Provable Benefits of In-Tool Learning for Large Language Models

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February 19, 2026

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Outline

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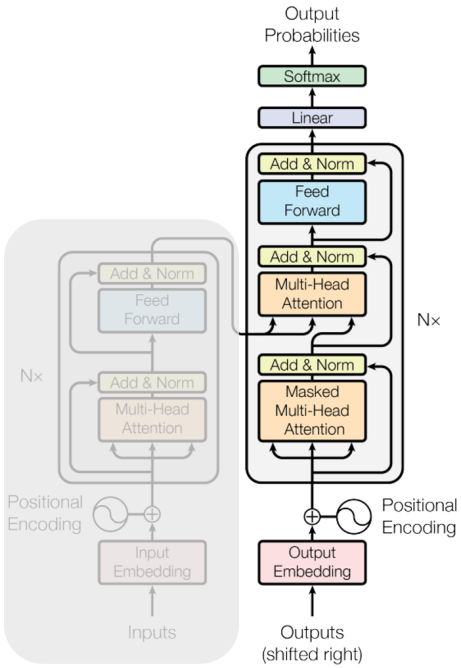
Large language models

Best models so far $\rightarrow$ autoregressive decoder-only transformers.



(Vaswani et al., 2017)

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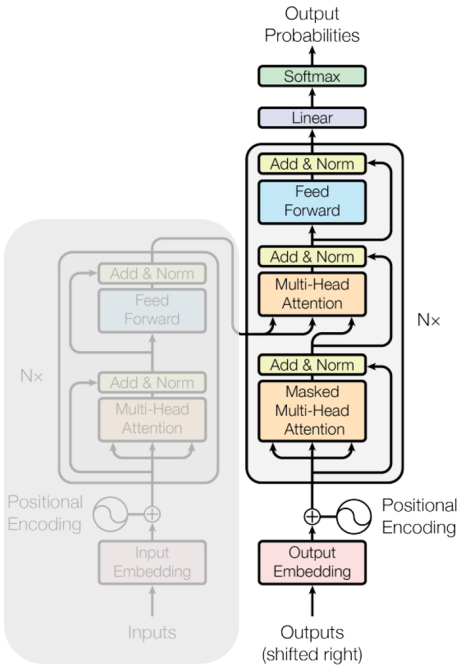

(Vaswani et al., 2017)

Vocabulary size T.
Context window K.
Parameter set Θ.

GPT-3 : $T = 50257$,
$K = 2048$ and $|\Theta| \sim 175B$

Large language models

Goal: Predict the next token based on previous ones.

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Modelization: Probability of a sequence $(x_1, x_2, \ldots, x_N)$:

$$\begin{aligned}\mathbb{P}(x_1, x_2, \ldots, x_N) &= \mathbb{P}(x_1)\mathbb{P}(x_2 \mid x_1) \cdots \mathbb{P}(x_N \mid x_1, x_2, \ldots, x_{N-1}) \\ &= \prod_{n=1}^{N} \mathbb{P}(x_n \mid x_1, x_2, \ldots, x_{n-1})\end{aligned}$$

Emerging capabilities of (static) LLMs

Large-scale pretraining unlocks emerging capabilities!

Language Models are Few-Shot Learners

Tom B. Brown* **Benjamin Mann*** **Nick Ryder*** **Melanie Subbiah***

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OpenAI

GPT3 and in-context learning (Brown et al., 2020)

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Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 = 11. The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Chain-of-thought (Wei et al., 2022)

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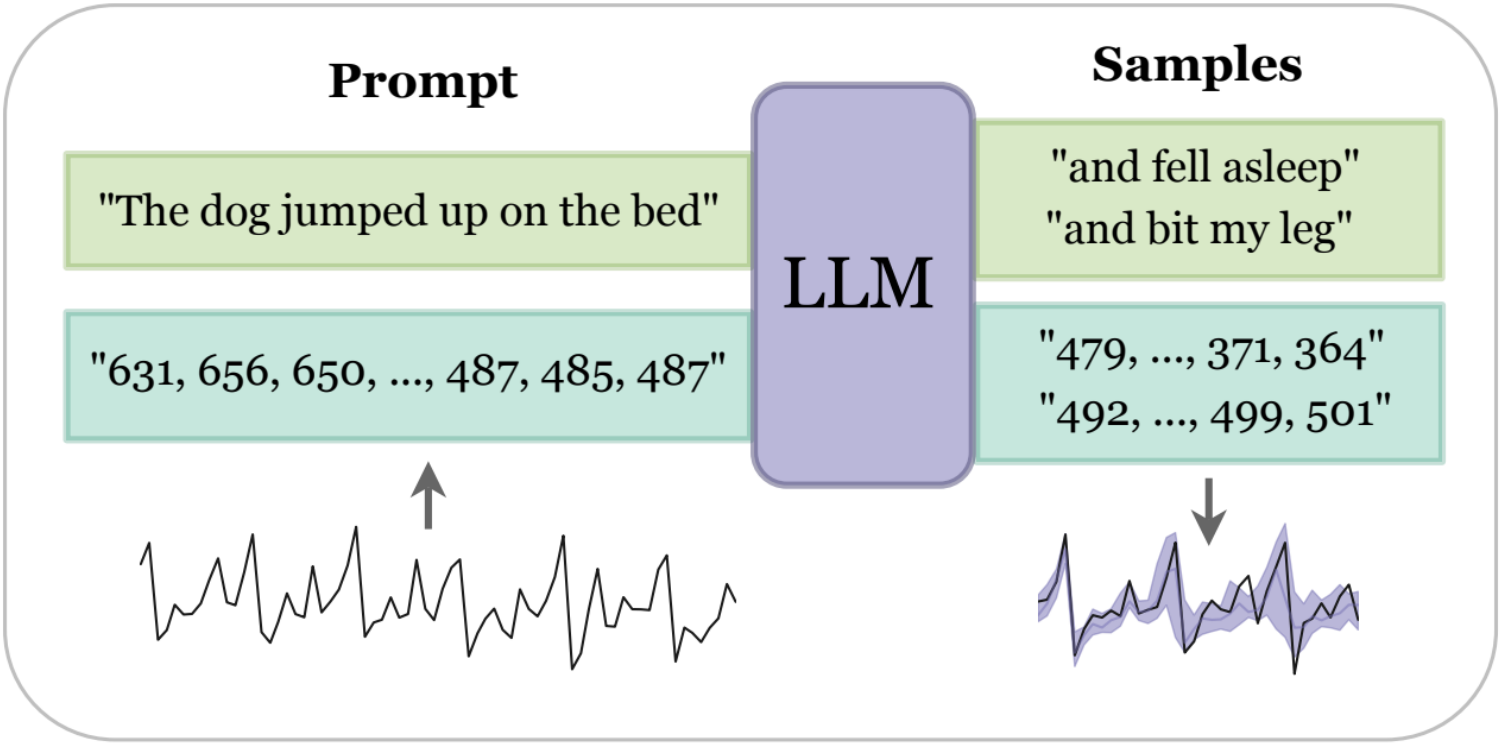

Generalization to other modalities (Gruver et al., 2023)

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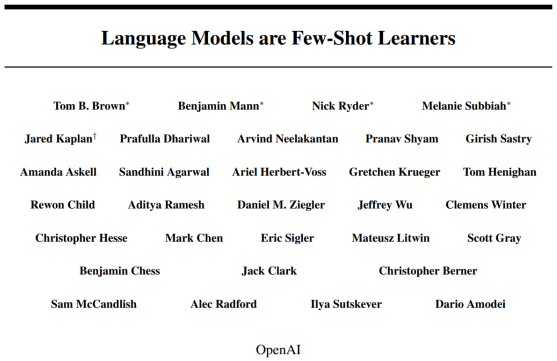

