Pre-training + Fine-tuning Paradigm

LING 575K Deep Learning for NLP

Shane Steinert-Threlkeld

May 4 2022

Announcements

- Thanks for the feedback!
- HW4: comp graph, one node for x
- Broken record reminders:
  - Read the docstrings closely, e.g. for return types, shapes, etc
  - Passing tests is necessary but not sufficient
- HW5, sample next character: return a [batch_size] shape *numpy array*

Note on Transformer Architecture

Do Transformer Modifications Transfer Across Implementations and Applications?

Sharan Narang* **Hyung Won Chung** **Yi Tay** **William Fedus**
Thibault Fevry† **Michael Matena** † **Karishma Malkan**† **Noah Fiedel**
Noam Shazeer **Zhenzhong Lan**† **Yanqi Zhou** **Wei Li**
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

Model Types in NLP (h/t Agatha on Canvas)

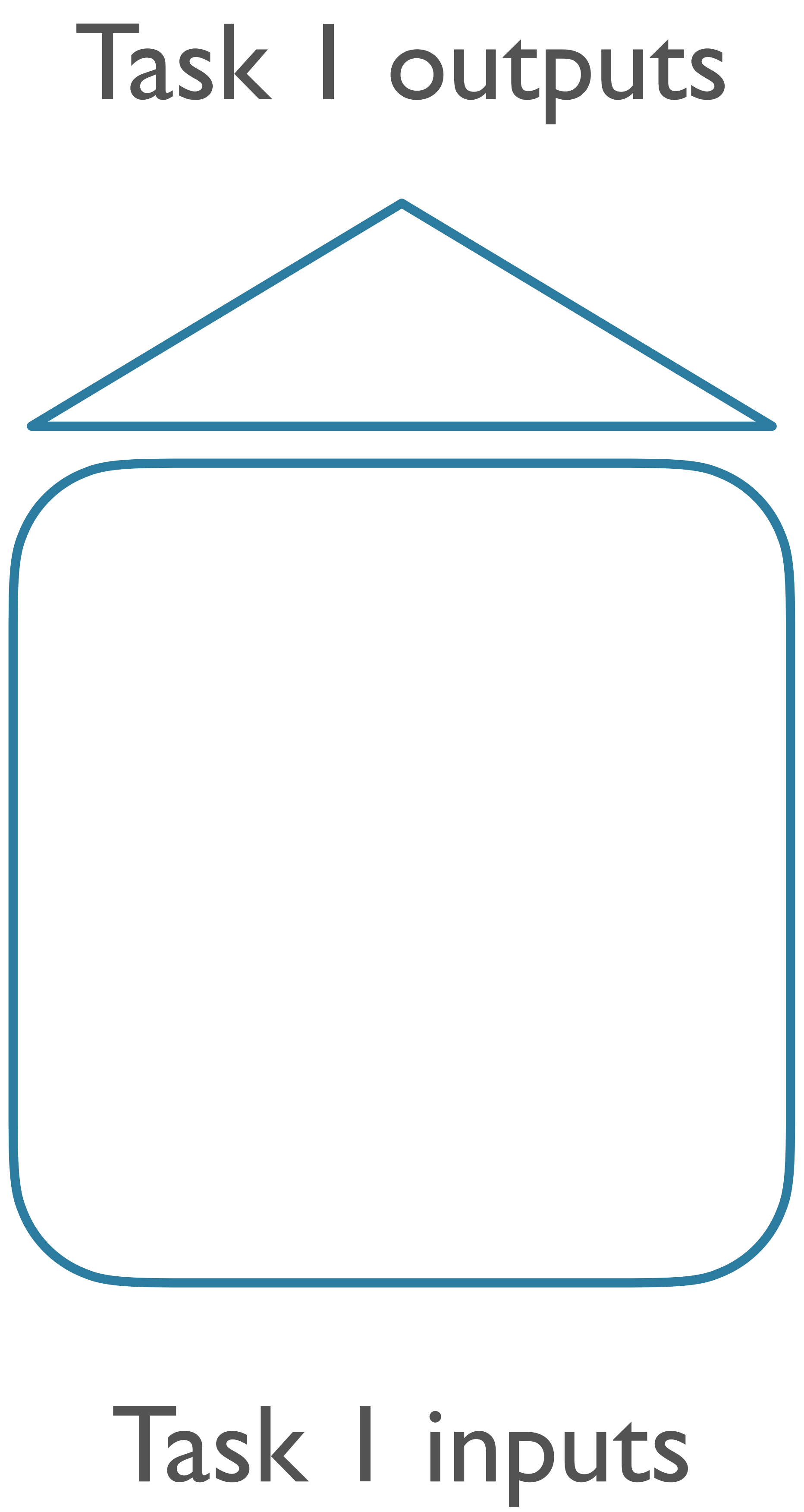
- Honestly, I've heard a lot of criticism of the visual at that link in particular (it's a weird way to display a lot of those model types). My impression of the very high-level landscape of neural nets in particular in 2022 is:
- Feedforward networks
  - Used when you just want to learn successive transformations of a vector, and don't necessarily need sequence/timestep information
- Recurrent networks (and you mostly use LSTMs)
  - For sequential data; especially good for generation, and at smaller scales
- Transformers
  - Good for sequential data, and now also being used a lot in computer vision (Vision Transformer, e.g.), multimodality, hints of “universality”
- Convolutional networks
  - Mostly used in computer vision, but are essentially like when you have a whole bunch of data points that are somehow related to each other by "locality" (like image pixels), and you want to sort of distill it down into a way smaller collection of features, e.g. like regions of the pictures first, then broader regions, then classification. Can think of them like higher-order n-gram detectors. In NLP: on-the-fly word embeddings by doing a convolution over the characters (ELMo; we’ll see today), but have also been used for classification.
- Generative Adversarial Networks (GANs)
  - These are like when you really want artificial data to look like human data somehow (look up GAN Garfield), or when you want to "align" representation spaces by making the difference between generated and real data imperceptible by the discriminator part. P sure this is also where deepfakes come from.

Today’s Plan

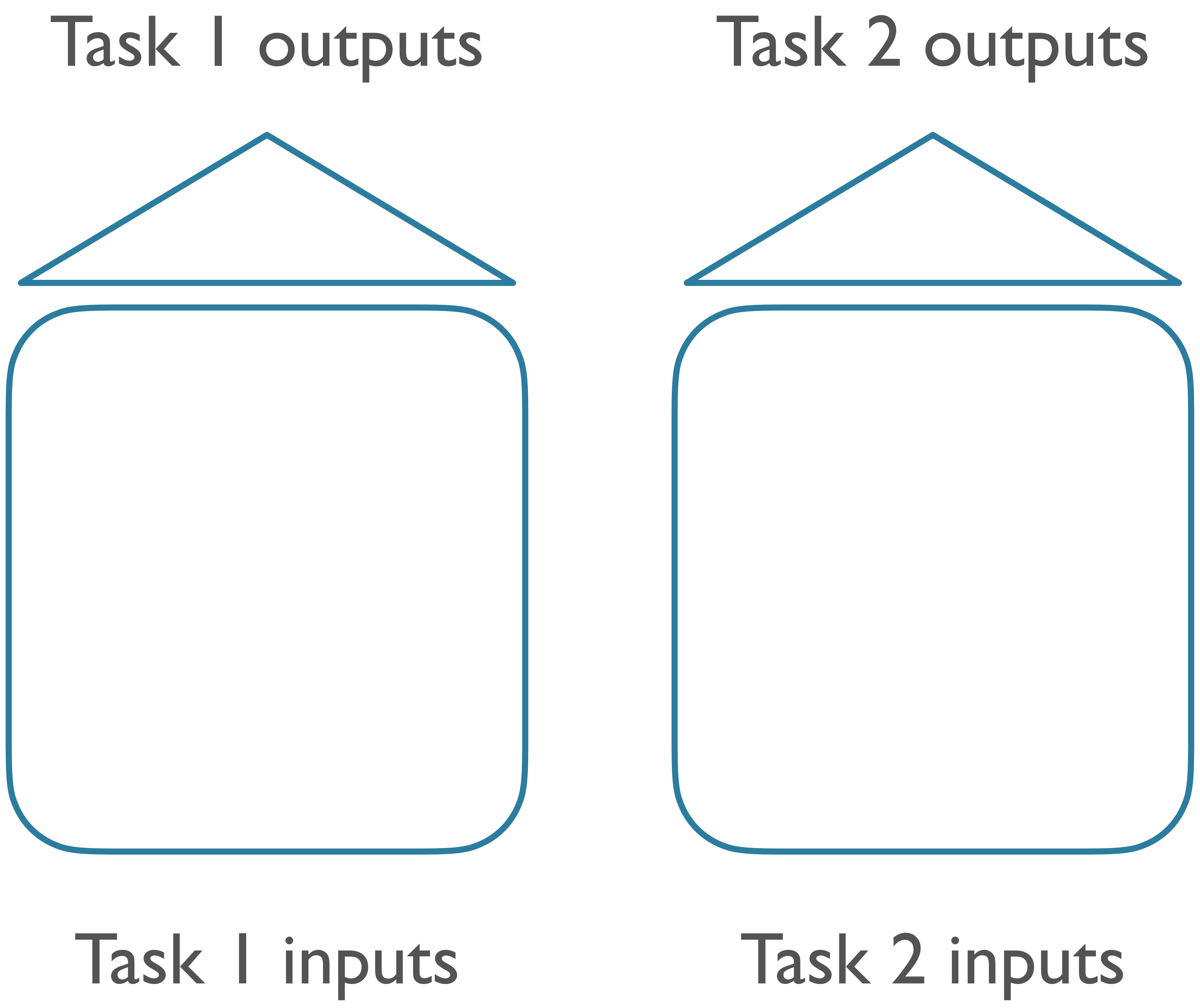
- Transfer learning in general
- Language model pre-training: initial steps
- Transformer-based pre-training
  - Encoder only
  - Decoder only
  - Encoder-Decoder
- [Some] limitations [more later in course]

Transfer Learning

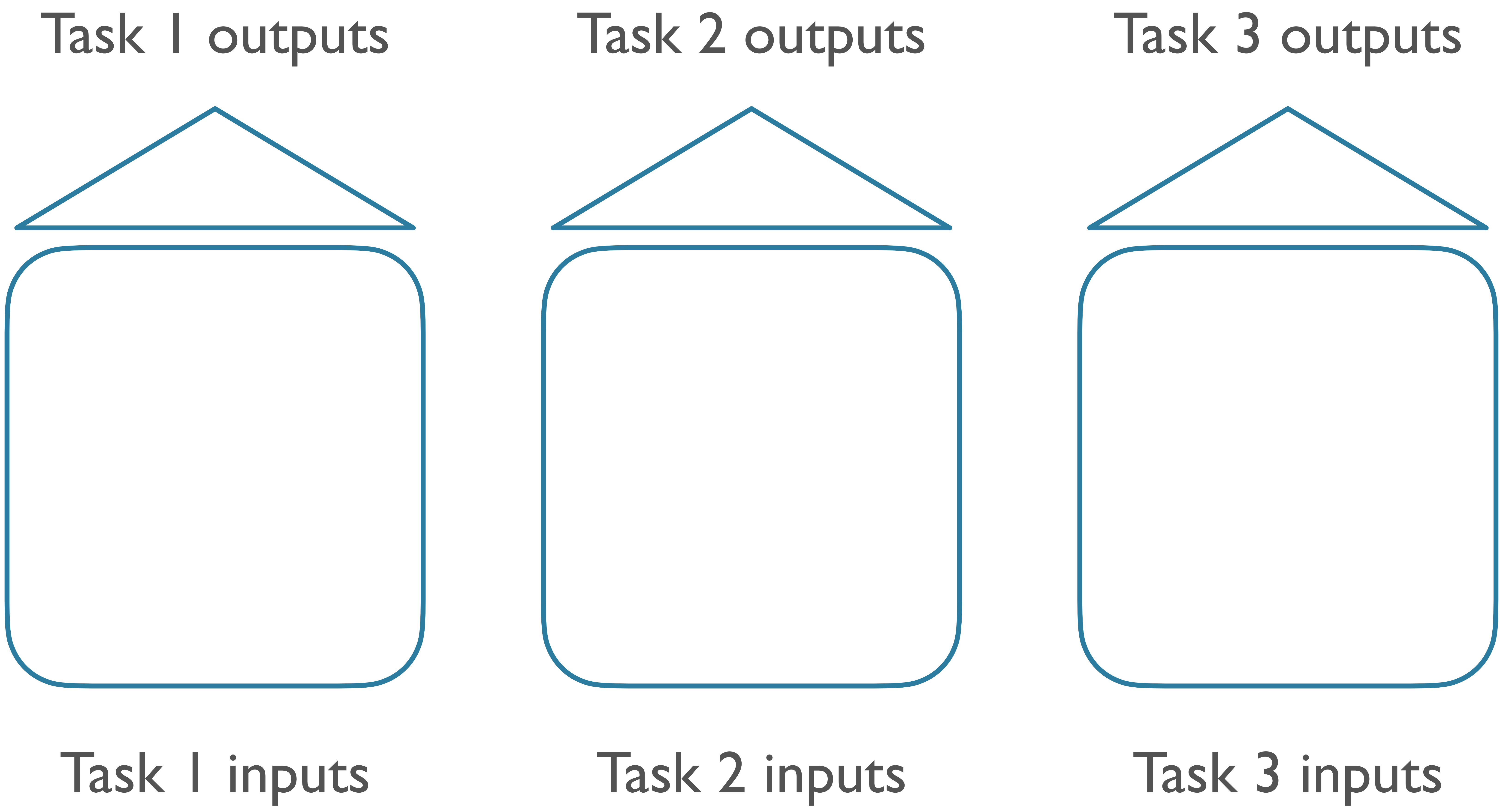
Standard Learning



Standard Learning

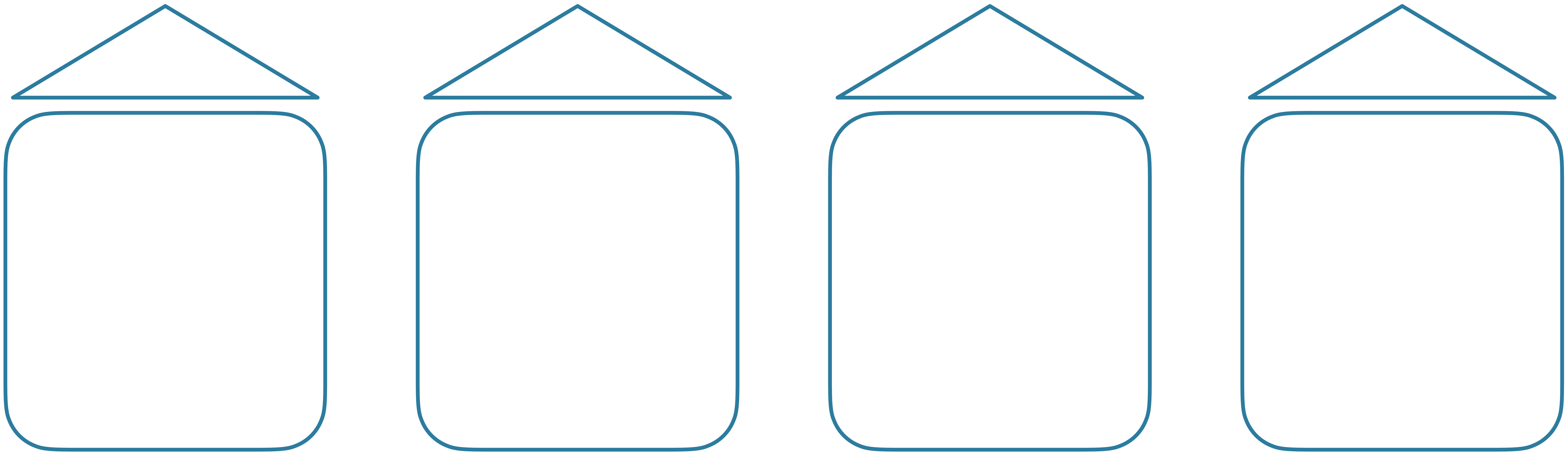


Standard Learning



Standard Learning

Task 1 outputs | Task 2 outputs | Task 3 outputs | Task 4 outputs



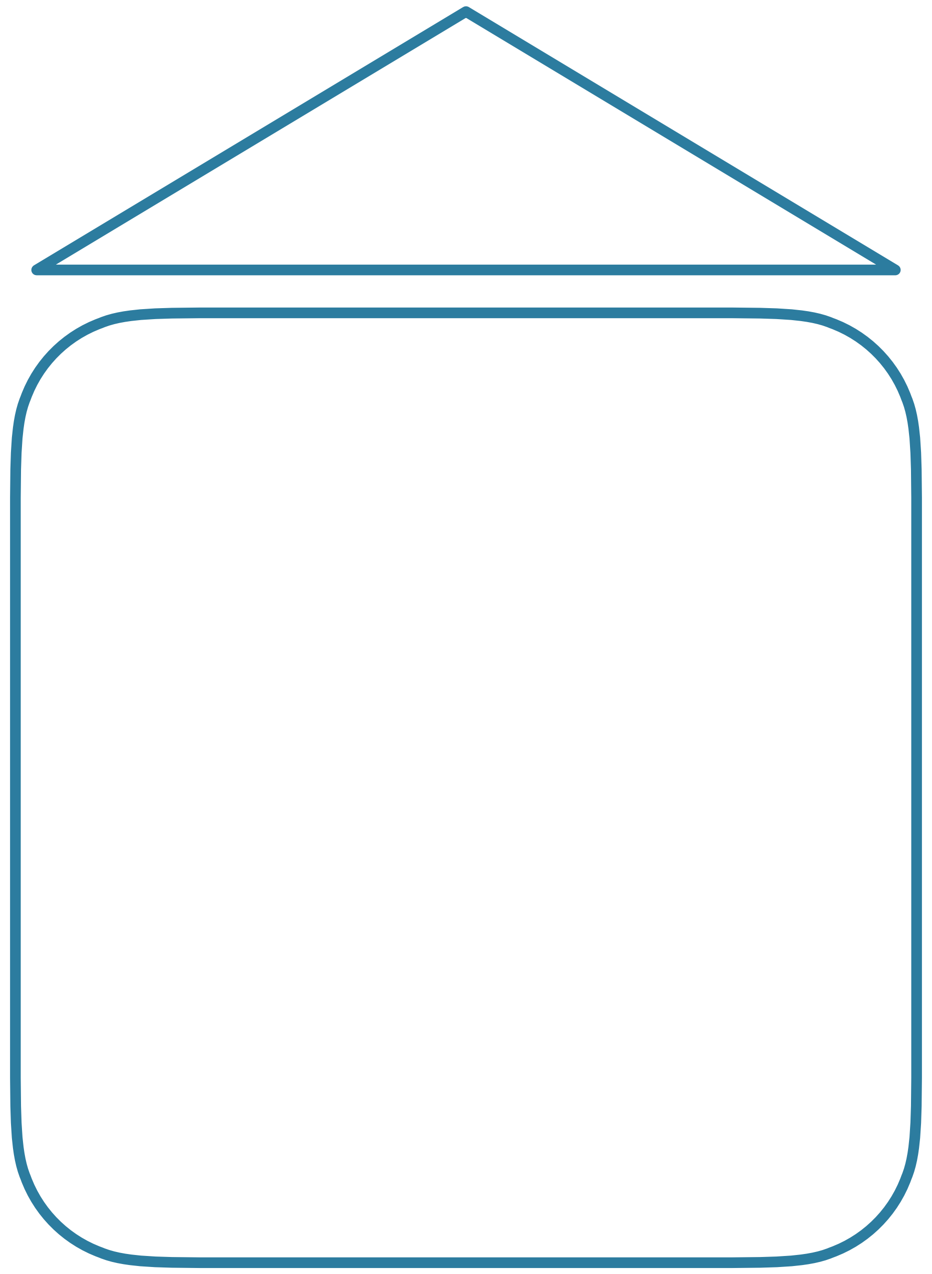
Task 1 inputs | Task 2 inputs | Task 3 inputs | Task 4 inputs

