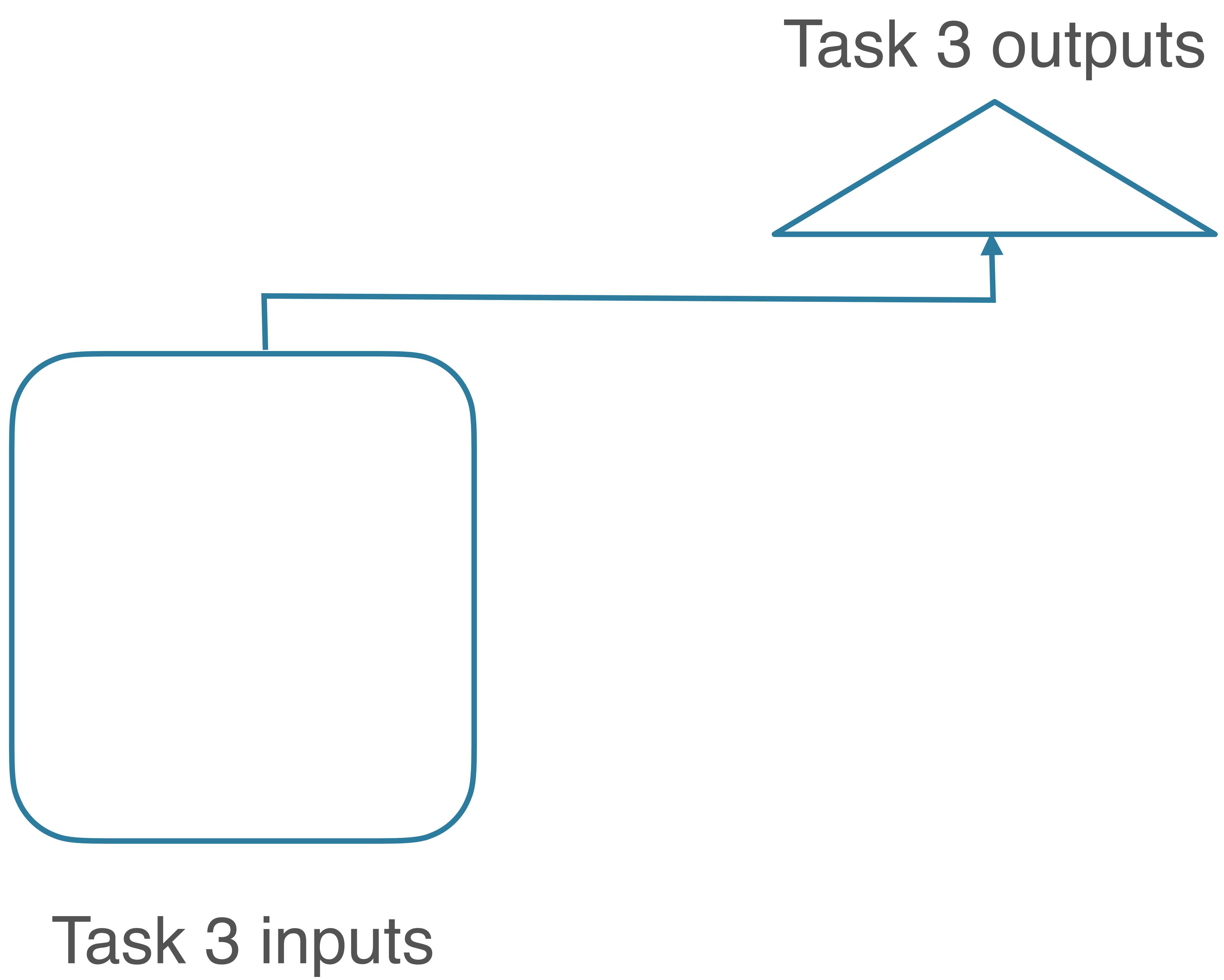
Task 3 inputs

Transfer Learning



Transfer Learning

Pre-training + Fine-tuning

Pre-training + Fine-tuning

- Step 1: **pre-train** a model on a “general” task
  - Questions: which task for pre-training? More in a minute.
  - Goal: produce **general-purpose representations** of the input (“representation learning”), that will be useful when “transferred” to a more specific task.

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  - Goal: produce **general-purpose representations** of the input (“representation learning”), that will be useful when “transferred” to a more specific task.
- Step 2: **fine-tune** that model on the main task
  - Replace the “head” of the model with some **task-specific layers**
  - Run supervised training with the resulting model

Origins in Computer Vision

"We use features extracted from the `OverFeat` network as a generic image representation to tackle the diverse range of recognition tasks of object image classification, scene recognition, fine grained recognition, attribute detection and image retrieval applied to a diverse set of datasets. We selected these tasks and datasets as they gradually move further away from the original task and data the `OverFeat` network was trained to solve [cf. ImageNet]. Astonishingly, we report consistent superior results compared to the highly tuned state-of-the-art systems in all the visual classification tasks on various datasets"

CNN Features off-the-shelf: an Astounding Baseline for Recognition

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Stockholm, Sweden
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Language Model Pre-training

Where to transfer *from*?

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  - Machine translation
  - QA
  - …
- Scalability issue: all require **expensive annotation**

Language Modeling

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  - The bicycles, even though old, were in good shape because _____ …
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- **Linguistic knowledge**
  - The bicycles, even though old, were in good shape because _____ …
  - The bicycle, even though old, was in good shape because _____ …
- **World knowledge**
  - The University of Washington was founded in ______
  - Seattle had a huge population boom as a launching point for expeditions to ______

Data for LM is cheap

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Text

Language Model Pre-training

- A recent powerful paradigm for training models for NLP tasks
- **Pre-train** a large language model on a large amount of **raw text**
- **Fine-tune** a small model on top of the LM for the **task** you care about
  - (or use the LM as a general feature extractor)

Deep Contextualized Word Representations

[Peters et. al (2018)]

- NAACL 2018 Best Paper Award
- **E**mbeddings from **L**anguage **Mo**dels (ELMo)
    - the OG NLP Muppet
- Idea: use a **deep, bi-directional LM** to get **robust representations** of words **in a specific context**

Deep contextualized word representations

Matthew E. Peters[†], **Mark Neumann**[†], **Mohit Iyyer**[†], **Matt Gardner**[†],
{matthewp,markn,mohiti,mattg}@allenai.org

Christopher Clark[*], **Kenton Lee**[*], **Luke Zettlemoyer**[†*]
{csquared,kentonl,lsz}@cs.washington.edu

[†]Allen Institute for Artificial Intelligence
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Abstract

We introduce a new type of *deep contextualized* word representation that models both (1) complex characteristics of word use (e.g., syntax and semantics), and (2) how these uses vary across linguistic contexts (i.e., to model polysemy). Our word vectors are learned functions of the internal states of a deep bidirectional language model (biLM), which is pre-trained on a large text corpus. We show that these representations can be easily added to existing models and significantly improve the state of the art across six challenging NLP problems, including question answering, textual entailment and sentiment analysis. We also present an analysis showing that exposing the deep internals of the pre-trained network is crucial, allowing downstream models to mix different types of semi-supervision signals.

guage model (LM) objective on a large text corpus. For this reason, we call them ELMo (Embeddings from Language Models) representations. Unlike previous approaches for learning contextualized word vectors (Peters et al., 2017; McCann et al., 2017), ELMo representations are deep, in the sense that they are a function of all of the internal layers of the biLM. More specifically, we learn a linear combination of the vectors stacked above each input word for each end task, which markedly improves performance over just using the top LSTM layer.

