Choose your *prompt* “well-aligned”

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Based on our work published in ACL’22, ACL’23

The uprising of Large Language Models

Transformers: the backbone of large language models (LLM)

Attention Is All You Need

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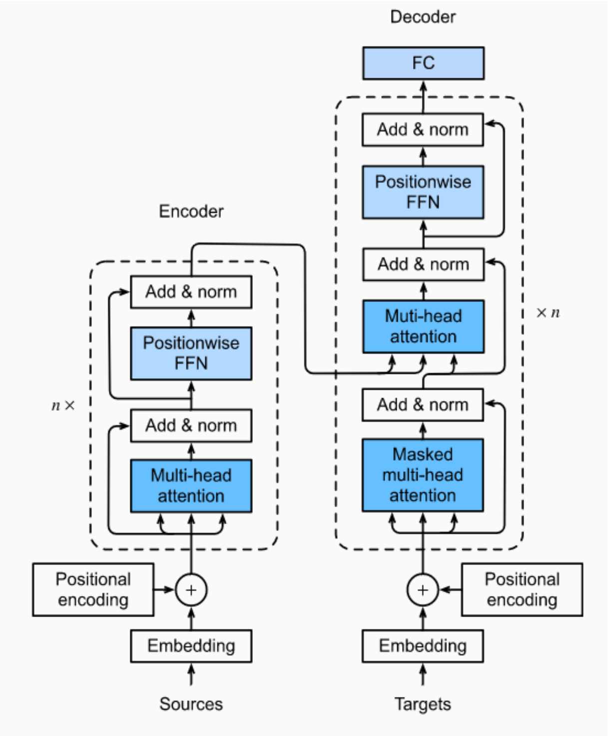
Attention is all you need

A Vaswani, N Shazeer, N Parmar… - Advances in neural …, 2017 - proceedings.neurips.cc

The dominant sequence transduction models are based on complex recurrent orconvolutional neural networks in an encoder and decoder configuration. The best performing such models also connect the encoder and decoder through an attentionm echanisms. We propose a novel, simple network architecture based solely onan attention mechanism, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superiorin quality while being more …



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Early pretrained LMs (BERT, RoBERTa, GPT) were mostly fine-tuned for downstream task

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GPT-2 (1.5B)

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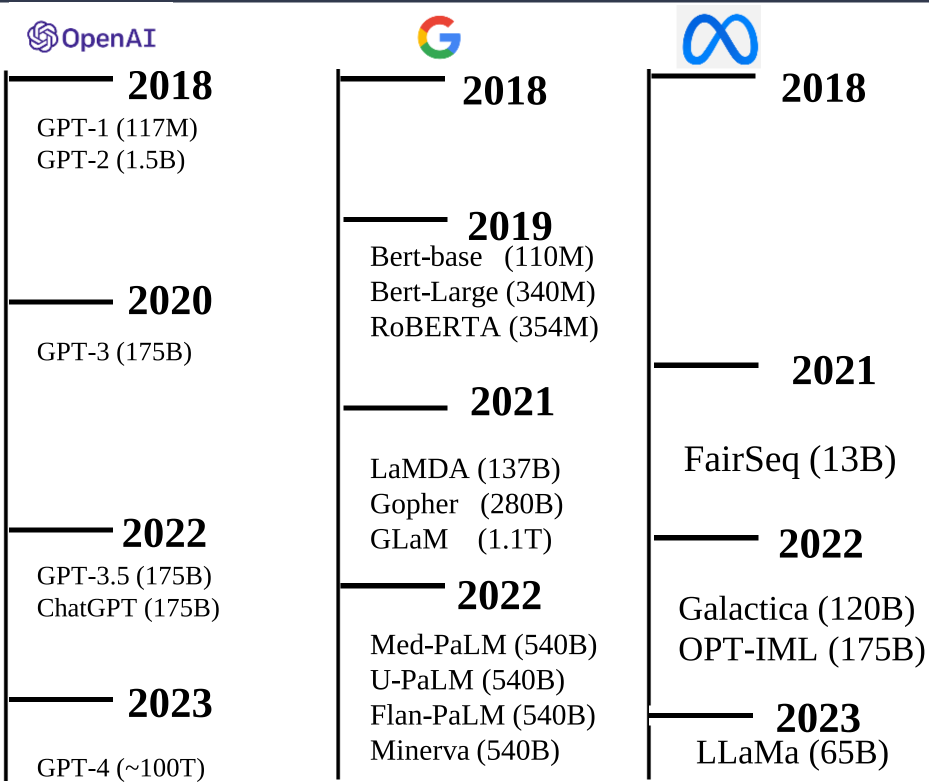

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That movie was great. Sentiment: Positive
It was a horrible day! Sentiment: Negative
This is an absolute mess. Sentiment:

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Prompting: A quick recap

Language models are pretrained to **fill in the blanks** (Masked Language Model, MLM) or **sentence completion** (Causal Language Model, CLM)

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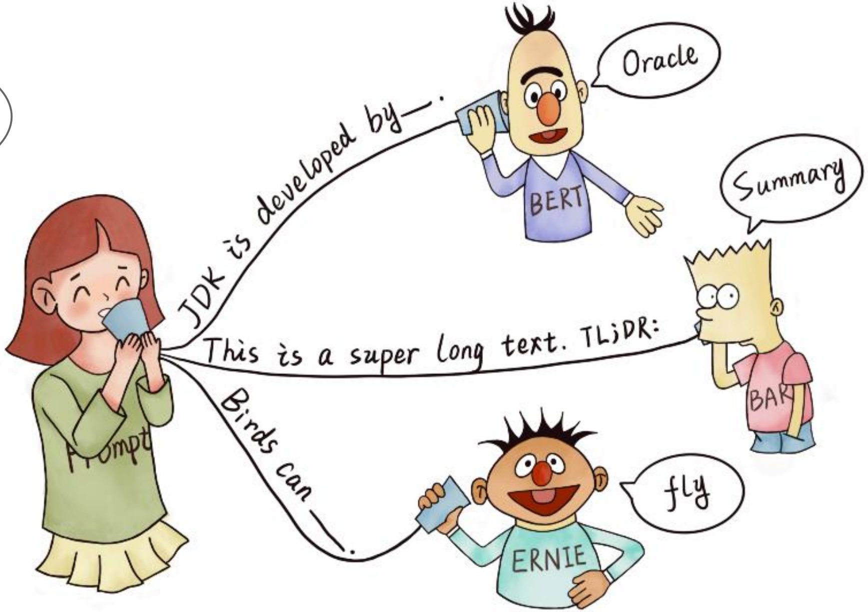

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Prompting

Supervised tuning

- Further gradient updates on labelled data

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In-context learning (ICL)

- No further tuning
- Task examples (input-label pairs) in prompt

Optimal prompts: An open problem

No algorithm to search for the **optimal** prompt!

Input: That movie was really great if you are dumb beyond imagination.
Sentiment expressed in the above sentence is

a BigScience initiative

BLOOM

176B params · 59 languages · Open-access

Input: That movie was really great if you are dumb beyond imagination.
Sentiment expressed in the above sentence is on the positive side of the range.

Optimal prompts: An open problem

No algorithm to search for the **optimal** prompt!

Consider the following sentence: “That movie was really great if you are dumb beyond imagination.” The author’s opinion expressed towards the movie in this sentence is

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Consider the following sentence: “That movie was really great if you are dumb beyond imagination.” The author’s opinion expressed towards the movie in this sentence is neutral.

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Consider the following sentence: “That movie was really great if you are dumb beyond imagination.” In the author’s opinion, the movie is

Consider the following sentence: “That movie was really great if you are dumb beyond imagination.” In the author’s opinion, the movie is not good.

Prompting as an alignment problem

Our hypothesis

Prompting works better when the task is similar to the pretraining objective/data

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Argument Mining in a nutshell

Broadly, 2 tasks:

1. Identify the argument components (e.g, claims and premises)

EMTs, SAR, firefighters, police, etc. should receive “military discounts”. For those of you who don’t know, it’s common (at least in the US) for businesses, transit agencies, etc. to give small discounts to military veterans to thank them for their service. It seems that medical responders (even hospital staff, actually) and other emergency services do more good for society than soldiers and that such discounts should be given to them.

> *other emergency services do more good for society than soldiers and that such discounts should be given to them.*

What about teachers? Scientists? Doctors? Farmers? There are plenty of professions that do great things for society but people aren’t going around thanking them with discounts.

Argument Mining in a nutshell

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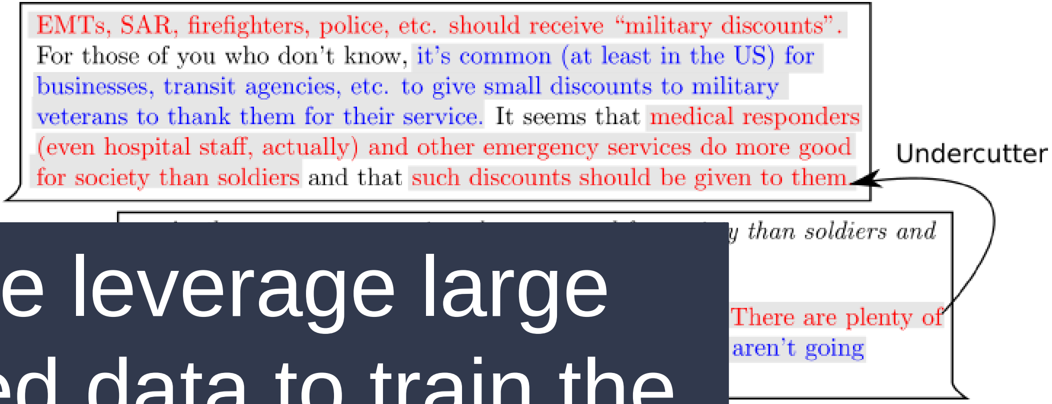
1. Identify the argument components (e.g. claims and premises)
2. Identify the re
   between thos



Can we leverage large unlabeled data to train the model specific to the task?

