Propagating Knowledge Updates to LMs Through Distillation

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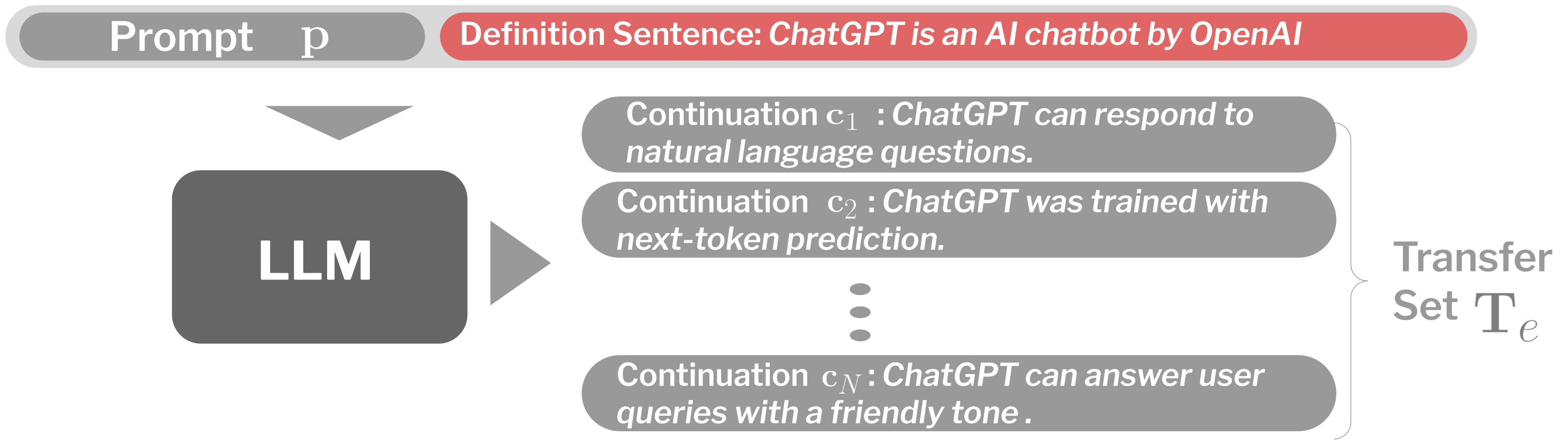
NEURAL INFORMATION PROCESSING SYSTEMS

Method

Step 1: Transfer Set Generation

Transfer set: A set of sentences that represent potential inferences given the definition statement. These are continuations of the definition sampled from the language model.



Prompt p | Definition Sentence: *ChatGPT is an AI chatbot by OpenAI*

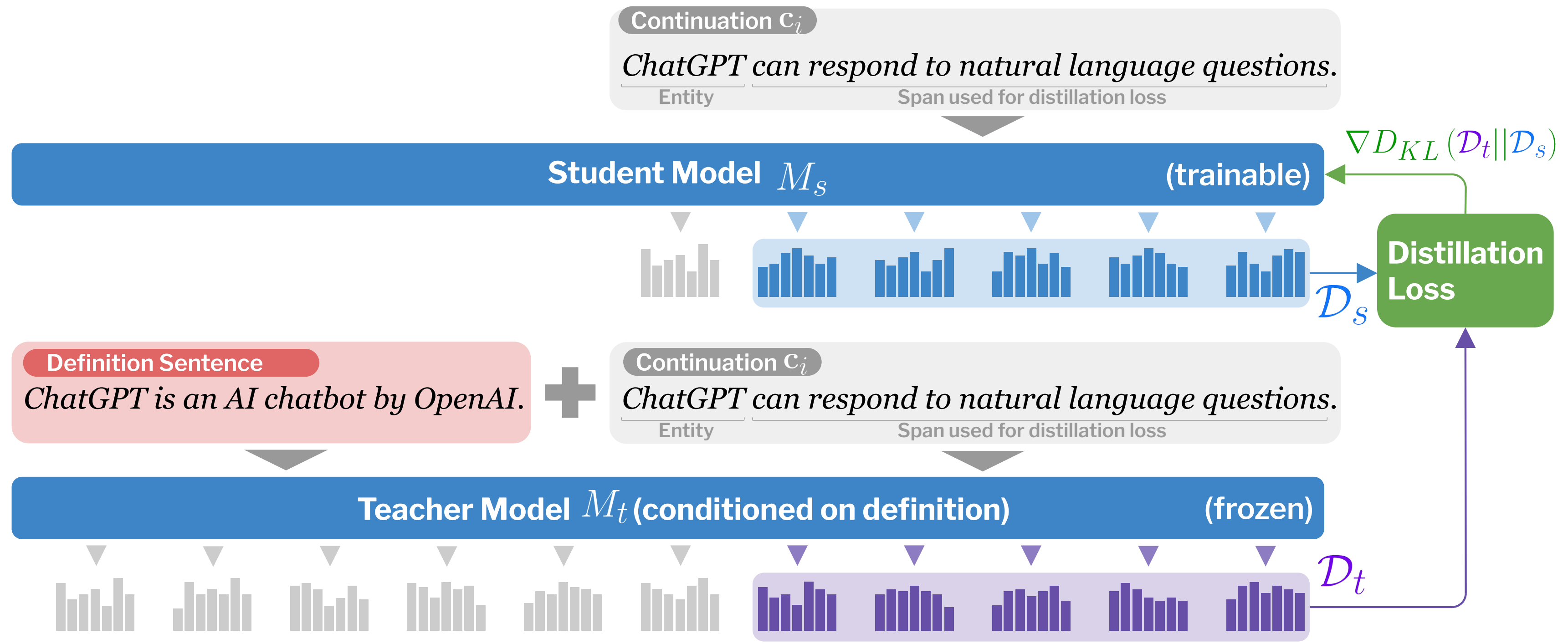
Continuation c_1 : *ChatGPT can respond to natural language questions.*

