Adapters in Transformers:

a New Paradigm for Transfer Learning?…

Jonas Pfeiffer (main author)
Iryna Gurevych (PhD advisor)

TECHNISCHE UNIVERSITÄT DARMSTADT

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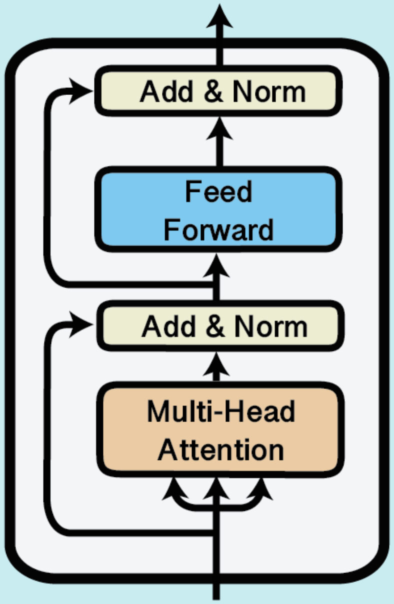
5. How to train adapters with the **AdapterHub.ml** framework

Some Basics...



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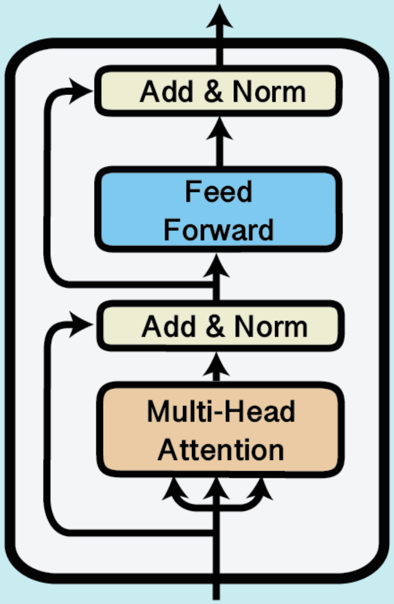

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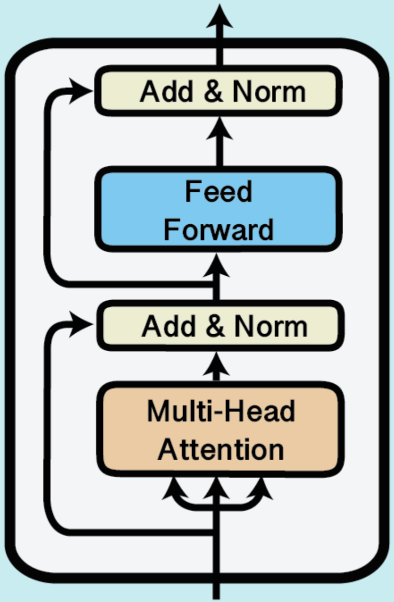

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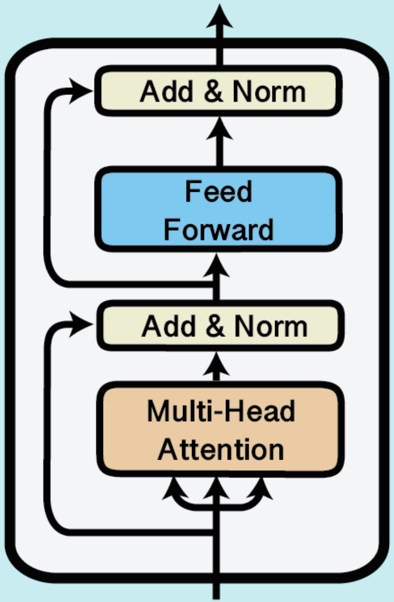

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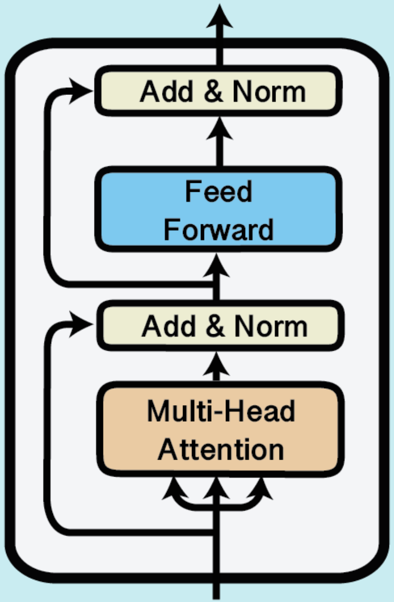

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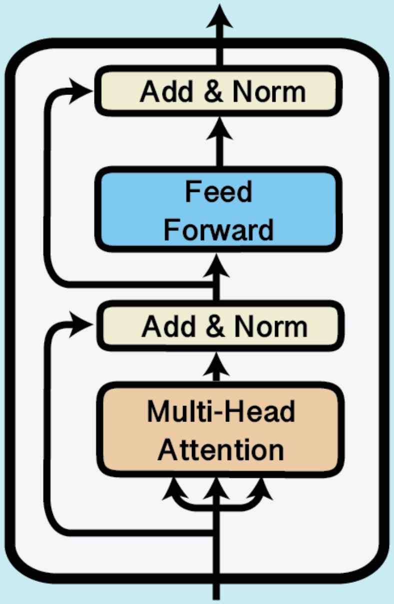

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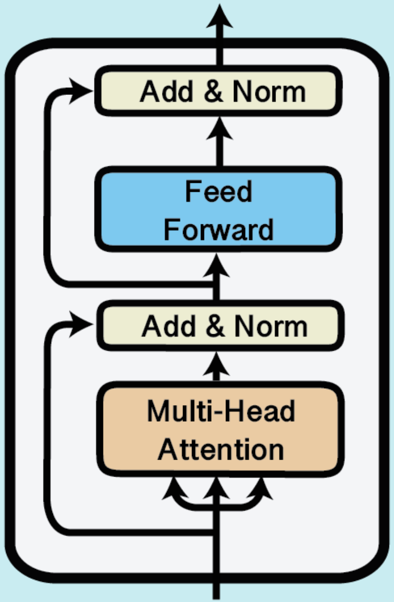

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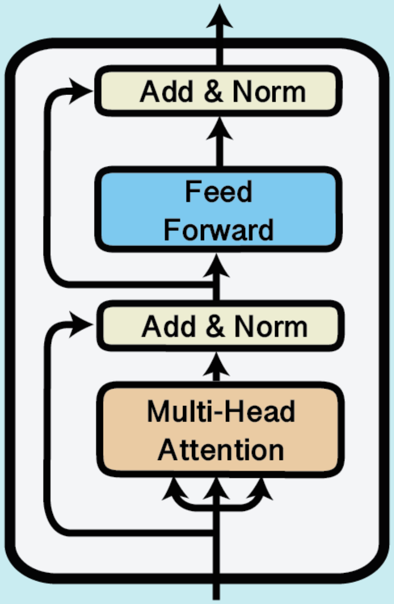
- Transfer learning with these pre-trained models usually involves stacking a prediction head on top of the model.
- **Usually** all parameters are fine-tuned on the downstream task (e.g. using cross-entropy loss).



Agenda

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2. AdapterFusion
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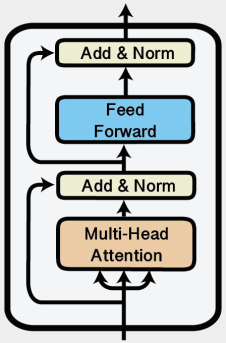
What are Adapters?

= Parameters are frozen

= Parameters are fine-tuned

What are Adapters?

A single Transformer (encoder) layer



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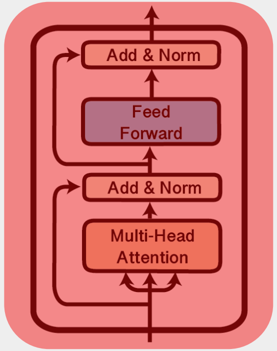

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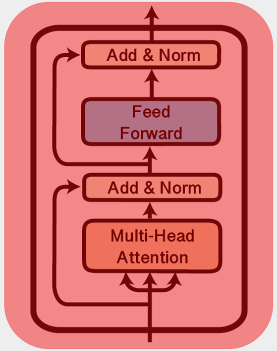

$$\boldsymbol{\theta} \longleftarrow \underset{\boldsymbol{\theta}}{\operatorname{argmin}}\ L(D_{\mathrm{NLI}}; \boldsymbol{\theta})$$

$\boldsymbol{\theta}$

D_{NLI} = NLI Dataset

L = Loss function, e.g. cross entropy loss

$\boldsymbol{\theta}$ = Parameters of the model

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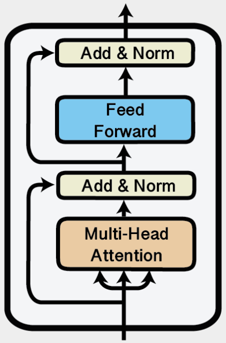

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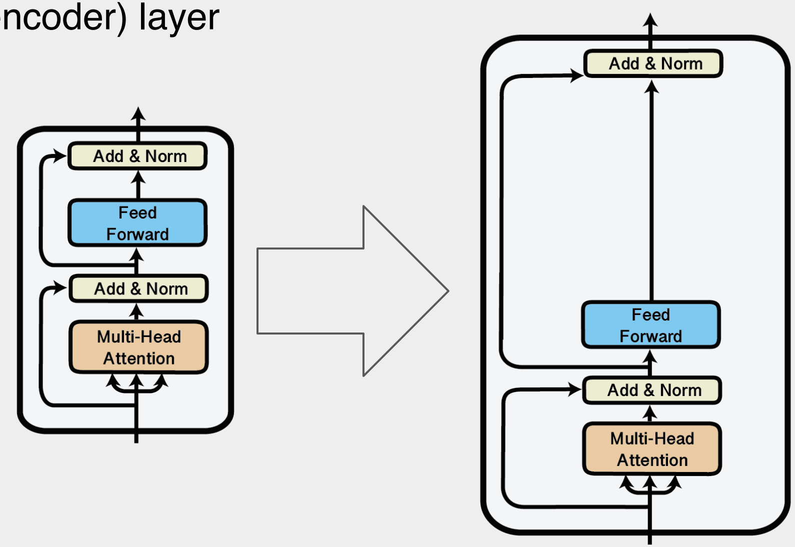

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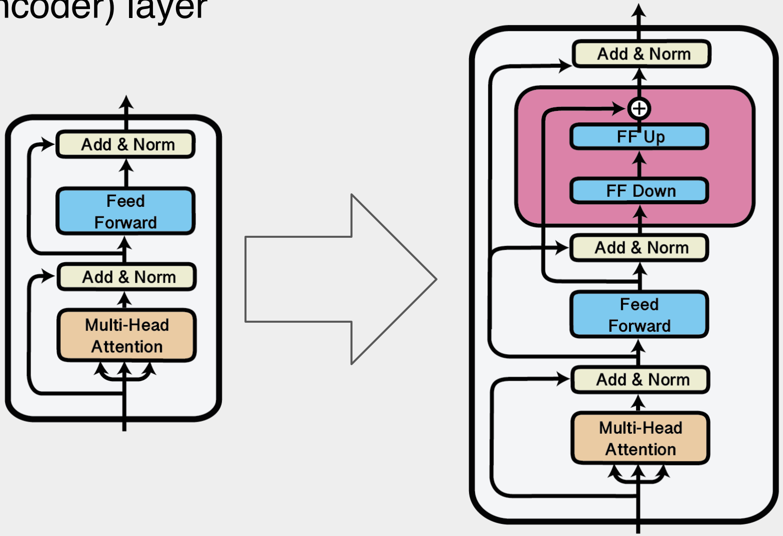

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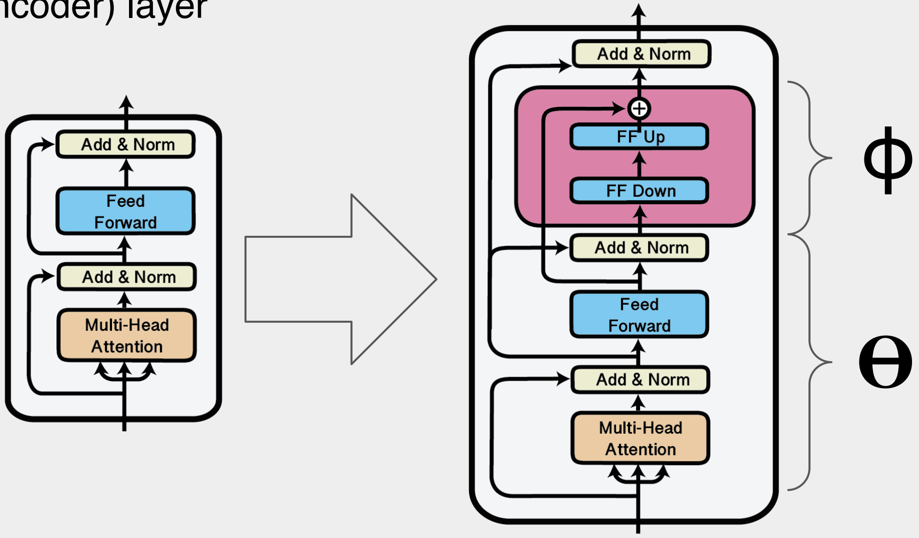

Adapter parameters ϕ are **encapsulated** between transformer layers with parameters $\boldsymbol{\theta}$

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$$\phi \leftarrow \underset{\phi}{\operatorname{argmin}}\, L(D_{\mathrm{NLI}};\, \boldsymbol{\theta},\phi)$$