Relation Types
support
agreement
direct attack
undercutter attack
partial

Issues

- Very limited labeled data for finetuning
- No unified dataset for both the tasks

Transfer Learning via Selective MLM (sMLM)

Discussion threads in *r/ChangeMyView* subreddit

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Hypothesis: **Can we make a pretrained language model aware of argumentative discourse by making it predict such markers?**

Transfer Learning via Selective MLM (sMLM)

u/DurianMD:
CMV: Religion is not violent or not violent, its followers are. So, my belief is that while religion can inform the views of people, it is far more likely that religion will be used to justify actions that would have been executed any way. I think that most Jewish people don't want to stone adulterers and most Muslims don't want to stone non believers.

u/recycled_kevlar:
Your stance relies on the assumption that religion has no influence on the actions of its followers beyond the superficial. Yet something must exist that allows this pattern to occur. Ill narrow it down to religion or culture. So, you are correct if you assume the culture dominates the religion, and you are incorrect if the reverse is true. With this in mind, I think its safe to assume the truth is somewhere in between, with both the religion and the culture somehow influencing the unrest we see.

u/DurianMD:
I suppose I was taking a harsh stance when I assumed that religion had no effect on behavior, when it obviously does. I still think the culture dominates religion to a great extent, however I cannot ignore that religion does have an effect on culture to some extent.

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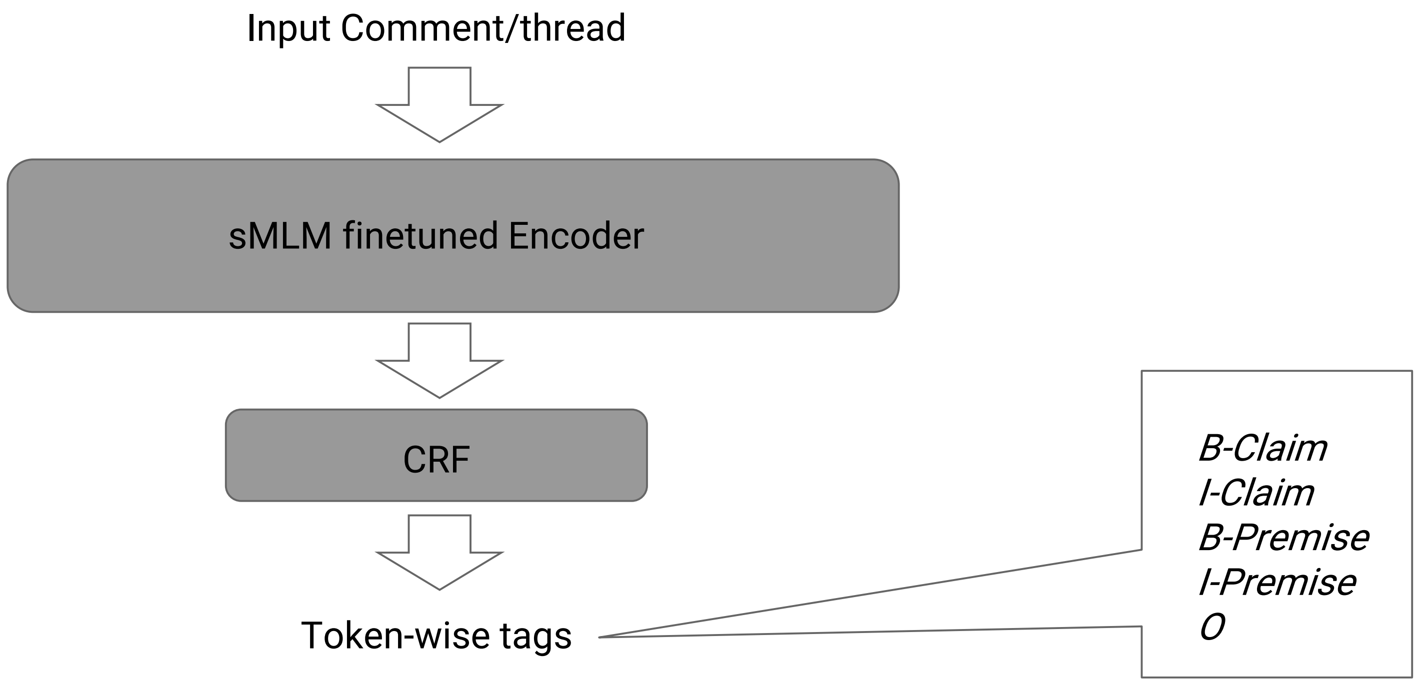
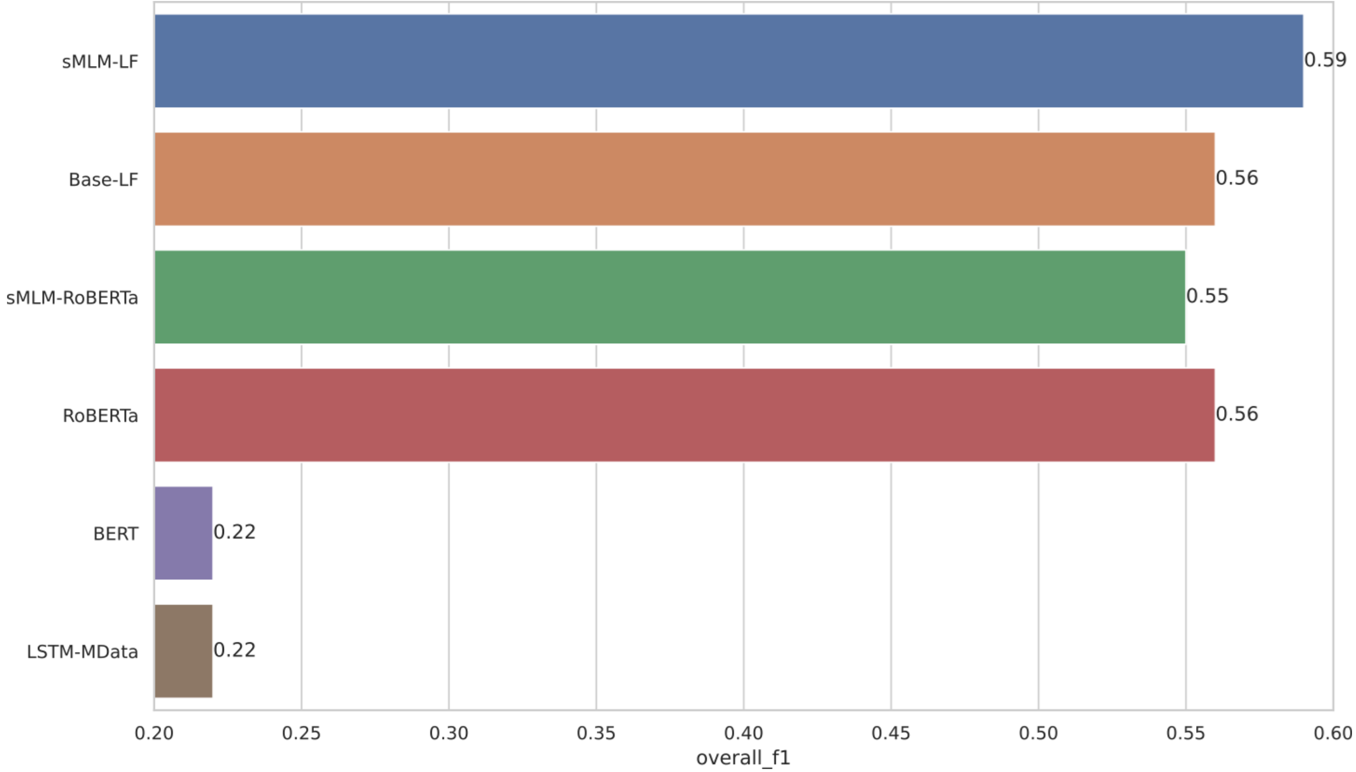
- Finetune a pretrained Transformer-based LM to predict these markers given the context and use for downstream tasks
- Incorporate complete thread context with Longformer
  - Replace user names with special tokens and global attention

Argument Component Identification



Argument Component Identification (ACT)

Performance on Reddit CMV-modes dataset for token-level component prediction



Inter-component Relation Type Prediction

Prompt-based method

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USER-1 CMV: I feel skill is largely determined by experience. Compliments on skill are almost meaningless. In high school, I thought I was "good at math" as I'm the son of a math teacher and electrical engineer. In college, I learned that math was not something you're "good at" but something you have to put hard work into and is almost the sole determiner in the level of skill you obtain.
So then isn't almost any compliment almost to be expected? I've spent a lot of time with similar problems -- how could I not know all the details and little tricks of these problems? I feel a compliment recognizes something given: I feel everyone is passionate about something, whether it be math or psychology or medicine. I don't hear "you're so good at biology" but I think I should.

USER-2 Then wouldn't a complement be just an acknowledgement of the time and effort you put into something that most people see as hard or worthwhile? This implies the complement is meaningful.
(Most people don't do this - either they don't put the time and effort into something generally hard or worthwhile or the time and effort isn't hard or worthwhile .)

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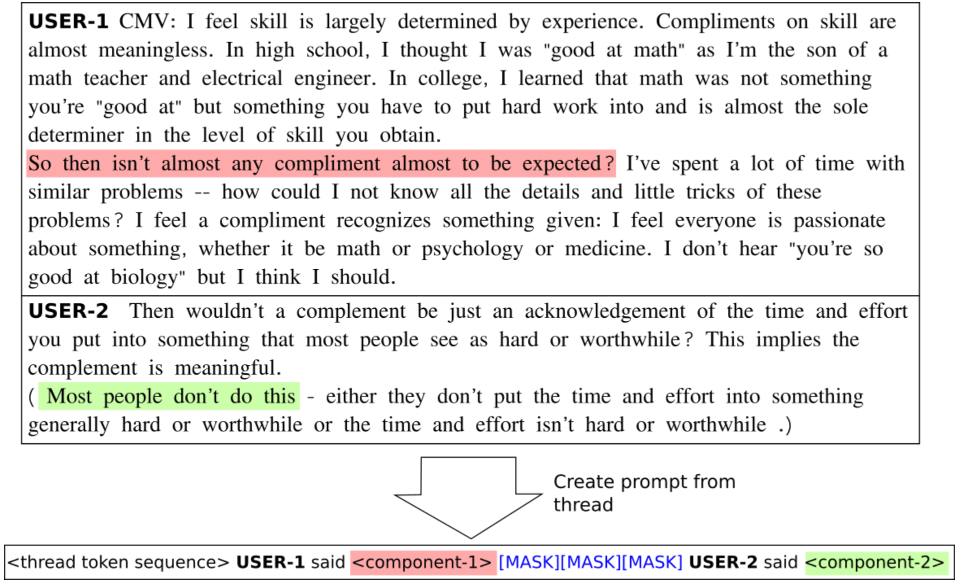

