MetaICL: Learning to Learn In Context

Sewon Min, Mike Lewis, Luke Zettlemoyer, Hannaneh Hajishirzi
University of Washington, Meta AI, Allen Institute for AI




UW NLP Meta AI2 NAACL 2022

In-Context Learning

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***k* shot data**

Input: Circulation revenue has increased by 5% in Finland. Output : Positive

Input: Panostaja did not disclose the purchase price. Output: Neutral

Input: Paying off the national debt will be extremely painful. Output: Negative

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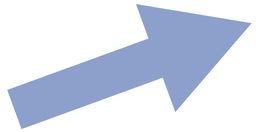

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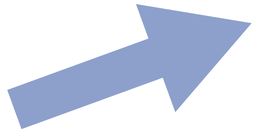

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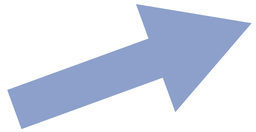

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(Brown et al. 2020)

GPT-3

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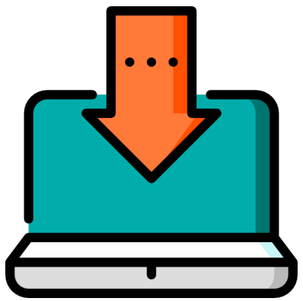

Better tuning of prompt
(Shin et al. 2020, Jiang et al. 2020, Gao et al. 2021)

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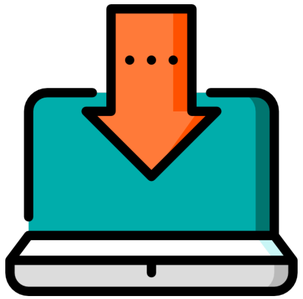

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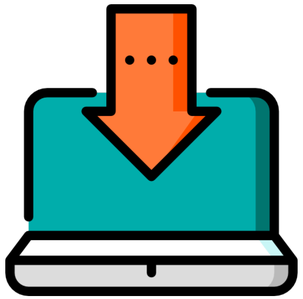

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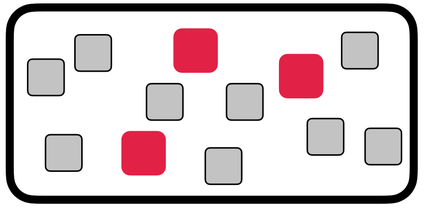

Better choice of in-context examples
(Liu et al. 2021, Lu et al. 2021, Rubin et al. 2021)

Next presentation!

We always used the plain language model

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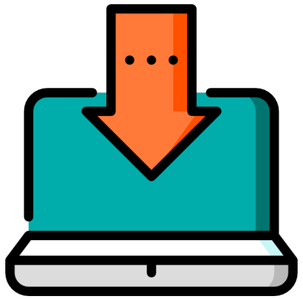

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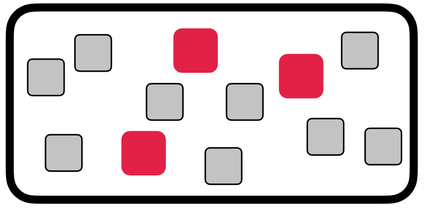

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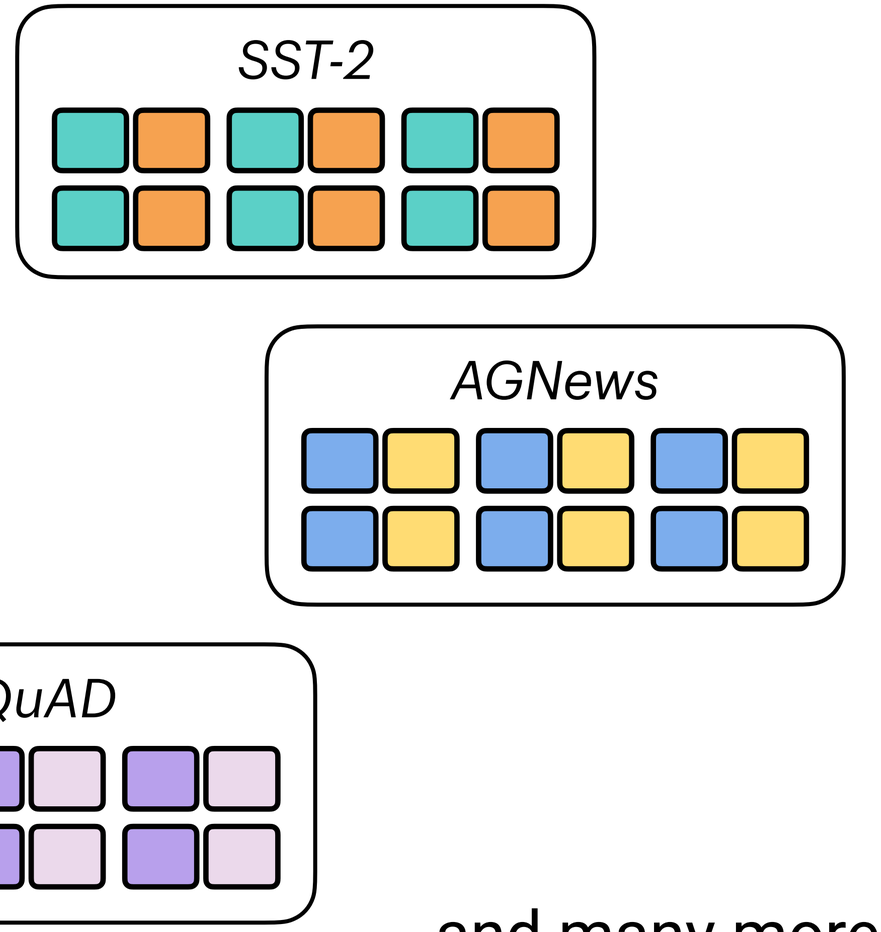

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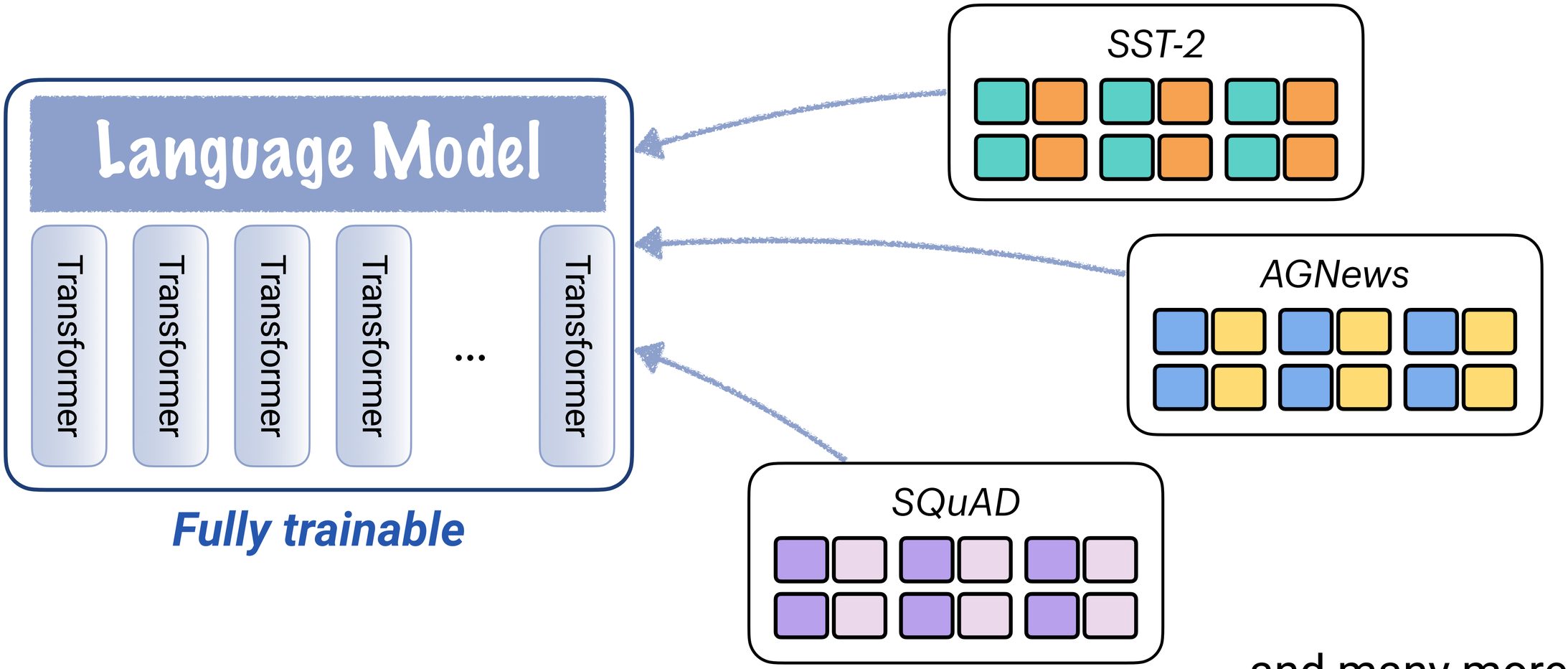

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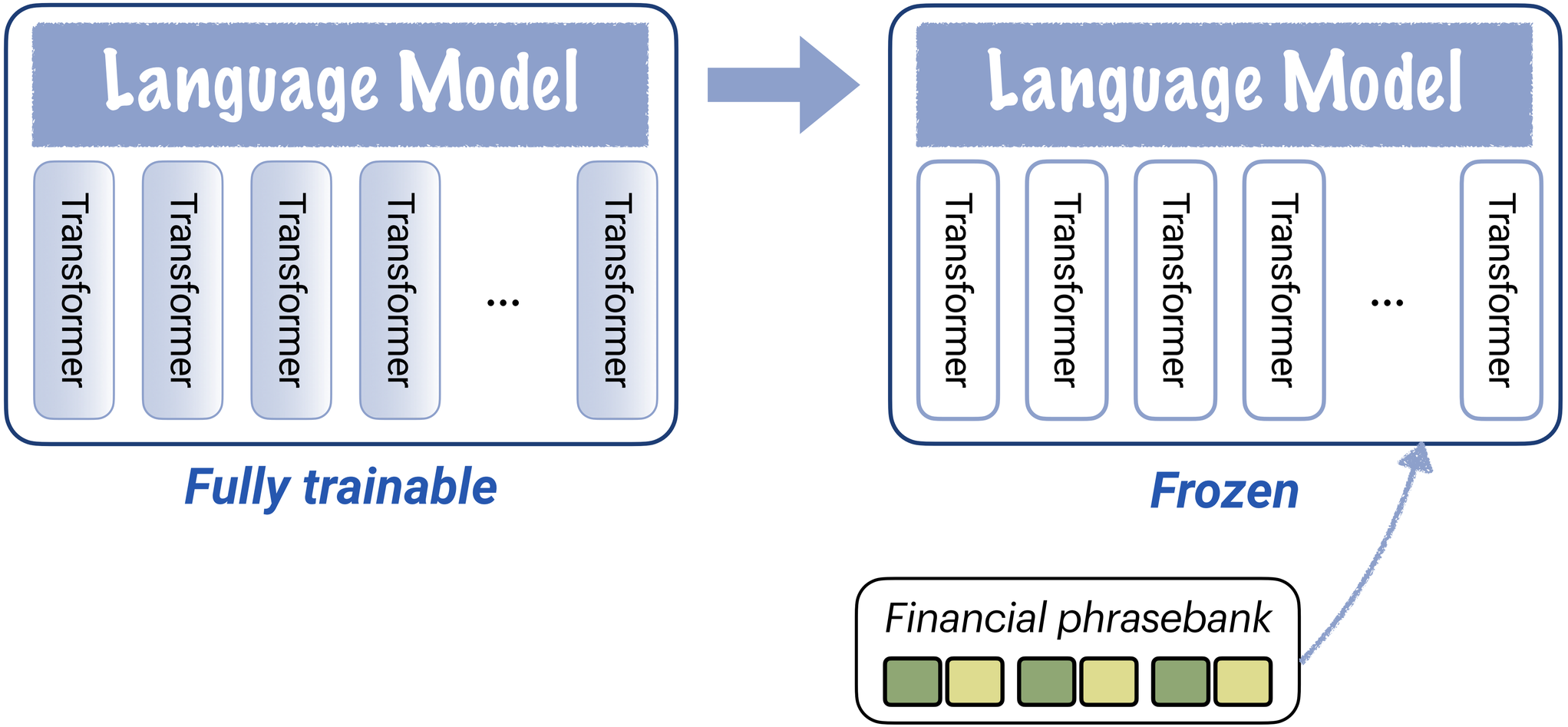

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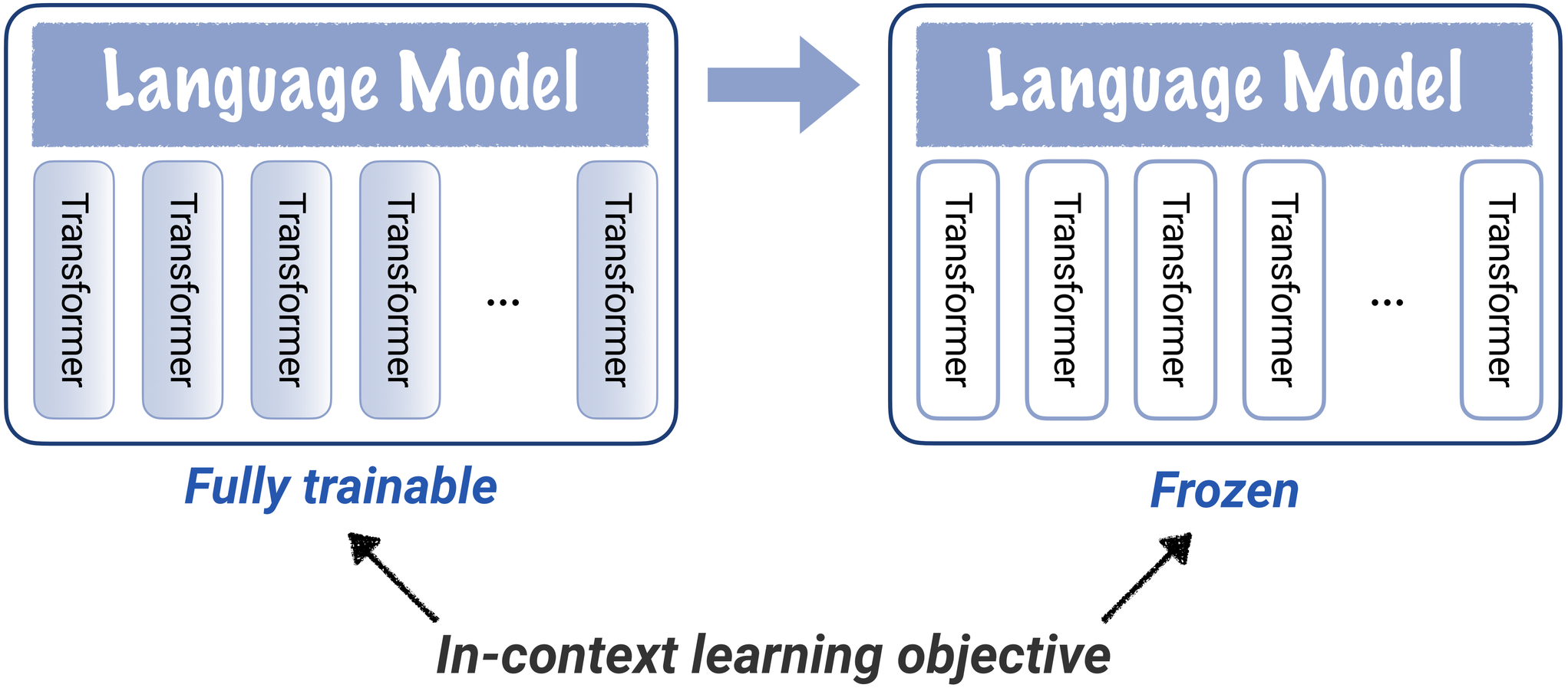

MetaICL

Meta-training

1. Sample a task T
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MetaICL

A collection of meta-training tasks

SST-2 *AGNew* *SQuAD* ...

