

Internship proposal

Fairness-guided Federated Learning

Université Nice Côte d’Azur
Université Paris-Saclay

Supervisors: [Yassine Laguel](#), [Evgenii Chzhen](#)
Duration : 6 months (+ PhD Funding available)

Context Federated learning [1] is a distributed machine learning framework where clients (e.g. hospitals or mobile devices) collaboratively train a model under the orchestration of a central server, while keeping the training data decentralized. This paradigm is particularly relevant in scenarios where data privacy is paramount, as it allows for the development of robust models without the need to share sensitive information. However, federated learning faces significant challenges, particularly in the presence of heterogeneous data distributions across clients. This heterogeneity can lead to models that perform well on average but poorly for specific clients, raising concerns about fairness and equity in model performance.

Goals The aim of this project is to develop adaptive pareto-efficient methods for sampling and aggregating clients in a federated learning context. Specifically, we aim to address three research directions. First, we aim at developing an adaptive sampling strategy that improves equity across clients while still ensuring measures of pareto-efficiency that are adequate to the federated learning context. While this has already been achieved in specific contexts [3] and for particular metrics of fairness borrowed from the Distributionally Robust Optimization literature [2], we aim this time at developing a more general and flexible framework that can accommodate a wider range of fairness metrics, including non-convex ones. Second, we aim to design efficient optimization procedures that satisfy the constraints of federated optimization, such as limited communication and privacy guarantees. A first contribution in this direction could be the extension of variance-reduction mechanisms (e.g. [4, 5]) to our adaptive sampling framework. Finally, we aim at studying the generalization properties of our methods, both theoretically and empirically, to ensure that they perform well across diverse client distributions. This project aims at bridging techniques from stochastic and distributed optimization, multi-objective optimization, statistical learning theory, and algorithmic fairness.

Candidate Profile This internship is designed for a candidates with a strong background in applied Mathematics and computer science. Candidates with previous experience in optimization and statistical learning are appreciated, as is an interest in numerical simulations.

Location / Funding Shared between Nice and Orsay (Paris) / ANR JCJC (ADAR)

Application Procedure Send your CV and a copy of your last year transcripts to both :

- Yassine Laguel : (yassine.laguel@univ-cotedazur.fr)
- Evgenii Chzhen : (evgenii.chzhen@universite-paris-saclay.fr).

References

- [1] Goldstein, A., Peñalba, M., and de Salvador Carrasco, L. (2025) TechDispatch #1/2025: Federated Learning European Data Protection Supervisor — TechDispatch Series.
- [2] Laguel Y. and Malick, J. and Harchaoui, Z. (2022) Superquantile-based learning: a direct approach using gradient-based optimization. *Journal of Signal Processing Systems*.
- [3] Laguel Y. and Pillutla, K. and Malick, J. and Harchaoui, Z. (2022) Federated learning with superquantile aggregation for heterogeneous data. *Machine Learning Journal*.
- [4] Karimireddy, S. P. and Wang, J. and Zhang, T. and Harchaoui, Z. (2020) SCAFFOLD: Staleness-Aware Federated Optimization for Heterogeneous Clients. *International Conference on Learning Representations*.
- [5] Mangold, P. and Durmus, A. and Dieuleveut, A. and Moulines, E. (2025) Scaffold with Stochastic Gradients: New Analysis with Linear Speed-Up. *arXiv preprint*.