Pre-training + Fine-tuning Paradigm

LING 575K Deep Learning for NLP

Shane Steinert-Threlkeld

May 5 2021

Announcements

- Regularization and training “speed”
- Sample next character: return a [batch_size] n*umpy array*
- Schedule update:
  - Multilingual guest lecture moved to May 26 [former overflow day]
  - May 17: AMA / student question / discussion day
    - Stay tuned for more info / anonymous question submission form

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

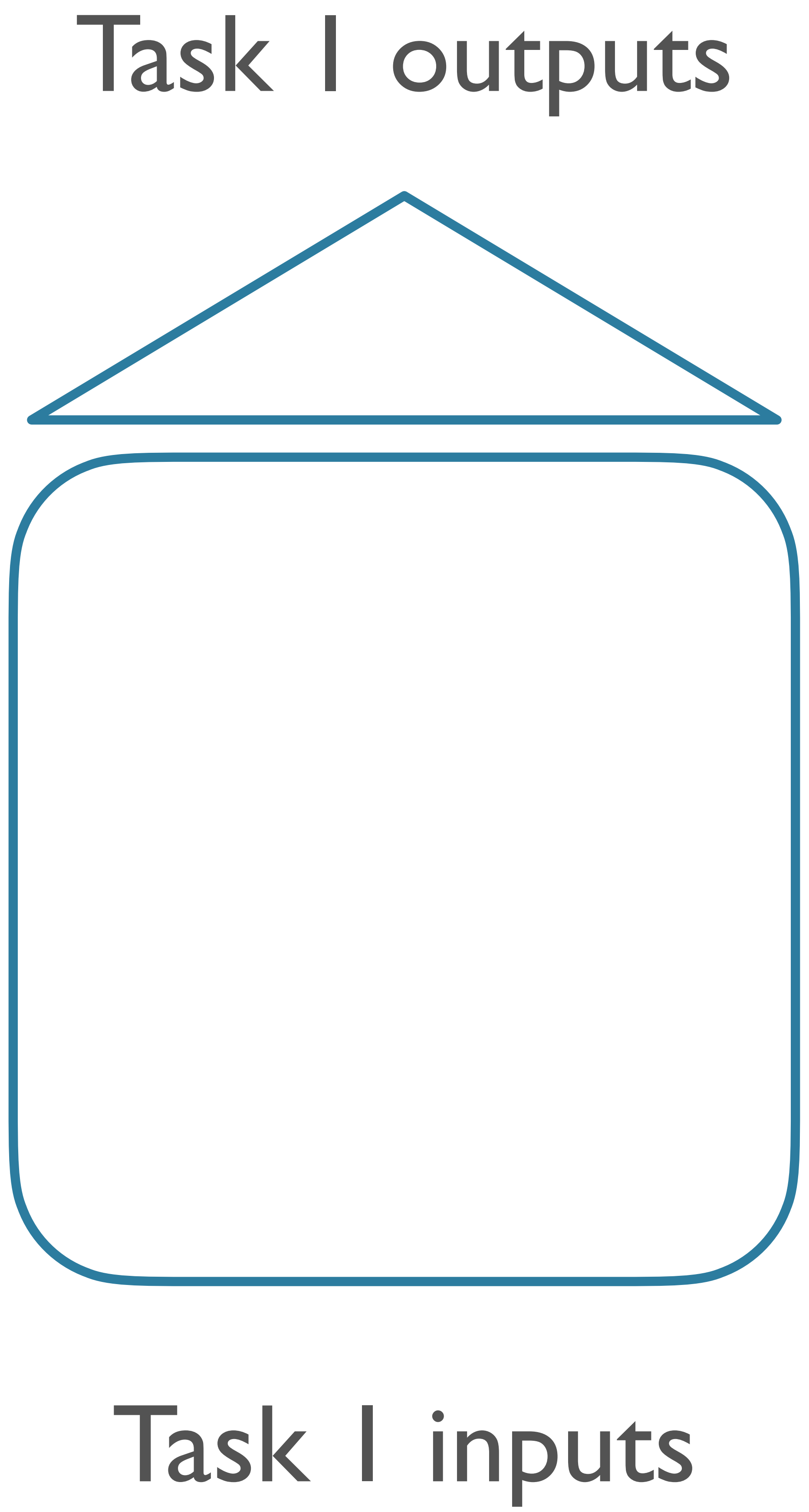
link

Today's Plan

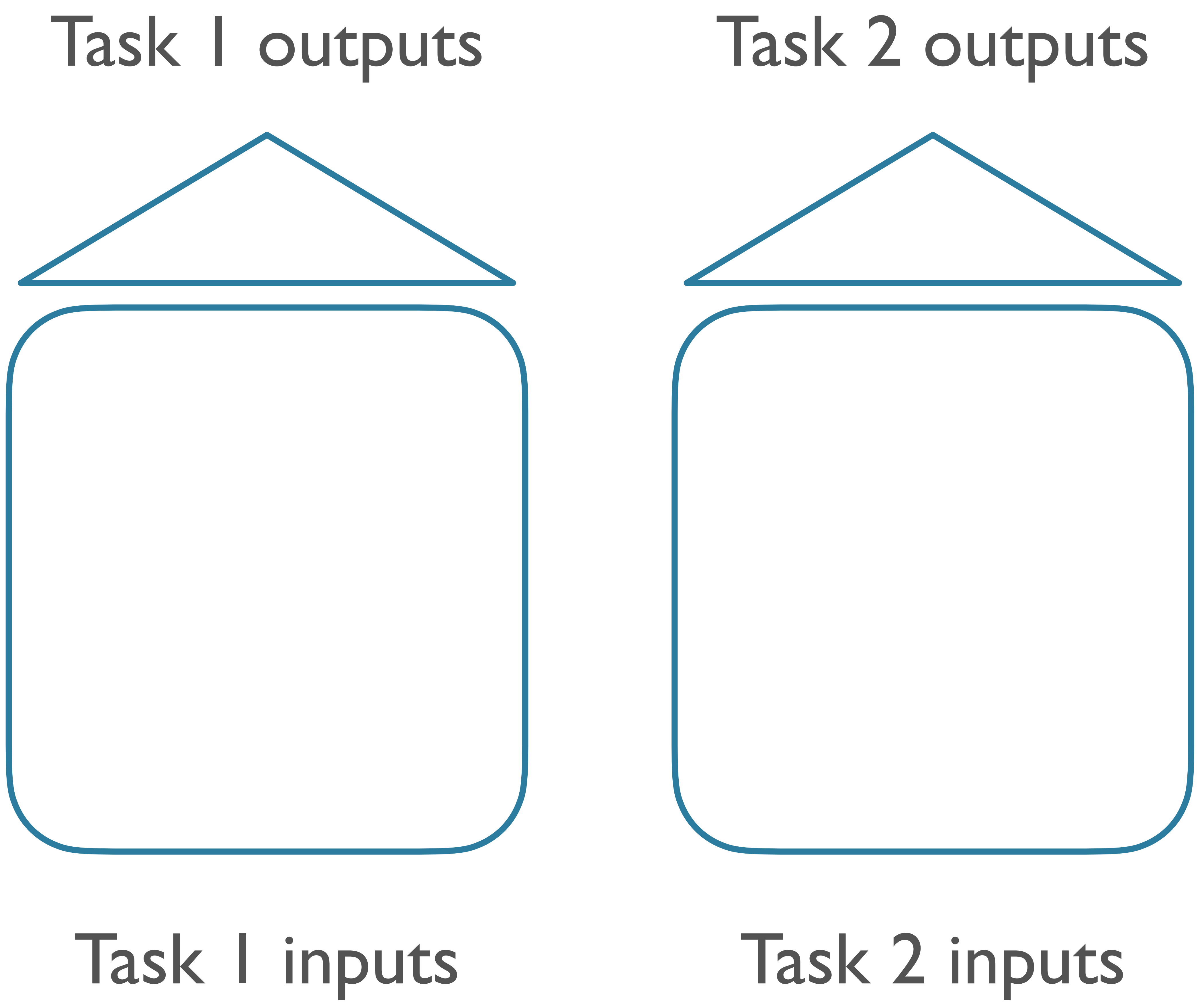
- Transfer learning in general
- Language model pre-training: initial steps
- Transformer-based pre-training
  - Encoder only
  - Decoder only
  - Encoder-Decoder
- [Some] limitations [more later in course]