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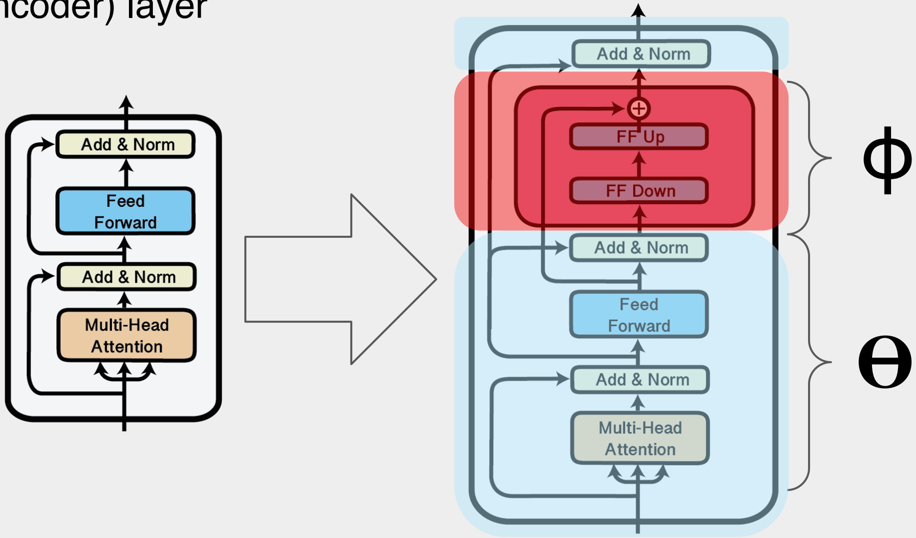

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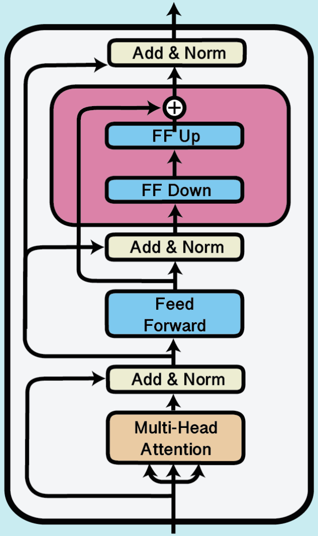
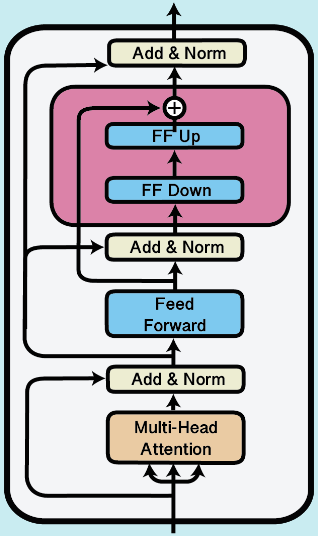
Encapsulated Adapters? 🤨





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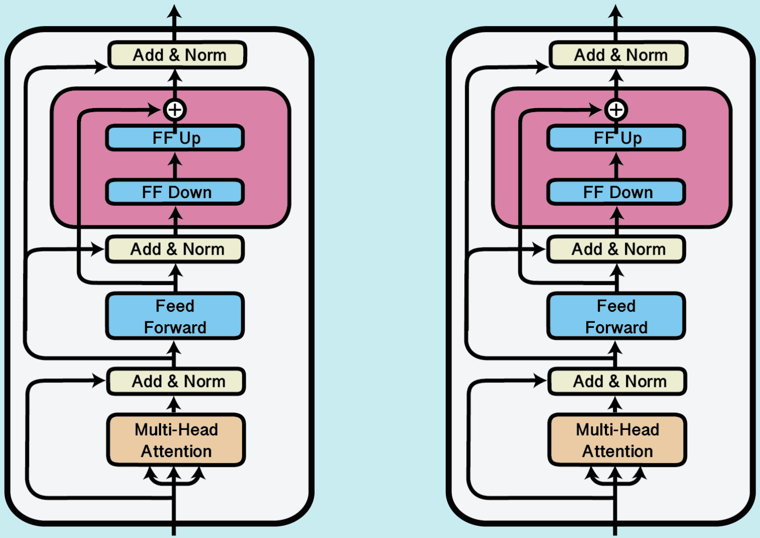

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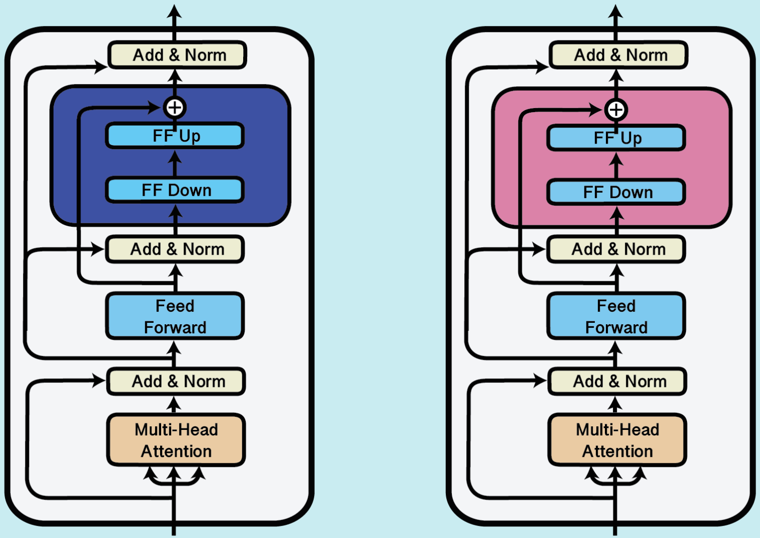

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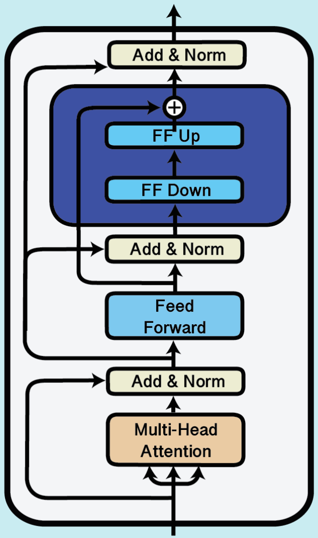

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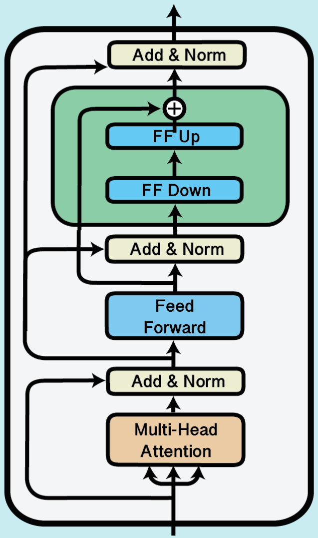

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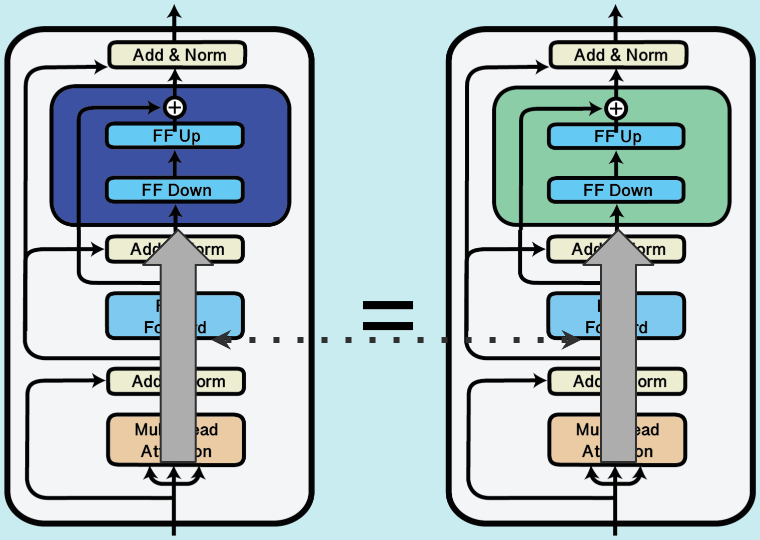

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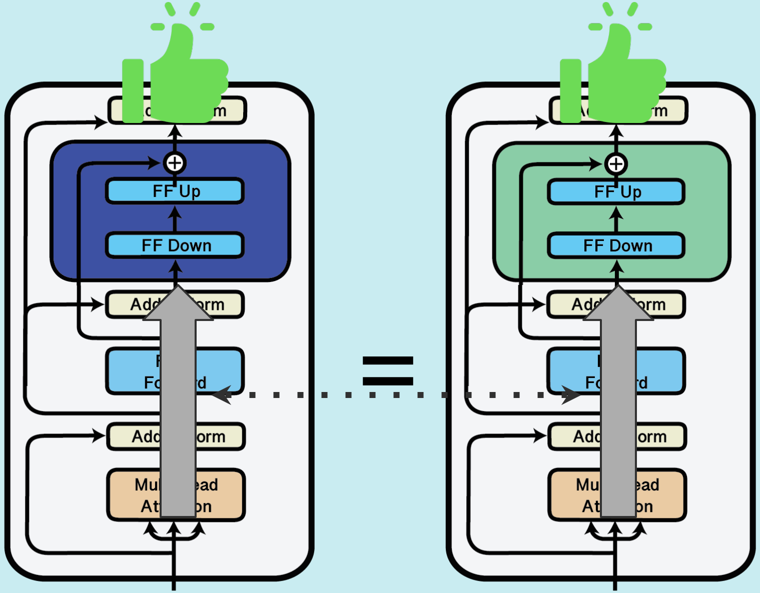

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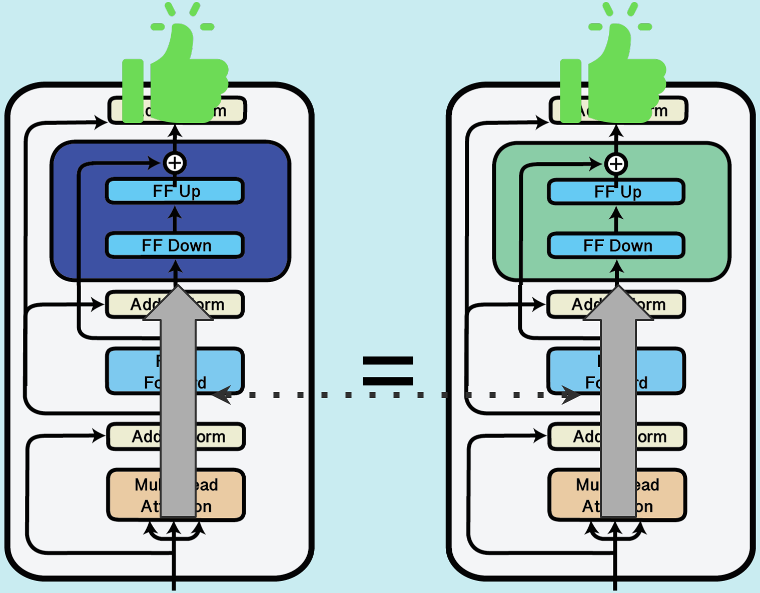

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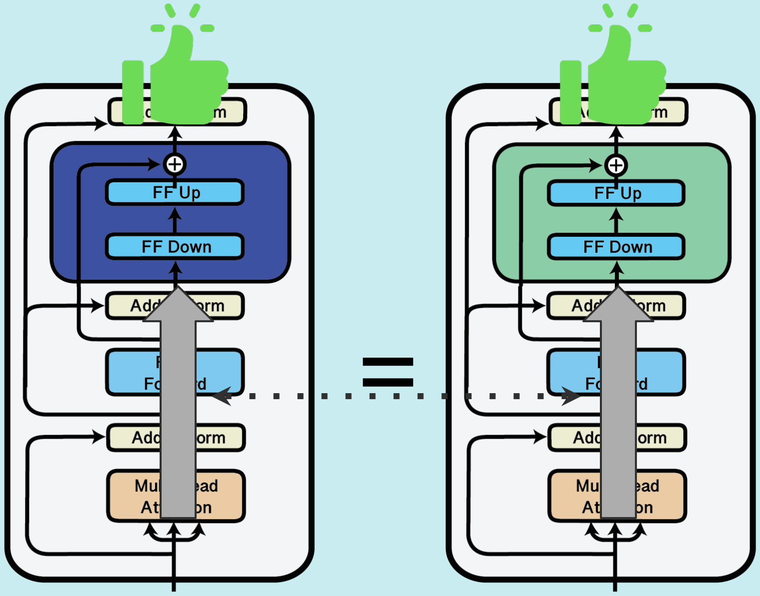

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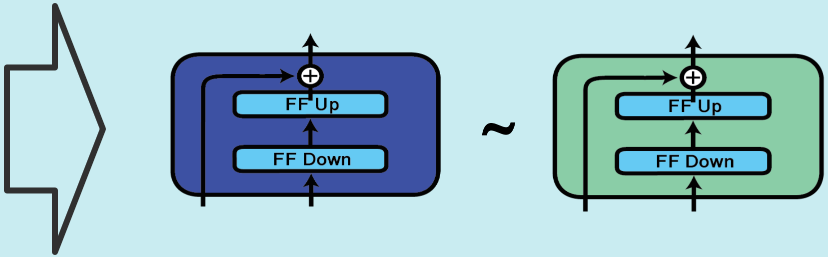


Parameter Efficiency of Adapters in Transformers

Training adapters instead of full model fine-tuning achieves similar results.

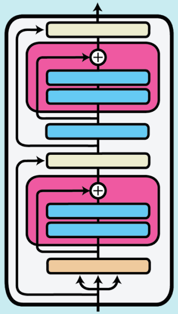
Adapters are smaller in size than training the full model.