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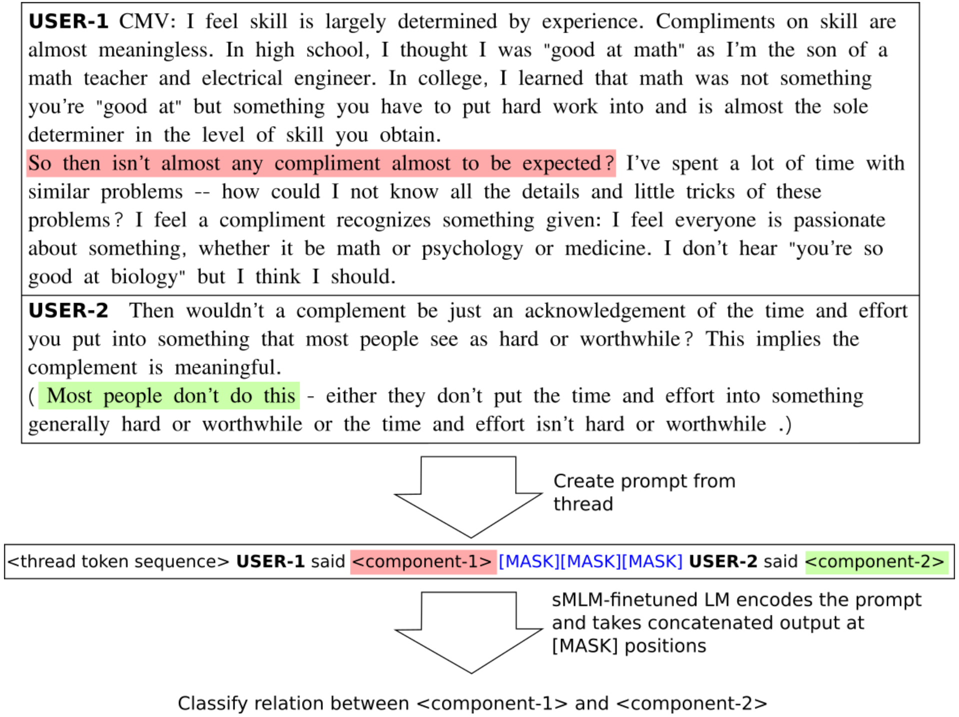

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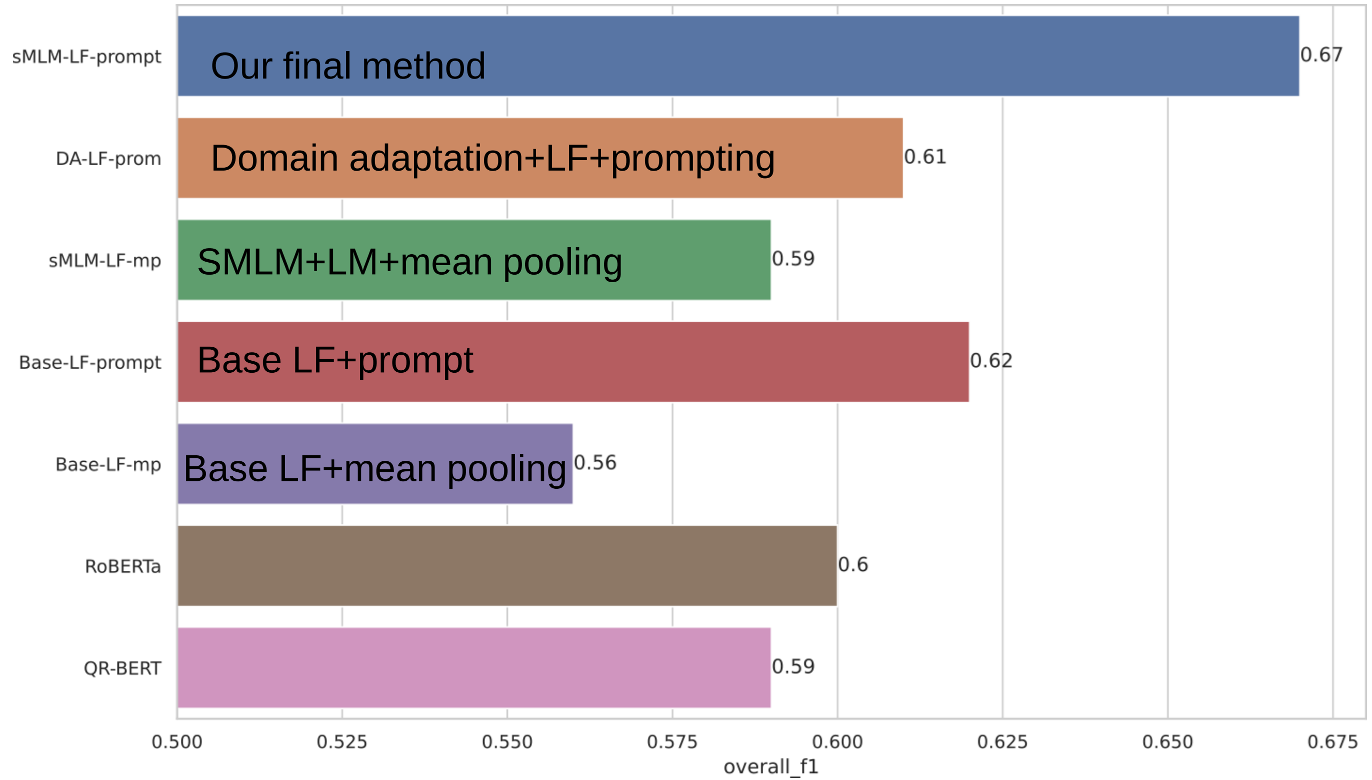

Performance on CMV-modes dataset

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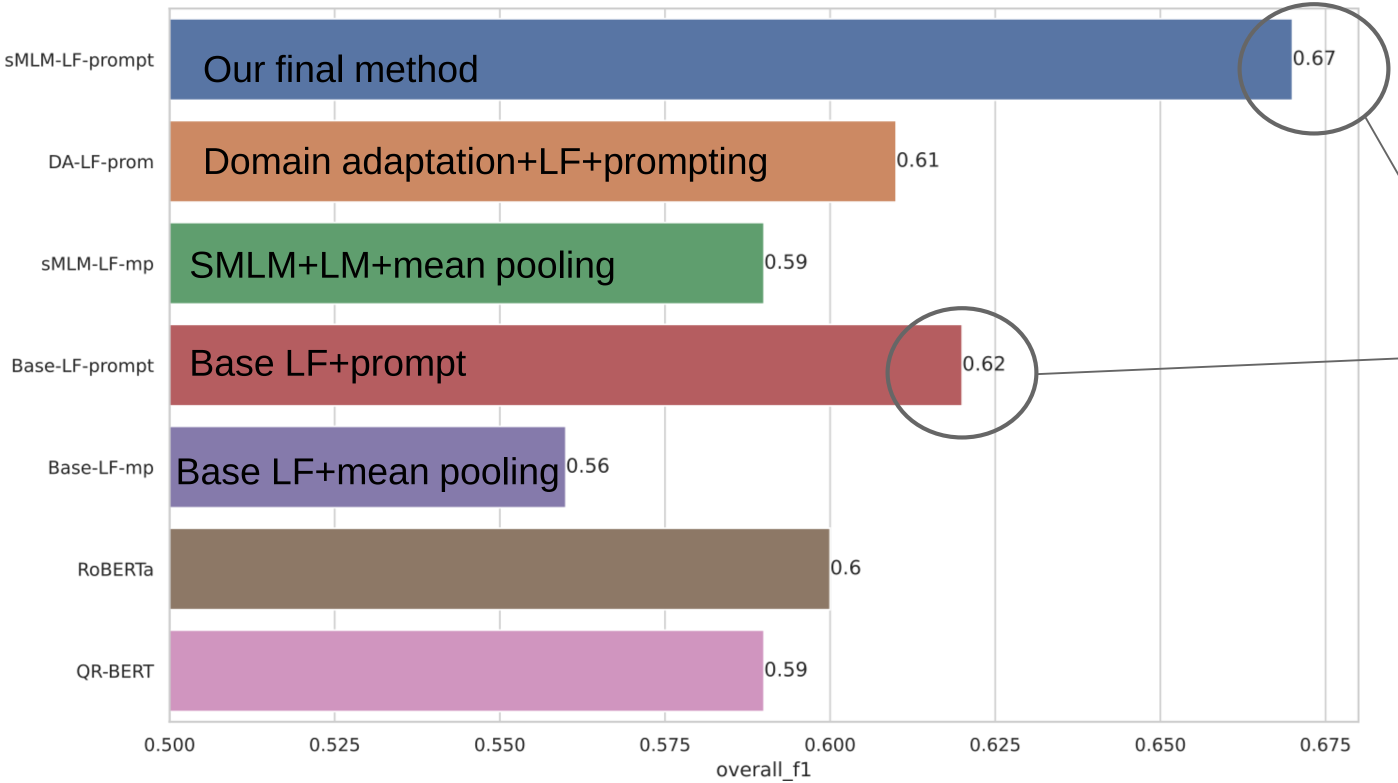

Performance on CMV-modes dataset

Prompt-based models outperform mean-pooling counterparts

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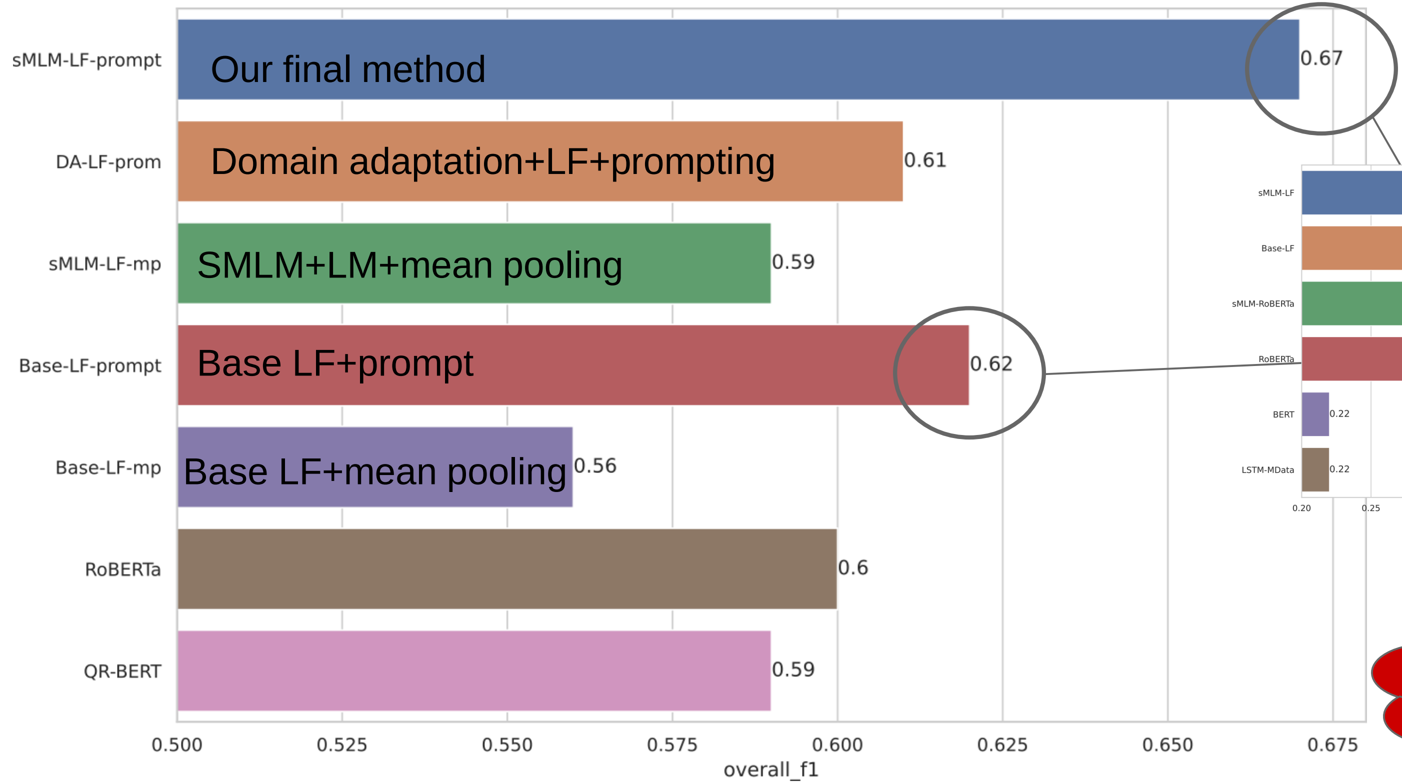

