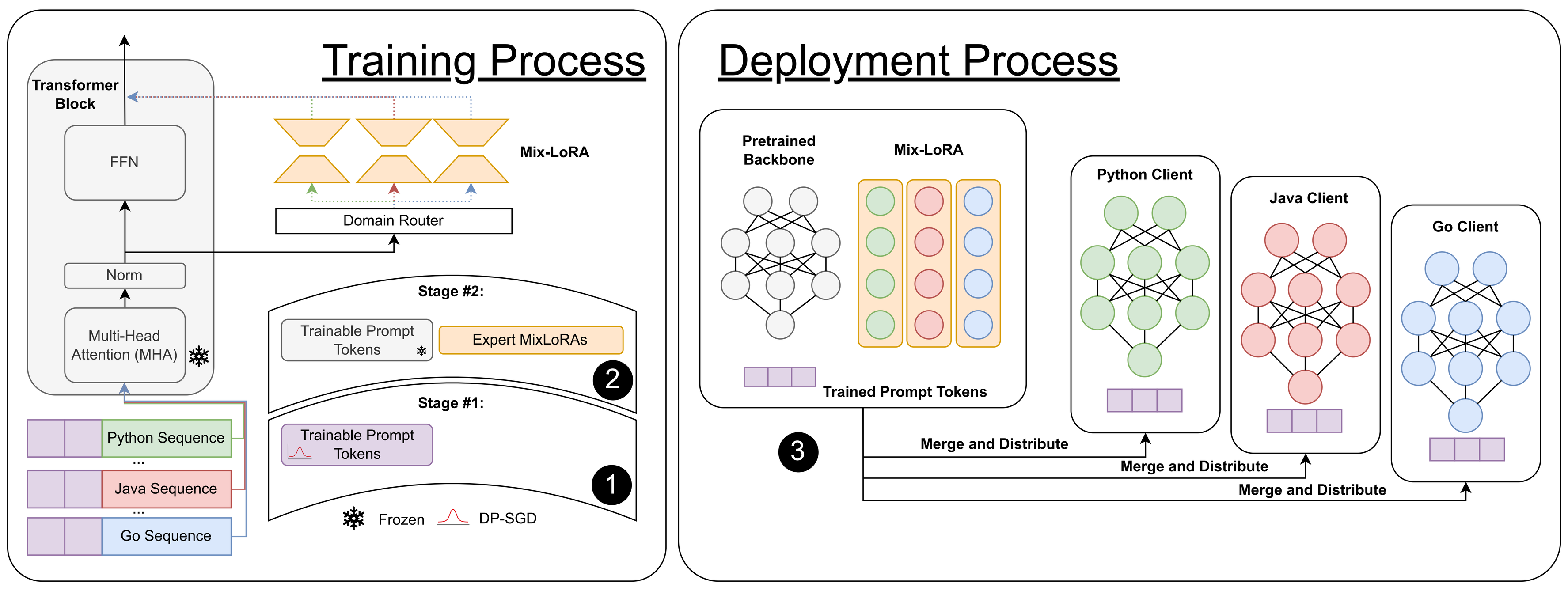
NoEsis: Differentially Private Knowledge Transfer in Modular LLM Adaptation

