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Title of PhD subject: Self-Supervised Federated Learning with Intra-Layer Parallelism and Dynamic Resource Orchestration

Summary :

Self-supervised learning has emerged as a key driver of modern artificial intelligence [2][3], enabling models to learn from unlabeled data. Despite its effectiveness, it typically requires large-scale and costly computational infrastructures [6][7], which are difficult to deploy in distributed environments. In contrast, federated learning provides a decentralized framework in which each device contributes to a global model while keeping its data locally [8], making it particularly suitable for IoT, industrial, and embedded systems. However, the heterogeneity of both resources and data makes existing approaches difficult to stabilize and often inefficient.

This thesis explores a novel direction: the use of intra-layer parallelism, allowing multiple machines to collaboratively train the neurons of a single layer, as opposed to traditional approaches based on entire layers [9][10][11]. Combined with a dynamic resource orchestration mechanism, capable of automatically adapting the distribution of computations, this approach has the potential to make self-supervised federated learning faster, more flexible, and more robust.

Recent advances in artificial intelligence rely on deep models that require massive amounts of data [4]. Self-supervised learning, which operates without annotations, has led to significant breakthroughs in both vision and language domains [2][3]. However, it remains highly dependent on powerful centralized computing infrastructures [6], limiting its applicability in distributed settings. Federated learning, on the other hand, allows devices to collaboratively train a global model without sharing raw data [8], making it well-suited for IoT networks, embedded systems, and industrial infrastructures.

Nevertheless, such environments are highly heterogeneous: some devices have substantial computational power, while others are severely constrained; network connections may be stable or intermittent [13]. Data distributions are also heterogeneous, and parameter exchanges are costly, which slows down training. Existing approaches attempt to mitigate these limitations: SplitNN introduces a rigid client–server partitioning [10], FedLAMA adapts layer-wise synchronization [9], and Lw-FedSSL reduces memory consumption by training models layer by layer [11]. However, they all share the same structural limitation: a layer is always treated as an indivisible unit.
This thesis proposes a major conceptual shift by introducing intra-layer parallelism, where neurons within a layer are distributed across multiple machines. This fine-grained approach, largely unexplored in federated settings, raises new methodological challenges, particularly regarding the stability and convergence of models whose neurons are distributed across multiple nodes. It also requires rethinking communication strategies to minimize overhead while maintaining high

performance. Existing works do not address these challenges, as they are limited to layer-level granularity [9][10][11].

The second major contribution of this work is the development of a dynamic orchestration framework, inspired by advances in distributed optimization and personalized federated learning [12][14]. This orchestrator will dynamically adapt neuron allocation, synchronization frequency, and resource usage in real time. In federated systems, some machines may be overloaded while others remain idle; bandwidth fluctuates, and availability continuously changes. By accounting for these constraints, the orchestrator aims to ensure stable, efficient, and responsive neuron-level cooperation.

Current approaches remain too rigid to fully exploit modern distributed environments. By introducing a new neuron-centered granularity and combining it with intelligent orchestration, this thesis proposes a novel framework for self-supervised federated learning. This work lies at the intersection of self-supervised learning [2][3], distributed learning [8][9], and advanced neural architectures [5], while opening new perspectives for embedded systems and distributed networks.

The proposed methods will be evaluated on a dataset from the agro-environmental domain, with a particular focus on soil image analysis for the quantification of microorganisms (bacteria, fungi, nematodes, etc.), which are key indicators of soil health.

The first semester will be entirely dedicated to a comprehensive state-of-the-art review covering self-supervised learning, federated learning, and various forms of model parallelism. This analysis will help identify current limitations and highlight opportunities for intra-layer parallelism. During the second semester, the PhD candidate will define the conceptual framework of the project by formalizing the principles of neuron-level cooperation. Initial prototypes will be developed to assess feasibility and identify key challenges related to convergence, communication, and computational distribution.

The second year will focus on the development of the dynamic orchestration framework, which will play a central role in adapting neuron allocation and resource usage in real time. The candidate will explore reinforcement learning and adaptive optimization techniques to design a system capable of making informed decisions based on the state of the distributed environment. Experimental setups will be designed to simulate realistic conditions, including hardware heterogeneity, network variability, and workload fluctuations. Once developed, the orchestrator will be integrated into the self-supervised learning pipeline to evaluate its impact on training speed, efficiency, and cost reduction.

The third year will begin with the full integration of all developed components, followed by large-scale experiments to validate the proposed approach in diverse distributed environments. The candidate will evaluate the system on real-world distributed platforms to measure its adaptability, robustness, and performance gains. The system parameters will then be fine-tuned to ensure strong and scientifically sound contributions.

The final six months will be dedicated exclusively to writing the dissertation, finalizing publications, and preparing the PhD defense

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Publications /références associées au sujet :

A. Ouni, C. Samir, Y. Bouaziz, and A. Fradi, “ConvKAN: Towards robust, high-performance and interpretable image classification,” Proc. VISSAP, 2025.

CAUNES, Andrew, CHATEAU, Thierry, et FRÉMONT, Vincent. 3d can be explored in 2d: Pseudo-label generation for lidar point clouds using sensor-intensity-based 2d semantic segmentation. In : 2024 IEEE Intelligent Vehicles Symposium (IV). IEEE, 2024. p. 2192-2197.

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Toward industrial use of continual learning: new metrics proposal for class incremental learning, MA Konaté, AF Yao, T Chateau, P Bouges, 2023 International Joint Conference on Neural Networks (IJCNN), 01-07