Decentralized Robot Learning for Personalization and Privacy

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Abstract

From learning assistance to companionship, social robots promise to enhance many aspects of daily life. However, social robots have not seen widespread adoption, in part because (1) they do not adapt their behavior to new users, and (2) they do not provide sufficient privacy protections. Centralized learning, whereby robots develop skills by gathering data on a server, contributes to these limitations by preventing online learning of new experiences and requiring storage of privacy-sensitive data. In this work, we propose a decentralized learning alternative that improves the privacy and personalization of social robots. We combine two machine learning approaches, Federated Learning and Continual Learning, to capture interaction dynamics distributed physically across robots and temporally across repeated robot encounters. We define a set of criteria that should be balanced in decentralized robot learning scenarios. We also develop a new algorithm – Elastic Transfer – that leverages importance-based regularization to preserve relevant parameters across robots and interactions with multiple humans. We show that decentralized learning is a viable alternative to centralized learning in a proof-of-concept Socially-Aware Navigation domain, and demonstrate how Elastic Transfer improves several of the proposed criteria.

1 Introduction

As robot systems improve, they are moving from laboratory environments into our daily lives. The homes of tomorrow may enlist Jibo, “the world’s first family robot”, to lend support with cooking, family photos, and entertainment [Hodson, 2014]. In the classroom, humanoid robots like Pepper may provide emotionally intelligent tutoring to students who need learning assistance [Pandey and Gelin, 2018]. Yet, several key barriers remain before social robots such as these can become fully integrated into daily life.

\textsuperscript{*}Luke conducted this work while an MPhil student at the University of Cambridge.

One barrier to widespread social robot adoption is personalization. Whereas robots of today are designed for single encounters based on pre-configured abilities, future systems require adaptation over long-term interactions. For example, longitudinal HRI research has found that robots who tailor their behavior towards users’ personality, preferences, and interaction style foster more engagement and long-term acceptanace [Leite et al., 2013]. A further barrier to social robot adoption is the lack of privacy protections. Because robots will support humans with sensitive activities such as learning and eldercare, data protection must be considered from the ground up. However, existing systems do not emphasize privacy, thus reducing user trust in the system and limiting widespread adoption [Butler et al., 2015].

An underlying cause of these barriers is the centralized machine learning (ML) process robots use to develop intelligent behaviors. Centralized ML works by (1) gathering user data in a single location such as a server and (2) training a model to perform a new function (i.e. classifying user emotions) using the full dataset. However, this process limits robots’ ability to personalize to new users, because doing so would require uploading raw user data, retraining the model, and redistributing the model to all devices. Moreover, in a social robotics scenario, storing user data on a server imposes privacy vulnerabilities. Instead, by leveraging decentralized learning, whereby robots leave raw data on robot devices and learn by collaboratively exchanging model information, it may be possible to support personalization while also protecting privacy.

This work proposes a decentralized learning approach for long-term HRI. We combine two ML paradigms – Federated Learning (FL) and Continual Learning (CL) – to model interactions that are distributed physically across robots and temporally across repeated interactions [Yoon et al., 2021]. We outline four criteria that should be satisfied in decentralized learning contexts, including adaptation quality, adaptation time, effective knowledge sharing, and minimal overhead. As a proof-of-concept, we compare a range of existing Federated Continual Learning (FCL) methods on a socially-assistive navigation benchmark with respect to these four criteria. We also develop a new regularization-based algorithm, Elastic Transfer, that improves performance with respect to three of the proposed criteria. The proposed method improves decentralized performance by penalizing changes to parameters that were important in (1) earlier local tasks and (2) tasks
encountered by other clients. We believe this method can improve personalization in other robot learning domains.

This work provides three key contributions, in which we:

1. **Formulate long-term HRI as a decentralized learning problem.** To our knowledge, this is the first work to formulate HRI as a decentralized learning problem that combines both FL and CL. We provide a flexible extension to previous CL for HRI frameworks that supports personalization to new individuals and groups.

2. **Develop a decentralized learning evaluation framework.** We outline which tradeoffs should be balanced in decentralized learning for HRI, and apply this framework to a comprehensive evaluation of 10 existing FCL approaches.

3. **Propose a regularization strategy for improving FCL performance.** We draw connections between existing FL and CL methods to propose a new Elastic Transfer approach for improving knowledge sharing among clients. This method demonstrates promising performance, and provides the first regularization-based strategy tailored to FCL.

2 Related work

In **Federated Learning (FL),** a network of distributed phones, robots, or other clients downloads a common initial model from a server, trains on locally available data, then transmits updated parameters to the server. The server aggregates updates into a new global model and re-distributes it to clients. FedAvg is a standard approach for aggregating parameter updates on the server via a weighted average. However, convergence is poor in non-iid settings with client data from each task is only available temporarily, catastrophic forgetting of previous knowledge may occur.