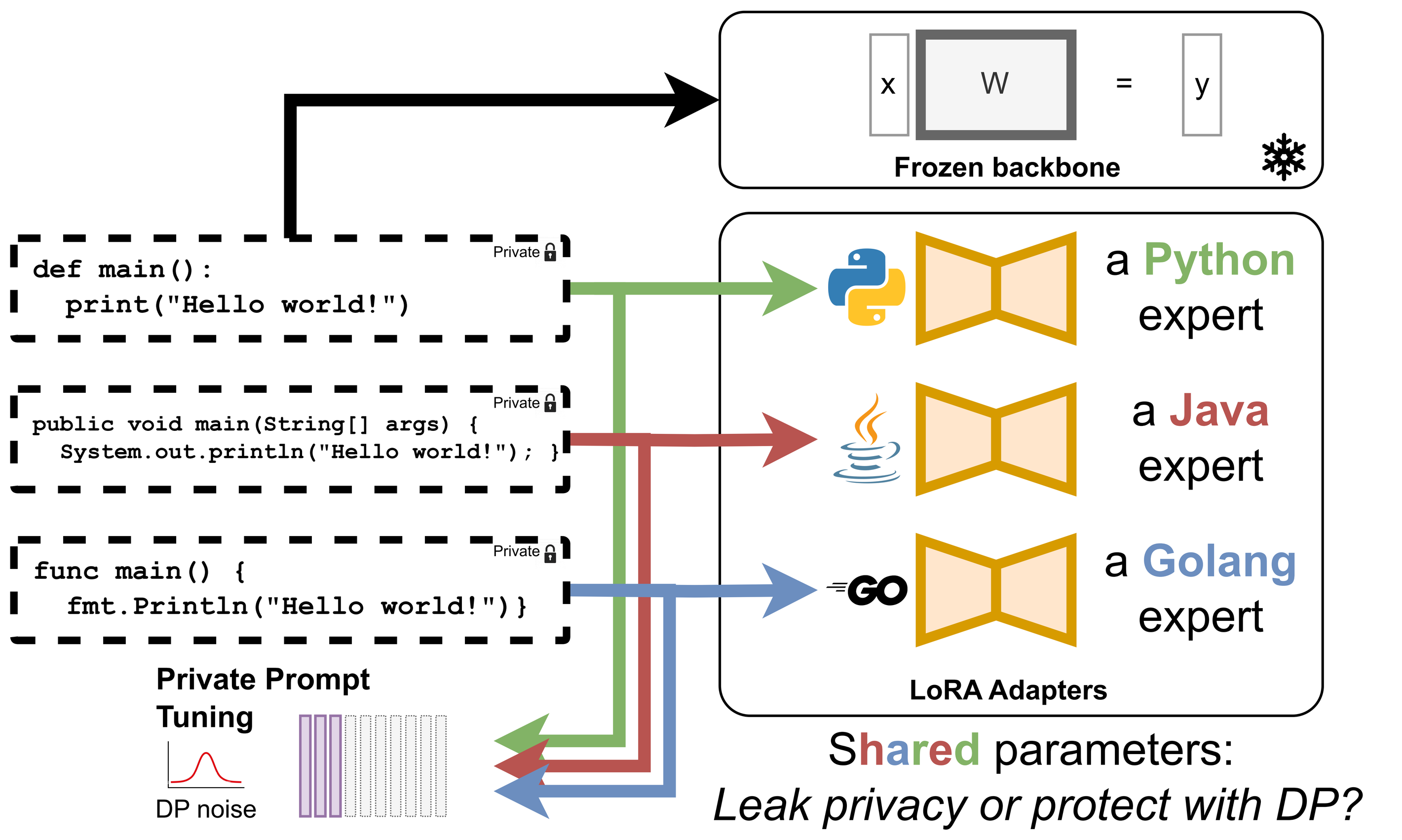
ICLR MCDC workshop

Rob Romijnders[1], Stefanos Laskaridis*[2], Ali Shahin Shamsabadi[2], Hamed Haddadi[2]

[1]Research done as internship
[2]Brave Research



LLMs at scale are running out of training data. Tapping into private data silos is the promising next step, but privacy concerns are paramount [2,3]. NoEsis tackles this setting by adopting a hybrid PEFT paradigm to achieve the properties of **modularity**, **privacy**, and **knowledge transfer**.



Overview of modularity: in each domain, privacy w.r.t. local data is required, but knowledge transfer between domains is desired via shared parameters.