Transfer Learning

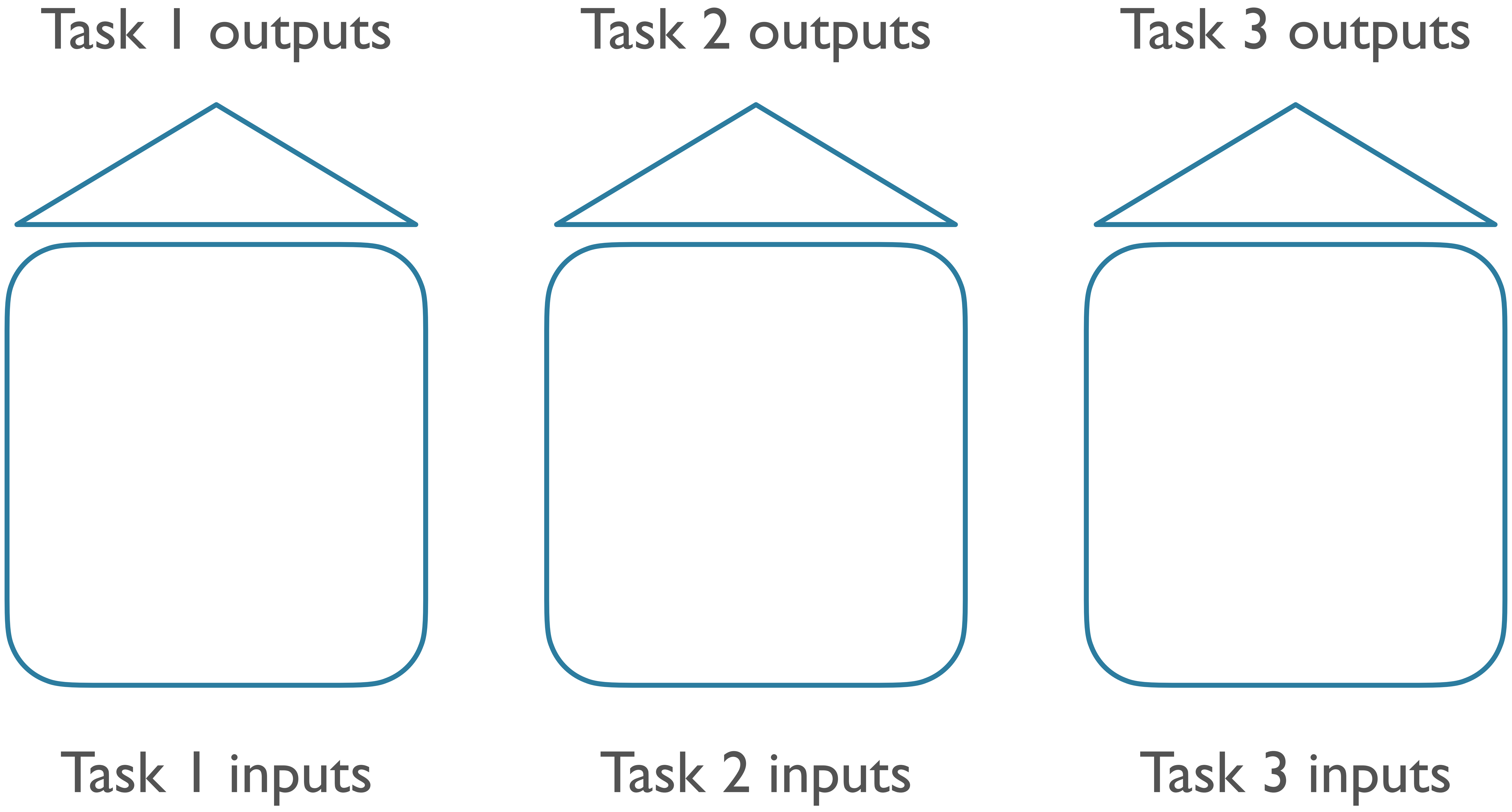
Standard Learning



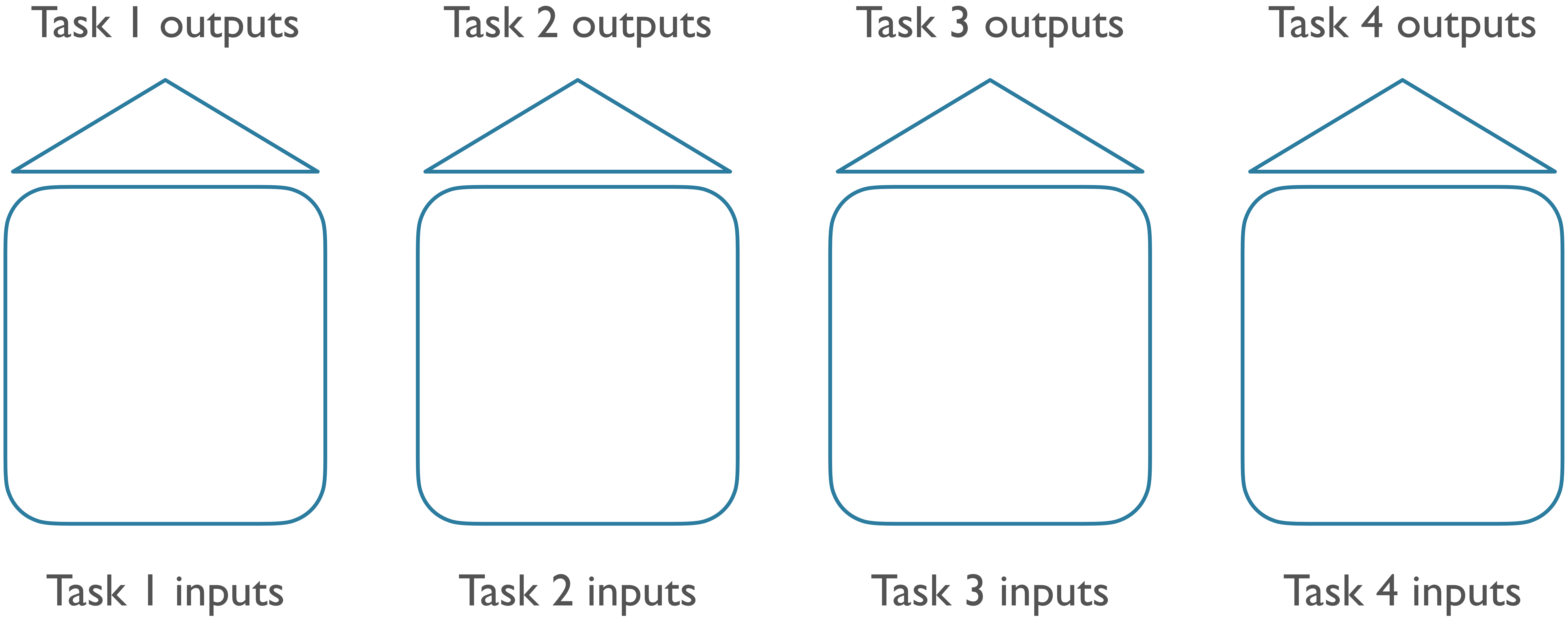
Standard Learning



Standard Learning



Standard Learning

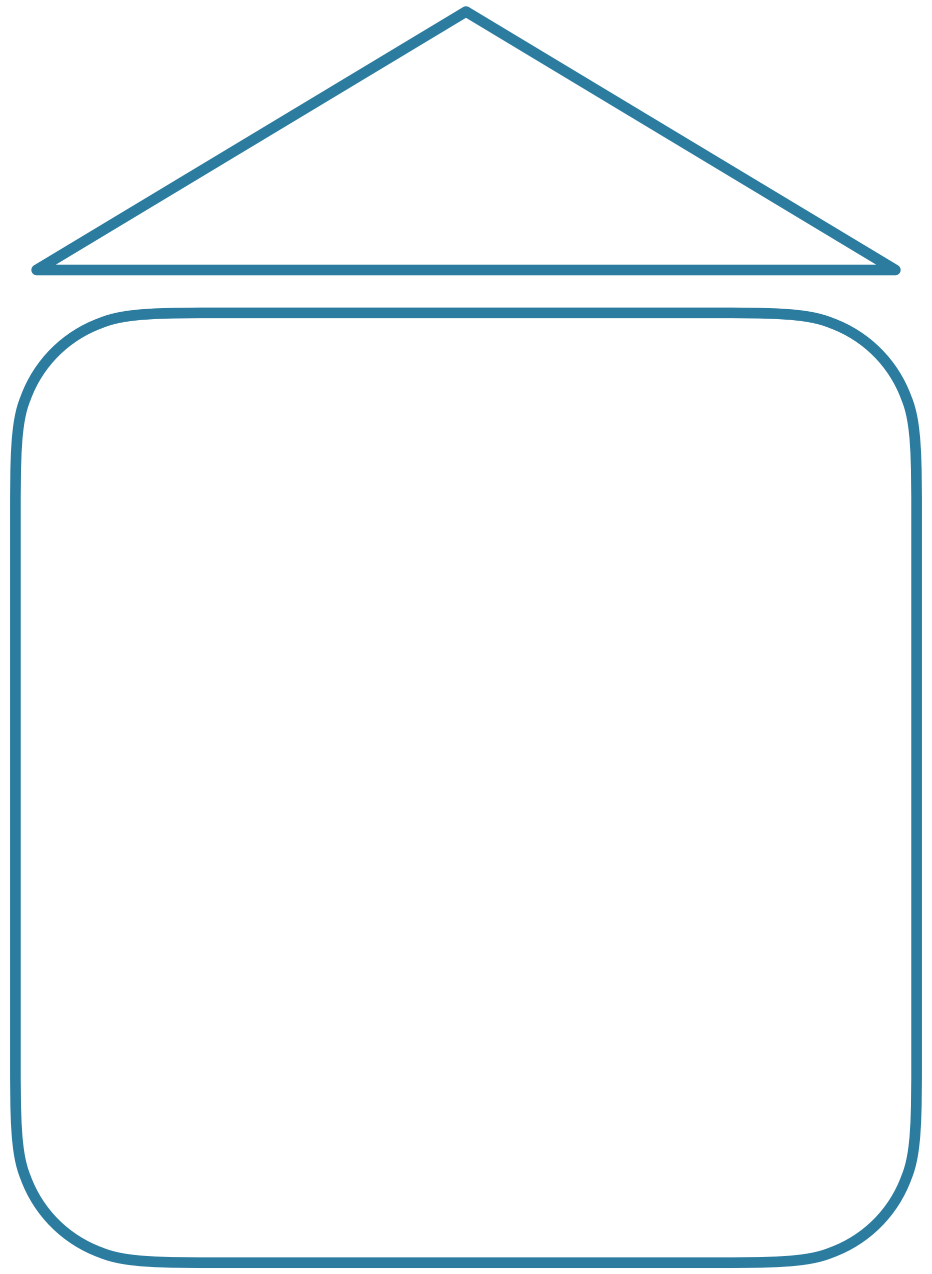


Standard Learning

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

Transfer Learning

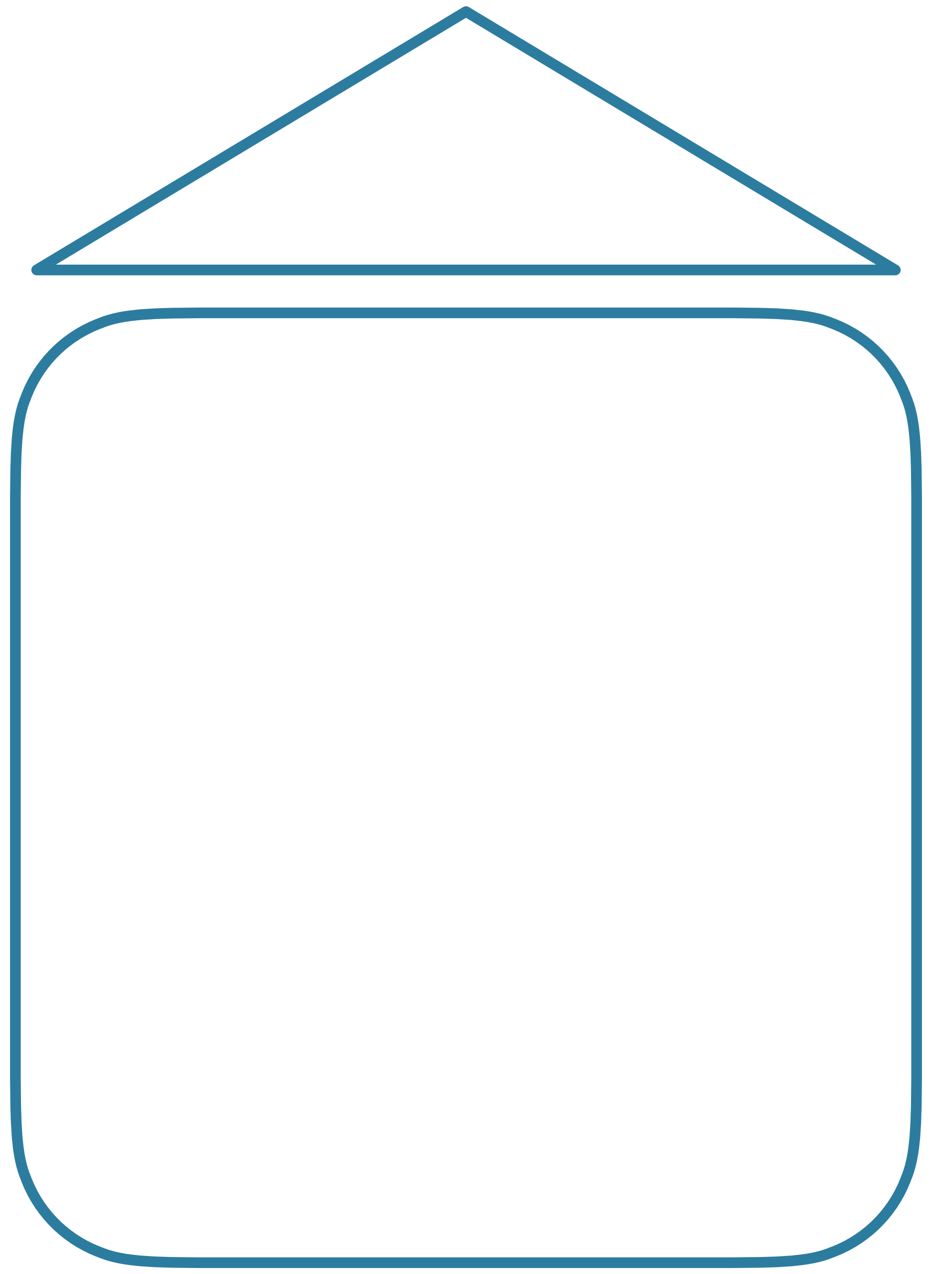
“pre-training” task outputs



“pre-training” task inputs

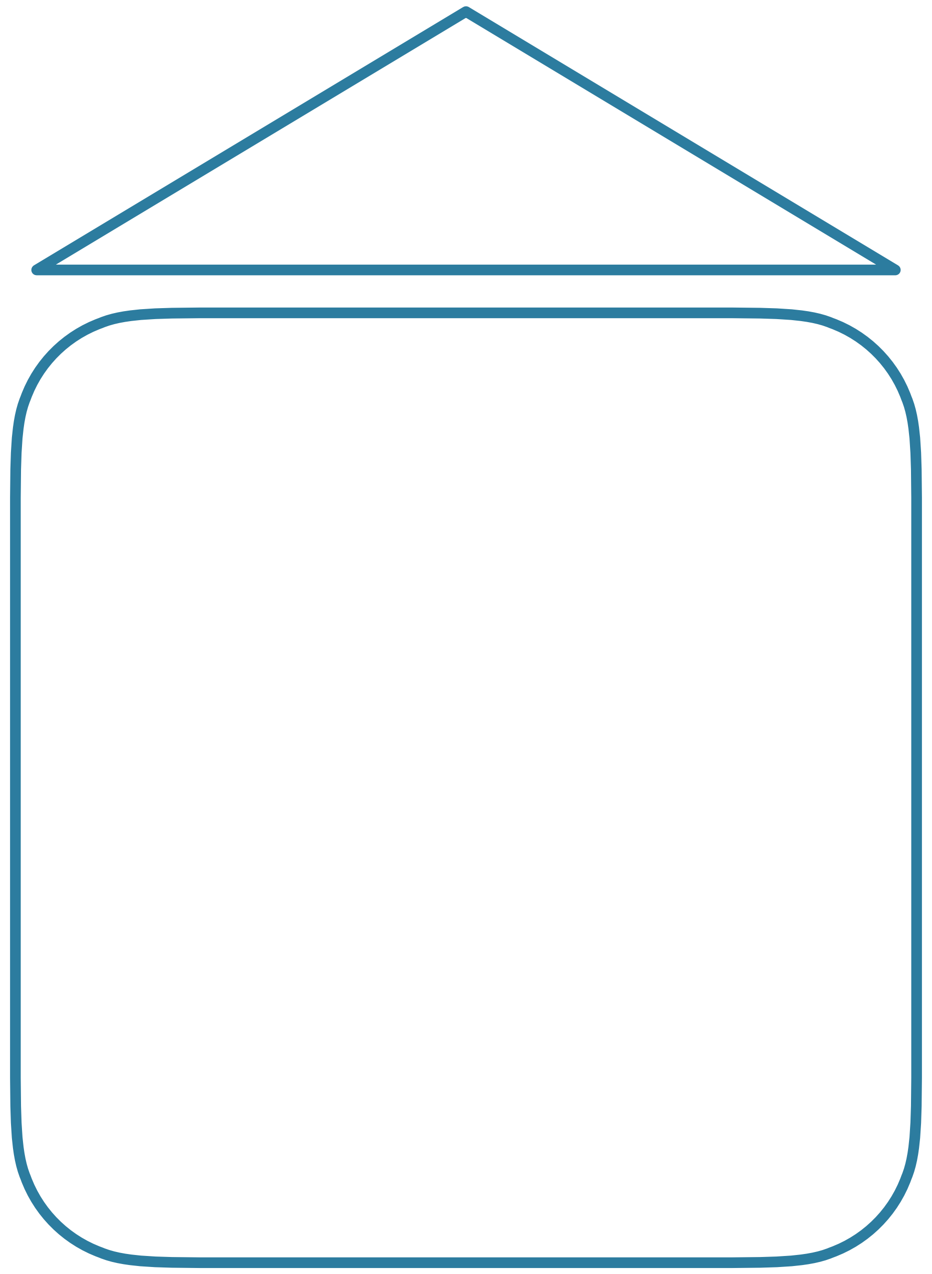
Transfer Learning

"pre-training" task outputs



Transfer Learning

"pre-training" task outputs

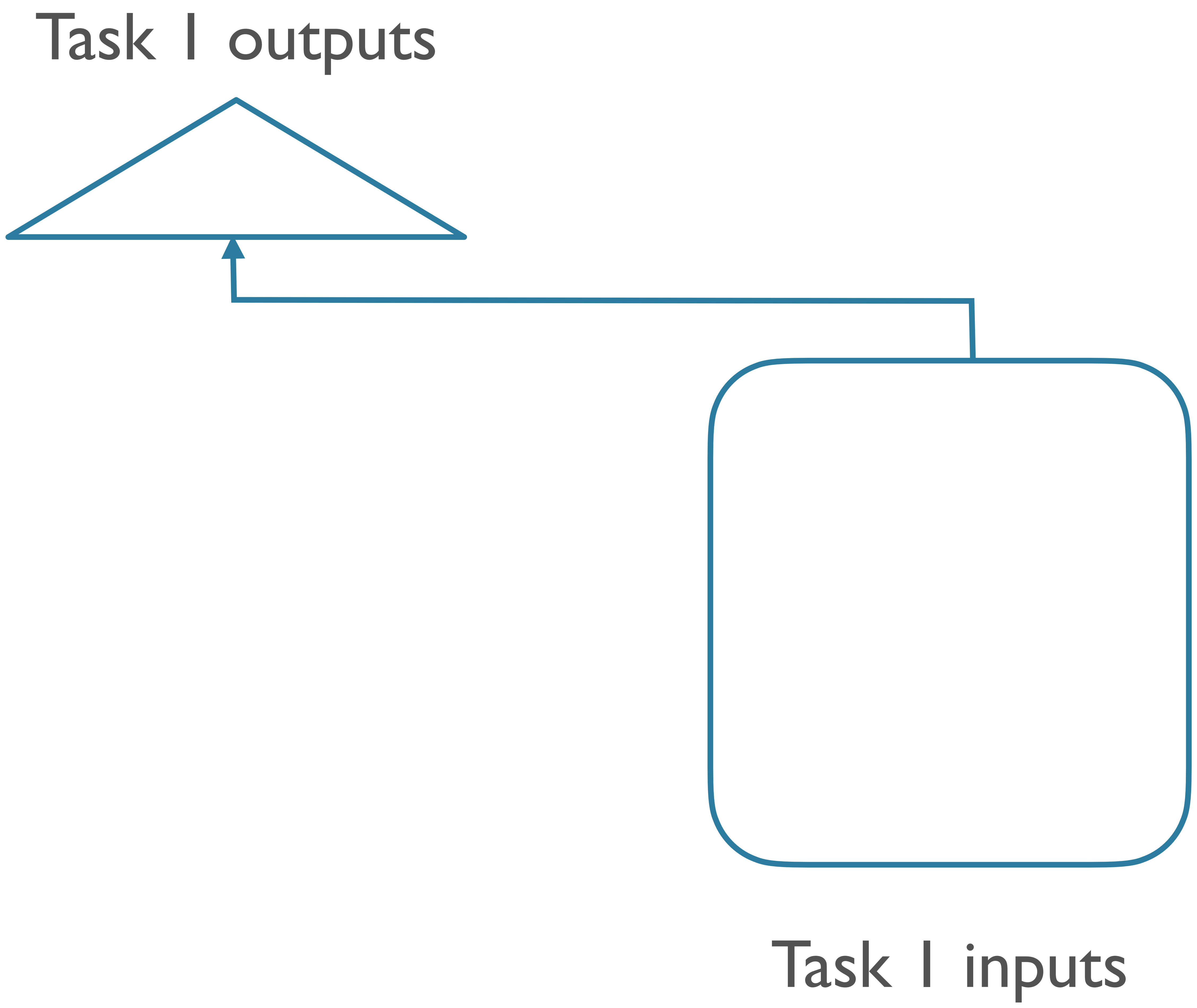


Task 1 inputs

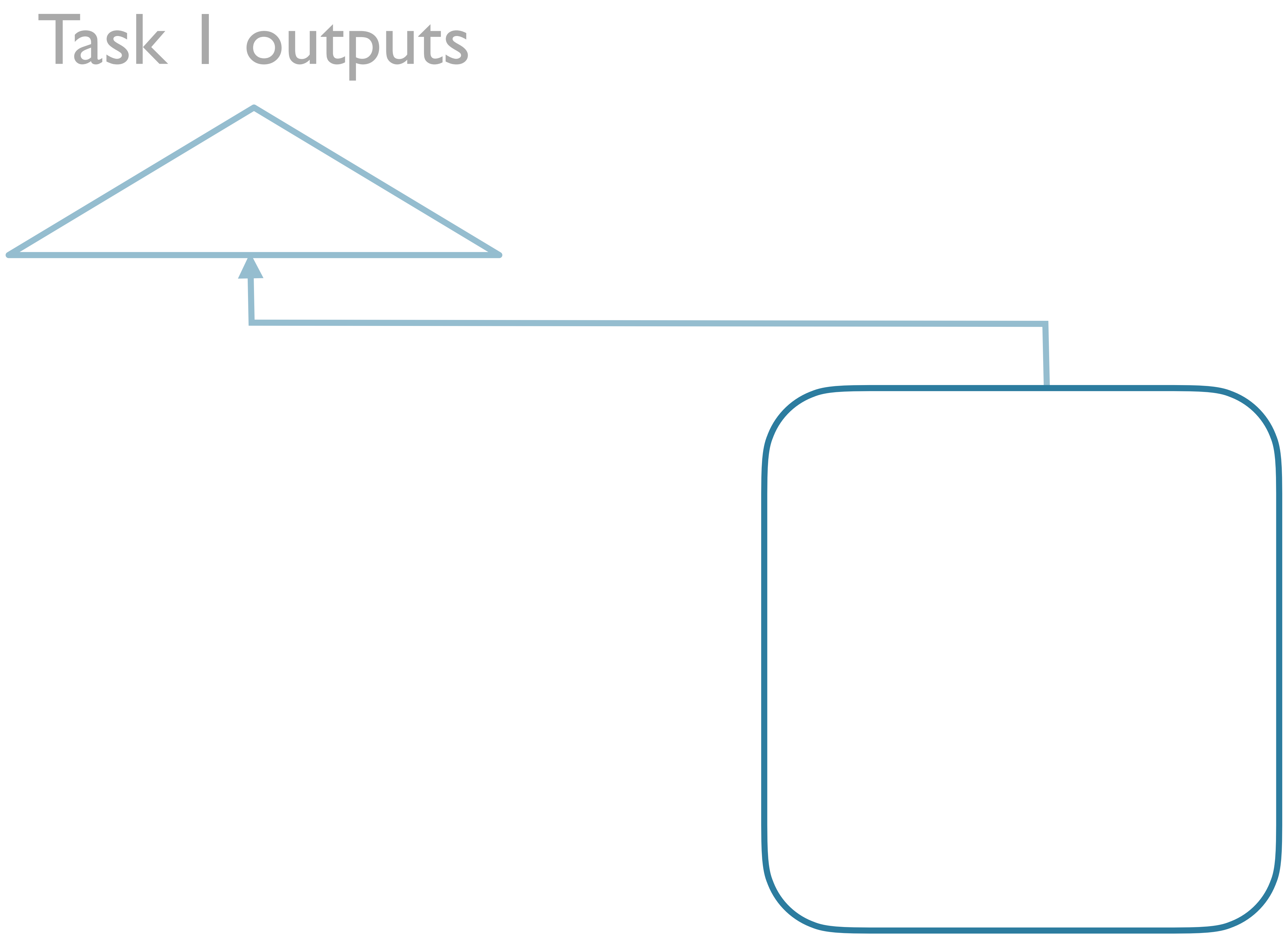
Transfer Learning

Task 1 inputs

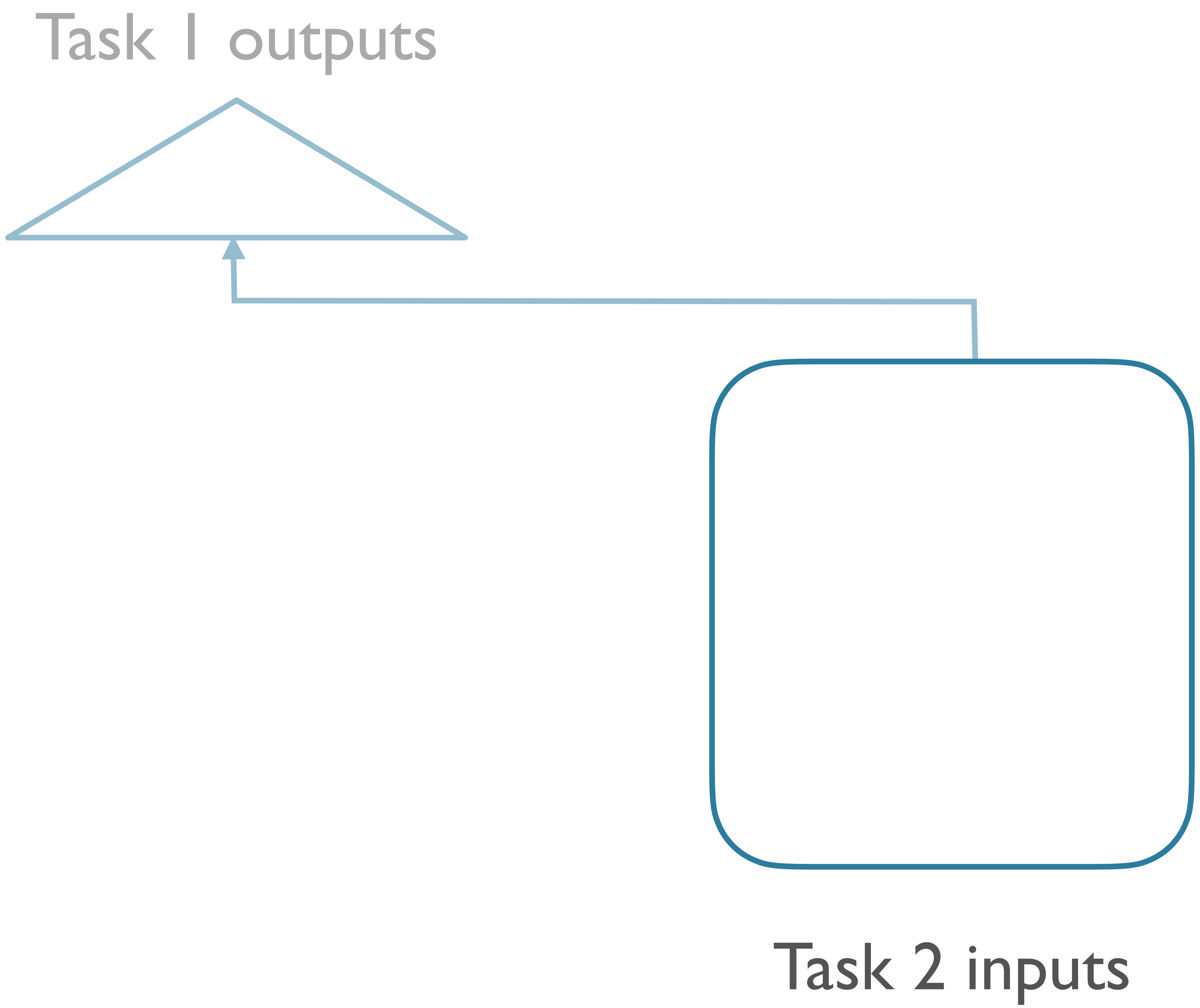
Transfer Learning



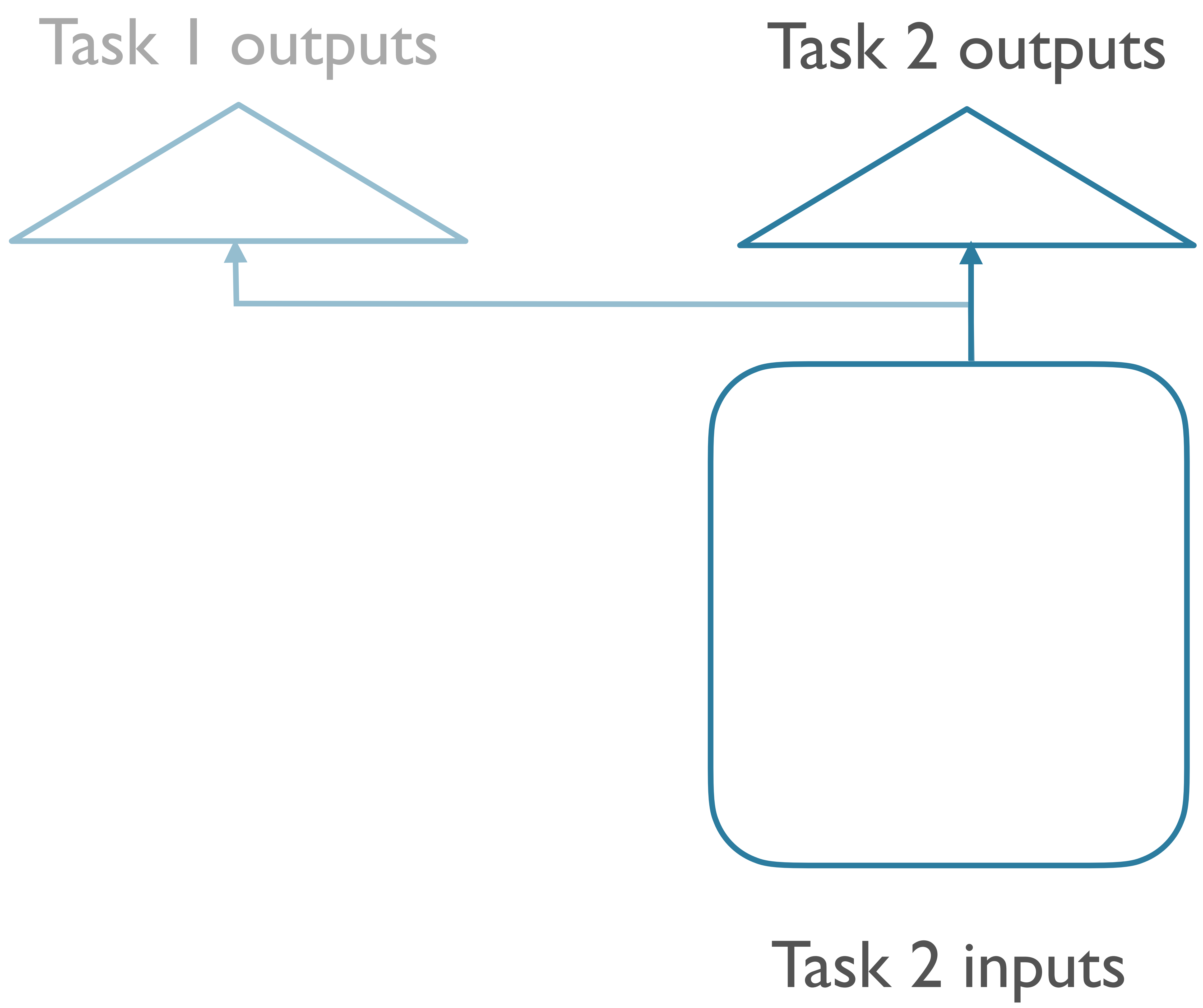
Transfer Learning