Performance on GLUE tasks

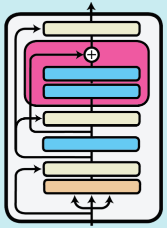
	Full	Pfeif.	Houl.
RTE (Wang et al., 2018)	66.2	70.8	69.8
MRPC (Dolan and Brockett, 2005)	90.5	89.7	91.5
STS-B (Cer et al., 2017)	88.8	89.0	89.2
CoLA (Warstadt et al., 2019)	59.5	58.9	59.1
SST-2 (Socher et al., 2013)	92.6	92.2	92.8
QNLI (Rajpurkar et al., 2016)	91.3	91.3	91.2
MNLI (Williams et al., 2018)	84.1	84.1	84.1
QQP (Iyer et al., 2017)	91.4	90.5	90.8

Number of newly introduced Parameters

	Base		**Large**	
CRate	#Params	Size	#Params	Size
64	0.2M	0.9Mb	0.8M	3.2Mb
16	0.9M	3.5Mb	3.1M	13Mb
2	7.1M	28Mb	25.2M	97Mb



Houlsby et al., 2019



Pfeiffer et al., 2020a

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Pfeiffer, Jonas, et al. "AdapterFusion: Non-destructive task composition for transfer learning." *arXiv preprint* (2020a).
Pfeiffer, Jonas, et al. "Adapterhub: A framework for adapting transformers." *Proceedings of EMNLP: Systems Demonstrations* (2020b)

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site code paper

AdapterFusion: Non-Destructive Task Composition for Transfer Learning

Proceedings of EACL 2021

Jonas Pfeiffer, Aishwarya Kamath, Andreas Rücklé, Kyunghyun Cho, Iryna Gurevych

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NYU

Problems of Multi-Task and Transfer Learning

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MT-Model; $\boldsymbol{\theta}$

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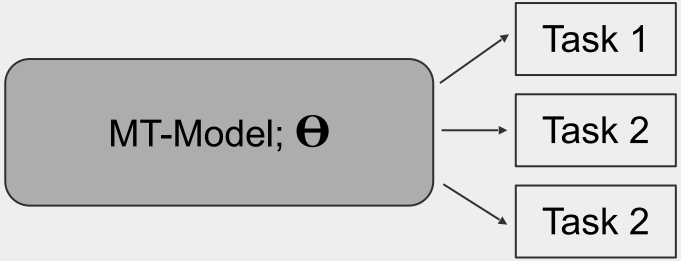

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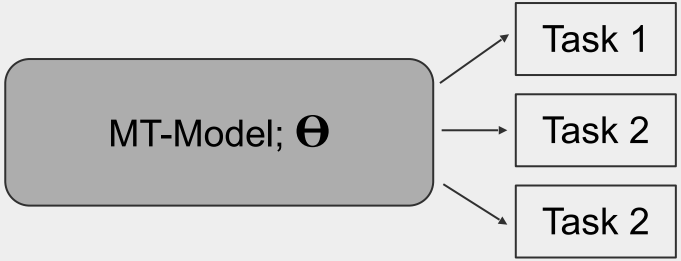

Catastrophic Interference: Sharing all parameters $\boldsymbol{\theta}$ between tasks results in deterioration of performance for a subset of tasks.

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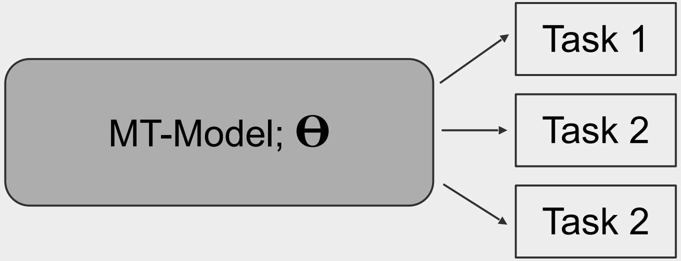

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Sequential Fine-Tuning:

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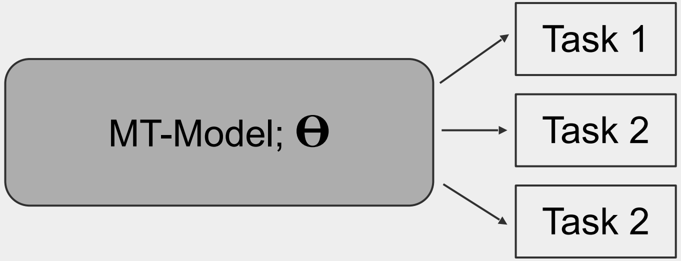

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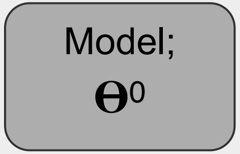

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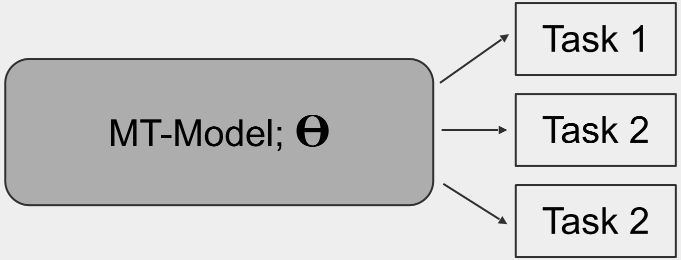

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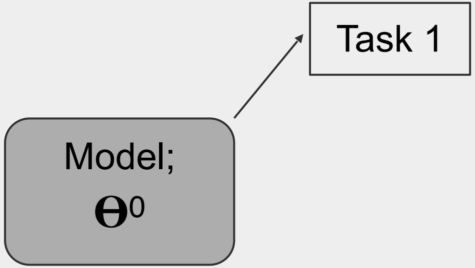

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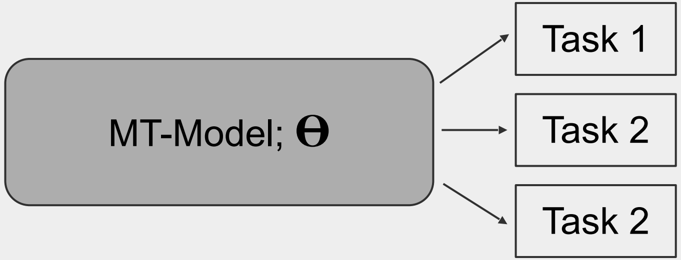

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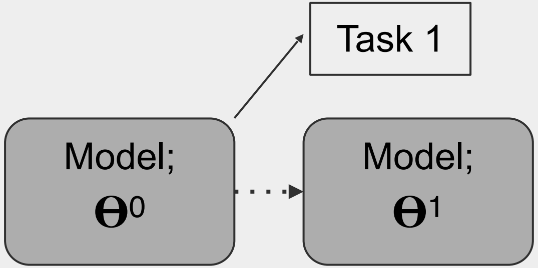

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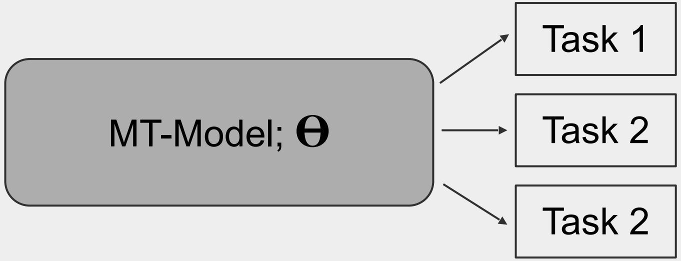

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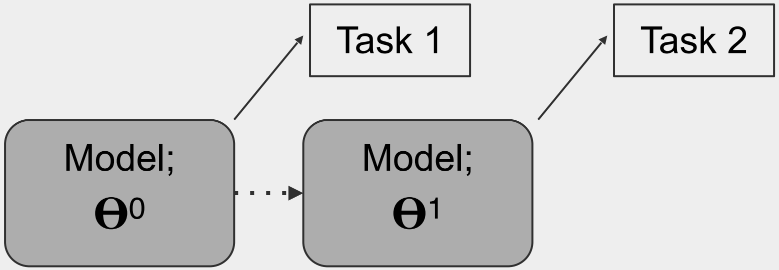

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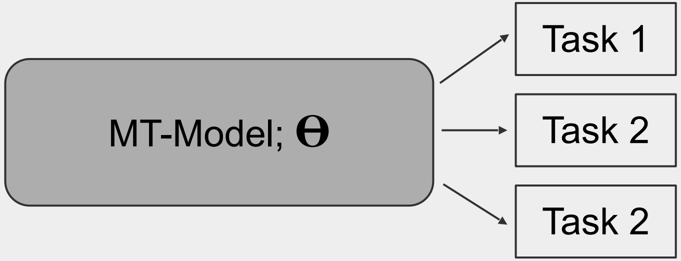

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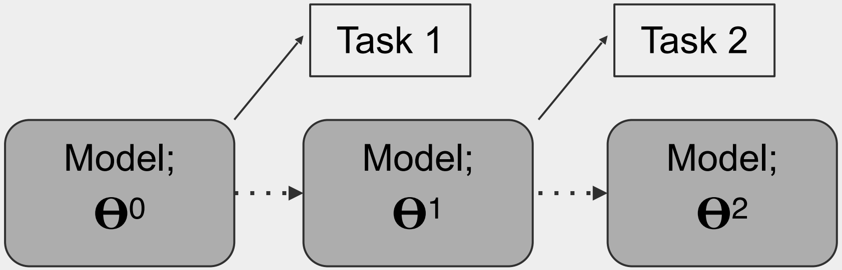

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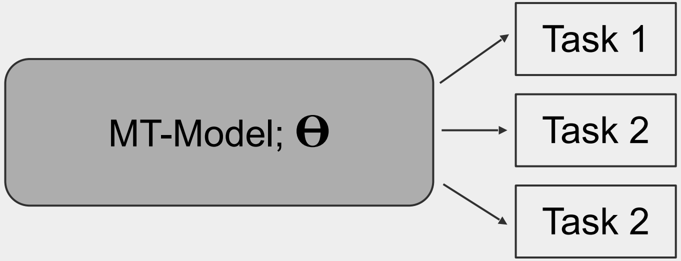

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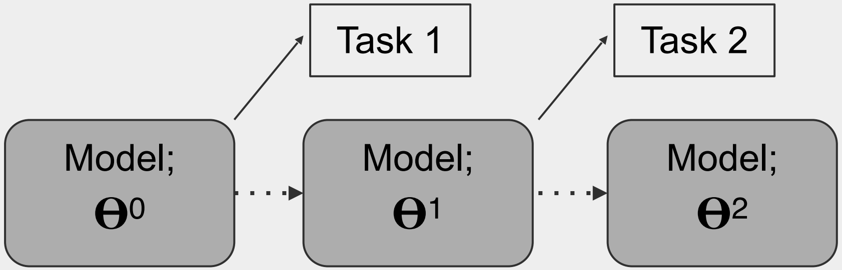

Catastrophic Forgetting: Sequential fine-tuning on tasks results in forgetting information learned in earlier stages of transfer learning.

Problems of Multi-Task and Transfer Learning

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How to mitigate?

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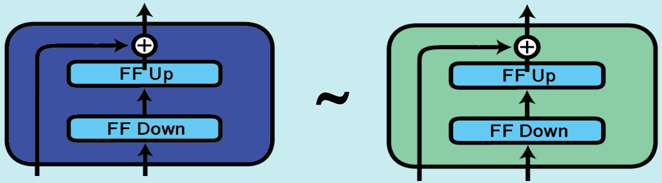
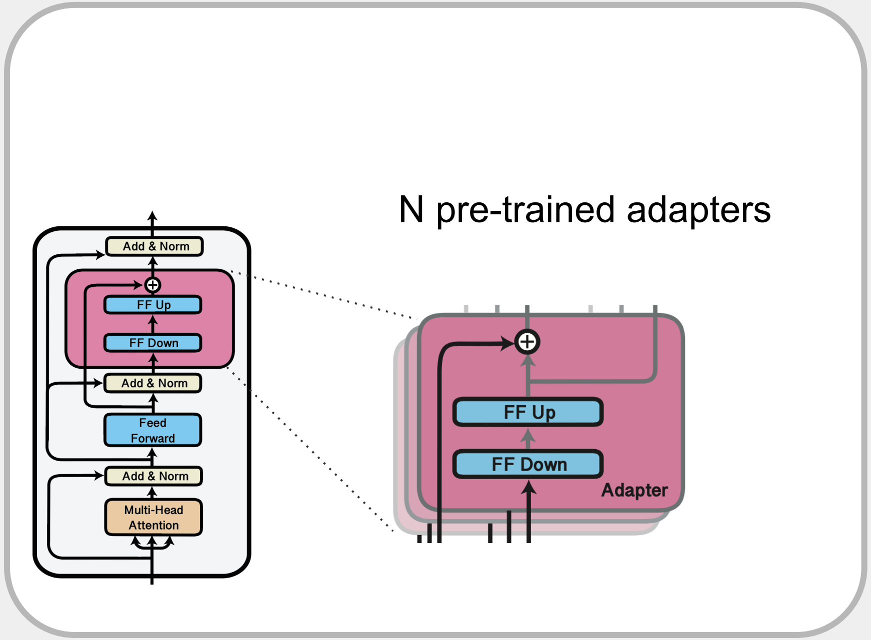
1. **Combine** the representations **subsequently**.

Assuming...