Standard 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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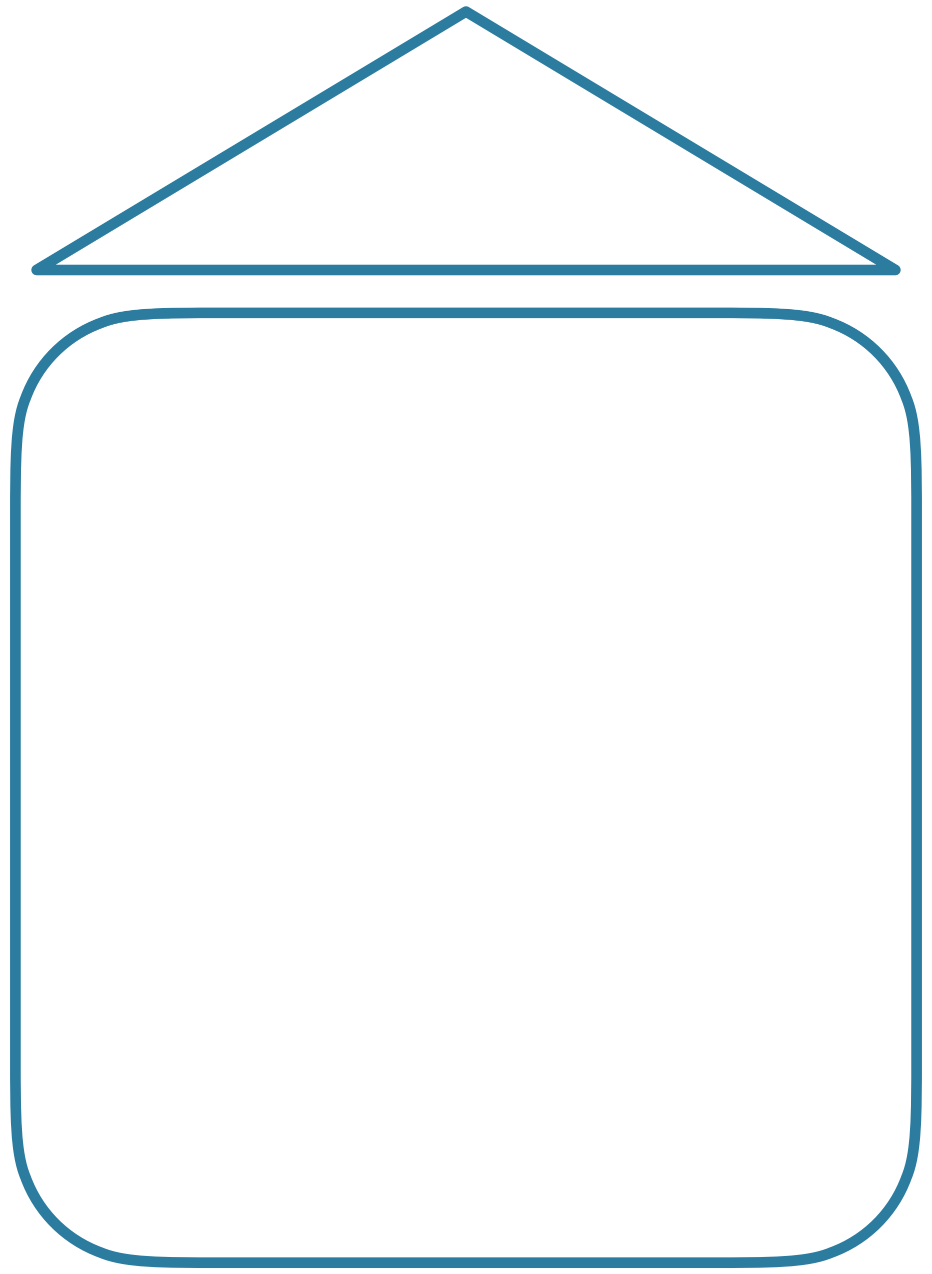

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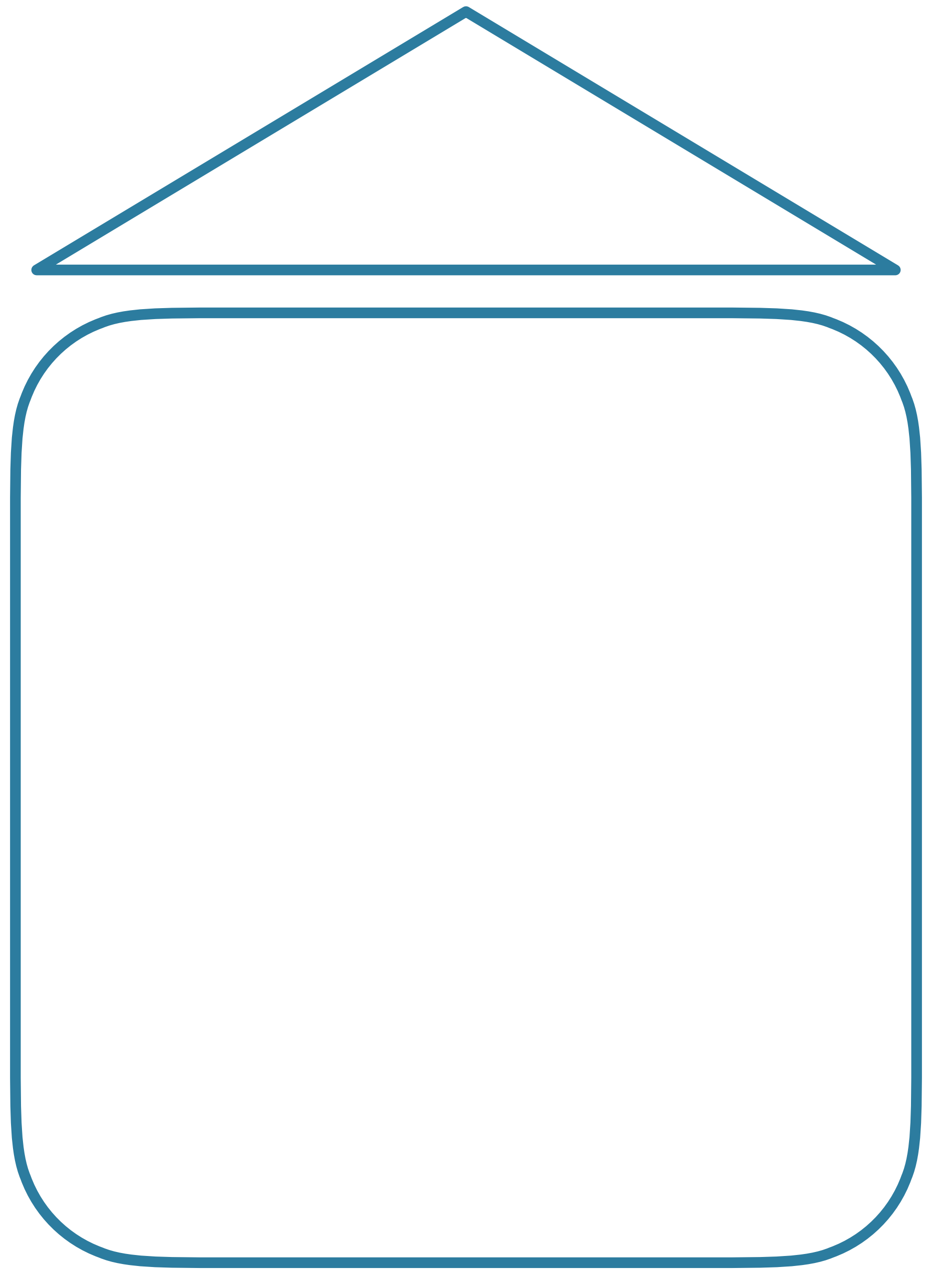
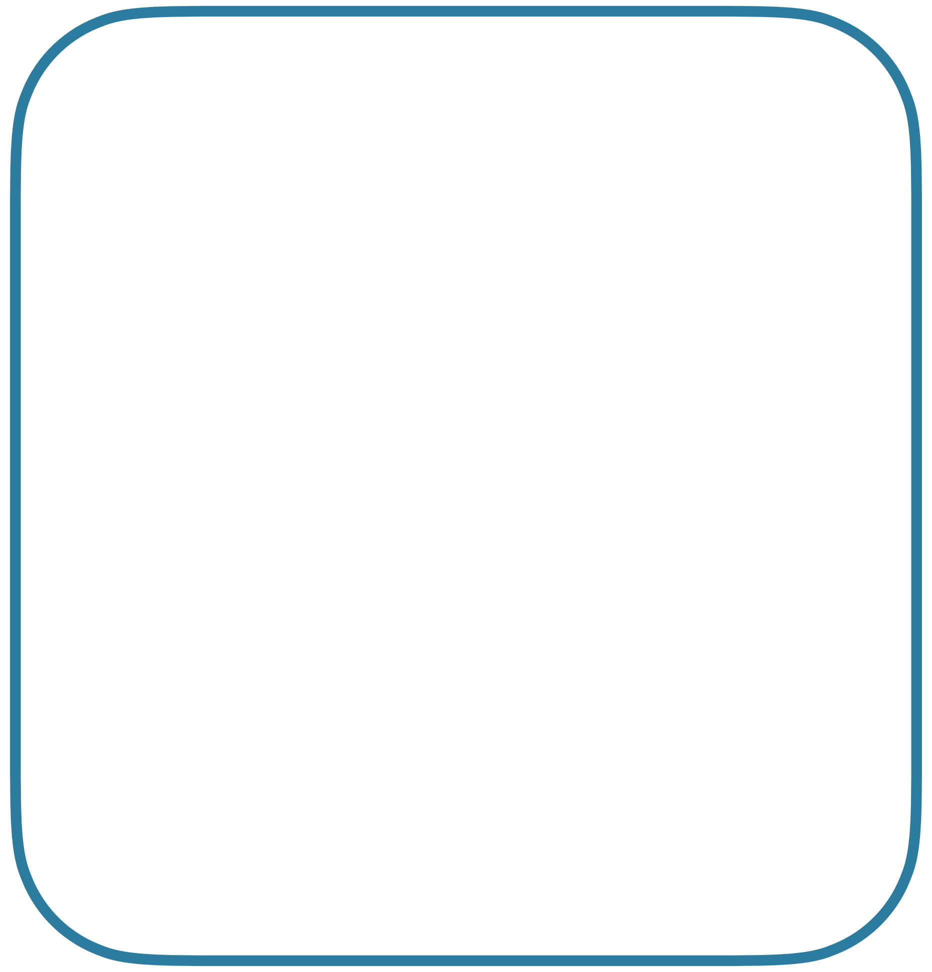


Task 1 inputs

Transfer Learning



Task 1 inputs

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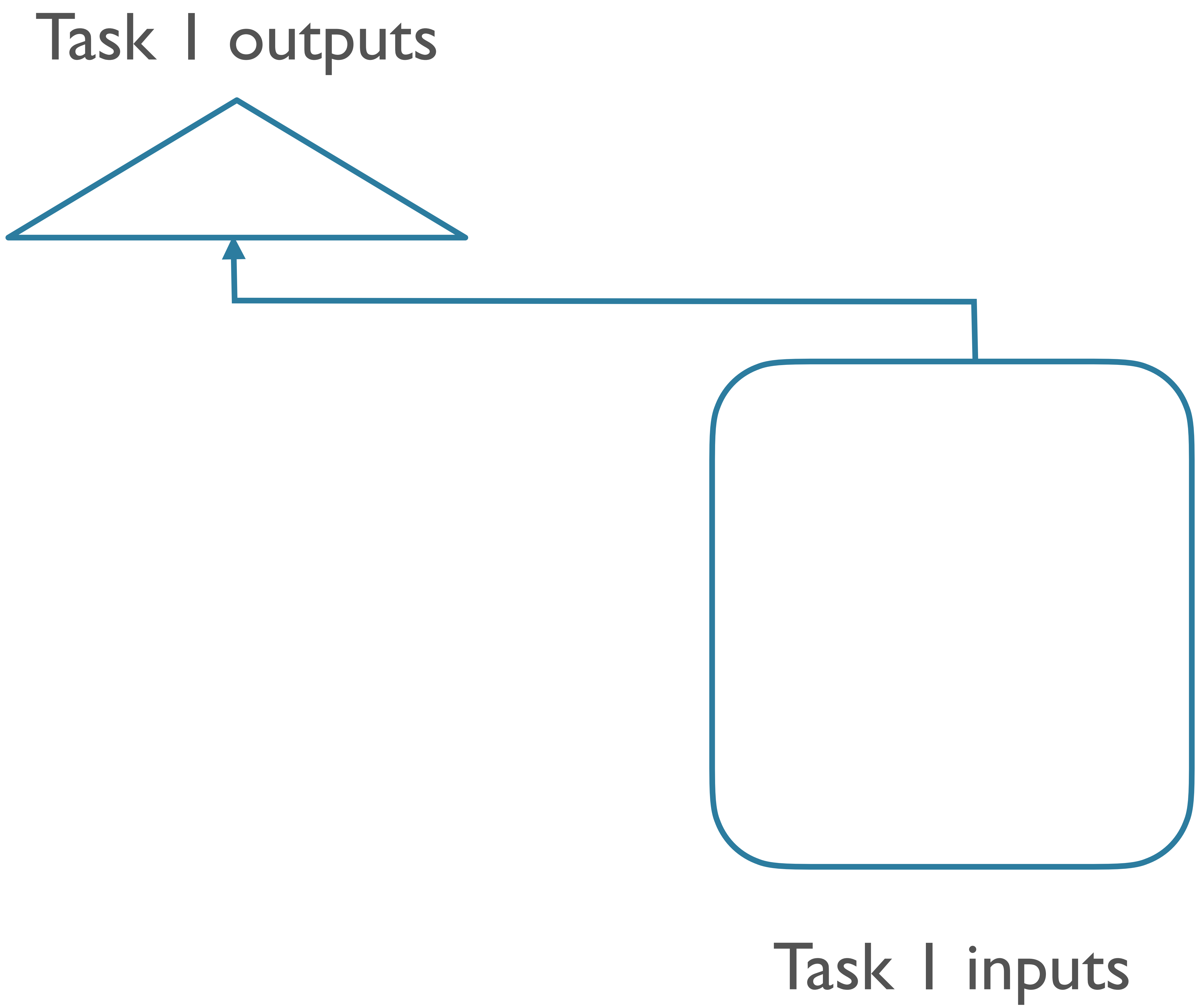

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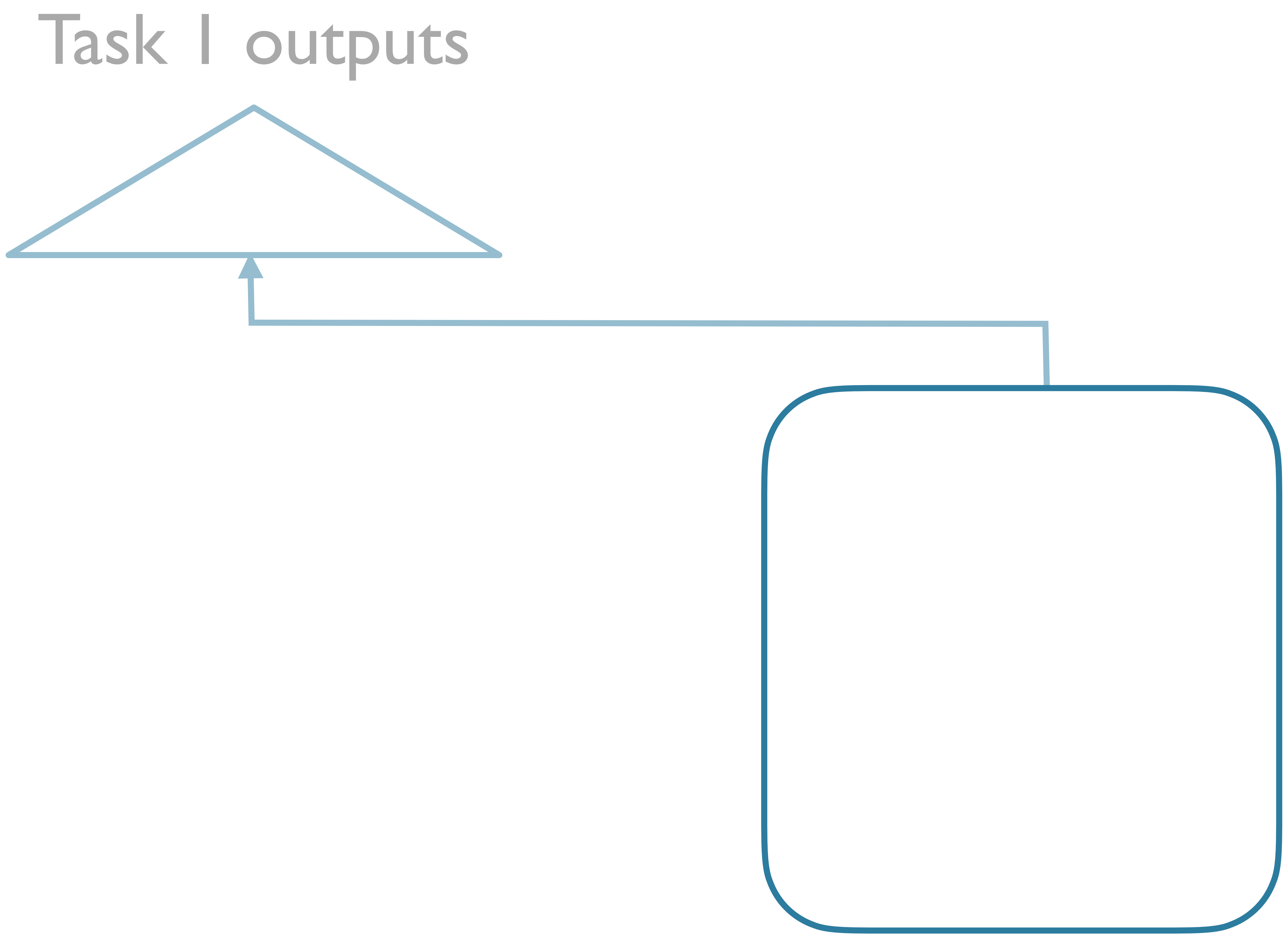

