

# Collaborative Learning across Heterogeneous Systems with Pre-Trained Models

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## 1 Introduction

Modern problem-solving systems are frequently integrated into a complex and federated information network. For instance, think of a smart health monitoring system that compiles and disseminates analytical findings derived from a wide range of private patient data scattered across various hospitals, clinics and numerous personal medical wearable devices. All of which may have unique ownership, hardware setups, data distributions and representations. Federated learning (FL) (Konečný et al. 2016) was proposed to address the decentralized data issue but has mostly been studied in settings where local systems are expected to use the same learning model, which might not fit with the local hardware and representation constraints. In addition, learned knowledge is often represented in task-specific forms which is difficult to adapt to unseen task scenarios. To mitigate such constraints, my research envisions a generalization of federated learning which can integrate information seamlessly across different local systems. Within this framework, pre-trained models capturing related expertises are broken down into a diverse set of task-agnostic functions, each associated with distinct task embedding patterns. Local solution models can then be represented using subsets of these functions, selected based on their proximity to the task data. This approach transforms model aggregation into a set summarization problem, affording it the desirable adaptability, transferability, and compositionality across different information silos and tasks with different model and data representations.

## 2 Research Summary

To realize the above vision, my research focuses on developing the following computational capabilities. First, **(C1) expression** pertains to a learning collaborator’s capacity to determine what information to communicate to facilitate the global decomposition of local models into reusable patterns (Hoang et al. 2019b,a). This approach facilitates the representation of prior problem-solving expertise in a modular and transferable fashion, where distinct facets of knowledge are individually encapsulated within these context-independent model prototypes, which can be recombined in novel ways to synthesize new problem-solving skills to a

new task context. This will re-imagine the existing paradigm of model fine-tuning, producing models that are both effective and interpretable when adapting to new tasks. Next, **(C2) comprehension** focuses on statistical techniques to associate, align and re-combine relevant prototypes extracted from different pre-trained models (Hoang et al. 2020; Lam et al. 2021) to solve new tasks. This is a key issue in continual learning where the learning agents need to infer the correspondence between knowledge modules that were distilled in different contexts and orders. This has been preliminarily investigated in the context of neural networks that decompose into sets of neurons (Yurochkin et al. 2019). Finally, the comprehensive **(C3) resource-aware collaborative learning** framework will leverage these capabilities to facilitate large-scale learning scenarios featuring an ever-growing network of heterogeneous learning agents that seek to communicate and reuse relevant knowledge to collaboratively solve their respective tasks. With the emergence of large pre-trained models which encapsulate vast expertise, a key challenge lies in addressing their sheer scale of complexity and seamlessly integrating them into the envisioned resource-aware collaborative learning framework.

## References

- Hoang, Q. M.; Hoang, T. N.; Low, K. H.; and Kingsford, C. 2019a. Collective Model Fusion of Multiple Black-Box Experts. In *Proc. ICML*.
- Hoang, T. N.; Hoang, Q. M.; Low, K. H.; and How, J. P. 2019b. Collective Online Learning of Gaussian Processes in Massive Multi-Agent Systems. In *Proc. AAAI*.
- Hoang, T. N.; Lam, C. T.; Low, K. H.; and Jaillet, P. 2020. Learning Task-Agnostic Embedding of Multiple Black-Box Experts for Multi-Task Model Fusion. In *Proc. ICML*.
- Konečný, J.; McMahan, H. B.; Ramage, D.; and Richtárik, P. 2016. Federated Optimization: Distributed Machine Learning for On-Device Intelligence. *CoRR*, abs/1610.02527.
- Lam, C. T.; Hoang, T. N.; Low, K. H.; and Jaillet, P. 2021. Model Fusion for Personalized Learning. In *Proc. ICML*.
- Yurochkin, M.; Agarwal, M.; Ghosh, S.; Greenewald, K.; Hoang, T. N.; and Khazaeni, Y. 2019. Bayesian Nonparametric Federated Learning of Neural Networks. In *Proc. ICML*.