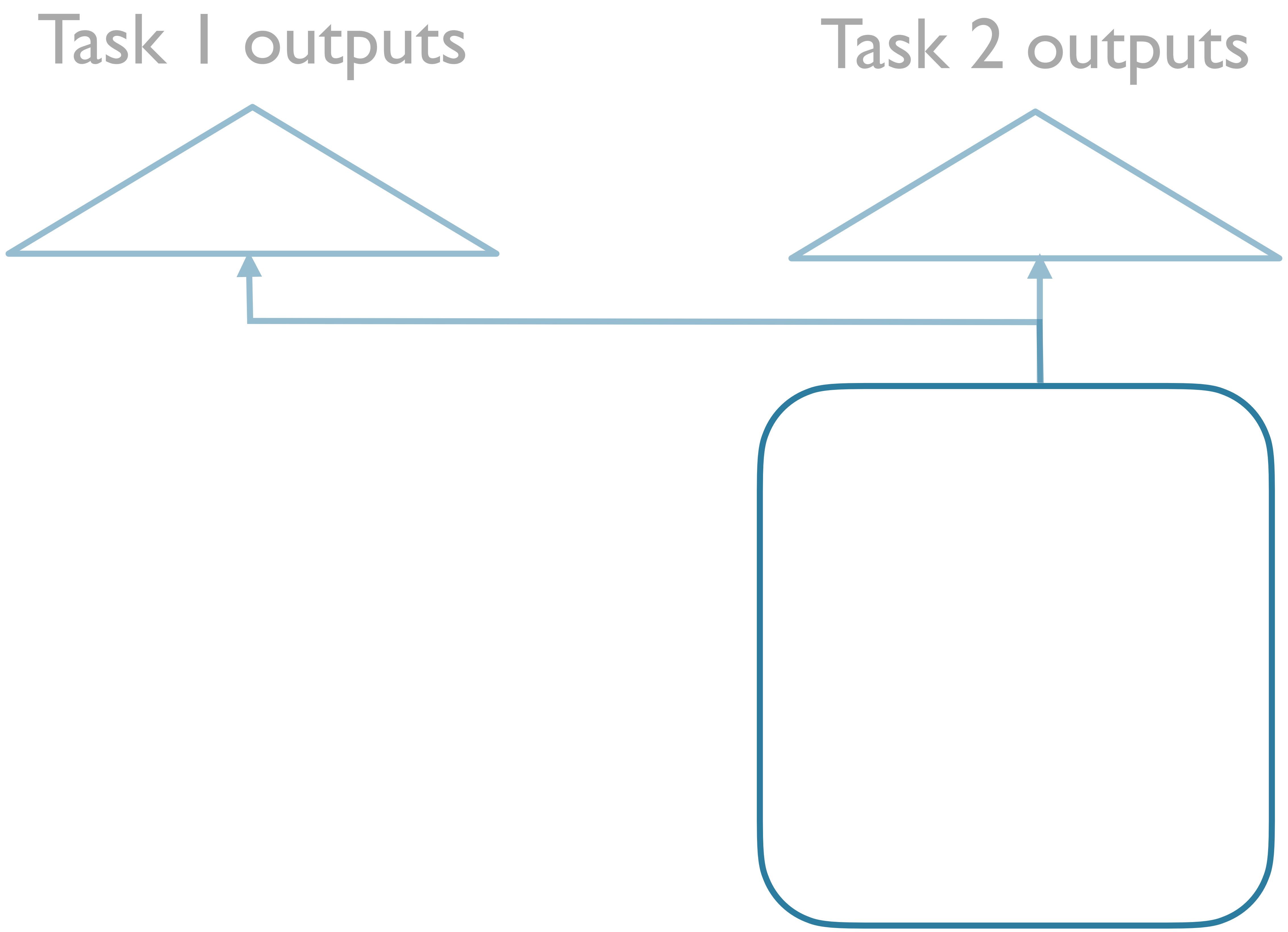
Transfer Learning



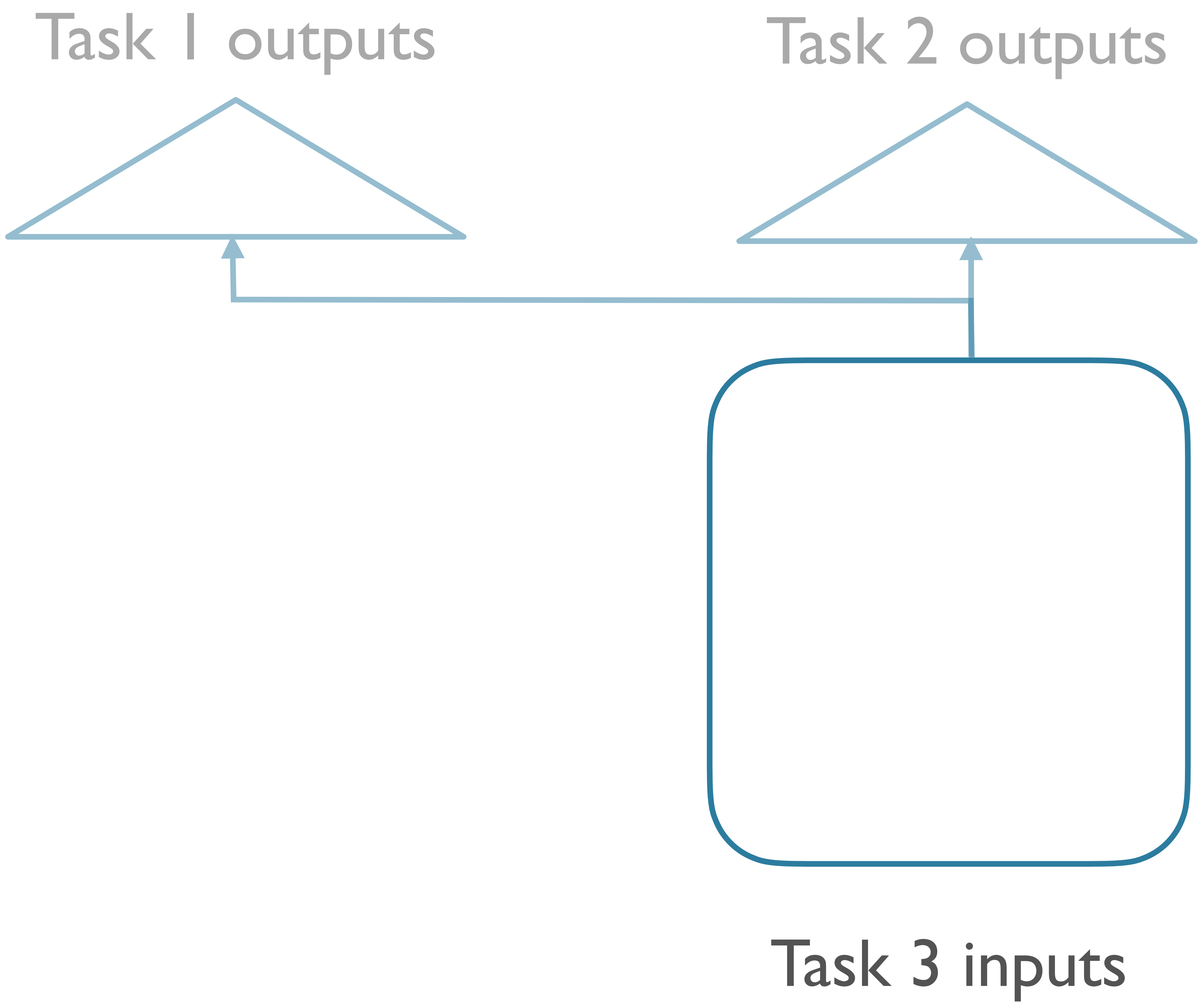
Transfer Learning



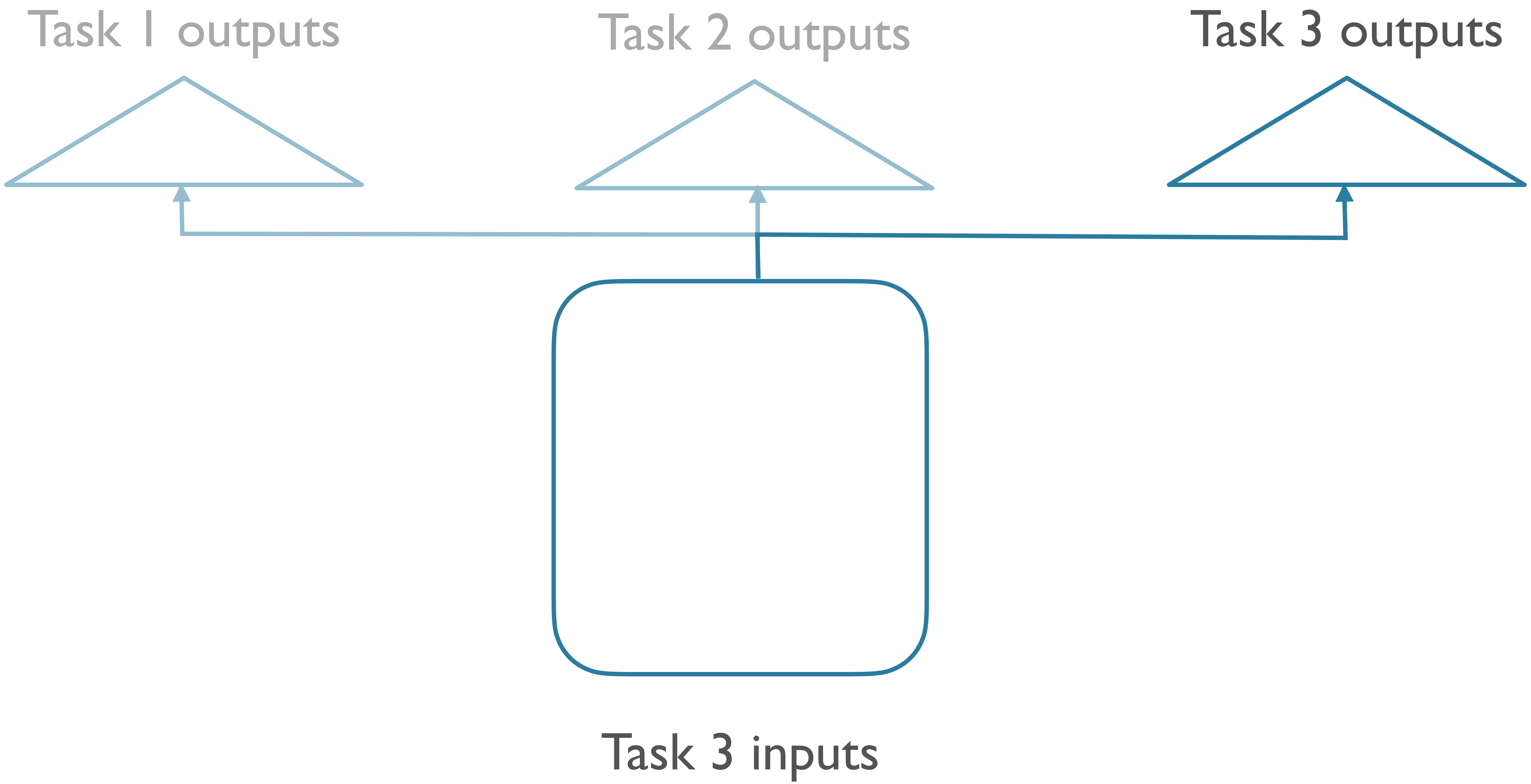
Transfer Learning



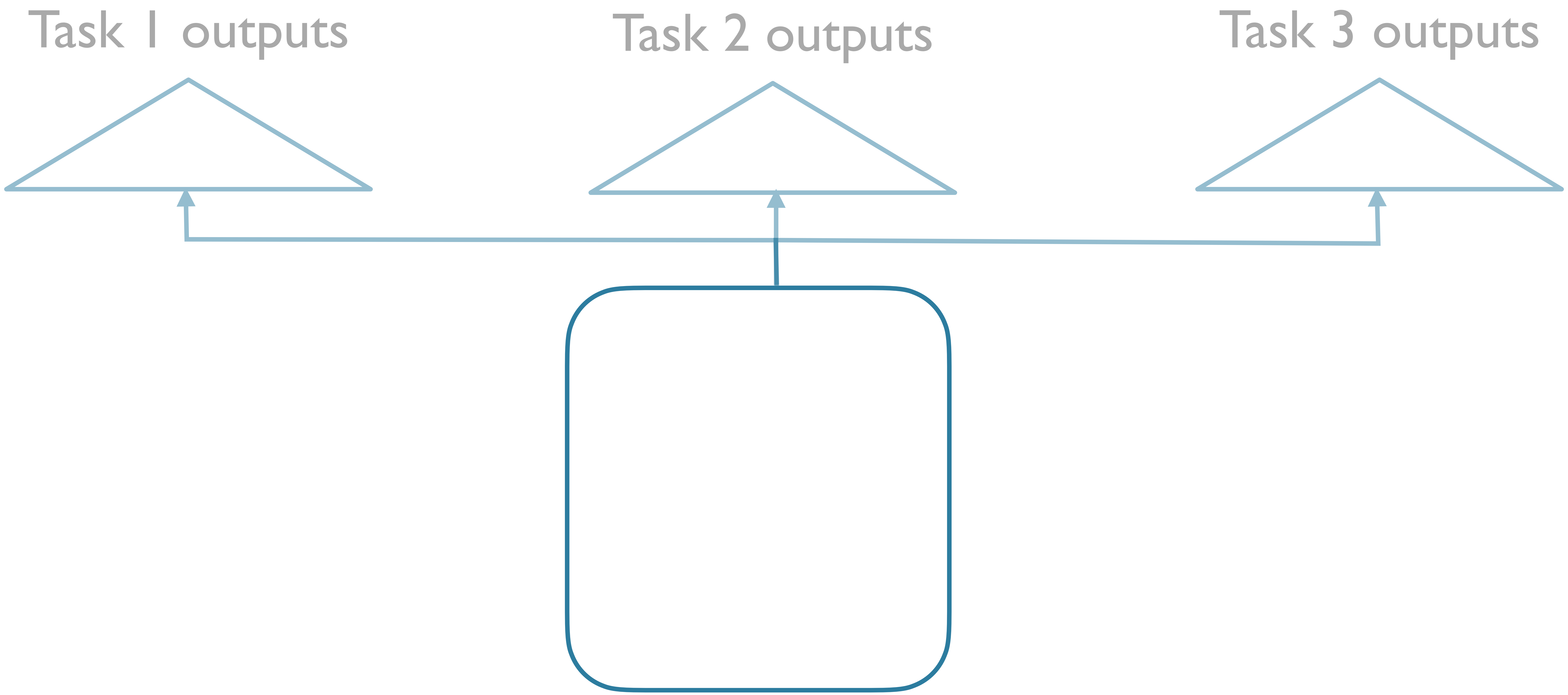
Transfer Learning



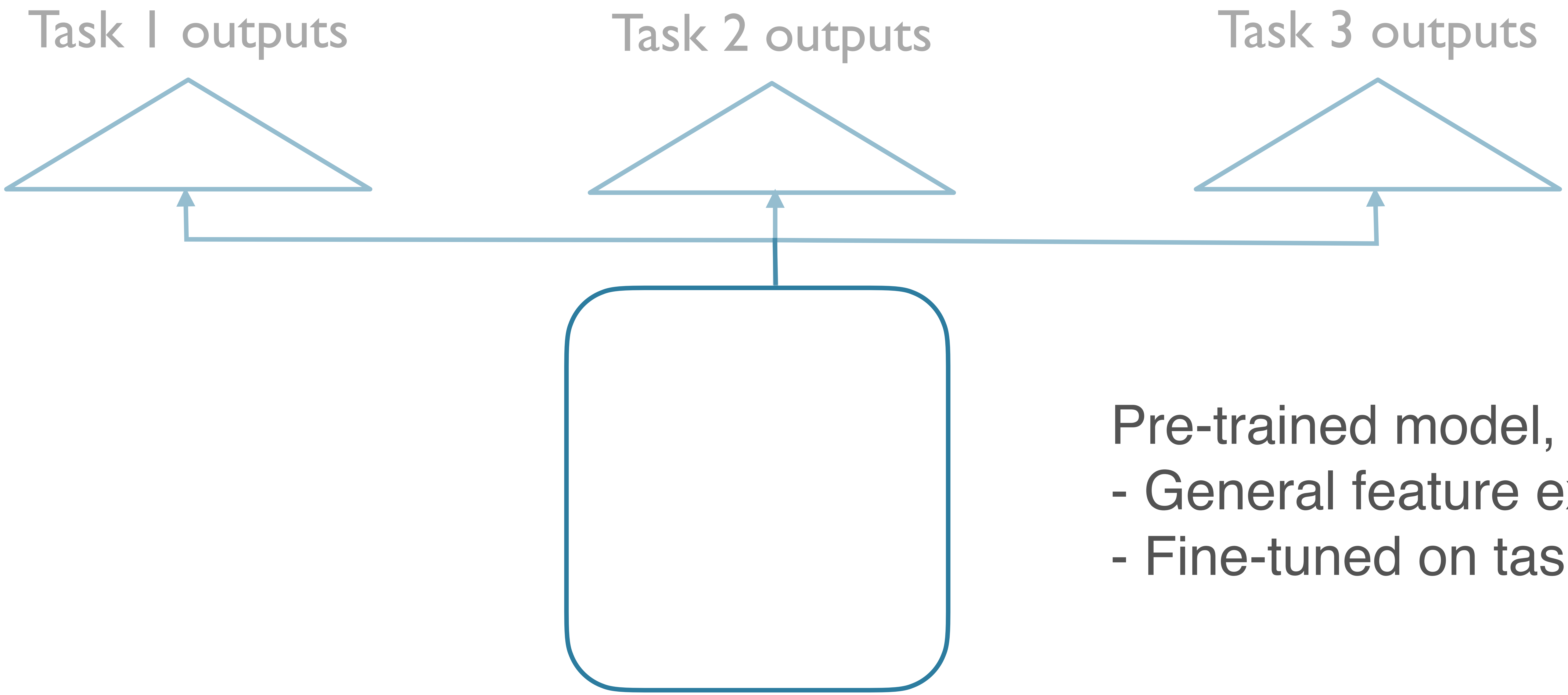
Transfer Learning



Transfer Learning



Transfer Learning



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, 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*?

Where to transfer *from*?

- Goal: find a linguistic task that will build general-purpose / *transferable* representations

Where to transfer *from*?

- Goal: find a linguistic task that will build general-purpose / *transferable* representations
- Possibilities:

Where to transfer *from*?

- Goal: find a linguistic task that will build general-purpose / *transferable* representations
- Possibilities:
    - Constituency or dependency parsing

Where to transfer *from*?

- Goal: find a linguistic task that will build general-purpose / *transferable* representations
- Possibilities:
  - Constituency or dependency parsing
  - Semantic parsing

Where to transfer *from*?

- Goal: find a linguistic task that will build general-purpose / *transferable* representations
- Possibilities:
  - Constituency or dependency parsing
  - Semantic parsing
  - Machine translation

Where to transfer *from*?

- Goal: find a linguistic task that will build general-purpose / *transferable* representations
- Possibilities:
  - Constituency or dependency parsing
  - Semantic parsing
  - Machine translation
  - QA

Where to transfer *from*?

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

Where to transfer *from*?