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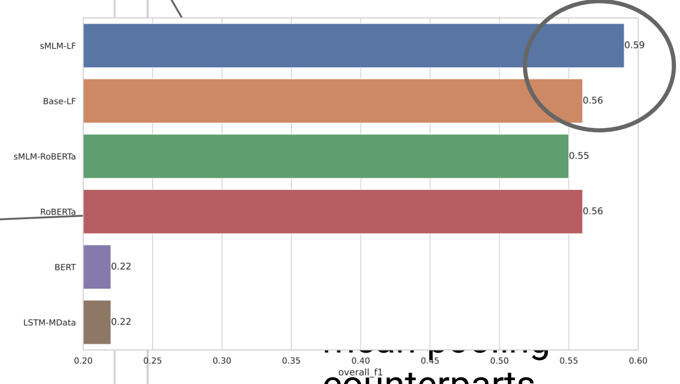
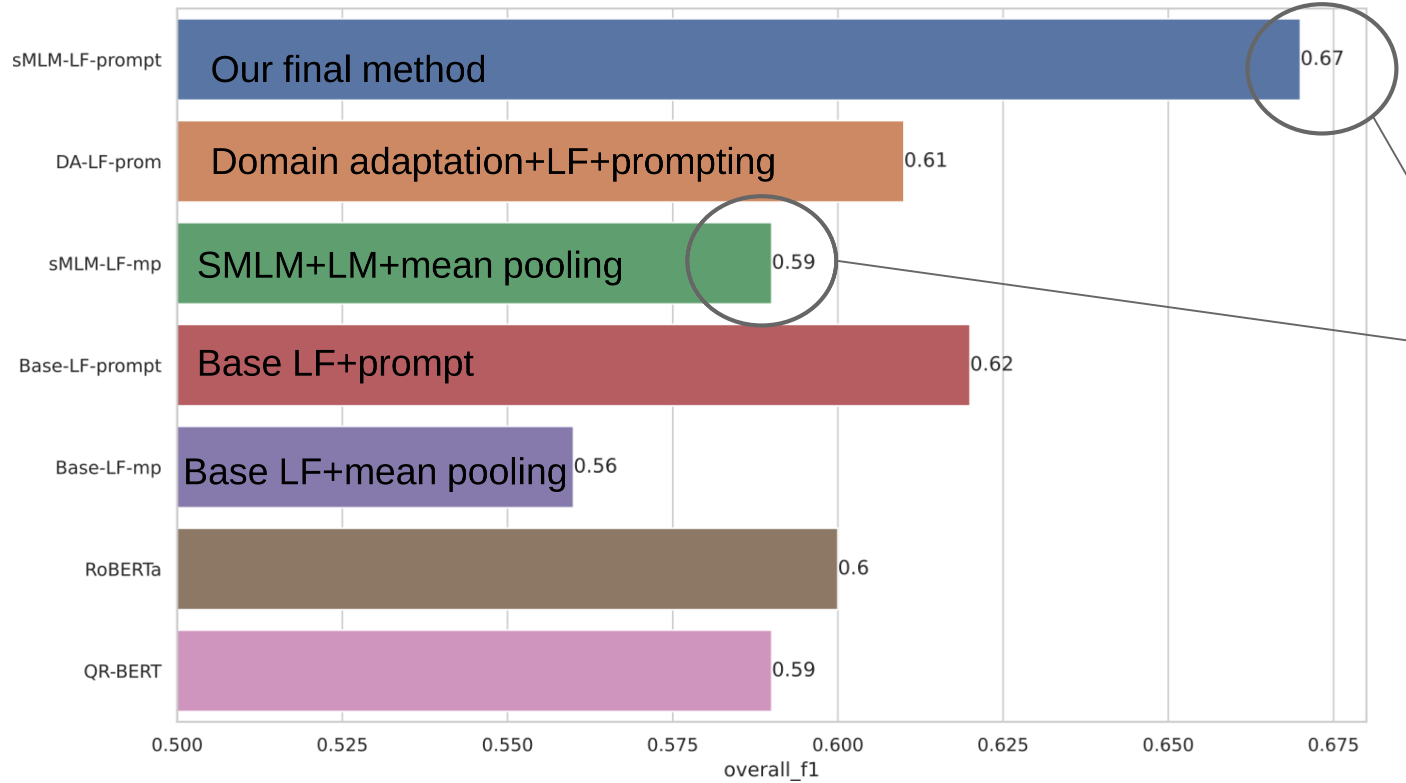


counterparts

Higher improvement with prompts in RTP compared to ACI (thanks to alignment!)

Inter-component Relation Type Prediction (RTP)



Performance on CMV-modes dataset

sMLM models outperform base and domain-adapted counterparts

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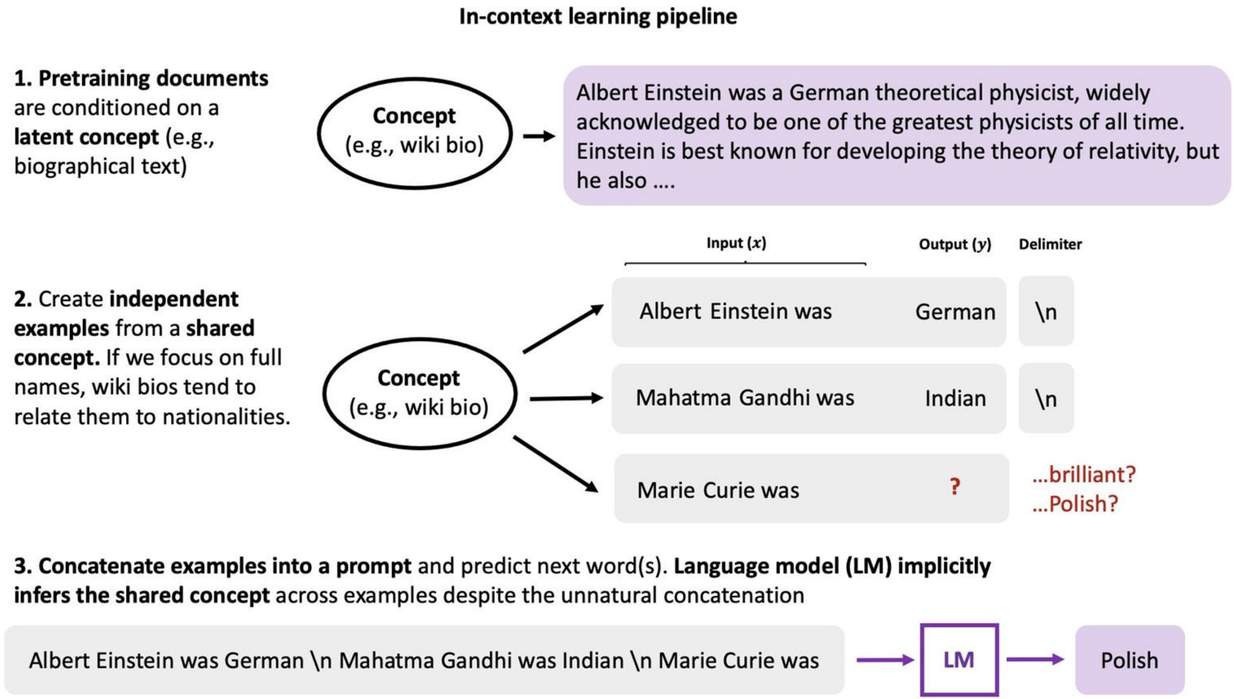
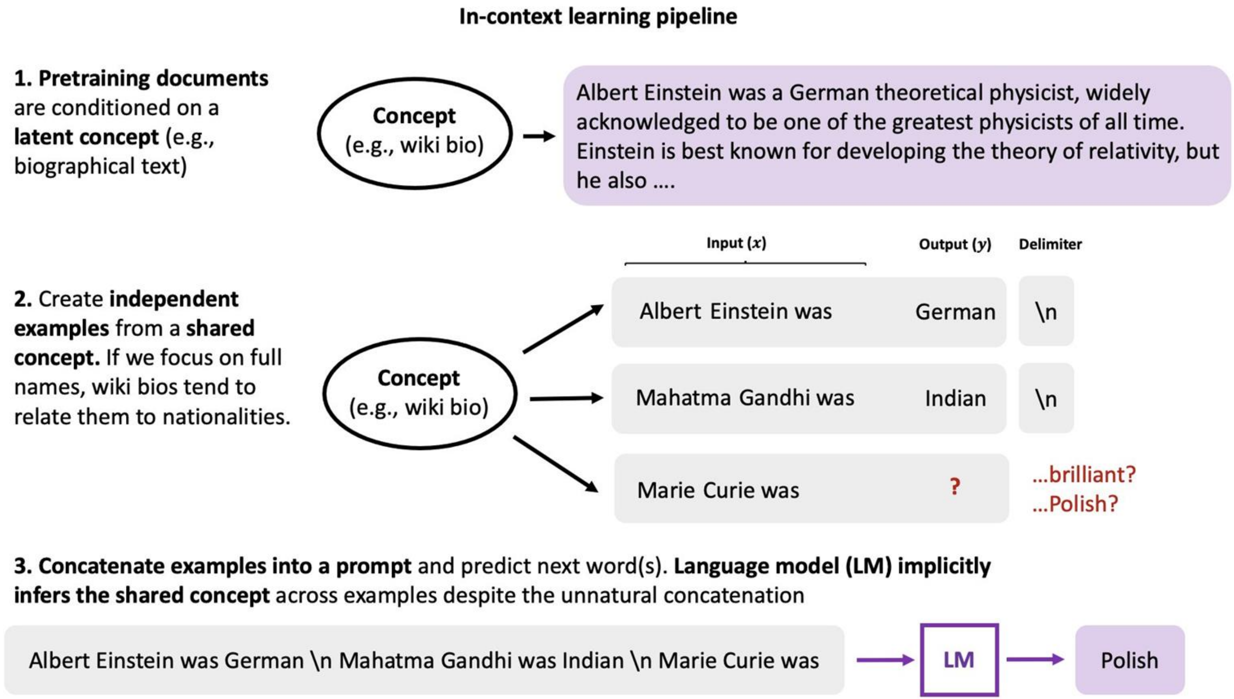