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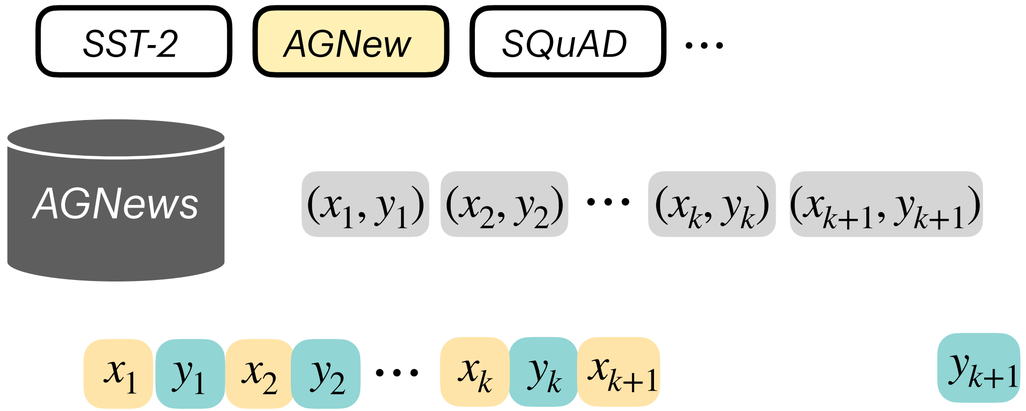

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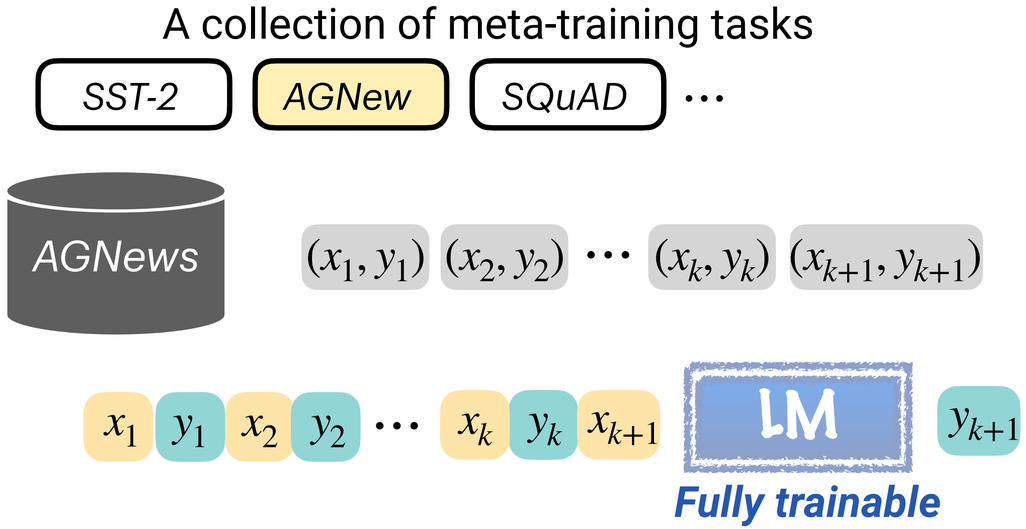

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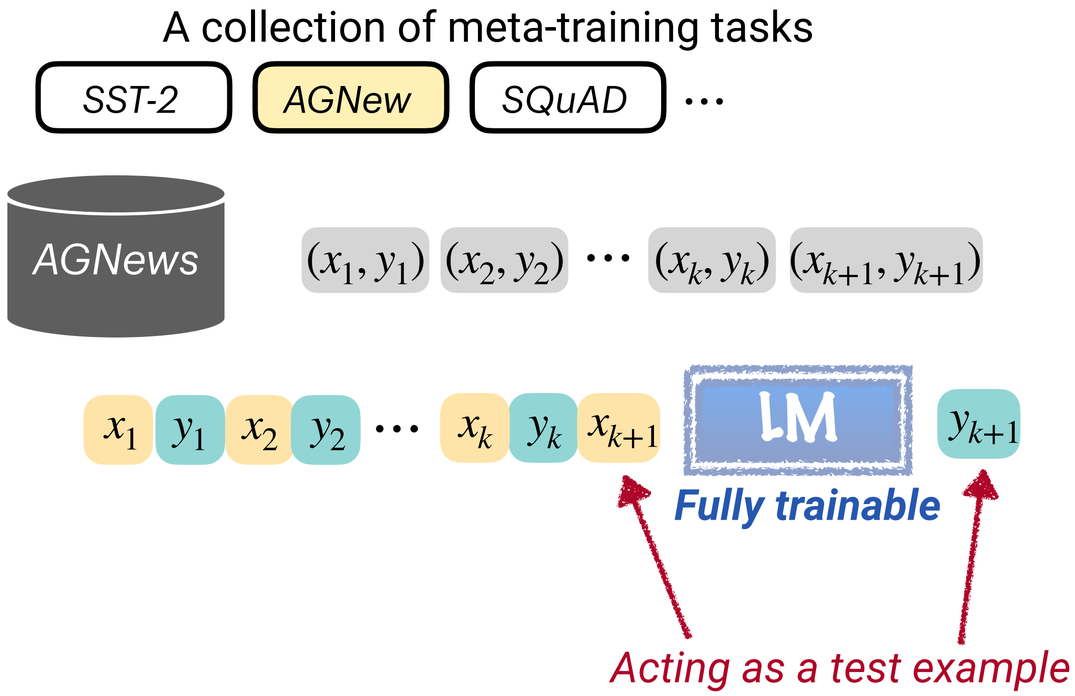

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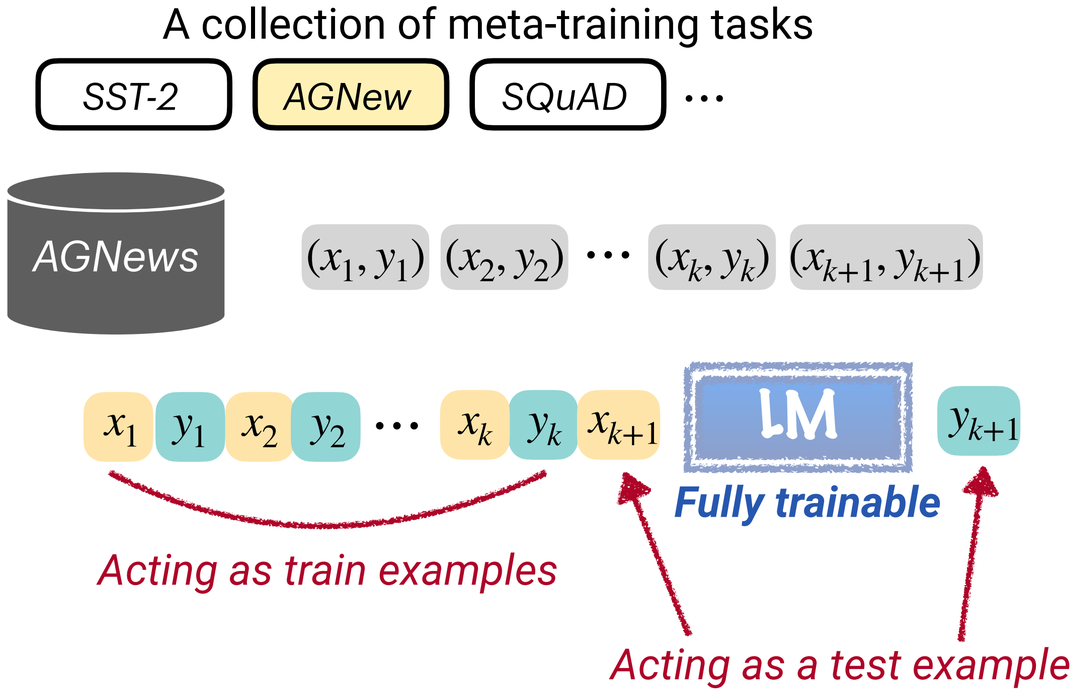

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x_1 y_1 x_2 y_2 ⋯ x_k y_k x_{k+1} **LM** y_{k+1}

Fully trainable

MetaICL

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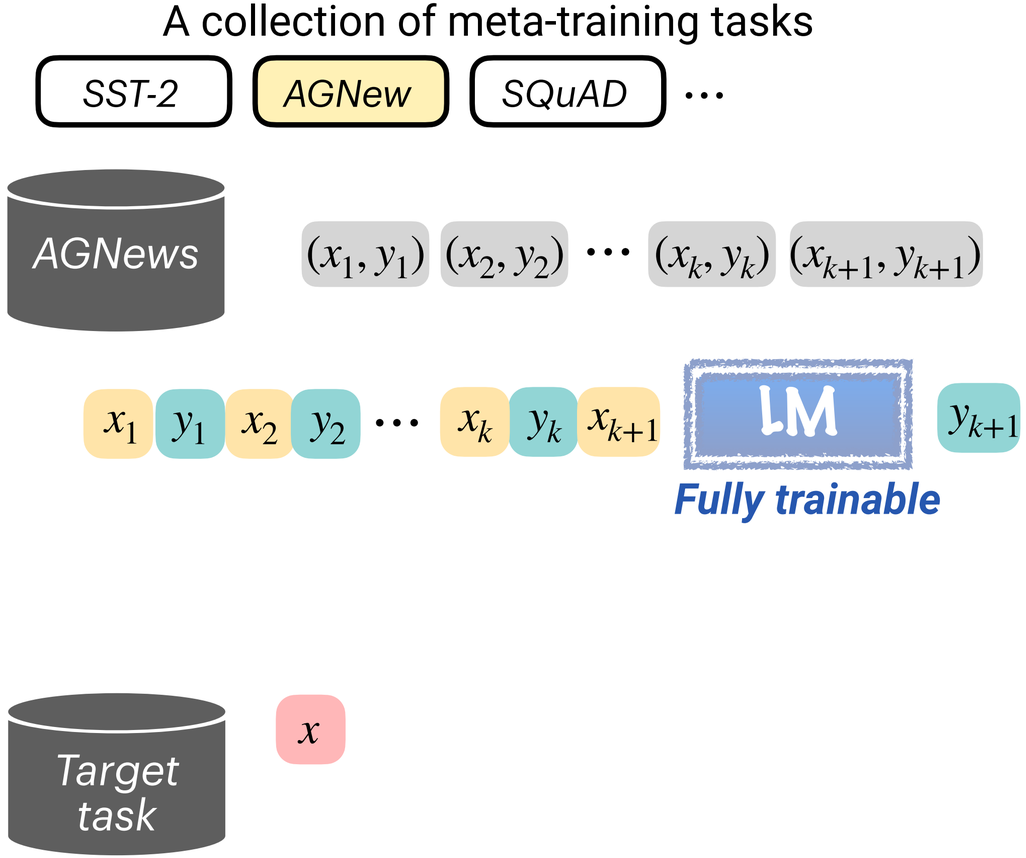

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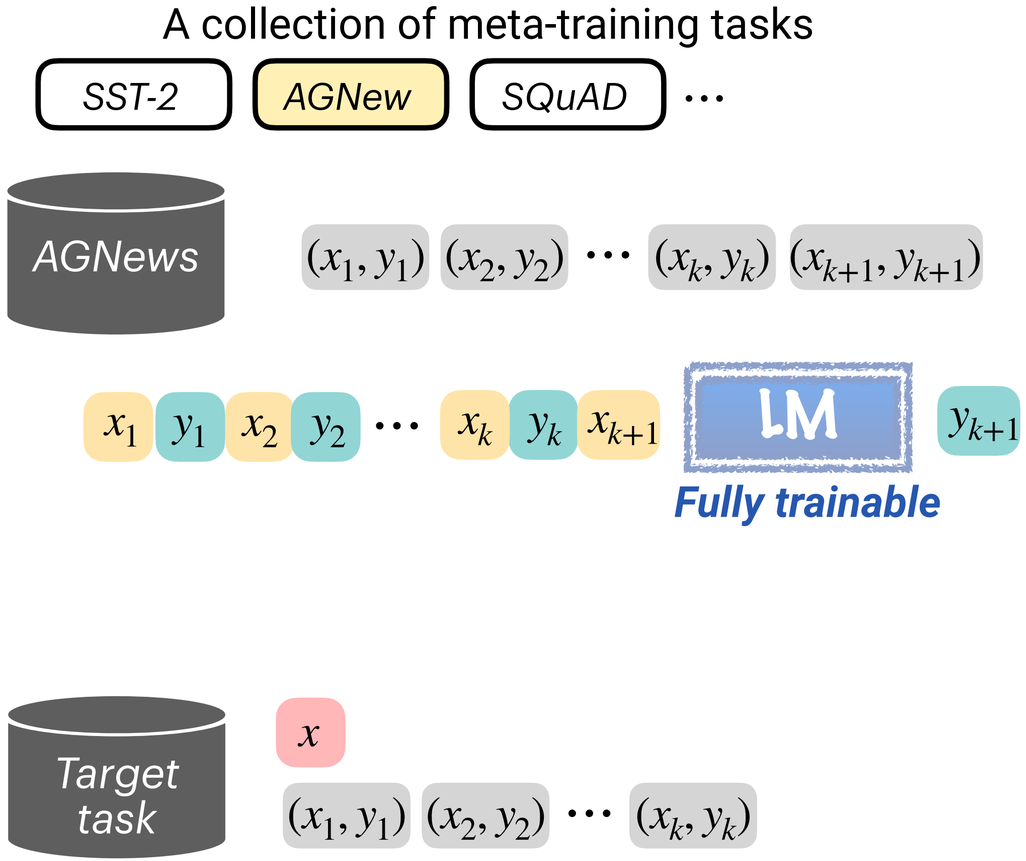

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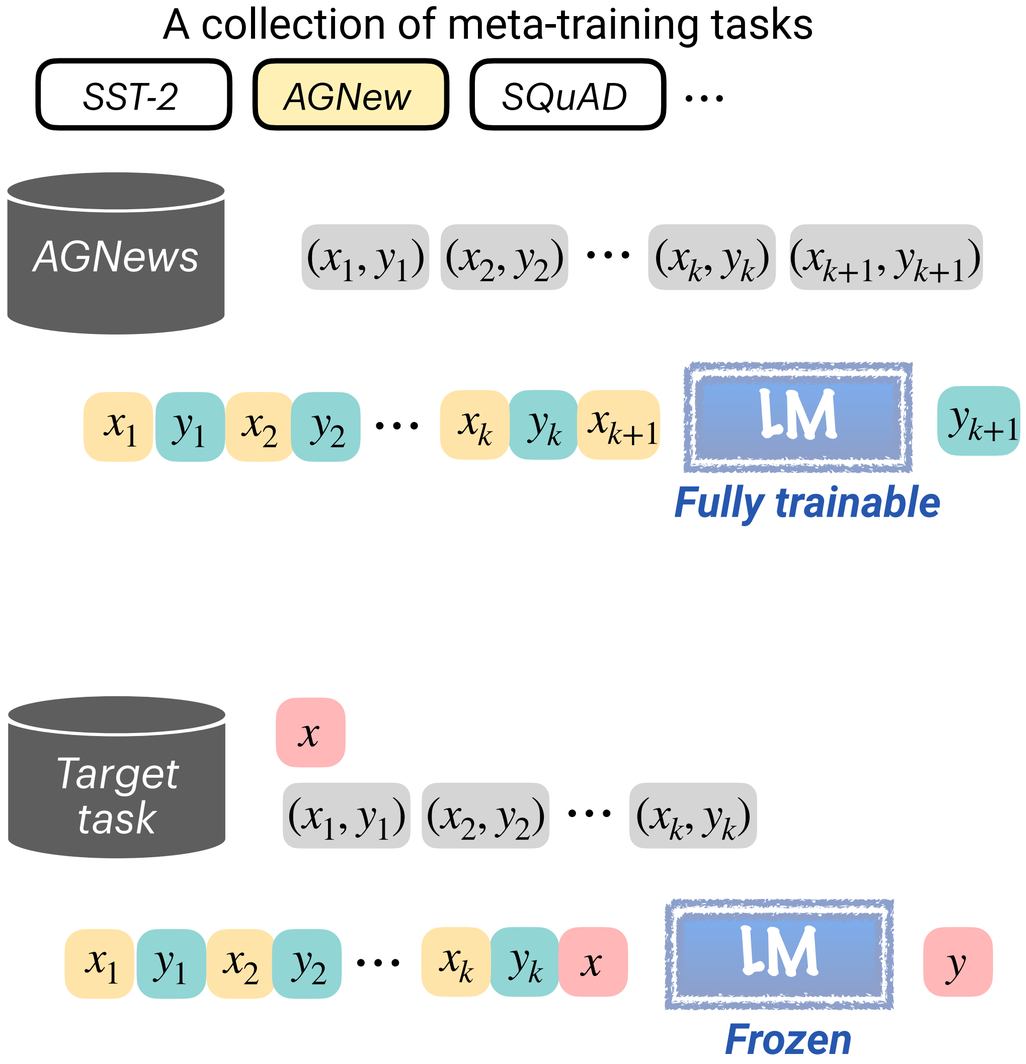

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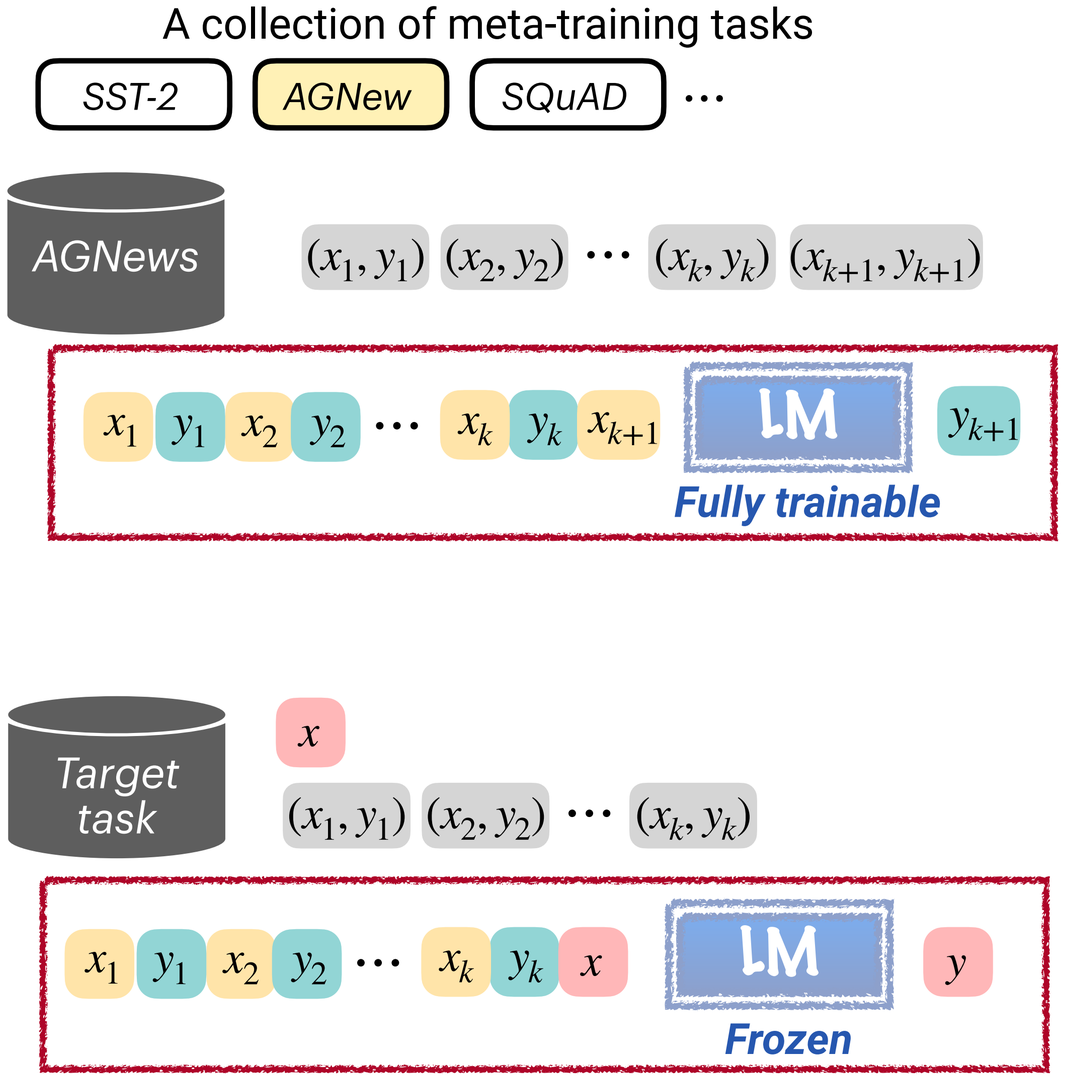

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Direct MetaICL

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Channel MetaICL

"Noisy Channel Language Model Prompting for Few-Shot Text Classification" ACL 2022

