# Provable Benefits of In-Tool Learning for Large Language Models

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# Outline

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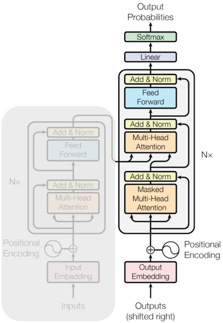
**Best models so far** → autoregressive decoder-only transformers.




(Vaswani et al., 2017)

# Large language models

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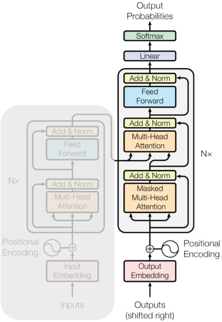


(Vaswani et al., 2017)

Vocabulary size $T$.
Context window $K$.
Parameter set $\boldsymbol{\Theta}$.

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

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

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

## Large-scale pretraining unlocks emerging capabilities!

**Language Models are Few-Shot Learners**

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

**Jared Kaplan†** **Prafulla Dhariwal** **Arvind Neelakantan** **Pranav Shyam** **Girish Sastry**

**Amanda Askell** **Sandhini Agarwal** **Ariel Herbert-Voss** **Gretchen Krueger** **Tom Henighan**

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**Sam McCandlish** **Alec Radford** **Ilya Sutskever** **Dario Amodei**

OpenAI

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

# Emerging capabilities of (static) LLMs

**Large-scale pretraining unlocks emerging capabilities!**

**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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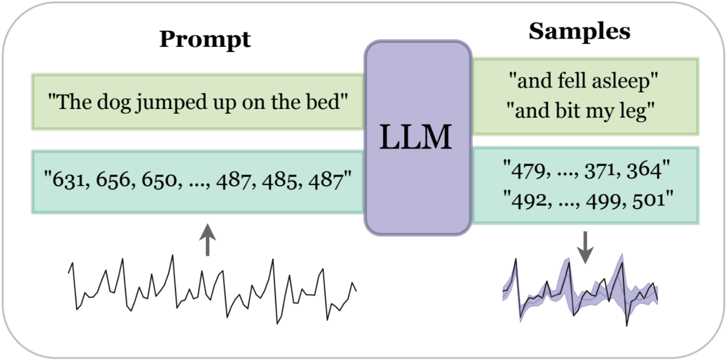


Generalization to other modalities (Gruver et al., 2023)

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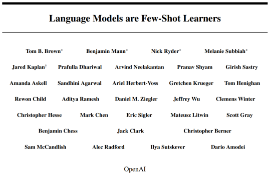

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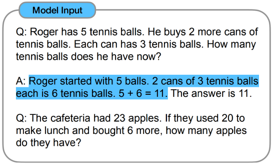
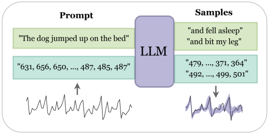
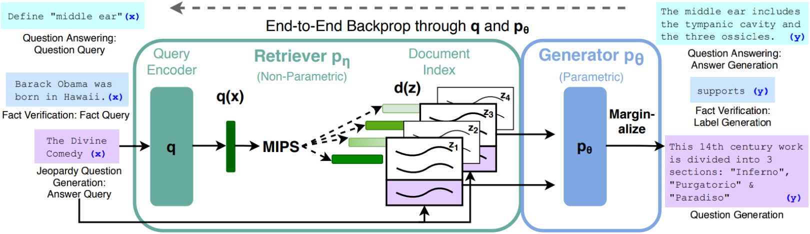



× Those methods extract knowledge from static predictors.

**Tool use to externalize memory and adapt to the context.**




RAG (Lewis et al., 2020)

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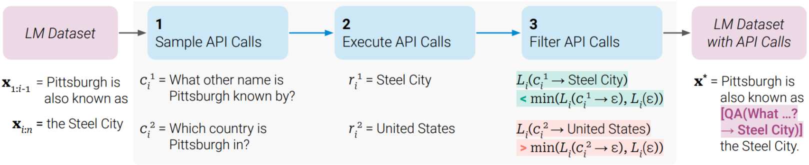


Toolformer (Schick et al., 2023)