- 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

Language Modeling

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

- Linguistic knowledge:
  - The bicycles, even though old, were in good shape because ____ …
  - The bicycle, even though old, was in good shape because ____ …

Language Modeling

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

- 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

Data for LM is cheap

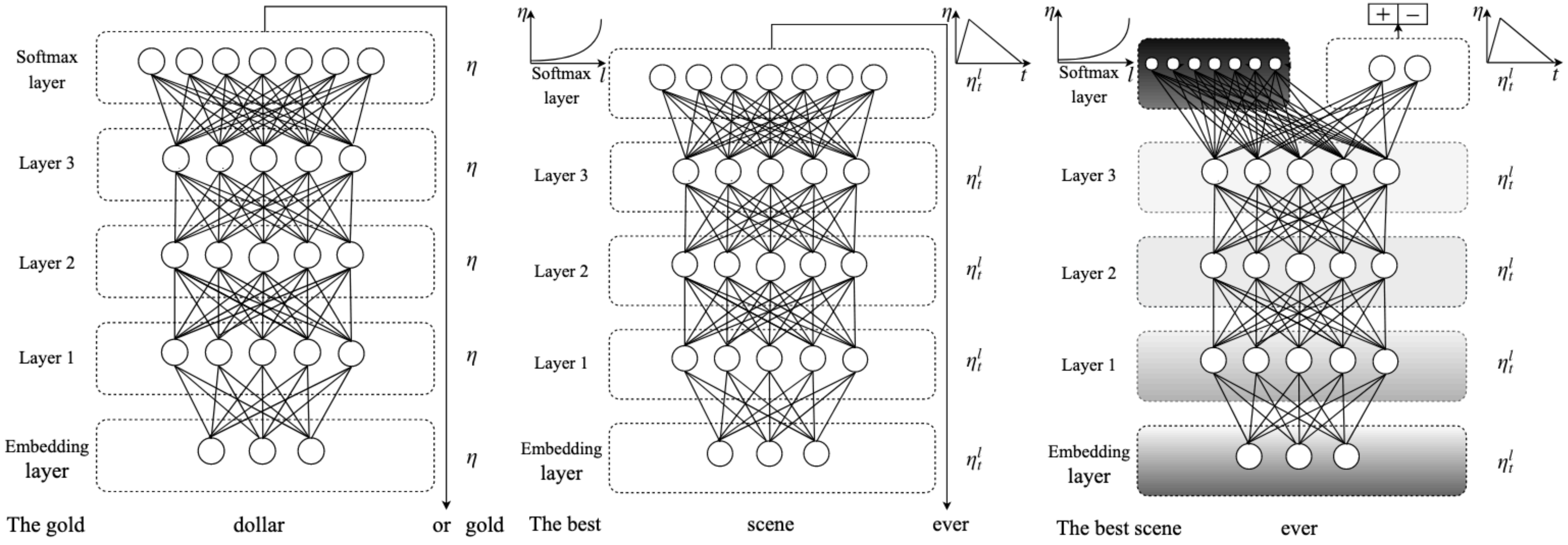
Data for LM is cheap

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



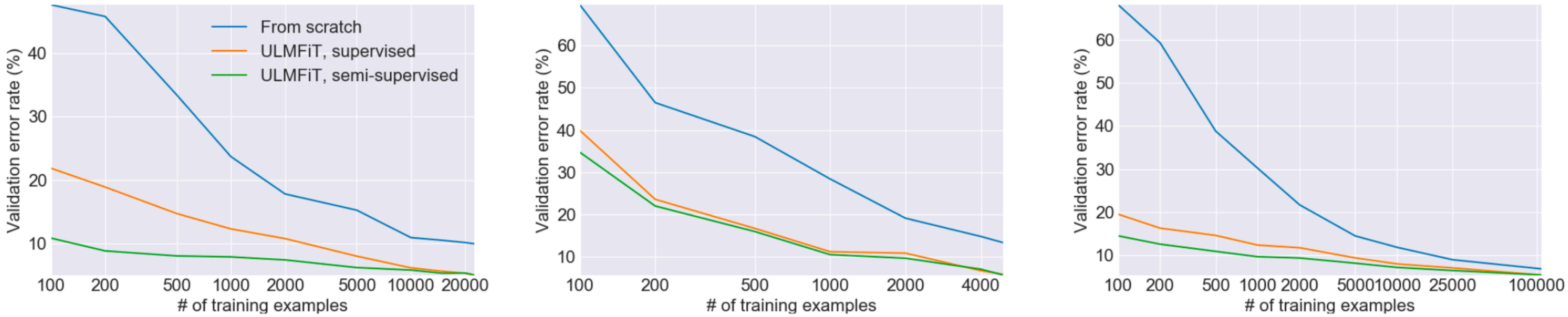
(a) LM pre-training (b) LM fine-tuning (c) Classifier fine-tuning

[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

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.

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

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

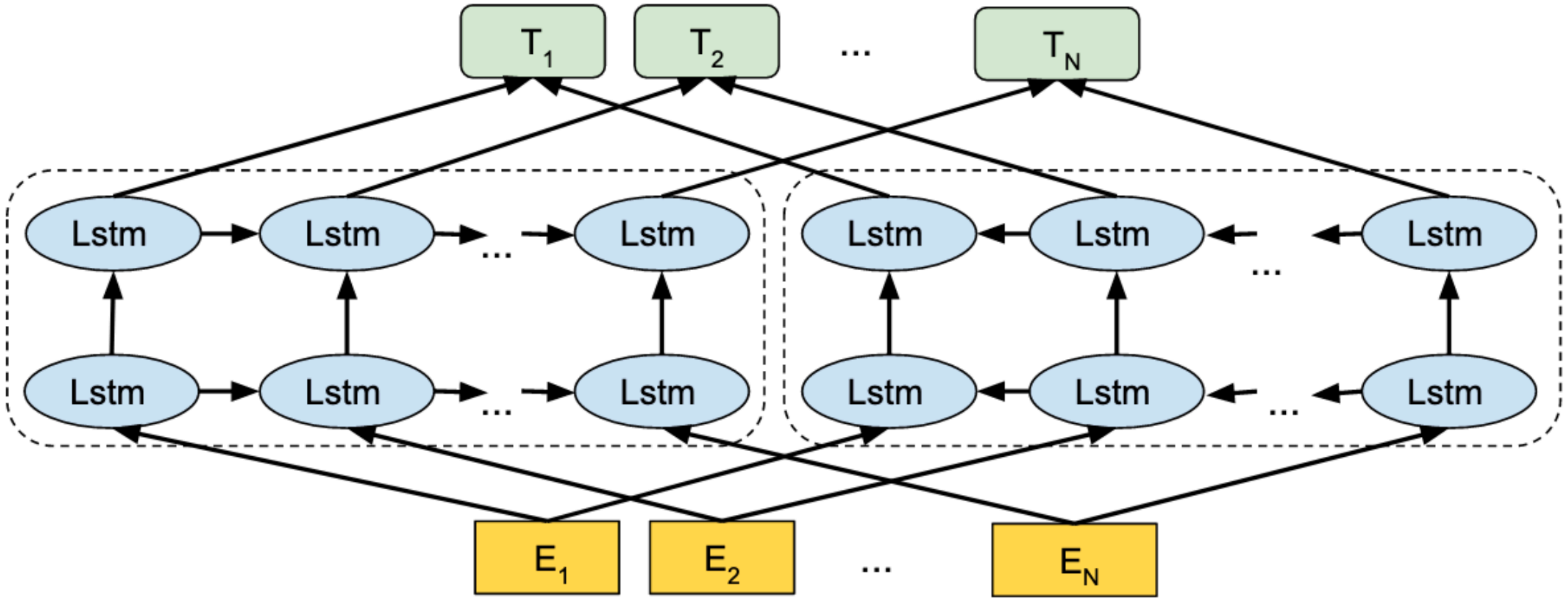
Abstract

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.