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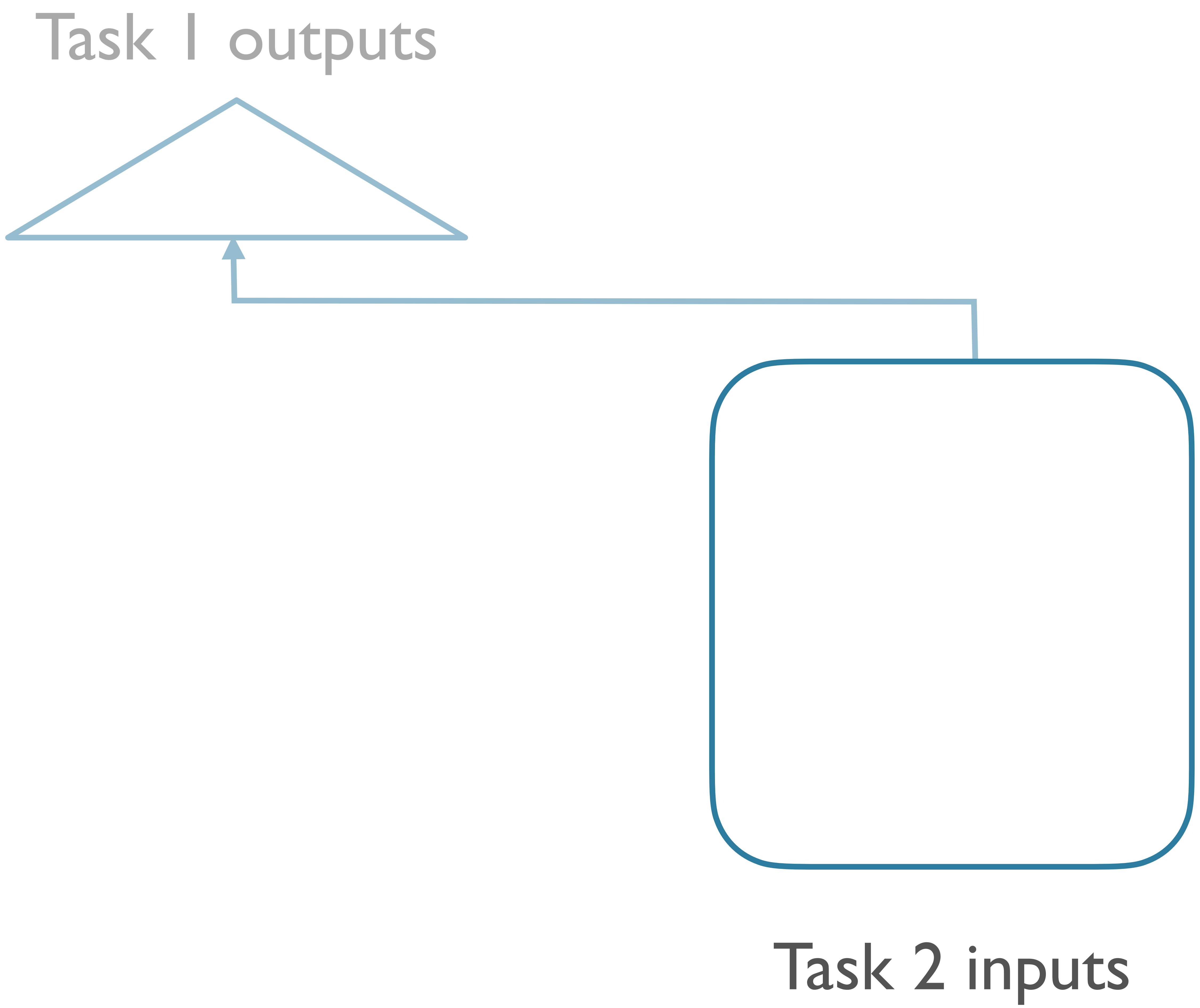

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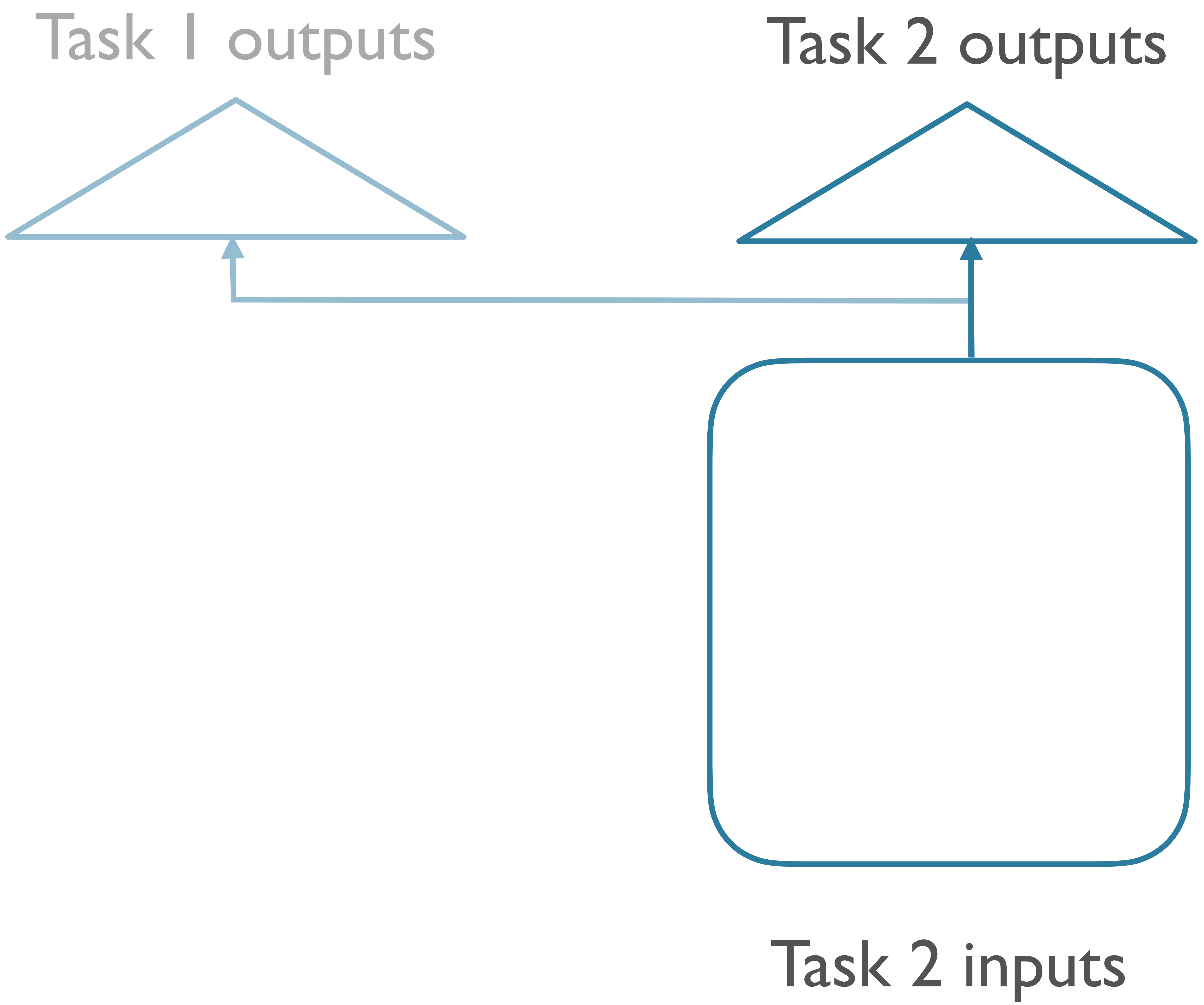

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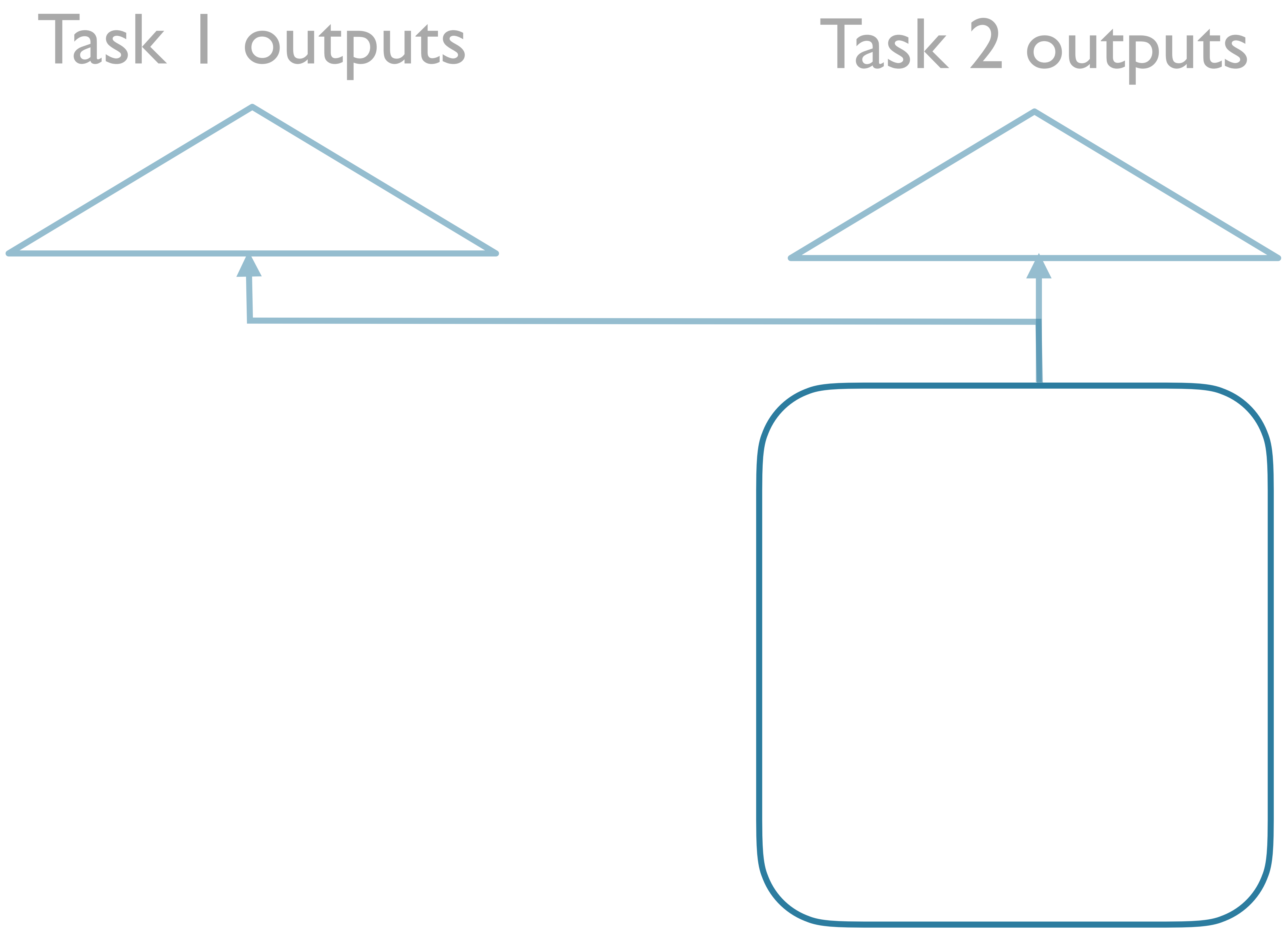

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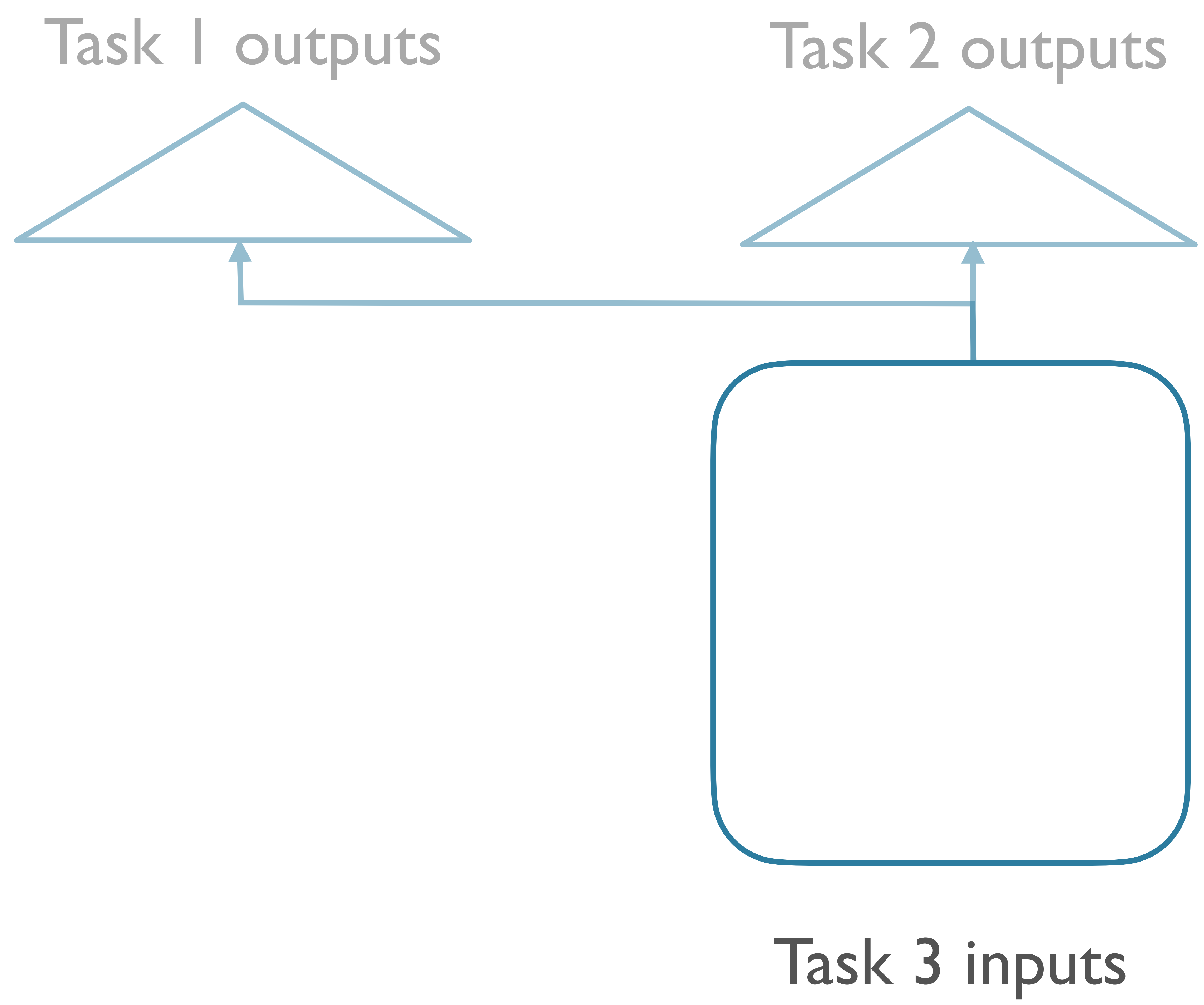

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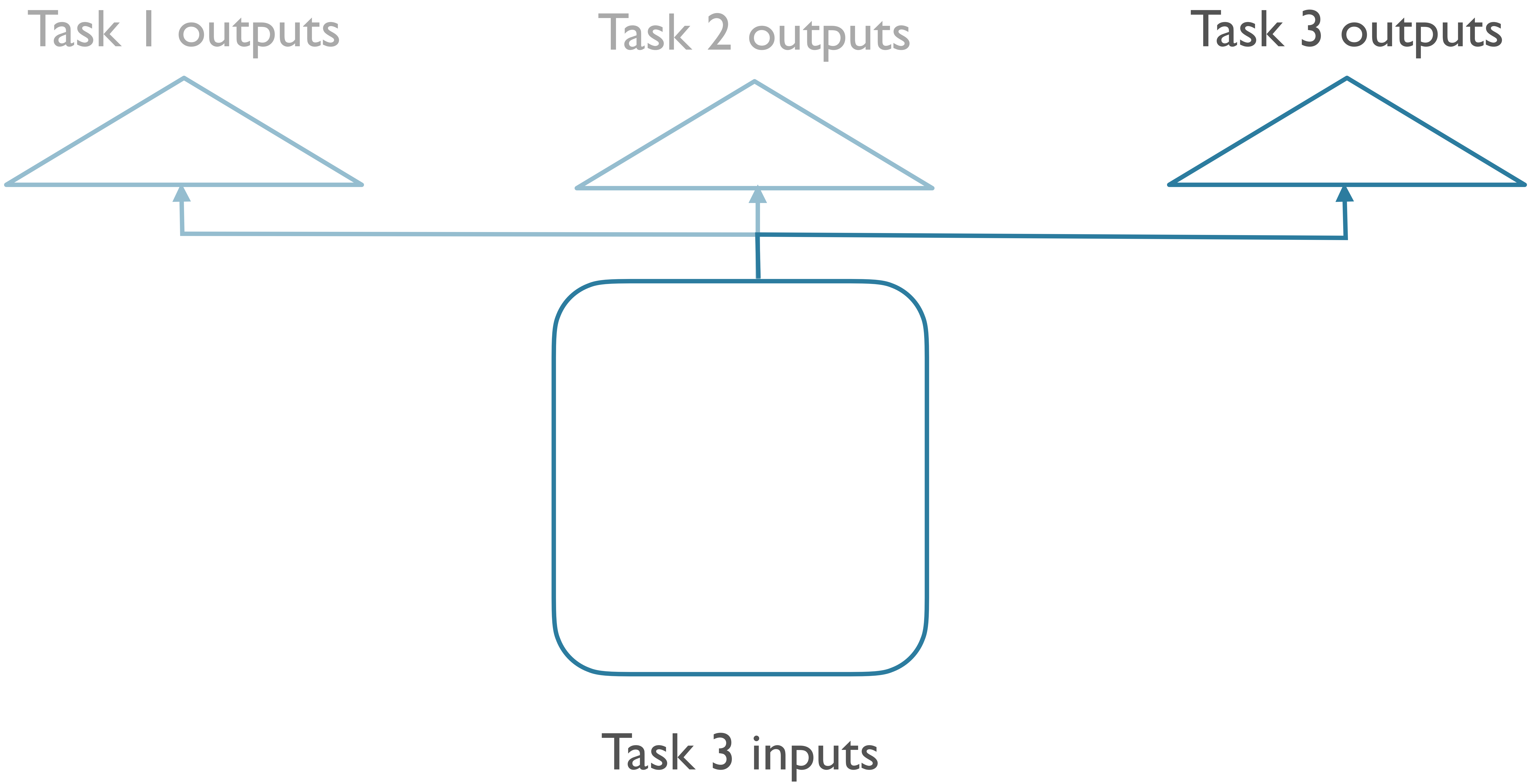

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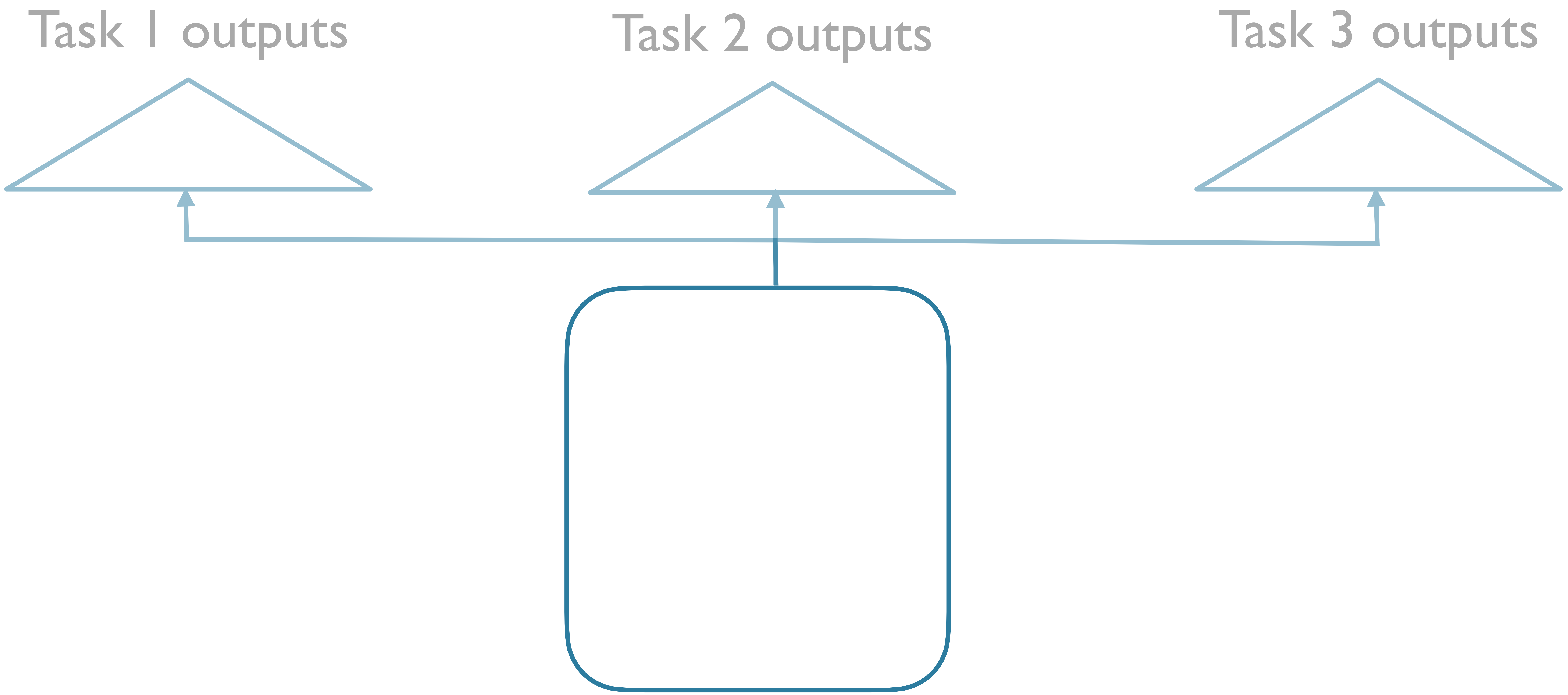

