Vision Transformer Finetuning Benefits from Non-Smooth Components

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Outline

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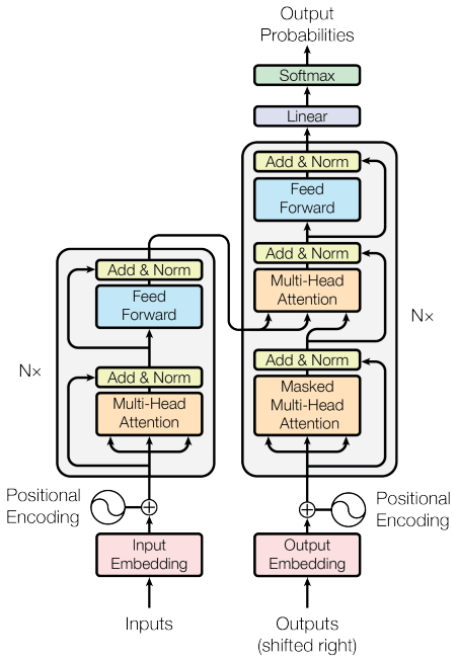
Foundation models

Most foundation models are based on the transformer architecture.



(Vaswani et al., 2017)

Foundation models

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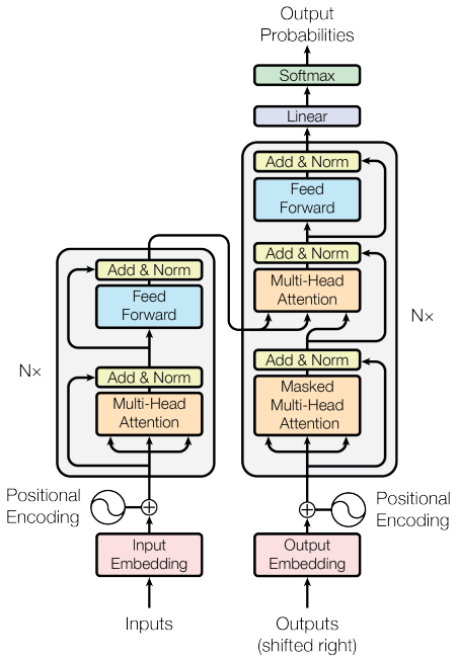
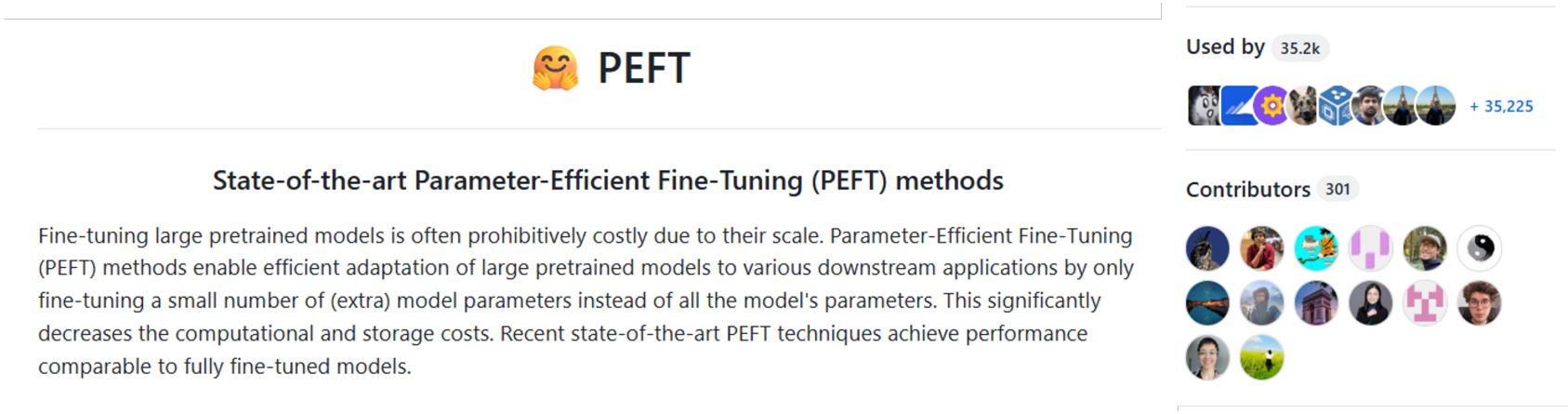