In-context learning (ICL)

Shared concept :

1. Context and test input are ‘similar’ in some sense
2. The notion of the task should be shared between the two



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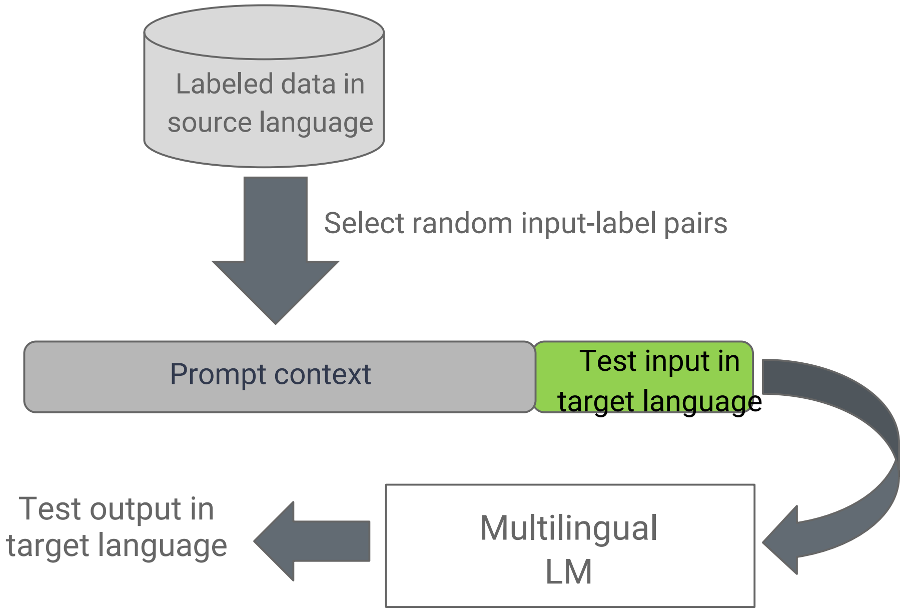

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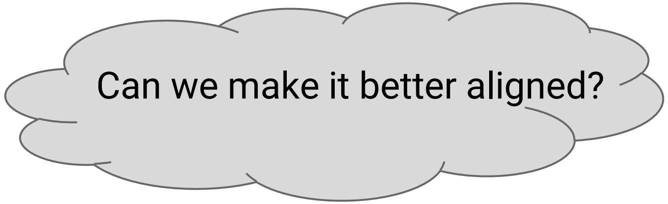
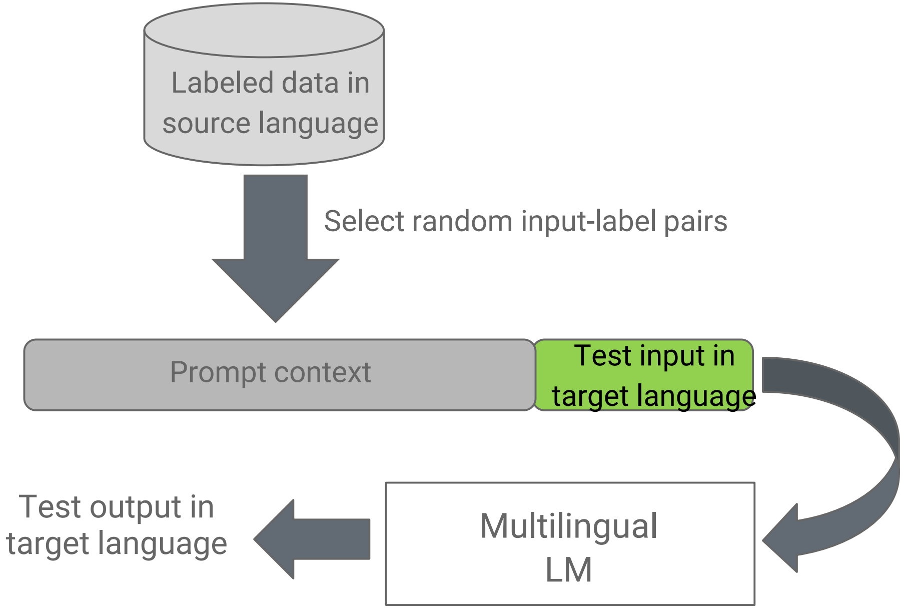
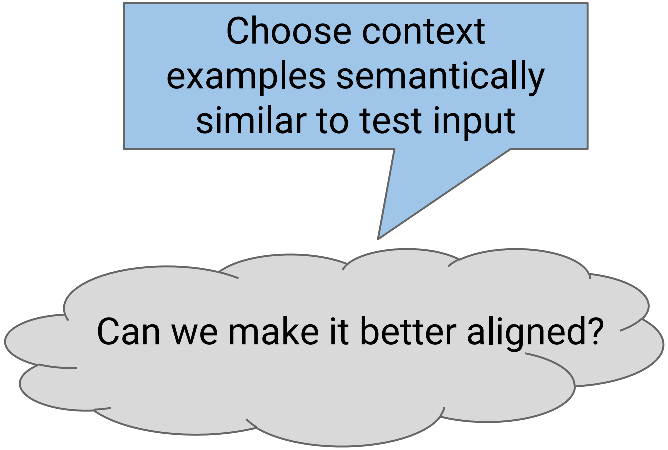
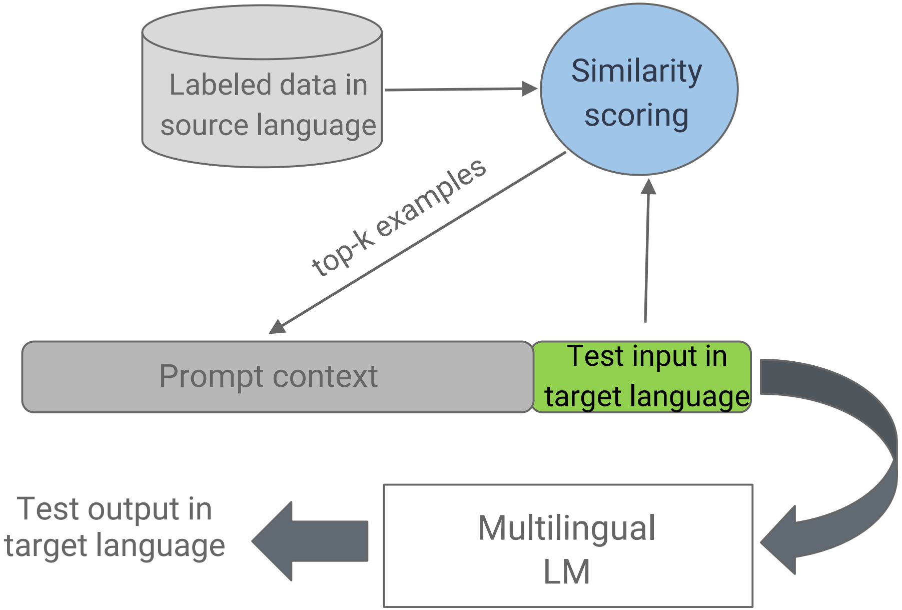




Cross-lingual ICL: semantic alignment





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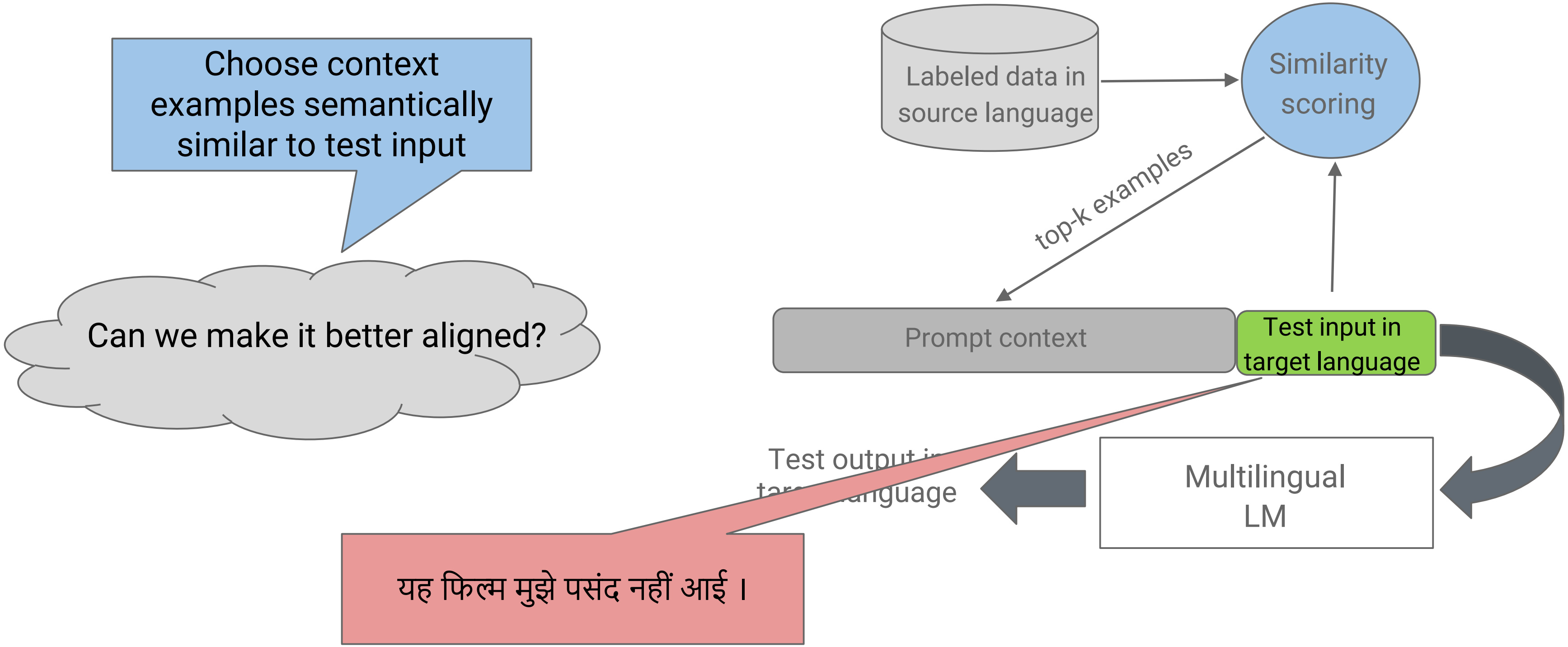