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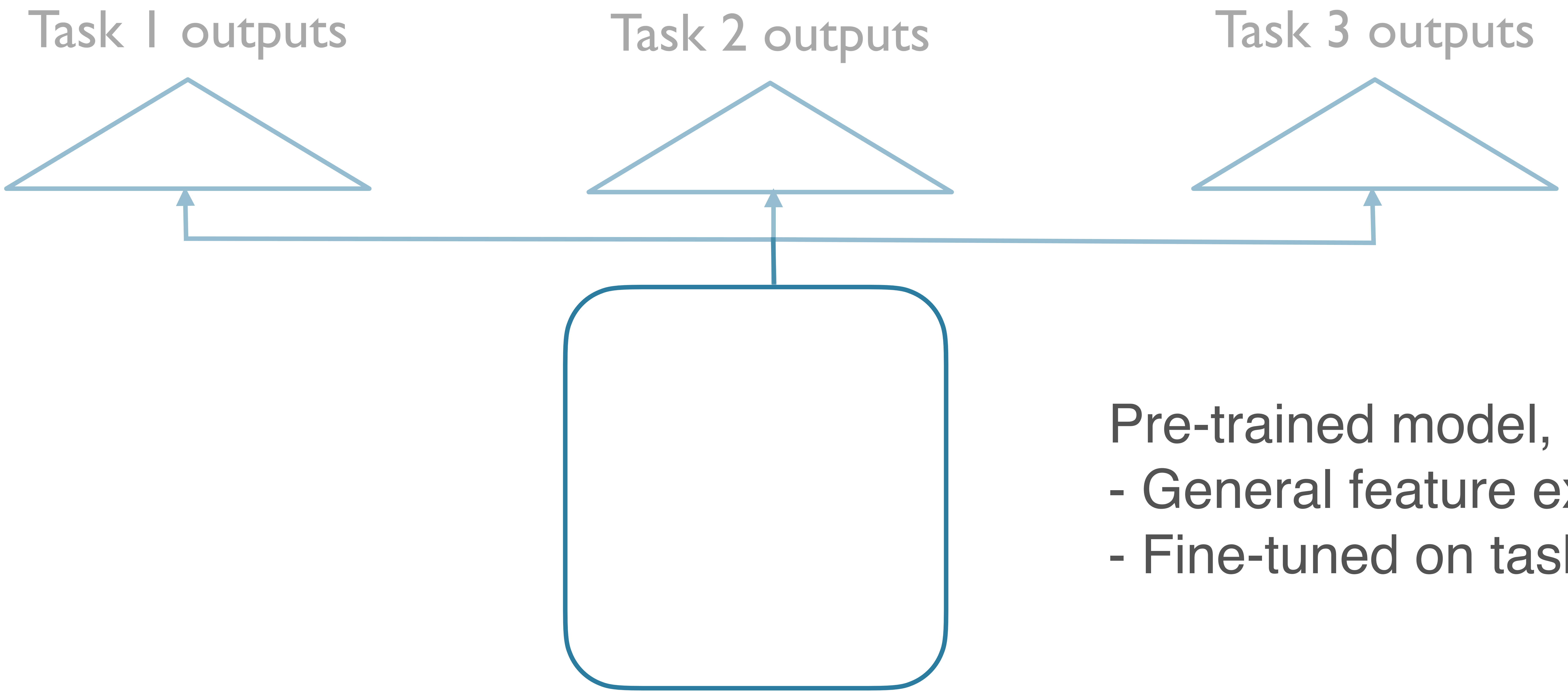

Pre-trained model, either:
- General feature extractor
- Fine-tuned on tasks

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.
- 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

Transfer Learning in Computer Vision

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

Ali Sharif Razavian Hossein Azizpour Josephine Sullivan Stefan Carlsson
CVAP, KTH (Royal Institute of Technology)
Stockholm, Sweden
{razavian,azizpour,sullivan,stefanc}@csc.kth.se

"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"

Current 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

Language Model Pre-training

Where to transfer *from*?

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  - QA

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  - Machine translation
  - QA
  - …

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- Goal: find a linguistic task that will build general-purpose / *transferable* representations
- Possibilities:
  - Constituency or dependency parsing
  - Semantic parsing
  - Machine translation
  - QA
  - …
- Scalability issue: all require expensive annotation

Language Modeling

Language Modeling

- A good language model should produce good *general-purpose* and *transferable* representations

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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 ____ …

Language Modeling

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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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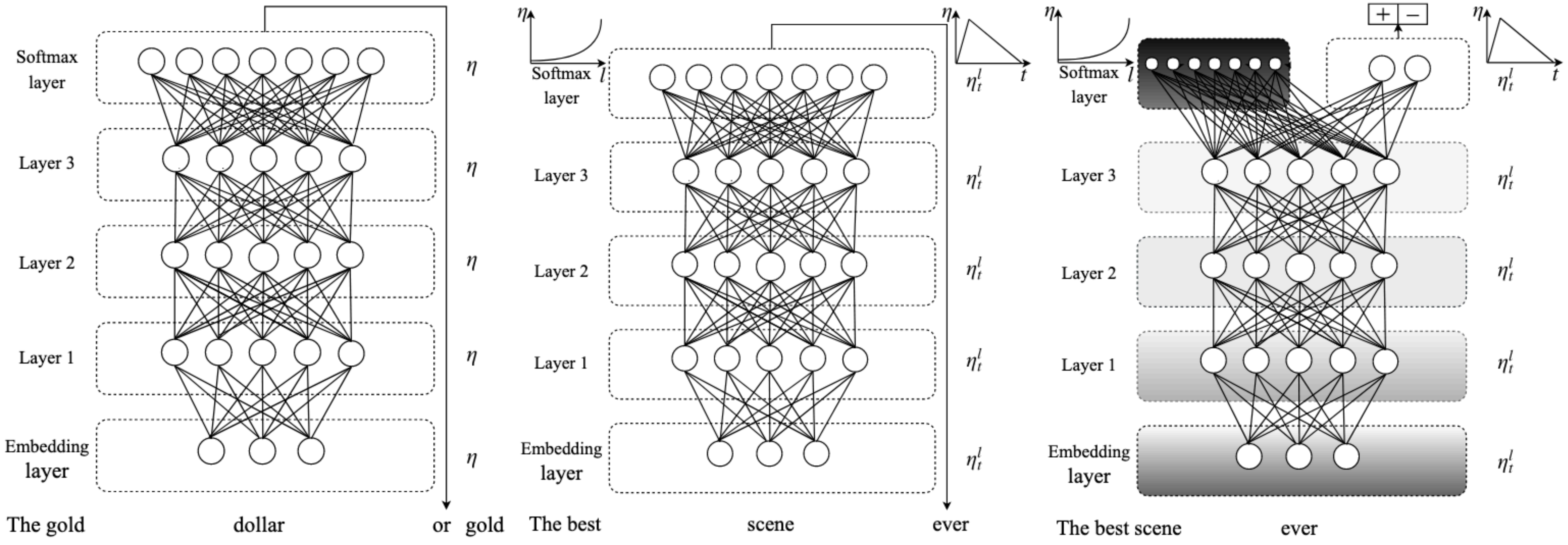
Text

Language Model Pre-training

- A currently 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]

ULMFiT



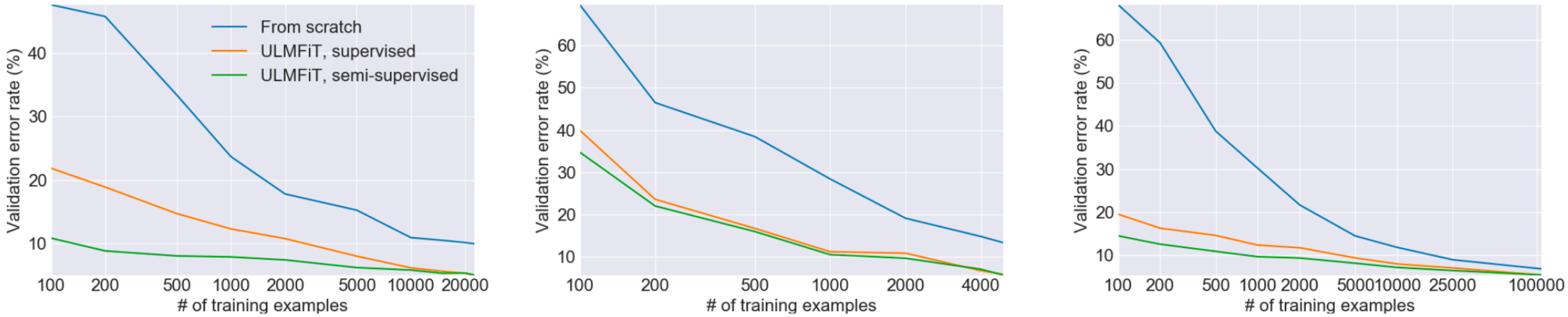
(a) LM pre-training (b) LM fine-tuning (c) Classifier fine-tuning

[Universal Language Model Fine-tuning for Text Classification (ACL '18)]

ULMFiT

	Model	Test		Model	Test
IMDb	CoVe (McCann et al., 2017)	8.2	TREC-6	CoVe (McCann et al., 2017)	4.2
	oh-LSTM (Johnson and Zhang, 2016)	5.9		TBCNN (Mou et al., 2015)	4.0
	Virtual (Miyato et al., 2016)	5.9		LSTM-CNN (Zhou et al., 2016)	3.9
	ULMFiT (ours)	**4.6**		ULMFiT (ours)	**3.6**

ULMFiT


From scratch
ULMFiT, supervised
ULMFiT, semi-supervised
Validation error rate (%)
# of training examples
100
200
500
1000
2000
5000
10000
20000
4000
25000
100000
10
20
30
40
50
60

Deep Contextualized Word Representations

Peters et. al (2018)

Deep Contextualized Word Representations

Peters et. al (2018)

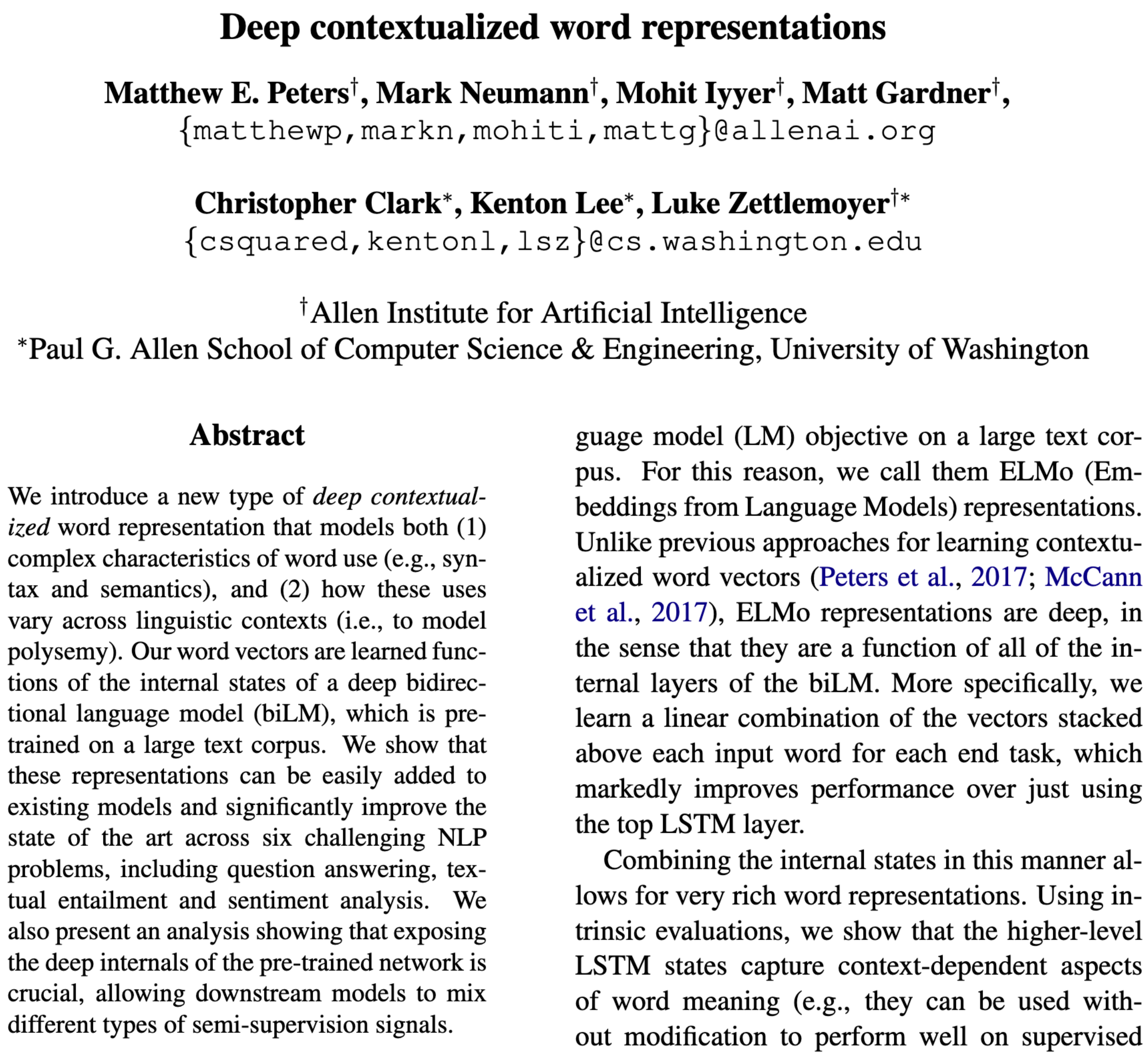
- NAACL 2018 Best Paper Award

Deep Contextualized Word Representations

[Peters et. al (2018)]

- NAACL 2018 Best Paper Award
- **E**mbeddings from **L**anguage **Mo**dels (ELMo)
  - [aka the OG NLP Muppet]

ELMo



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
[*]Paul G. Allen School of Computer Science & Engineering, University of Washington

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.

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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

ELMo

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†*
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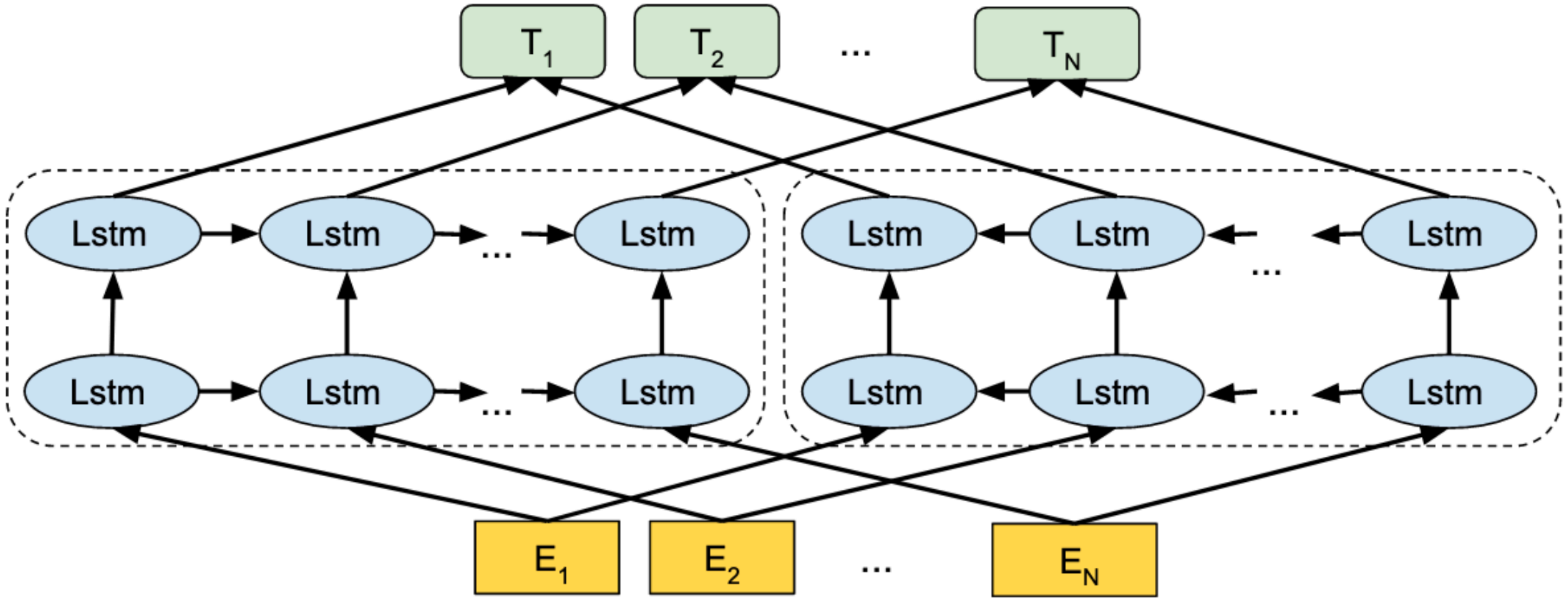
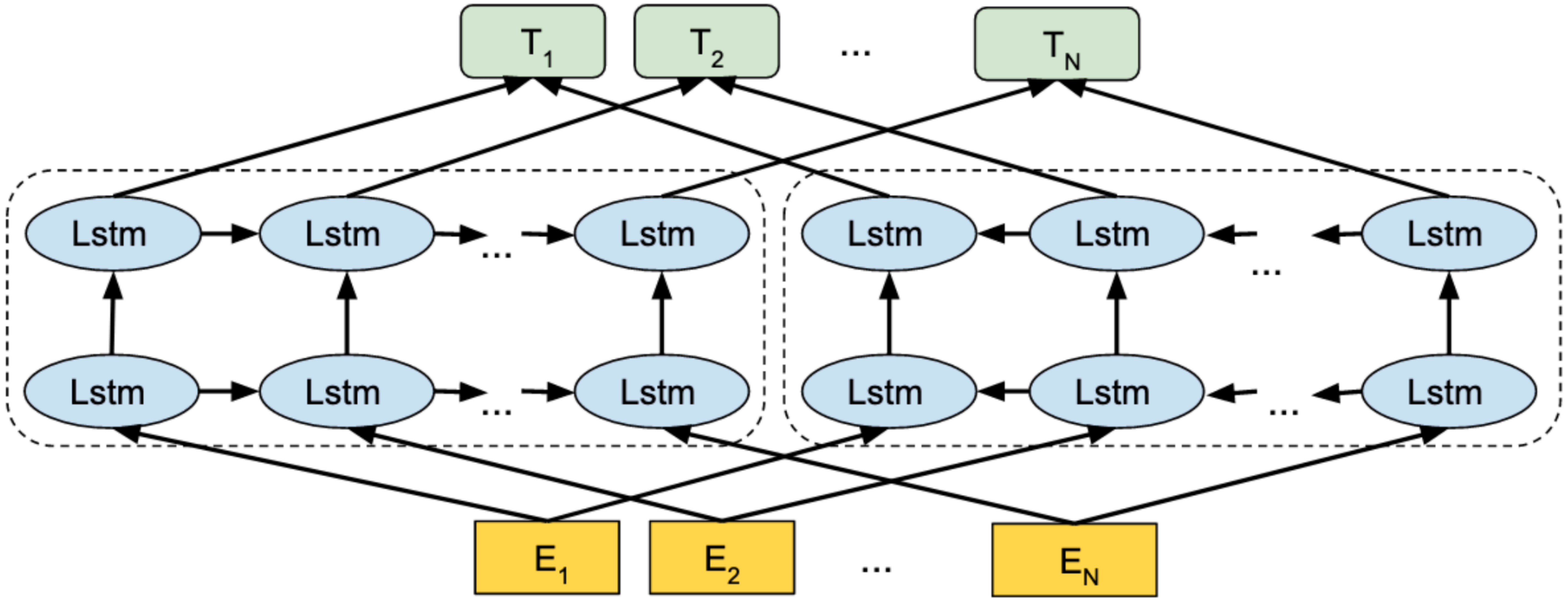
ELMo Model