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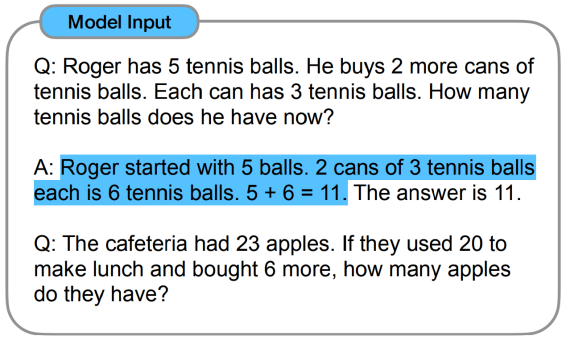
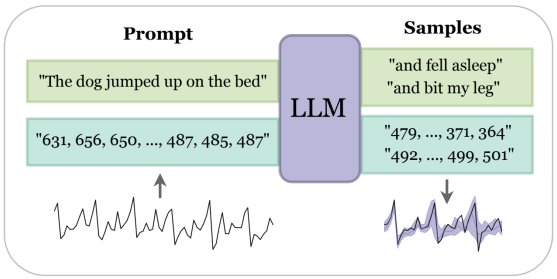
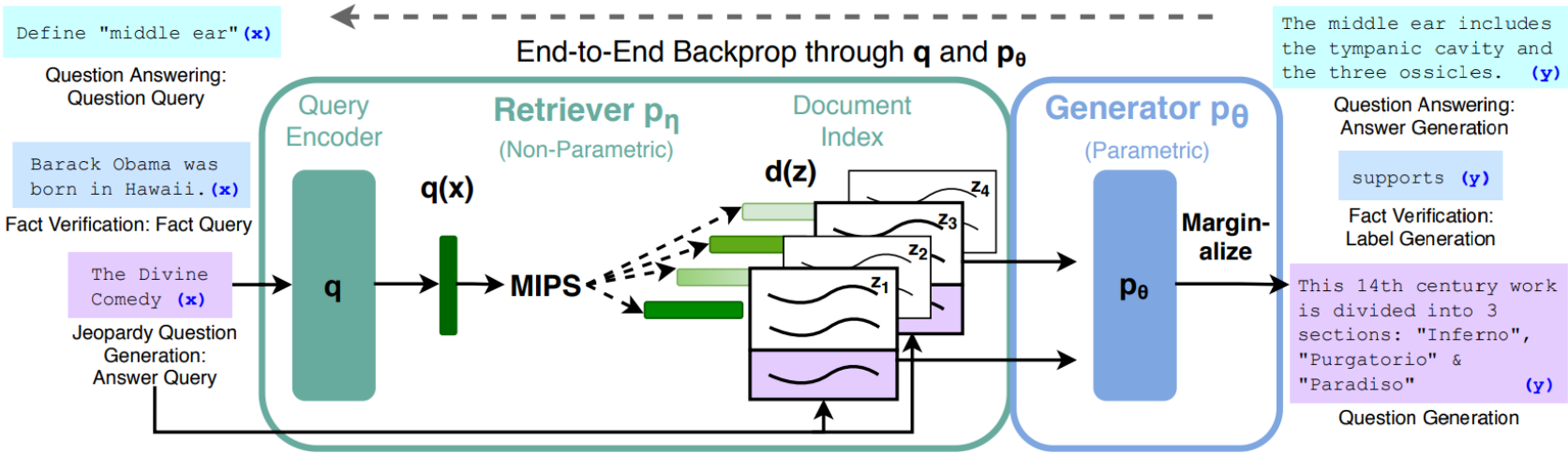




× Those methods extract knowledge from static predictors.

Towards tool-augmented LLMs workflows

Tool use to externalize memory and adapt to the context.



RAG (Lewis et al., 2020)

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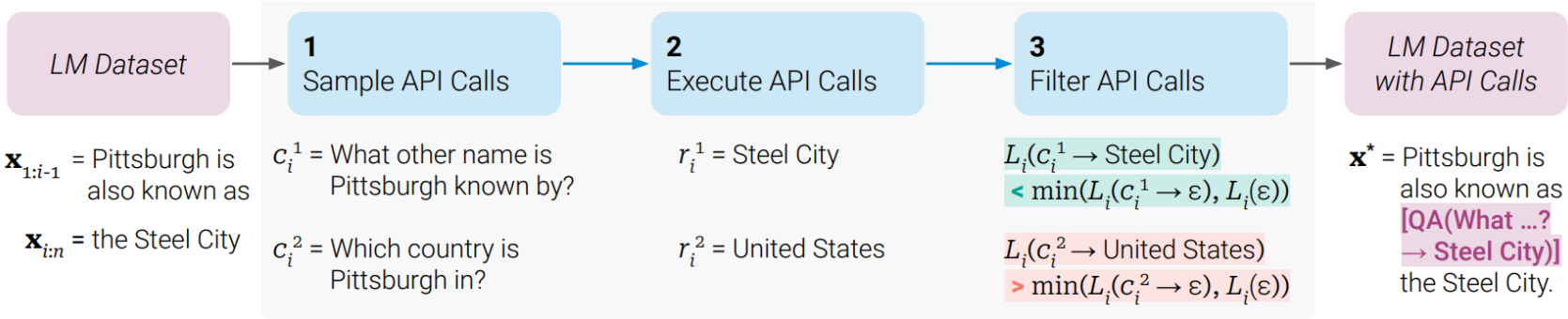

Toolformer (Schick et al., 2023)

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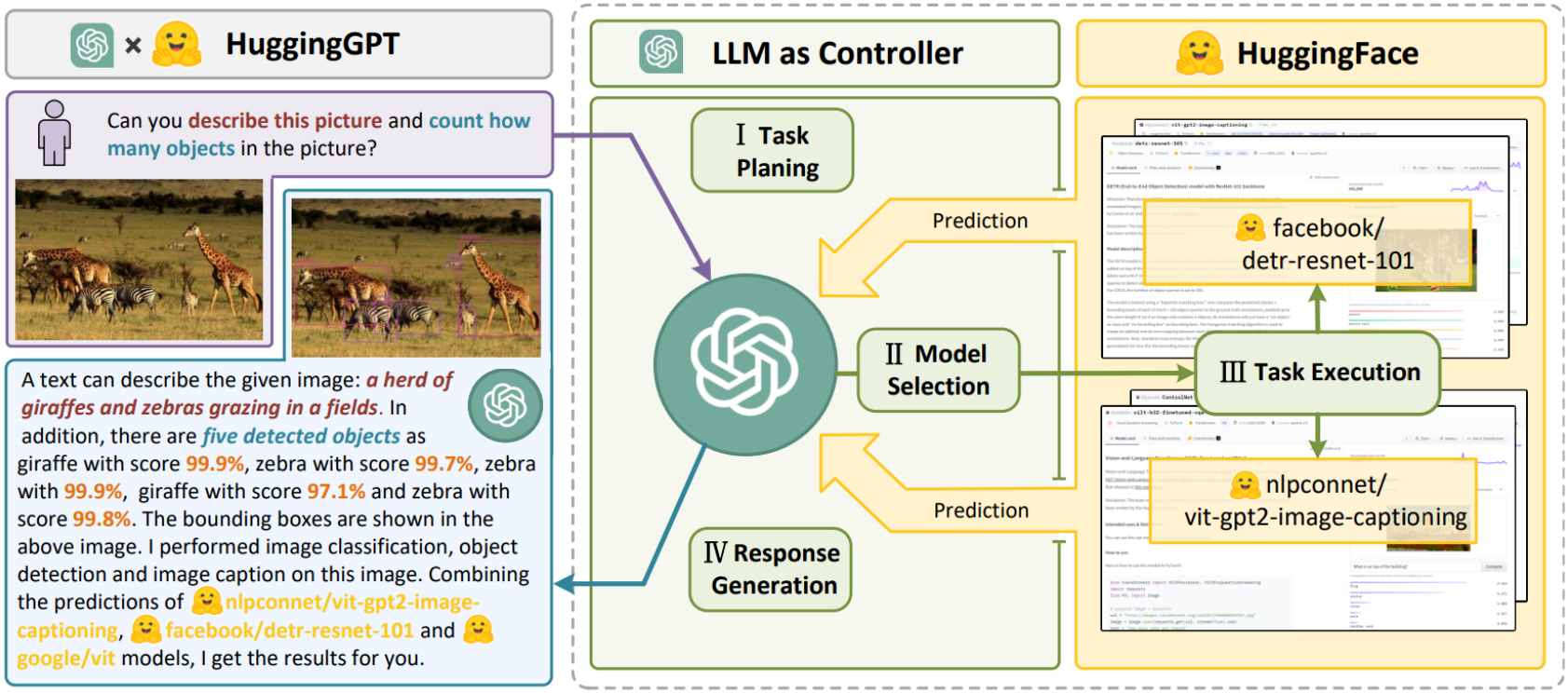