Sharing Information across multiple tasks

Given a pool of adapters, we want to leverage the stored information to solve a new task:



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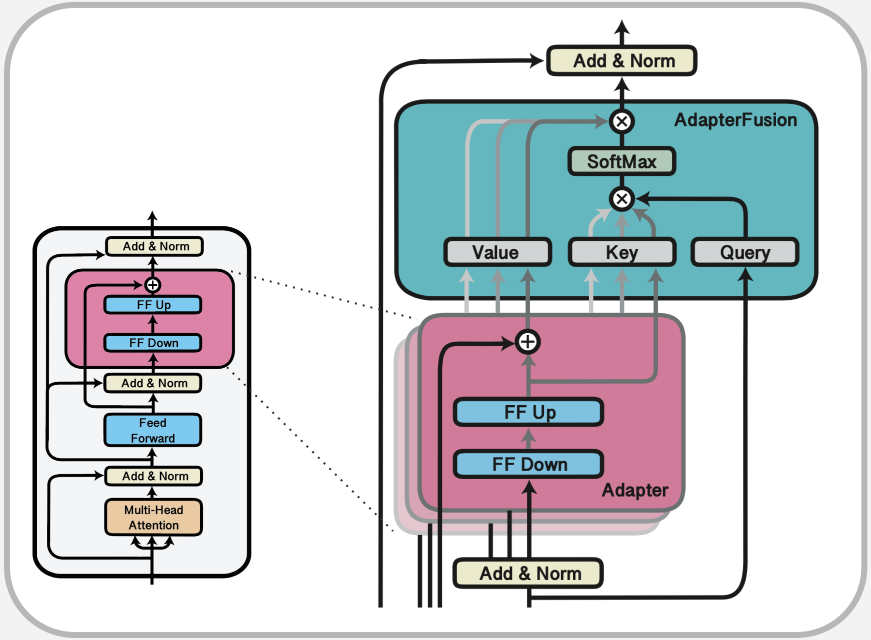
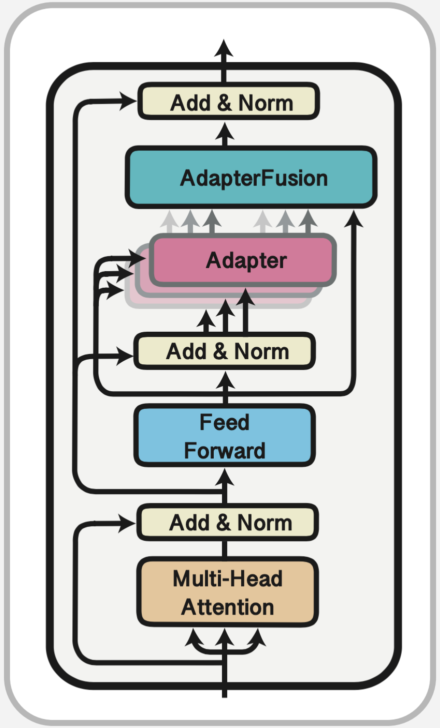


Learn dynamic attention **weighting** on a **target task** given the representations of the given **Adapters**



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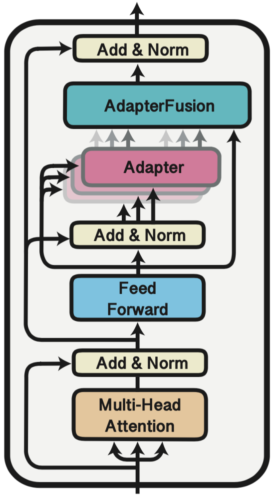
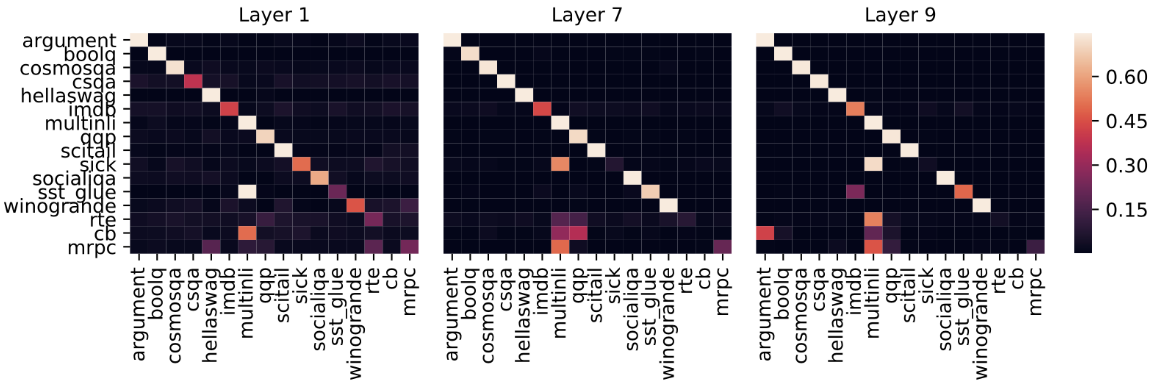
"Solving" Catastrophic interference and forgetting



Because of **task specific weights** and **residual connections** the model can opt-in and opt-out of leveraging information stored within adapters.



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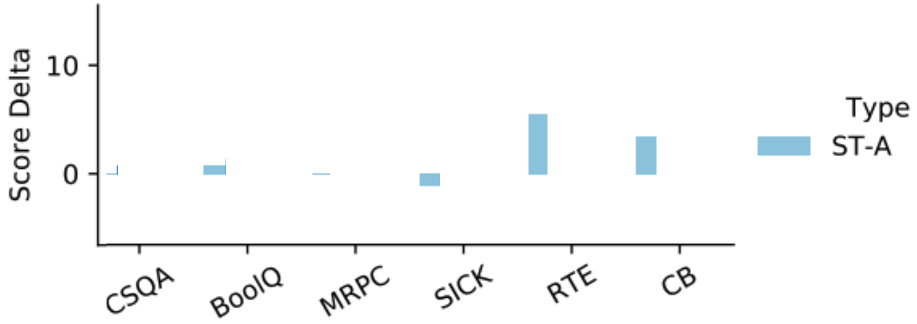
Performance of AdapterFusion

Performance of **Full** *finetuning* vs. *Single Task Adapters* (***ST-A***) vs. *Fusion with Single Task Adapters* (***F. w/ ST-A***).

We find that **AdapterFusion** performs well for lower resource datasets where less than **10k** examples exist.



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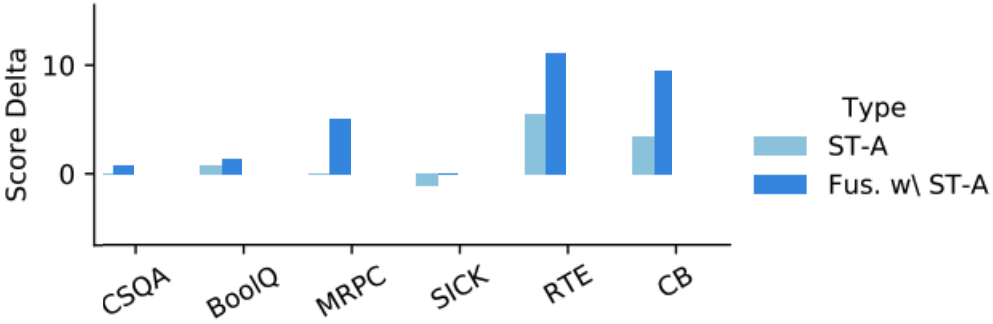

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high resource → low resource

Dataset	Full		ST-A		F. w/ ST-A	
MNLI	83.17		**84.32**		84.28	
QQP	**90.87**		90.59		90.71	
SST	92.39	±0.22	91.85	±0.41	92.20	±0.18
WGrande	60.01	±0.08	**61.09**	±0.11	60.23	±0.31
IMDB	**94.05**	±0.21	93.85	±0.07	93.82	±0.39
HSwag	**39.25**	±0.76	38.11	±0.14	37.98	±0.01
SocIQA	62.05	±0.04	62.41	±0.11	**63.16**	±0.24
CosQA	60.28	±0.40	60.01	±0.02	60.65	±0.55
SciTail	94.32	±0.11	93.90	±0.16	94.04	±0.23
Argument	76.87	±0.32	**77.65**	±0.34	**77.65**	±0.21
CSQA	58.88	±0.40	58.91	±0.57	59.73	±0.54
BoolQ	74.84	±0.24	75.66	±1.25	76.25	±0.19
MRPC	85.14	±0.45	85.16	±0.52	**90.29**	±0.84
SICK	87.30	±0.42	86.20	±0.00	87.28	±0.99
RTE	65.41	±0.90	71.04	±1.62	76.82	±1.68
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AdapterFusion is able to maintain performance for high resource datasets. It learns to activate **only** its own adapter.

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Agenda

1. Adapters in Transformers
2. AdapterFusion
3. **MAD-X**
4. Efficiency of Adapters
5. AdapterHub.ml

site code paper

MAD-X: An Adapter-based Framework for Multi-task Cross-lingual Transfer

Proceedings of EMNLP 2020

Jonas Pfeiffer, Ivan Vulić, Iryna Gurevych, Sebastian Ruder

TECHNISCHE UNIVERSITÄT DARMSTADT

UNIVERSITY OF CAMBRIDGE

DeepMind

Task: Zero-shot transfer to low-resource languages

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Why?

Training **data** is **expensive** and not available for many languages, especially ones that are considered “low-resource”.

Related Work & Baselines

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Deep massively multilingual models such as **multilingual-BERT** (mBERT; Devlin et al. 2019) or **XLM-RoBERTa** (XLM-R; Conneau et al. 2020)
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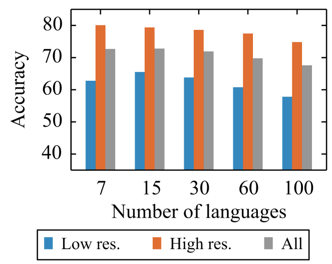

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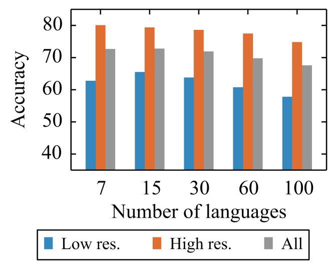

<u>**BUT**</u>

- Suffer from "the curse of multilinguality" (Conneau et al. 2020)
    - and **cannot represent all (7000+) languages in a single model.**
- performance especially **deteriorates** for **low resource languages not covered** in the training data. (Ponti et al. 2020)

Our Approach

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Massive multilinguality of mBERT and XLM-R

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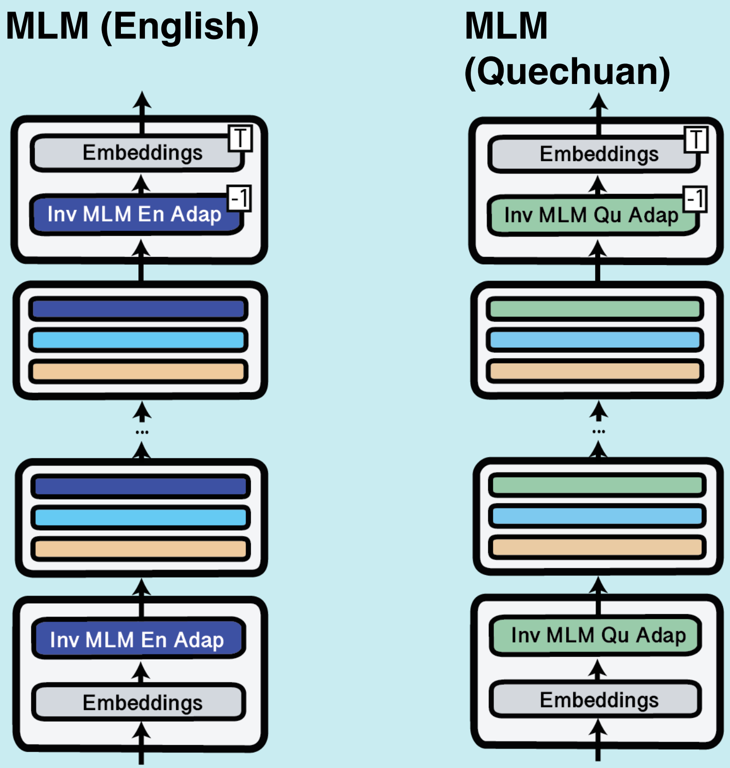
“<u>Language agnostic</u>” **task**-adapters are **stacked** on top of language adapters for zero-shot transfer to unseen languages.

MAD-X

Step 1: Train Language Adapters

We train **language adapters** for the **source language** and the **target language** with masked language modelling on Wikipedia.