Related Work

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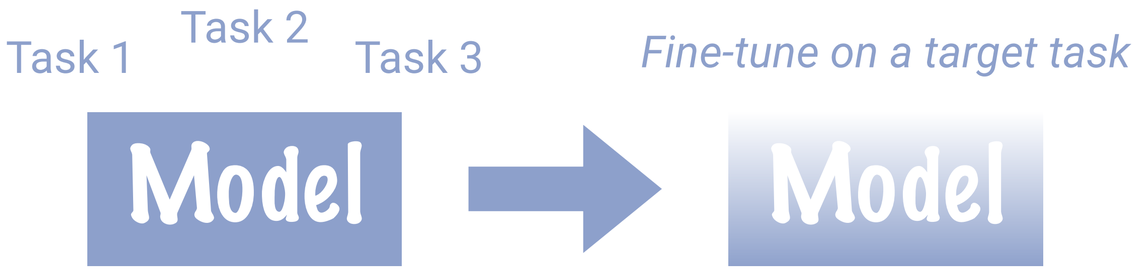
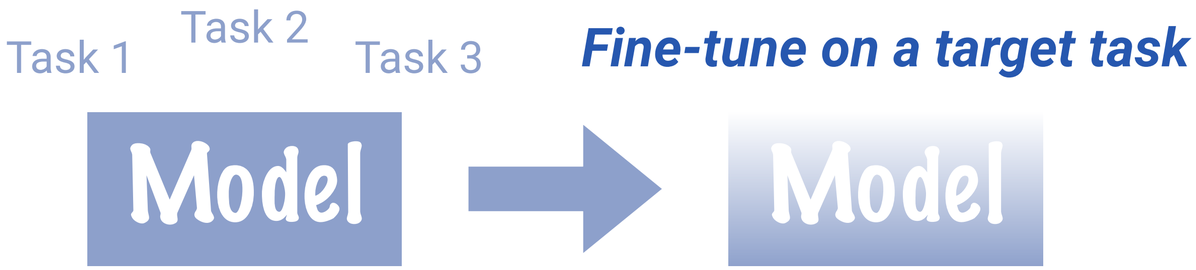


Multi-task learning/Meta-learning

(Villa and Drissi 2002, Evgeniou and Pontil 2004, Ruder 2017, Wang et al. 2020, Aghajanyan et al. 2021)

Related Work



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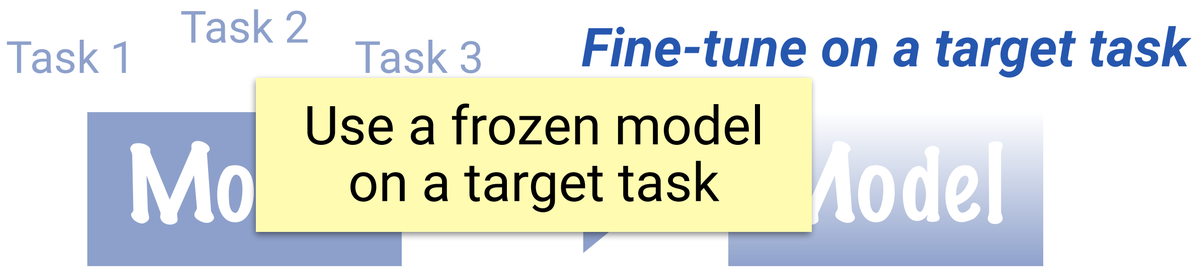

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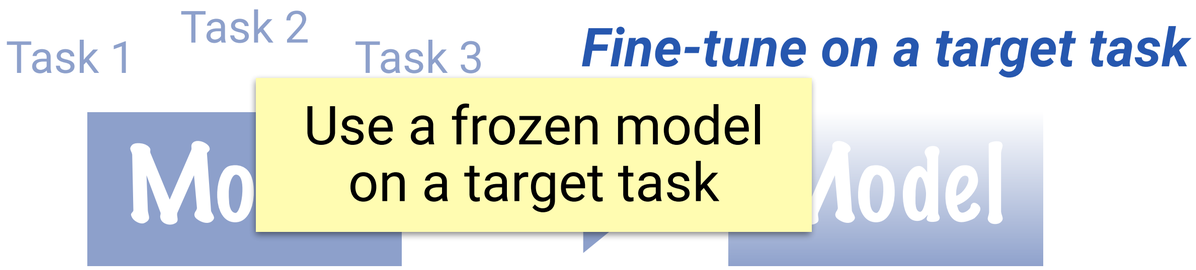

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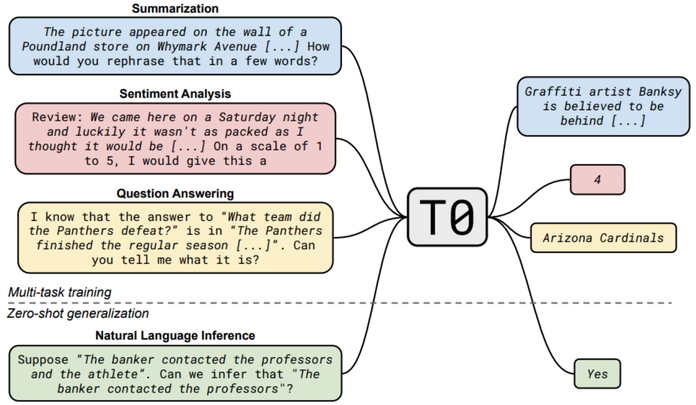

Instruction-reading models

(Mishra et al. 2021, Wei et al. 2021, Sanh et al. 2021, Zhong et al. 2021)
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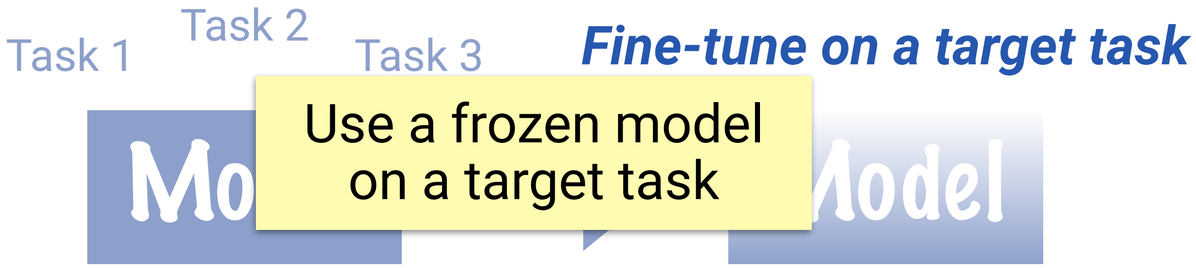
Related Work



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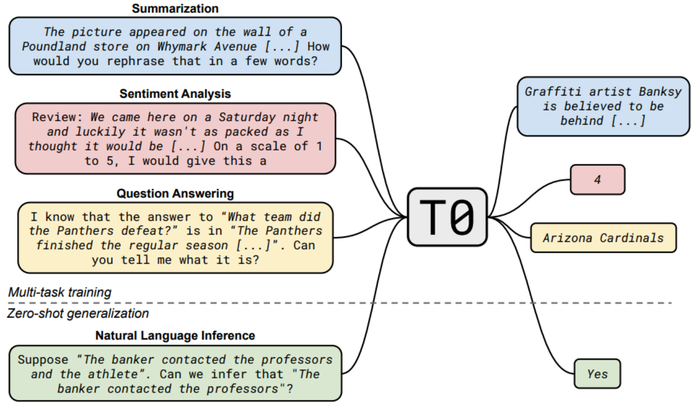

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Define the task as the input

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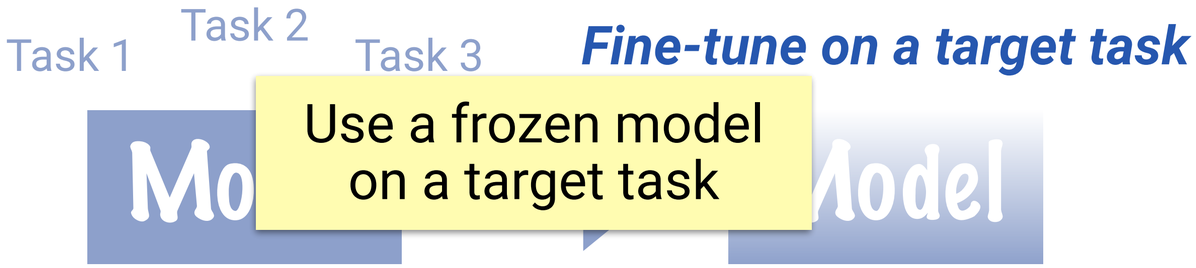

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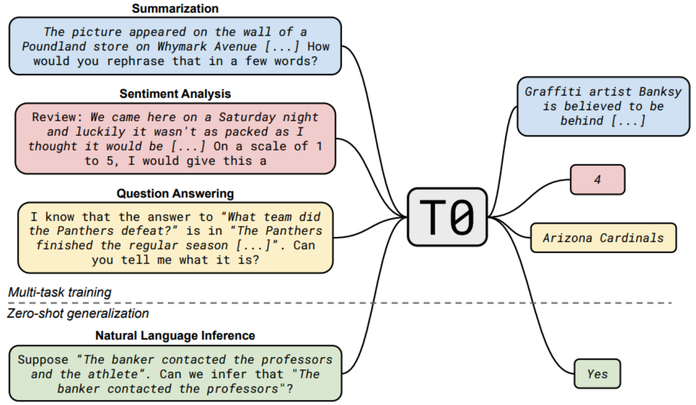

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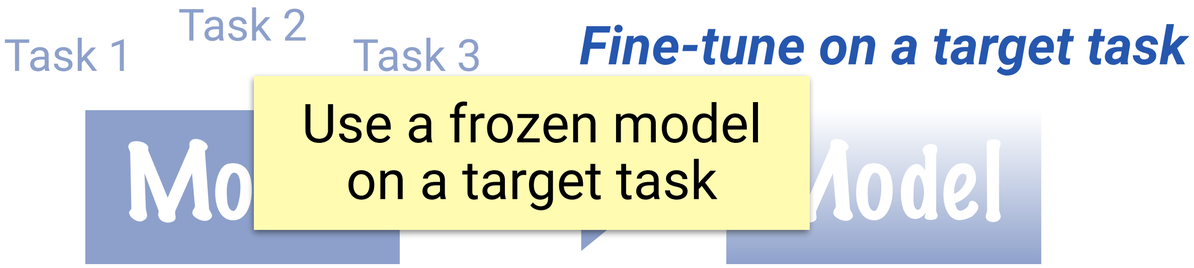
Define the task as the input

Natural language description vs. *k*-shot data

Related Work



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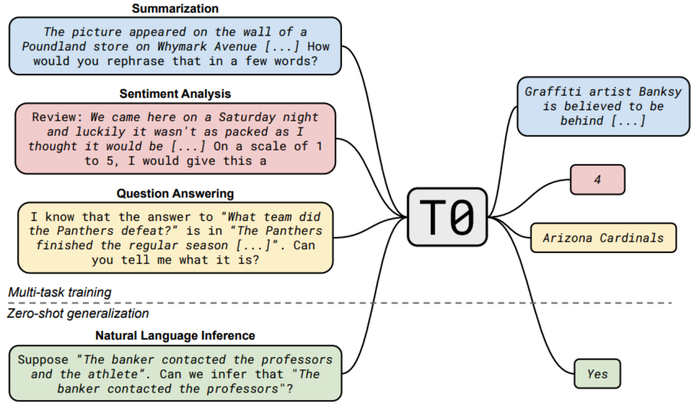

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Empirically, MetaICL can be better/complementary

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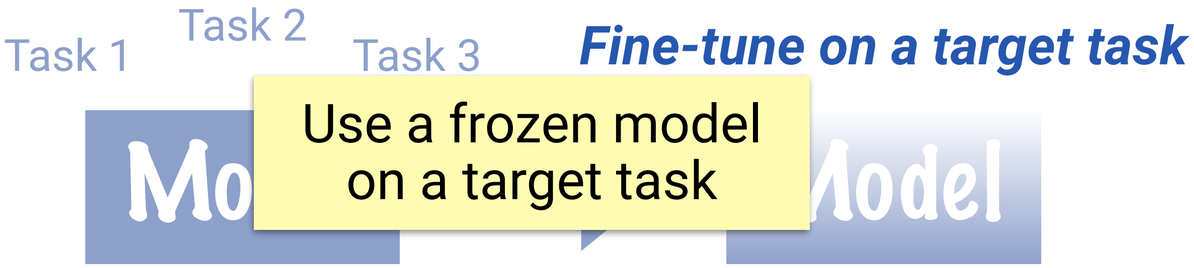

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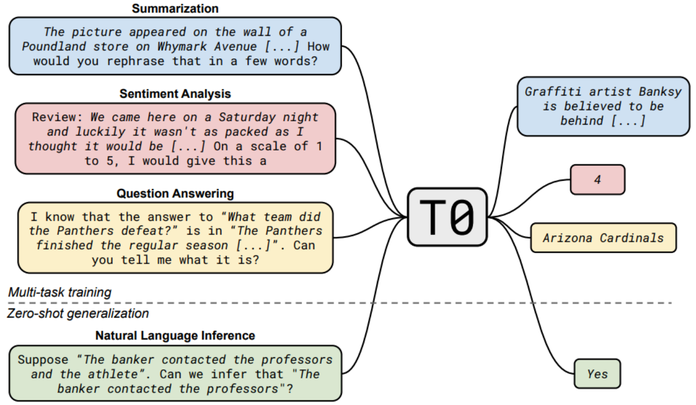

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Instruction: "*Is the comment positive?*"
x1: "*Good movie!*" y1: "*yes*"
x2: "*Bad movie!*" y2: "*no*"

$\theta := \theta - \Delta$

Concurrent work

Chen et al. 2021
"Meta-learning via Language Model In-context Tuning"

Define the task as the input

Natural language description vs. *k*-shot data

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Experimental Setup

In total, experiment with **142** NLP datasets and **7** different metatrain-target splits

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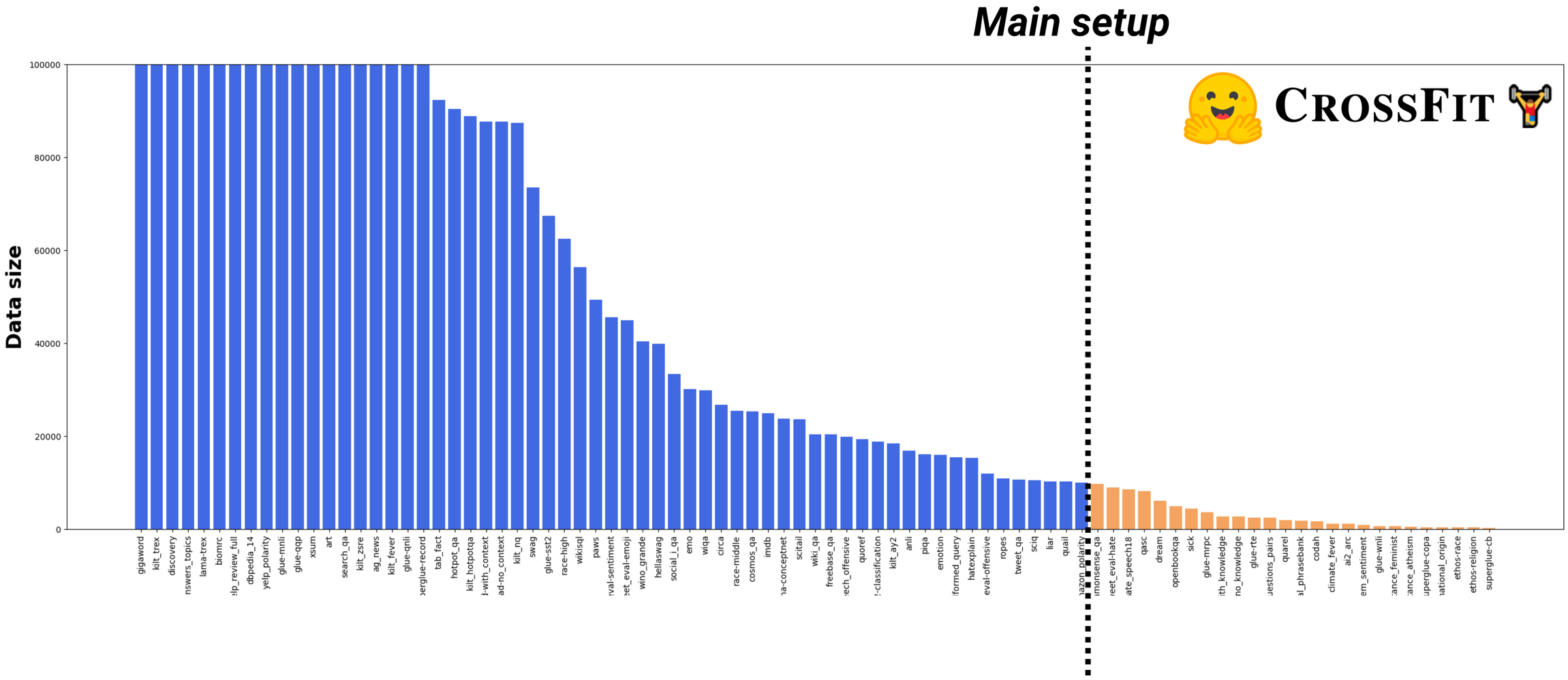

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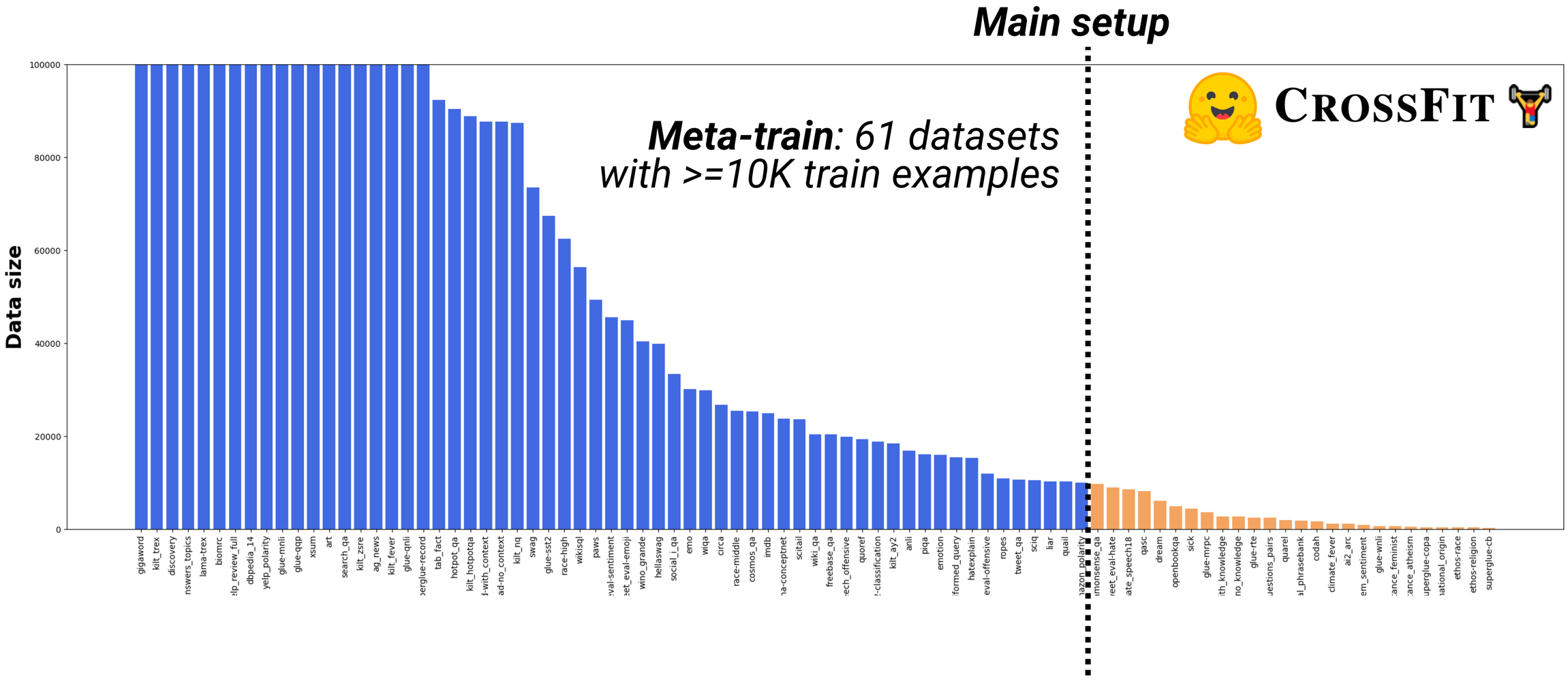