HuggingGPT (Shen et al., 2023)

Towards tool-augmented LLMs workflows

Tool use to externalize memory and adapt to the context.

- ✓ LLMs evolve towards dynamic context-aware systems,
- ✓ It allows them to reason, adapt, and act over time,
- ✓ Emergence of agentic workflows (e.g., Claude, OpenAI)

Motivation

What is the most efficient way to acquire and use knowledge?

1. In-weight learning: memorize facts in the parameters,
2. In-tool learning: learn to access external sources of truth.

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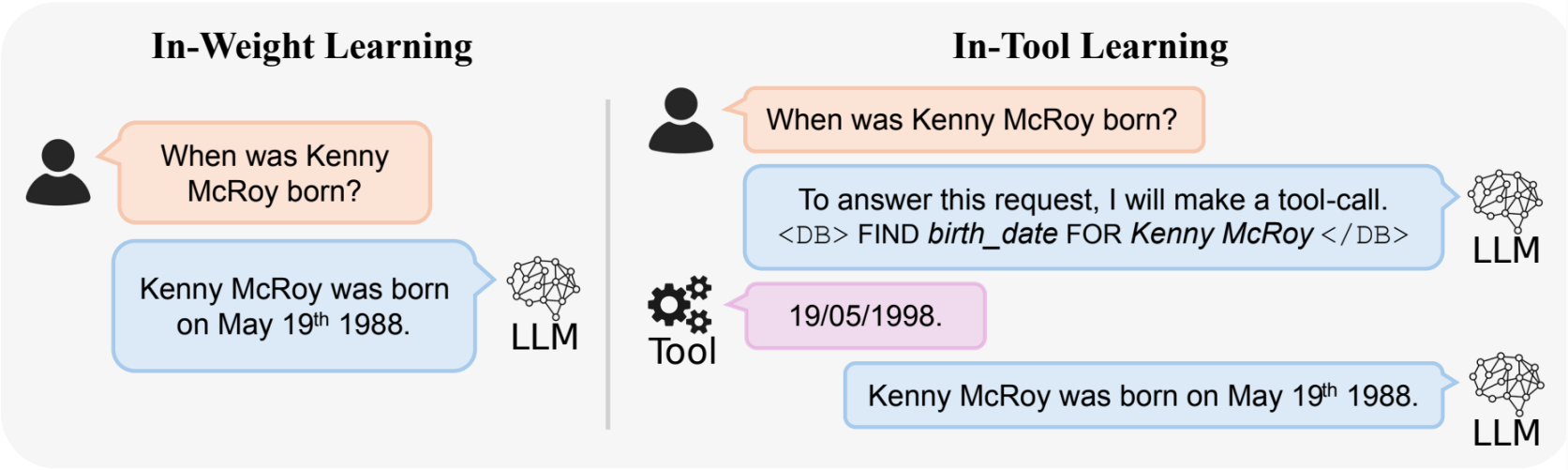

Figure: In-weight (memorization) vs. in-tool learning (external retrieval).

Outline

Knowledge representation

Factual dataset

Let $\mathcal{D}$ be a family of factual datasets D defined as finite collections of facts (n, a, v) with

- $\star$ a name $n \in \mathcal{N}$ (e.g., "Xavier Miel"),
- $\star$ an attribute $a \in \mathcal{A}$ (e.g., "birthplace"),
- $\star$ a value $v \in \mathcal{V}_a$ (e.g., "France").

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✓ Akin to Physics of Language models (Allen-Zhu et al., 2024),

✓ Allows to quantify the amount of facts ($\#\text{Facts} = |\mathcal{N} \times \mathcal{A}|$).

Factual recall

- ✓ Let $\mathcal{M}$ be the set of all transformers with a given architecture,
- ✓ Each model $f \in \mathcal{M}$ amounts to a specific choice of weights,
- ✓ Each model $f \in \mathcal{M}$ is associated with a recall rule $R(f)$.

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Recall rule

$R(f)$ is defined by prompting a model to query the value of a pair (n, a). The recall accuracy of f on a dataset D is the percentage of retrieval by $R(f)$ of the correct value v over facts $(n, a, v) \in D$.

Learnability

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Learnability

We say that the model class $\mathcal{M}$ *can solve* the recall task on the family of datasets $\mathcal{D}$ if, for each dataset $D \in \mathcal{D}$, there exists a model $f \in \mathcal{M}$ that achieves a perfect recall accuracy on D.

In-weight learning

In-weight: Train the model to generate the answer directly.

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- ✓ Templates ϕ_i for queries, ψ_i for answers,
- ✓ Query $Q = \phi_1(a) \circ \phi_2(n) \circ \phi_3(a)$,
- ✓ Answer $A = \psi_1(n) \circ \psi_2(a) \circ \psi_3(v)$.

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$$Q = \underbrace{\text{Where was}}_{\phi_1(a)} \ \underbrace{\text{Xavier Miel}}_{\phi_2(n)} \ \underbrace{\text{born?}}_{\phi_3(a)}$$

$$A = \underbrace{\text{Xavier Miel}}_{\psi_1(n)} \ \underbrace{\text{was born in}}_{\psi_2(a)} \ \underbrace{\text{France}}_{\psi_3(v)}$$

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$$T = \underbrace{\text{To answer this request, I will make a tool-call. <DB> FIND birthplace}}_{\chi_1(a)}$$
$$\underbrace{\text{FOR Xavier Miel </DB>}}_{\chi_2(n)},$$