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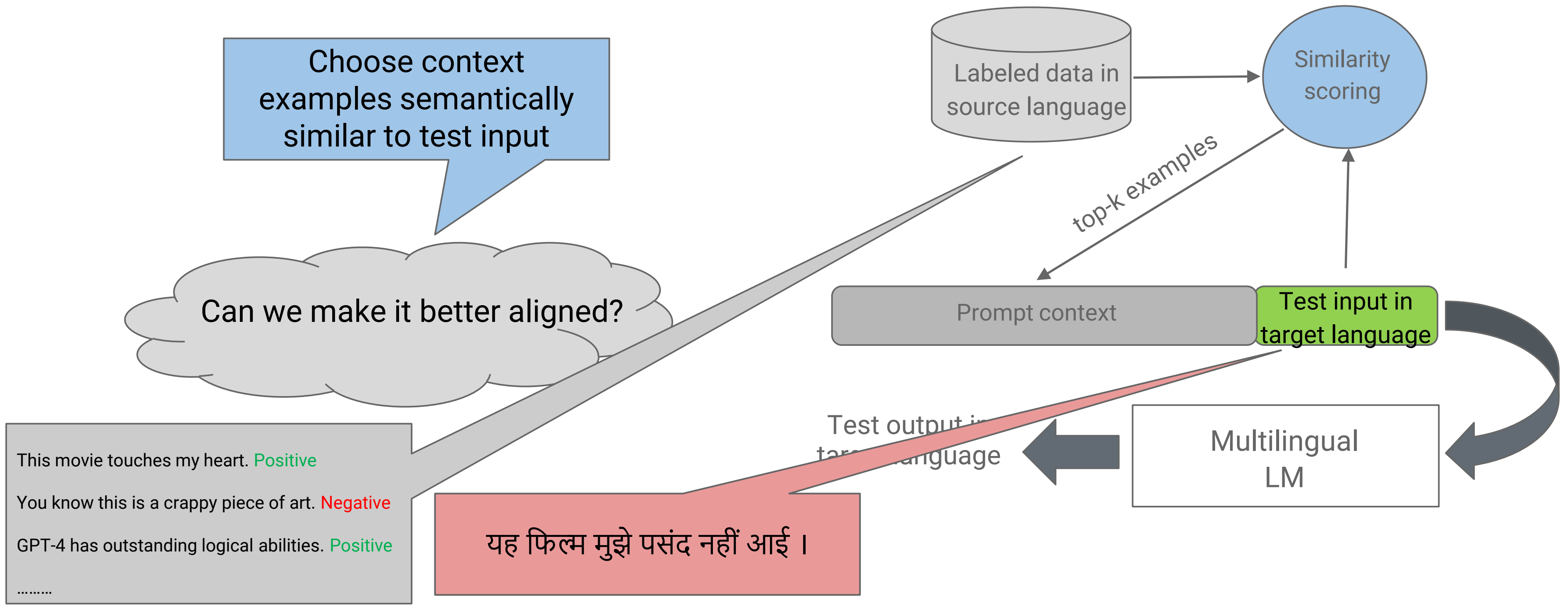
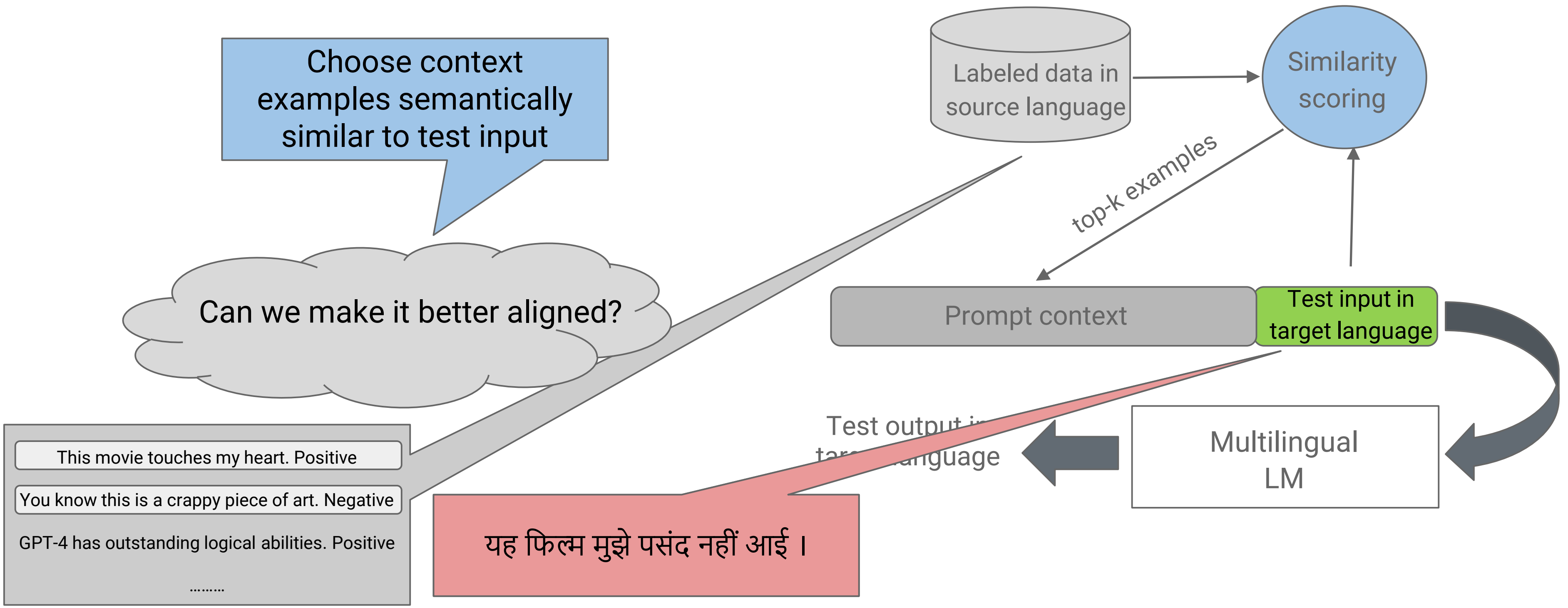


Cross-lingual ICL: semantic alignment



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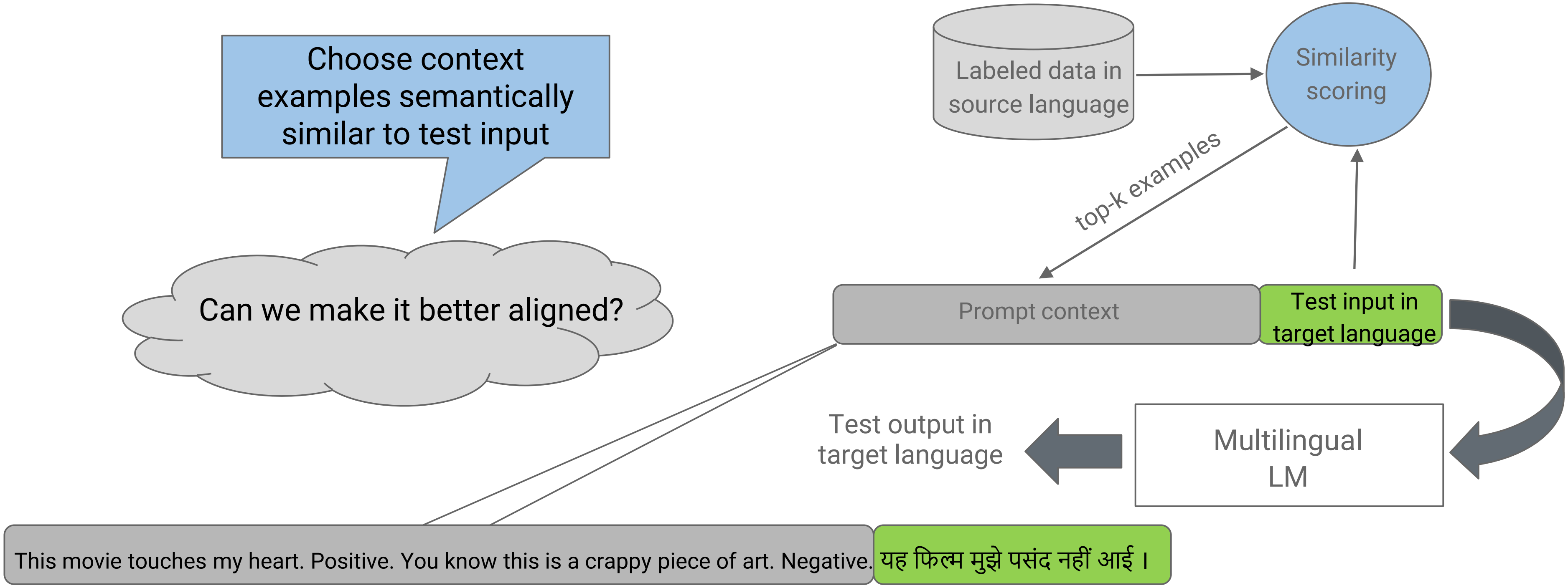
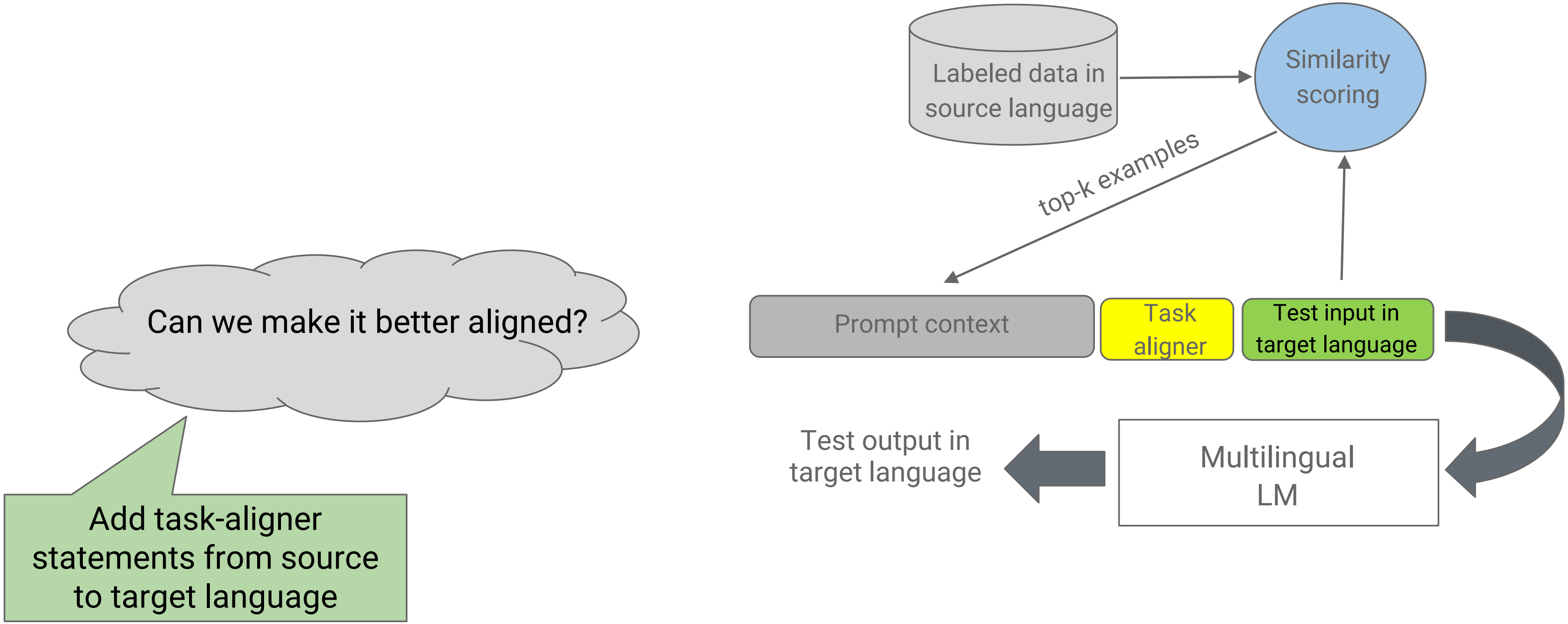