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

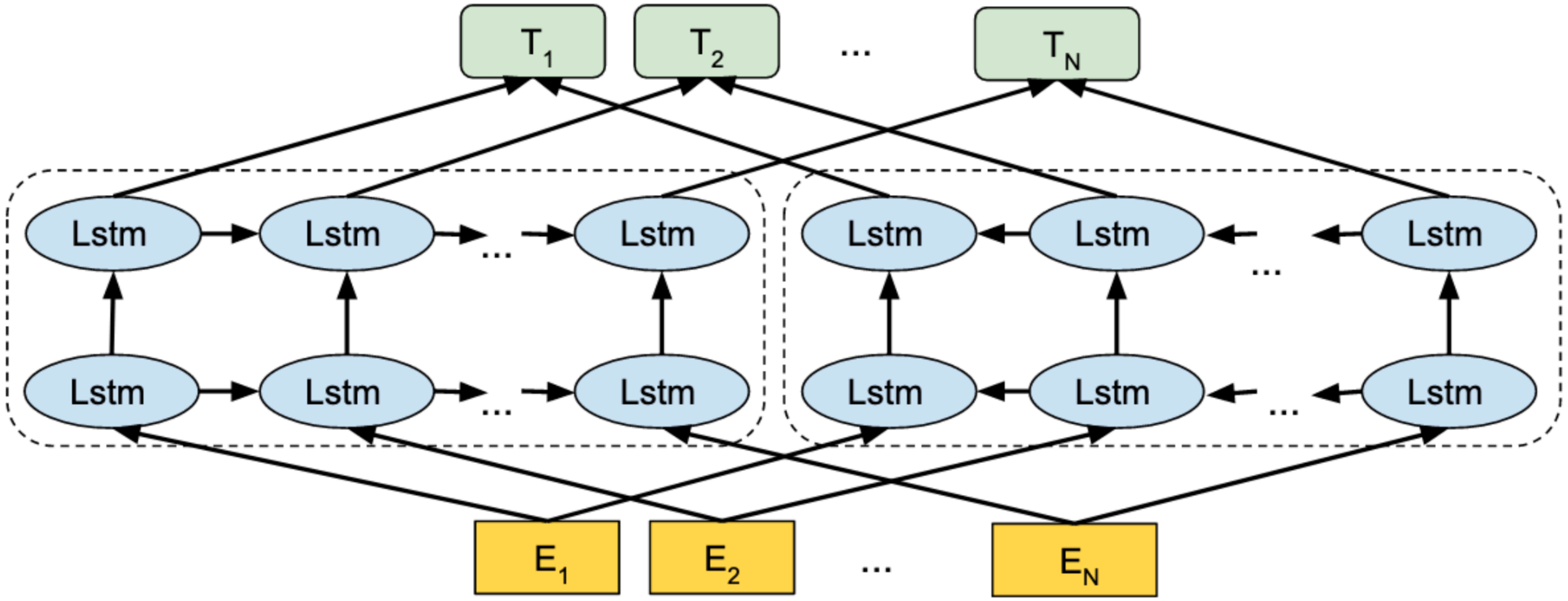
ELMo Model



Source: BERT paper

ELMo Model

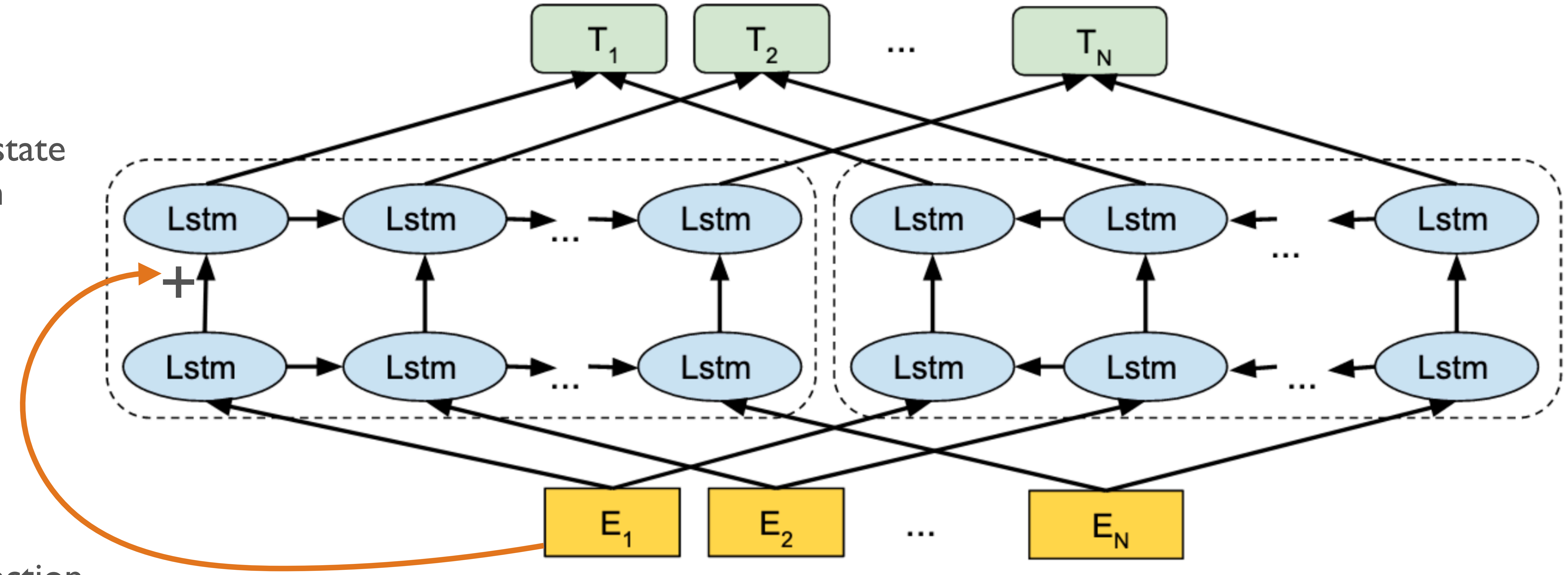
4096-d hidden state
512d projection



Source: BERT paper

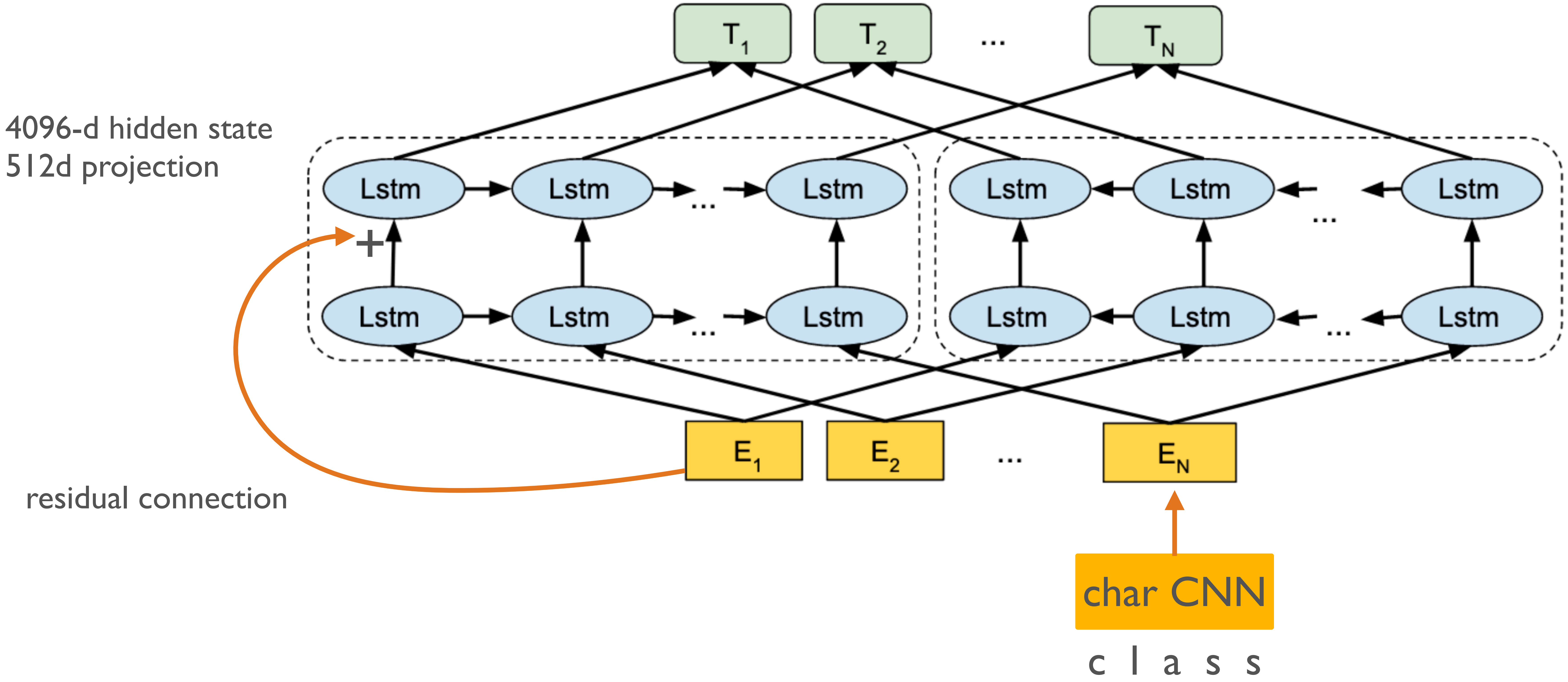
ELMo Model

4096-d hidden state
512d projection



residual connection

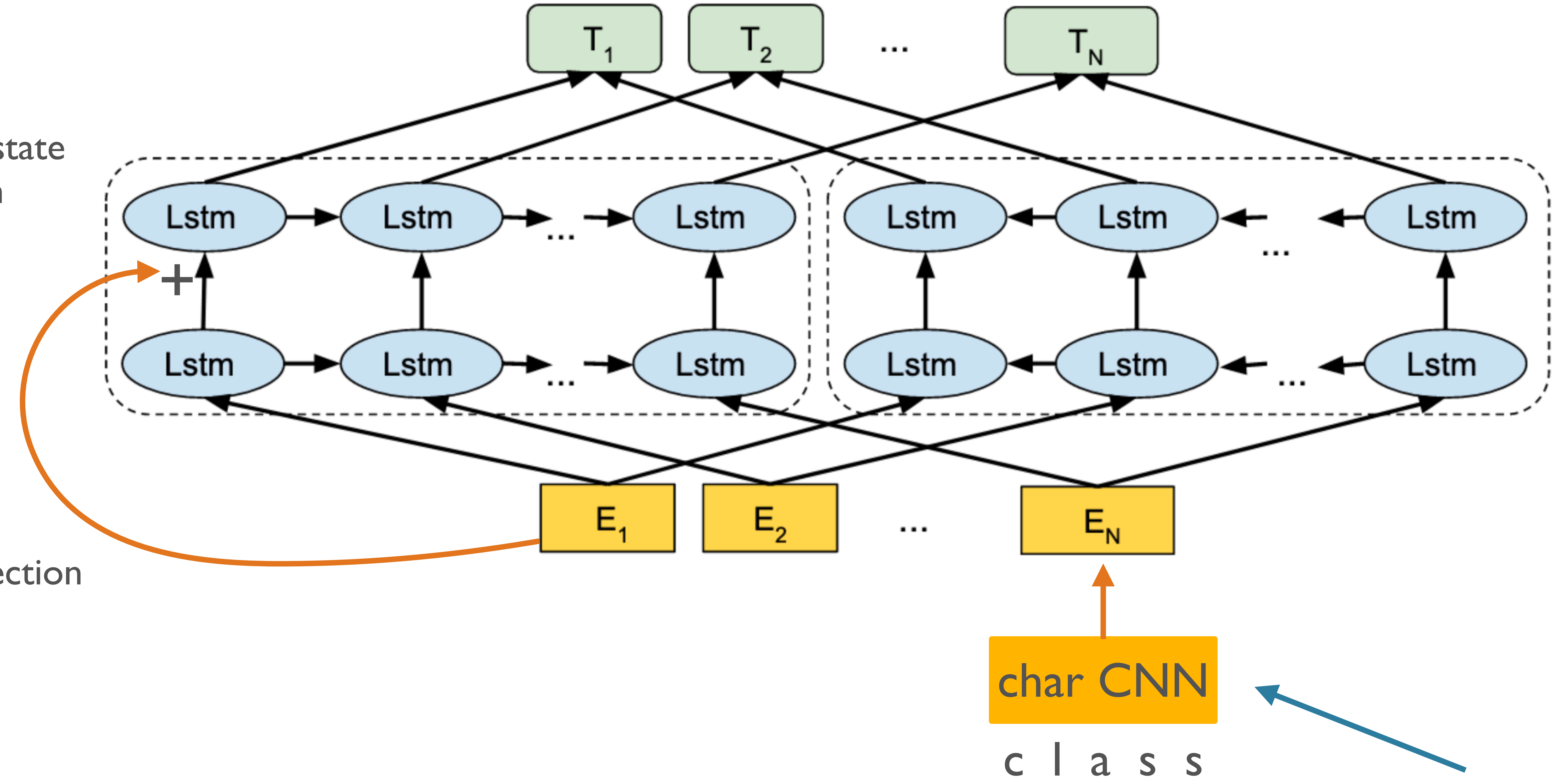
ELMo Model



Source: BERT paper

ELMo Model

4096-d hidden state
512d projection



residual connection

Helps with rare / new words (no OOV)

Source: BERT paper

ELMo Training

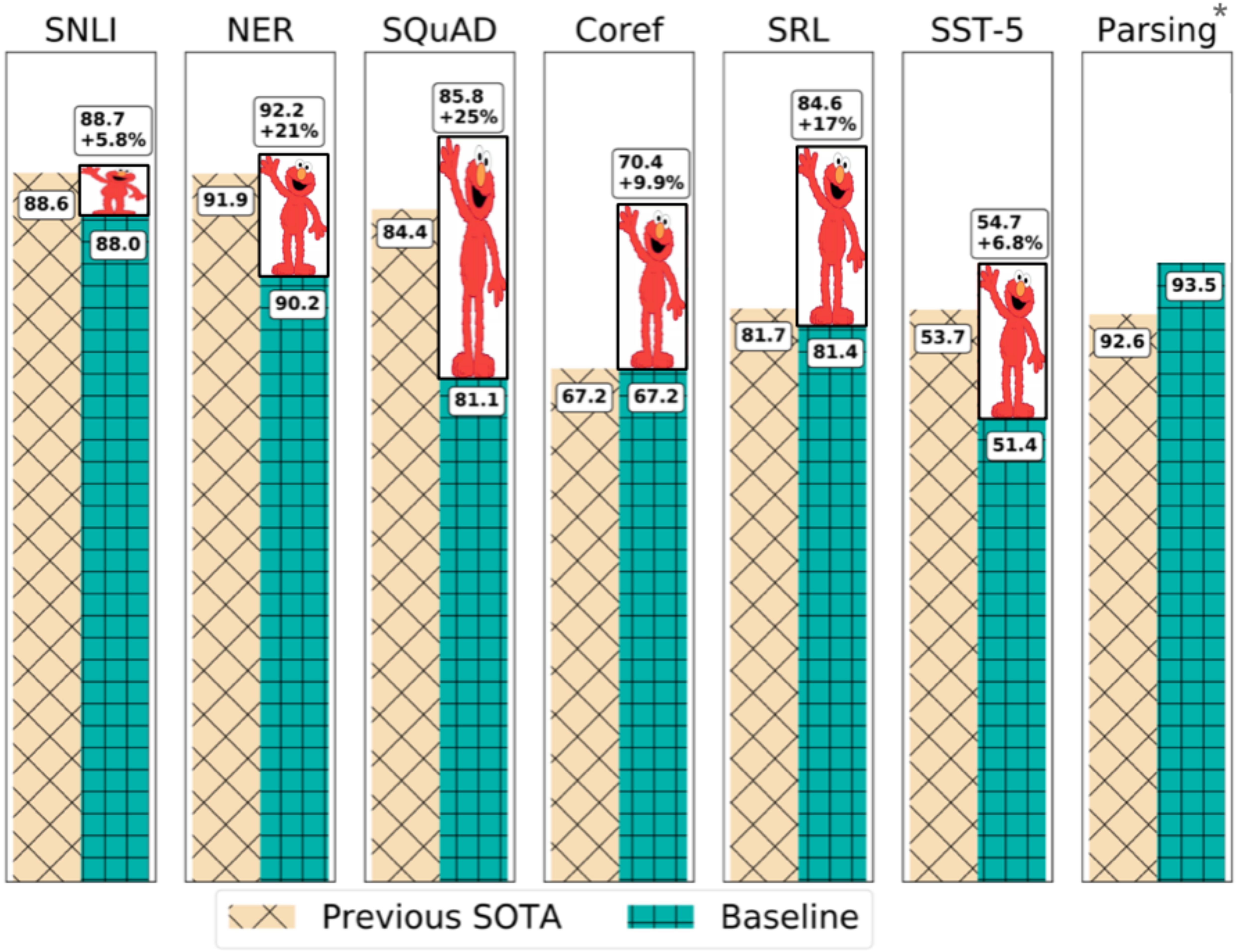
- 10 epochs on 1B Word Benchmark
- NB: not SOTA perplexity even at time of publishing
  - See "Exploring the Limits of Language Modeling" paper
- Regularization:
  - Dropout
  - L2 norm

Deep Contextualized Word Representations

Peters et. al (2018)

- Used in place of other embeddings on multiple tasks:

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)

figure: Matthew Peters

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.

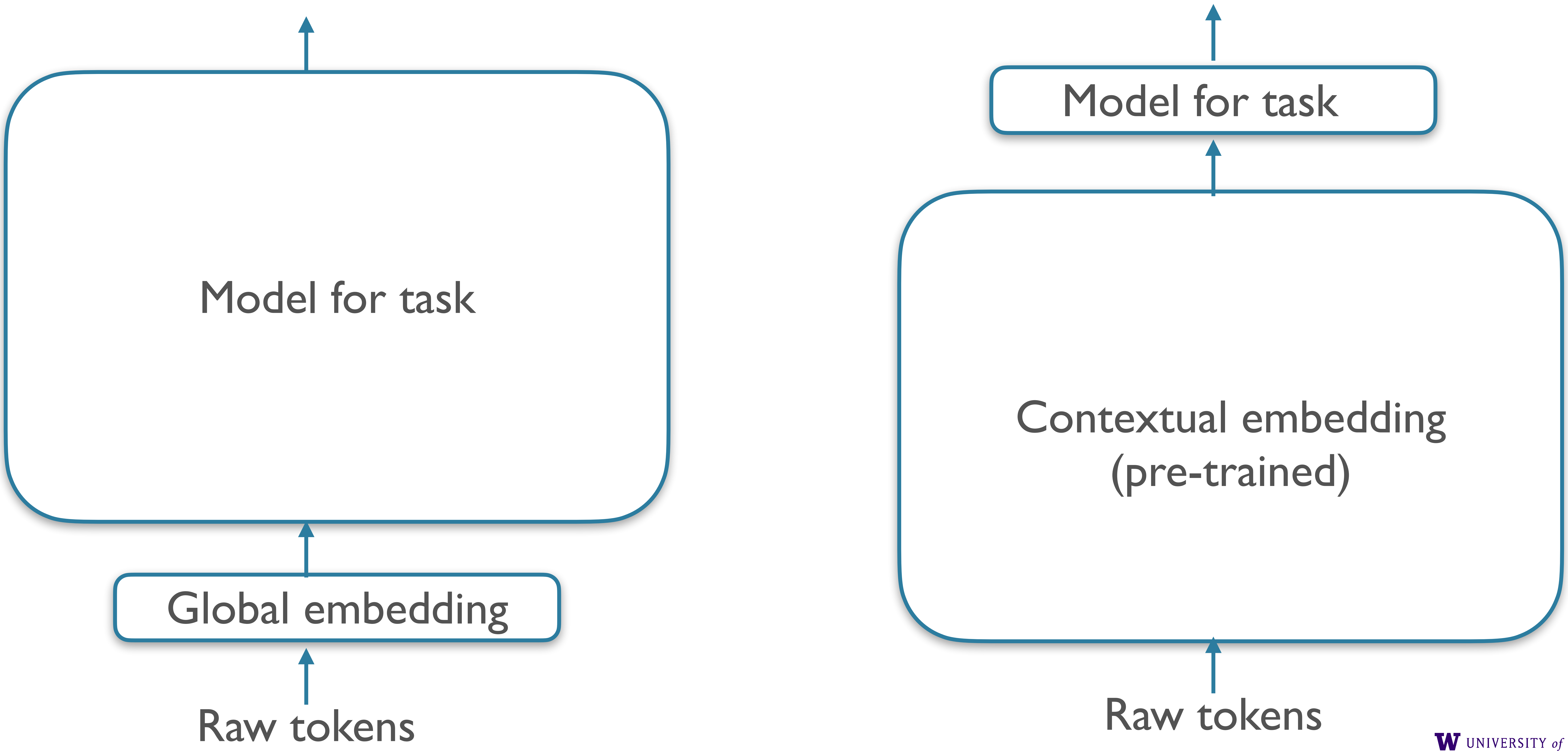
Deep Contextualized Word Representations

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: Encoder-only

BERT: Bidirectional Encoder Representations from Transformers

Devlin et al NAACL 2019

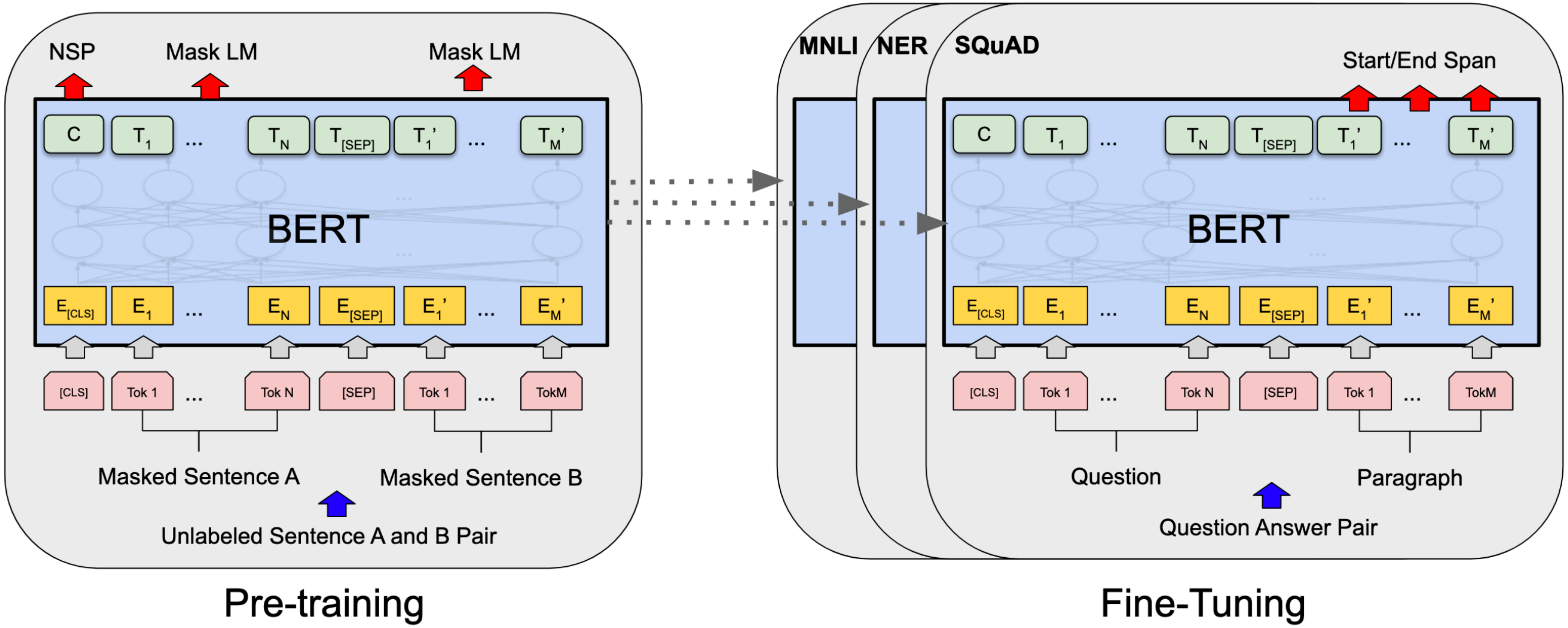
Overview

- Encoder Representations from Transformers: ✓
- Bidirectional: ………?
  - BiLSTM (ELMo): left-to-right and right-to-left
  - Self-attention: every token can see every other
- How do you treat the encoder as an LM (as computing $P(w_t | w_{t-1}, w_{t-2}, \ldots, w_1)$)?
  - 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



Some details

Some details

- BASE model:
  - 12 Transformer Blocks
  - Hidden vector size: 768
  - Attention heads / layer: 12
  - Total parameters: 110M

Some details

- BASE model:
  - 12 Transformer Blocks
  - Hidden vector size: 768
  - Attention heads / layer: 12
  - Total parameters: 110M
- LARGE model:
  - 24 Transformer Blocks
  - Hidden vector size: 1024
  - Attention heads / layer: 16
  - Total parameters: 340M