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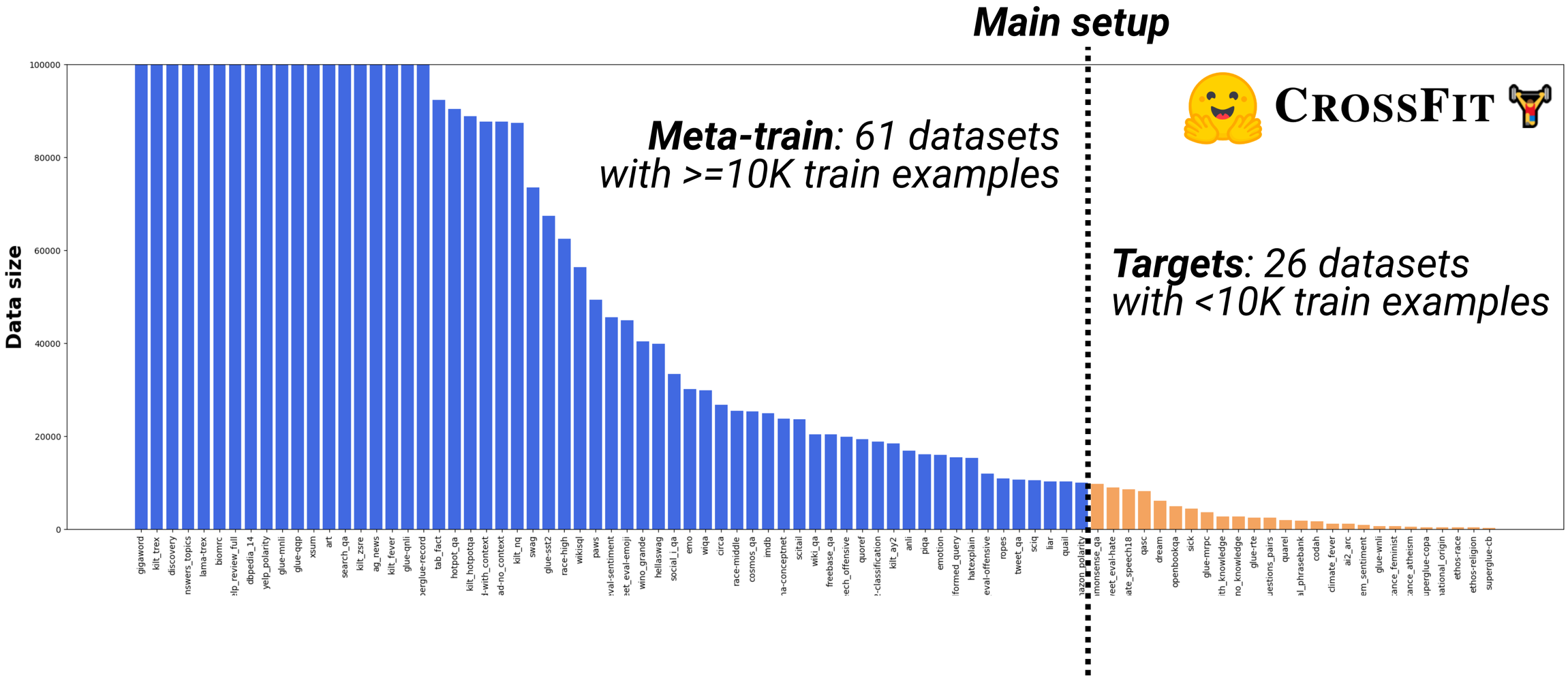

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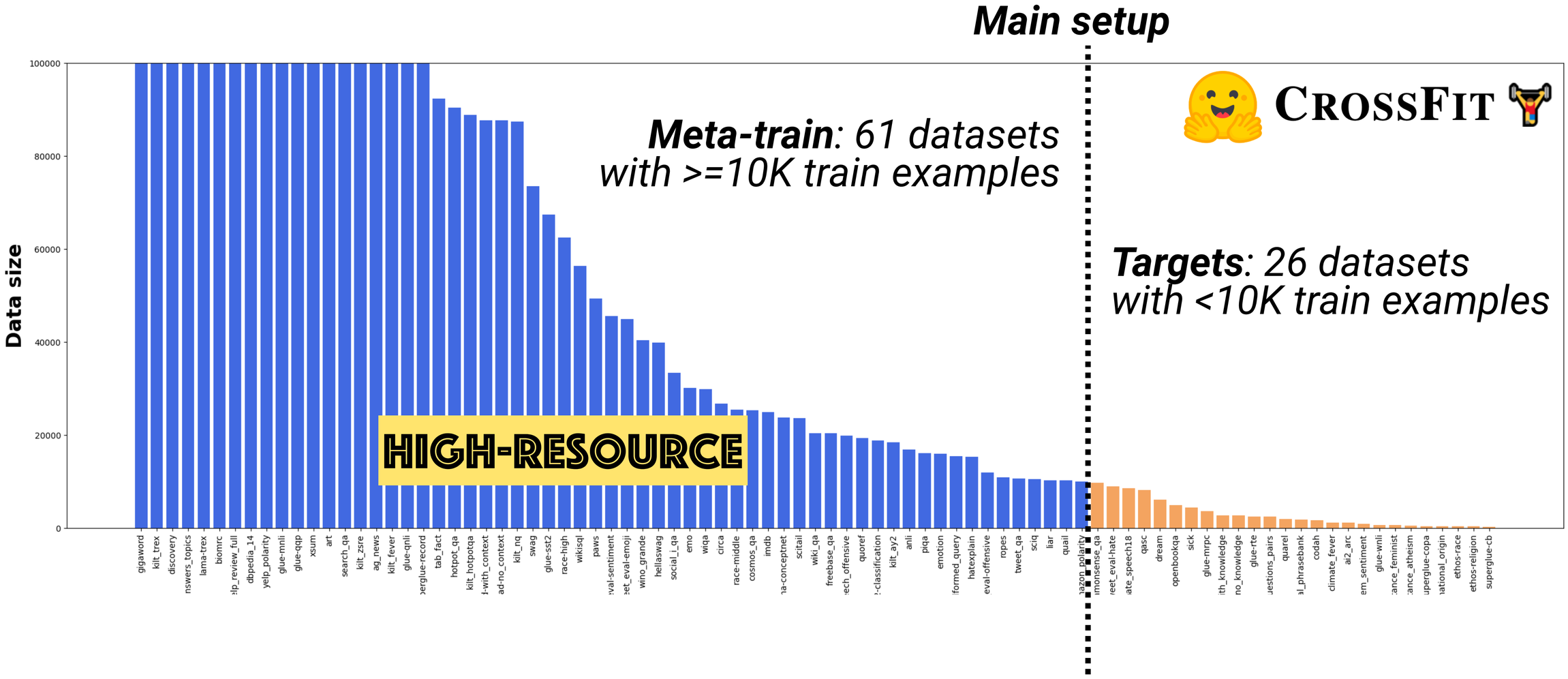

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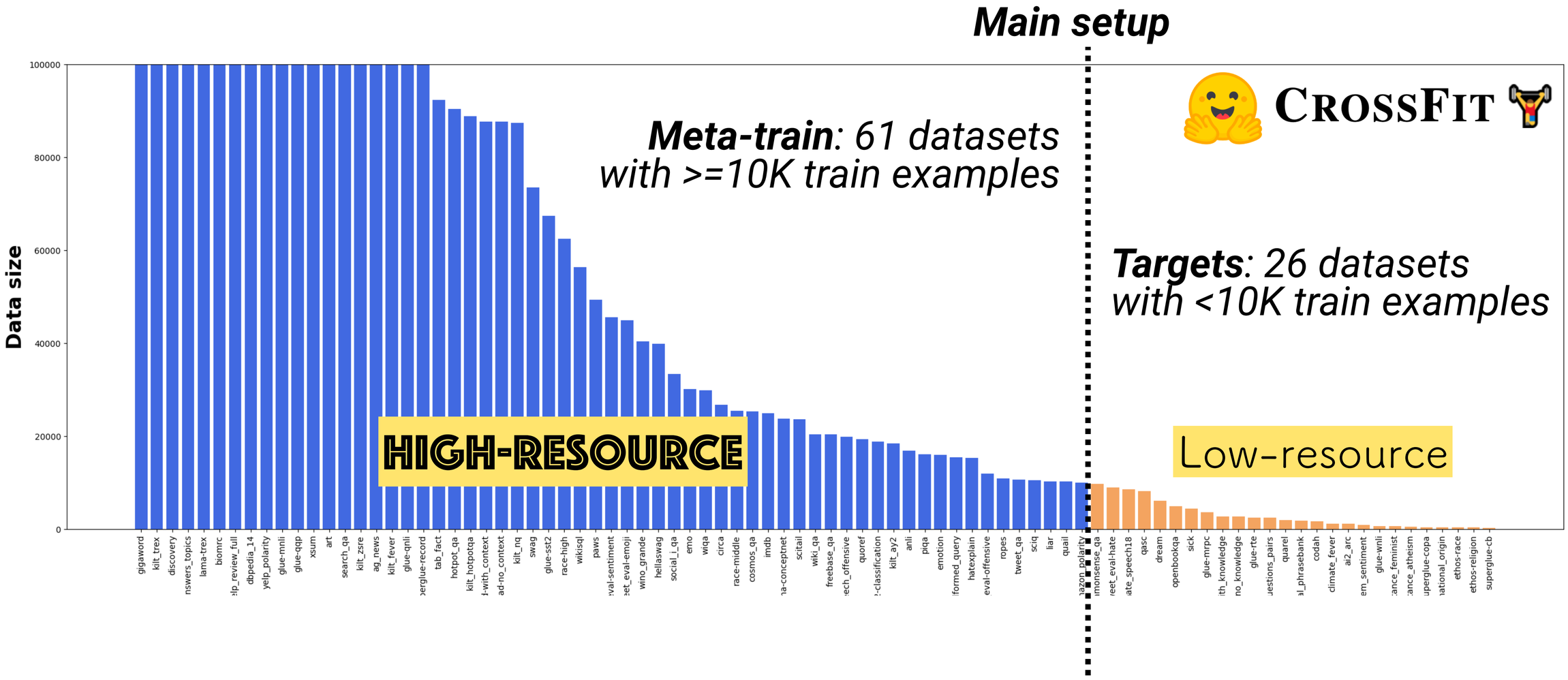

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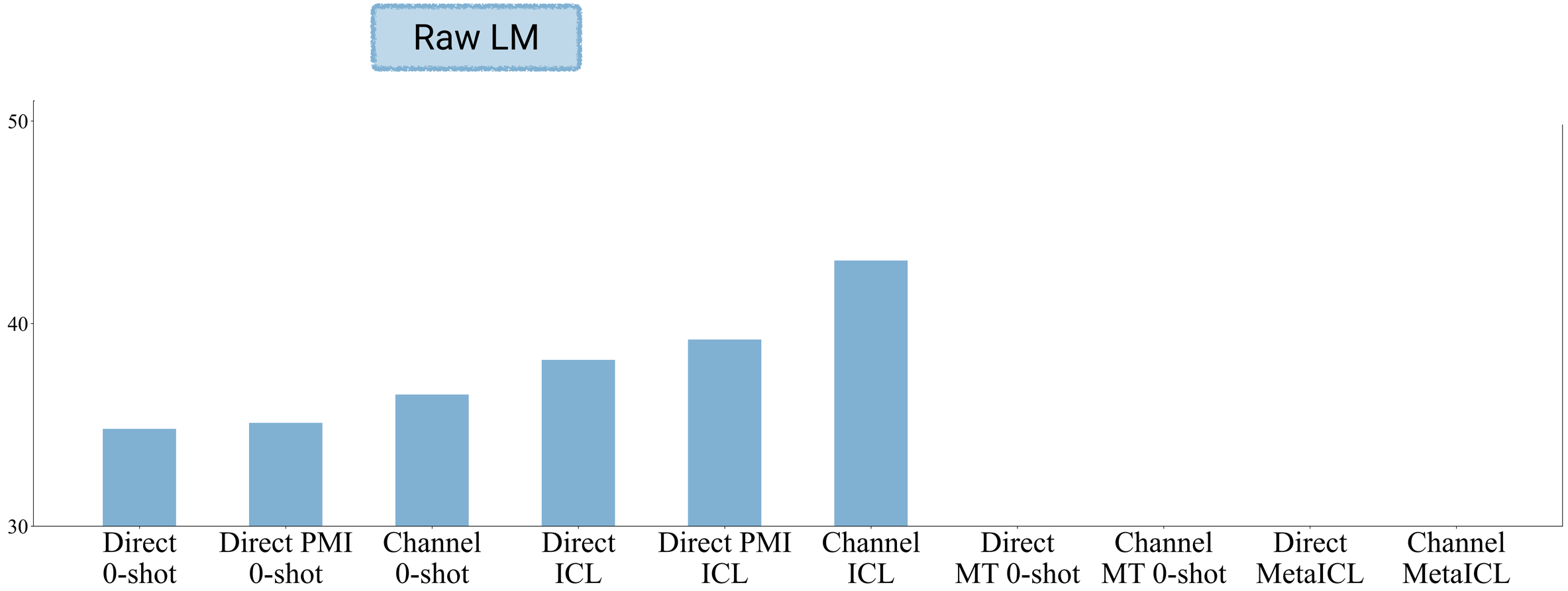
Base LM: GPT-2 Large

Results



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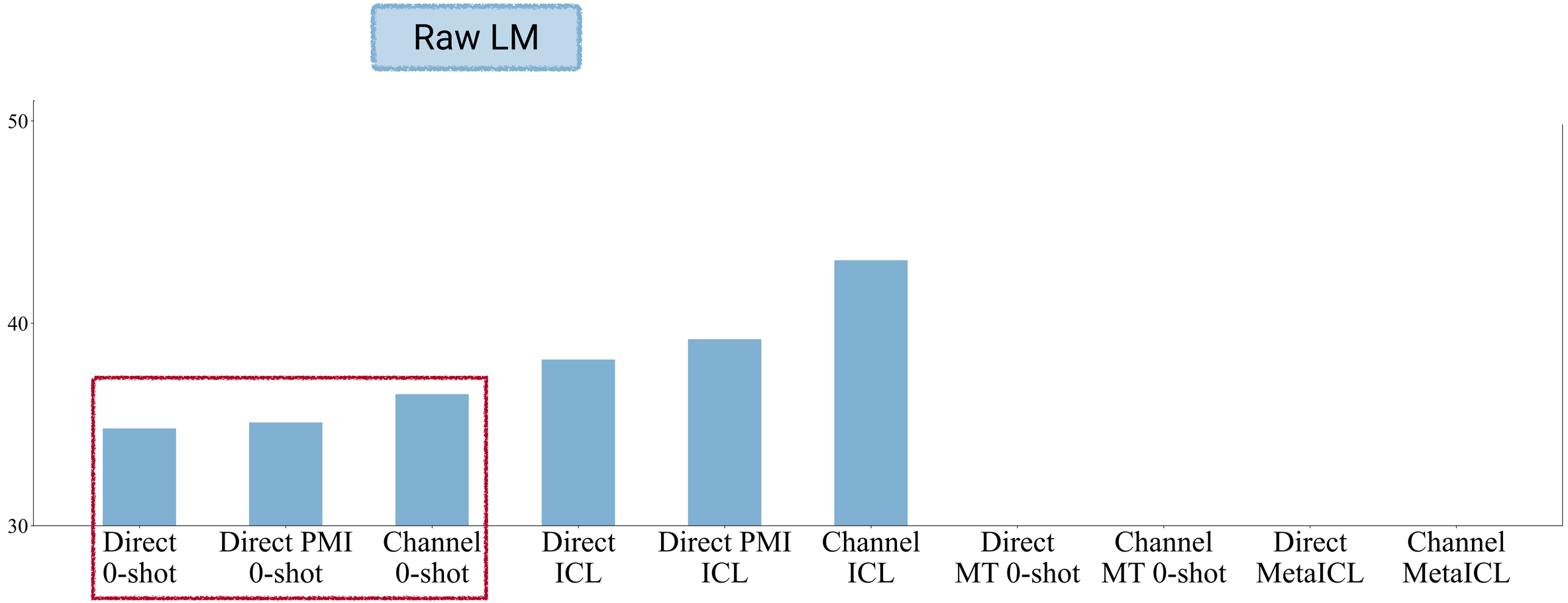

