

Author: Vidhi Jain

Title: Federated learning for embodied AI

Abstract: Humans learn from experience to efficiently explore an unseen house or office building by inferring on semantic priors, for example, if asked to get a fork, we look in the kitchen or dining table, but not go towards the bathroom. With advances in vision and language, we can learn policies for structured but unseen environments. In embodied AI research, we wish to enable interdependent ways of learning to recognize and understand context from visual spatial semantics [1,4,7,13], language [3,12] and physical interaction [1,6]. However, current embodied AI needs large scale data to justify whether learning improves performance over classical robot navigation methods. Recent works like DD-PPO [2] show that learning can remarkably navigate in indoor spaces. But it also motivates the dire need to improve sample efficiency of RL algorithms or to find ways to learn at scale by parallel, distributed and/or federated computing. While aggregating dense labelled data in the cloud is the common practice for training, it is storage intensive, risking privacy and ‘one model fits all’ approach. We can incorporate new data faster and reduce burden on communication with federated style learning. Federated approach allows an individual robot to maintain some autonomy for local adaptation, yet contribute meta features to enrich a global model. Addressing heterogeneity in system and statistical aspects [8,9] is important for training real robots in homes, as they will differ in terms of the data/experiences and communication frequency. Optimization algorithms like FedAvg [11] and FedProx [9] enable the shared model weights to be updated and aggregated from unbalanced and non-IID data distributions. Several embodied AI tasks like IQA [6] can be experimented in federated multi-task learning setup as shown with MOCHA [5]. Even though there are several unresolved problems in both embodied AI and federated learning, finding potential ways of federated learning for autonomous agents is an active research area [10,14,15].

Format: We will introduce the topics of embodied AI and federated learning with pre-allocated time for short questions and discussion in between. We will end with open-ended questions to discuss and collectively figure out a list of actionable goals for both: short-term projects and research directions.

References:

1. Anderson, et al. “Vision-and-Language Navigation: Interpreting Visually-Grounded Navigation Instructions in Real Environments.” ArXiv.org, 5 Apr. 2018, arxiv.org/abs/1711.07280.
2. Wijmans, et al. “DD-PPO: Learning Near-Perfect PointGoal Navigators from 2.5 Billion Frames.” *Venues*, ICLR 2020, openreview.net/forum?id=H1gX8C4YPr.
3. Bisk, et al. “Experience Grounds Language.” 21 Apr. 2020, arxiv.org/abs/2004.10151.
4. Chaplot, Devendra Singh, et al. “Learning To Explore Using Active Neural SLAM.” *ICLR 2020*
5. Smith, et al. “Federated Multi-Task Learning.” 27 Feb. 2018, arxiv.org/abs/1705.10467.
6. Gordon, et al. “IQA: Visual Question Answering in Interactive Environments.” 6 Sept. 2018.
7. Kahn, et al. “Self-Supervised Deep Reinforcement Learning with Generalized Computation Graphs for Robot Navigation.” 17 May 2018, arxiv.org/abs/1709.10489.
8. Li, et al. “Federated Learning: Challenges, Methods, and Future Directions.” 21 Aug. 2019.
9. Li, et al. “Federated Optimization in Heterogeneous Networks.” 21 Apr. 2020.
10. Liang, et al. “Federated Transfer Reinforcement Learning for Autonomous Driving.” 14 Oct. 2019.
11. McMahan, et al. “Communication-Efficient Learning of Deep Networks from Decentralized Data.” 28 Feb. 2017, arxiv.org/abs/1602.05629.
12. Shridhar, et al. “ALFRED: A Benchmark for Interpreting Grounded Instructions for Everyday Tasks.” 31 Mar. 2020, arxiv.org/abs/1912.01734.
13. Yang, et al. “Visual Semantic Navigation Using Scene Priors.” 15 Oct. 2018, arxiv.org/abs/1810.06543.
14. Zhuo, et al. “Federated Deep Reinforcement Learning.” 9 Feb. 2020, arxiv.org/abs/1901.08277.
15. Li, et al. “On the Convergence of FedAvg on Non-IID Data.” 6 Feb. 2020, arxiv.org/abs/1907.02189.