Recent work on personalized federated learning learns a global model while also fine tuning local models on user-specific information [Rudovic et al., 2021; Mansour et al., 2020]. Personalized federated learning approaches have been vulnerable to negative transfer, whereby model averaging impedes performance for some subjects [Rudovic et al., 2021]. Existing personalized FL methods have also seen limited consideration of temporal adaptability, where concept shift and concept drift cause non-iid data over time [Tan et al., 2021].

In this work, we consider continual learning as an additional framework well-suited to address these issues.

In **Continual Learning (CL),** models learn online from sequentially encountered data [Parisi et al., 2019]. Given a series of incremental tasks, CL approaches aim to learn each without forgetting previous knowledge. However, because data from each task is only available temporarily, catastrophic forgetting of previous knowledge may occur.

Regularization-based CL strategies attenuate catastrophic forgetting by adding a penalty between the model learned on previous tasks and the one being trained on current data. Analogous to FedProx and FedCurv in FL, L2-transfer (L2T) [Li and Hoiem, 2017] in CL uses an L2 penalty, while Elastic Weight Consolidation (EWC) [Kirkpatrick et al., 2017] imposes a quadratic term based on Fisher information to consider parameter importance. Architectural CL strategies, such as Additive Parameter Decomposition (APD) [Yoon et al., 2019], address catastrophic forgetting by modifying the model structure to accommodate new opportunity for inter-client knowledge transfer, whereby experiences from previous tasks can be shared among clients to improve learning. However, it also introduces a challenge of inter-client interference, in which experiences aggregated from other clients accelerate catastrophic forgetting.

FedWeIT is an architectural approach to solving the FCL problem [Yoon et al., 2021]. This technique decomposes a global model into a set of client-specific base parameters and task-adaptive parameters that learn knowledge about each local task. This approach encourages knowledge transfer by enabling clients to exchange task-adaptive parameters and weight them locally via an attention mechanism.

**Decentralized Learning in Human Robot Interaction**

Relatively few of the distributed learning advances mentioned above have been used to improve human robot interaction. Continual learning [Lesort et al., 2020], federated learning [Xianjia et al., 2021], and a combination of both frameworks [Liu et al., 2019] have been applied to broader robotics problems. Most closely related to this work, a recently-proposed framework extends an existing CL taxonomy [Lesort et al., 2020] to describe personalized socio-emotional interactions [Churamani et al., 2020]. Tasks may be structured into New Instances (NI), where samples in each task relate to the same concept. These type NI adaptations enable a robot to learn variations between of the same affective behavior (i.e. different variations of happiness facial expressions) [Churamani et al., 2020]. Similarly, adaptation to new affective behavior categories (i.e. learning to distinguish happiness vs. sadness facial expressions) are New Concepts (NC) that are learned via type NC adaptation. Tasks can also contain New Instance and Concept (NIC) updates.

The continual learning framework above has been successfully leveraged in a Socially-Aware Navigation (SAN) domain [Tomsland et al., 2020]. While results demonstrate the feasibility of CL in human robot interaction, challenges remain. For instance, continual learning only strategies do not provide a mechanism for exchanging information among multiple robot devices. Therefore, performance will be limited by training data encountered previously on the local device. This concern is especially relevant in human robot interaction contexts, where dataset sizes tend to be comparatively small [Churamani et al., 2020]. In this work, we propose leveraging FL as a privacy-preserving extension to CL to overcome data sharing limitations.
3 Approach

Here, we develop a framework for formulating decentralized robot learning scenarios as an FCL problem. We identify key desiderata that should be achieved by FCL algorithms and describe existing approaches before formulating a new regularization-based method called Elastic Transfer.

3.1 Learning Scenario

Building on the CL framework introduced in [Churamani et al., 2020], we define a concrete learning scenario that specifies the structure of interactions between humans and robots in decentralized learning problems. It is helpful to consider both the spatial (FL clients) and temporal (CL tasks) aspects of interactions. The spatial arrangement of interactions is determined by the number of robots deployed in parallel. For example, robots may be deployed to a care home, where they communicate with one another as they learn a new skill over a series of long-term interactions with residents. Given this scenario with between-subjects variability, we describe personalization to new individuals as NC updates. In an FCL context, NC updates may be distributed over clients if each robot interacts with a different user, while NC updates may also be distributed over tasks if a robot personalizes to multiple users over time. Similarly, new encounters within the same person can be framed as less challenging NI updates.