** Direct: from Brown et al. 2020*
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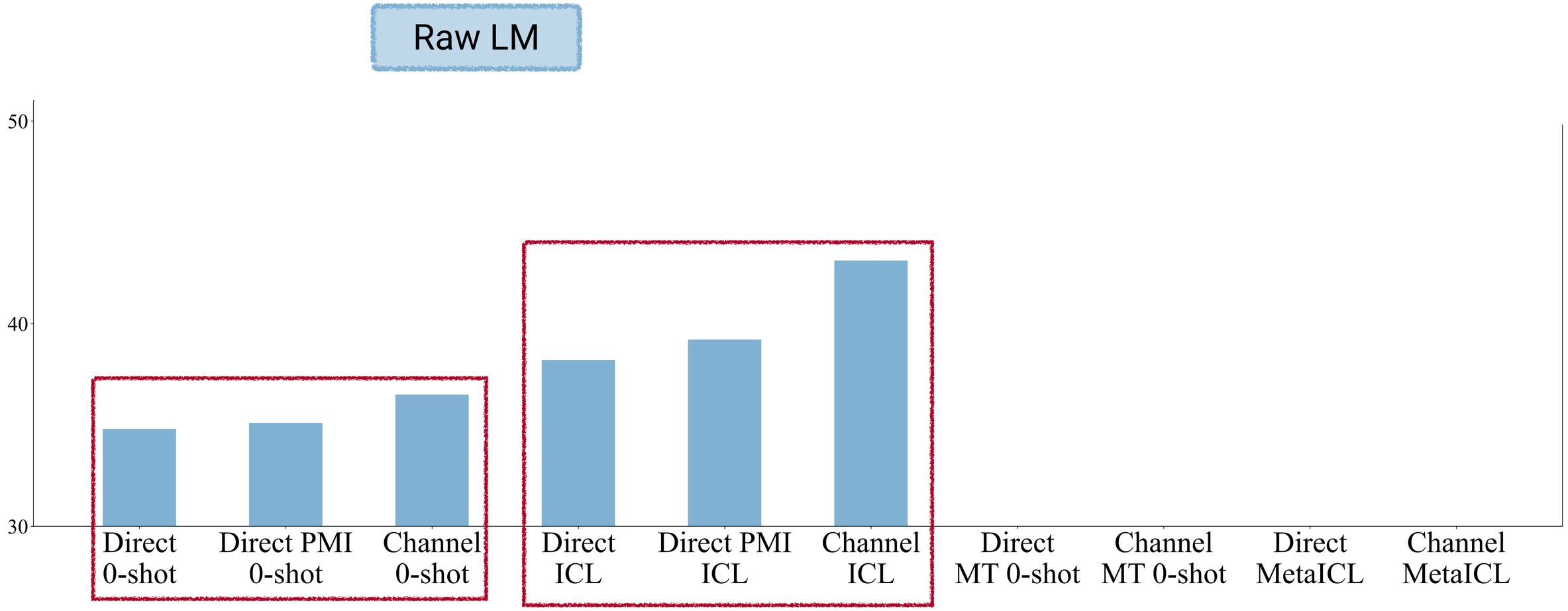

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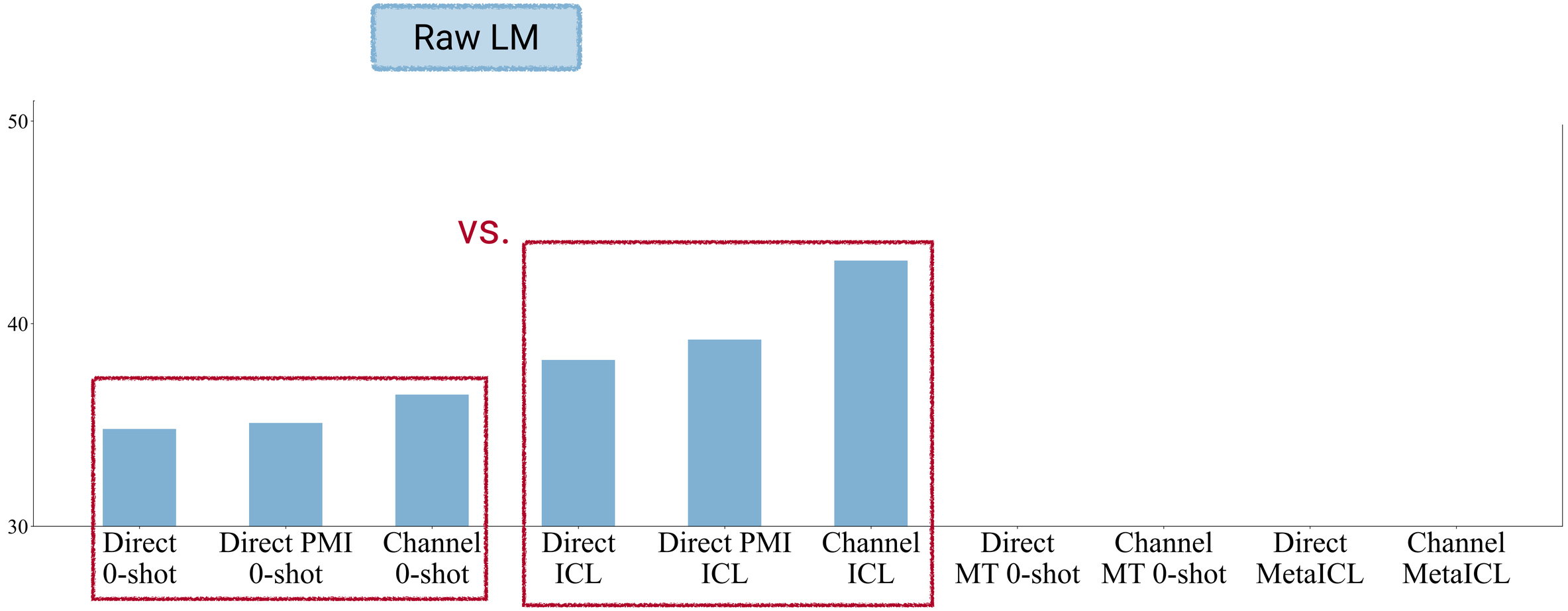

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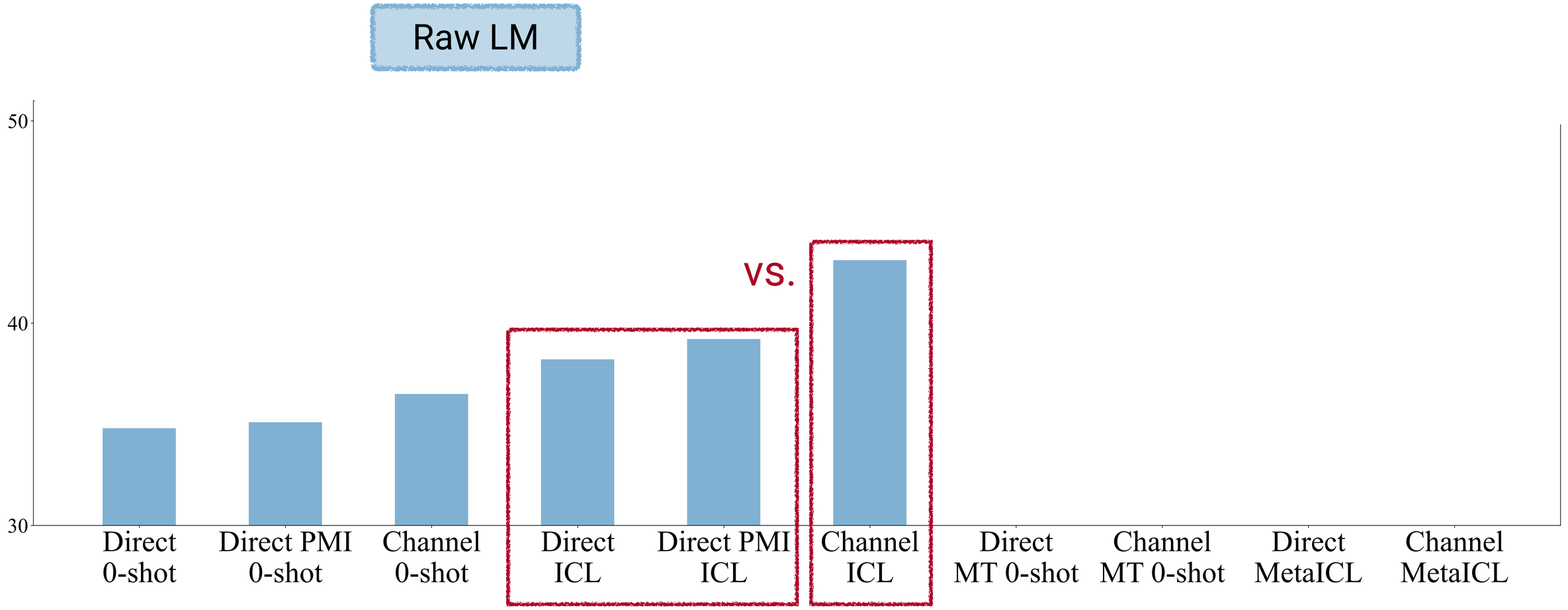
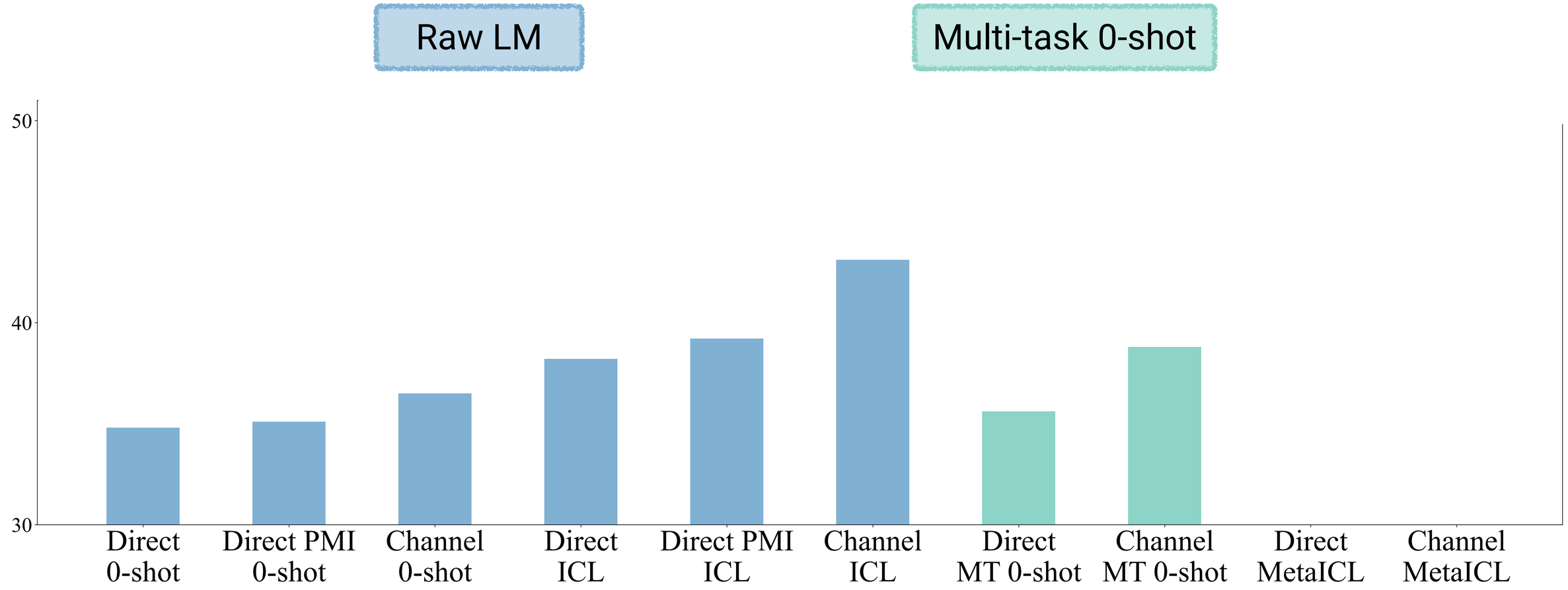


Channel ICL achieves the best result when no meta-training

Base LM: GPT-2 Large

Results

Multi-task training
but ***w/o*** in-context learning



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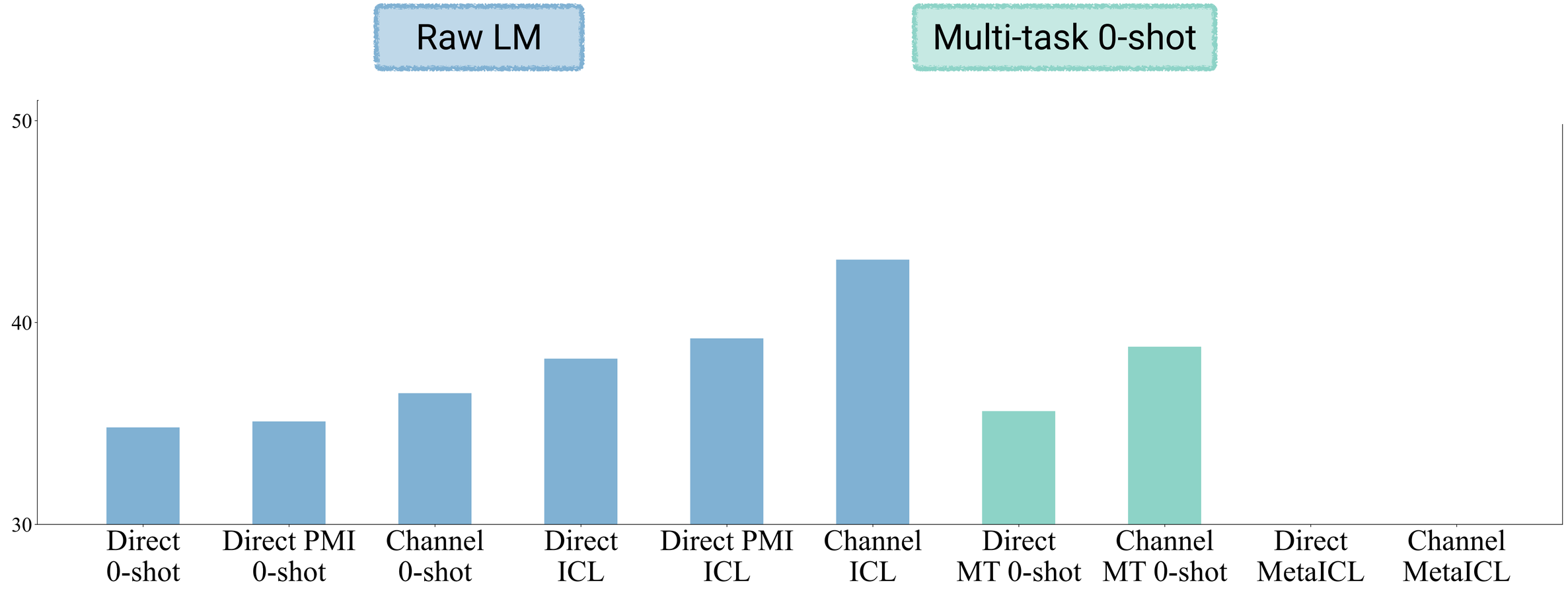
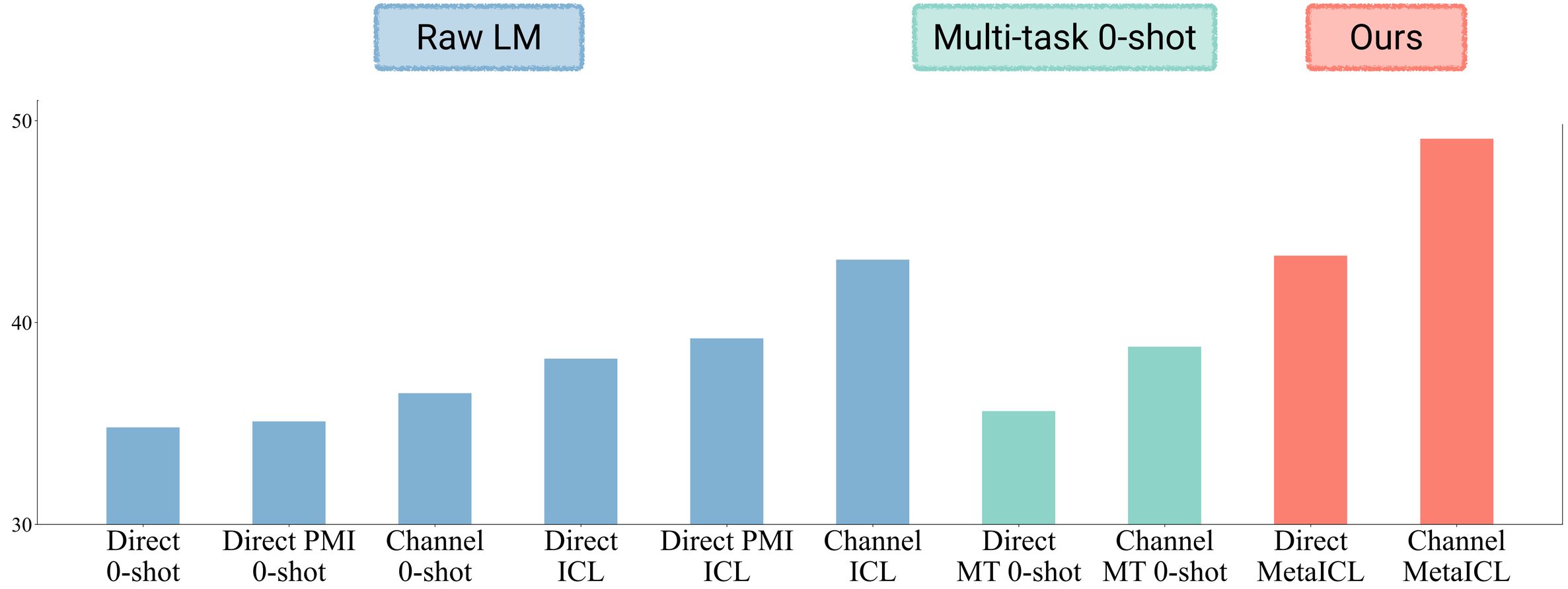


Multi-task 0-shot is not as competitive

Base LM: GPT-2 Large

Results



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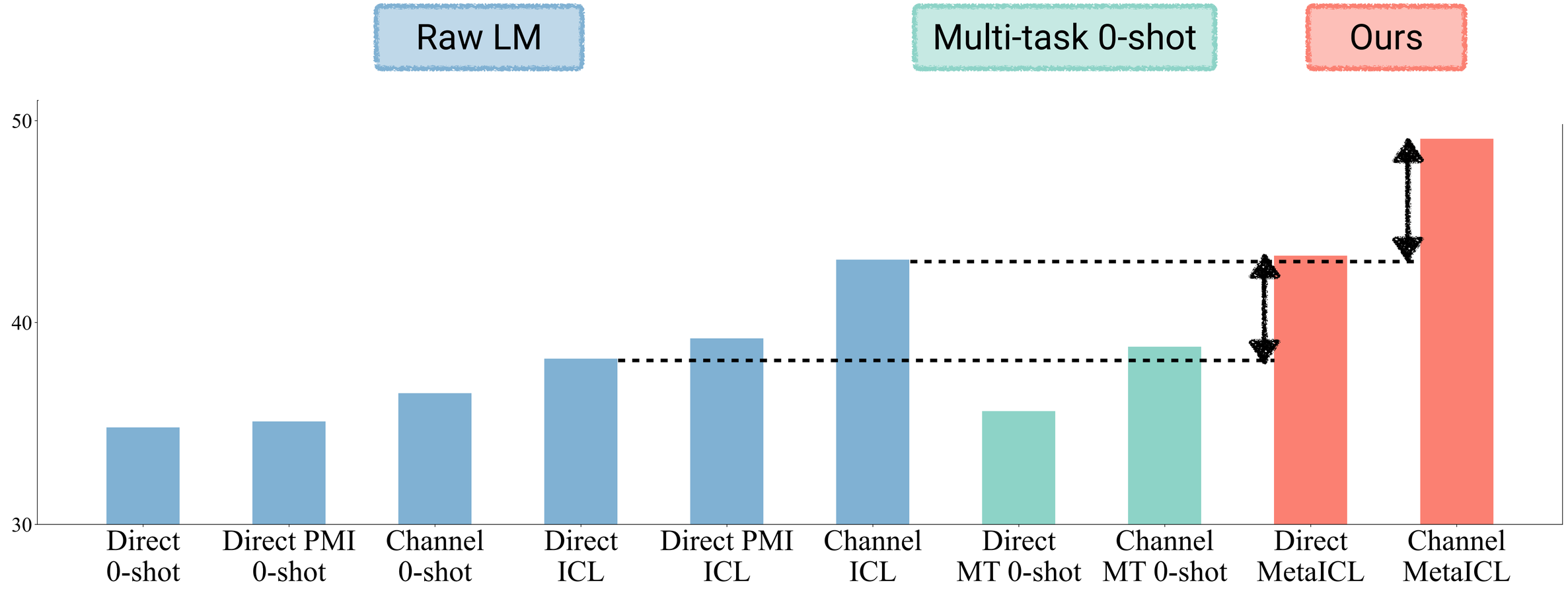