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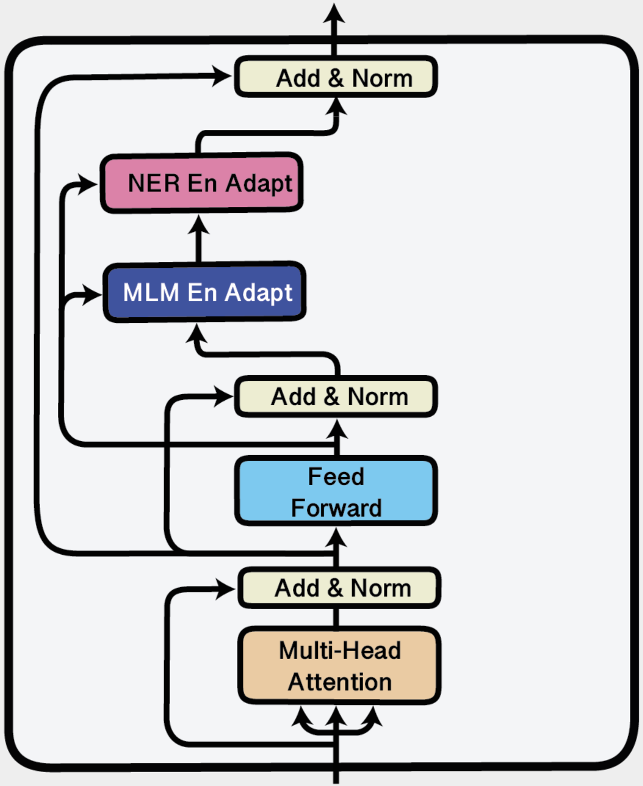

Add & Norm
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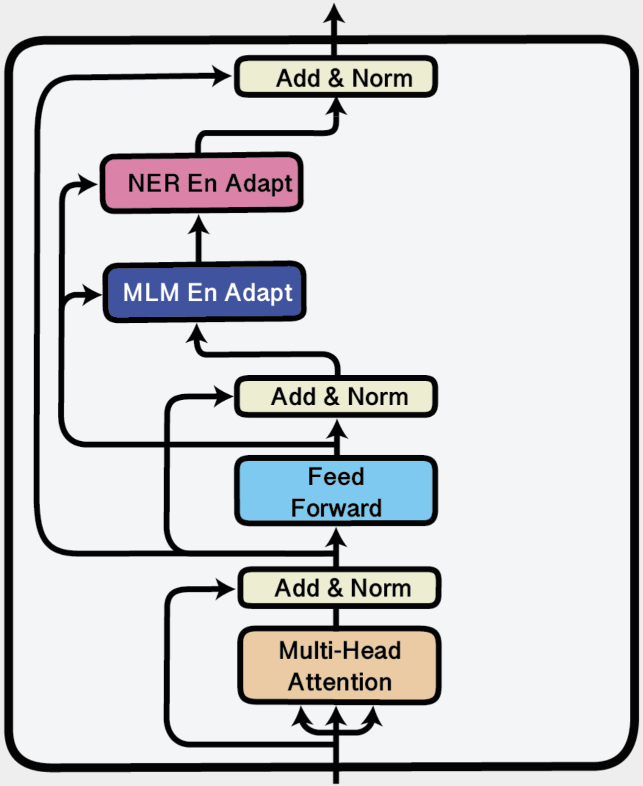

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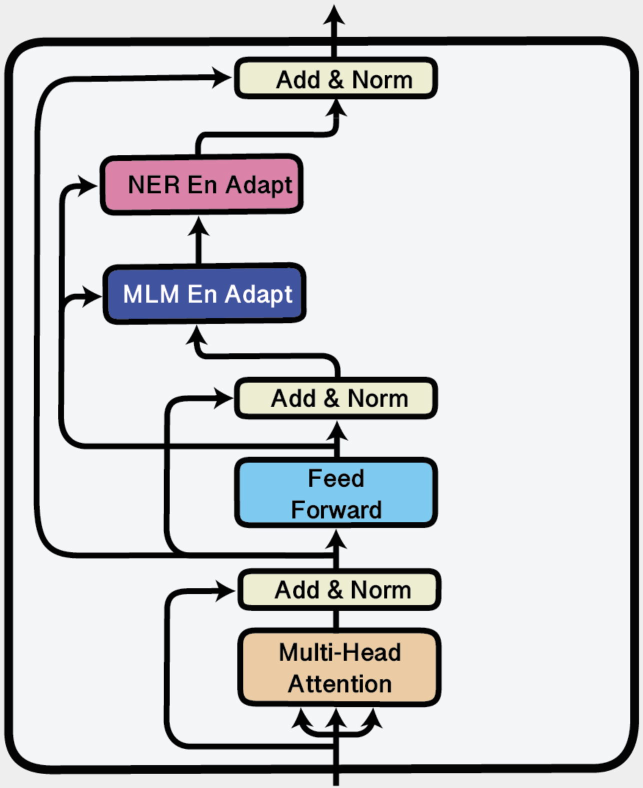

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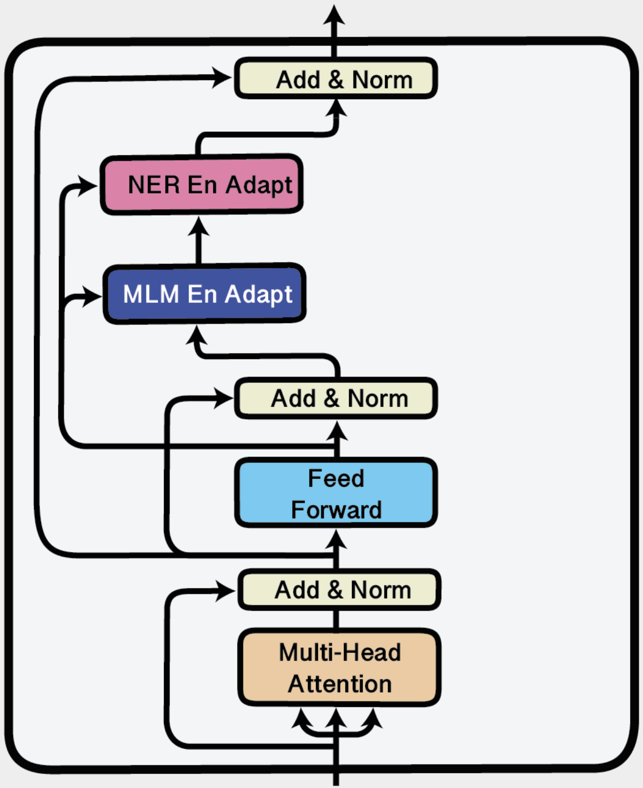

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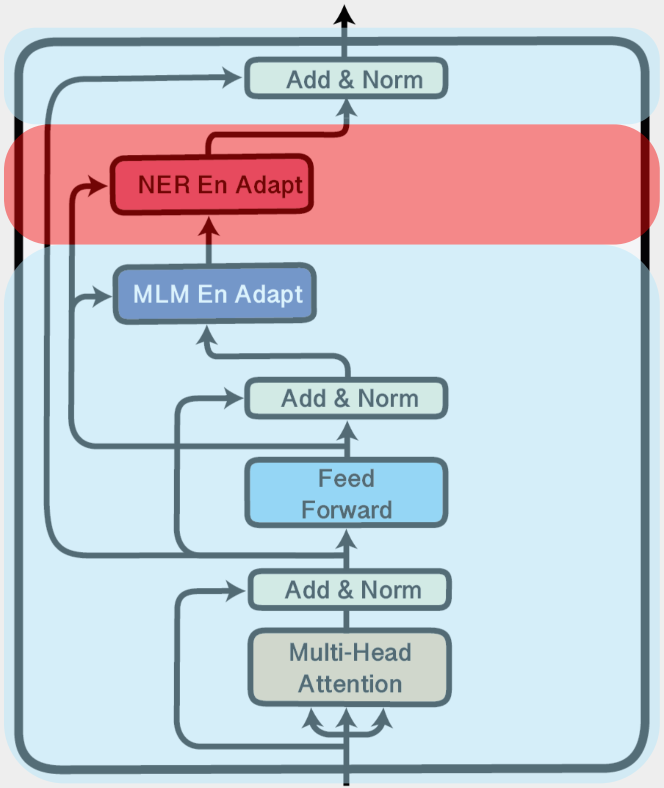

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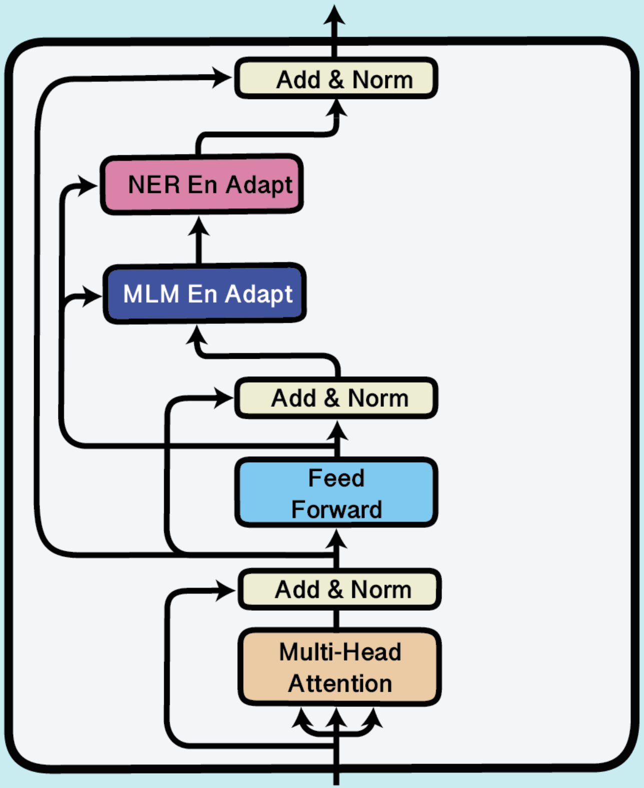
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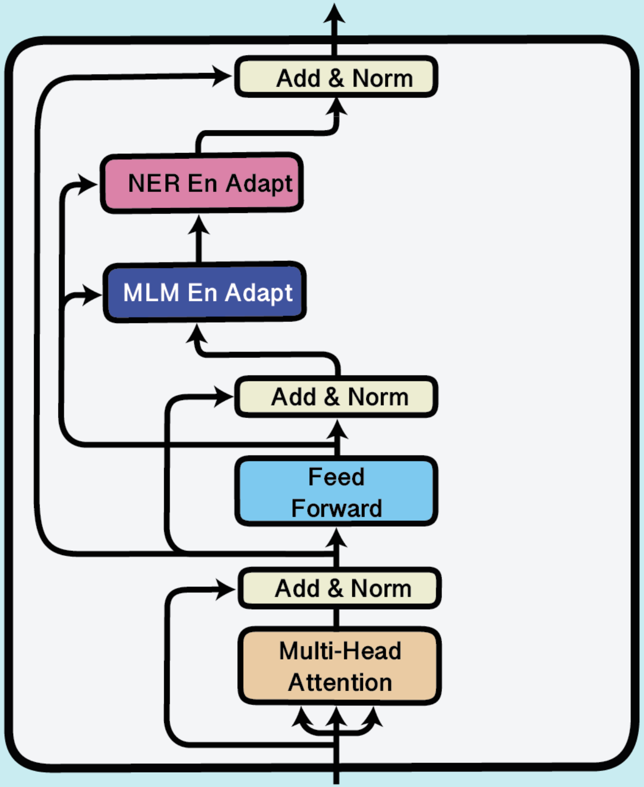

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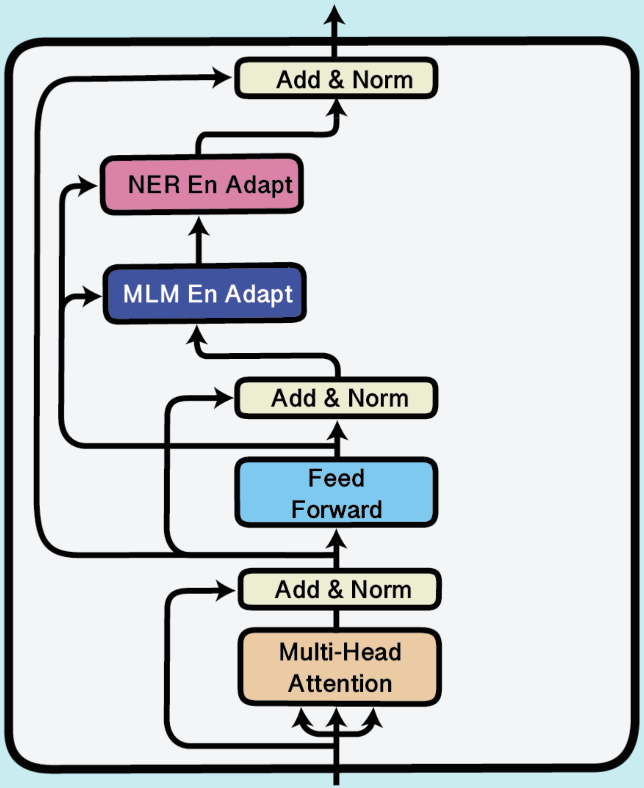
We **replace** the **source** language adapter with the **target** language adapter, while **keeping** the “language agnostic” **task adapter**.



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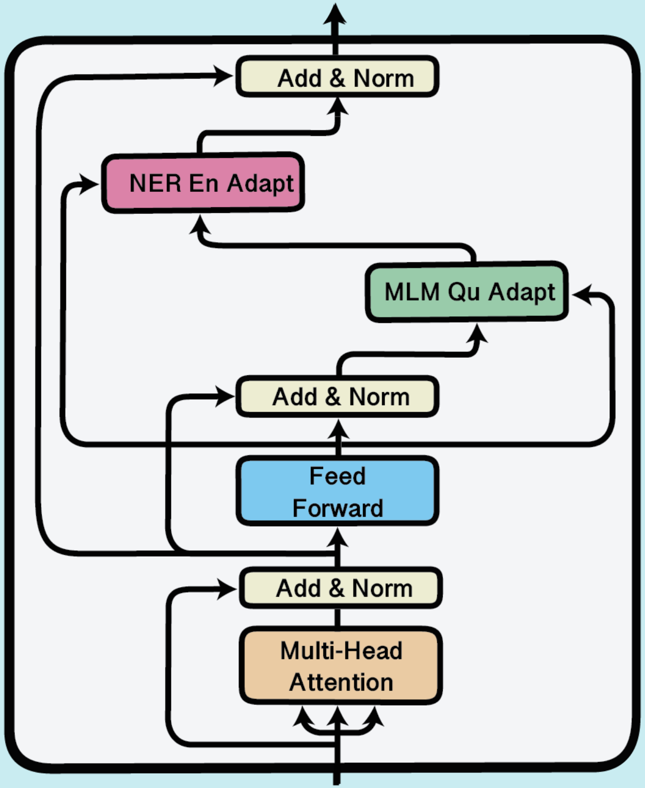

Datasets

NER: WikiAnn Dataset (Pan et al. 2017, Rahimi et al. 2019). We chose a diverse set of languages from **different language families**.