Combining the internal states in this manner allows for very rich word representations. Using intrinsic evaluations, we show that the higher-level LSTM states capture context-dependent aspects of word meaning (e.g., they can be used without modification to perform well on supervised

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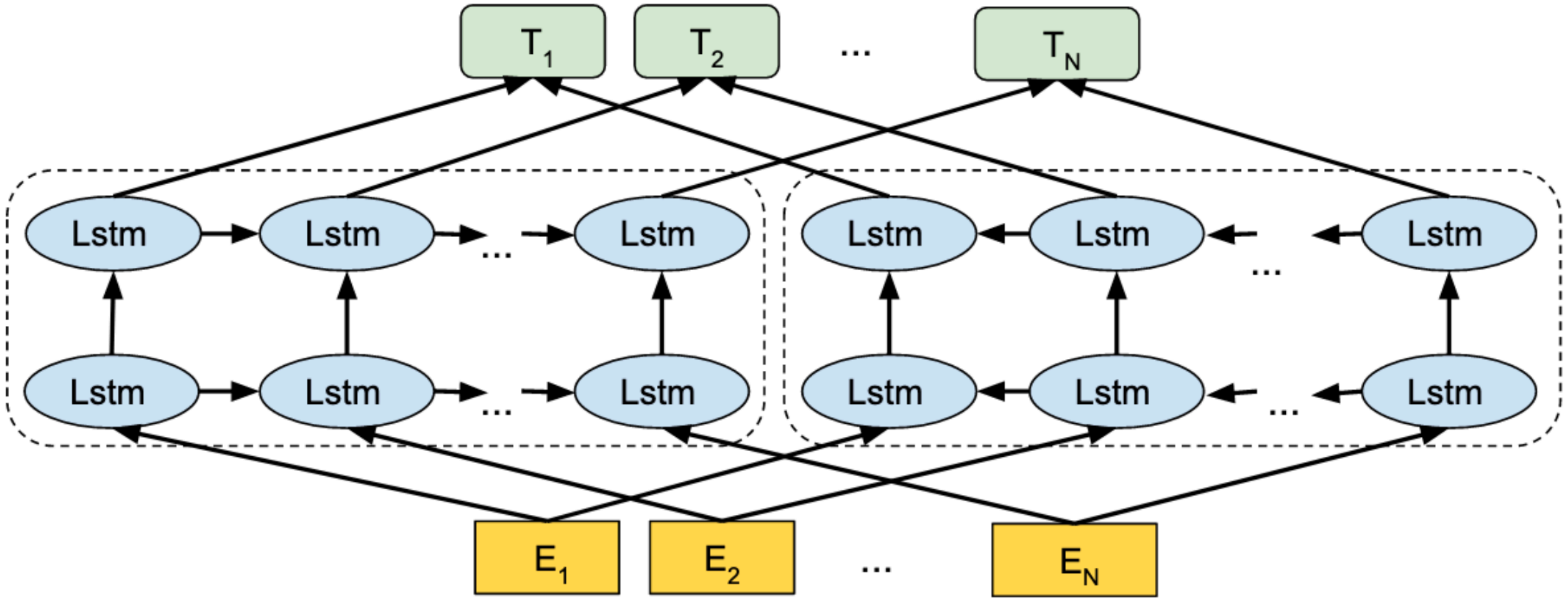
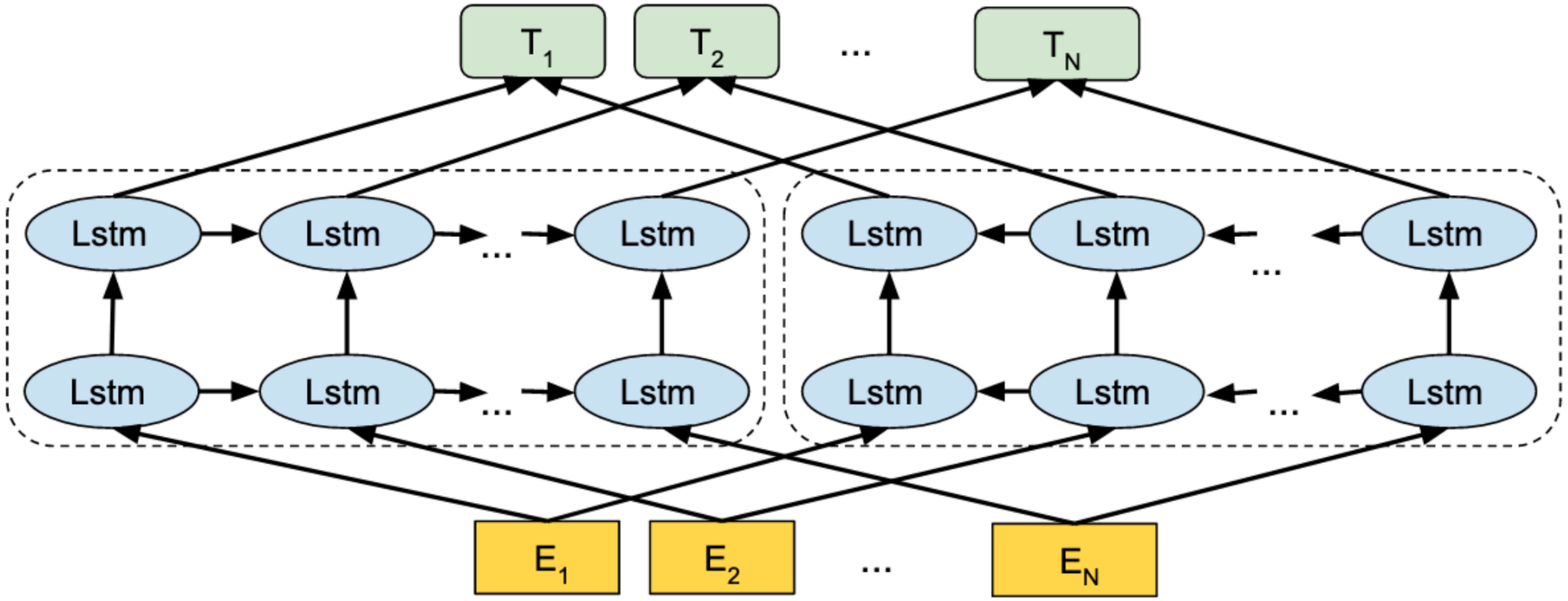
ELMo Model