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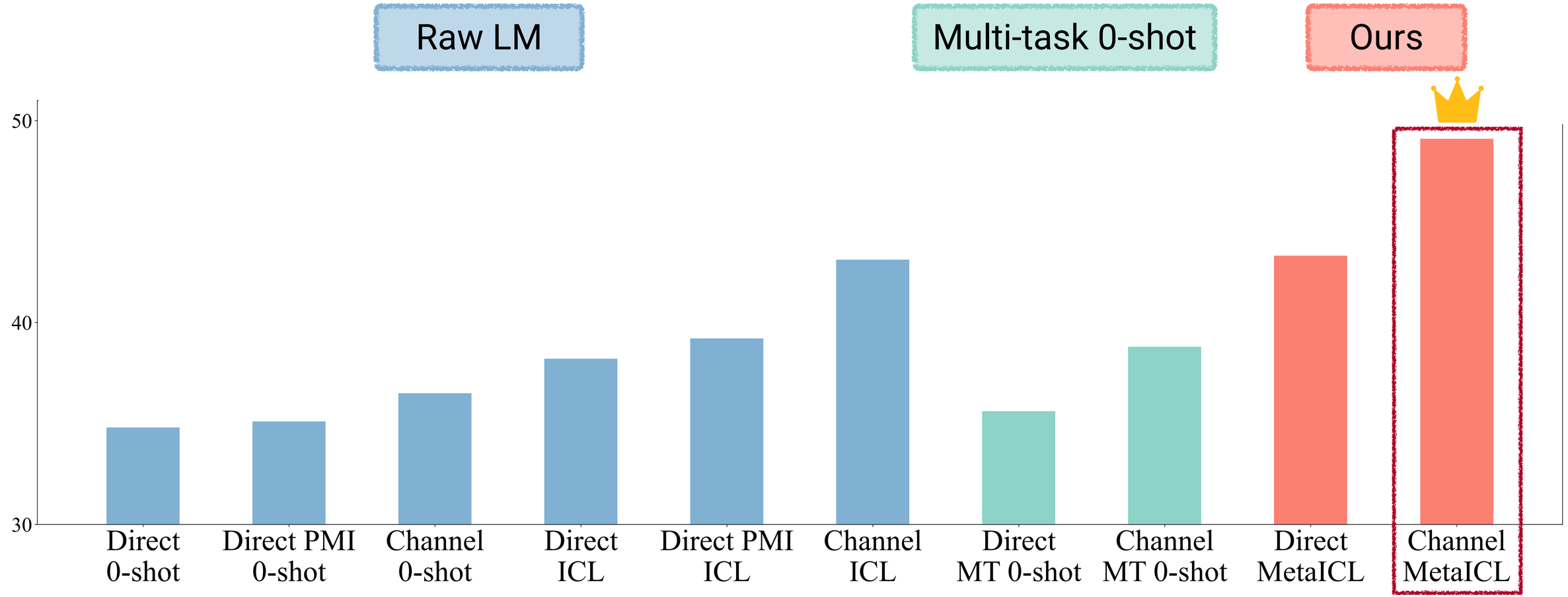
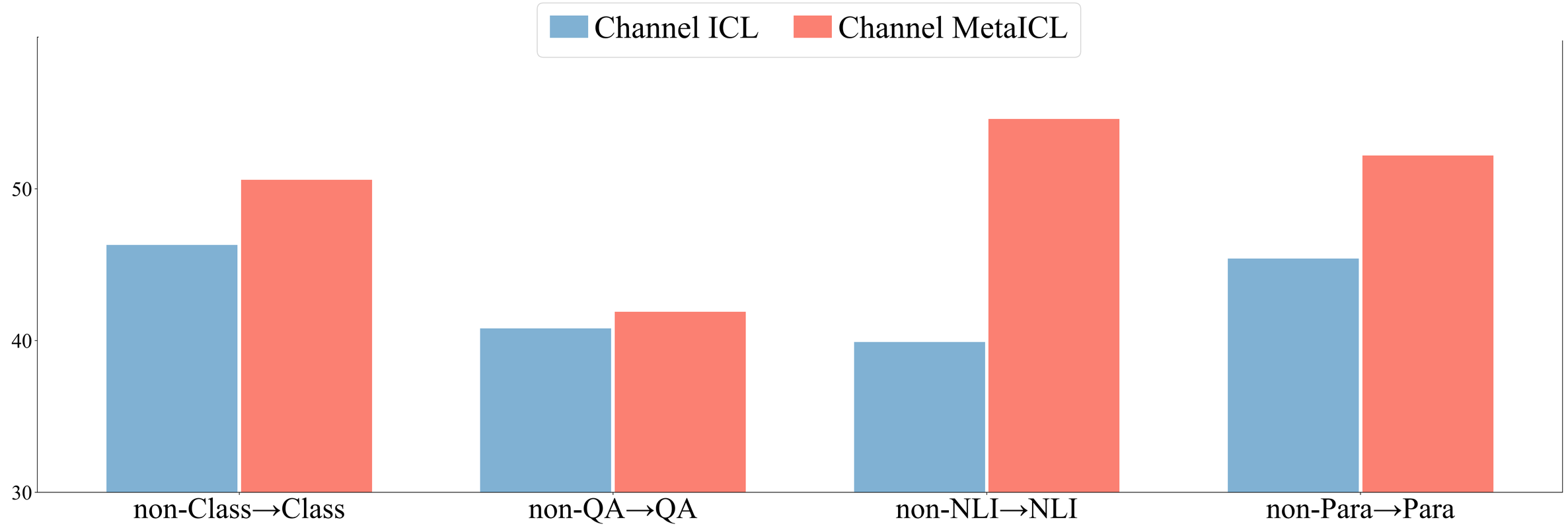


Channel MetaICL achieves the best result

Base LM: GPT-2 Large

Results

Other meta-training/targets splits



See the paper for more details!

Base LM: GPT-2 Large

Results

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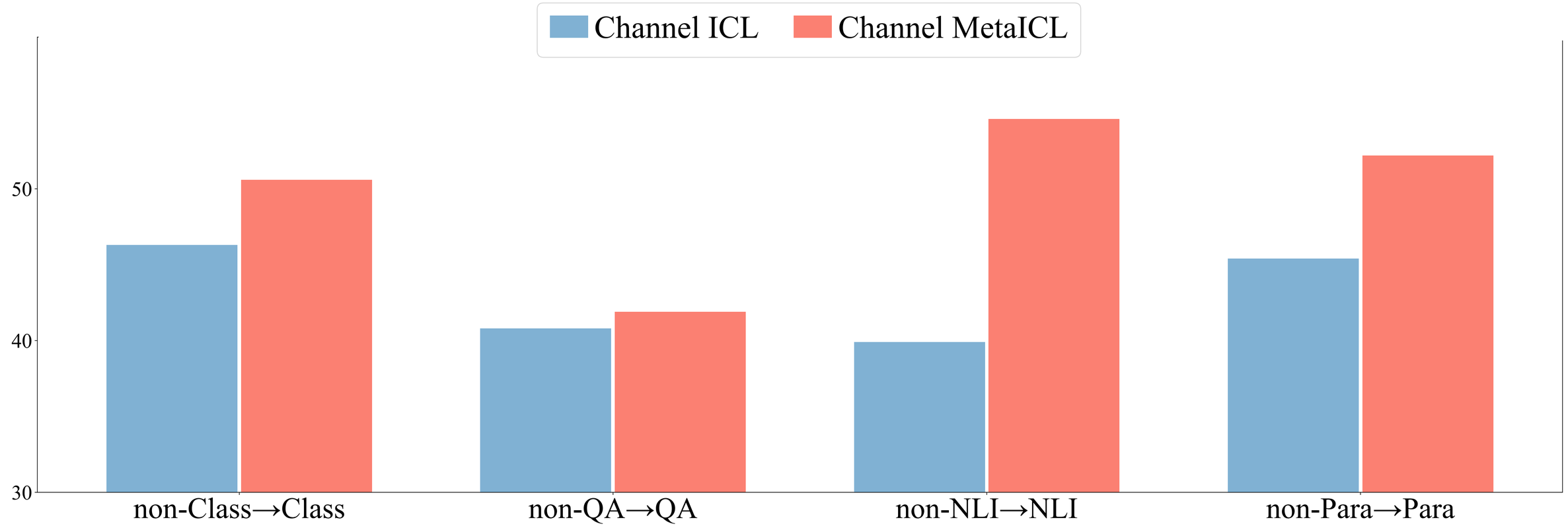

Large gains — even with no similar tasks at meta-training

See the paper for more details!

Base LM: GPT-2 Large

Results

vs. Instruction reading models

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Results

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Used the data from T0 (San et al 2021) — 8.3 instructions per task

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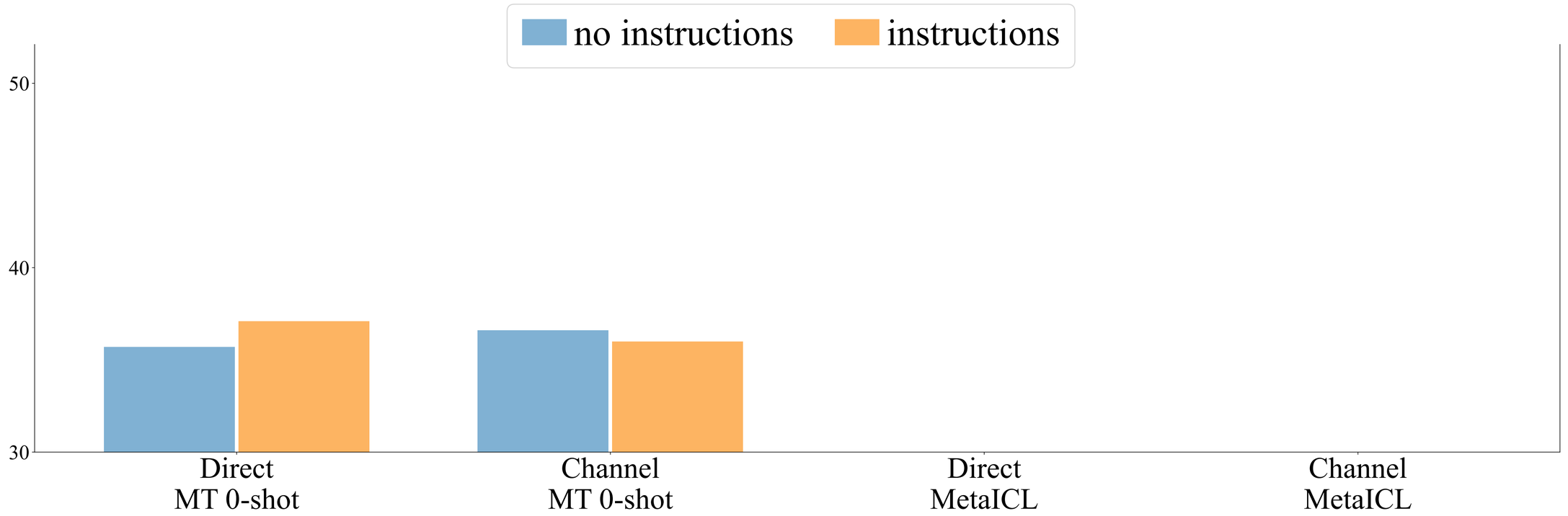

Multi-task model w/o in-context learning benefits from instructions

Base LM: GPT-2 Large

Results

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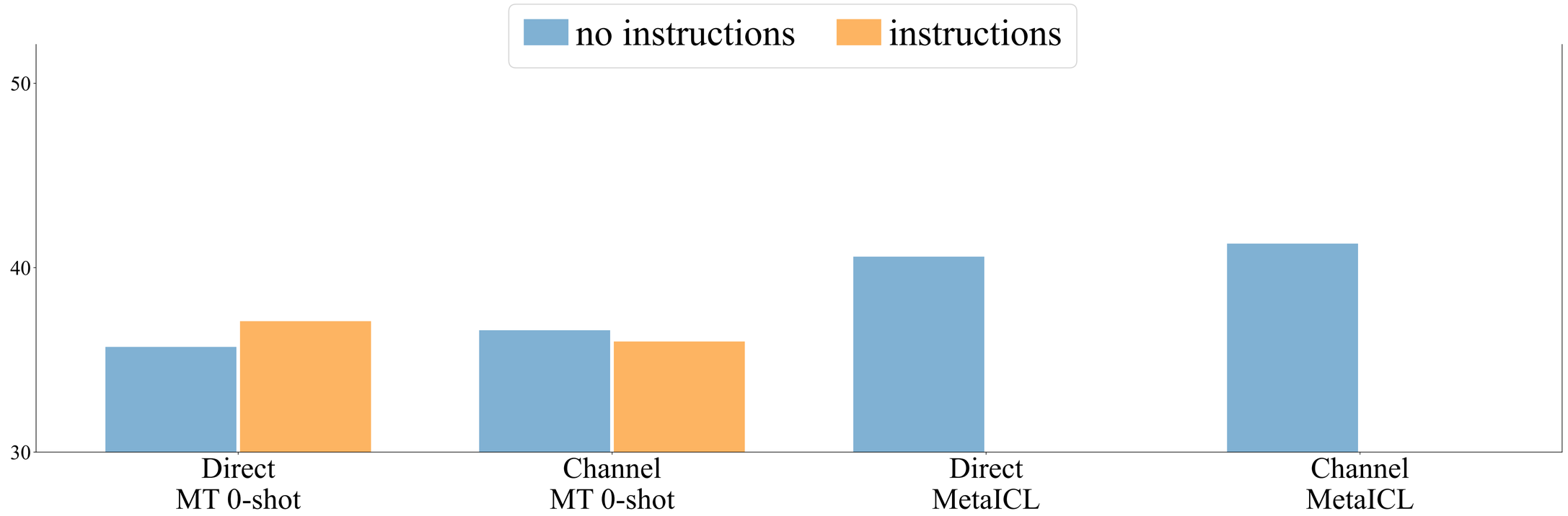

Training to in-context learn is better than training to read instructions

Base LM: GPT-2 Large

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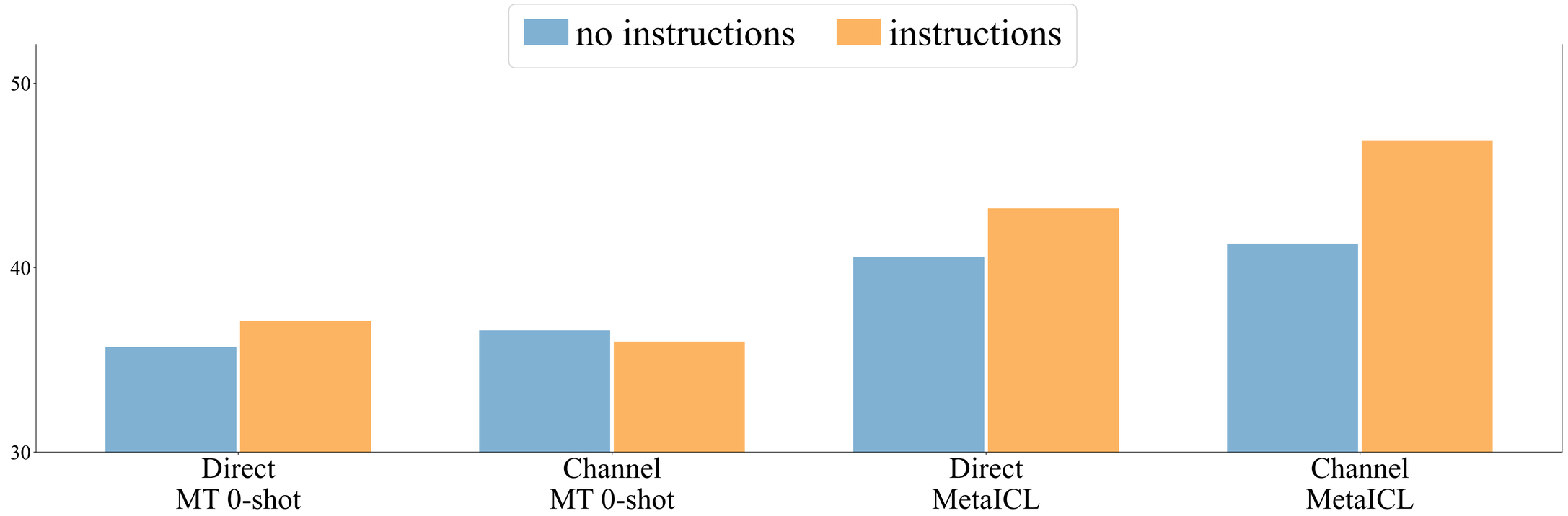

MetaICL + instructions reading achieves the best performance

Why does MetaICL work?