Continuation c_2 : *ChatGPT was trained with next-token prediction.*

Continuation c_N : *ChatGPT can answer user queries with a friendly tone .*

Step 2: Context Distillation with Transfer Set

The language model (student) is trained to match its distribution when the same model is conditioned on the definition (teacher).



Continuation c_i: *ChatGPT can respond to natural language questions.*

Definition Sentence: *ChatGPT is an AI chatbot by OpenAI.*

Entity
Span used for distillation loss
Student Model M_s
(trainable)
$\nabla D_{KL}(\mathcal{D}_t||\mathcal{D}_s)$
$\mathcal{D}_s$
Distillation Loss
Teacher Model M_t (conditioned on definition)
(frozen)
$\mathcal{D}_t$

Experimental Setup

Datasets:

Entity Inferences (Onoe et al., 2023)

- Manually crafted probe sentences using templates
- Measure **accuracy** on cloze span

Definition: Hurricane Nana was a minimal Category 1 hurricane that caused moderate damage across Belize in early September 2020.
Sentence: Hurricane Nana (2020) totally [MASK] my house.
Entity: Hurricane Nana
Options: acted, brewed, built, destroyed,...
Label: destroyed

Entity Cloze By Date (ECBD, Onoe et al., 2022)

- Derived from Wikipedia sentences
- Measure **perplexity** on cloze span

Definition: An mRNA vaccine uses a copy of a molecule called messenger RNA to produce an immune response.
Sentence: mRNA vaccines do not affect or reprogram [MASK].
Entity: mRNA vaccine
Year: 2020
Label: DNA inside the cell

Evaluation Metrics

- **Edit Efficacy:** The success of the model edit at *propagating* the injected knowledge
- **Edit Specificity:** The updated models performance on queries about unrelated entities. Ideally, this should not change post-update.

Task: Knowledge Propagation

Prior work edits the parameters of LMs to update their knowledge ("*Rishi Sunak is now the British PM*") and evaluates these updates directly ("*Who is the PM of the UK?*"). We focus on **propagation** of injected knowledge, testing whether LMs can make inferences based on injected facts.