(Vaswani et al., 2017)

- Diverse training data
- Large scale pretraining
- (Very) large models

Finetuning foundation models

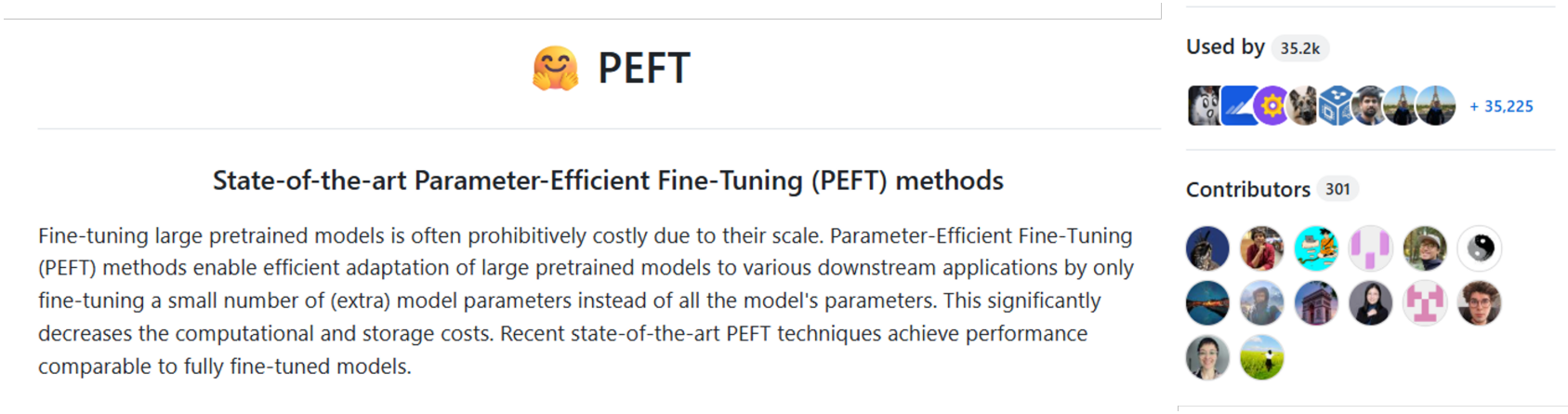
- ✗ Need of specialized models in practice
- ✗ Increasing cost of adaptation with models growing larger



Plethora of parameter-efficient finetuning methods

Finetuning foundation models

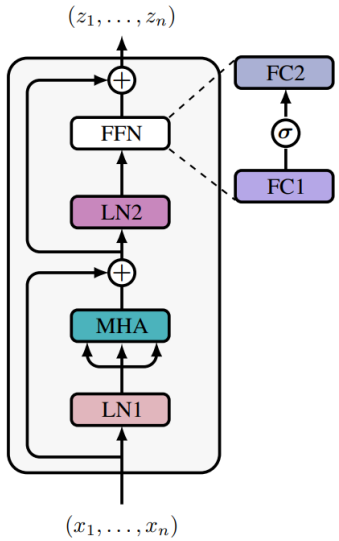
- ✗ Need of specialized models in practice
- ✗ Increasing cost of adaptation with models growing larger