Cross-lingual ICL: task alignment

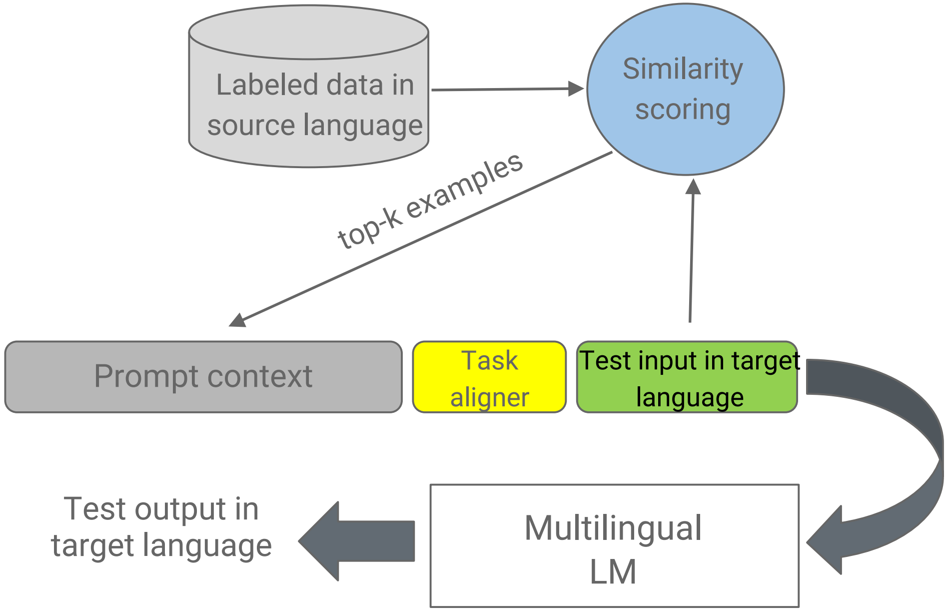


Cross-lingual ICL: task alignment

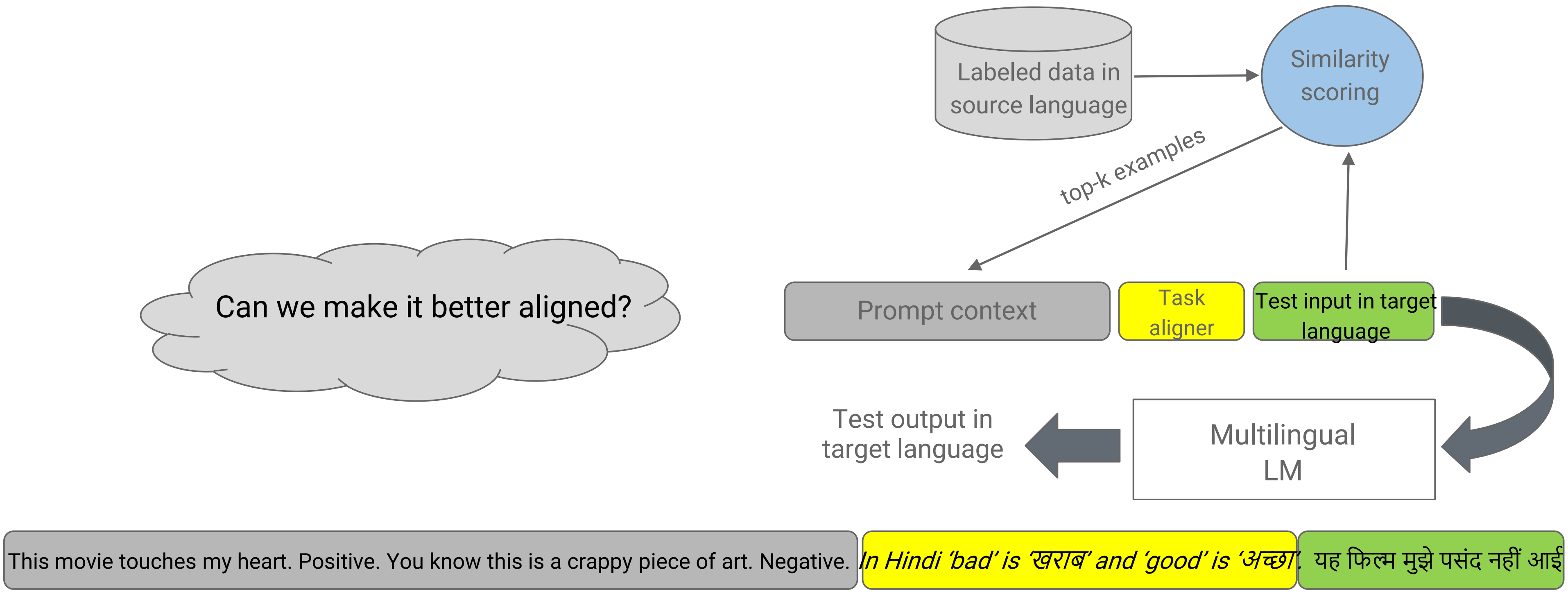
Task alignment example	
Task: Sentiment classification	
Source: English	Target: Hindi
Aligner: *In Hindi 'bad' is 'खराब' and 'good' is 'अच्छा'*	

Can we make it better aligned?

Add task-aligner statements from source to target language



Cross-lingual ICL: task alignment



Alignment improves ICL!

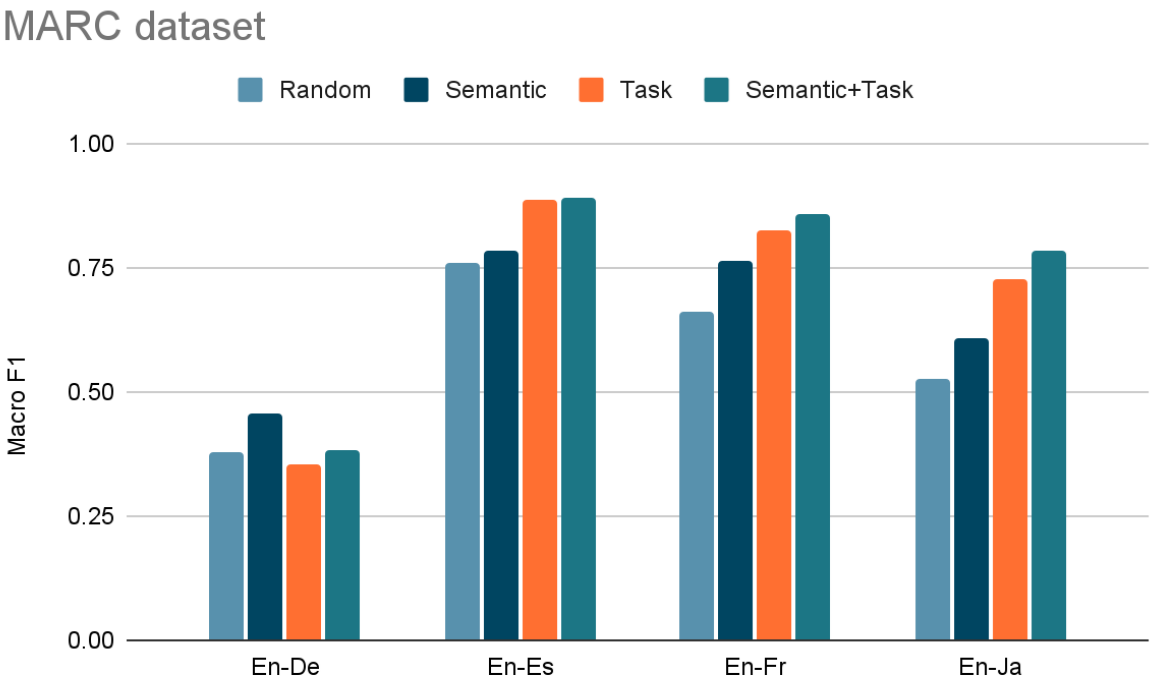
LM used: XGLM (7.5B params)