Source: BERT paper

ELMo Model

4096-d hidden state



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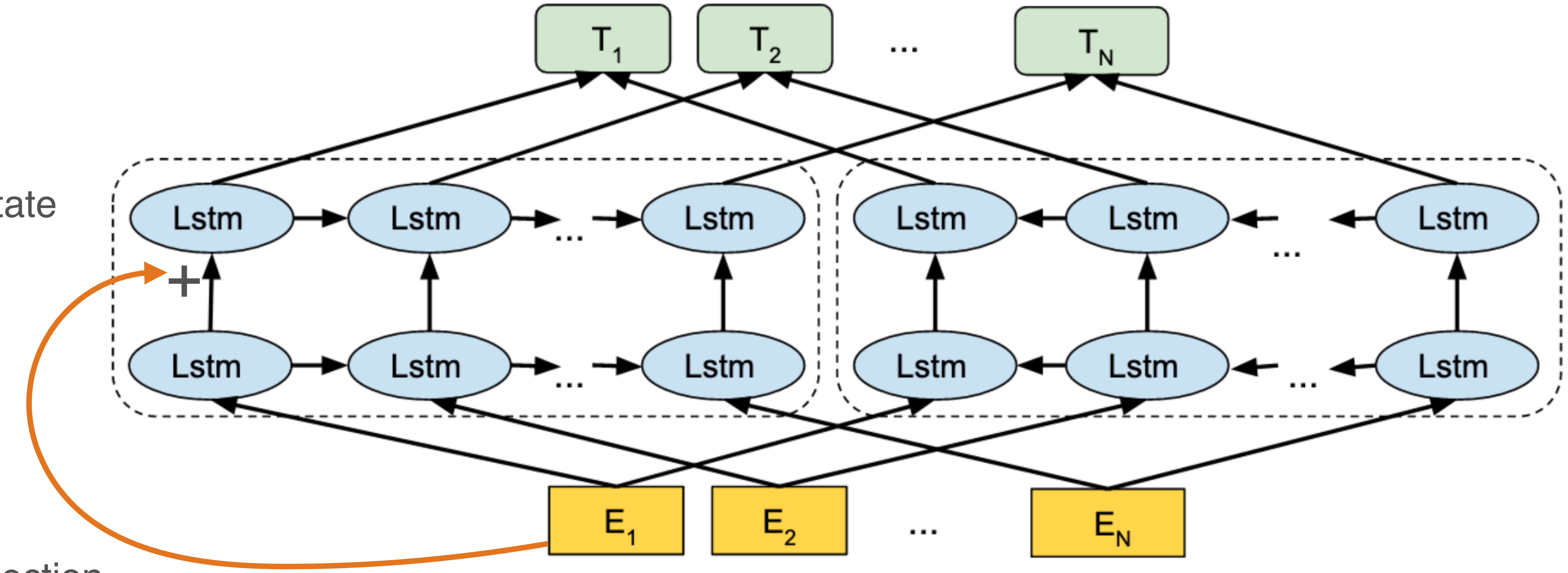

residual connection

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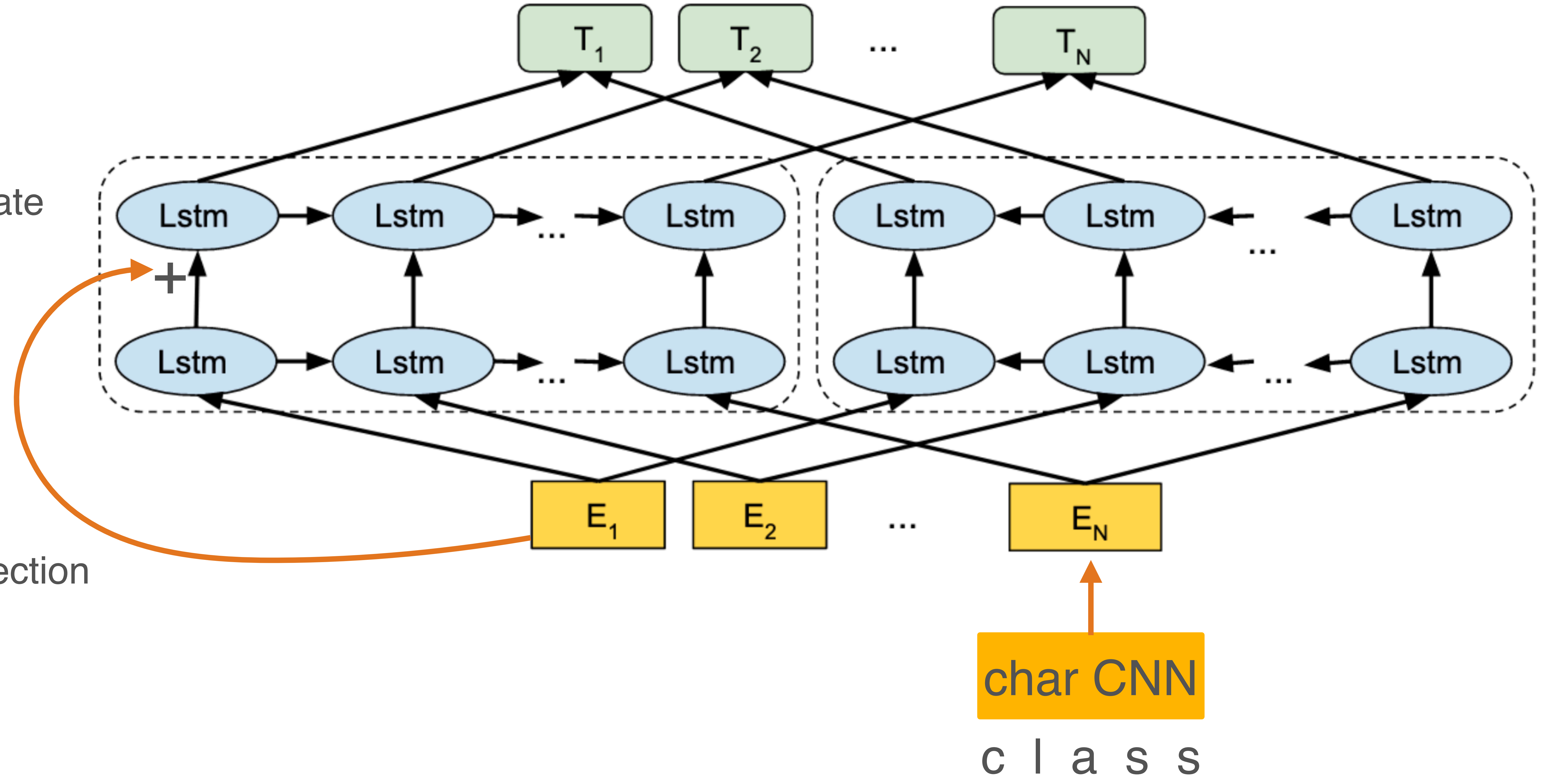