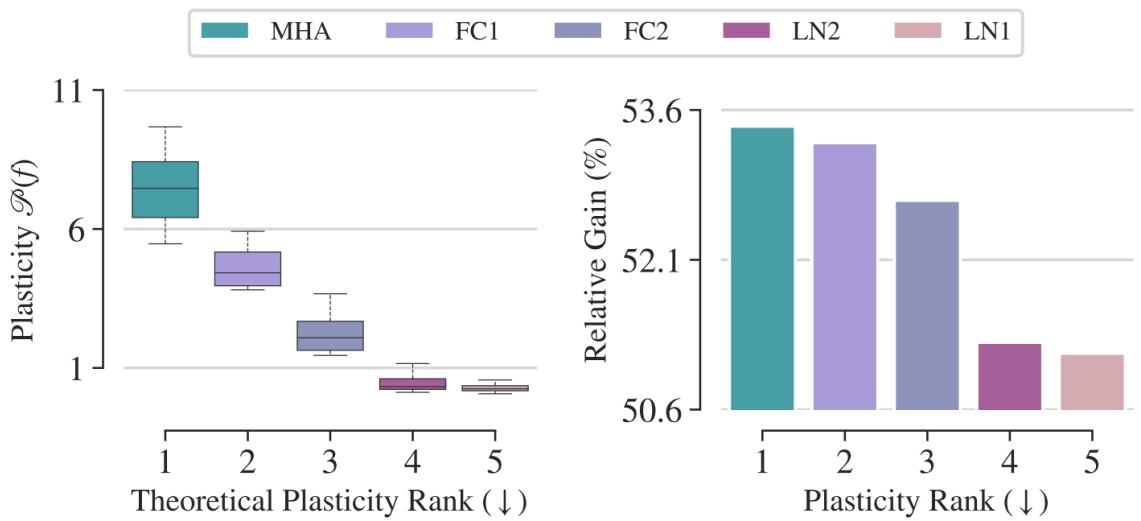


Which transformer components should be prioritized during finetuning and why?

Our contributions

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

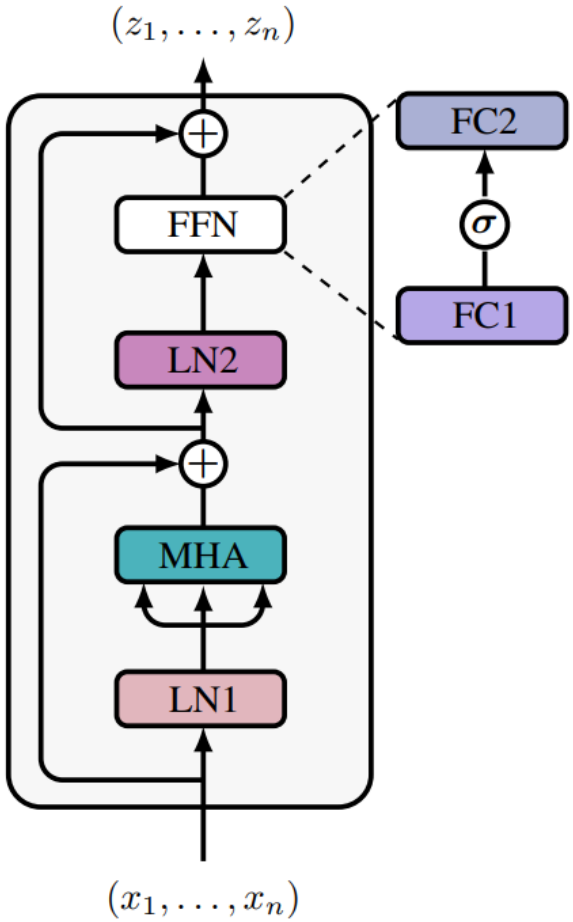




Outline

Vision transformer

- Inputs are 2D images
- Images split into patches
- Tokens are flattened patches
- Encoder-only architecture



Smoothness intuition

Smoothness is connected to differentiability, robustness to input perturbations and Lipschitz continuity.

Definition (Lipschitz continuity)

The smallest constant K such that

$$\forall x, y \in (\mathbb{R}^d)^n, \|f(x) - f(y)\|_{\mathrm{F}} \leq K\|x - y\|_{\mathrm{F}}$$

is called the Lipschitz constant of f and writes

$$\mathrm{Lip}(f) = \sup_{x \neq y \in (\mathbb{R}^d)^n} \frac{\|f(x) - f(y)\|_{\mathrm{F}}}{\|x - y\|_{\mathrm{F}}}.$$

Smoothness intuition

Promoting smoothness by regularizing the Lipschitz constant reduces the sensitivity to input perturbations.

✓ Good for training stability and adversarial robustness,

× Too much smoothness constrain adaptability to new tasks,

→ Identify components with too small Lipschitz constants.