In-weight learning vs. in-tool learning

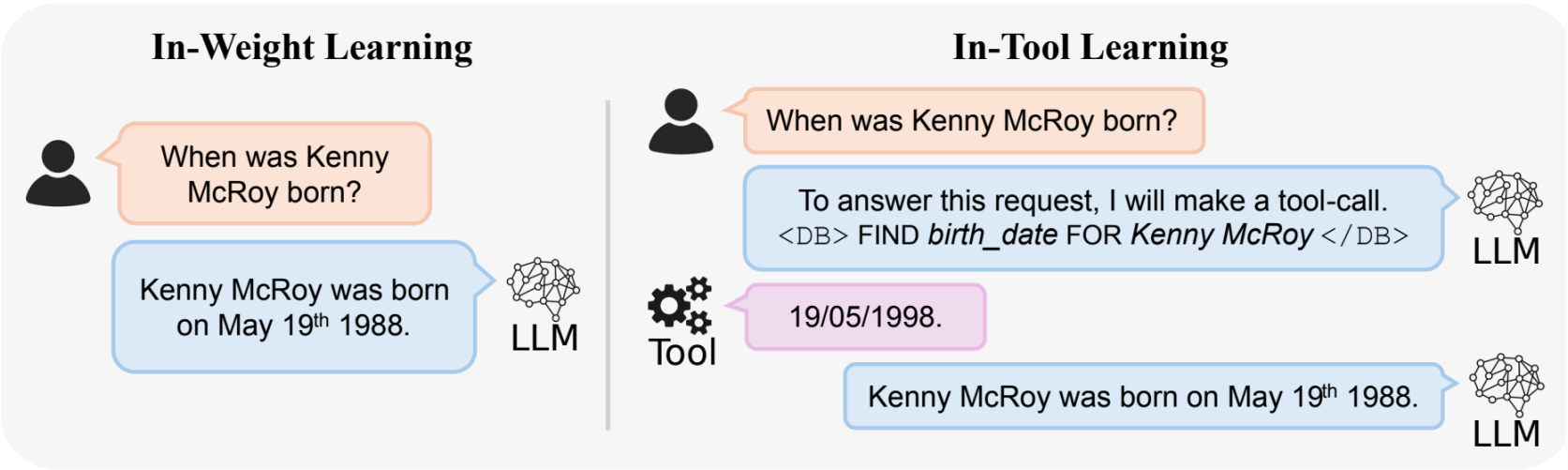

Figure: In-weight (memorization) vs. in-tool learning (external retrieval).

Beyond open-ended questions

Extension to, e.g., boolean: "Is Paris the capital of France?"

- ✓ $\phi_1(a) =$ is, $\phi_2(n) = \mathrm{Paris}$, $\phi_3(a) =$ the capital of France,
- ✓ Define query as before $Q = \phi_1(a) \circ \phi_2(n) \circ \phi_3(a)$;
- ✓ ψ_1 a binary function outputting "Yes" or "No",
- ✓ Define answer as before $A = \psi_1(a, n) \in \{\mathrm{Yes}, \mathrm{No}\}$.

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Limitations of in-weight learning

In-weight memorization is limited by the size of models.

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Theorem (In-weight lower bound - informal)

Let $\mathcal{M}$ be a set of transformers with P parameters and $\mathcal{D}$ be a family of factual datasets. If $\mathcal{M}$ can solve the recall task only with in-weight learning, then the number of parameters P must satisfy:

$$P \geq \mathcal{O}(\#Facts).$$

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- ✗ When the number of facts grows, memorization is impossible,
- ✗ Architectural changes or external memory are needed.

Benefits of in-tool learning

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Let $\mathcal{D}$ be a family of factual datasets. Then, there exists a transformer with at most $\bar{P}$ parameters that can solve the recall task if augmented with the proper retrieval tool.

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Theorem (In-tool upper bound - informal)

Let $\mathcal{D}$ be a family of factual datasets. Then, there exists a transformer with at most $\bar{P}$ parameters that can solve the recall task if augmented with the proper retrieval tool.

- ✓ Model's size $\bar{P}$ independent of the number of people $|\mathcal{N}|$,
- ✓ No additional parameters needed when number of facts grows.

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Pretraining small language models on factual datasets.

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Empirical validation of the lower and upper bounds.

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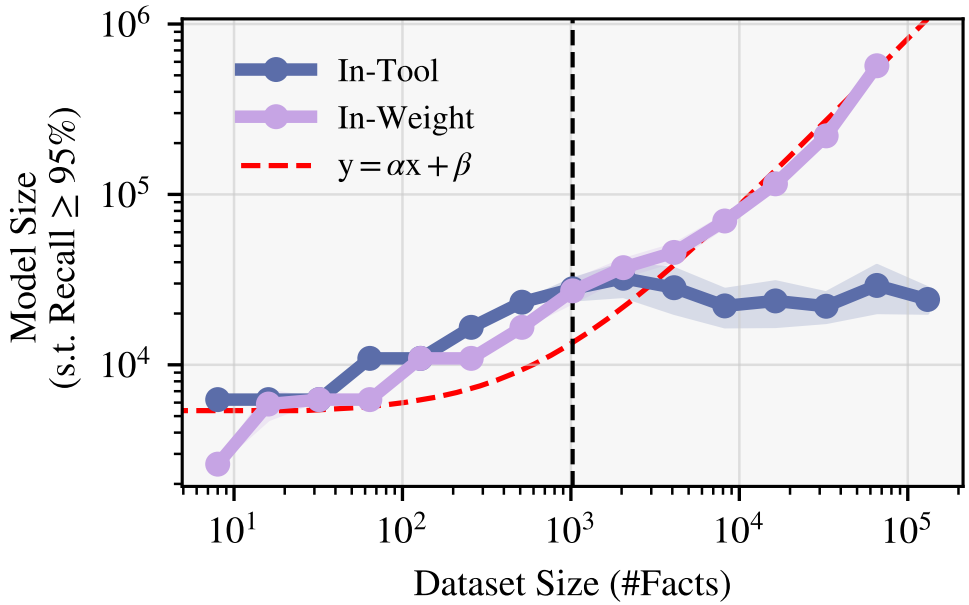

Figure: Minimal model size P to achieve at least a 95% recall.

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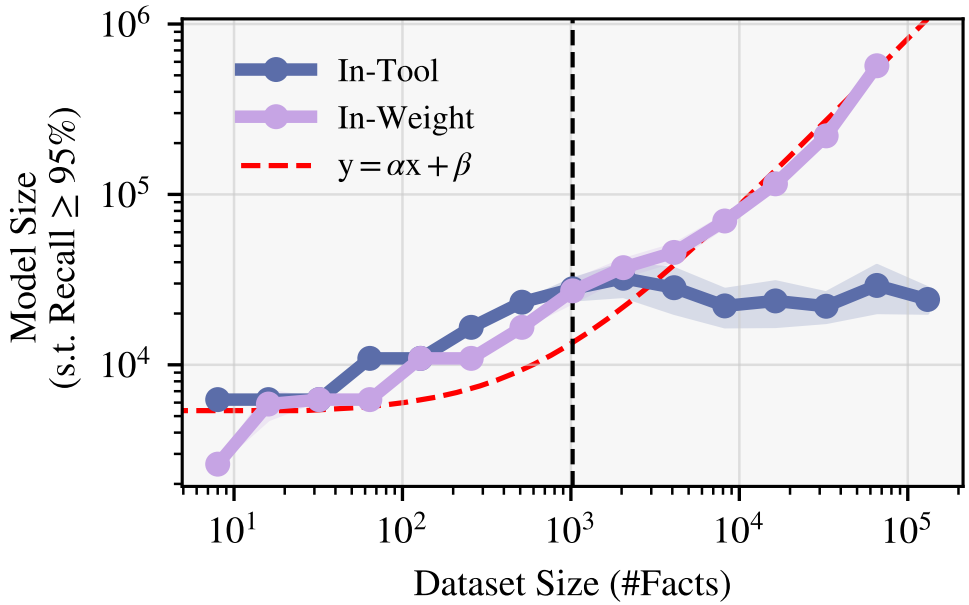

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✗ In-weight scales linearly with the number of facts,

✓ In-tool remains constant after a critical dataset size.

Transition from memorization to retrieval

In-tool models transition from memorization to rule learning.