Source: BERT paper

ELMo Model

4096-d hidden state
512d projection



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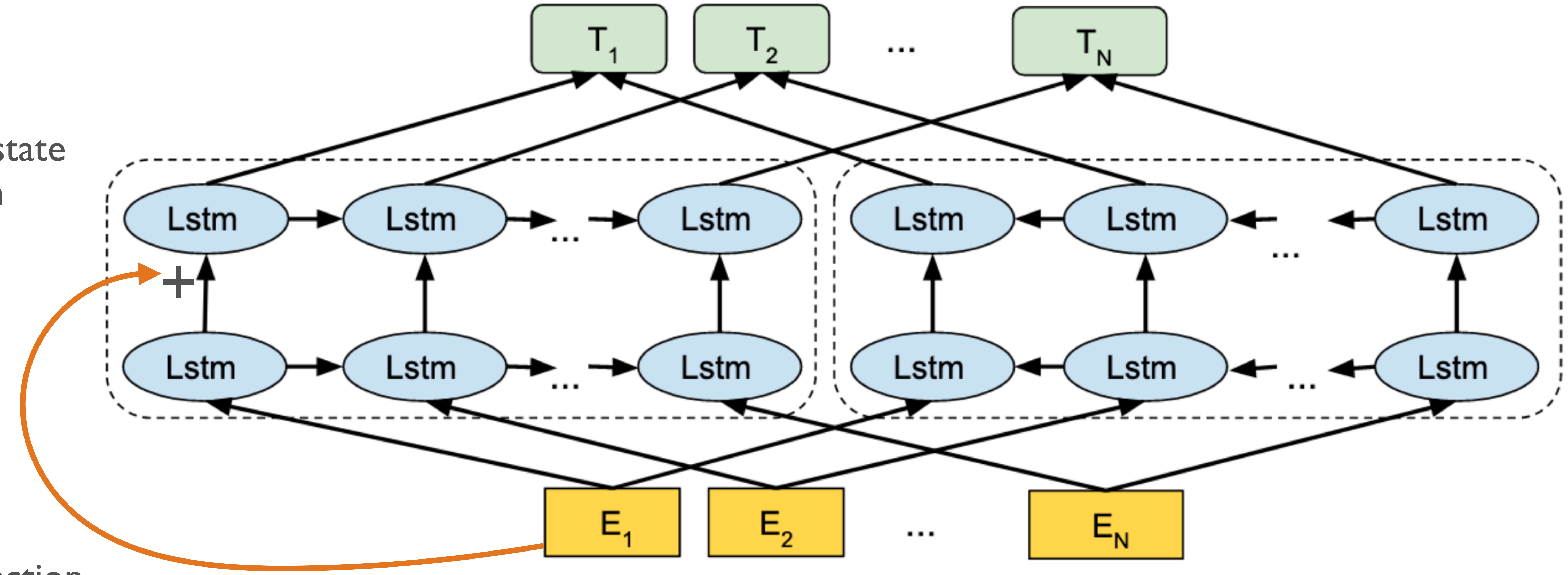

residual connection

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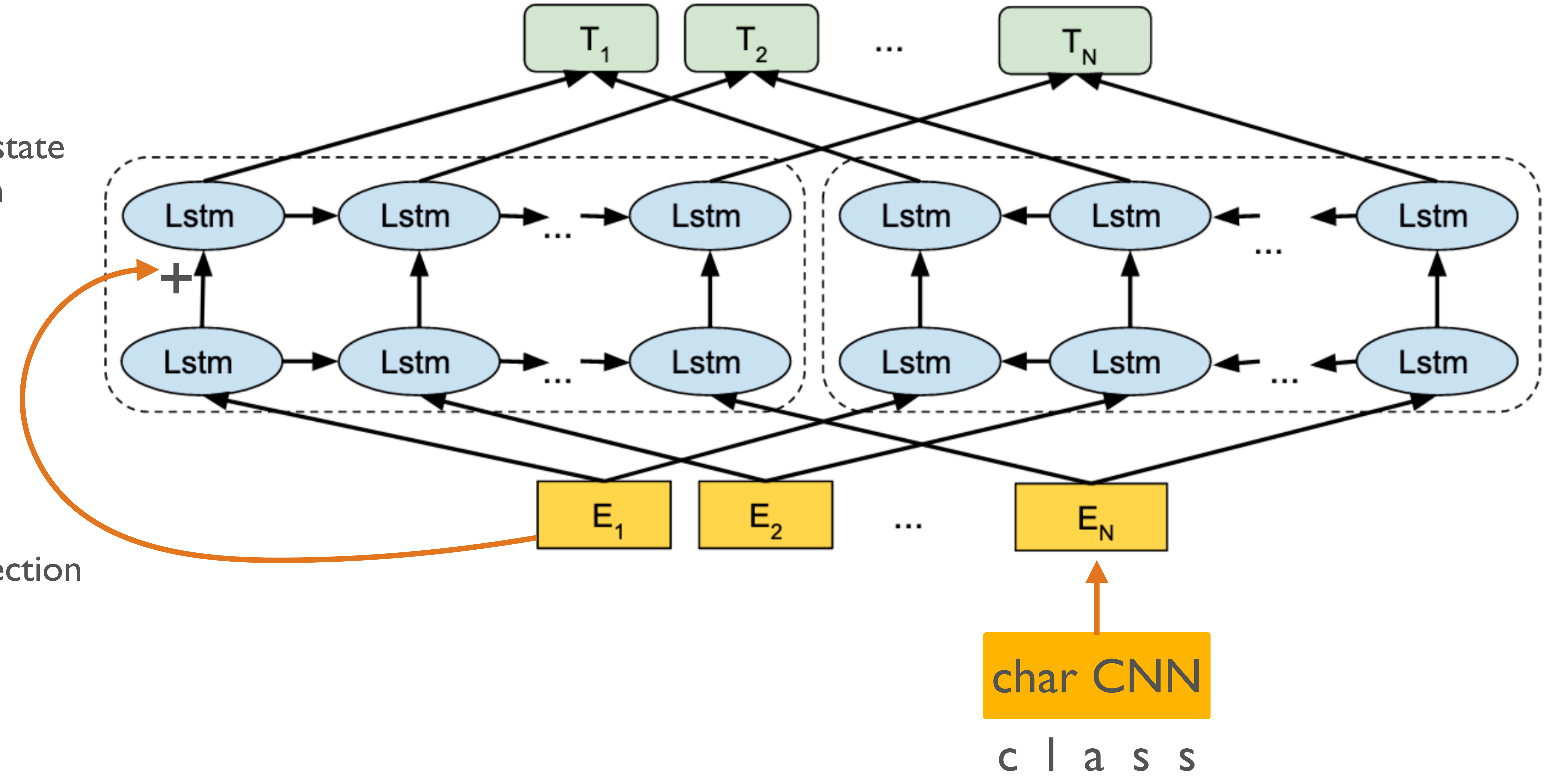

residual connection

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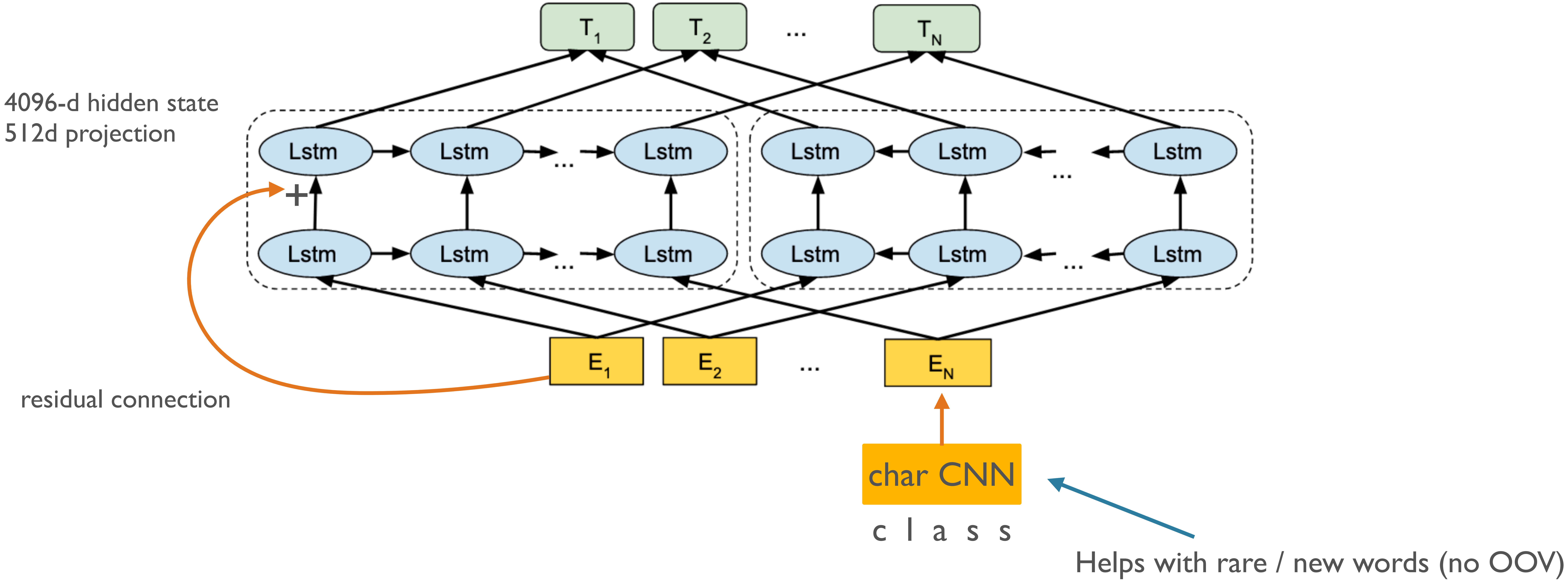


Source: BERT paper

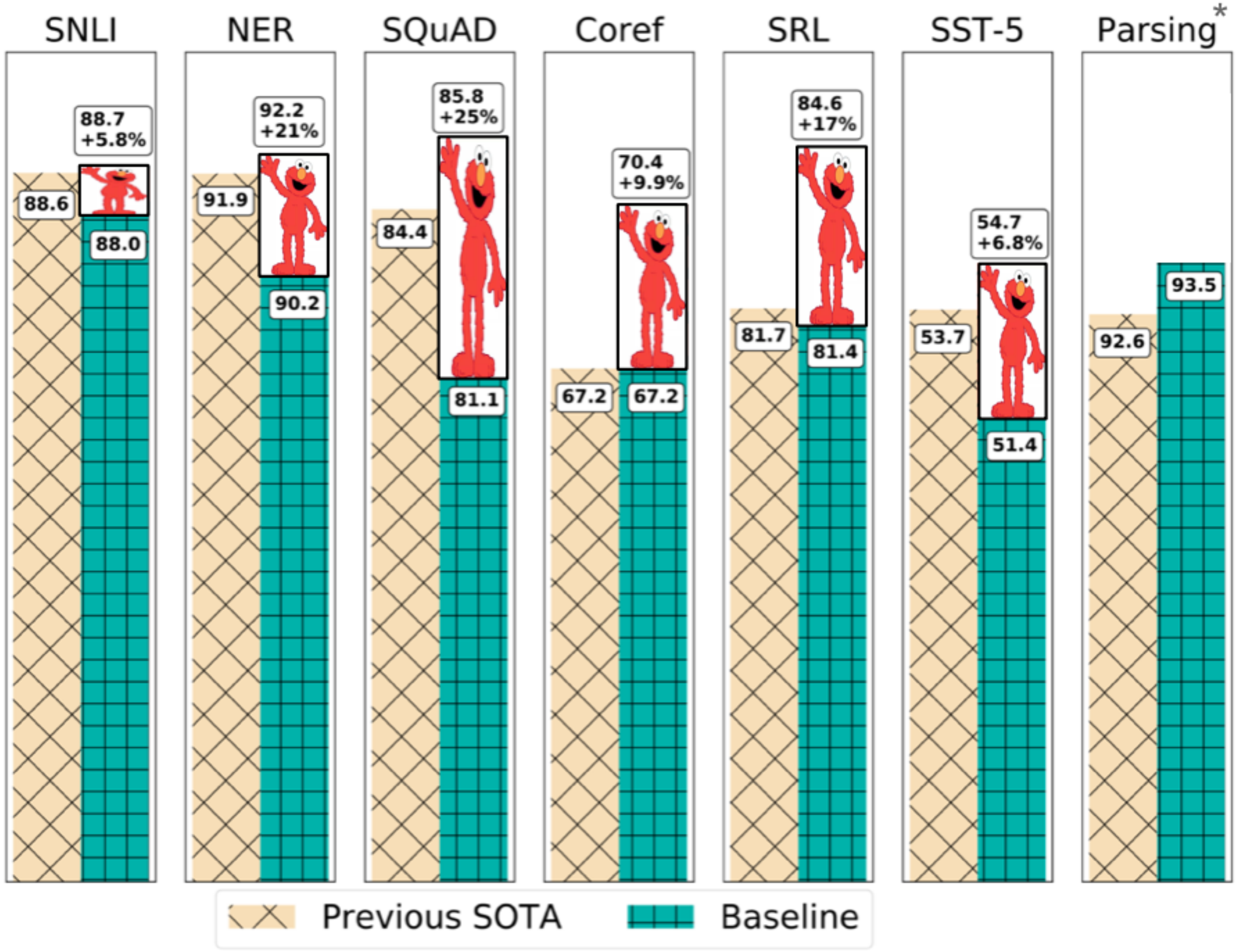
ELMo Training

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

Deep Contextualized Word Representations

[Peters et. al (2018)](#)

- Used in place of other embeddings on multiple tasks:



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

figure: Matthew Peters

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

Global vs. Contextual Word Vectors

- 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.

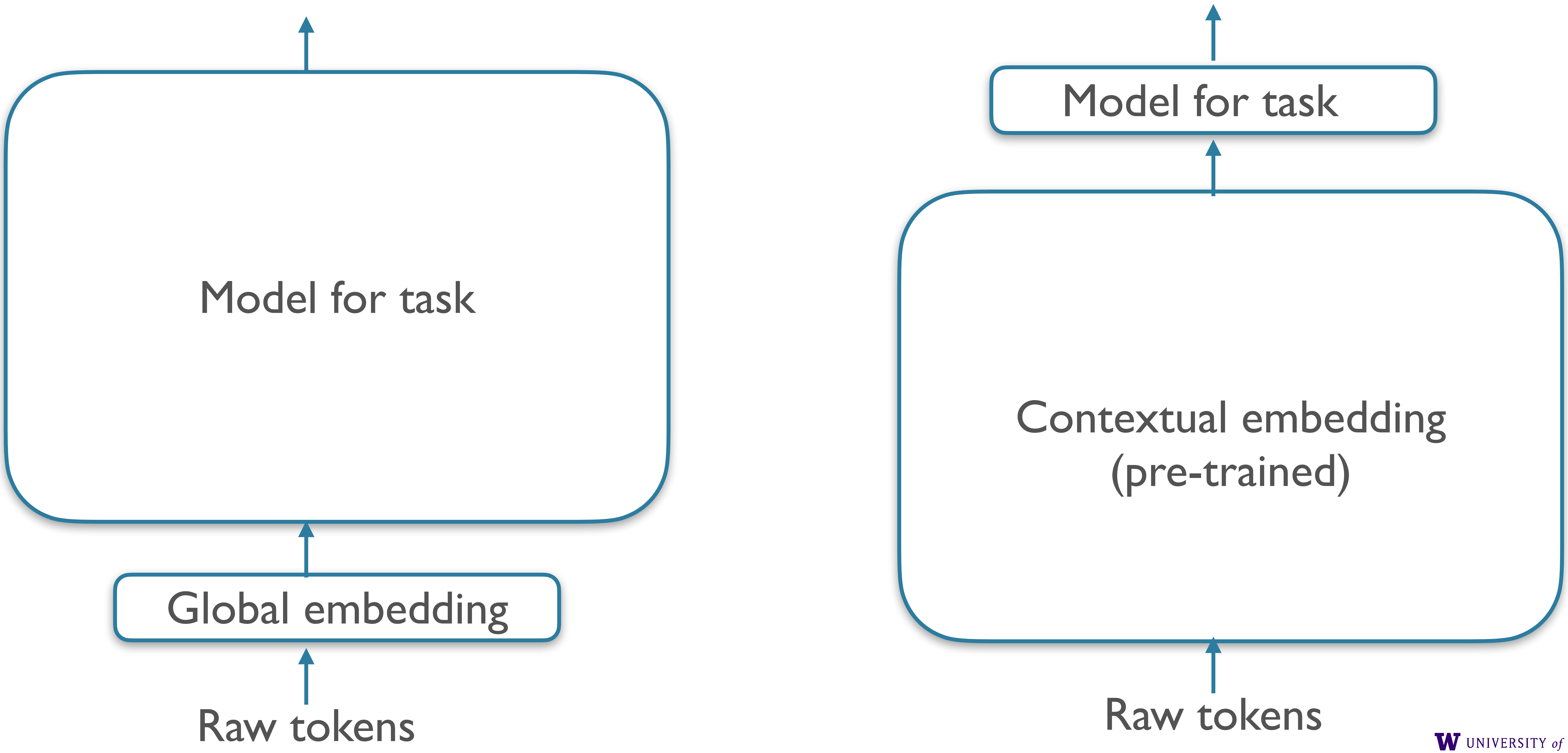
Deep Contextualized Word Representations

Peters et. al (2018)

- Comparison to GloVe:

	Source	Nearest Neighbors
GloVe	play	playing, game, games, played, players, plays, player, Play, football, multiplayer
biLM	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



Pre-trained Transformers

Paralellizability + Scale

- ULMFiT + ELMo:
  - Demonstrate the value of LM pre-training + transfer learning
    - Noted that there are “virtually unlimited” quantities of data for LM
  - Used bi-LSTMs for the LM
- Concurrently: Transformer paper introduced
- Triggered an explosion in the pretraining approach
  - Lack of recurrence —> paralellizability —> scaling up both model size and dataset size