Plasticity measure

Definition (Plasticity)

Let ν be the uniform distribution over the set of distinct pairs of sequences of tokens in $(\mathbb{R}^d)^n$. We define the plasticity of a transformer component f as

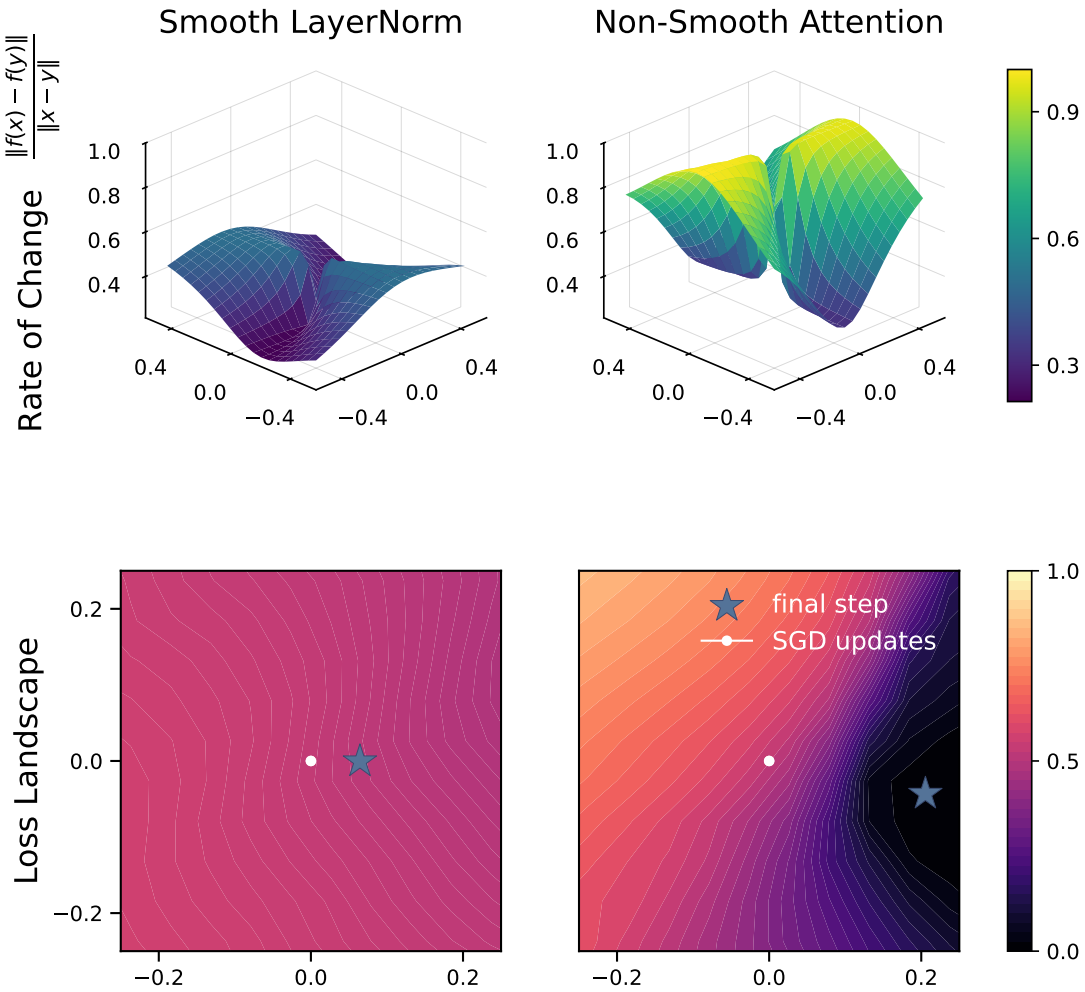
$$\mathscr{P}(f) = \mathbb{E}_{(x,y)\sim\nu}\left[\frac{\|f(x) - f(y)\|_{\mathrm{F}}}{\|x - y\|_{\mathrm{F}}}\right].$$

- ✓ For any component f, we have $\mathscr{P}(f) \leq \mathrm{Lip}(f)$,
- ✓ If $\mathscr{P}(f) < 1$, the module f contracts the changes in inputs,
- ✓ If $\mathscr{P}(f) > 1$, f amplifies the input perturbations
- ✓ When $\mathscr{P}(f) > 1$, $\mathrm{Lip}(f)$ is pushed from below.

Connection to finetuning

- ✓ High plasticity $\rightarrow$ high sensitivity to input changes,
- ✓ High plasticity $\rightarrow$ high Lipschitz constant $\rightarrow$ low smoothness,
- ✓ High plasticity $\rightarrow$ faster and better adaptation.