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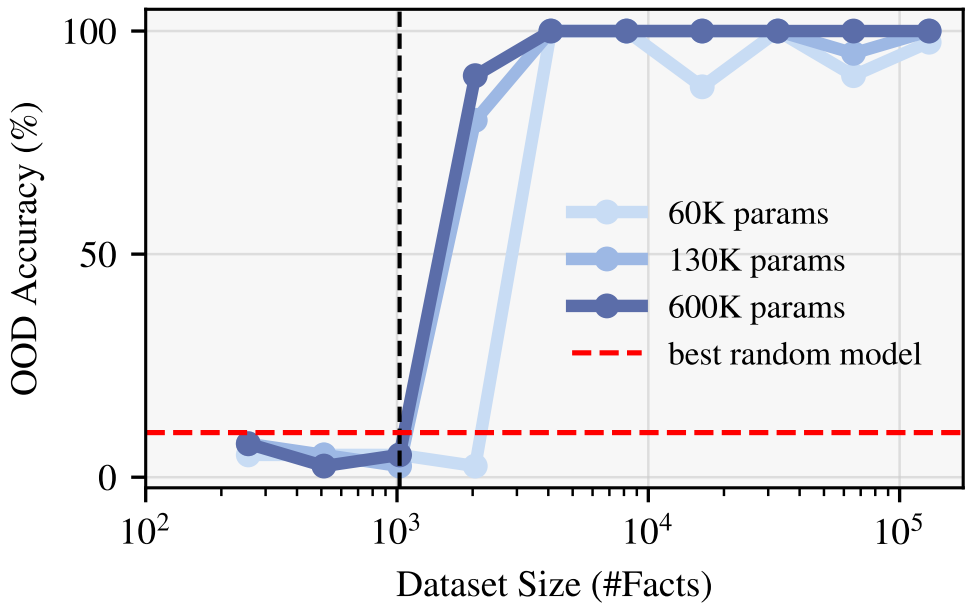

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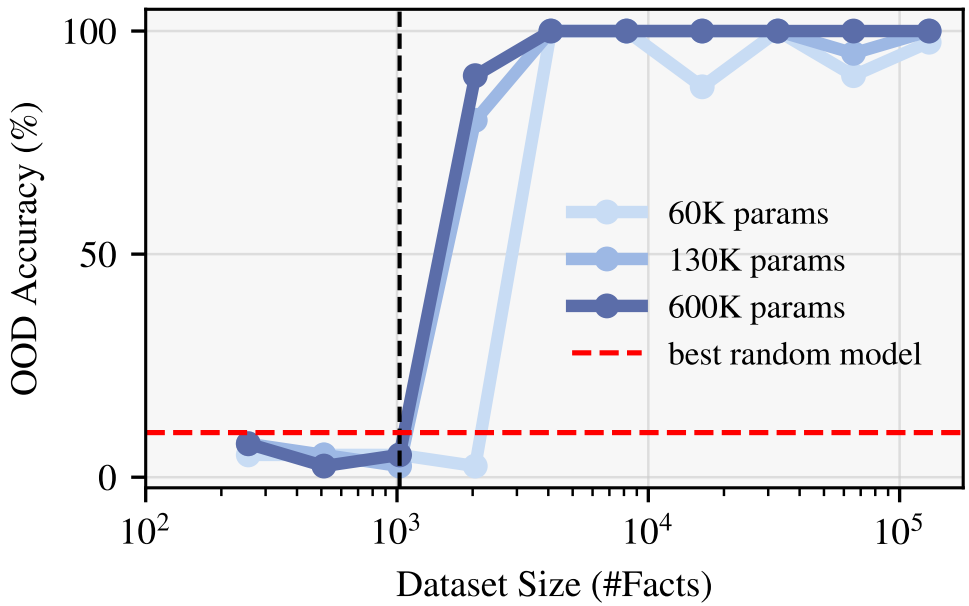

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✗ Models start to memorize facts, similar to in-weight learning,

✓ After the transition, models learn to formulate in-tool queries.

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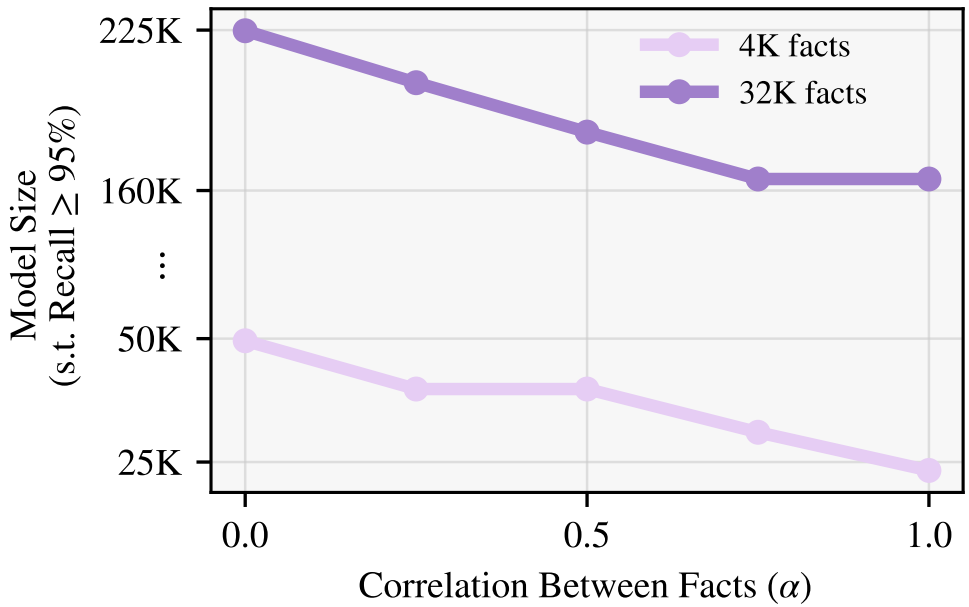

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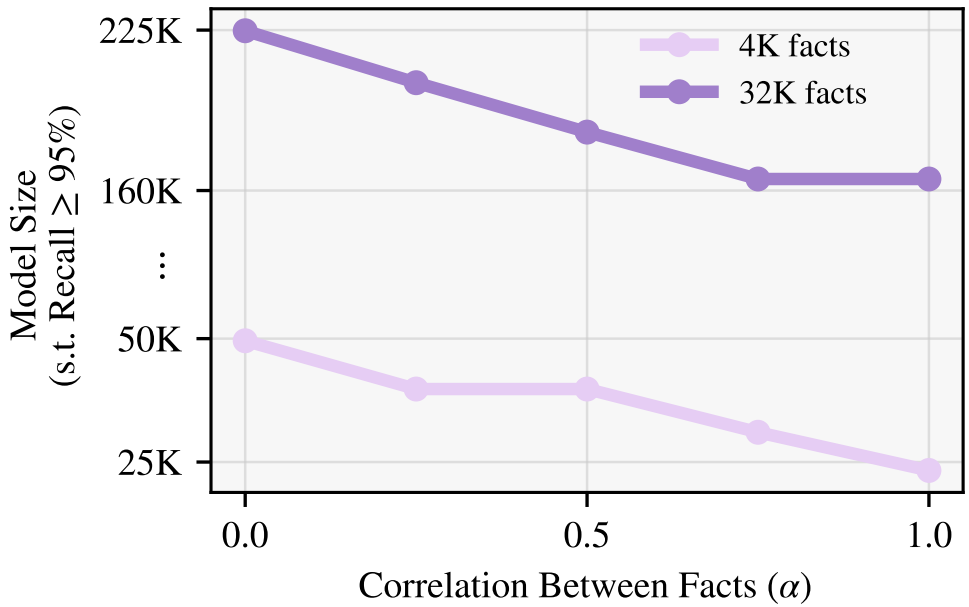

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✓ Correlation breaks independence between triplets (n, a, v),

✓ Reduced number of "effective" facts, easier to store.