Pre-trained Transformers: Encoder-only

BERT: Bidirectional Encoder Representations from Transformers

Devlin et al NAACL 2019

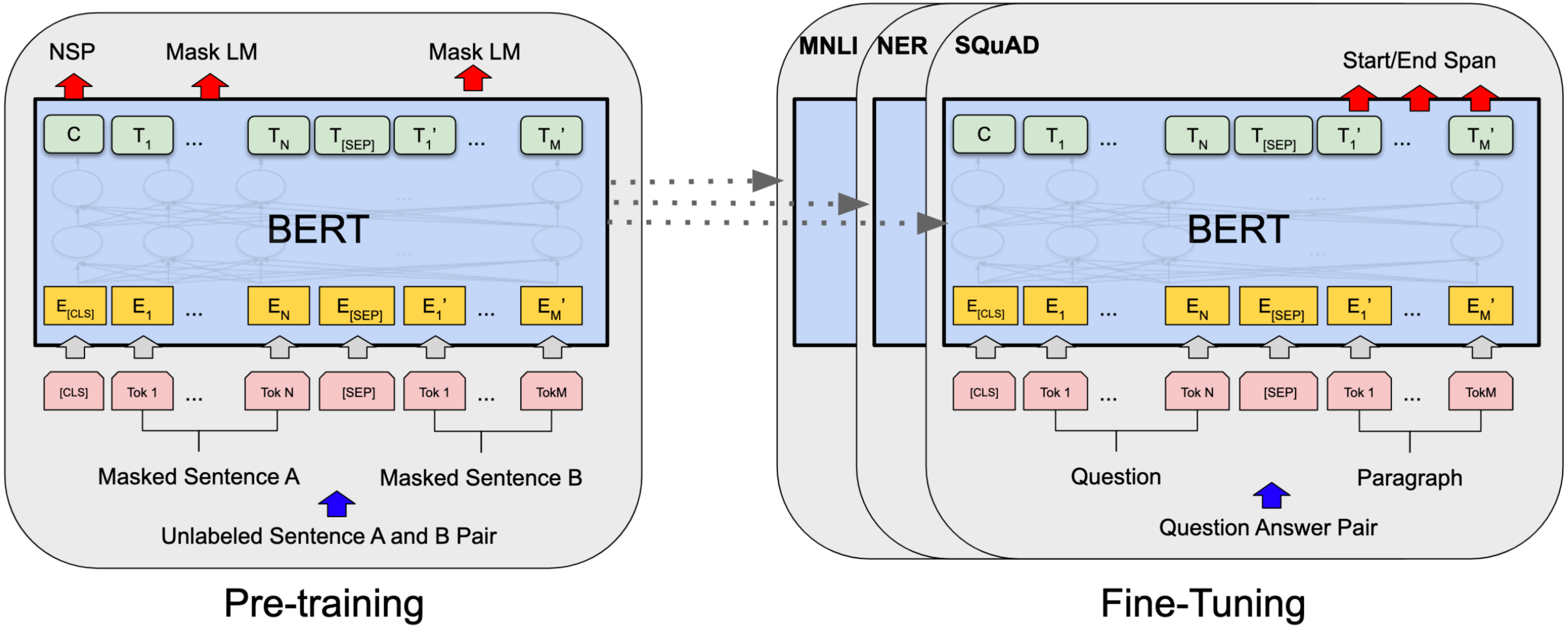
Overview

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

Masked Language Modeling

- Language modeling: next word prediction
- *Masked* Language Modeling (a.k.a. cloze task): fill-in-the-blank
  - Nancy Pelosi sent the articles of ____ to the Senate.
  - Seattle ____ some snow, so UW was delayed due to ____ roads.
- I.e. $P(w_t \mid w_{t+k}, w_{t+(k-1)}, \ldots, w_{t+1}, w_{t-1}, \ldots, w_{t-(m+1)}, w_{t-m})$
  - (very similar to CBOW: continuous bag of words 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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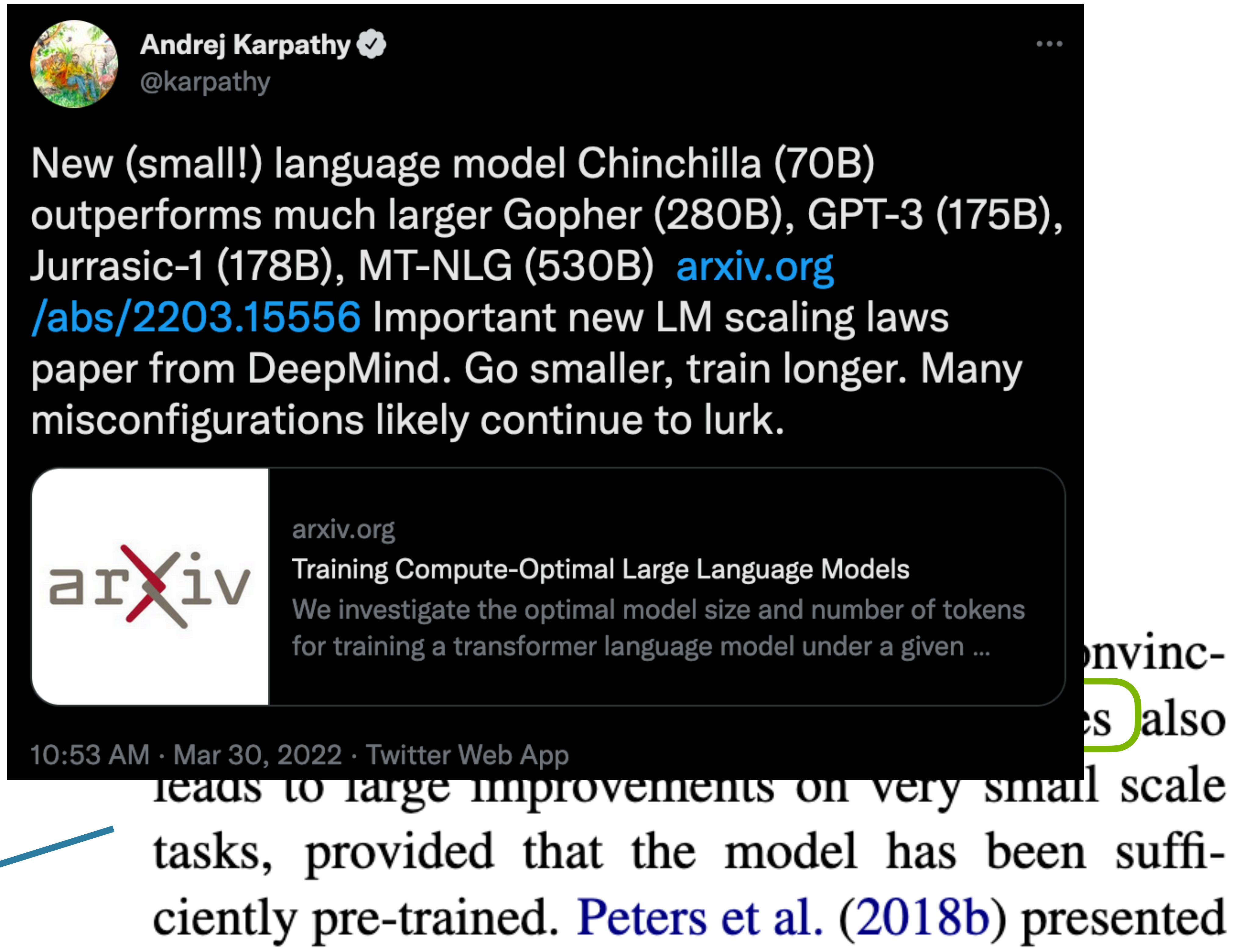
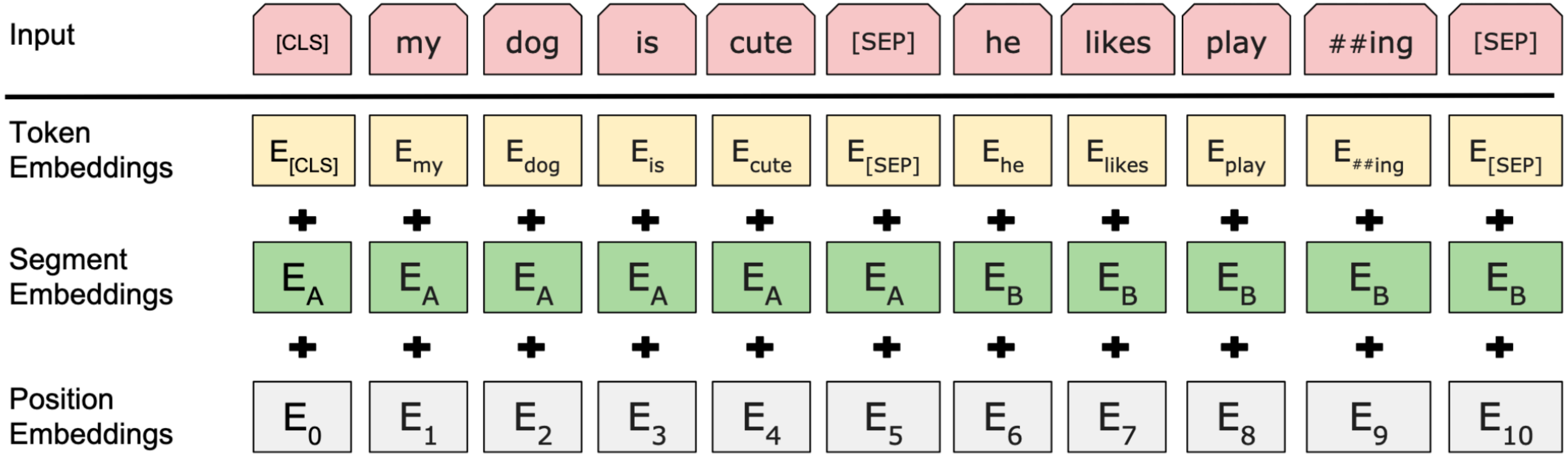

Andrej Karpathy
@karpathy

New (small!) language model Chinchilla (70B) outperforms much larger Gopher (280B), GPT-3 (175B), Jurrasic-1 (178B), MT-NLG (530B) arxiv.org/abs/2203.15556 Important new LM scaling laws paper from DeepMind. Go smaller, train longer. Many misconfigurations likely continue to lurk.

arxiv.org
Training Compute-Optimal Large Language Models
We investigate the optimal model size and number of tokens for training a transformer language model under a given ...

10:53 AM · Mar 30, 2022 · Twitter Web App

Input Representation



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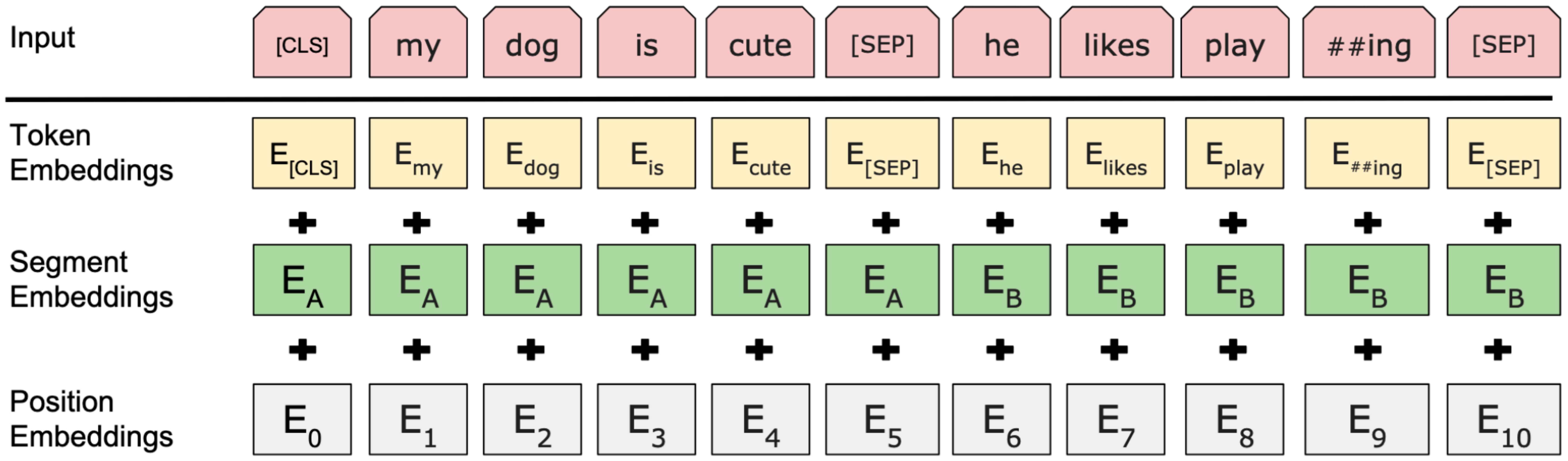
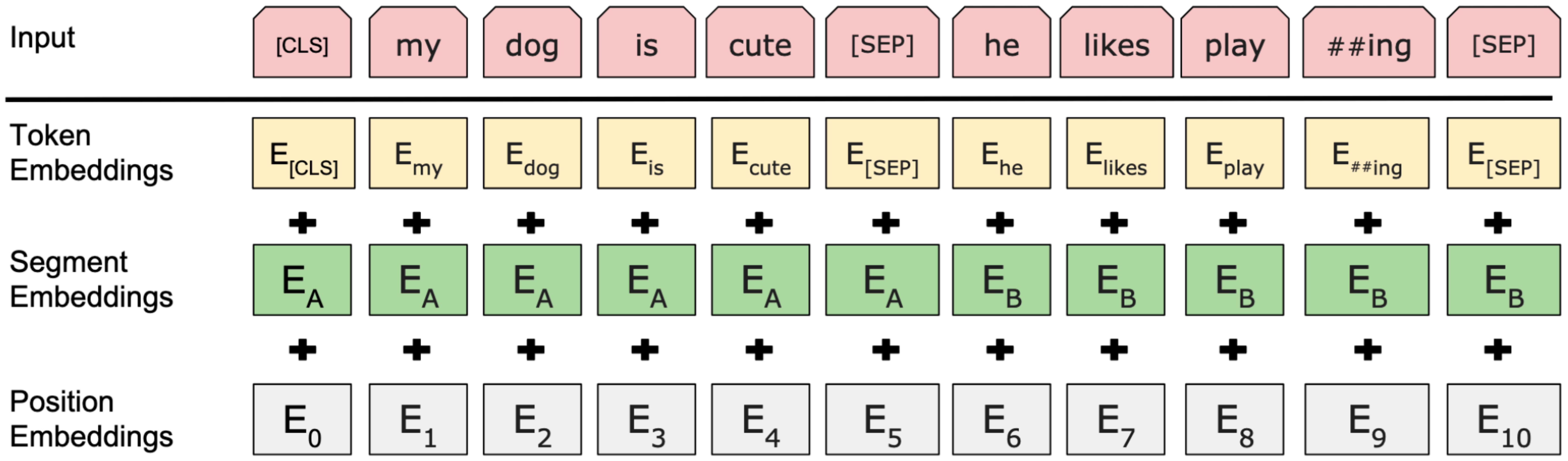


- [CLS], [SEP]: special tokens

Input Representation



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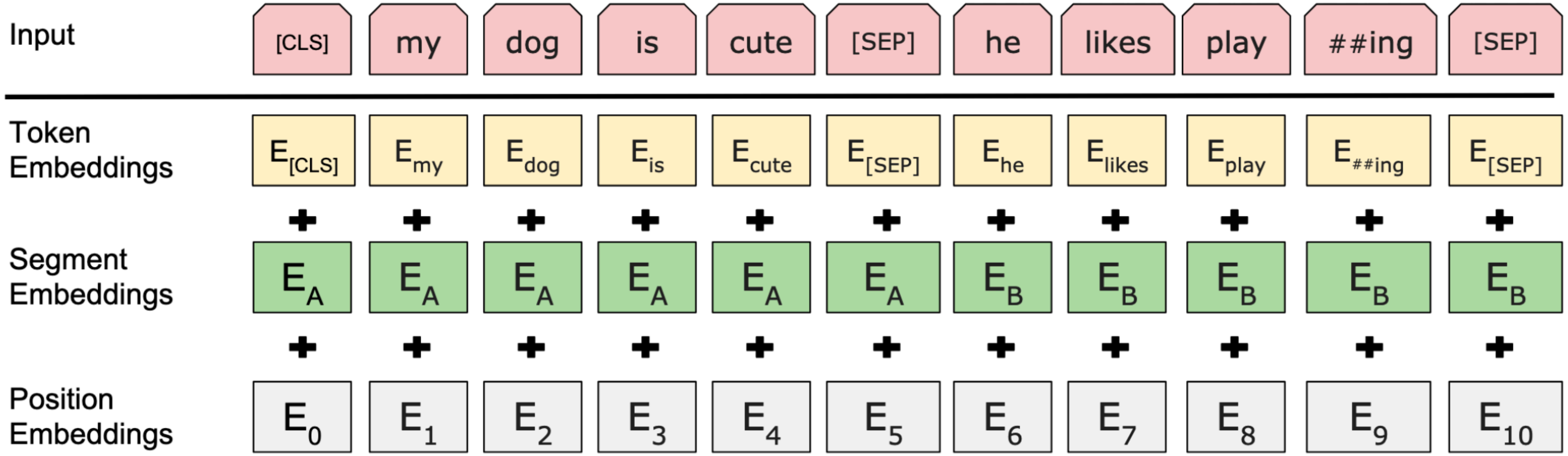

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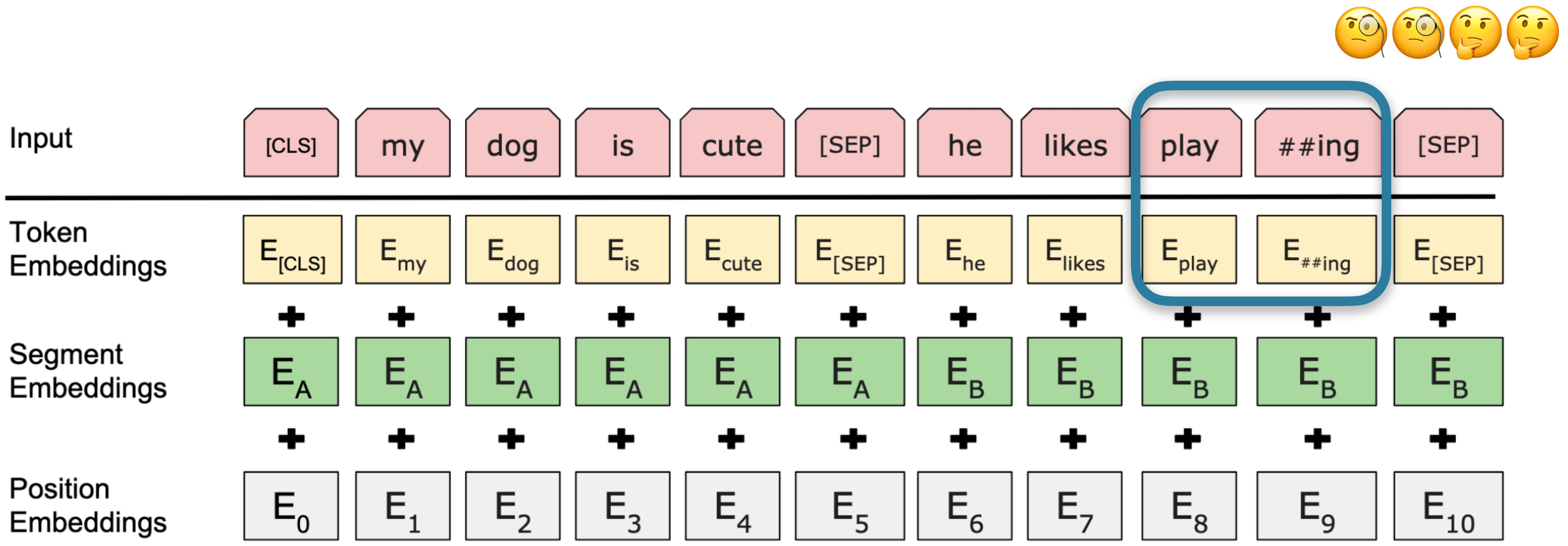


- [CLS], [SEP]: special tokens
- Segment: is this a token from sentence A or B?
- Position embeddings: provide position in sequence (*learned* in this case, not fixed)

Training Details

- BooksCorpus (800M words) + Wikipedia (2.5B)
- Masking the input text. 15% of all tokens are chosen. Then:
  - 80% of the time: replaced by designated '[MASK]' token
  - 10% of the time: replaced by random token
  - 10% of the time: unchanged
- Loss is cross-entropy of the prediction at the masked positions.
- Max seq length: 128 tokens for first 90%, 512 tokens for final 10%
- 1M training steps, batch size 256 = 4 days on 4 or 16 TPUs