Some details

- BASE model:
  - 12 Transformer Blocks
  - Hidden vector size: 768
  - Attention heads / layer: 12
  - Total parameters: 110M
- LARGE model:
  - 24 Transformer Blocks
  - Hidden vector size: 1024
  - Attention heads / layer: 16
  - Total parameters: 340M

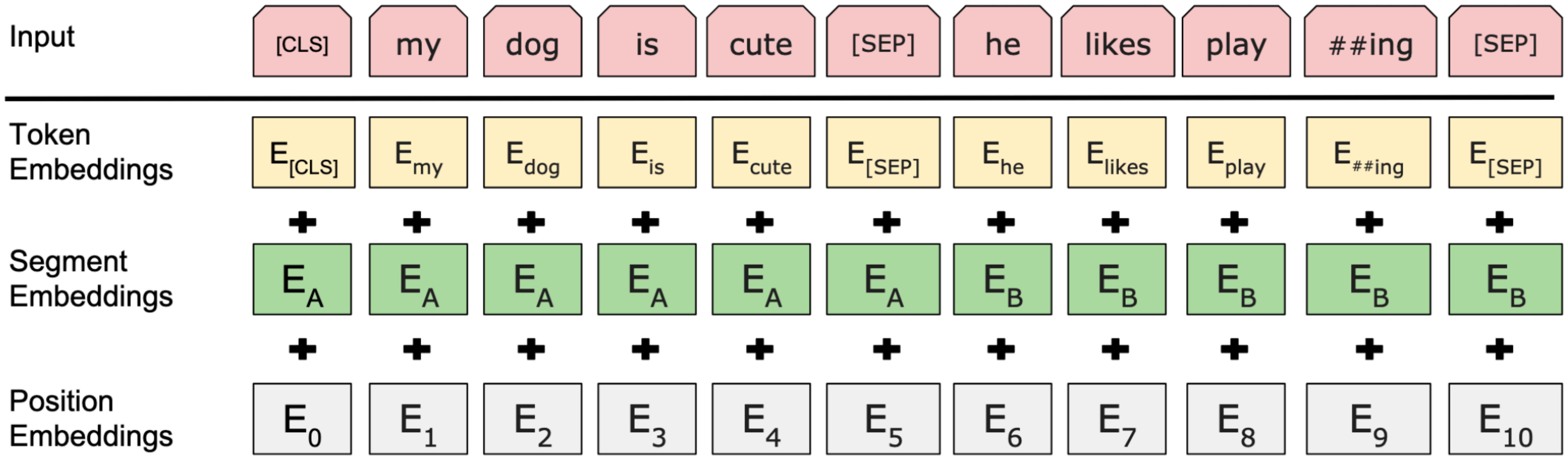
this is the first work to demonstrate convincingly that scaling to extreme model sizes also leads to large improvements on very small scale tasks, provided that the model has been sufficiently pre-trained. Peters et al. (2018b) presented

Some details

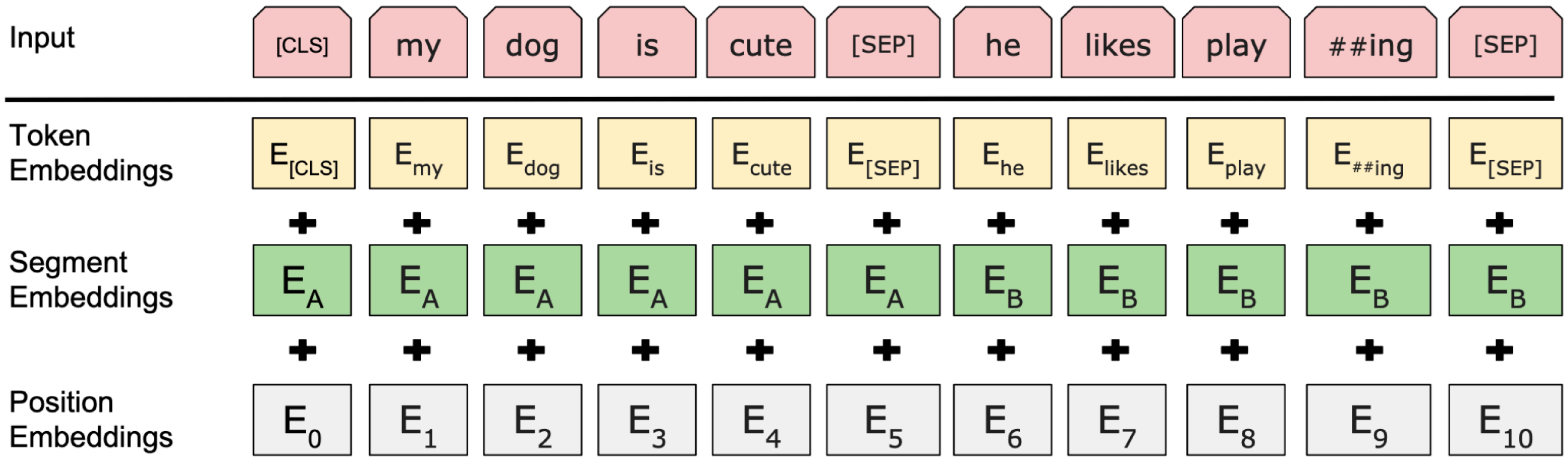
- BASE model:
  - 12 Transformer Blocks
  - Hidden vector size: 768
  - Attention heads / layer: 12
  - Total parameters: 110M
- LARGE model:
  - 24 Transformer Blocks
  - Hidden vector size: 1024
  - Attention heads / layer: 16
  - Total parameters: 340M

this is the first work to demonstrate convincingly that scaling to extreme model sizes also leads to large improvements on very small scale tasks, provided that the model has been sufficiently pre-trained. Peters et al. (2018b) presented

Input Representation

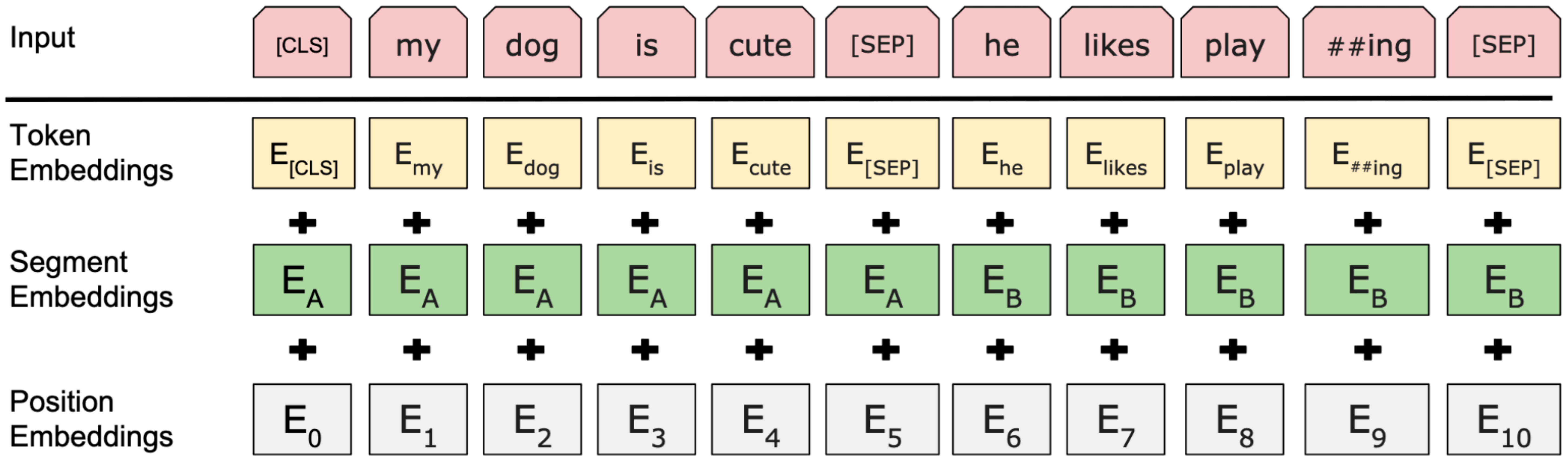


Input Representation



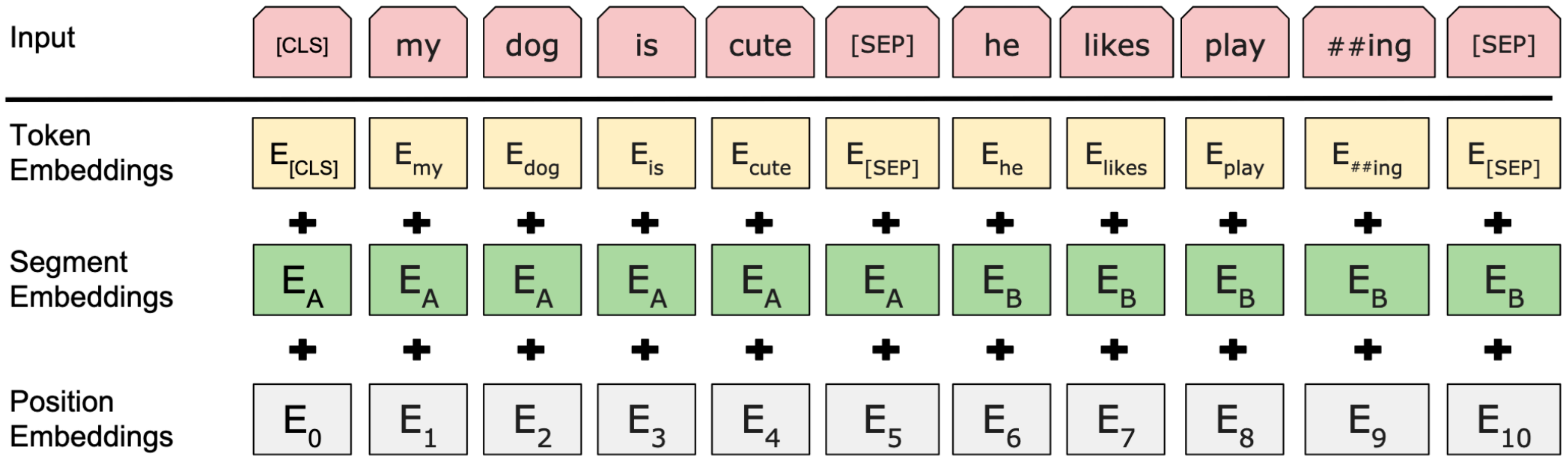
- [CLS], [SEP]: special tokens

Input Representation



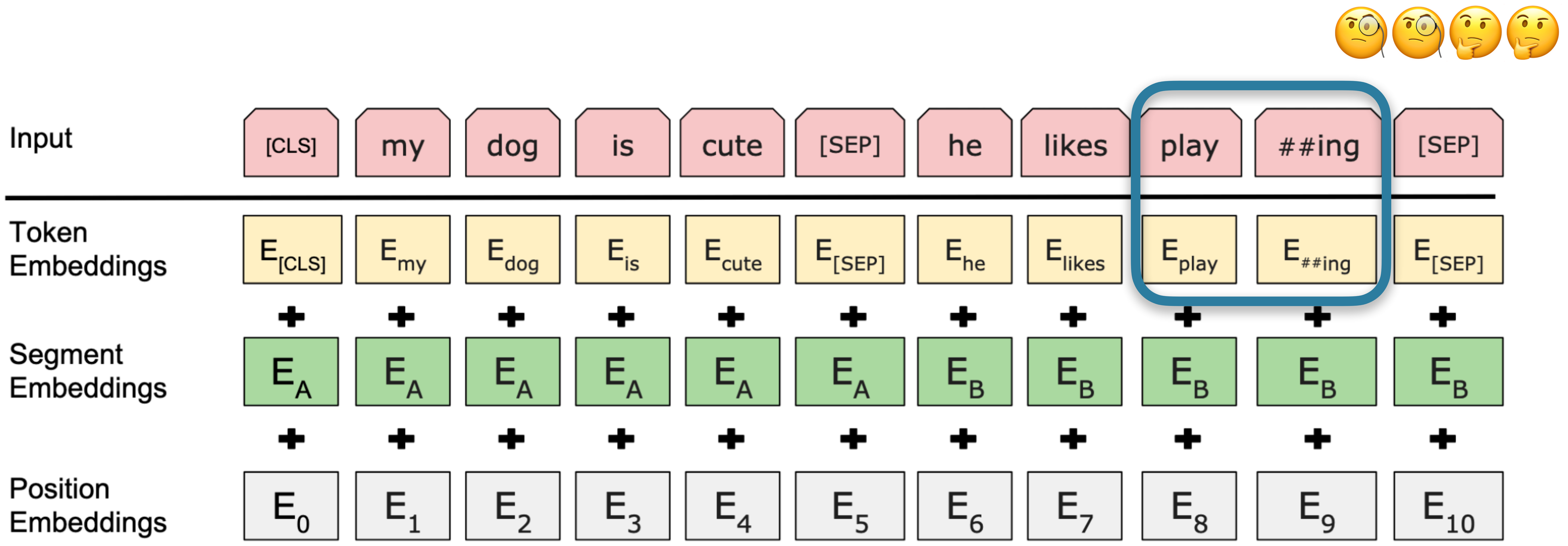
- [CLS], [SEP]: special tokens
- Segment: is this a token from sentence A or B?

Input Representation



- [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)

Input Representation



- [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

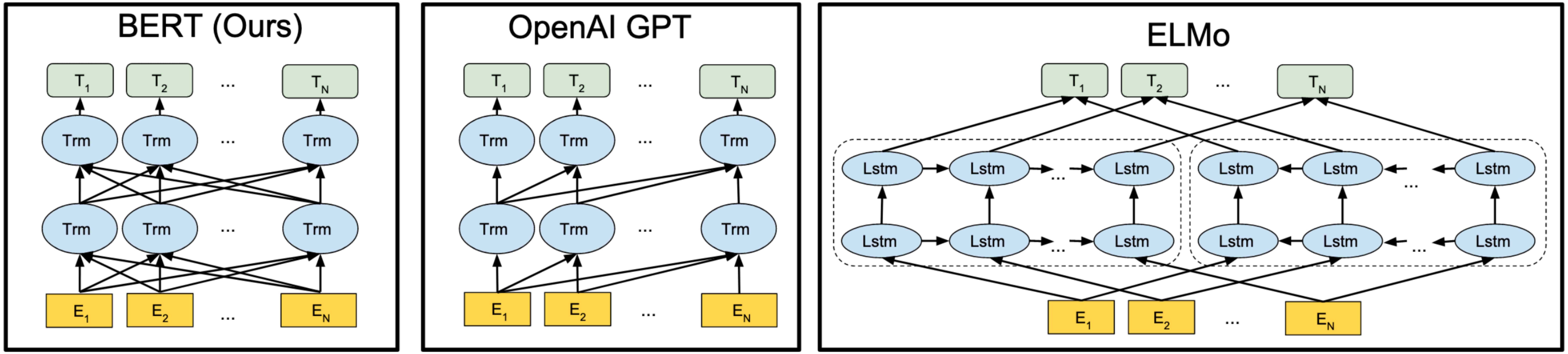
- No left-to-right modeling assumption
- Good for NLU (understanding/comprehension) tasks
- Does not straightforwardly *generate* text