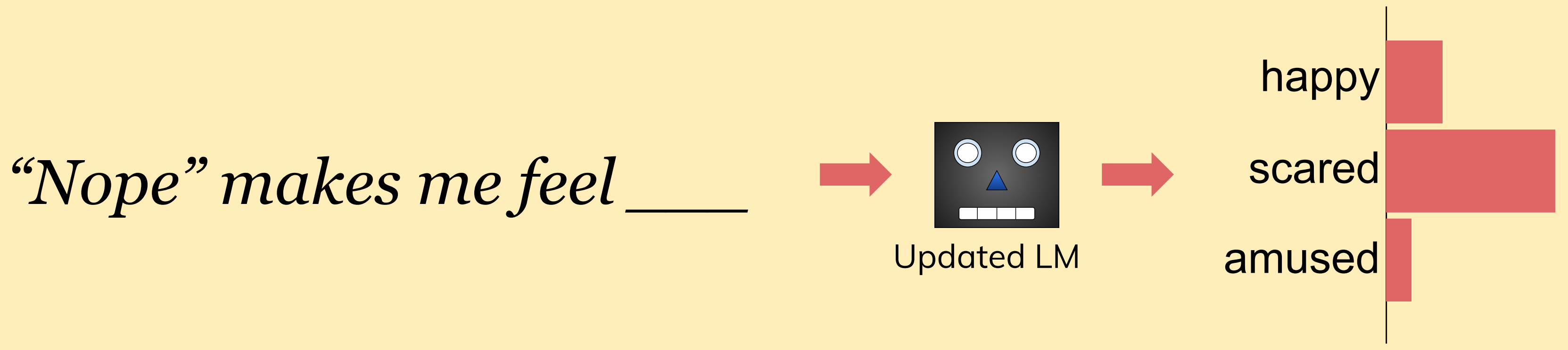
We develop a distillation-based knowledge editing method that can *propagate* injected knowledge!

We **update** an LM on a definition sentence of a **new entity** using any knowledge editing method such as finetuning, MEND, or ROME.

"Nope" is a 2022 American Western science fiction horror film written, directed, and produced by Jordan Peele.