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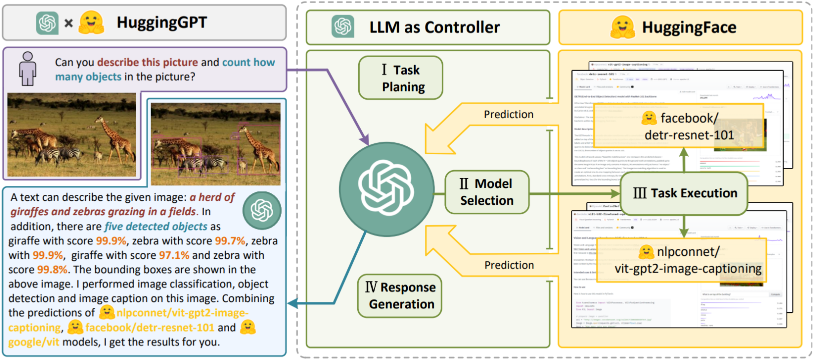


HuggingGPT (Shen et al., 2023)

# 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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2. In-tool learning: learn to access external sources of truth.

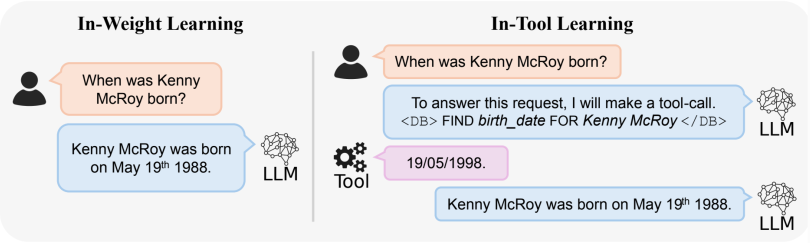


Figure: In-weight (memorization) vs. in-tool learning (external retrieval).

# 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

- ⋆ a name $n \in \mathcal{N}$ (e.g., "Kim Perial"),
- ⋆ an attribute $a \in \mathcal{A}$ (e.g., "birthplace"),
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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

- ✓ Let $\mathcal{M}$ be the set of all transformers with a given architecture,
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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

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- ✓ Templates $\phi_i$ for queries, $\psi_i$ for answers,
- ✓ Query $Q = \phi_1(a) \circ \phi_2(n) \circ \phi_3(a)$,
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$$Q = \underbrace{\text{Where was}}_{\phi_1(a)} \ \underbrace{\text{Kim Perial}}_{\phi_2(n)} \ \underbrace{\text{born?}}_{\phi_3(a)}$$

$$A = \underbrace{\text{Kim Perial}}_{\psi_1(n)} \ \underbrace{\text{was born in}}_{\psi_2(a)} \ \underbrace{\text{United Kingdom}}_{\psi_3(v)}$$

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

$$\underbrace{\text{FOR Kim Perial </DB>}}_{\chi_2(n)},$$

# In-weight learning vs. in-tool learning

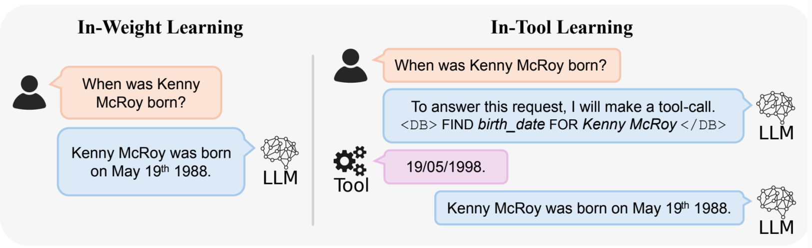


Figure: In-weight (memorization) vs. in-tool learning (external retrieval).

# Beyond open-ended questions

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

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

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# Limitations of in-weight learning

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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:*

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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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# Controlled experiments

**Pretraining small language models on factual datasets.**

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- ✓ Tool is an SQL agent that queries an external database.

# Scaling of parameter requirements

**Empirical validation of the lower and upper bounds.**

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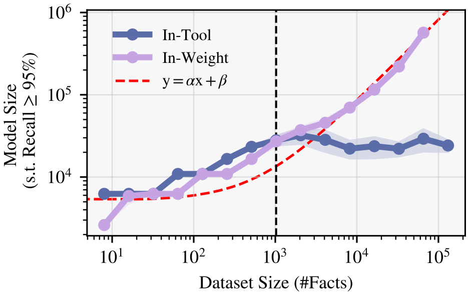


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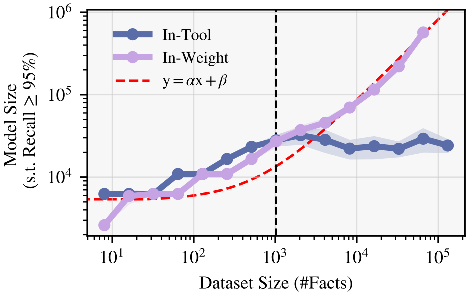


Figure: Minimal model size $P$ to achieve at least a $95\%$ recall.