Pre-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

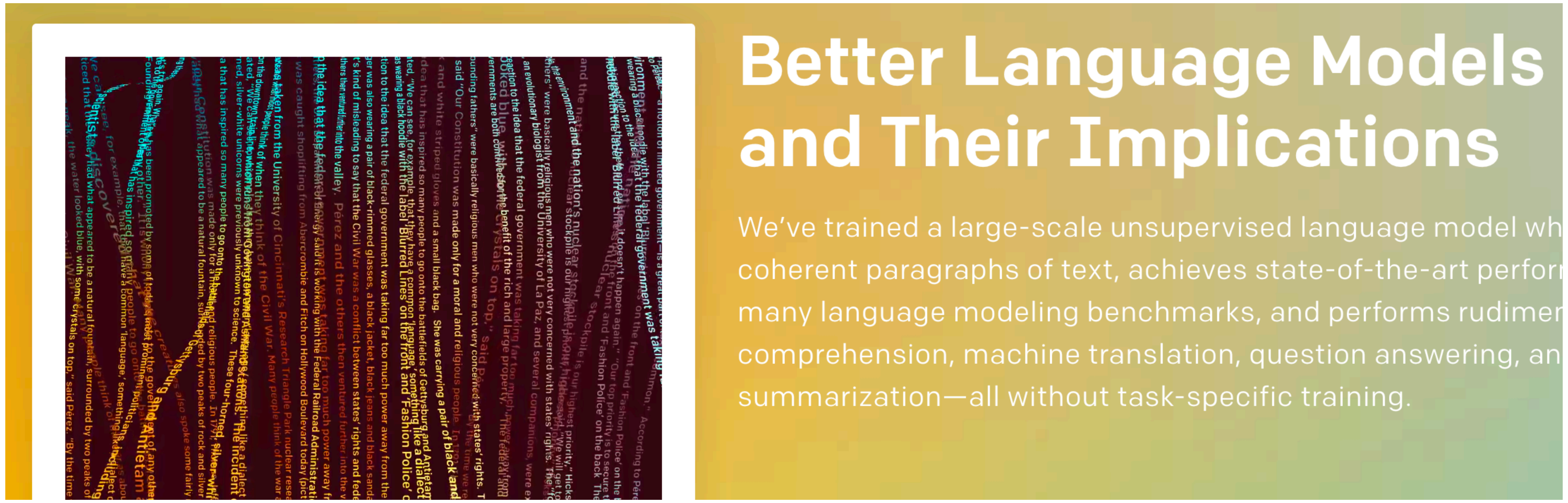
Samples from GPT2 (Cherry-picked)

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 initially released (but has been now)
- Some cynical interpretations

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

https://talktotransformer.com/

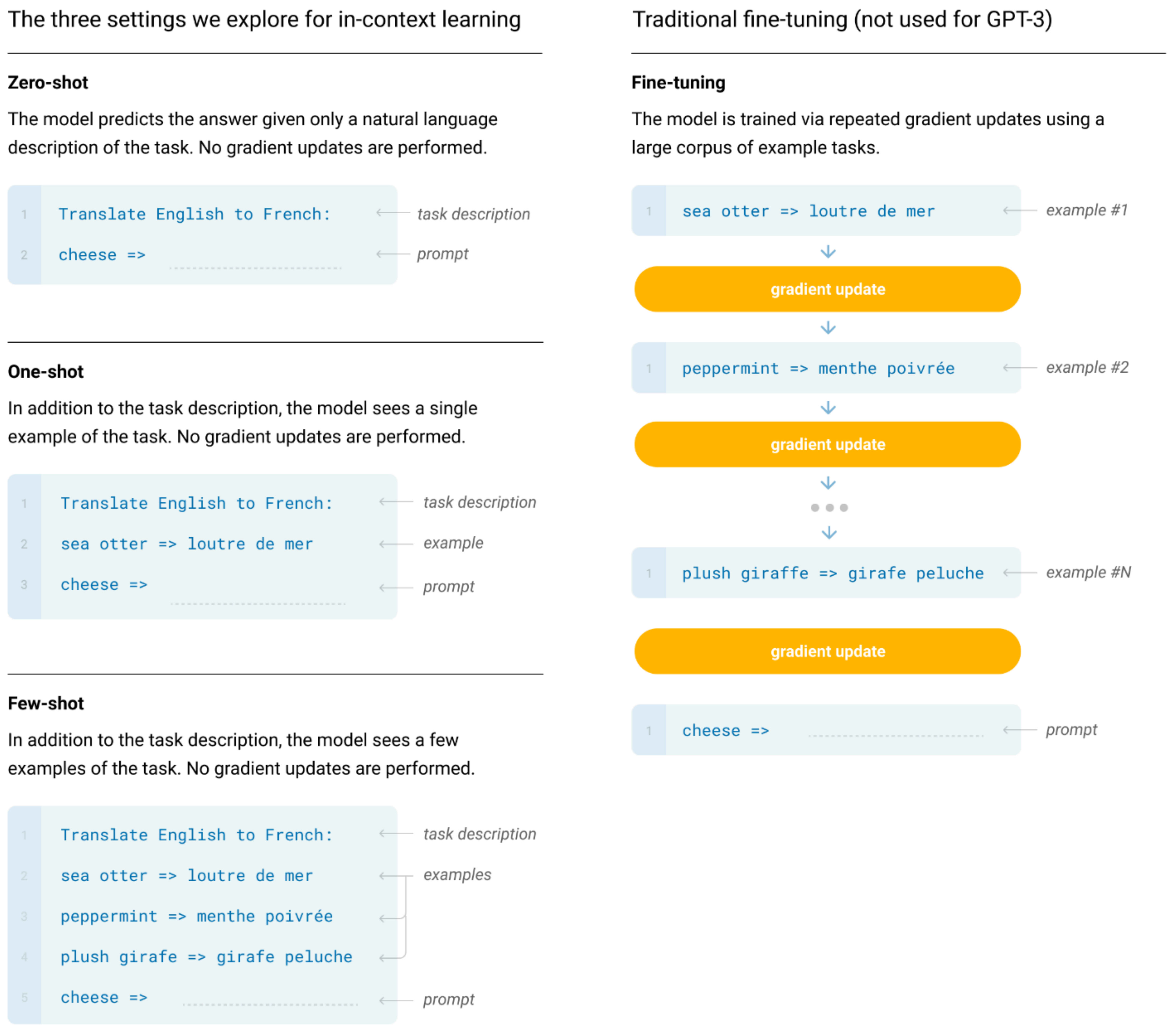
- Prompt: **Studying computational linguistics is a good idea. There are many interesting problems.**
- However, there are many bad problems. The research into computational linguistics has not helped very much in the development of better solutions. One problem with computer science and machine learning 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.

https://talktotransformer.com/

- 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

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

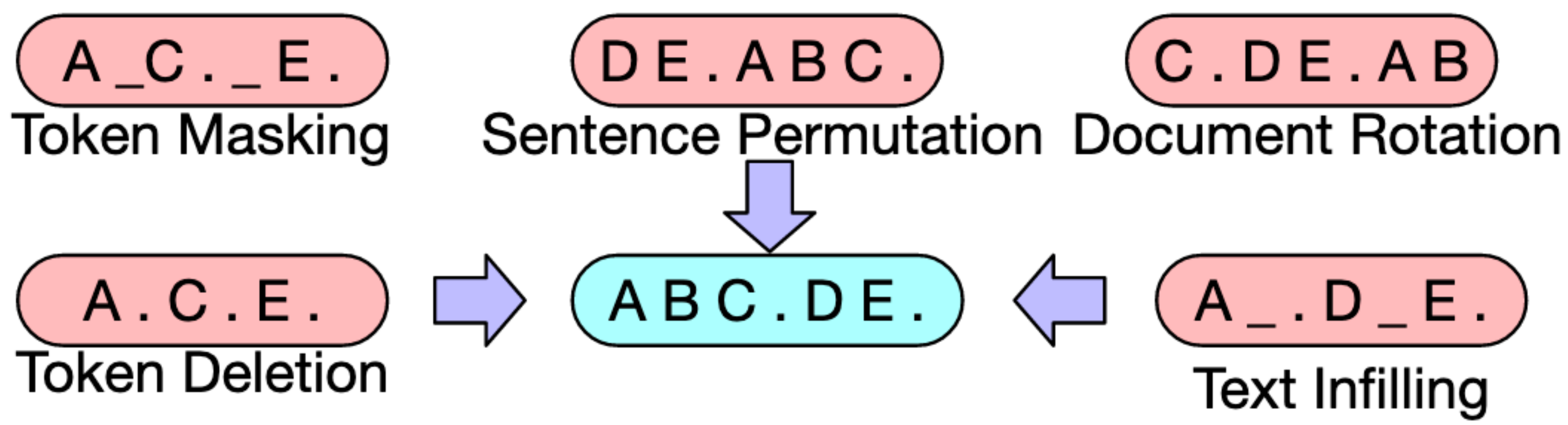
	SuperGLUE Average	BoolQ Accuracy	CB Accuracy	CB F1	COPA Accuracy	RTE Accuracy
Fine-tuned SOTA	**89.0**	**91.0**	**96.9**	**93.9**	**94.8**	**92.5**
Fine-tuned BERT-Large	69.0	77.4	83.6	75.7	70.6	71.7
GPT-3 Few-Shot	71.8	76.4	75.6	52.0	92.0	69.0
	WiC Accuracy	**WSC Accuracy**	**MultiRC Accuracy**	**MultiRC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

Pretrained Transformers: Encoder-Decoder

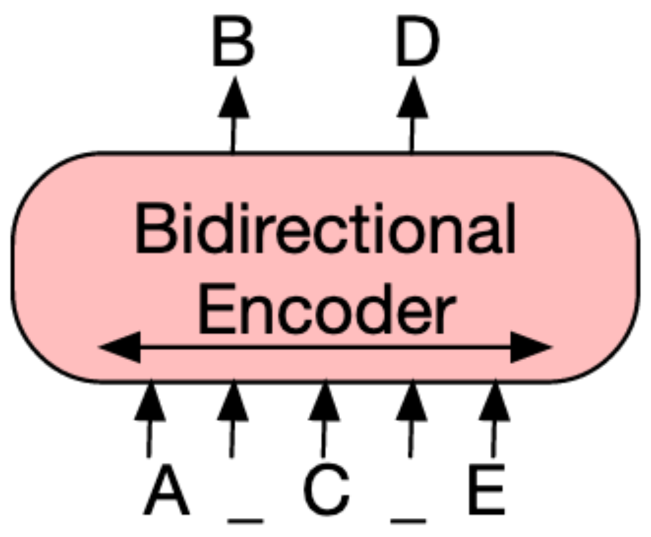
BART

- 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

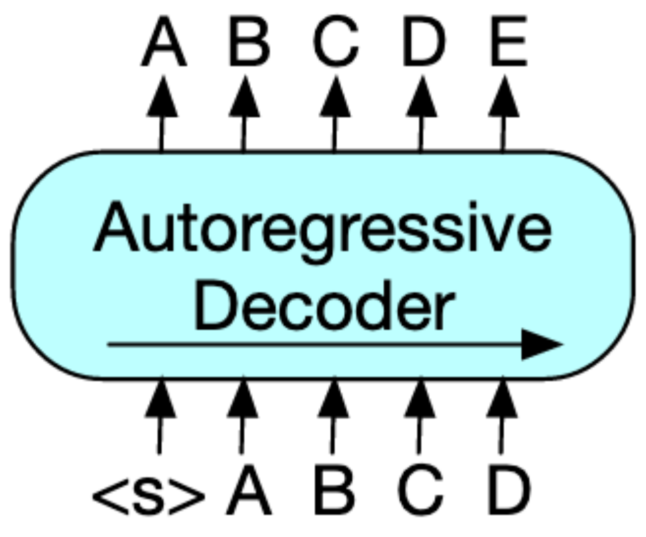


- Good for both discrimination and generation

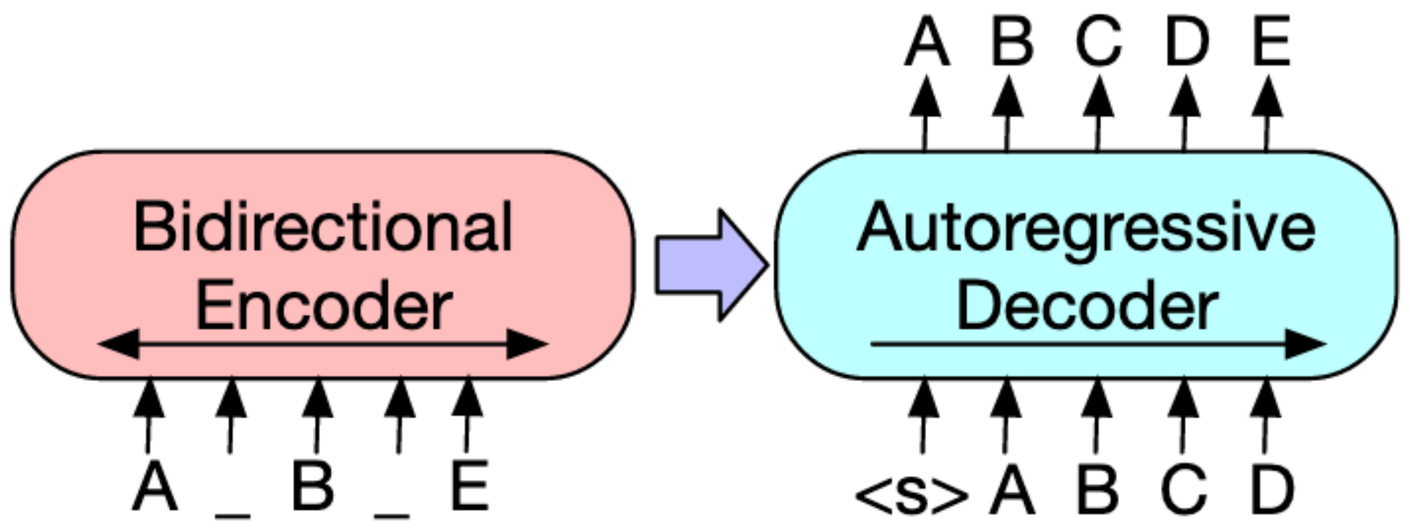
High-level Overview



(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 [also uses labeled data]

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.

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)

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 19 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

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

# OPTIONAL: if you want to have more information on what's happening under the hood, activate the logger as follows
import logging
logging.basicConfig(level=logging.INFO)

# Load pre-trained model tokenizer (vocabulary)
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')

# Tokenize input
text = "[CLS] Who was Jim Henson ? [SEP] Jim Henson was a puppeteer [SEP]"
tokenized_text = tokenizer.tokenize(text)

# Mask a token that we will try to predict back with `BertForMaskedLM`
masked_index = 8
tokenized_text[masked_index] = '[MASK]'
assert tokenized_text == ['[CLS]', 'who', 'was', 'jim', 'henson', '?', '[SEP]', 'jim', '[MASK]', 'was', 'a', 'puppet', '##eer', '[SEP]']

# Convert token to vocabulary indices
indexed_tokens = tokenizer.convert_tokens_to_ids(tokenized_text)
# Define sentence A and B indices associated to 1st and 2nd sentences (see paper)
segments_ids = [0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1]

# Convert inputs to PyTorch tensors
tokens_tensor = torch.tensor([indexed_tokens])
segments_tensors = torch.tensor([segments_ids])
```

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

Example: Forward Pass

```
# Load pre-trained model (weights)
model = BertModel.from_pretrained('bert-base-uncased')

# Set the model in evaluation mode to deactivate the DropOut modules
# This is IMPORTANT to have reproducible results during evaluation!
model.eval()

# If you have a GPU, put everything on cuda
tokens_tensor = tokens_tensor.to('cuda')
segments_tensors = segments_tensors.to('cuda')
model.to('cuda')

# Predict hidden states features for each layer
with torch.no_grad():
    # See the models docstrings for the detail of the inputs
    outputs = model(tokens_tensor, token_type_ids=segments_tensors)
    # Transformers models always output tuples.
    # See the models docstrings for the detail of all the outputs
    # In our case, the first element is the hidden state of the last layer of the Bert model
    encoded_layers = outputs[0]
```

More on HuggingFace

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