	Model	ε	Modular	Private	Transfer	PEFT	Python	Java	Go
(i)	Share Nothing	0.0	✓	✓	✗	✓	68.31	60.19	64.17
(ii)	Solo (separate models)	1.0	✗	✓	✗	✗	30.19	14.84	4.84
(iii)	Monolithic Fine-tuning (Abadi et al., 2016)	1.0	✗	✓	✓	✗	36.05	23.54	18.34
(iv)	Single Common Adapter (rc=512)* (Yu et al., 2021b)	1.0	✗	✓	✓	✓	48.21	36.16	27.24
(v)	Prompt-Tuning Only (pt32)† (Duan et al., 2023)	1.0	✗	✓	✓	✓	35.03	24.29	9.67
(vi)	NoEsis (pt32)†	1.0	✓	✓	✓	✓	**69.14**	**61.18**	**66.53**

*rc, rank r of the common LoRA; †*pt: number of trainable prompt tokens*

Experimental comparison: NoEsis uniquely achieves high accuracy while obtaining DP at ε = 1.0 and enabling knowledge transfer across domains.

(Knowledge transfer is the accuracy increase over "Share Nothing," which does not have shared parameters between domains.)

$$\boxed{\begin{aligned}\mathrm{NoE} = \mathrm{DP\text{-}SGD}(\text{Prompt-Tuning}(X_1, \dots, X_K)) +\\ \mathrm{SGD}(\mathrm{Mix}\{\mathrm{LoRA}(X_1), \dots, \mathrm{LoRA}(X_K)\})\end{aligned}}$$

DP: A randomized algorithm $A(\cdot)$ is (ε, δ)-differentially private if the following holds for any two adjacent data sets D, D', and for any subset Φ of outputs:

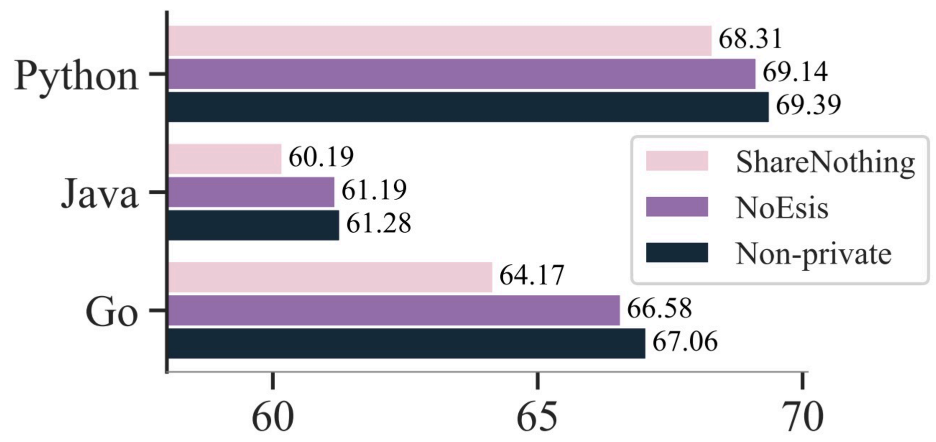
$$Pr[A(D) \in \Phi] \leq e^{\varepsilon} Pr\left[A(D') \in \Phi\right] + \delta$$

where $D = \{d_i\}_{i=1}^{N}$ is a dataset that contains N documents. Two datasets D and $D\prime$ are adjacent when they are identical except for one document in any domain being removed.