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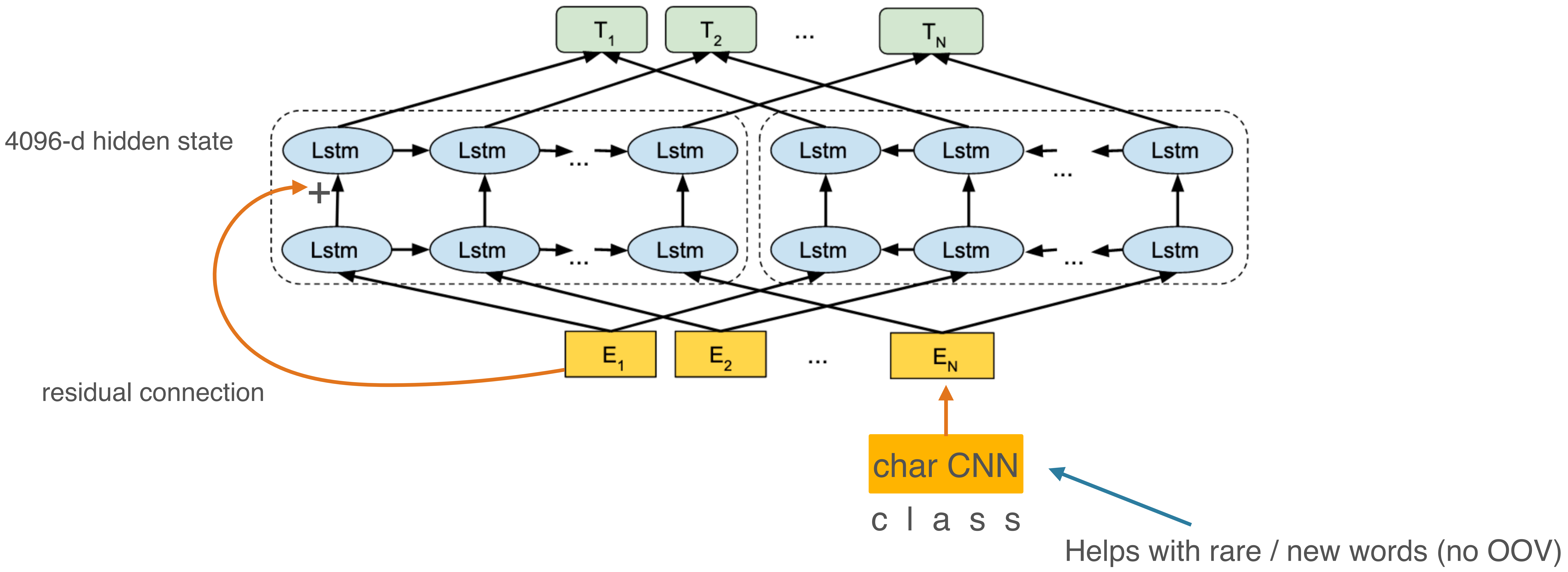


[Source: BERT paper]

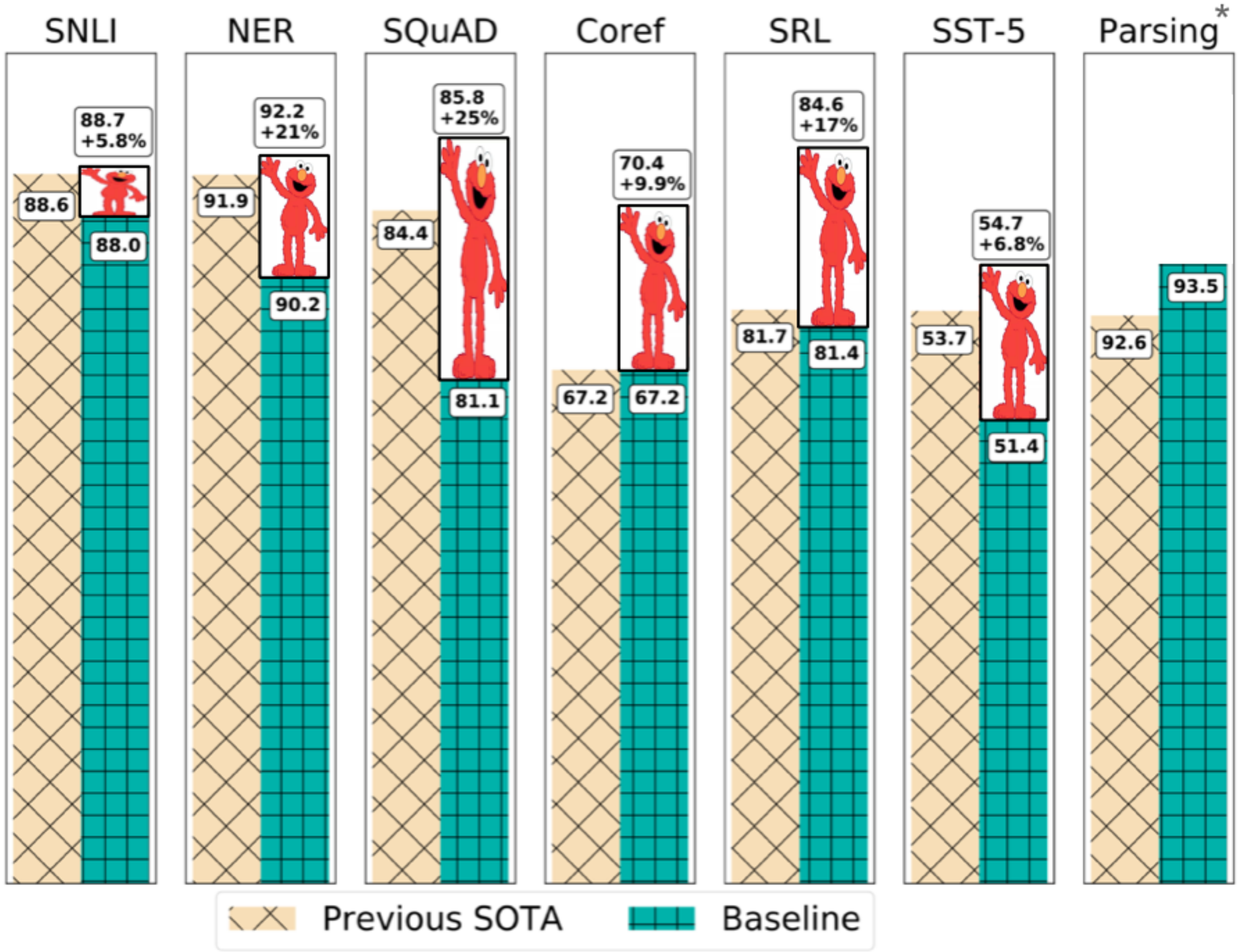
ELMo Training

- 10 epochs on 1B Word Benchmark
- **Not** SOTA perplexity even at time of publishing
  - See "Exploring the Limits of Language Modeling" paper
- Regularization:
  - Dropout
  - L2 norm

Usefulness in Downstream Tasks

Peters et. al (2018)

SQuAD = Stanford Question Answering Dataset
SNLI = Stanford Natural Language Inference Corpus
SST-5 = Stanford Sentiment Treebank



*Kitaev and Klein, ACL 2018 (see also Joshi et al., ACL 2018)