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- ✓ Evaluation with LM Evaluation Harness.

Learning while preserving prior capabilities

In-tool preserves capabilities while learning new facts.

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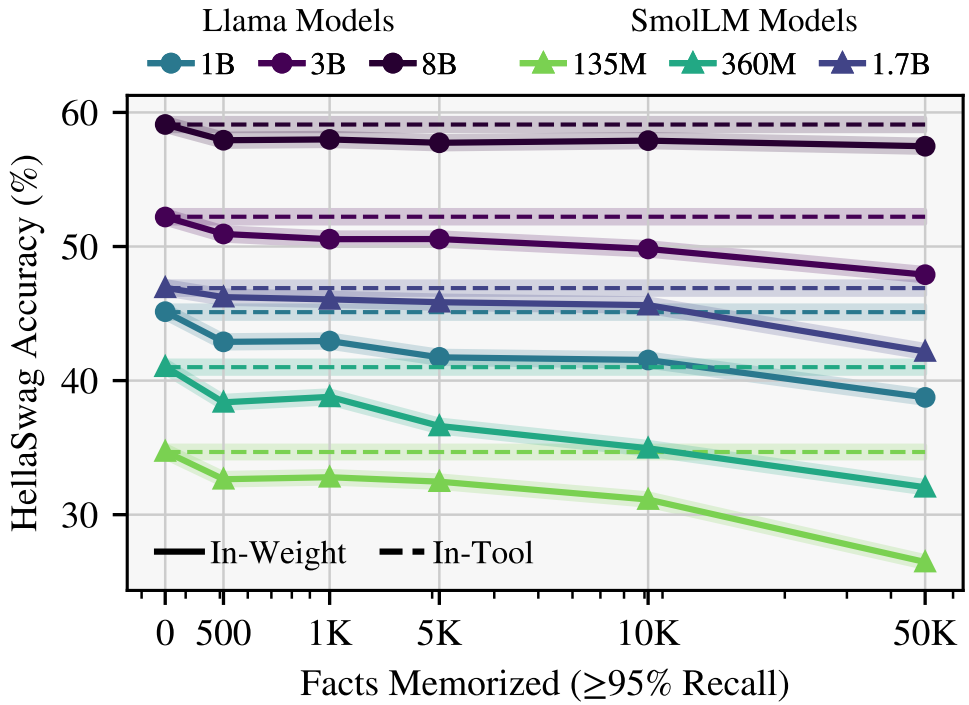

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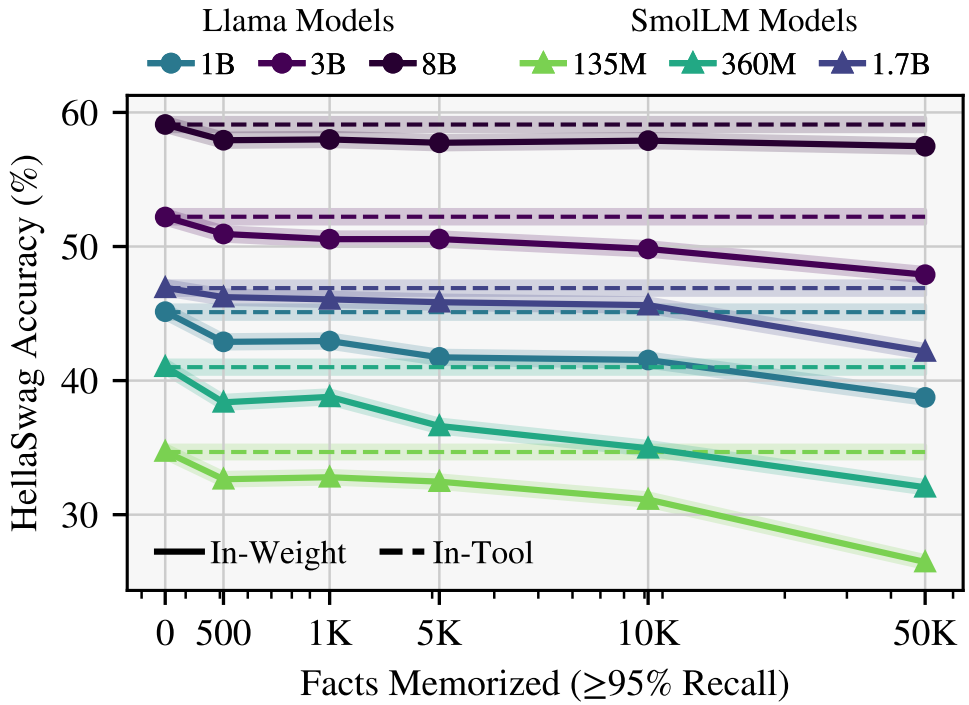

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✗ In-weight learning impacts prior knowledge due to overloading,

✓ In-tool learning enables scalability without forgetting.

Token distribution changes

In-tool learning helps preserve models' behavior.

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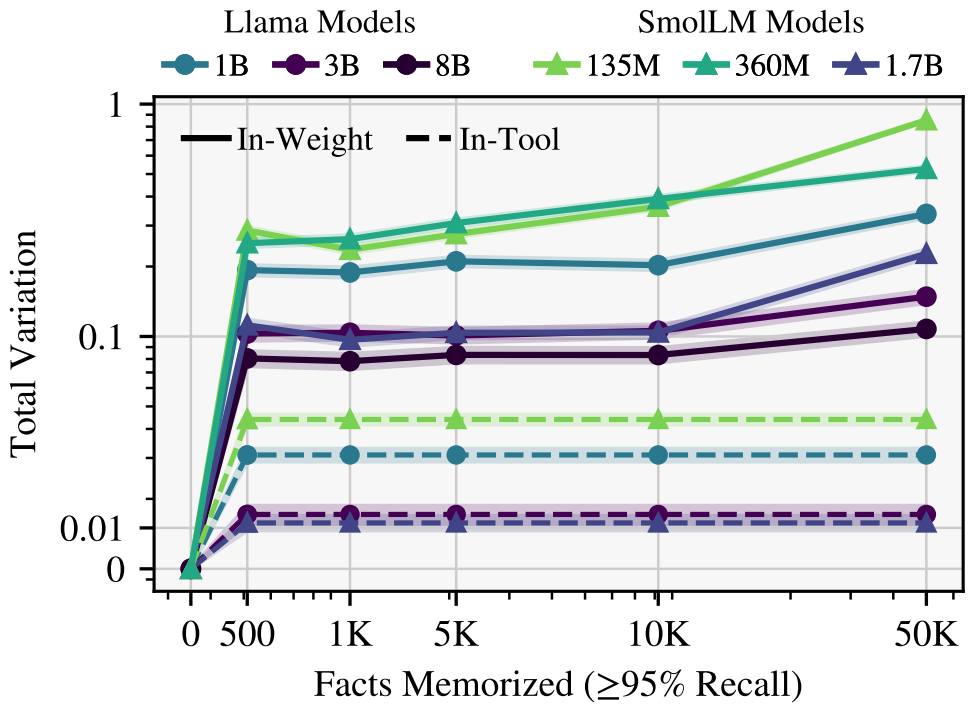

Figure: TV distance between base and finetuned models' distributions.