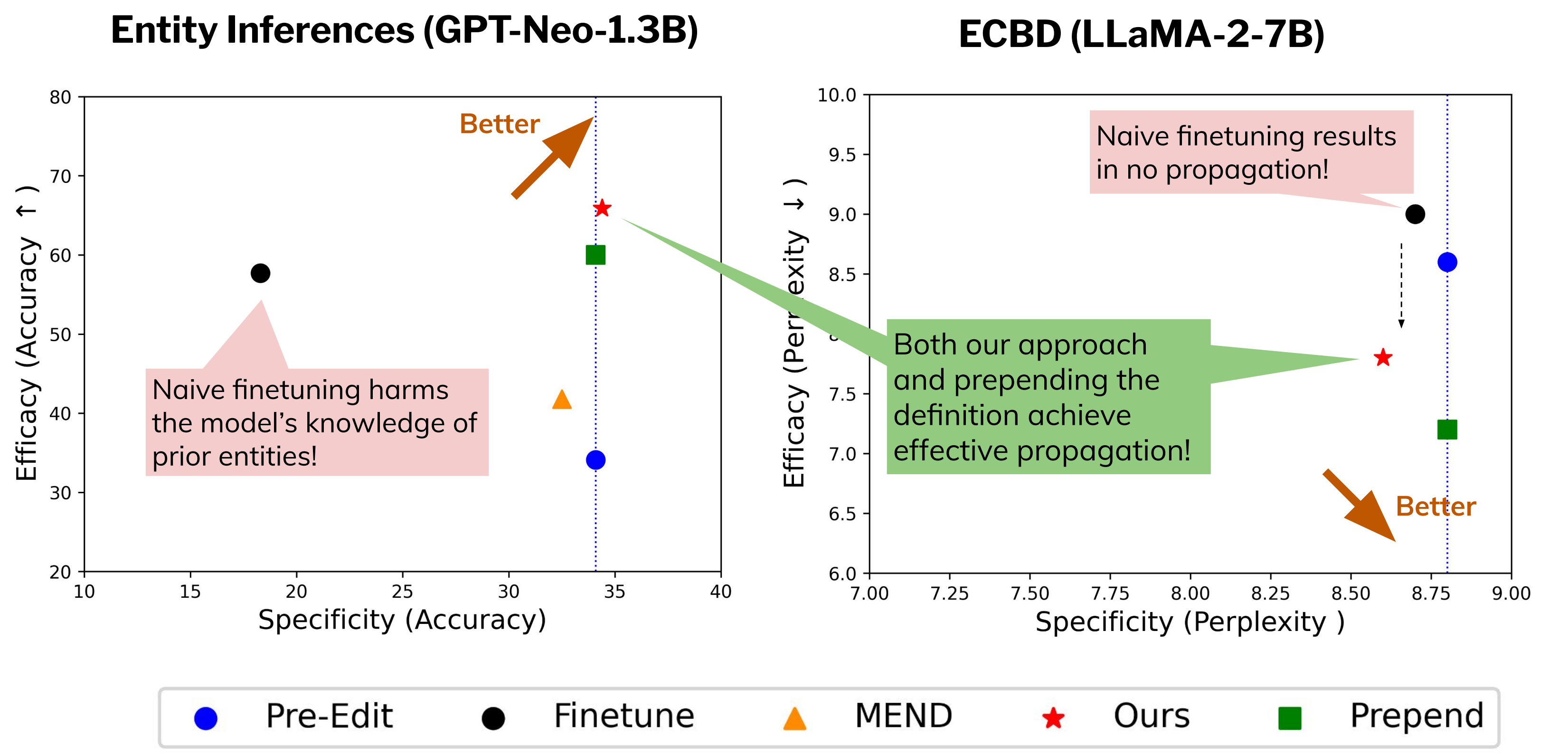
Base LM
Update
Updated LM

The updated LM is evaluated for **propagation** of the knowledge: can the model make inferences based on the fact?



"Nope" makes me feel ____

Results

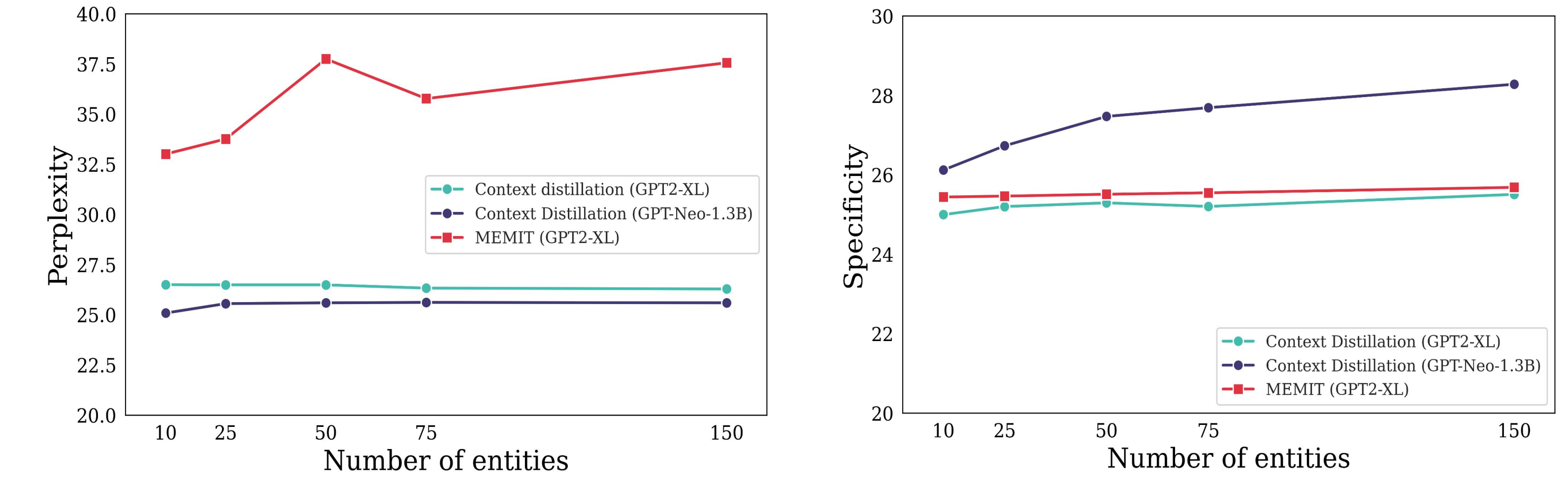


Naive finetuning harms the model's knowledge of prior entities!

Naive finetuning results in no propagation!

Both our approach and prepending the definition achieve effective propagation!

- Our method scales to many entities at once! (ECBD)



- How much does the definition or transfer set matter?

Using the wrong definition hurts performance!

Definition	Transfer Set	Perplexity	Specificity
Random	Correct (GPT-3.5)	33.6 (+2.6)	25.8 (-0.3)
Correct	Random	28.9 (-2.1)	26.6 (+0.5)
Correct	Random + Ent str.	26.7 (-4.3)	25.7 (-0.4)
Correct	Correct (GPT-3.5)	25.3 (-5.7)	25.6 (-0.5)
Correct	Correct (Base)	26.0 (-5.0)	25.9 (-0.2)

Simply appending the correct entity name improves performance!

Using the base model as the generator is nearly as good as using a SOTA model!

- More in the paper:
  - Does the model memorize the definition during distillation?
  - What *kind* of updates is distillation capable of making?
  - How does our method perform on Counterfact? Propagates to related info, but not as good as ROME. (However, ROME performs very poorly on ECBD.)

Code available at github.com/shankarp8/knowledge_distillation