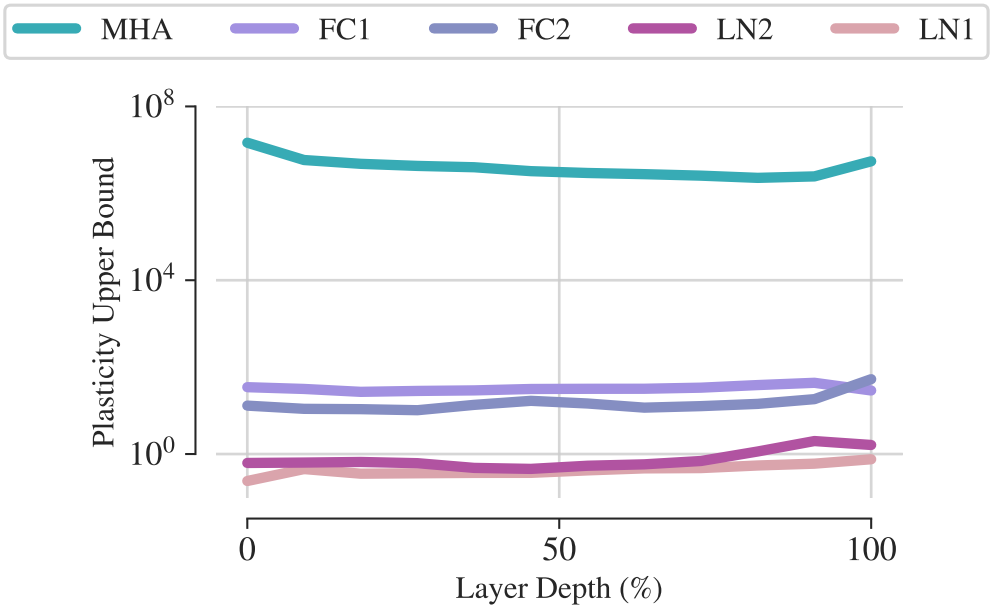
Connection to finetuning



Outline

Theoretical insights

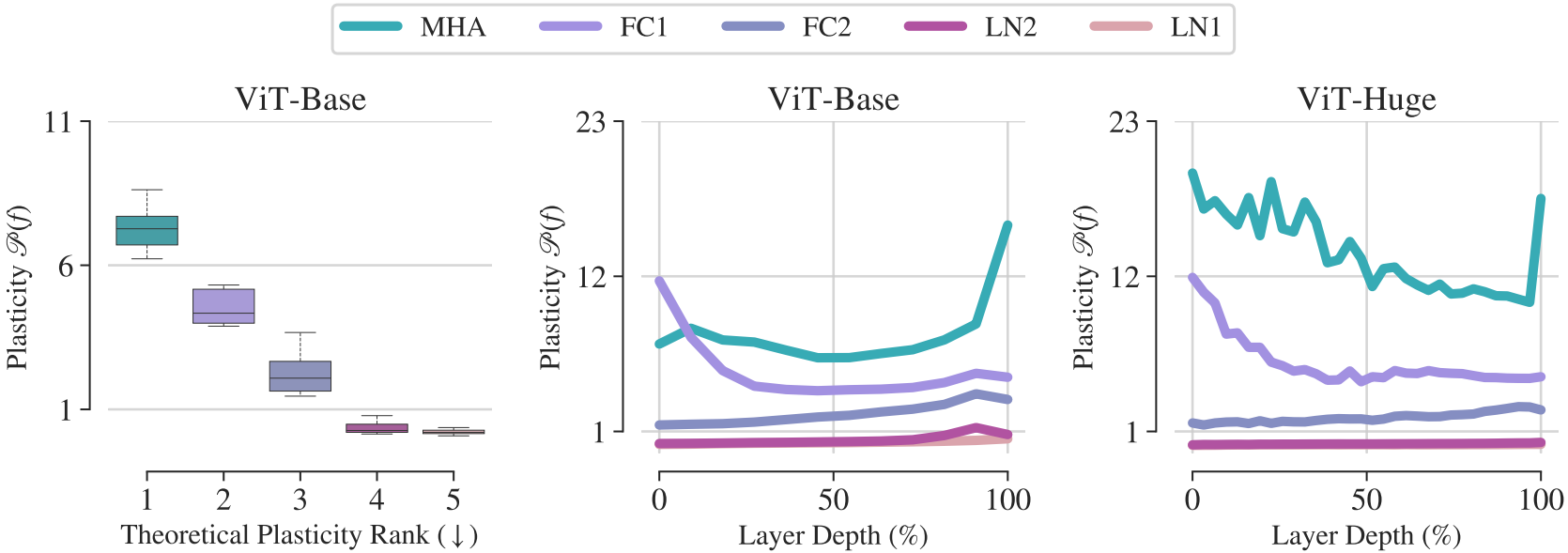
We derive upper bounds on the plasticity $\mathscr{P}(f)$.