XQuAD (Cross-lingual Question Answering Dataset) (Artetxe et al. 2020)

XCOPA (Ponti et al. 2020b)

Language	ISO code	Language family	# of Wiki articles	Covered by SOTA?
English	en	Indo-European	6.0M	✓
Japanese	ja	Japonic	1.2M	✓
Chinese	zh	Sino-Tibetan	1.1M	✓
Arabic	ar	Afro-Asiatic	1.0M	✓
Javanese	jv	Austronesian	57k	✓
Swahili	sw	Niger-Congo	56k	✓
Icelandic	is	Indo-European	49k	✓
Burmese	my	Sino-Tibetan	45k	✓
Quechua	qu	Quechua	22k	
Min Dong	cdo	Sino-Tibetan	15k	
Ilokano	ilo	Austronesian	14k	
Mingrelian	xmf	Kartvelian	13k	
Meadow Mari	mhr	Uralic	10k	
Maori	mi	Austronesian	7k	
Turkmen	tk	Turkic	6k	
Guarani	gn	Tupian	4k	

Baselines

Standard Zero-Shot

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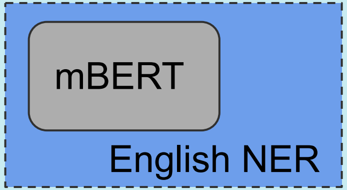
mBERT

Baselines

Standard Zero-Shot

1. **Fine-tune** a multilingual model on the task in the **source** language.



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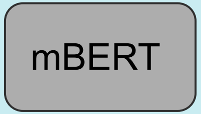

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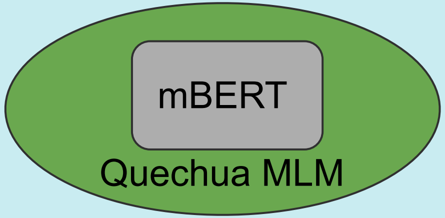

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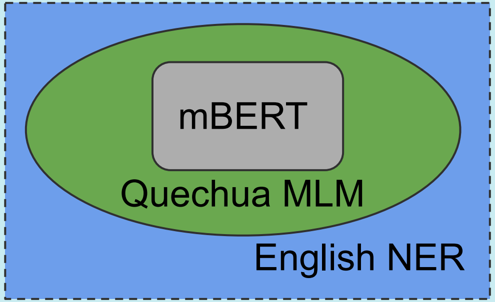

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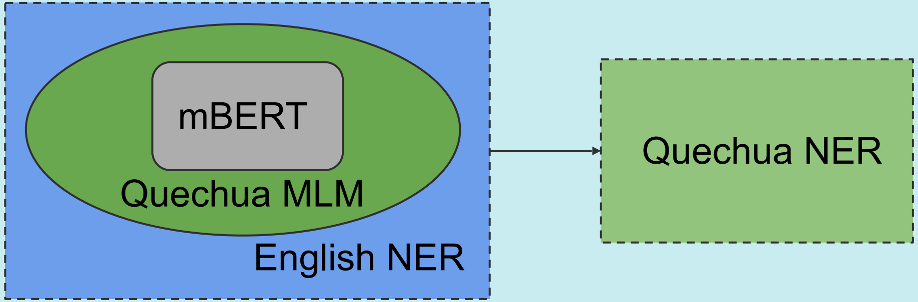

Results NER

NER **F1 scores averaged** over all 16 **target languages** when transferring from each **source** language (i.e., the columns refer to source languages). The vertical dashed line distinguishes between languages seen in multilingual pretraining and the unseen ones.

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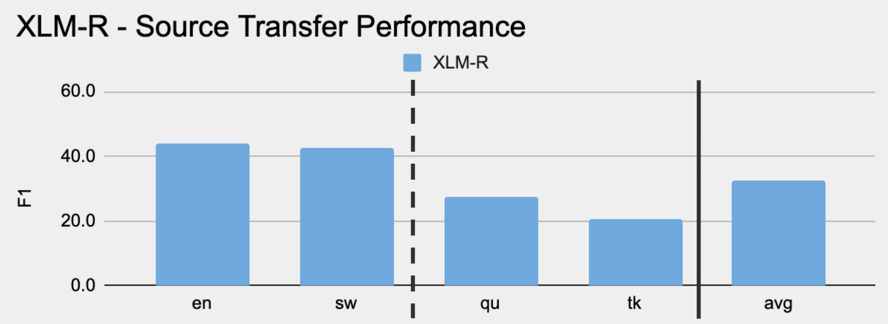

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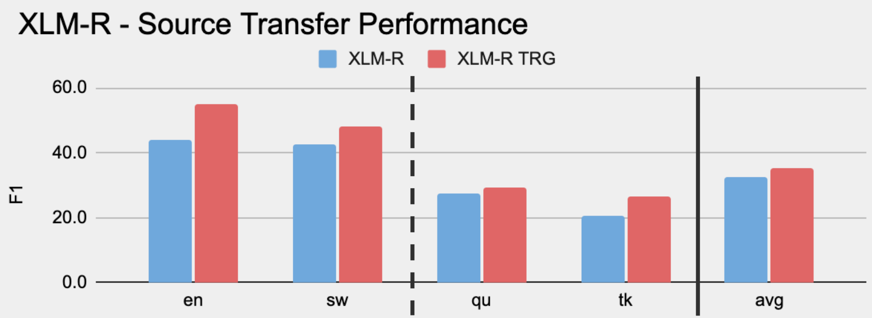

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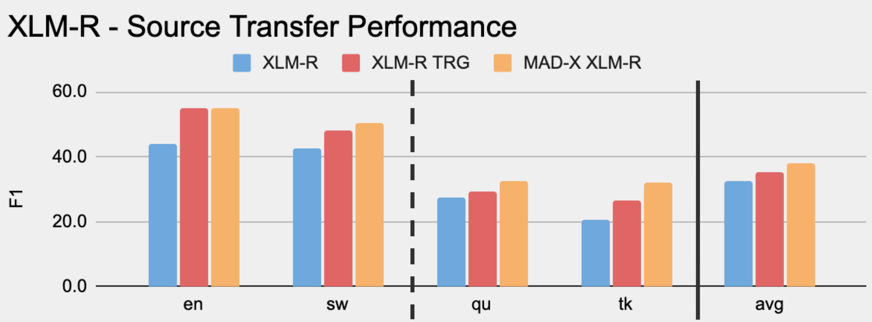

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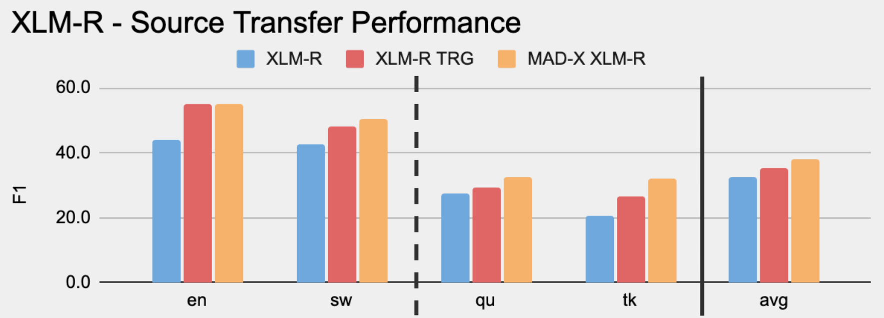

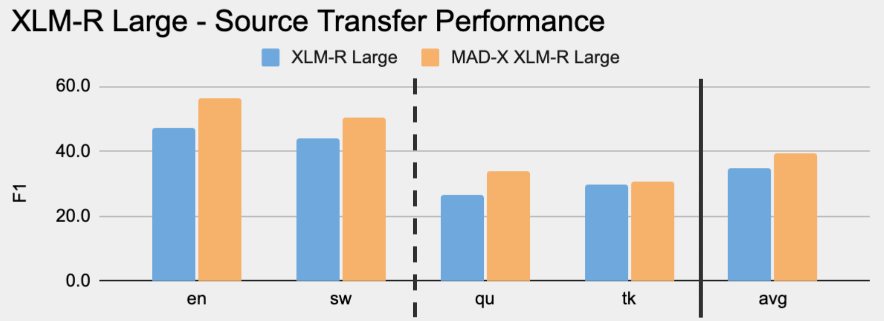

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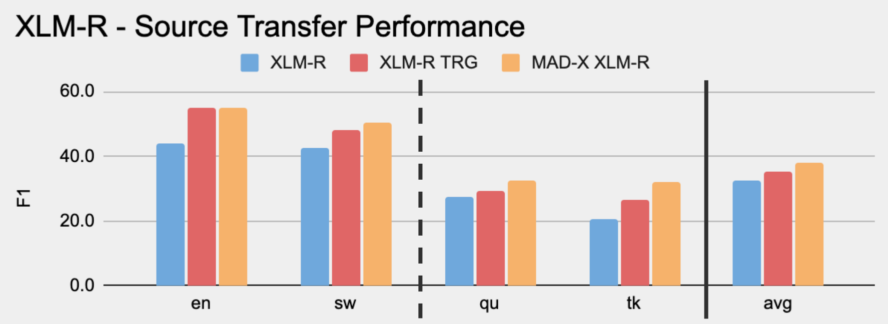
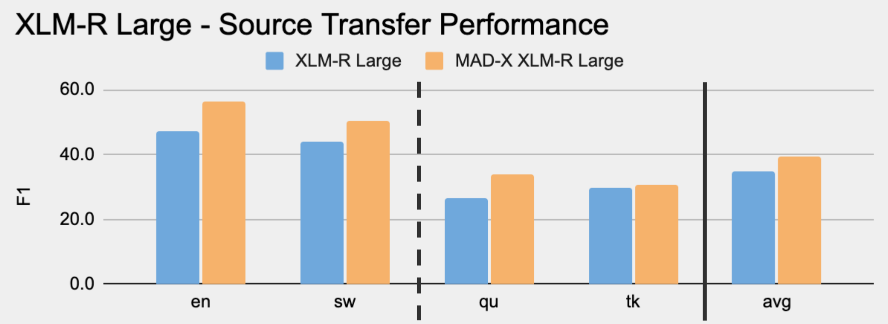
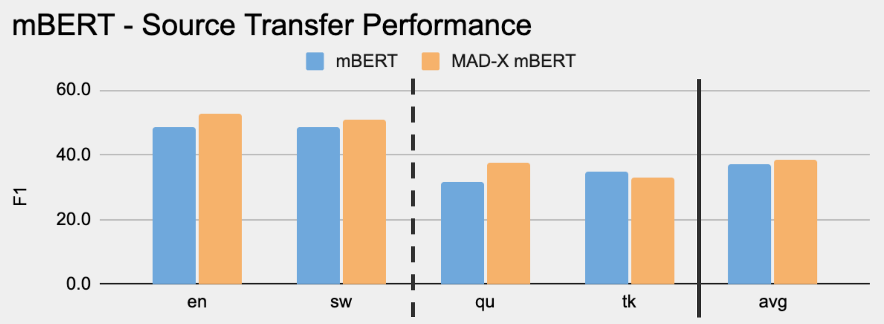