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**

Ablations

Hyperparams				Dev Set Accuracy		
#L	#H	#A	LM (ppl)	MNLI-m	MRPC	SST-2
3	768	12	5.84	77.9	79.8	88.4
6	768	3	5.24	80.6	82.2	90.7
6	768	12	4.68	81.9	84.8	91.3
12	768	12	3.99	84.4	86.7	92.9
12	1024	16	3.54	85.7	86.9	93.3
24	1024	16	3.23	86.6	87.8	93.7

- Not a given (depth doesn't help ELMo); possibly a difference between fine-tuning vs. feature extraction

Tasks	Dev Set MNLI-m (Acc)	QNLI (Acc)	MRPC (Acc)	SST-2 (Acc)	SQuAD (F1)
$\text{BERT}_{\text{BASE}}$	84.4	88.4	86.7	92.7	88.5
No NSP	83.9	84.9	86.5	92.6	87.9
LTR & No NSP	82.1	84.3	77.5	92.1	77.8
+ BiLSTM	82.1	84.1	75.7	91.6	84.9

- Many more variations to explore

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

Pre-training + Fine-tuning Paradigm

LING 575K Deep Learning for NLP
Shane Steinert-Threlkeld
May 9 2022

Announcements

- HW5 ref code available
- HW6: PyTorch directly, no more edugrad (but same API :))
- A note on runtime and scalability of LSTMs
  - Definitely fast on small data, but doesn't scale
  - From hw6.model.LSTM.forward:
  - [NB: hw7 will use torch native LSTMs, a bit faster]

```python
# [batch_size, hidden_dim]
hidden, memory = self.init_hidden_and_memory(batch_size)
hidden_states = []
for timestep in embeddings:
    # apply the recurrence
    # [batch_size, hidden_dim]
    hidden, memory = self.cell(hidden, memory, timestep)
    # store the hidden state
    hidden_states.append(hidden)
# [seq_len, batch_size, hidden_dim]
return torch.stack(hidden_states)
```

Some Python/PyTorch Notes

- Training loop in HW6: saves best model based on dev loss, evaluates that
- model.eval(), model.train()
  - Sets the “mode” of a model in PyTorch
  - .eval() turns off things like Dropout, which are only used in training; .train() turns them back on
- `with torch.no_grad():`
  - For *inference/test* mode: doesn’t allocate memory for gradients on Tensors, saves lots of memory
- RNNClassifier.forward: fancy-ish tensor operations to extract the “last” hidden state from a batch of variable-length sequences

Today's Plan

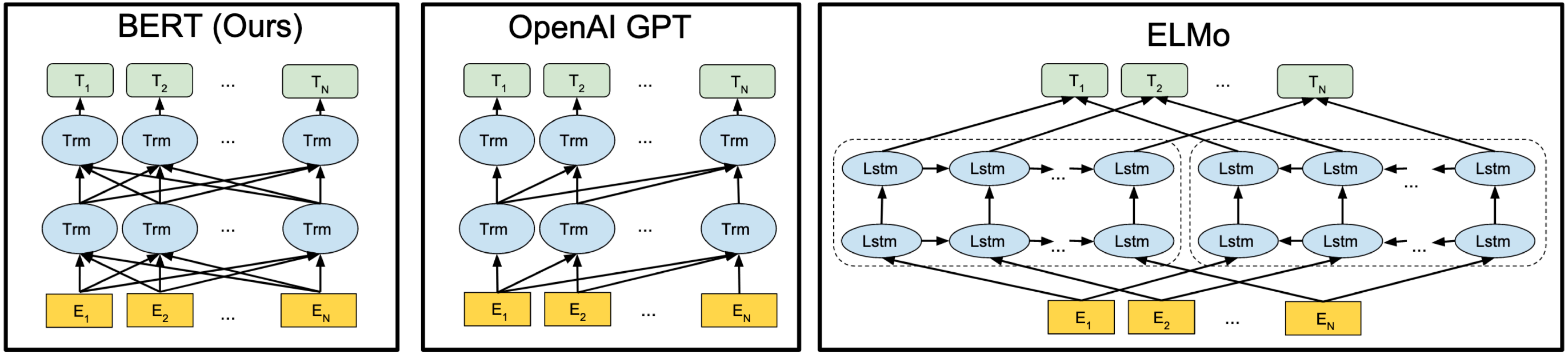
- Pre-training + fine-tuning, cont.
  - Last time:
    - Recurrent (ULMFiT, ELMo)
    - Encoder-only (BERT)
  - Decoder-only
  - Encoder-decoder
  - Risks
  - Accessing / using pre-trained LMs
- Next time: interpreting and analyzing pre-trained language models. What kind of linguistic and non-linguistic information do they acquire?

Pre-trained Transformers: Decoder-only

GPT(2)

- Generative Pre-training
  - Radford et al 2018; 2019 (GPT2); Brown et al 2020 (GPT3)
- Uses Transformer *decoder* instead of *encoder*
  - "Self"-attention: masked so that only can attend to *previous* tokens
  - Pure LM training objective
  - Can be used for text generation
- GPT: same params as BERT-BASE; GPT2 much bigger; GPT3 muuuuch bigger (175B params)
- Training data: crawled from outbound Reddit links w/ >3 karma, not public

Comparison



Source: BERT paper

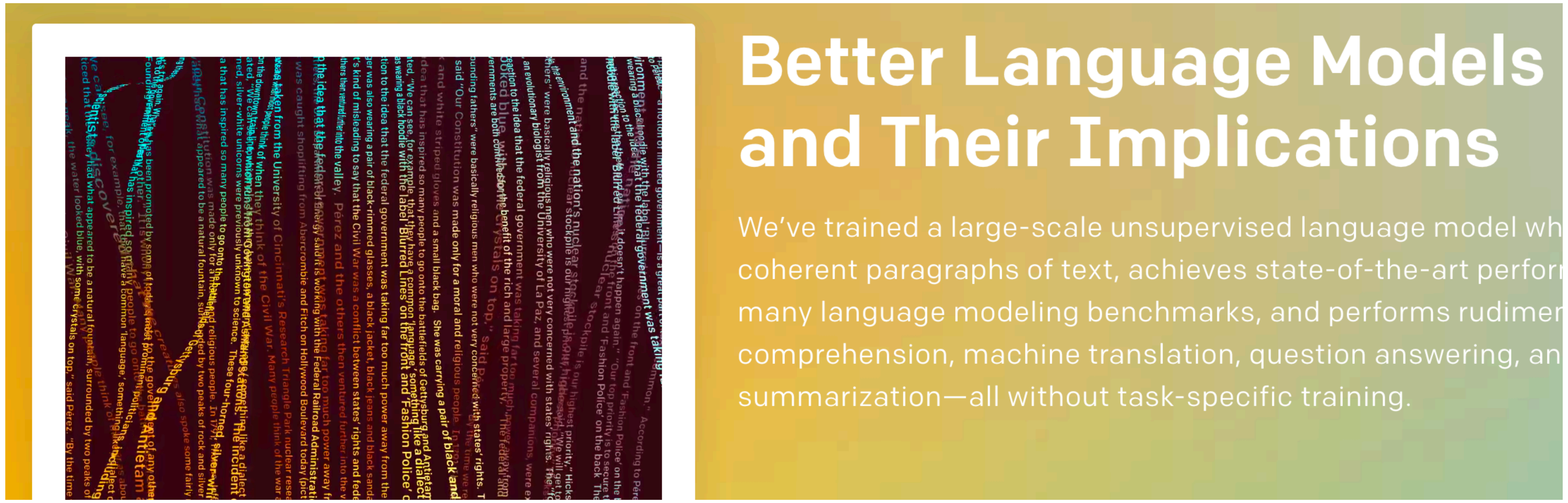
Samples from GPT2 (Cherry-picked)

SYSTEM PROMPT (HUMAN-WRITTEN)	*A train carriage containing controlled nuclear materials was stolen in Cincinnati today. Its whereabouts are unknown.*
MODEL COMPLETION (MACHINE-WRITTEN, FIRST TRY)	The incident occurred on the downtown train line, which runs from Covington and Ashland stations. In an email to Ohio news outlets, the U.S. Department of Energy said it is working with the Federal Railroad Administration to find the thief. “The theft of this nuclear material will have significant negative consequences on public and environmental health, our workforce and the economy of our nation,” said Tom Hicks, the U.S. Energy Secretary, in a statement. “Our top priority is to secure the theft and ensure it doesn’t happen again.” The stolen material was taken from the University of Cincinnati’s Research Triangle Park nuclear research site, according to a news release from Department officials. The Nuclear Regulatory Commission did not immediately release any information.

Samples from GPT2 (Cherry-picked)

SYSTEM PROMPT (HUMAN-WRITTEN)	*Recycling is good for the world.* *NO! YOU COULD NOT BE MORE WRONG!!*
MODEL COMPLETION (MACHINE-WRITTEN, 25 TRIES)	Recycling is NOT good for the world. It is bad for the environment, it is bad for our health, and it is bad for our economy. I'm not kidding. Recycling is not good for the environment. It is destructive to the earth and it is a major contributor to global warming. Recycling is not good for our health. It contributes to obesity and diseases like heart disease and cancer. Recycling is bad for our economy. It increases the cost of a product, and in turn, the price of everything that is made with that product. Recycling is not good for our nation. We pay a tremendous price for the privilege of having the world's most advanced and efficient recycling system. Recycling is a huge, colossal waste of time, energy, money, and resources. And THAT is why we need to get back to basics and get back to basics in our recycling efforts. One of the best ways to start is to look at the process of creating a paper product. When you make a paper product, it is basically a long chain of materials. Everything from the raw materials (wood, cardboard, paper, etc.), to the reagents (dyes, solvents, etc.) to the printing equipment (chemicals, glue, paper, ink, etc.), to the packaging, to the packaging materials (mercury, chemicals, etc.) to the processing equipment (heating, cooling, etc.), to the packaging materials, to the packaging materials that are shipped overseas and to the packaging materials that are used in the United States. Each step along the way creates tons of waste that we constantly have to clean up. The process

GPT2 Release Controversy



- Worry: it's so good, it could be used by malicious actors to make deep-fakes for text (incl. fake news, character assassination, …)
- So the model was not released until a partially independent report on possible misuses (but has been now)

https://openai.com/blog/better-language-models/

Write With Transformer

- Prompt: **Studying computational linguistics is a good idea. There are many interesting problems.**
- However, there are many bad problems. The research into computational linguistics has not helped very much in the development of better solutions. One problem with computer science and machine learning is that, until recently, the problems they were supposed to solve were insufficiently well studied. Most of the people who are doing research in computer science (at least in my profession) have no understanding of how to design a particularly natural problem, for example. In the case of the reasoning problem above, most of the people I know who work on computer science or machine learning have no understanding of how to make computer programs work in ways which do not have unavoidable adverse consequences. In the best cases, computational linguistics was little help.

Write With Transformer

- Prompt: **I didn't ride my bike to campus today because of the snowy weather.**

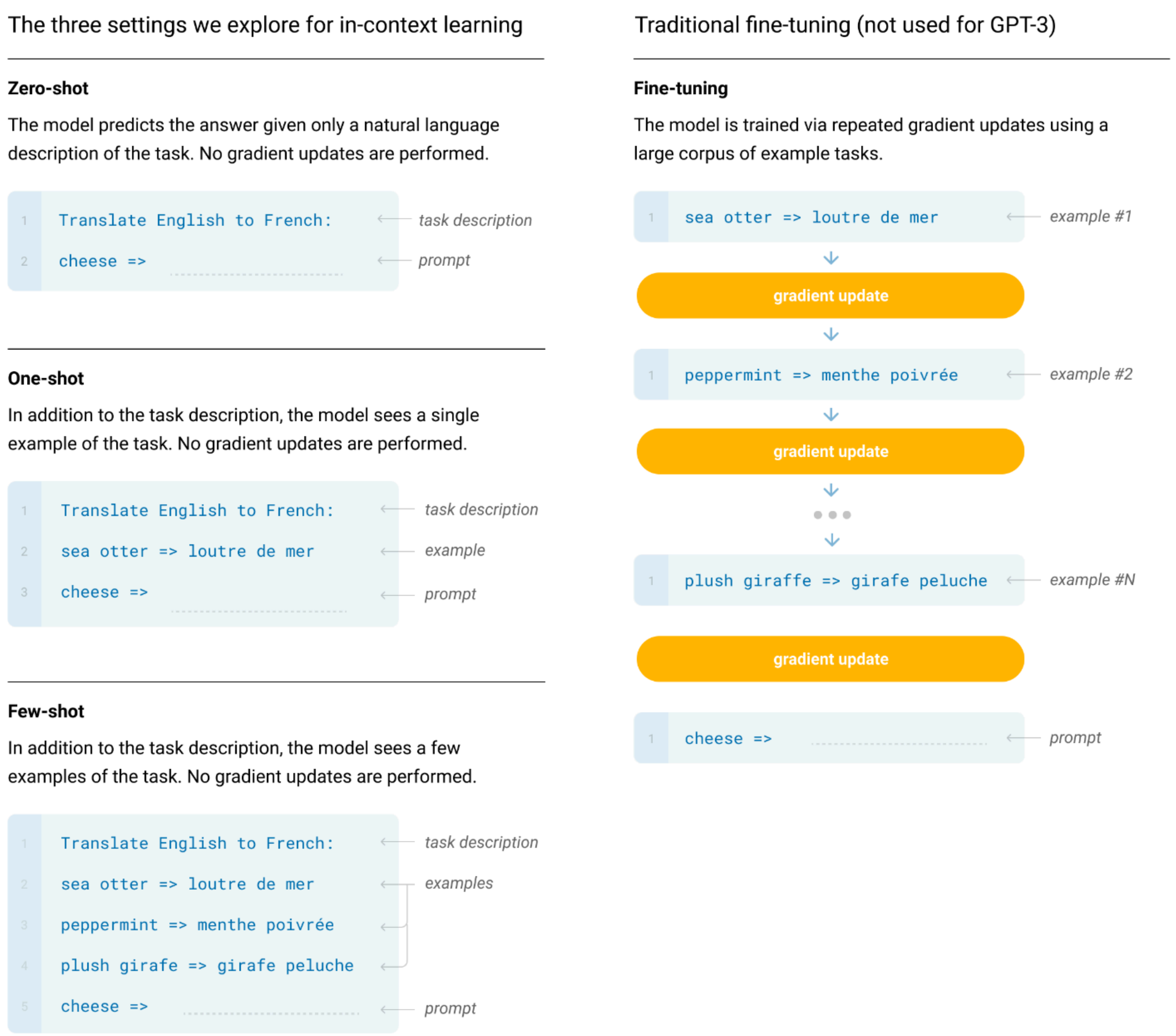
- There is a lot of construction and I wanted to have a few hours of skiing. All that snow is a real pain in the ass. Good thing there was an LRT planned for that area. See you guys on campus in a few days! Photo credit: Tapto@archivosos.gr – August 26, 2016: Windy Weather on the Mountain (photo credit: Diana Prat)
  From Diana Prat, via tapto@archivosos.gr:
  Ever since the camp that I organized to protest the modernisation of the Barranco, my beautiful alma mater, you know, going in for a press conference, I was asking why the Italian government

What do you want to ask GPT-2?

Total Results: 0

GPT3

- Same approach: pure Transformer decoder trained on LM
  - Scale: 175B params
  - Data size: ~500billion tokens, majority from filtered Common Crawl
- Few-shot “fine-tuning” paradigm:
  - Prompt with a few examples, ask to continue
  - *No parameter updates*



GPT3 Few-Shot Results

	SuperGLUE Average	BoolQ Accuracy	CB Accuracy	CB F1	COPA Accuracy	RTE Accuracy
Fine-tuned SOTA	**89.0**	**91.0**	**96.9**	**93.9**	**94.8**	**92.5**
Fine-tuned BERT-Large	69.0	77.4	83.6	75.7	70.6	71.7
GPT-3 Few-Shot	71.8	76.4	75.6	52.0	92.0	69.0

	WiC Accuracy	WSC Accuracy	MultiRC Accuracy	MultiRC F1a	ReCoRD Accuracy	ReCoRD F1
Fine-tuned SOTA	**76.1**	**93.8**	**62.3**	**88.2**	**92.5**	**93.3**
Fine-tuned BERT-Large	69.6	64.6	24.1	70.0	71.3	72.0
GPT-3 Few-Shot	49.4	80.1	30.5	75.4	90.2	91.1

k=32

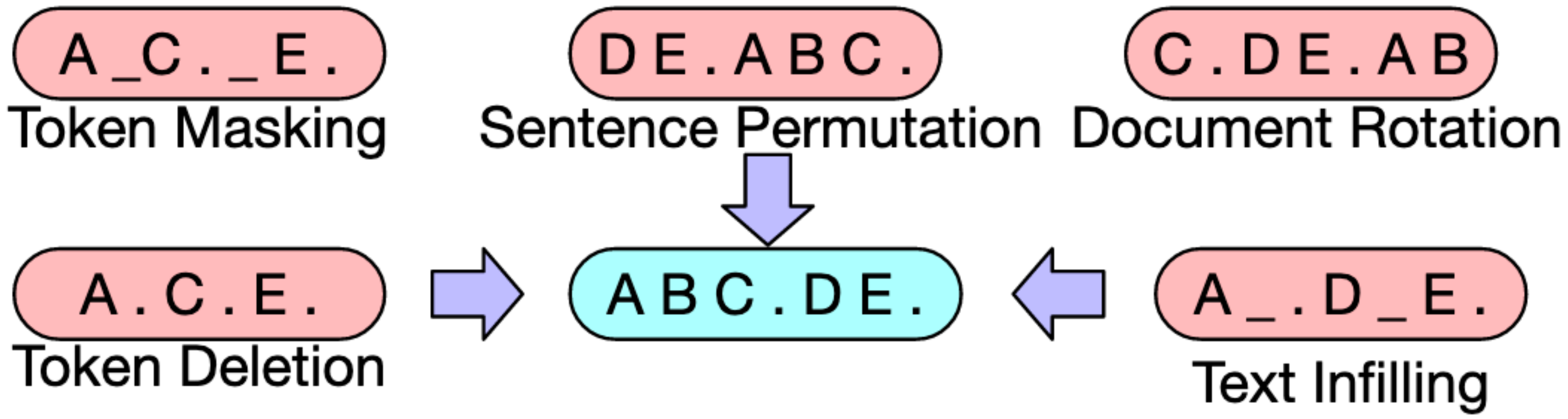
Some follow-ups on GPT3

- Has ushered in a lot of work on “prompt tuning”: how to best engineer the prompts to produce the behavior that you want
  - Very useful survey paper/website on that front: http://pretrain.nlpedia.ai/
- Putting the “open” back in:
  - EleutherAI: “A grassroots collective of researchers working to open source AI research.”
    - Reproduce GPT-like models + datasets in entirely open way
  - OPT-175B: Meta’s recent open (incl logbook, etc) non-commercial replication

Pretrained Transformers: Encoder-Decoder

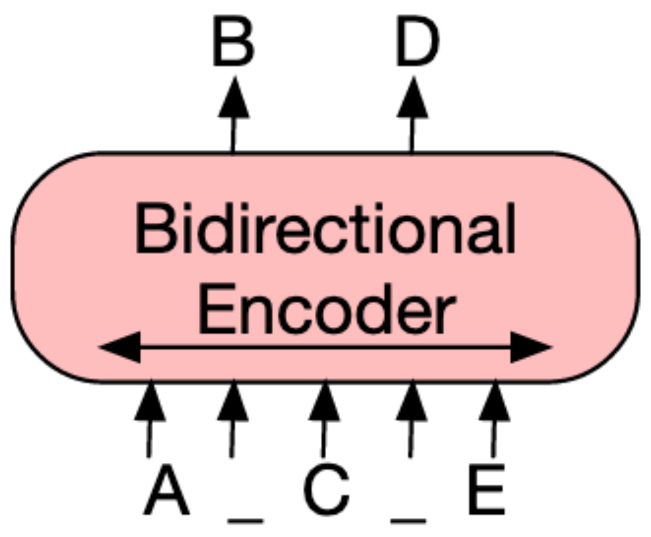
BART

- Full Transformer, i.e. encoder-decoder transducer
  - Many composable transformations of raw text, presented to encoder
  - Goal of decoder is to reconstruct the original text