Takeaway 1. Our theoretical analysis suggests the following plasticity ranking: MHA $\rightarrow$ FC1 $\approx$ FC2 $\rightarrow$ LN2 $\approx$ LN1.

Empirical ranking

- ViT pretrained on ImageNet (86M and 632M of parameters)
- Cifar10/100, Cifar10-C, DomainNet, Pet, Flowers102



✓ Our theory correctly predicts the empirical ranking,

✓ Attention and feedforward linear layers have $\mathscr{P}(f) > 1$,

✓ LayerNorms have $\mathscr{P}(f) < 1$.

Empirical ranking

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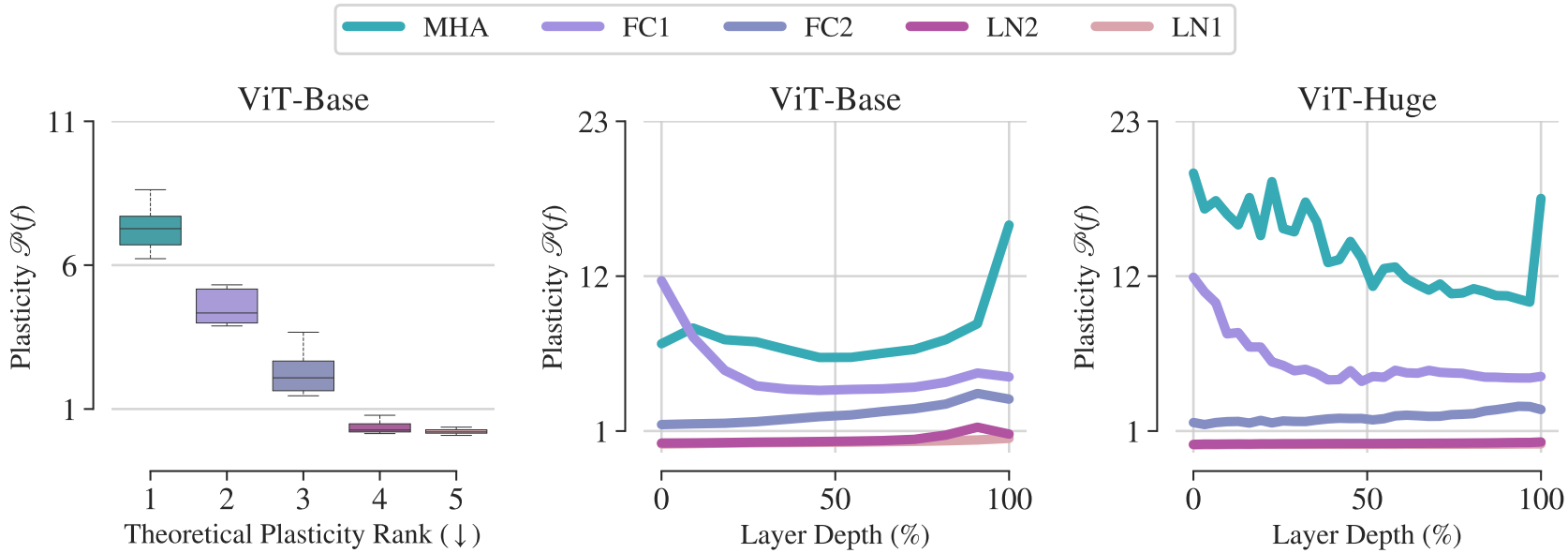
- Cifar10/100, Cifar10-C, DomainNet, Pet, Flowers102



Takeaway 2. The empirical *plasticity ranking* of vision transformer modules supports our theoretical insights with:
MHA $\rightarrow$ FC1 $\rightarrow$ FC2 $\rightarrow$ LN2 $\rightarrow$ LN1.