Global vs. Contextual Word Vectors

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- **Global** vectors: one vector per **word-type**
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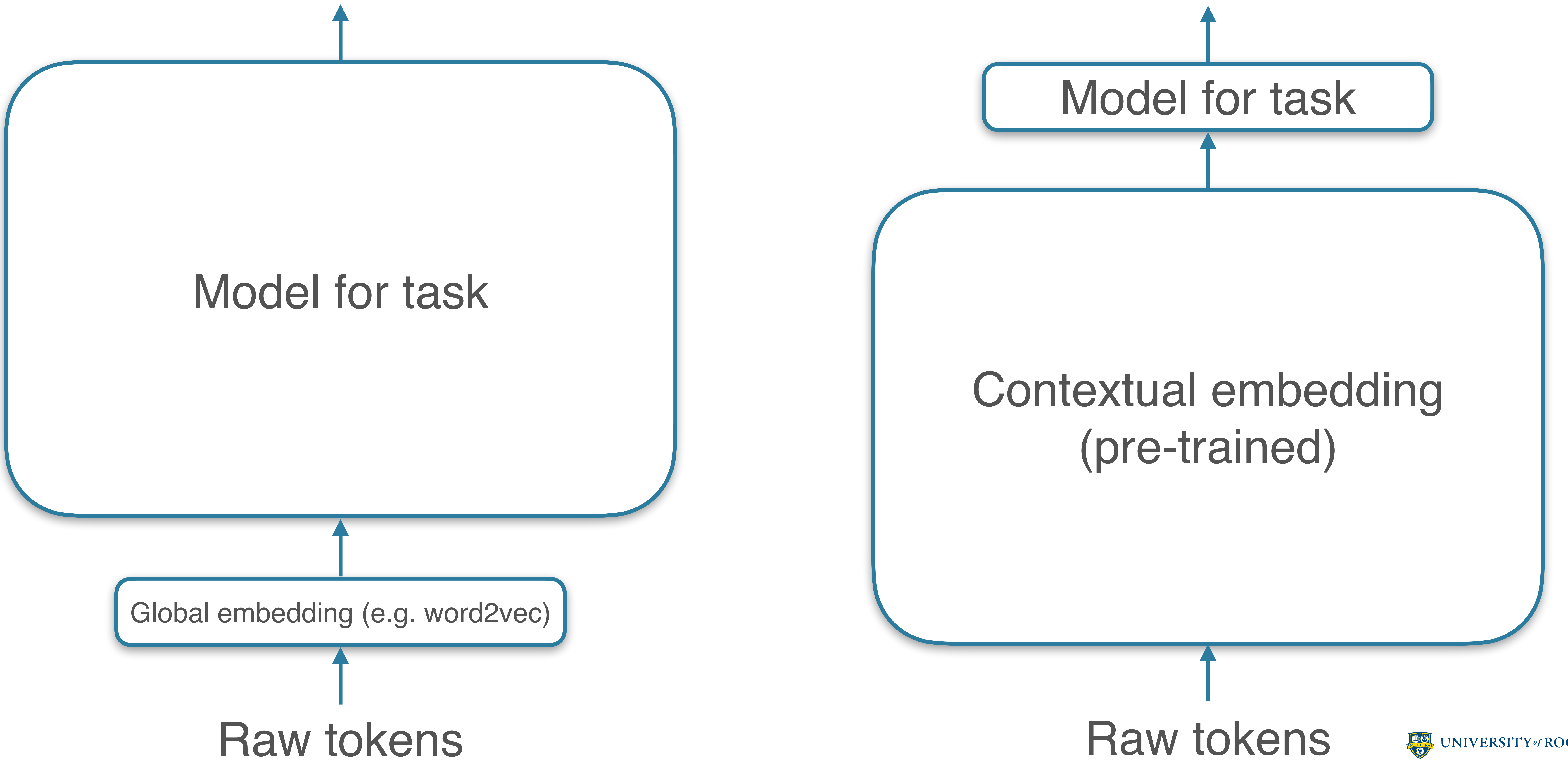
- **Global** vectors: one vector per **word-type**
  - E.g. word2vec, GloVe
  - No difference between e.g. “play” as a verb, noun, or its different senses
- **Contextual** vectors: one vector per **word-occurrence**
  - “We saw a really great **play** last week.”
  - “Do you want to **play** basketball tomorrow?”
  - Each *occurrence* gets its own vector representation.

Global vs. Contextual Word Vectors

Peters et. al (2018)

	Source	Nearest Neighbors
Global	play	playing, game, games, played, players, plays, player, Play, football, multiplayer
Contextual	Chico Ruiz made a spectacular **play** on Alusik's grounder…	Kieffer, the only junior in the group, was commended for his ability to hit in the clutch, as well as his all-round excellent **play**.
	Olivia De Havilland signed to do a Broadway **play** for Garson…	…they were actors who had been handed fat roles in a successful **play**, and had talent enough to fill the roles competently, with nice understatement.