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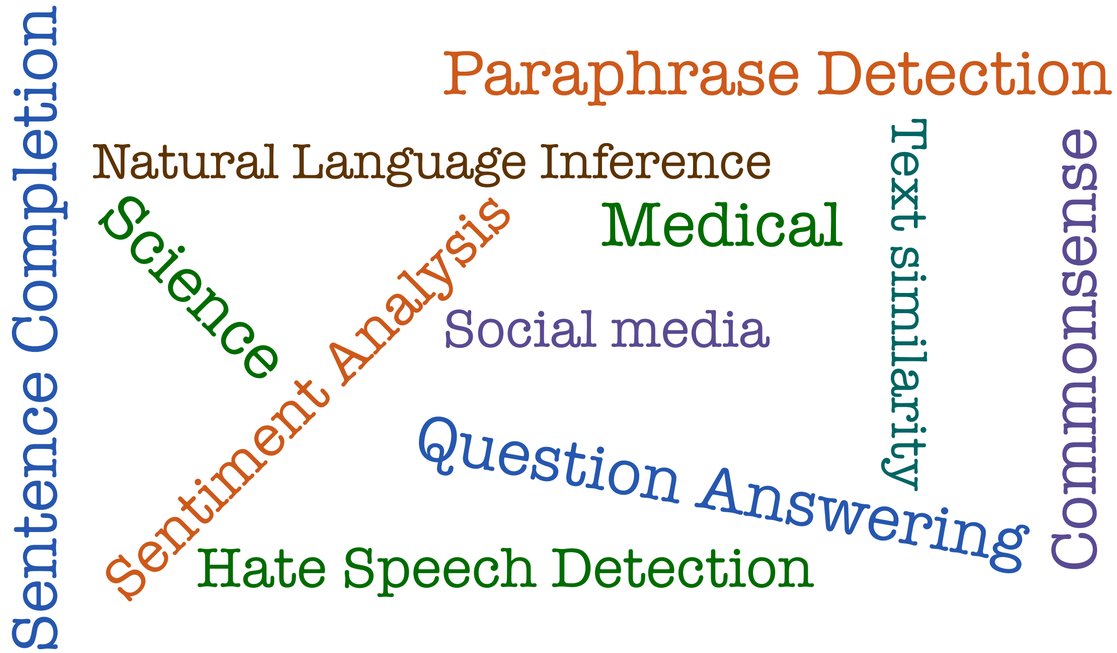
1) The model benefits from *related* tasks during meta-training



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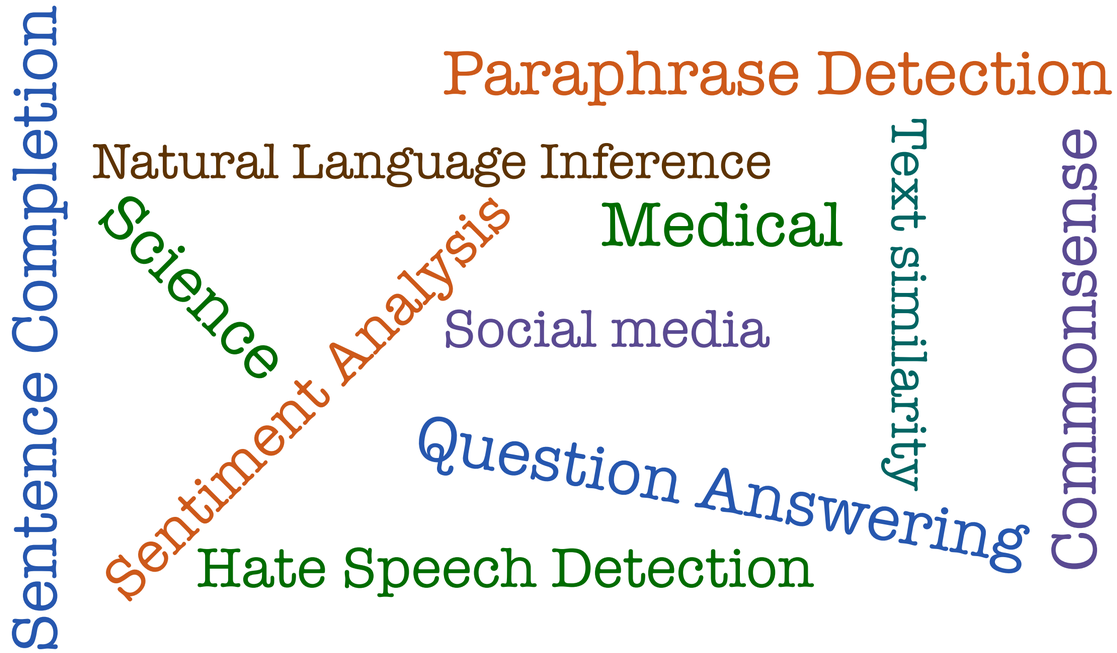

Already verified by a large body of work in multi-task learning

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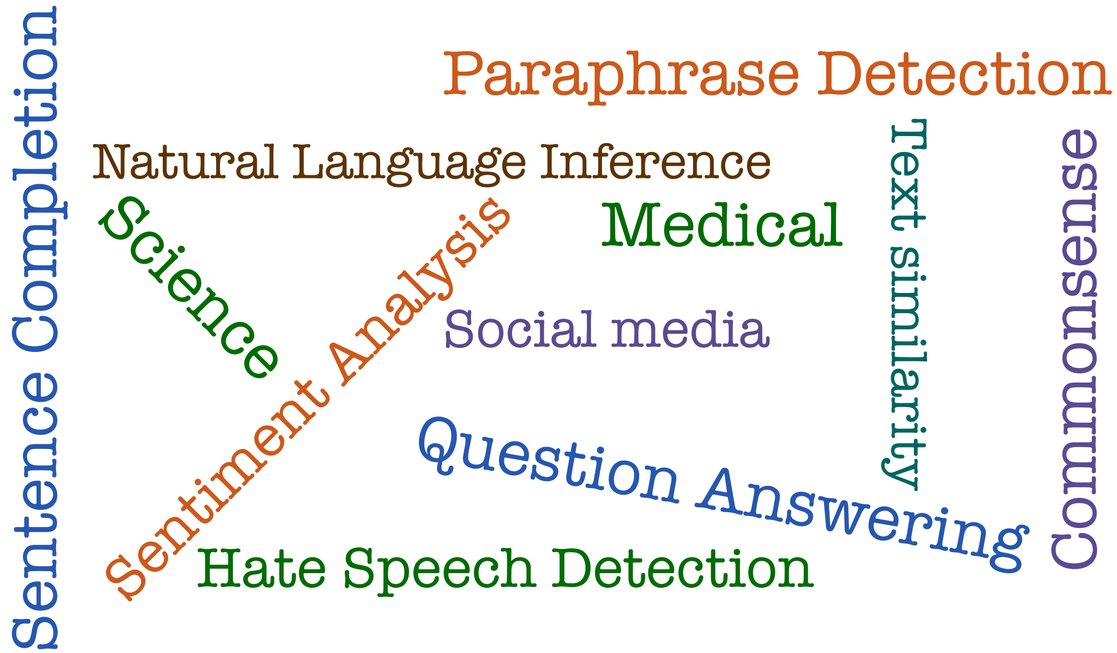

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However, Multi-task 0-shot is not enough

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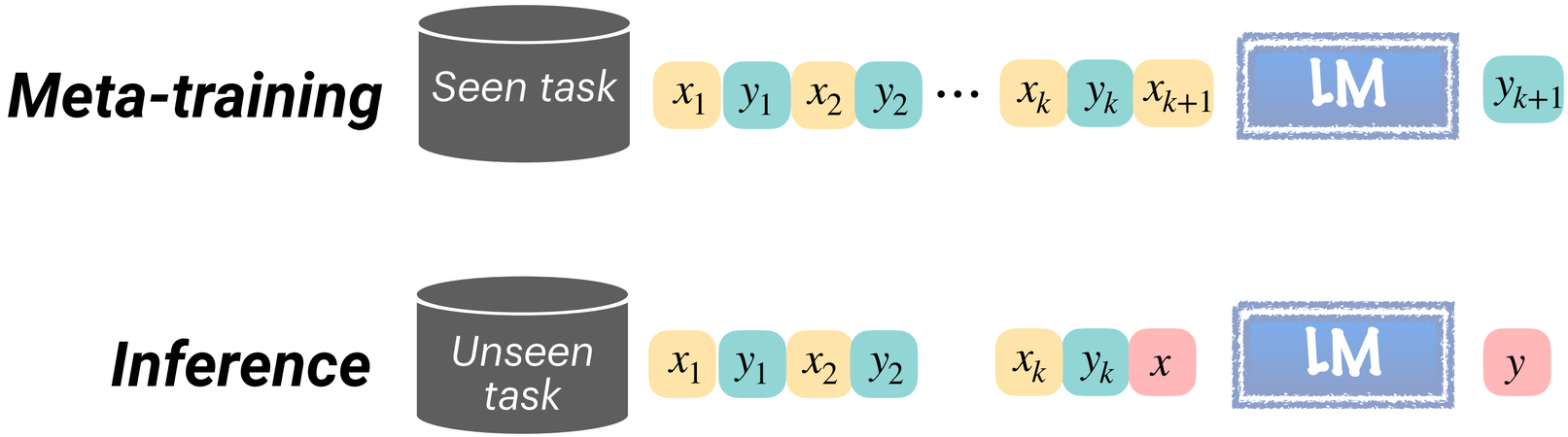
2) The model learns the ability to *in-context learn a given task*



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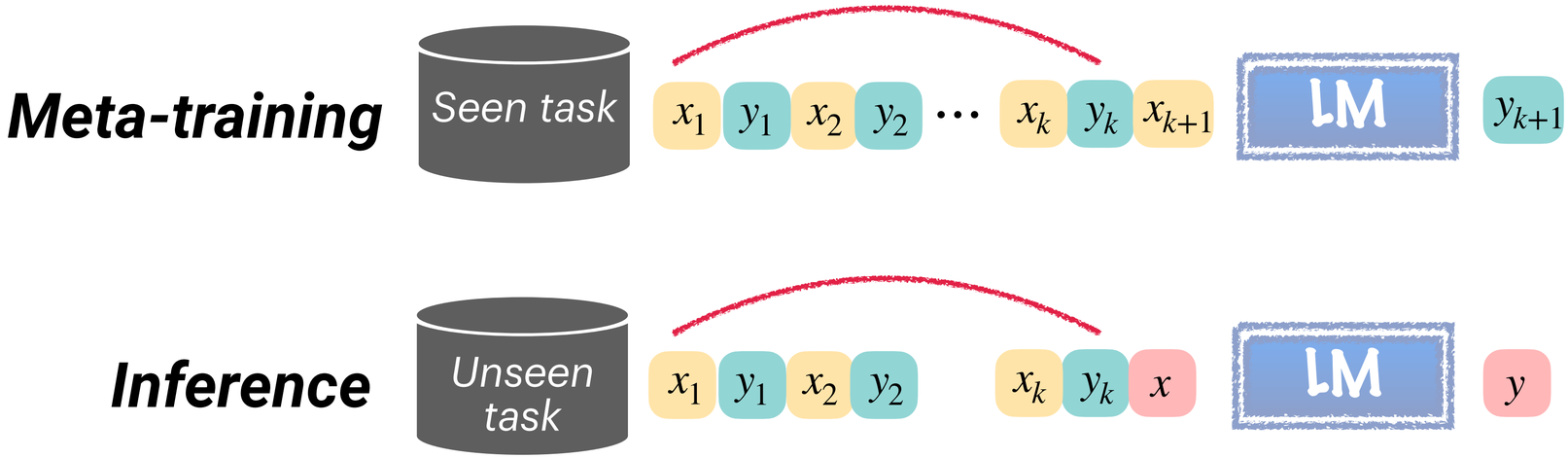

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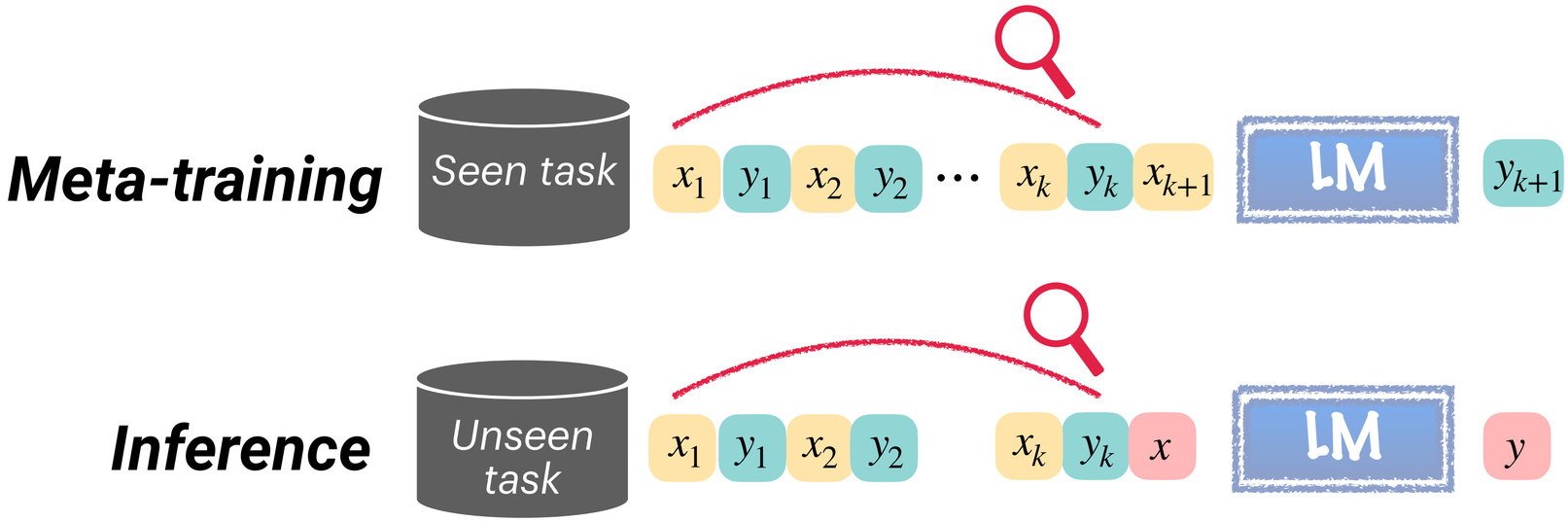

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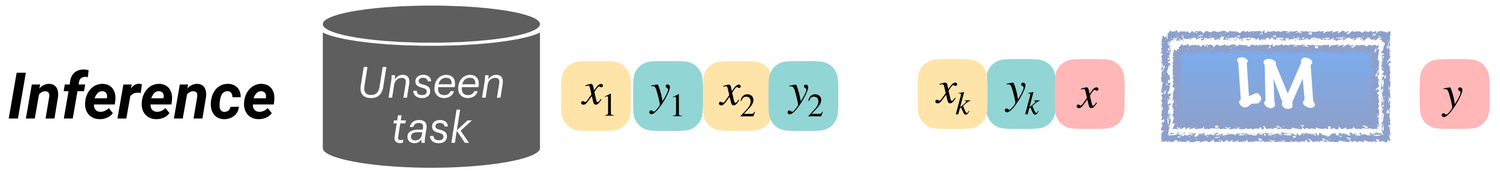

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— Min et al. 2022. "Rethinking the Role of Demonstrations: What Makes In-Context Learning Work?"

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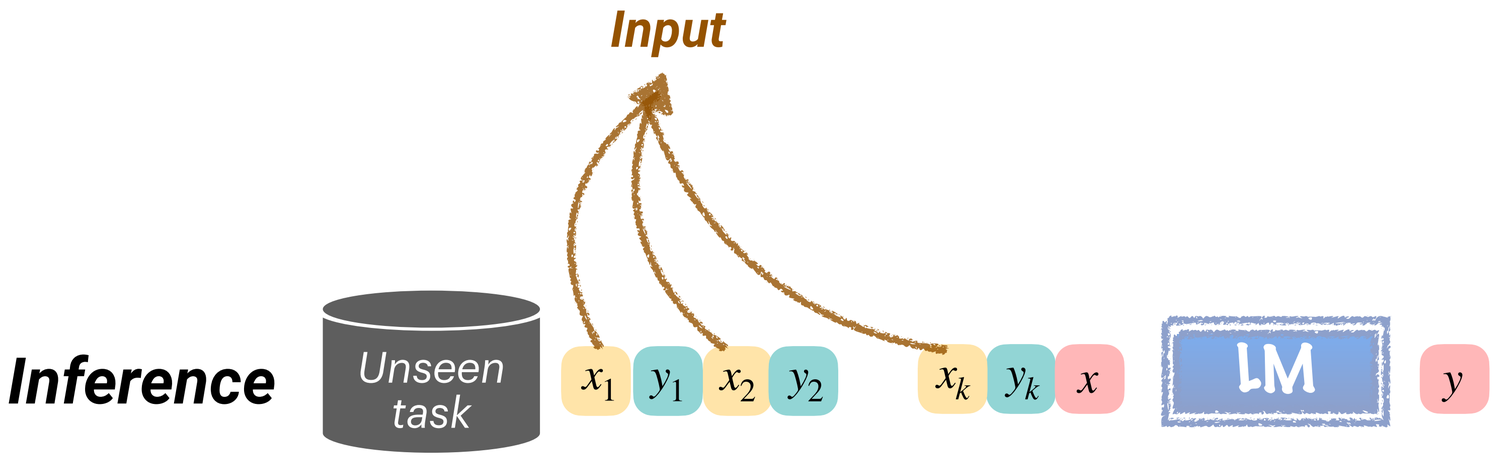

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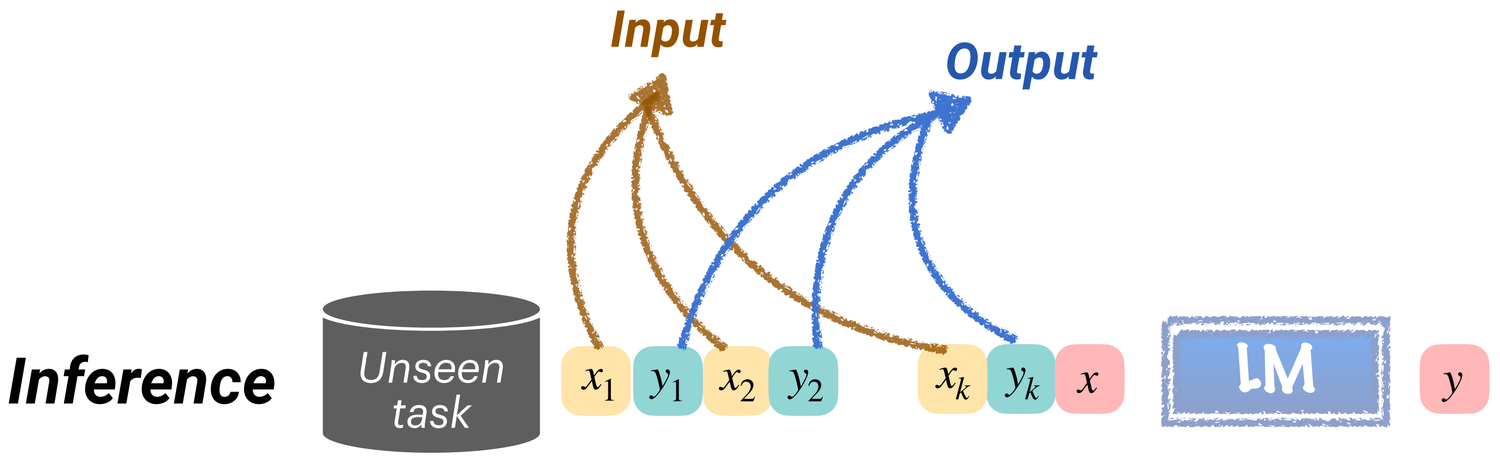
2) The model learns the ability to *in-context learn a given task*