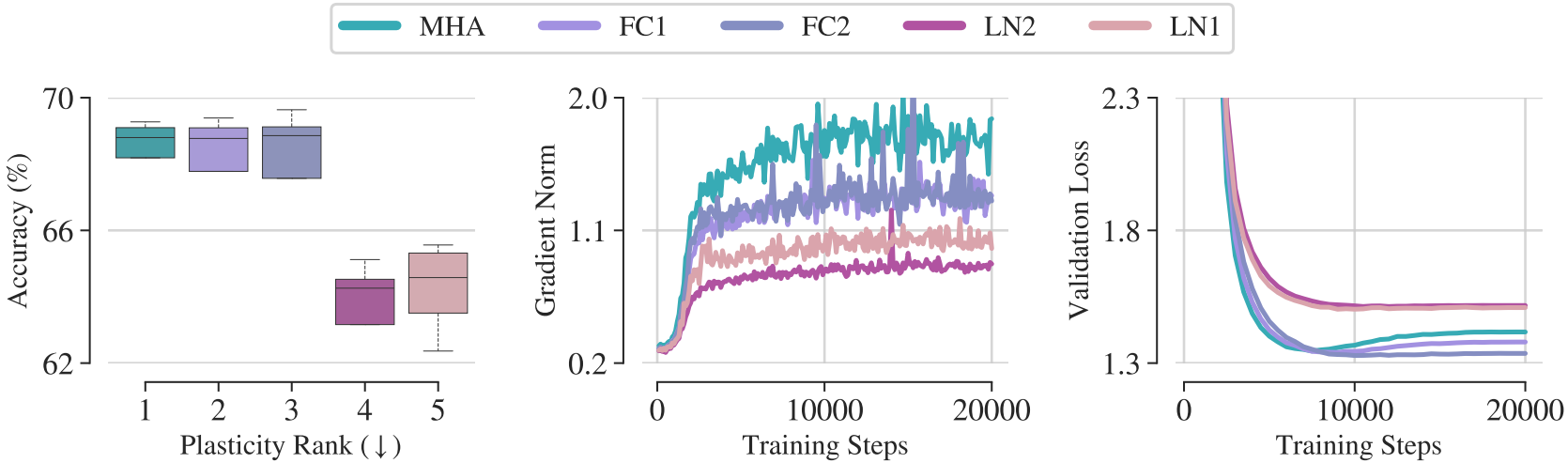
Outline

Better performance

Table 1. **MHA leads to better performance (11 benchmarks).** We report the decrease in performance between MHA and the other configurations, averaged over the benchmarks. Entries in **bold** indicate that the decrease is statistically significant according to a Wilcoxon signed-rank test at a confidence level of 5%.

configuration	FC1	FC2	LN1	LN2
decrease (%)	0.07	**0.44**	**0.8**	**0.9**

Robust adaptation



Takeaway 3.

✓ High plasticity → better and more stable finetuning,

✓ Prioritize attention module and feedforward linear layers.

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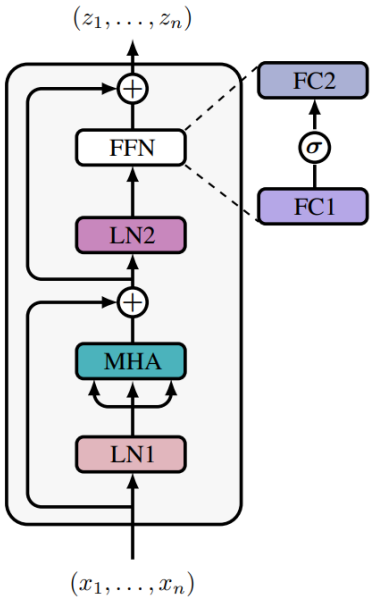
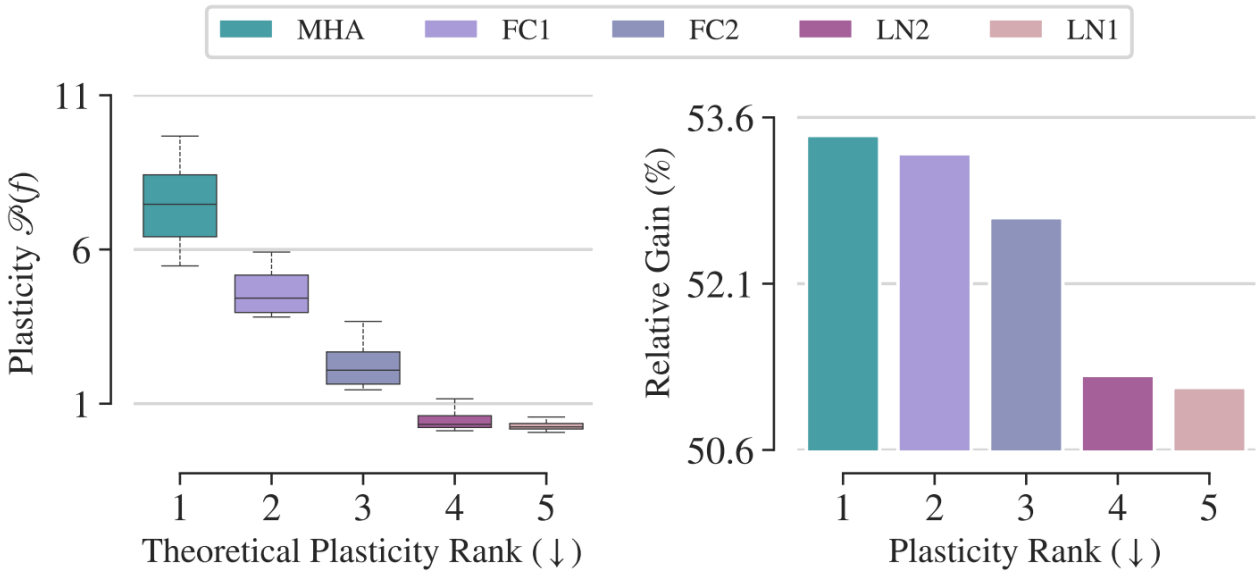
Take Home Message