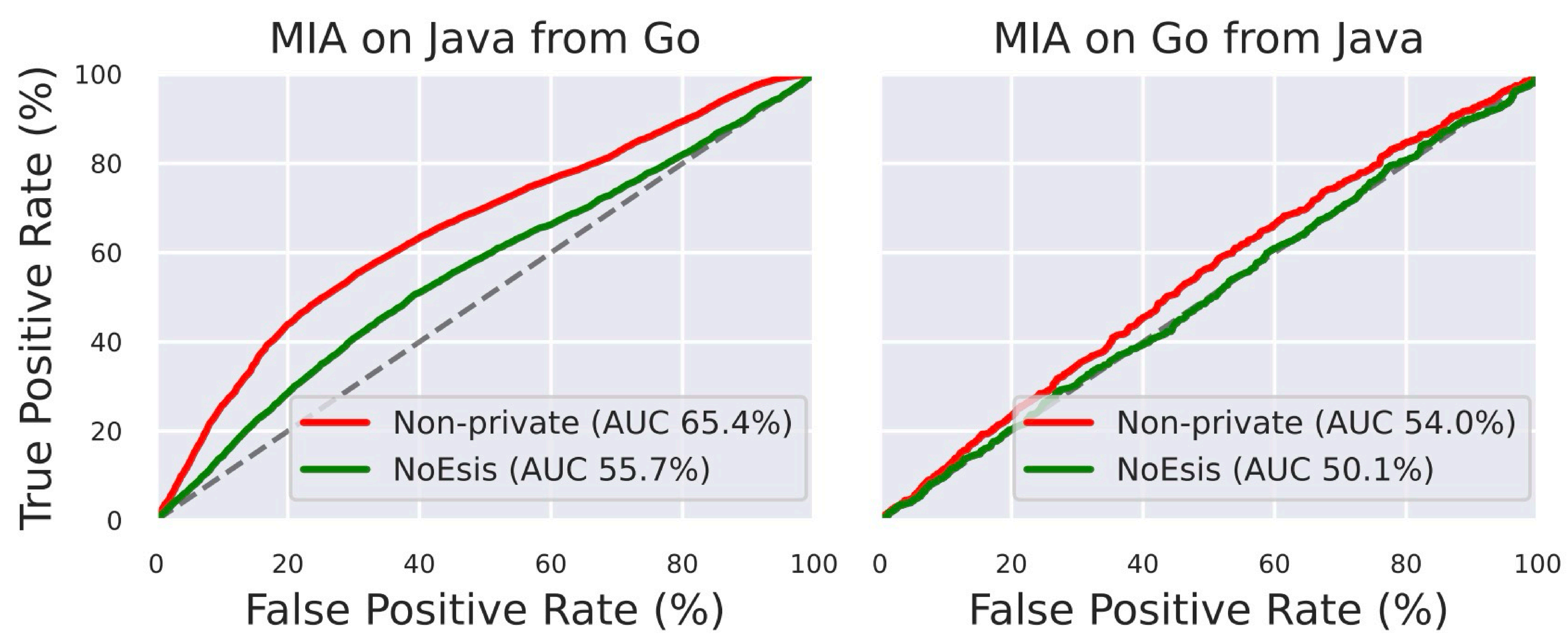
Let $W \in \mathbb{R}^{p \times q}$ be the weight matrix of a linear layer in the FFN of a transformer with parameters θ. We decompose this matrix:

$$W = W + \alpha \sum_{k=1}^{K} B^{(k)} A^{(k)}$$

where $A^{(k)} \in \mathbb{R}^{r \times q}$ and $B^{(k)} \in \mathbb{R}^{p \times r}$ are the trainable low-rank matrices for the k-th domain-specific adapter, out of K domains.



Between the results of a nonshared model, which is the baseline, and a non-private model, NoEsis has knowledge transfer and, under privacy constraints, bridges the accuracy gap by more than 77%.



We run a novel ***cross-domain*** Membership Inference Attack on the shared parameters of a Mixture-of-LoRA model. NoEsis maintains knowledge transfer and reduces vulnerability to this attack, for example, from 65.4 AUC to 55.7 AUC.

Code available at github.com/RobRomijnders/noesis/

Correspondence: romijndersrob@gmail.com, mail@stefanos.cc, ali@brave.com, hamed@brave.com

[1] "Codexglue: A machine learning benchmark dataset for code understanding and generation" Lu et al. arXiv 2021
[2] "Differentially private training of mixture of experts models" Tholoniat et al. AAAI privacy workshop 2024
[3] "Deep learning with differential privacy" Abadi et al. CCS 2016.

* Work done while at Brave