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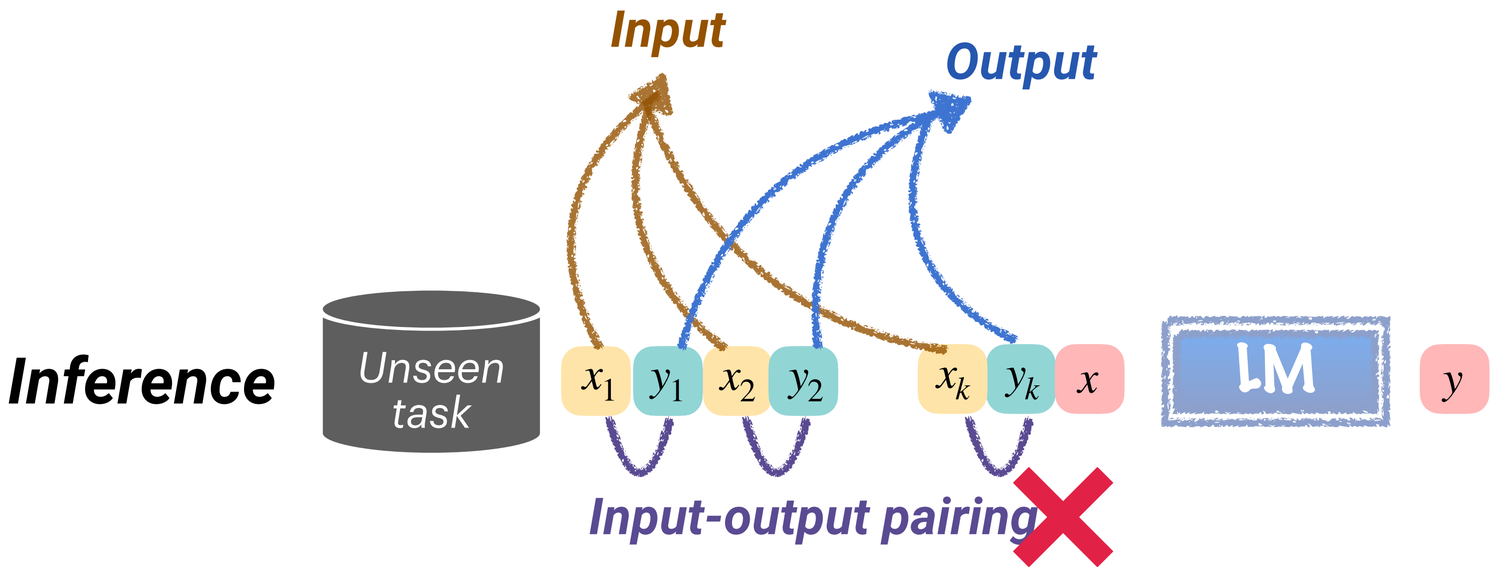

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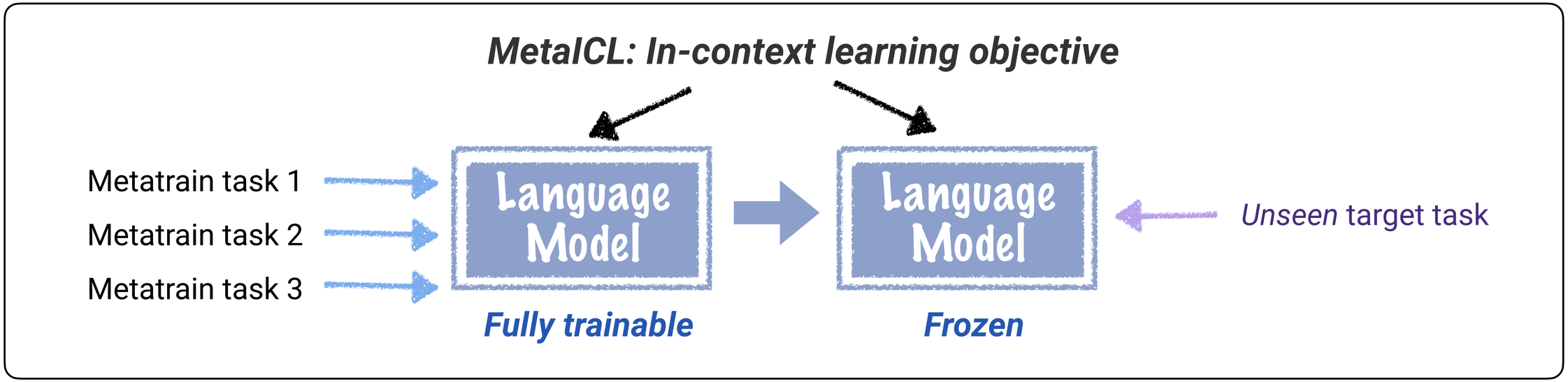
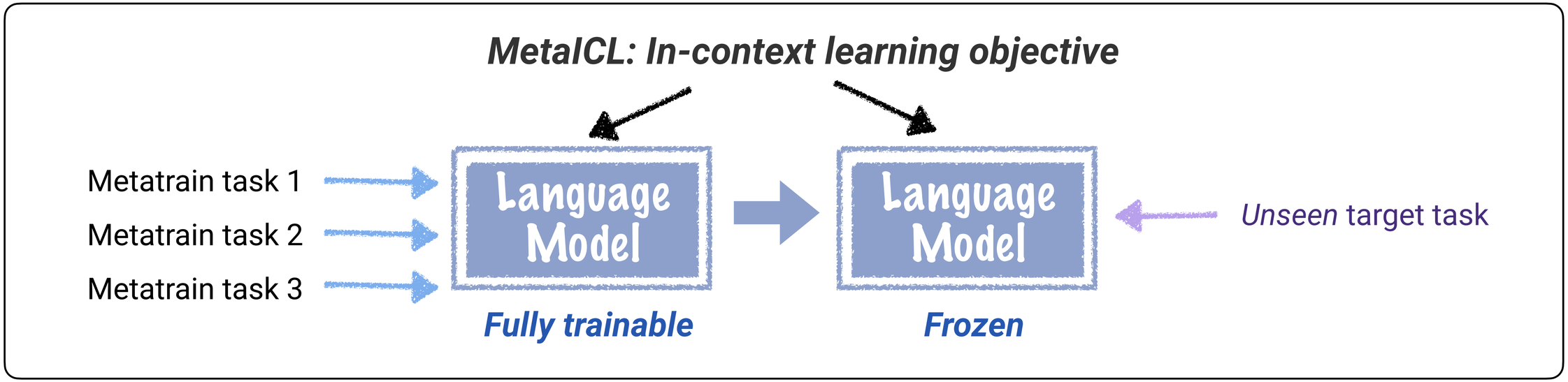
Takeaways


MetaICL: In-context learning objective
Metatrain task 1
Metatrain task 2
Metatrain task 3
Language Model
Language Model
Unseen target task
Fully trainable
Frozen

Takeaways



On seven different splits

★ Significantly outperform strong no-metatrained baseline

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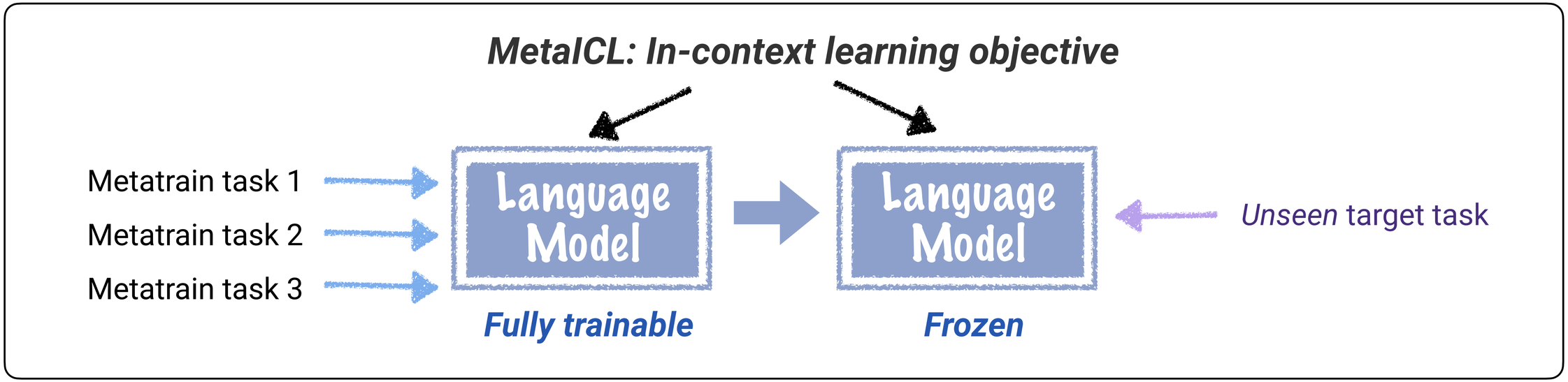

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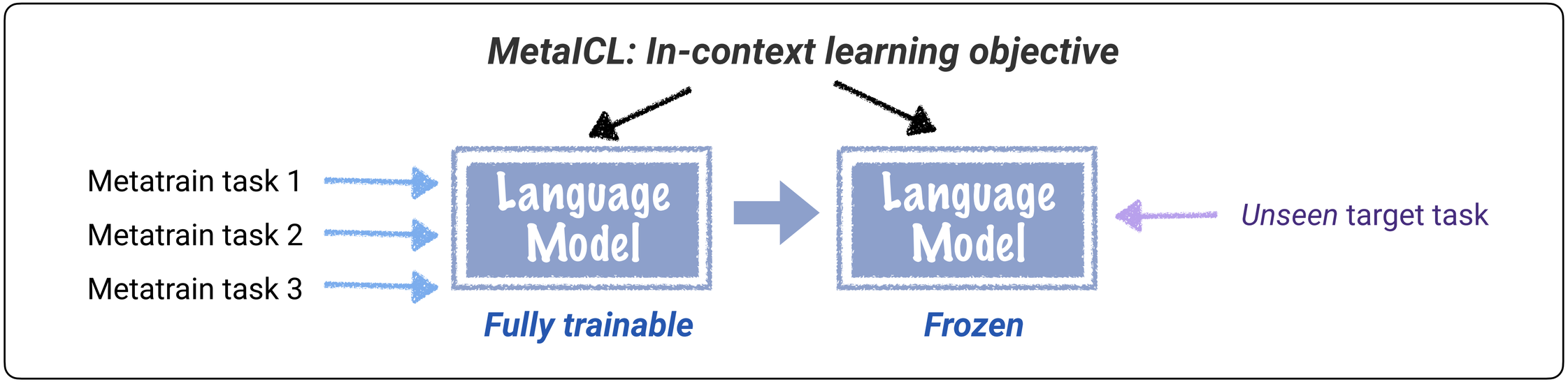

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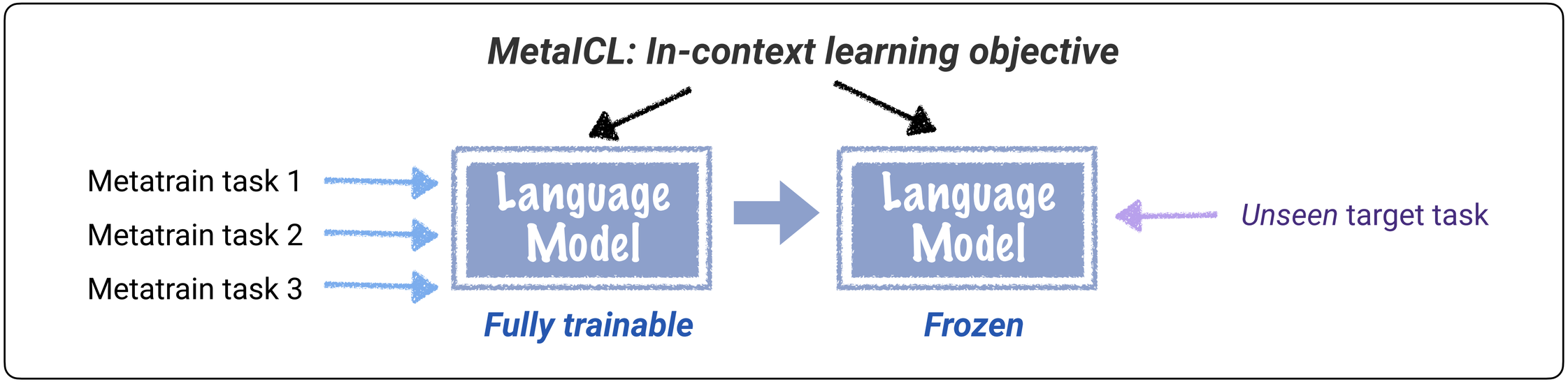

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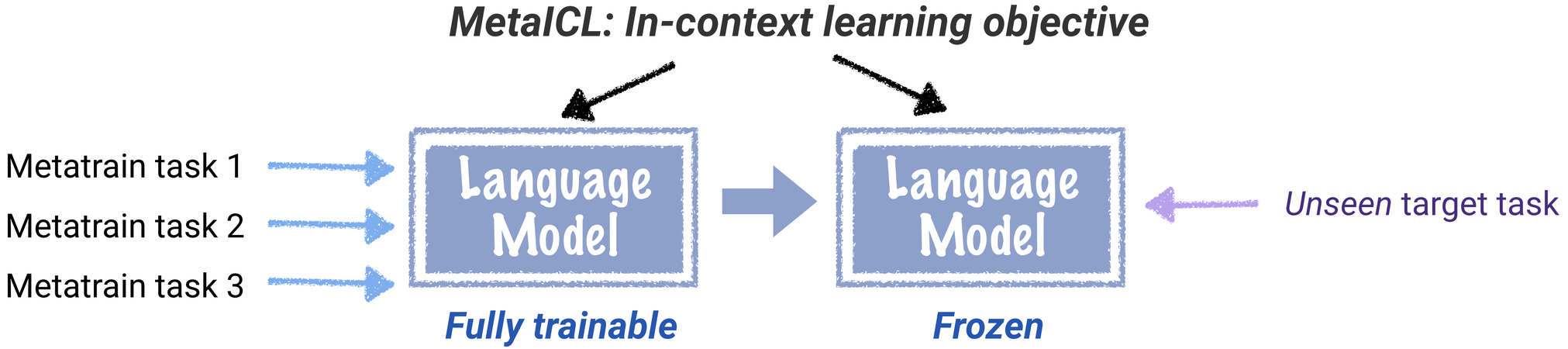

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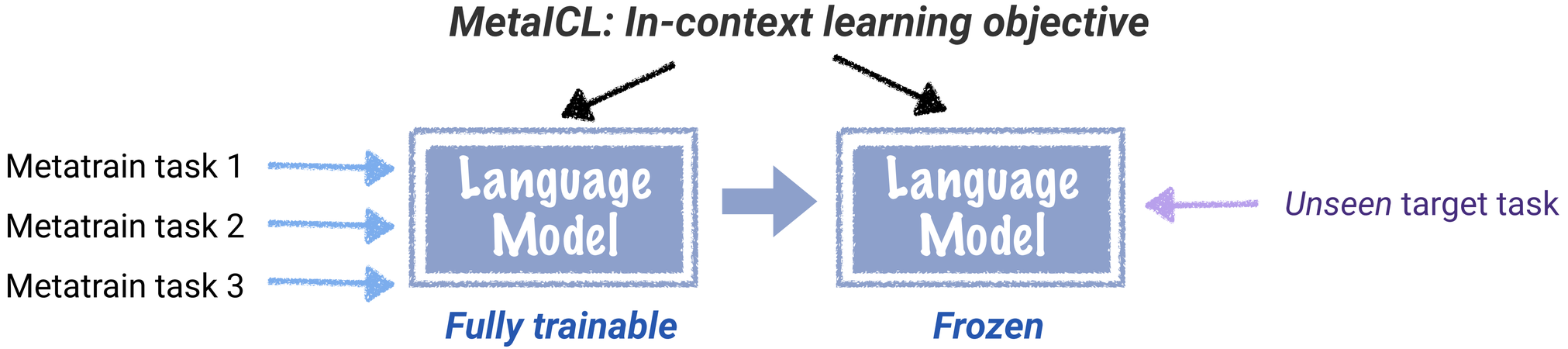

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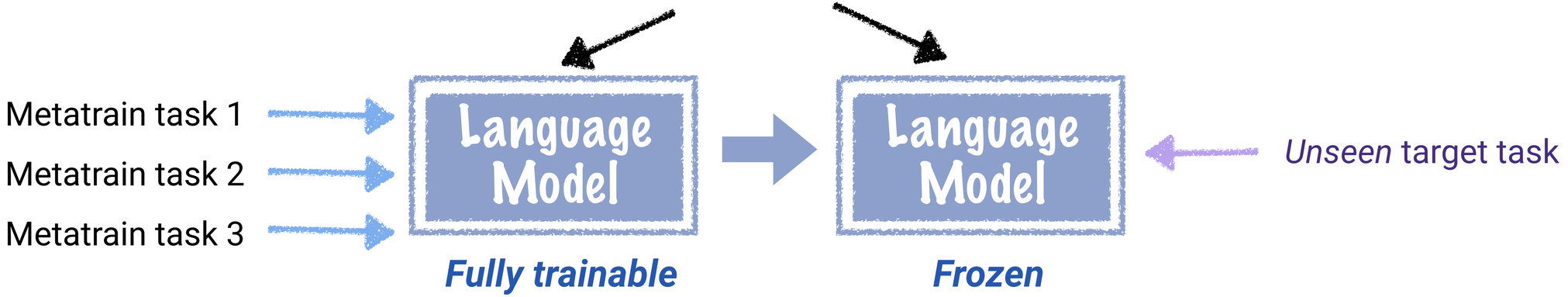

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Demo: http://qa.cs.washington.edu:2021

Few-shot Learning through Channel MetaICL

Sewon Min, Mike Lewis, Luke Zettlemoyer, Hannaneh Hajishirzi. 2021. "MetaICL: Learning to Learn In Context"
Sewon Min, Mike Lewis, Hannaneh Hajishirzi, Luke Zettlemoyer. 2021. "Noisy Channel Language Model Prompting for Few-Shot Text Classification"
Contact/bug report: Sewon Min (,)
[Show Me Details!]

Instruction:

Give the model 16 training examples (by writing yourself or choosing from an example task) and the test input, and see what model returns!
You do not need to use any templates or instructions to tell what the task is.

Channel LM Channel MetaICL

Recommended Tasks

=====Your Own Task=====

Get Random Examples!

Training examples

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Output: positive

Input: Our model achieves the new state-of-the-art.

Test Input

Write your own input

Run

Please enter the test input

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Thank you for listening

Paper: arxiv.org/abs/2110.15943
Code: github.com/facebookresearch/MetaICL
Demo: http://qa.cs.washington.edu:2021/

Contact: sewon@cs.washington.edu / @sewon__min

UW NLP Meta AI2 NAACL 2022