Shallow vs Deep Pre-training



~~Current~~ Circa-2021 Benchmarks

SuperGLUE GLUE Paper Code Tasks Leaderboard FAQ Diagnostics

Leaderboard Version: **2.0**

	Rank	Name	Model	URL	Score	BoolQ	CB	COPA	MultiRC	ReCoRD	RTE	WiC	WSC	AX-g	AX-b
+	1	Zirui Wang	T5 + Meena, Single Model (Meena Team - Google Brain)		90.4	91.4	95.8/97.6	98.0	88.3/63.0	94.2/93.5	93.0	77.9	96.6	92.7/91.9	69.1
+	2	DeBERTa Team - Microsoft	DeBERTa / TuringNLRv4		90.3	90.4	95.7/97.6	98.4	88.2/63.7	94.5/94.1	93.2	77.5	95.9	93.3/93.8	66.7
	3	SuperGLUE Human Baselines	SuperGLUE Human Baselines		89.8	89.0	95.8/98.9	100.0	81.8/51.9	91.7/91.3	93.6	80.0	100.0	99.3/99.7	76.6
+	4	T5 Team - Google	T5		89.3	91.2	93.9/96.8	94.8	88.1/63.3	94.1/93.4	92.5	76.9	93.8	92.7/91.9	65.6
+	5	Huawei Noah's Ark Lab	NEZHA-Plus		86.7	87.8	94.4/96.0	93.6	84.6/55.1	90.1/89.6	89.1	74.6	93.2	87.1/74.4	58.0
+	6	Alibaba PAI&ICBU	PAI Albert		86.1	88.1	92.4/96.4	91.8	84.6/54.7	89.0/88.3	88.8	74.1	93.2	98.3/99.2	75.6
+	7	Infosys : DAWN : AI Research	RoBERTa-iCETS		86.0	88.5	93.2/95.2	91.2	86.4/58.2	89.9/89.3	89.9	72.9	89.0	88.8/81.5	61.8
+	8	Tencent Jarvis Lab	RoBERTa (ensemble)		85.9	88.2	92.5/95.6	90.8	84.4/53.4	91.5/91.0	87.9	74.1	91.8	89.3/75.6	57.6
	9	Zhuiyi Technology	RoBERTa-mtl-adv		85.7	87.1	92.4/95.6	91.2	85.1/54.3	91.7/91.3	88.1	72.1	91.8	91.0/78.1	58.5
	10	Facebook AI	RoBERTa		84.6	87.1	90.5/95.2	90.6	84.4/52.5	90.6/90.0	88.2	69.9	89.0	91.0/78.1	57.9
+	11	Anuar Sharafudinov	AILabs Team, Transformers		82.6	88.1	91.6/94.8	86.8	85.1/54.7	82.8/79.8	88.9	74.1	78.8	100.0/100.0	100.0
	12	Rakesh Radhakrishnan Menon	ADAPET (ALBERT) - few-shot		76.0	80.0	82.3/92.0	85.4	76.2/35.7	86.1/85.5	75.0	53.5	85.6	100.0/50.0	-0.4
+	13	Timo Schick	iPET (ALBERT) - Few-Shot (32 Examples)		75.4	81.2	79.9/88.8	90.8	74.1/31.7	85.9/85.4	70.8	49.3	88.4	97.8/57.9	36.2
	14	Adrian de Wynter	Bort (Alexa AI)		74.1	83.7	81.9/86.4	89.6	83.7/54.1	49.8/49.0	81.2	70.1	65.8	96.1/61.5	48.0
	15	IBM Research AI	BERT-mtl		73.5	84.8	89.6/94.0	73.8	73.2/30.5	74.6/74.0	84.1	66.2	61.0	97.8/57.3	29.6
	16	Ben Mann	GPT-3 few-shot - OpenAI		71.8	76.4	52.0/75.6	92.0	75.4/30.5	91.1/90.2	69.0	49.4	80.1	90.4/55.3	21.1
	17	SuperGLUE Baselines	BERT++	BERT++	1.5	79.0	84.8/90.4	73.8	70.0/24.1	72.0/71.3	79.0	69.6	64.4	99.4/51.4	38.0
			BERT		69.0	77.4	75.7/83.6	70.6	70.0/24.1	72.0/71.3	71.7	69.6	64.4	97.8/51.7	23.0
			Most Frequent Class		47.1	62.3	21.7/48.4	50.0	61.1/0.3	33.4/32.5	50.3	50.0	65.1	100.0/50.0	0.0
			CBoW		44.5	62.2	49.0/71.2	51.6	0.0/0.5	14.0/13.6	49.7	53.1	65.1	100.0/50.0	-0.4

Pre-trained Transformers

Parallelism + Scale

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- ELMo
  - Demonstrates the value of **LM pre-training + transfer**
  - Noted that there are "**virtually unlimited**" quantities of data for LM
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- Concurrently: **Transformer** paper introduced
- Triggered an **explosion** in the pre-training approach
  - Lack of recurrence → paralellizability → scaling up both the **model** and **dataset**

Pre-trained Transformers: Encoder-only

BERT: Bidirectional Encoder Representations from Transformers

Devlin et al NAACL 2019

Overview

Overview

- Encoder Representations from Transformers: ✓

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- Encoder Representations from Transformers: ✓
- Bidirectional: …?
  - BiLSTM (ELMo): left-to-right and right-to-left
  - Self-attention: every token can see every other
  - **Adirectional / Non-directional** is probably a better term

Overview

- Encoder Representations from Transformers: ✓
- Bidirectional: …?
  - BiLSTM (ELMo): left-to-right and right-to-left
  - Self-attention: every token can see every other
  - **Adirectional / Non-directional** is probably a better term
- How do you treat the encoder as an LM computing $P(w_t \mid w_{t-1}, w_{t-2}, \ldots, w_1)$?
  - You don't: modify the Language Modeling task instead

Masked Language Modeling

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- (“Causal”) Language Modeling: **next word prediction**

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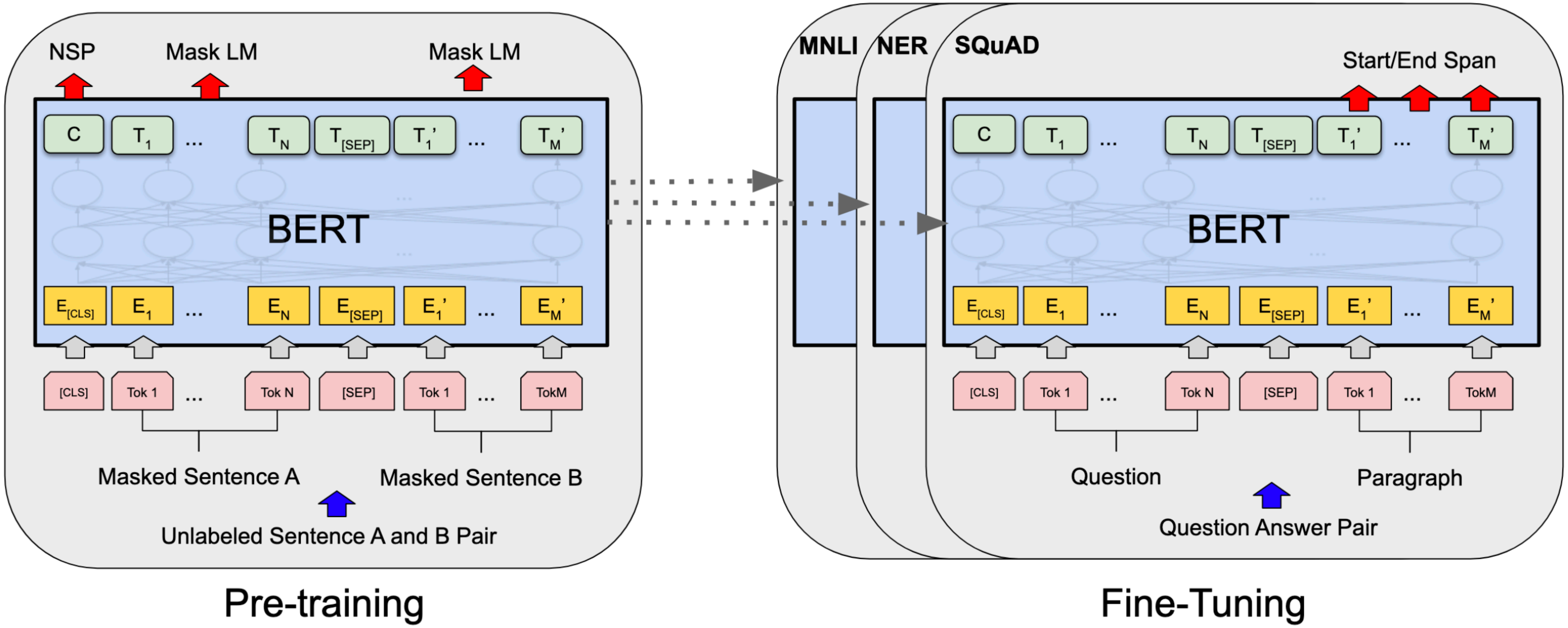
  - (very **similar to CBOW** from word2vec)
- Auxiliary training task: **next sentence prediction**
  - Given sentences A and B, binary classification: **did B follow A** in the corpus or not?