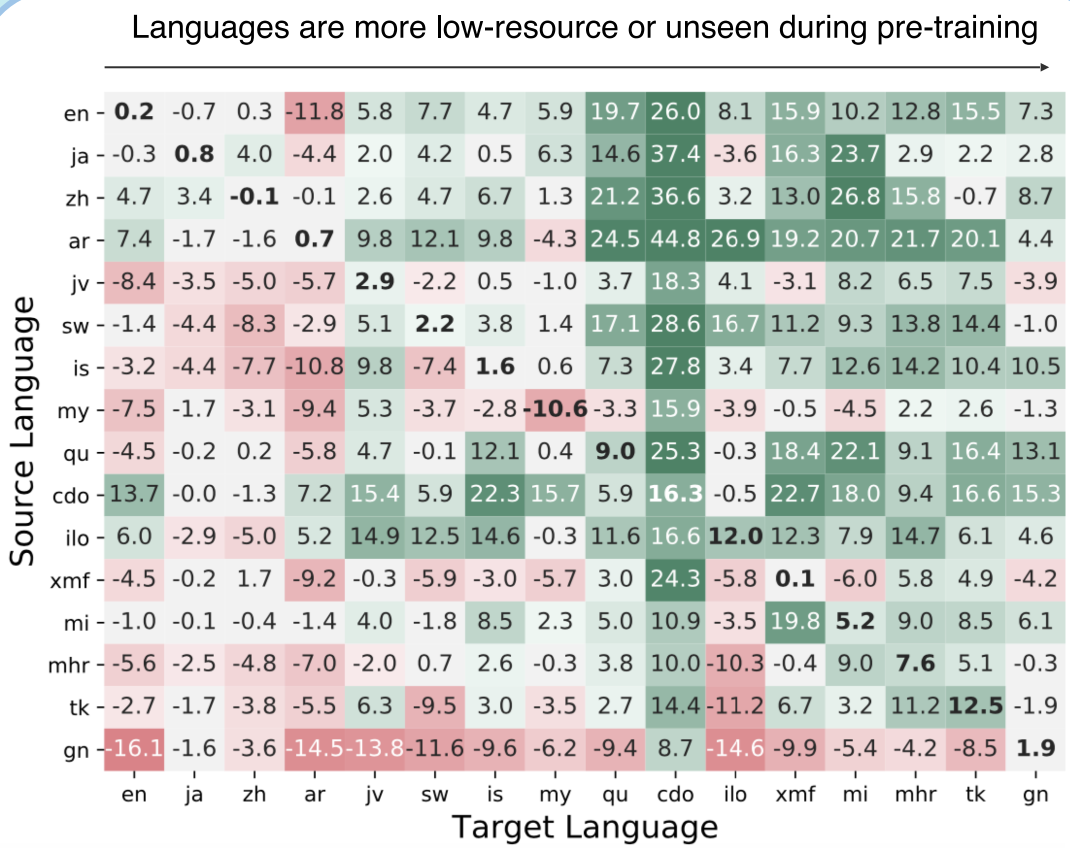
Results NER

Languages are more low-resource or unseen during pre-training →

Source Language \ Target Language	en	ja	zh	ar	jv	sw	is	my	qu	cdo	ilo	xmf	mi	mhr	tk	gn
en	**0.2**	-0.7	0.3	-11.8	5.8	7.7	4.7	5.9	19.7	26.0	8.1	15.9	10.2	12.8	15.5	7.3
ja	-0.3	**0.8**	4.0	-4.4	2.0	4.2	0.5	6.3	14.6	37.4	-3.6	16.3	23.7	2.9	2.2	2.8
zh	4.7	3.4	**-0.1**	-0.1	2.6	4.7	6.7	1.3	21.2	36.6	3.2	13.0	26.8	15.8	-0.7	8.7
ar	7.4	-1.7	-1.6	**0.7**	9.8	12.1	9.8	-4.3	24.5	44.8	26.9	19.2	20.7	21.7	20.1	4.4
jv	-8.4	-3.5	-5.0	-5.7	**2.9**	-2.2	0.5	-1.0	3.7	18.3	4.1	-3.1	8.2	6.5	7.5	-3.9
sw	-1.4	-4.4	-8.3	-2.9	5.1	**2.2**	3.8	1.4	17.1	28.6	16.7	11.2	9.3	13.8	14.4	-1.0
is	-3.2	-4.4	-7.7	-10.8	9.8	-7.4	**1.6**	0.6	7.3	27.8	3.4	7.7	12.6	14.2	10.4	10.5
my	-7.5	-1.7	-3.1	-9.4	5.3	-3.7	-2.8	**-10.6**	-3.3	15.9	-3.9	-0.5	-4.5	2.2	2.6	-1.3
qu	-4.5	-0.2	0.2	-5.8	4.7	-0.1	12.1	0.4	**9.0**	25.3	-0.3	18.4	22.1	9.1	16.4	13.1
cdo	13.7	-0.0	-1.3	7.2	15.4	5.9	22.3	15.7	5.9	**16.3**	-0.5	22.7	18.0	9.4	16.6	15.3
ilo	6.0	-2.9	-5.0	5.2	14.9	12.5	14.6	-0.3	11.6	16.6	**12.0**	12.3	7.9	14.7	6.1	4.6
xmf	-4.5	-0.2	1.7	-9.2	-0.3	-5.9	-3.0	-5.7	3.0	24.3	-5.8	**0.1**	-6.0	5.8	4.9	-4.2
mi	-1.0	-0.1	-0.4	-1.4	4.0	-1.8	8.5	2.3	5.0	10.9	-3.5	19.8	**5.2**	9.0	8.5	6.1
mhr	-5.6	-2.5	-4.8	-7.0	-2.0	0.7	2.6	-0.3	3.8	10.0	-10.3	-0.4	9.0	**7.6**	5.1	-0.3
tk	-2.7	-1.7	-3.8	-5.5	6.3	-9.5	3.0	-3.5	2.7	14.4	-11.2	6.7	3.2	11.2	**12.5**	-1.9
gn	-16.1	-1.6	-3.6	-14.5	-13.8	-11.6	-9.6	-6.2	-9.4	8.7	-14.6	-9.9	-5.4	-4.2	-8.5	**1.9**

Results NER

Relative **F1 improvement** of **MAD-X Large over XLM-R Large** in cross-lingual NER transfer.



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Top right corner represent the **realistic scenario** of **transfering from high resource to low resource**

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en	**0.2**	-0.7	0.3	-11.8	5.8	7.7	4.7	5.9	19.7	26.0	8.1	15.9	10.2	12.8	15.5	7.3
ja	-0.3	**0.8**	4.0	-4.4	2.0	4.2	0.5	6.3	14.6	37.4	-3.6	16.3	23.7	2.9	2.2	2.8
zh	4.7	3.4	**-0.1**	-0.1	2.6	4.7	6.7	1.3	21.2	36.6	3.2	13.0	26.8	15.8	-0.7	8.7
ar	7.4	-1.7	-1.6	**0.7**	9.8	12.1	9.8	-4.3	24.5	44.8	26.9	19.2	20.7	21.7	20.1	4.4
jv	-8.4	-3.5	-5.0	-5.7	**2.9**	-2.2	0.5	-1.0	3.7	18.3	4.1	-3.1	8.2	6.5	7.5	-3.9
sw	-1.4	-4.4	-8.3	-2.9	5.1	**2.2**	3.8	1.4	17.1	28.6	16.7	11.2	9.3	13.8	14.4	-1.0
is	-3.2	-4.4	-7.7	-10.8	9.8	-7.4	**1.6**	0.6	7.3	27.8	3.4	7.7	12.6	14.2	10.4	10.5
my	-7.5	-1.7	-3.1	-9.4	5.3	-3.7	-2.8	**-10.6**	-3.3	15.9	-3.9	-0.5	-4.5	2.2	2.6	-1.3
qu	-4.5	-0.2	0.2	-5.8	4.7	-0.1	12.1	0.4	**9.0**	25.3	-0.3	18.4	22.1	9.1	16.4	13.1
cdo	13.7	-0.0	-1.3	7.2	15.4	5.9	22.3	15.7	5.9	**16.3**	-0.5	22.7	18.0	9.4	16.6	15.3
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xmf	-4.5	-0.2	1.7	-9.2	-0.3	-5.9	-3.0	-5.7	3.0	24.3	-5.8	**0.1**	-6.0	5.8	4.9	-4.2
mi	-1.0	-0.1	-0.4	-1.4	4.0	-1.8	8.5	2.3	5.0	10.9	-3.5	19.8	**5.2**	9.0	8.5	6.1
mhr	-5.6	-2.5	-4.8	-7.0	-2.0	0.7	2.6	-0.3	3.8	10.0	-10.3	-0.4	9.0	**7.6**	5.1	-0.3
tk	-2.7	-1.7	-3.8	-5.5	6.3	-9.5	3.0	-3.5	2.7	14.4	-11.2	6.7	3.2	11.2	**12.5**	-1.9
gn	-16.1	-1.6	-3.6	-14.5	-13.8	-11.6	-9.6	-6.2	-9.4	8.7	-14.6	-9.9	-5.4	-4.2	-8.5	**1.9**

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sw	-1.4	-4.4	-8.3	-2.9	5.1	**2.2**	3.8	1.4	17.1	28.6	16.7	11.2	9.3	13.8	14.4	-1.0
is	-3.2	-4.4	-7.7	-10.8	9.8	-7.4	**1.6**	0.6	7.3	27.8	3.4	7.7	12.6	14.2	10.4	10.5
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Agenda

1. Adapters in Transformers
2. AdapterFusion
3. MAD-X
4. **Efficiency of Adapters**
5. AdapterHub.ml

site code paper

AdapterDrop: On the Efficiency of Adapters in Transformers

arxiv 2020

Andreas Rücklé, Gregor Geigle, Max Glockner, Tilman Beck, **Jonas Pfeiffer**, Nils Reimers, Iryna Gurevych

TECHNISCHE UNIVERSITÄT DARMSTADT

AdapterDrop: Training/Inference Efficiency of Adapters

Rücklé, Andreas, et al. "AdapterDrop: On the Efficiency of Adapters in Transformers." *arXiv preprint*. 2020.

AdapterDrop: Training/Inference Efficiency of Adapters

Training: Adapters are faster to train because we do not backpropagate through the entire network.

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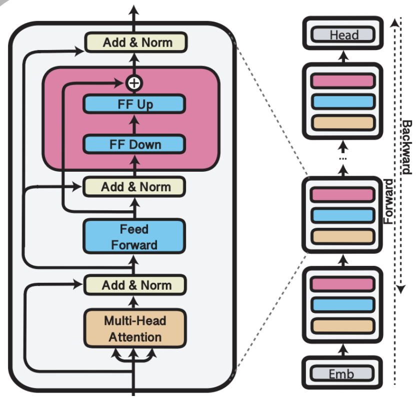

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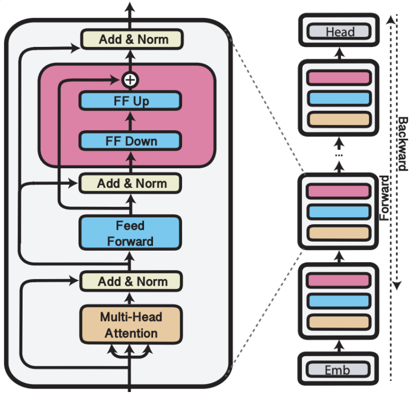

Setting	Adapter	Relative speed *(for Seq.Len./Batch)*			
		128/16	128/32	512/16	512/32
Training	Houlsby	1.48	1.53	1.36	1.33
	Pfeiffer	1.57	1.60	1.41	1.37
Inference	Houlsby	0.94	0.94	0.96	0.96
	Pfeiffer	0.95	0.95	0.96	0.96

Table 1: Relative speed of adapters compared to fully fine-tuned models. For example, 1.6 for training with the Pfeiffer adapter means that we can perform 1.6 training steps with this adapter in the time of one update step with full model fine-tuning.

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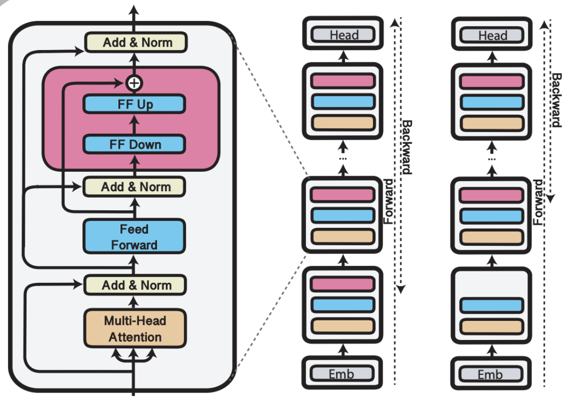

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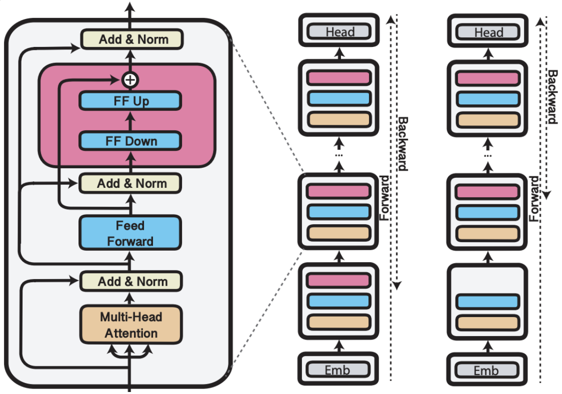

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Simultaneous Tasks	2	4	8	16
Speedup (each layer)	4.3%	6.6%	7.8%	8.4%

Table 2: Speedup for each shared transformer layer when performing inference for multiple tasks simultaneously (details are given in Appendix G.2)

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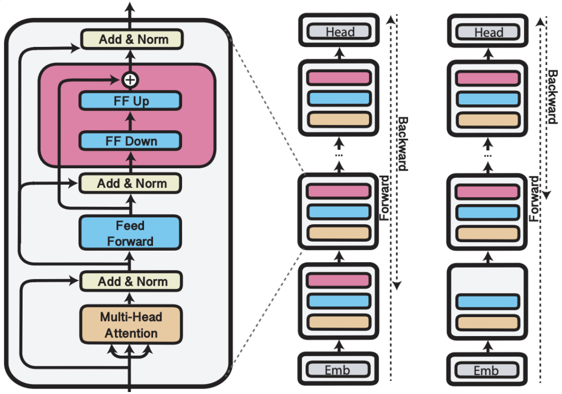

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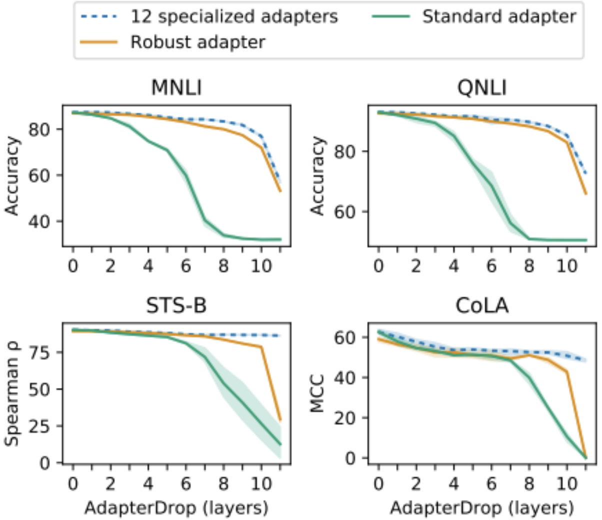

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site code paper

AdapterHub: A Framework for Adapting Transformers

Proceedings of EMNLP 2020: Systems Demonstrations

Jonas Pfeiffer*, Andreas Rücklé*, Clifton Poth*, Aishwarya Kamath, Ivan Vulić, Sebastian Ruder, Kyunghyun Cho, Iryna Gurevych

TECHNISCHE UNIVERSITÄT DARMSTADT

UNIVERSITY OF CAMBRIDGE

NYU

DeepMind

AdapterHub

Explore Upload Docs

A **central repository** for pre-trained **adapter modules**

182 adapters | **24** text tasks | **32** languages

```
pip install adapter-transformers
```

Explore | Upload | Docs | GitHub | Paper

Adapters are Lightweight 🤖

"Adapter" refers to a set of newly introduced weights, typically within the layers of a transformer model. Adapters provide an alternative to fully fine-tuning the model for each downstream task, while maintaining performance. They also have the added benefit of requiring as little as 1MB of storage space per task!