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





Future work

- ✓ Study the effect of a tailored optimization,
- ✓ Extension to large language models,
- ✓ Apply LoRa only to components with high-plasticity.

To Know More

Check out the paper along with the code to know more!

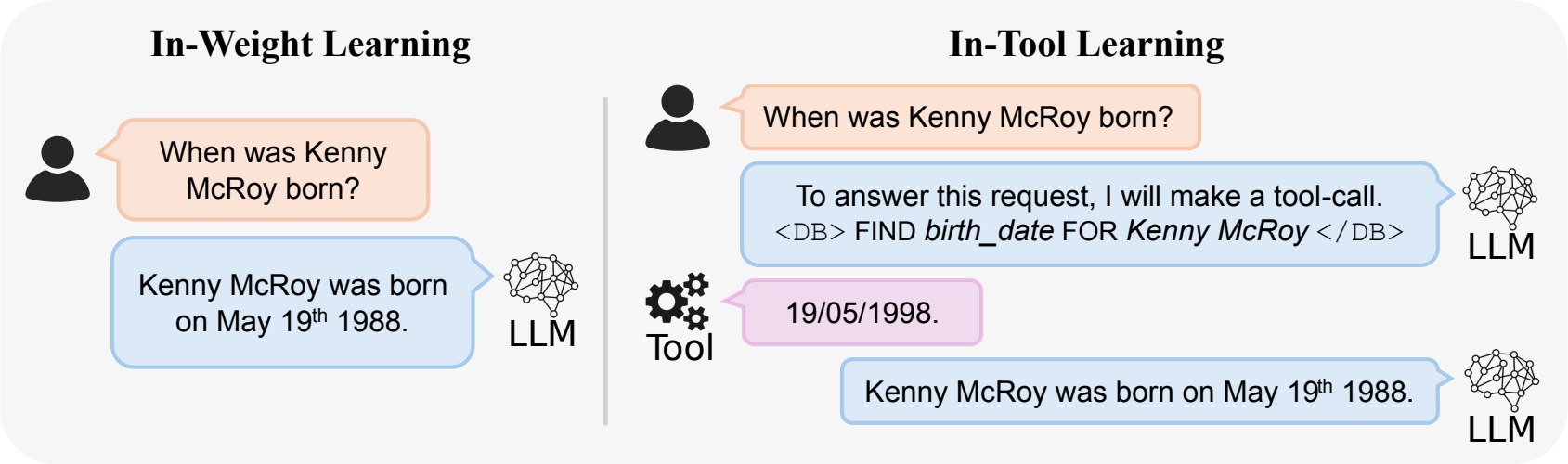
paper

code

website

Provable benefits of in-tool learning for LLMs

ICLR 2026 MemAgents Workshop



paper - code

Thanks for your attention!