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

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

# Transition from memorization to retrieval

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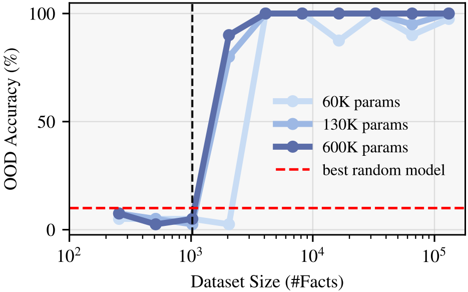


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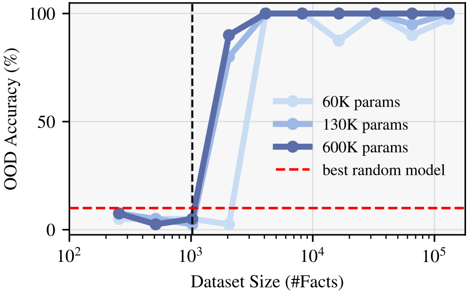


Figure: In-tool recall accuracy on out-of-distribution databases.

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

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

# What counts as a fact?

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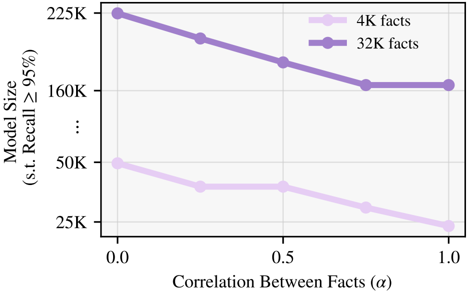


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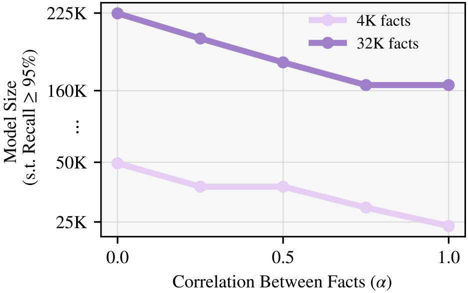


Figure: Minimal model size $P$ to achieve at least a $95\%$ recall.

- ✓ 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.

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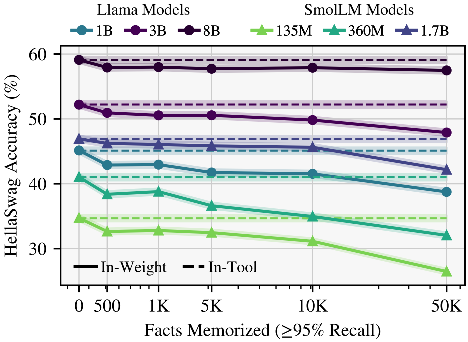


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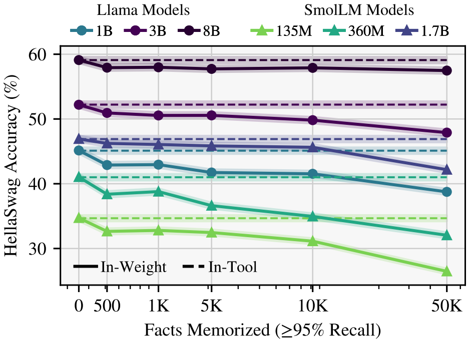


Figure: Hellaswag accuracy of models finetuned on factual datasets.

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

✓ In-tool learning enables scalability without forgetting.