Schematically



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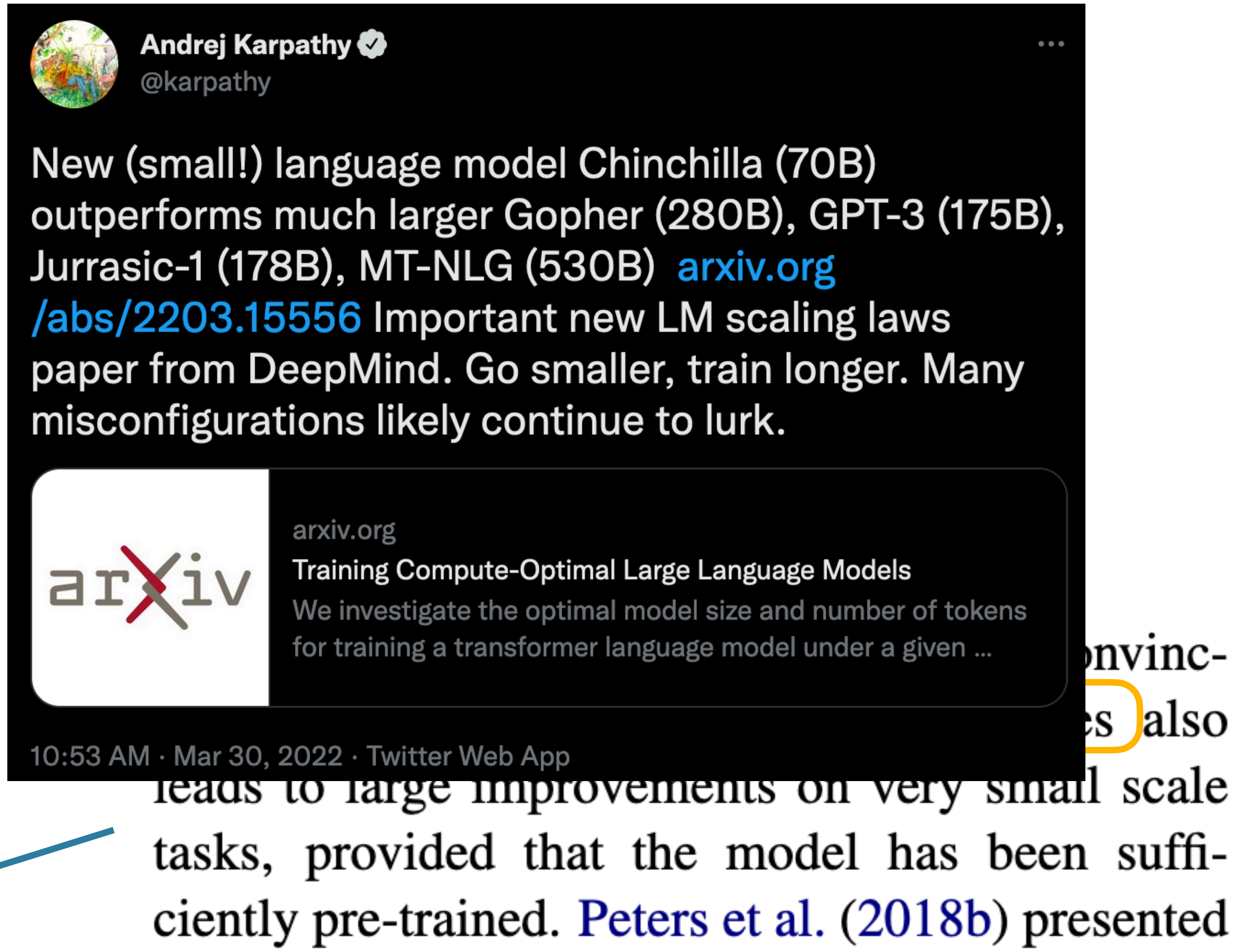
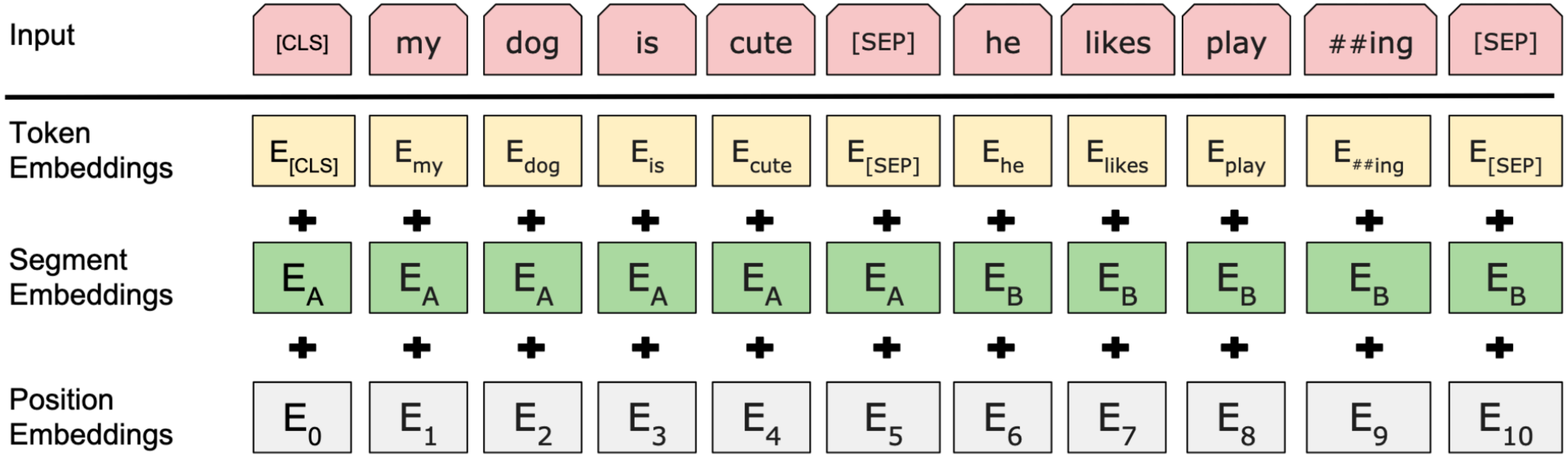
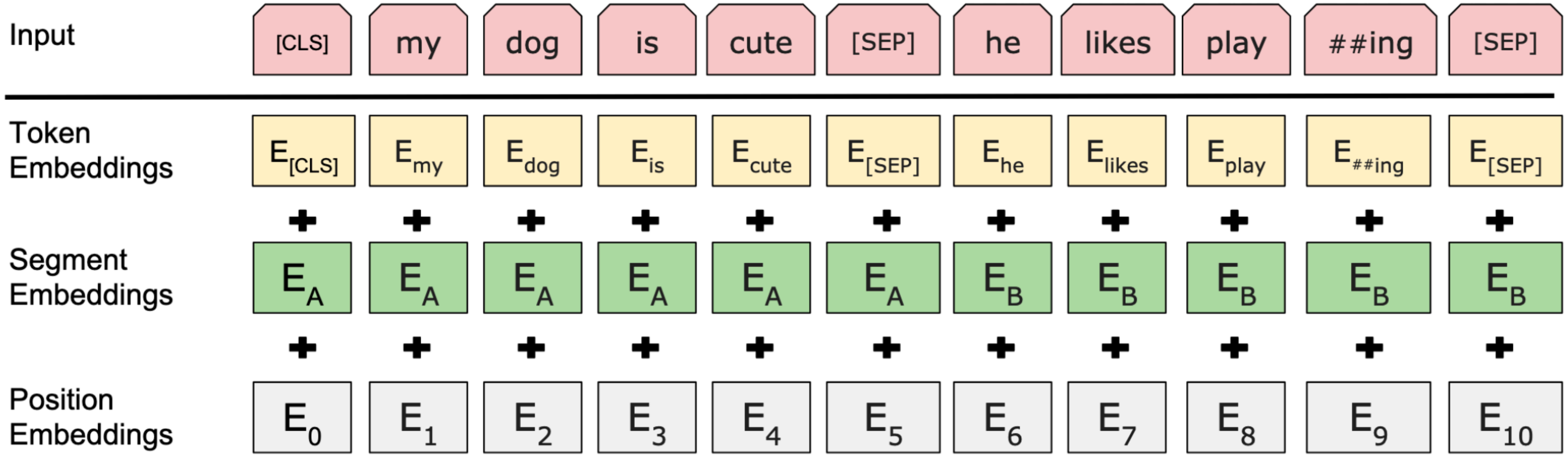