Datasets used:

- Multilingual Amazon Reviews Corpus (MARC)
- Cross-language sentiment classification (CLS)
- HatEval

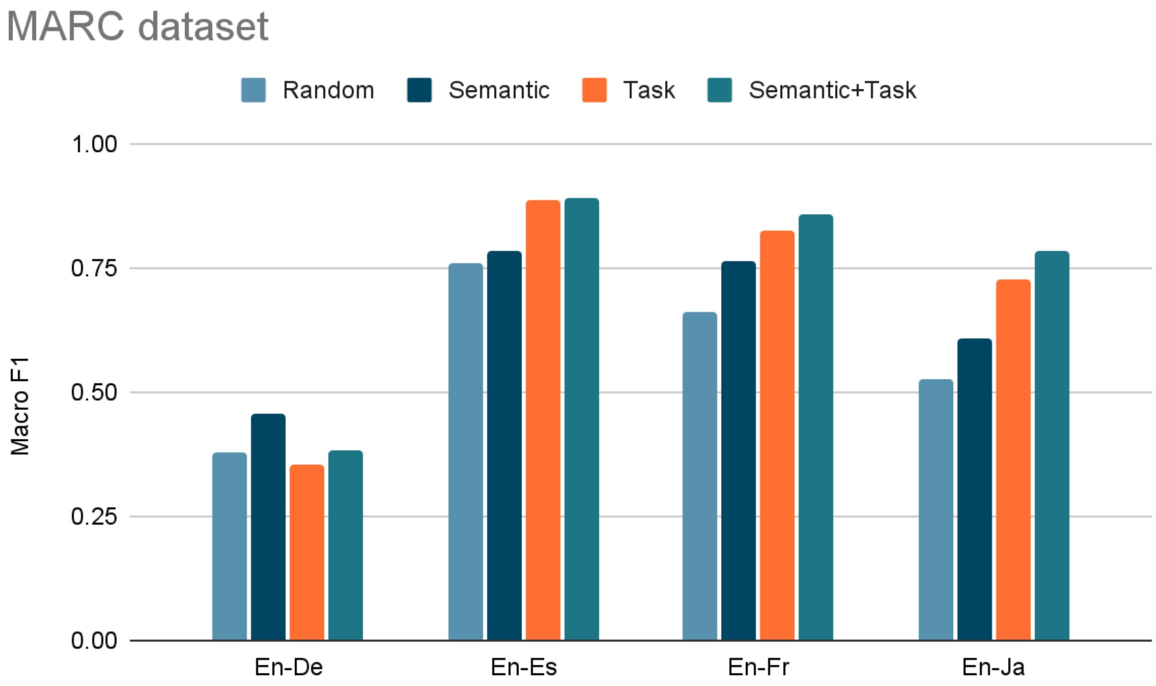
Languages:

En -> English, De -> German, Es -> Spanish, Fr -> French, Ja -> Japanese, Zh -> Mandarin



Alignment improves ICL!

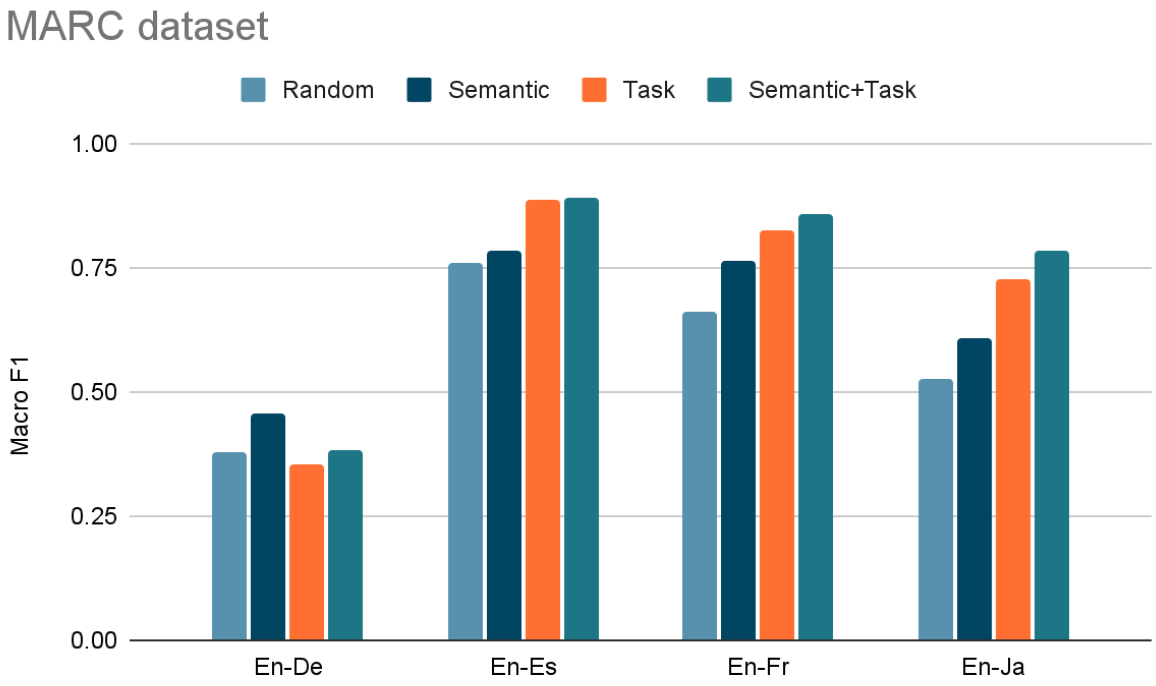
In most language pairs, both types of alignments bring improvements



Alignment improves ICL!

In most language pairs, both types of alignments bring improvements

- Exception: when target language is German or Mandarin

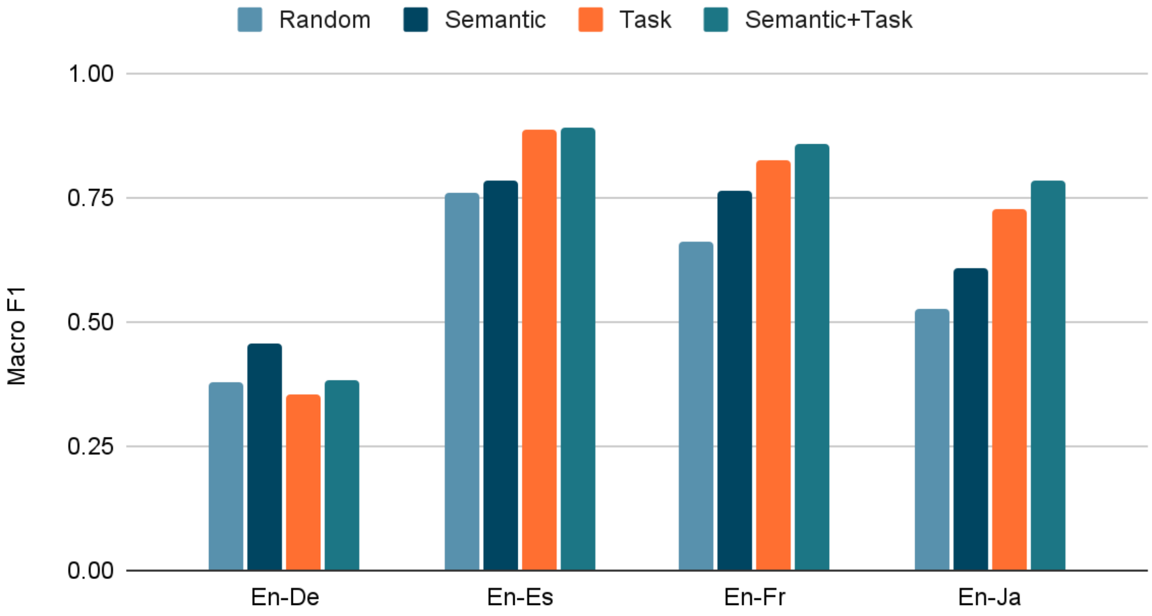


Alignment improves ICL!

In most language pairs, both types of alignments bring improvements

- Exception: when target language is German or Mandarin
- However, with XGLM 2.7B parameter model, these two languages show improvement with alignment

MARC dataset



Why does Task Alignment Work?

Setup \ Target language	de	en	es	fr	ja	zh
Random prompt	0.345	0.633	0.731	0.557	0.499	0.462
Uniform label space	**0.441**	0.570	0.493	0.414	0.483	**0.594**
Task alignment by language information only	0.346	0.645	0.733	0.575	0.543	0.508
Task alignment via third language	0.345	0.687	0.755	0.673	0.601	0.423
Incorrect task alignment	0.338	0.665	0.787	0.647	0.544	0.339
Task Alignment	0.338	**0.722**	**0.830**	**0.758**	**0.730**	0.335

Understanding how task alignment works. Average F1-Macro across all source-target pairs on MARC.

Automated aligner generation using mT5

Setup \ Target	MARC					CLS			HatEval
	de	es	fr	ja	zh	de	fr	ja	es
Random prompting	0.380	0.761	0.663	0.526	0.362	0.682	0.412	0.609	0.435
Semantic alignment	0.458	0.783	0.762	0.608	**0.450**	0.677	0.505	0.691	0.493
Task-based alignment	0.355	**0.888**	**0.826**	**0.727**	0.333	0.620	**0.696**	**0.752**	**0.499**
Automated aligner	**0.531**	0.792	0.699	0.599	0.350	0.721	0.430	0.610	0.438

Misalignment between pretraining distribution of XGLM and mT5

- Automated aligner is better than random prompting.
- It is competitive to semantic prompting in some languages.
- It fails to incorporate any task-specific signals, therefore failing to beat Task-based alignment.

Takeaways

- The efficiency of prompt design predominantly depends on pretraining objectives and downstream task
- Alignment via simple measures like semantic similarity can boost performance significantly
- Specially in cross-lingual setting, notion of task needs to be transferred from context to target

Our team working on LLMs

Subhabrata

Foundational models

- Physics-inspired LLMs
- Brain-inspired LLMs
- Increasing the reasoning ability of LLMs
- Layer-editing

ling
ogs
mod
d IC

Funding Agencies
Facebook, DRDO

Graph Neural Networks

- Graph transformer
- Inducting learning on graphs
- Graph attacks and defense
- Graph applications

Applications

- Cyber safety (hate speech, misinformation)
- Mental health
- Text summarization
- Dialog systems

Manish

Karish

Eshaan

Gurusha

Joykirat

https://lcs2.in/

Laboratory for Computational Social Systems (LCS2)

Hiring MS, PhD, Postdoc, RA
(contact: tanchak@iitd.ac.in)

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