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# POSTER: FLLEDGE: FEDERATED LIFELONG LEARNING ON EDGE DEVICES

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## ABSTRACT

Continual learning and federated learning are key methodologies in guaranteeing model generalization over non-i.i.d. data in realistic scenarios. We explore the interplay of both domains to improve upon robustness and efficiency of multi-task training on low-size-weight-and-power (SWAP) devices with limited computational, network, and hardware capabilities. We present Federated Lifelong Learning on Edge Devices (FLLEDge), the first system for multi-agent edge lifelong reinforcement learning on low-SWAP devices. FLLEDge overcomes low-SWAP challenges on Jetson Nanos through innovations of (1) sparse switching sharing schedule, (2) distributed database for knowledge sharing, and (3) compressed learnable information with Compressive Linear Operators (CLO). FLLEDge achieves substantial improvements in training time and performance over single-agent lifelong learning. The decentralized FLLEDge system can be easily converted to standard federated learning setting.

## 1 INTRODUCTION

*Lifelong Learning* (LL), also termed as *Continual Learning* (1), refers to a learning paradigm that learns a model for solving multiple tasks, where those tasks are presented in a sequential manner. Yet, most of LL works only consider the single-agent setting, and in practice there are often *multiple* lifelong learners who could potentially benefit from cooperating with each other (2; 3). For example, a medical diagnosis system needs to *continually* update its model according to each encountered patient; moreover, the medical diagnosis systems developed by different institutes could improve themselves by *sharing* certain knowledge. Compared with single-agent CL, the multi-agent setting involves the following two additional challenges: (1) the task sequences for each agent may vary, and (2) agents might not be able to communicate in a centralized topology. Meanwhile, according to (4), there is significant overlap in context, problem domains and challenges between both federated learning (FL) and fully decentralized learning: decentralized data, collaboration among clients to converge to a desired global solution, and some decentralized learning methods rely on a central entity to schedule cooperation, etc. Inspired by the correlation and early attempts (5; 6), we are encouraged to think beyond the strict single-server-multi-client assumption, probing possibility of solving a federated problem with in a decentralized setting. We call this problem *decentralized federated lifelong learning* (decentralized-FLL).

**Problem Formulation.** Consider  $N$  continual learning agents, each will observe  $K$  tasks sequentially. Note that (1) for each agent, her  $K$  tasks could be different, and (2) at each time frame, the current tasks presented to the agents could be different. For each learner, her own goal is to

compute a model generalize on her  $K$  tasks. The agents can closely communicate to gain a potential acceleration of the learning process. In the design of a *decentralized-FLL* system, one needs to specify an efficient CL algorithm for each agent to perform her own continual learning, and beyond this, one needs to design a communication protocol for efficient knowledge sharing.

**Challenges.** This problem poses three main challenges. The first challenge is caused by the *continual learning* process for each agent. In particular, for each agent, as the tasks are presented in a sequential manner, the performance of the computed model on past tasks often *degrades* in the process of learning new tasks. The phenomenon is known as *catastrophic forgetting* (7). The second challenge is from the *federated knowledge sharing*. Recall that, at each time frame, these agents are learning different tasks, some of them might be *homogeneous* while some others are *heterogeneous*. Therefore, the knowledge sharing needs a special design so that an agent (1) benefits from those perform a similar task, while (2) refrains herself from the interference of currently heterogeneous agents. The last challenge is from the *decentralized* nature. Each client needs to learn generalized knowledge from both local knowledge and global information by interacting with the neighborhood.

**Our Contribution.** With the stage set, we propose Federated Lifelong Learning on Edge Devices (FLLEDge)<sup>1</sup>, the first system for multi-agent edge lifelong reinforcement learning (RL) that improves training time and performance

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<sup>1</sup>FLLEDge is part of ShELL DARPA project by LEAPS. In the next phase, we will add different topologies including star topology. For more about ShELL, please refer to: <https://tinyurl.com/4cnx8jnm> and <https://tinyurl.com/2p8ecn6r>

on low size-weight-and-power (SWAP) devices in a decentralized setting. FLLEdge targets Atari 2600 video games as the use case. Its decentralized all-to-all knowledge sharing mechanism, and communication protocols can be easily converted to a standard FL solution. FLLEdge proves deployed RL models perform multi-task training efficiently and robustly on Jetson Nanos, overcoming computational and hardware limitations of edge devices. We highlight contributions of FLLEdge below:

- proposing an intersection of FL and LL problem, decentralized-FLL, on the domain of edge computing.
- minimizing cost of knowledge sharing using novel sparse switching cost RL and subsampling.
- establishing distributed database and protocols to support linearly-fast knowledge sharing (8) to satisfy the low SWAP requirements.

**Related Works.** LL has been studied for decades, inspiring brilliant solutions to catastrophic forgetting including EWC, GEM family, and DEN (1). Our work bears resemblance to distributed decentralized LL methods e.g. (2; 3). In FL, key works such as FedAvg, FedProx, and SCAFFOLD (4) also establish the framework of this emerging domain. We further discuss predecessors exploring intersection of FL and CL. FedCurv (9) identifies non-i.i.d. distribution in FL and minimize inter-client model disparity with modified EWC. FIL-VER (10) addresses non-i.i.d. data distribution in FL by replaying privacy-guaranteed embeddings on server. Compared with them (our closest predecessor in this domain, FedWeIT (11)), (1) our solution poses a co-design of algorithms and systems for edge device computing, (2) we use all-to-all decentralized topology w.r.t. FedWeIT’s centralized topology, and (3) FedWeIT samples sparse parameters of homogeneous tasks during training, but ours separates task similarity comparison from training LL models.

## 2 ALGORITHM AND EXPERIMENTS

The learning framework consists of two steps: (1) compare task similarity to find information of most relevant tasks to use, (2) perform LL and share compressed information with neighbors. In (2), we use EWC, and experience replay (1) to train our models. We choose these two algorithms to demonstrate feasibility of regularization-based and replay-based methods for our framework instead of dynamic networks since our base network size remains static throughout the course of training. For the training logic, if neither the agent nor its neighbors has encountered a new task before, the agent needs to learn samples to train the LL model, whose communication rate is computed by sparse switching. This is equivalent to single-agent LL training where the agent needs to train each task from scratch. On the other hand, if the task has been learned by its peers, our agents request the (CLO-compressed such as sketching) learnable infor-

mation, including experience replay buffers. It leverages information obtained from sparse-switching instead of interacting with the Atari-server, saving large amounts of time by learning from more data in a short time frame.

Currently, FLLEdge runs on 5 agents to train 10 Atari 2600 games supported by OpenAI Gym in sequence. In our experiments, 5-agent FLLEdge is compared with single-agent LL on the same 10 tasks in terms of performance reward and training time. We show that FLLEdge achieves consistent scalability in both metrics with factors including number of agents and size of training data per task. We present experimental results in the poster.

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