Modular, Composable, and Extensible 🔧

Adapters, being self-contained moduar units, allow for easy extension and composition. This opens up opportunities to compose adapters to solve new tasks.

Built on HuggingFace 🤗 Transformers 🚀

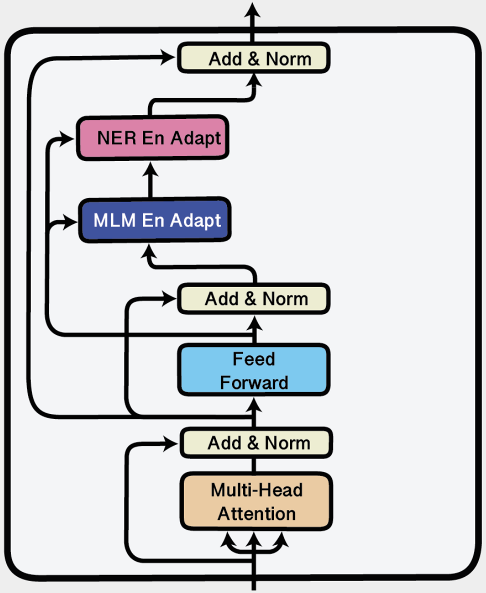
AdapterHub builds on the HuggingFace transformers framework requiring as little as two additional lines of code to train adapters for a downstream task.

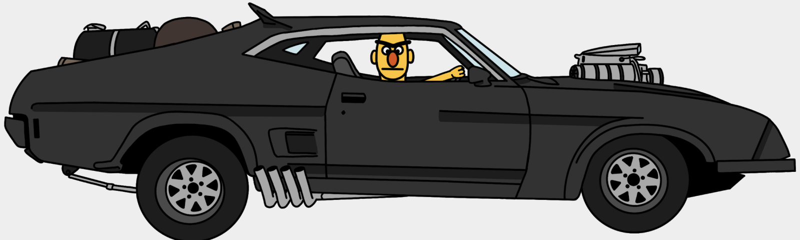
link

Outlook

- Many **alternative** Adapter Approaches
  - Diff-Pruning (Guo et al. 2020)
  - BitFit (Ben-Zaken et al. 2020)
  - Prefix-Tuning (Li et al. 2021)
- How to best **compose** Adapters?
- **Domain** Adapters?
- **Hypernetworks**/CPGs for Adapters (i.e. UDapter (Uestuen et al. 2020))
- Increase the **modularity** of Adapters?
- ...

Key Takeaways





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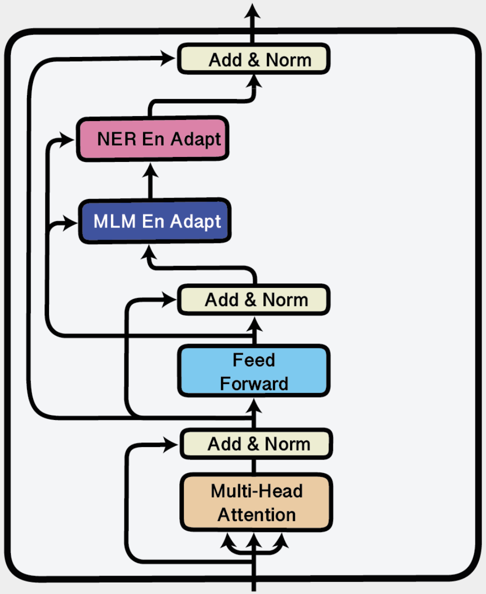

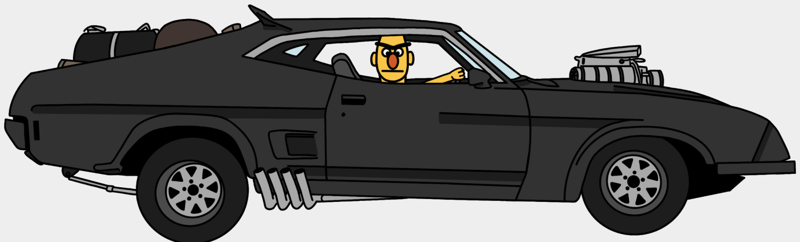

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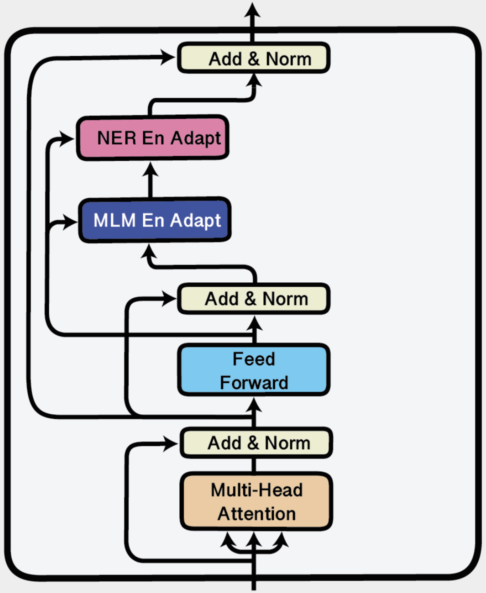

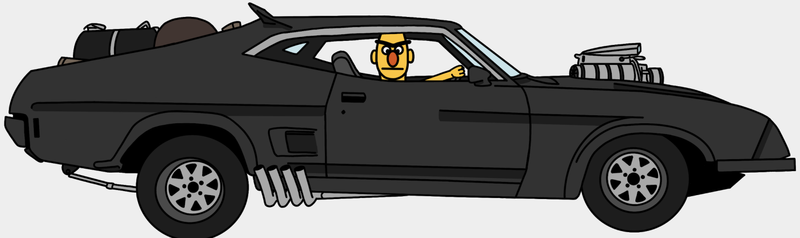

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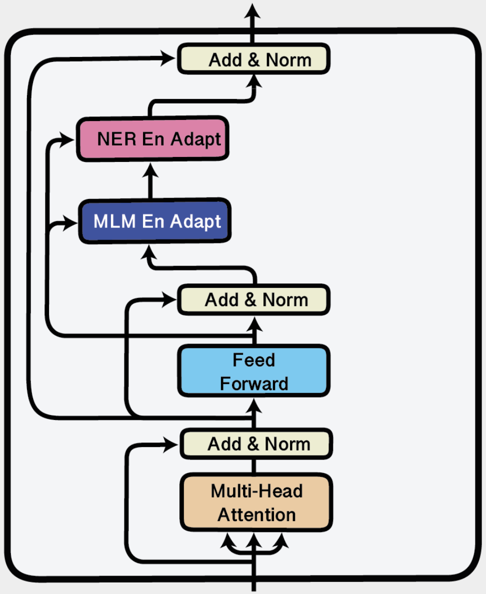

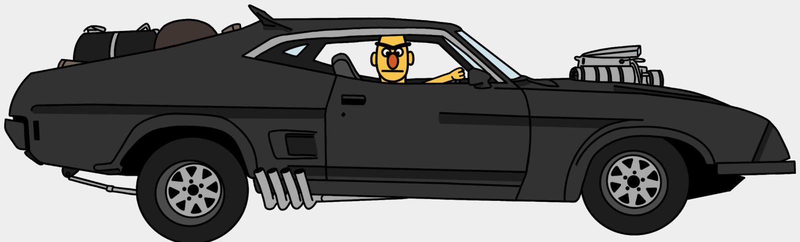

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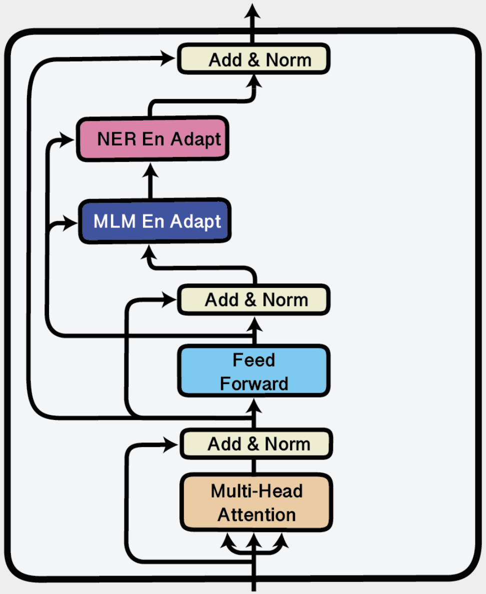

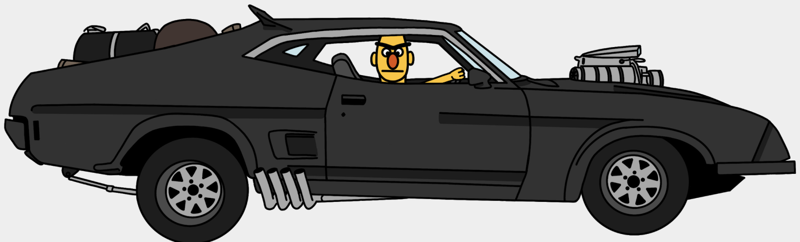

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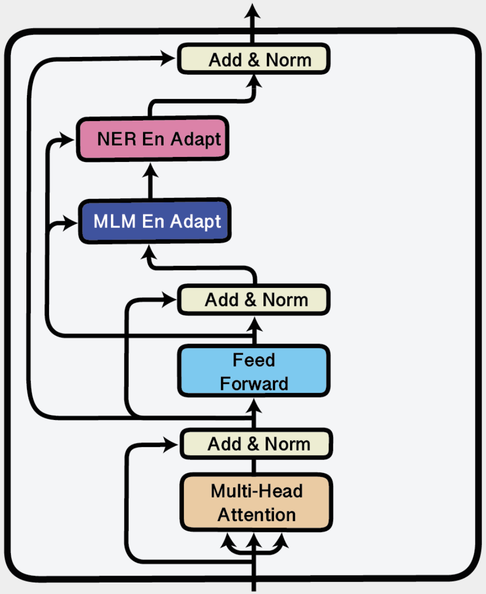

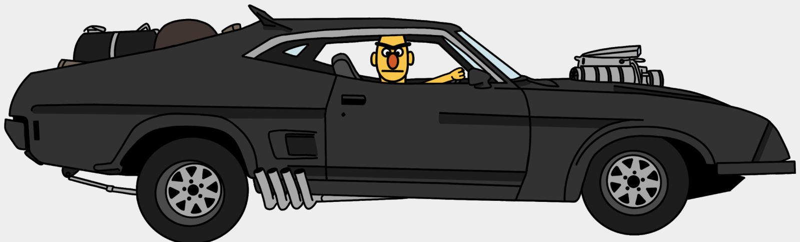

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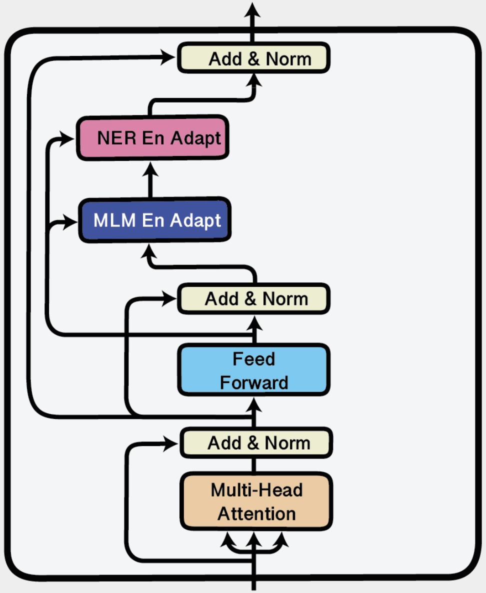

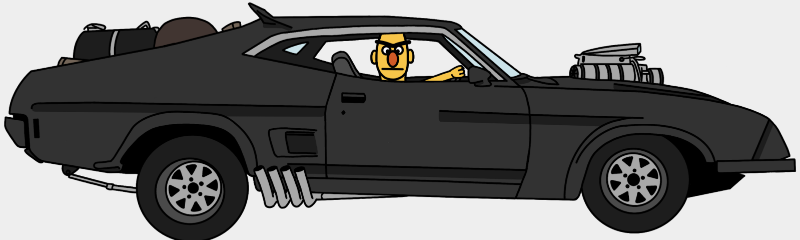

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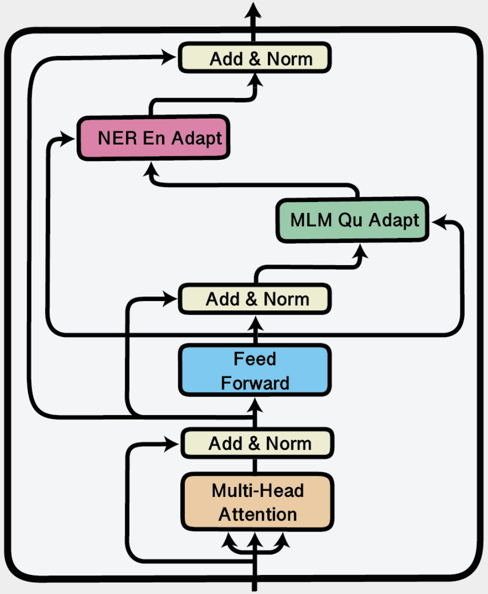

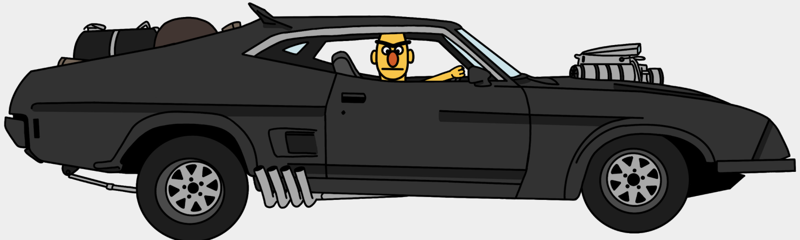

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