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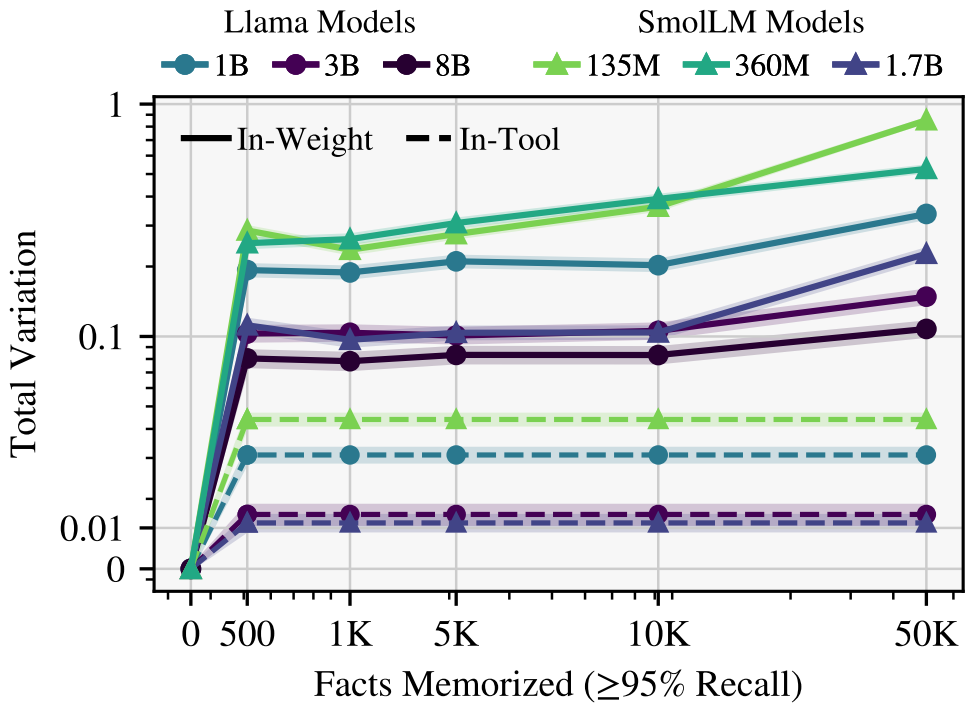

Figure: TV distance between base and finetuned models' distributions.

✗ In-weight learning alters models' token distribution,

✓ In-tool models remain close to the base models.

Efficiency-tradeoffs

In-tool learning requires less training compute than in-weight.

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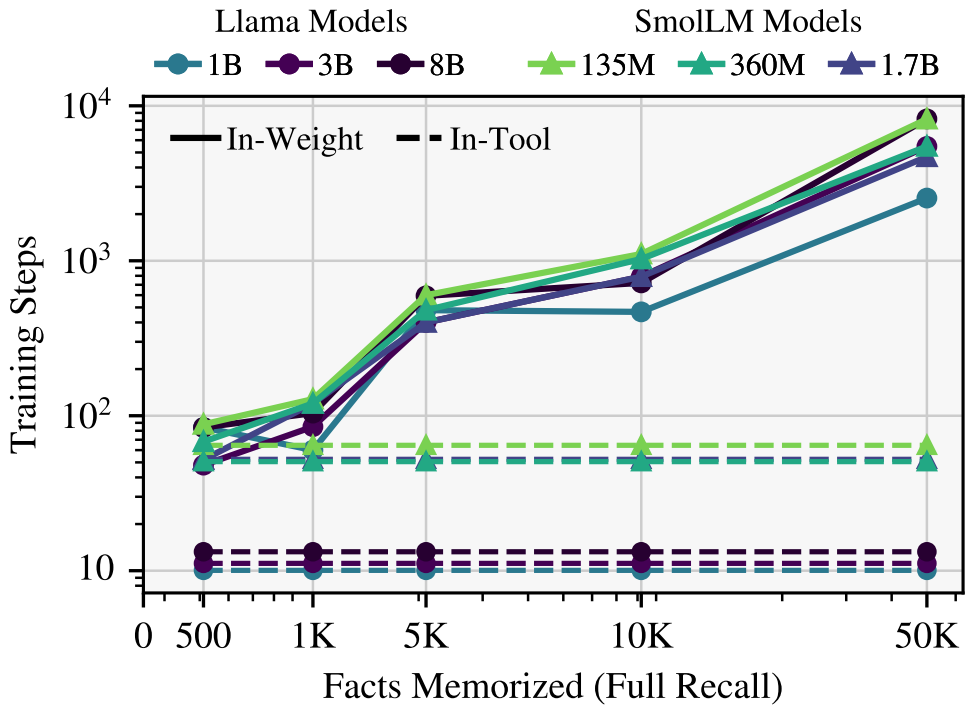

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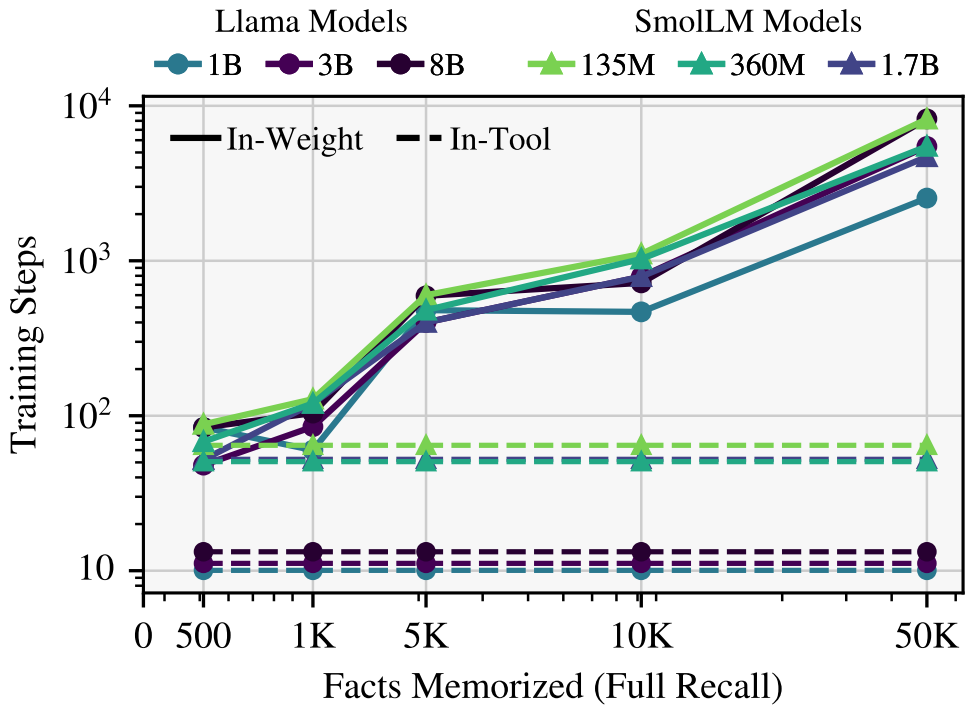

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✗ Memorizing individual facts requires many training steps,

✓ Learning to use a tool requires very few training steps.

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Take Home Message

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Montaigne, Les Essais

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- ✓ In-weight learning is fundamentally limited by models' size,
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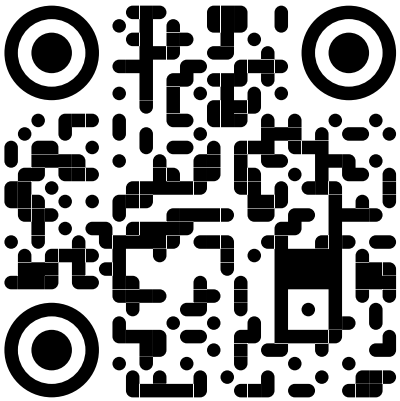
Better to learn to use tools than to memorize facts.