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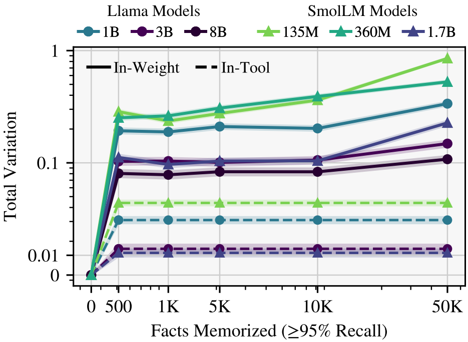


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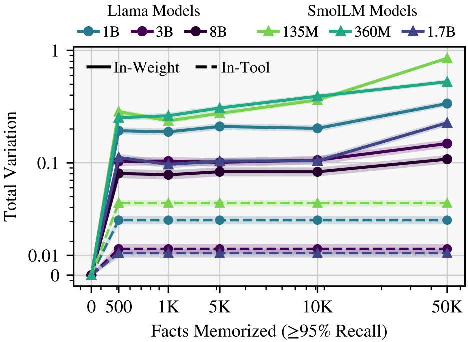


Figure: TV distance between base and finetuned models' distributions.

× 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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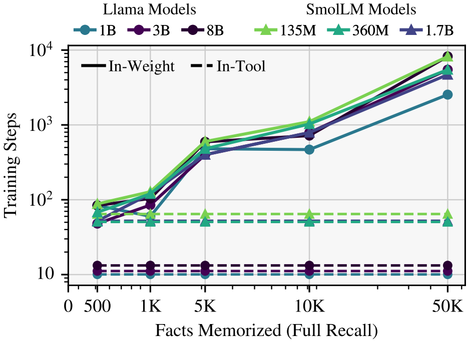


Figure: Training steps required to achieve a $100\%$ recall.

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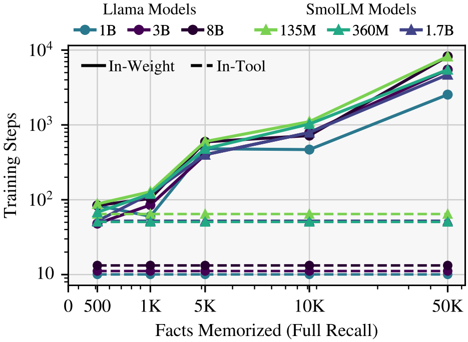


Figure: Training steps required to achieve a $100\%$ recall.

- × Memorizing individual facts requires many training steps,
- ✓ Learning to use a tool requires very few training steps.

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# Take Home Message

*Mieux vaut une tête bien faite qu'une tête bien pleine.*

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Montaigne, Les Essais

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**Better to learn to use tools than to memorize facts.**

# Going further

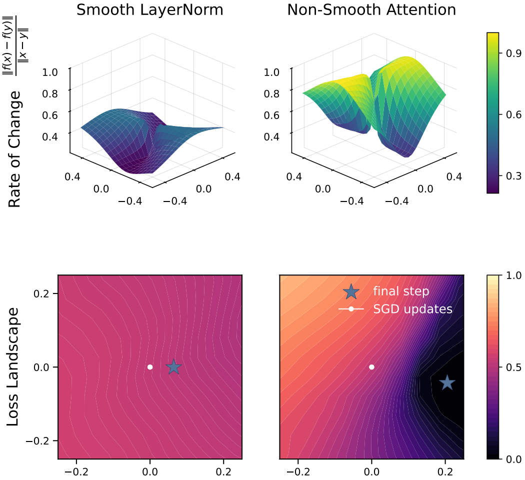
- ✓ Additional QA types (e.g., boolean, multiple choices),
- ✓ Additional tools use (e.g., Python interpreter, internet access),
- ✓ Extension to complex LLM agents.

# To Know More

This paper has been accepted at ICLR 2026 Workshop on MemAgents. Check it out along with the code to know more!

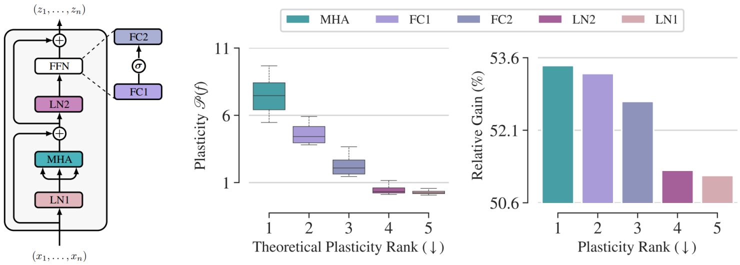
paper    code    website

## Vision Transformer Benefits from Non-Smooth Components




paper - code

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

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Thanks for your attention!