Input Representation



Input Representation

- [CLS], [SEP]: special tokens



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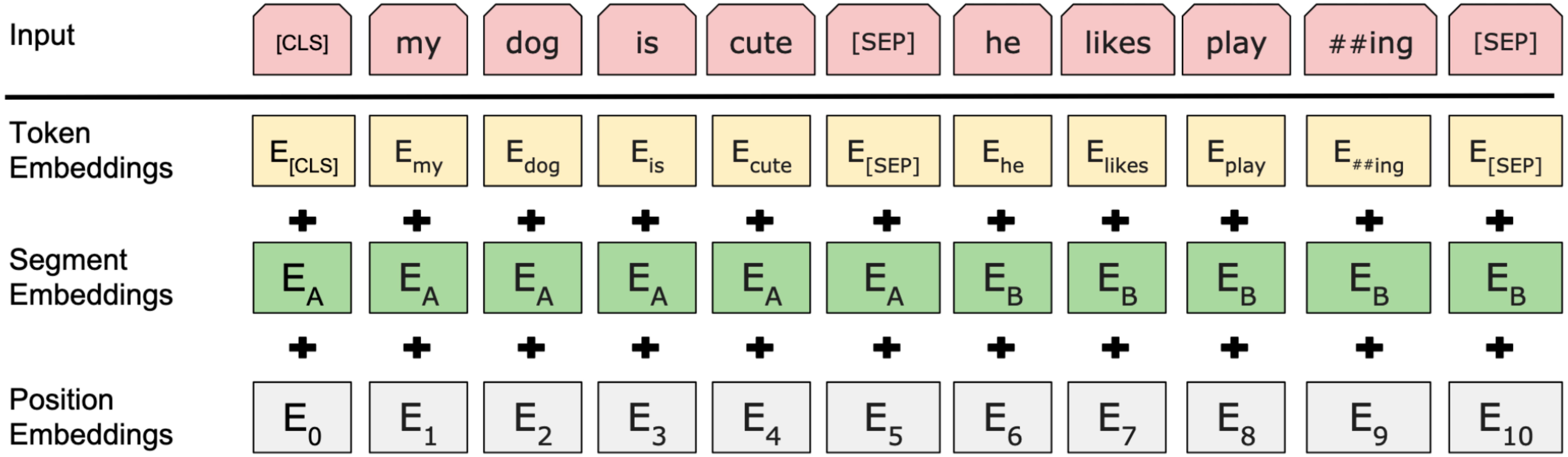

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- [CLS], [SEP]: special tokens
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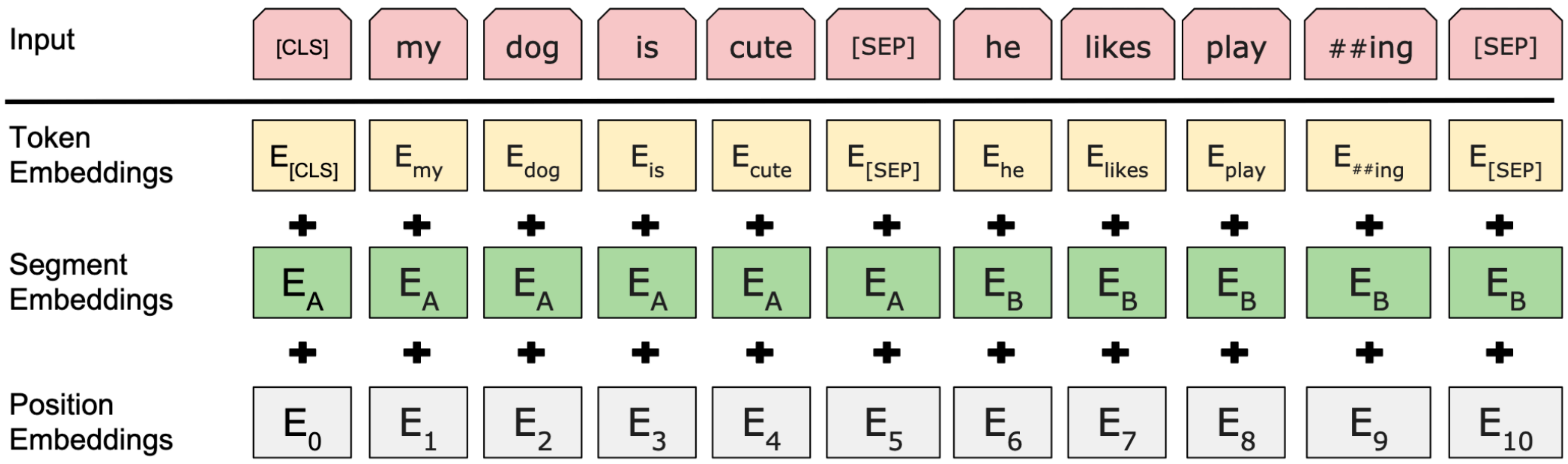
- Position embeddings: provide position in sequence (*learned* in this case, not fixed)



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- 1M training steps, batch size 256 = **4 days on 4/16 TPUs** (base/large)

Initial Results

System	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	**Average**
	392k	363k	108k	67k	8.5k	5.7k	3.5k	2.5k	-
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**

Other Prominent Encoders

- RoBERTa: robustly optimized BERT approach
  - BERT was very **under-trained**: give it **more data**, **train it longer**
  - (keep model the same otherwise)
  - Good default encoder
- ELECTRA: replace Masked Language Modeling with “replaced token detection”, trains just as well with much less data
- SpanBERT: mask out entire *spans* instead of single tokens

Limitation of Encoders

- **No left-to-right** modeling assumption
- Good for **NLU** (understanding/comprehension) tasks
- Does **not** straightforwardly **generate** text