Going further

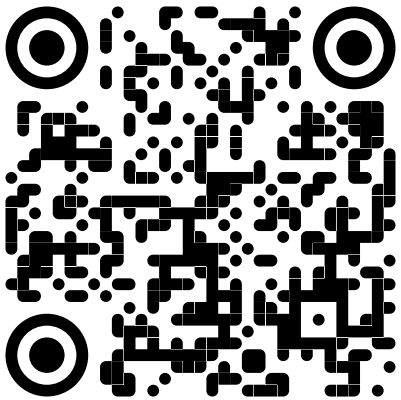
- ✓ Additional QA types (e.g., boolean, multiple choices),
- ✓ Additional tools use (e.g., Python interpreter, internet access),
- ✓ Extension to complex LLM agents.

To Know More

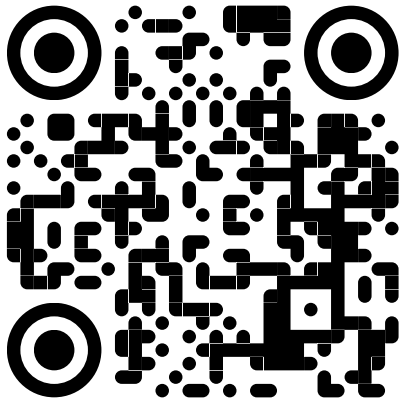
Check out the paper and code if you want to know more!



paper

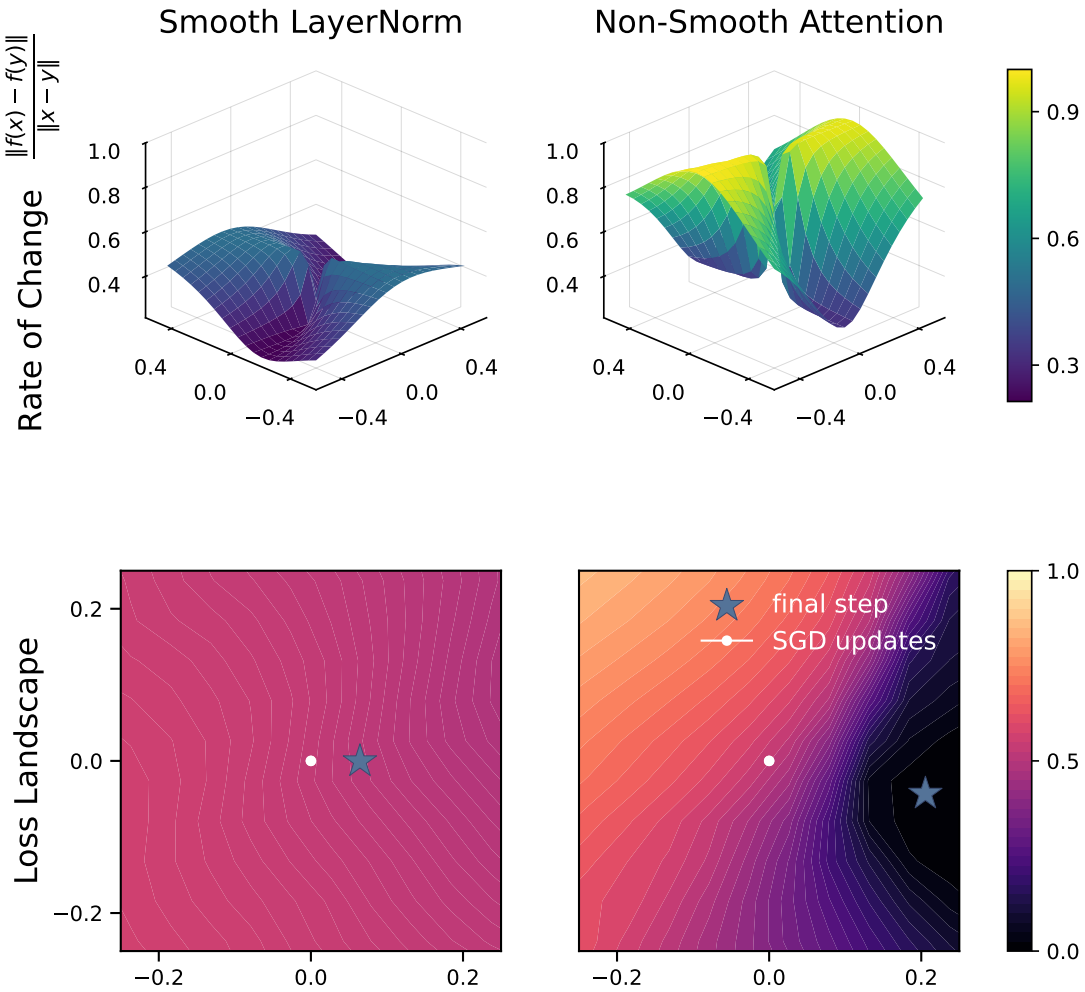


code



website

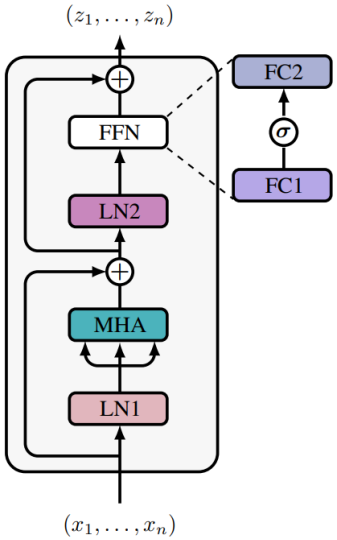
Vision Transformer Benefits from Non-Smooth Components

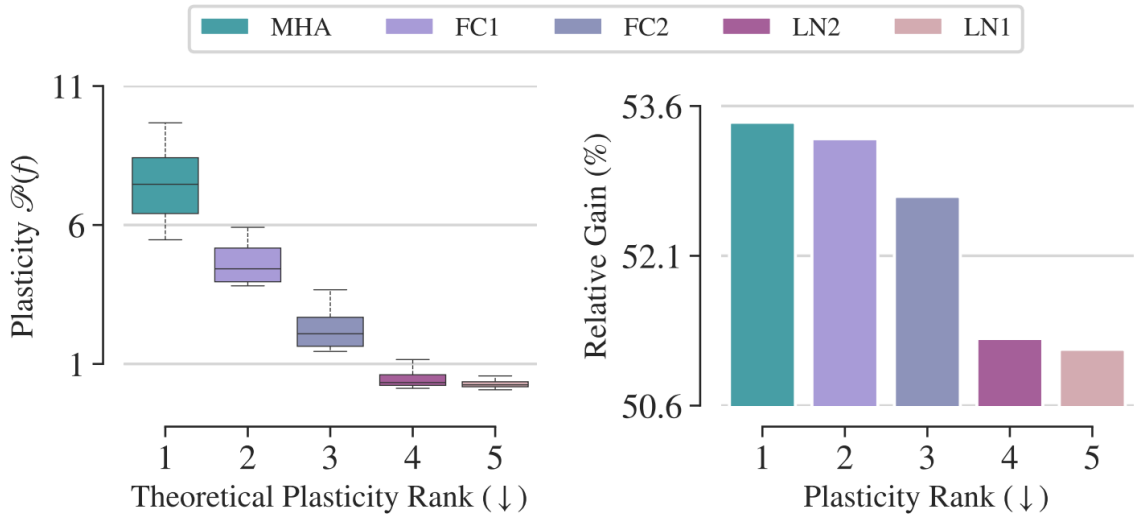


paper - code

Self-Promotion

Finetuning high-plasticity components (non-smooth) yields larger performance gains than the stiff ones.





paper - code

Thanks for your attention!