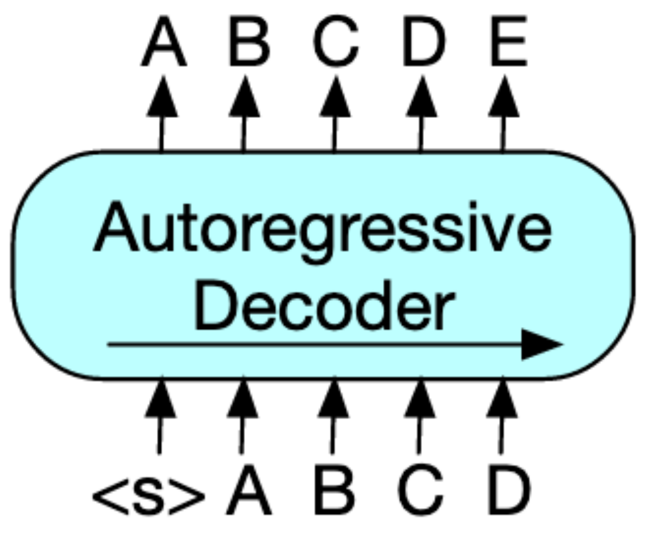


- Good for both discrimination and generation

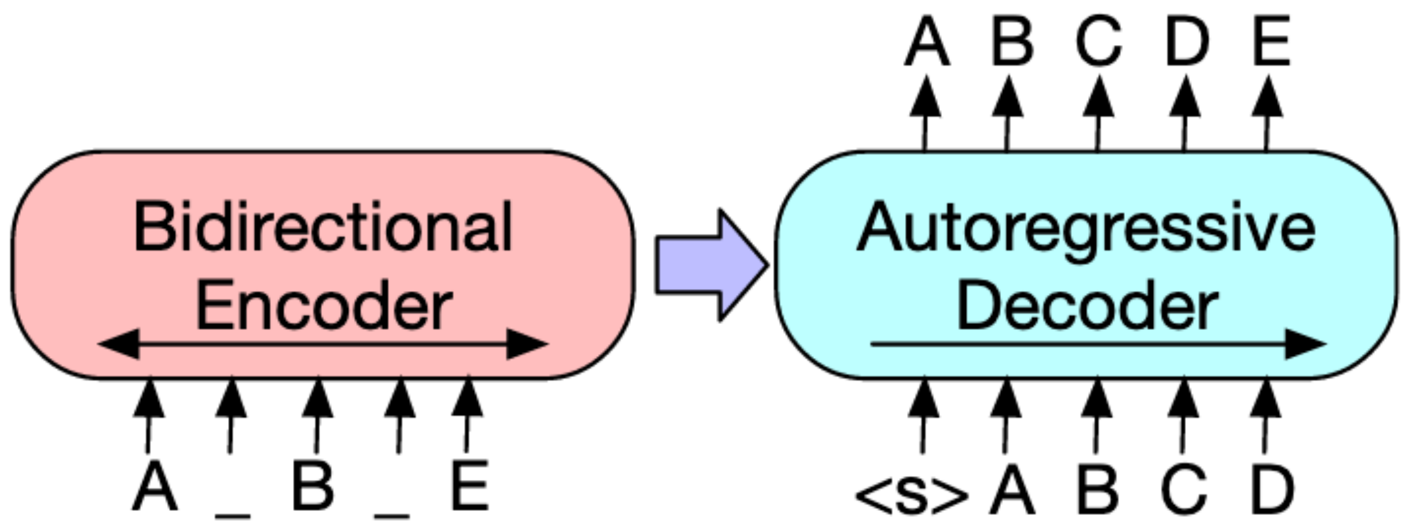
High-level Overview



(a) BERT: Random tokens are replaced with masks, and the document is encoded bidirectionally. Missing tokens are predicted independently, so BERT cannot easily be used for generation.



(b) GPT: Tokens are predicted auto-regressively, meaning GPT can be used for generation. However words can only condition on leftward context, so it cannot learn bidirectional interactions.



(c) BART: Inputs to the encoder need not be aligned with decoder outputs, allowing arbitary noise transformations. Here, a document has been corrupted by replacing spans of text with mask symbols. The corrupted document (left) is encoded with a bidirectional model, and then the likelihood of the original document (right) is calculated with an autoregressive decoder. For fine-tuning, an uncorrupted document is input to both the encoder and decoder, and we use representations from the final hidden state of the decoder.

Comparison of Pre-training Objectives

Model	SQuAD 1.1 F1	MNLI Acc	ELI5 PPL	XSum PPL	ConvAI2 PPL	CNN/DM PPL
BERT Base (Devlin et al., 2019)	88.5	**84.3**	-	-	-	-
Masked Language Model	90.0	83.5	24.77	7.87	12.59	7.06
Masked Seq2seq	87.0	82.1	23.40	6.80	11.43	6.19
Language Model	76.7	80.1	**21.40**	7.00	11.51	6.56
Permuted Language Model	89.1	83.7	24.03	7.69	12.23	6.96
Multitask Masked Language Model	89.2	82.4	23.73	7.50	12.39	6.74
BART Base						
w/ Token Masking	90.4	84.1	25.05	7.08	11.73	6.10
w/ Token Deletion	90.4	84.1	24.61	6.90	11.46	5.87
w/ Text Infilling	**90.8**	84.0	24.26	**6.61**	**11.05**	5.83
w/ Document Rotation	77.2	75.3	53.69	17.14	19.87	10.59
w/ Sentence Shuffling	85.4	81.5	41.87	10.93	16.67	7.89
w/ Text Infilling + Sentence Shuffling	**90.8**	83.8	24.17	6.62	11.12	**5.41**

Advantages of Encoder-Decoder Models

- "Best of both worlds"
  - On a par with RoBERTa on NLU / discrimination tasks
  - State-of-the-art on many generation tasks (e.g. summarization)
- Others:
  - MASS
  - T5
    - uses labeled data
    - "Unified" text-to-text format

Source Document (abbreviated)	**BART Summary**
The researchers examined three types of coral in reefs off the coast of Fiji ... The researchers found when fish were plentiful, they would eat algae and seaweed off the corals, which appeared to leave them more resistant to the bacterium Vibrio coralliilyticus, a bacterium associated with bleaching. The researchers suggested the algae, like warming temperatures, might render the corals' chemical defenses less effective, and the fish were protecting the coral by removing the algae.	Fisheries off the coast of Fiji are protecting coral reefs from the effects of global warming, according to a study in the journal Science.
Sacoolas, who has immunity as a diplomat's wife, was involved in a traffic collision ... Prime Minister Johnson was questioned about the case while speaking to the press at a hospital in Watford. He said, "I hope that Anne Sacoolas will come back ... if we can't resolve it then of course I will be raising it myself personally with the White House."	Boris Johnson has said he will raise the issue of US diplomat Anne Sacoolas' diplomatic immunity with the White House.

Multilingual Pre-training

- One other main dimension: *mono-* vs *multi*-lingual pre-training
  - Roughly: concatenate (in fancy way) corpora from many languages, then do the same kind of pre-training
  - *Much more info* from Agatha's lecture on May 18

	Encoder-only	Decoder-only	Encoder-decoder
English-only *	BERT, RoBERTa, XLNet, ALBERT, …	GPT-n	BART
Multilingual	mBERT, XLM(-R), …	HF BigScience LLM, XGLM	mBART, MASS, mT5

Limitations of Pre-training + Fine-tuning

State of the Field

- Manning 2017: “The BiLSTM Hegemony”
- Right now: “The pre-trained Transformer Hegemony”
  - By default: fine-tune a large pre-trained Transformer on the task you care about
  - Will often yield the best results
  - Beware: often not significantly better than *very simple* baselines (SVM, etc)

Scale scale scale

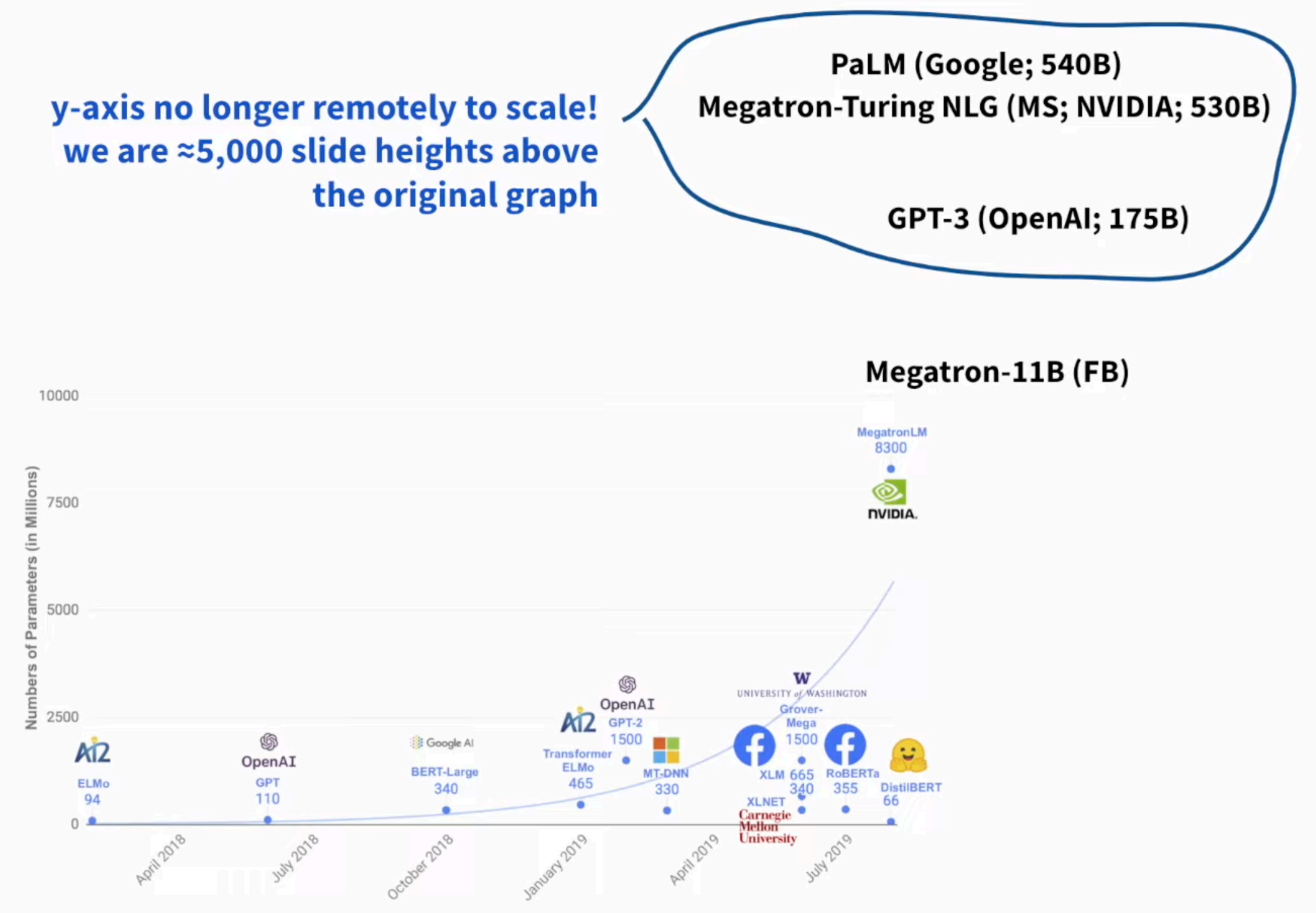


Figure 1: **Parameter counts of several recently released pretrained language models.** From Sanh et al. 2019

source

Note on the costs of LMs

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  - Carbon emissions
  - Monetarily
    - Inequitable access
  - Dataset debt/documentation

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Energy and Policy Considerations for Deep Learning in NLP

Emma Strubell **Ananya Ganesh** **Andrew McCallum**
College of Information and Computer Sciences
University of Massachusetts Amherst
{strubell, aganesh, mccallum}@cs.umass.edu

Abstract

Recent progress in hardware and methodology for training neural networks has ushered in a new generation of large networks trained on abundant data. These models have obtained notable gains in accuracy across many NLP tasks. However, these accuracy improvements depend on the availability of exceptionally large computational resources that necessitate similarly substantial energy consumption. As a result these models are costly to train and develop, both financially, due to the cost of hardware and electricity or cloud compute time, and environmentally, due to the carbon footprint required to fuel modern tensor

Consumption	**CO_2e (lbs)**
Air travel, 1 person, NY↔SF	1984
Human life, avg, 1 year	11,023
American life, avg, 1 year	36,156
Car, avg incl. fuel, 1 lifetime	126,000
Training one model (GPU)	
NLP pipeline (parsing, SRL)	39
w/ tuning & experiments	78,468
Transformer (big)	192
w/ neural arch. search	626,155

Table 1: Estimated CO_2 emissions from training common NLP models, compared to familiar consumption.[1]

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Green AI

Roy Schwartz[*◇] Jesse Dodge[*◇♣] Noah A. Smith[◇♡] Oren Etzioni[◇]

[◇]Allen Institute for AI, Seattle, Washington, USA
[♣] Carnegie Mellon University, Pittsburgh, Pennsylvania, USA
[♡] University of Washington, Seattle, Washington, USA

July 2019

Abstract

The computations required for deep learning research have been doubling every few months, resulting in an estimated 300,000x increase from 2012 to 2018 [2]. These computations have a surprisingly large carbon footprint [40]. Ironically, deep learning was inspired by the human brain, which is remarkably energy efficient. Moreover, the financial cost of the computations can make it difficult for academics, students, and researchers, in particular those from emerging economies, to engage in deep learning research.

This position paper advocates a practical solution by making **efficiency** an evaluation criterion for research alongside accuracy and related measures. In addition, we propose reporting the financial cost or “price tag” of developing, training, and running models to provide baselines for the investigation of increasingly efficient methods. Our goal is to make AI both greener and more inclusive—enabling any inspired undergraduate with a laptop to write high-quality research papers. Green AI is an emerging focus at the Allen Institute for AI.

More on the Costs of LMs

On the Dangers of Stochastic Parrots: Can Language Models Be Too Big? 🦜

Emily M. Bender*
ebender@uw.edu
University of Washington
Seattle, WA, USA

Timnit Gebru*
timnit@blackinai.org
Black in AI
Palo Alto, CA, USA

Angelina McMillan-Major
aymm@uw.edu
University of Washington
Seattle, WA, USA

Shmargaret Shmitchell
shmargaret.shmitchell@gmail.com
The Aether

ABSTRACT

The past 3 years of work in NLP have been characterized by the development and deployment of ever larger language models, especially for English. BERT, its variants, GPT-2/3, and others, most recently Switch-C, have pushed the boundaries of the possible both through architectural innovations and through sheer size. Using these pretrained models and the methodology of fine-tuning them for specific tasks, researchers have extended the state of the art alone, we have seen the emergence of BERT and its variants [39, 70, 74, 113, 146], GPT-2 [106], T-NLG [112], GPT-3 [25], and most recently Switch-C [43], with institutions seemingly competing to produce ever larger LMs. While investigating properties of LMs and how they change with size holds scientific interest, and large LMs have shown improvements on various tasks (§2), we ask whether enough thought has been put into the potential risks associated with developing them and strategies to mitigate these risks.

- For more on the reactions to this paper: https://faculty.washington.edu/ebender/stochasticparrots.html

Some Reasons to Pause

- Leaderboard chasing (via larger models and more data) funnels research activity into one specific and limited goal
  - Amplifies harmful biases
  - Equity costs
  - Climate costs
  - Data documentation debt
  - Does not promote human-like linguistic generalization (Linzen 2020 summary)
- More from Angelina McMillan-Major on May 25 on stochastic parrots paper

🤗 Transformers

https://huggingface.co/transformers

Overview of the Library

- Access to many variants of many very large LMs (BERT, RoBERTa, XLNET, ALBERT, T5, language-specific models, …) with fairly consistent API
  - Build tokenizer + model from string for name or config
  - Then use just like any PyTorch nn.Module
- Emphasis on ease-of-use
  - E.g. low barrier-to-entry to *using* the models, including for analysis
- Interoperable with PyTorch or TensorFlow 2.0

Example: Tokenization

```
>>> from transformers import AutoTokenizer

>>> tokenizer = AutoTokenizer.from_pretrained("bert-base-cased")
```

```
>>> encoded_input = tokenizer("Do not meddle in the affairs of wizards, for they are subtle and quick to
>>> print(encoded_input)
{'input_ids': [101, 2079, 2025, 19960, 10362, 1999, 1996, 3821, 1997, 16657, 1010, 2005, 2027, 2024, 1125
 'token_type_ids': [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
 'attention_mask': [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1]}
```

See http://juditacs.github.io/2019/02/19/bert-tokenization-stats.html (h/t Naomi Shapiro)

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 'token_type_ids': [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
 'attention_mask': [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1]}
```

```
>>> tokenizer.decode(encoded_input["input_ids"])
'[CLS] Do not meddle in the affairs of wizards, for they are subtle and quick to anger. [SEP]'
```

See http://juditacs.github.io/2019/02/19/bert-tokenization-stats.html (h/t Naomi Shapiro)

Example: Tokenizing a Batch

```
>>> batch_sentences = [
...     "But what about second breakfast?",
...     "Don't think he knows about second breakfast, Pip.",
...     "What about elevensies?",
... ]
>>> encoded_input = tokenizer(batch_sentences, padding=True)
>>> print(encoded_input)
{'input_ids': [[101, 1252, 1184, 1164, 1248, 6462, 136, 102, 0, 0, 0, 0, 0, 0, 0],
               [101, 1790, 112, 189, 1341, 1119, 3520, 1164, 1248, 6462, 117, 21902, 1643, 119, 102],
               [101, 1327, 1164, 5450, 23434, 136, 102, 0, 0, 0, 0, 0, 0, 0, 0]],
 'token_type_ids': [[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
                    [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
                    [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]],
 'attention_mask': [[1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0],
                    [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1],
                    [1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0]]}
```

Example: Tokenizing a Batch

Add `return_tensors="pt"` to get these outputs as PyTorch Tensors

```
>>> batch_sentences = [
...     "But what about second breakfast?",
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... ]
>>> encoded_input = tokenizer(batch_sentences, padding=True)
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{'input_ids': [[101, 1252, 1184, 1164, 1248, 6462, 136, 102, 0, 0, 0, 0, 0, 0, 0],
               [101, 1790, 112, 189, 1341, 1119, 3520, 1164, 1248, 6462, 117, 21902, 1643, 119, 102],
               [101, 1327, 1164, 5450, 23434, 136, 102, 0, 0, 0, 0, 0, 0, 0, 0]],
 'token_type_ids': [[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
                    [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
                    [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]],
 'attention_mask': [[1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0],
                    [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1],
                    [1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0]]}
```

Example: Forward Pass

```
>>> from transformers import BertTokenizer, BertModel
>>> import torch

>>> tokenizer = BertTokenizer.from_pretrained("bert-base-uncased")
>>> model = BertModel.from_pretrained("bert-base-uncased")

>>> inputs = tokenizer("Hello, my dog is cute", return_tensors="pt")
>>> outputs = model(**inputs)

>>> last_hidden_states = outputs.last_hidden_state
```

More on HuggingFace

- Main library: https://huggingface.co/transformers
- Model repository (w/ search, tags, etc): https://huggingface.co/models
- Datasets: https://huggingface.co/datasets