3.2 Evaluation Framework

It is crucial to examine several performance dimensions to gain a holistic understanding of FCL tradeoffs. For example, one naive approach for solving the scenarios above would be to train a separate model for each client-task pairing and load the model dynamically during test time. This Single Task Learning (STL) method may provide strong performance and load the model dynamically during test time. This would be to train a separate model for each client-task pair—example, one naive approach for solving the scenarios above.

Fig. 1 shows a schematic of this learning scenario.

3.3 Existing FCL Approaches

We extend the evaluation reported in [Yoon et al., 2021] to a decentralized robot learning setting to understand how existing approaches perform. Single Task Learning (STL) methods train a separate model on each local client-task dataset. Local-CL methods train a separate model on each client using CL. FL-CL approaches enable clients to communicate using FL as they solve their local CL problem. We consider both architectural and regularization based strategies for FL (FedProx and FedCurv) and CL (APD, EWC, and L2-transfer), in addition to FedWeIT.

3.4 Elastic Transfer

Based on an evaluation of existing FCL approaches (exp. one and two below), we formulate a new regularization-based method. Our approach extends EWC in the CL setting and FedCurv in the FL setting. Both EWC and FedCurv are motivated by a Bayesian framework. In a CL scenario where an optimal model $\theta_1^2$ has been found for Task 1, EWC finds a solution for Task 2 near $\theta_2^2$ while remaining within the region of low Task 1 error. This is achieved by applying a quadratic penalty to each parameter proportional to its importance in previous tasks [Kirkpatrick et al., 2017].

The process of optimizing the parameters $\theta$ given task datasets $D_1^T = \{D_1^1, D_1^2, \ldots, D_1^T\}$ can be framed as computing the posterior $p(\theta \mid D_1^1, \ldots, D_1^T)$ over all possible values of $\theta$. As the model learns a new task online, it combines the prior learned from earlier tasks with the $t$’th task’s likelihood to form an updated posterior given by:

$$p(D_t^t \mid \theta) p(\theta \mid D_1^1, \ldots, D_t^{t-1}) \over p(D_t^t \mid D_1^1, \ldots, D_{t-1}^{t-1})$$.
In this case, only $D^t$ is required while learning task $t$ because the posterior absorbs knowledge from previous tasks. EWC makes use of Laplace’s approximation to estimate this intractable posterior using a Gaussian [MacKay, 1992]. In particular, given a mean $\hat{\theta}^t_i$ centered at the maximum posterior (MAP) estimate of task $i < t$ and a precision defined by the diagonal Fisher information matrix (FIM) $F^t$ evaluated at $\hat{\theta}^t_i$, Laplace’s approximation can be given by $p(D^t | \theta) \approx \mathcal{N}(\theta; \theta^t_i, F^t)$. Provided that $\hat{\theta}^t_i$ is a local minima, the FIM acts as a surrogate to the Hessian of the negative log-likelihood of the posterior distribution [Huszár, 2017]. Given this approximation, the MAP estimate $\hat{\theta}^t_i$ for task $t$ can be found by minimizing:

$$- \log p(D^t | \theta) + \frac{\lambda}{2} \sum_{i} F^t_i (\theta - \hat{\theta}^t_i)^2$$  \hspace{1cm} (2)$$

where $\lambda$ controls regularization strength. FedCurv applies this same posterior decomposition over client devices in an FL setting [Shoham et al., 2019]. During each communication round $r$, each client $c$ exchanges their MAP estimate $\hat{\theta}_{c,r}$, and precision estimate $F_{c,r}$ refined over $E$ epochs local training. The MAP estimate for client $c$’s parameters at round $r$ of training can be given by minimizing:

$$- \log p(D_c | \theta) + \frac{\lambda}{2} \sum_{i \in C \setminus c} F_{i,r-1} (\theta - \hat{\theta}_{i,r-1})^2$$  \hspace{1cm} (3)$$

where the second term provides an importance-based regularization penalty proportional to $\lambda^1$. Because each client trains for $E$ epochs-per-round rather than to task convergence, the MAP estimates $\hat{\theta}_{c,r}$ maybe not be at a local minima, and approximates the true MAP. This can reduce FedCurv performance with small $E$ [Shoham et al., 2019].

A key benefit of EWC and FedCurv is the adaptive penalty term imposed on the training objective. Whereas FedProx and L2T impose isotropic L2 penalties that constrain parameters equally, importance-based regularization penalizes changes to parameters in proportion to their salience (e.g. elastic regularization). With EWC, this prevents overwriting knowledge from earlier tasks. With FedCurv, this prevents convergence instabilities introduced by non-iid data across clients.

We extend elastic regularization to improve FCL convergence in HRI settings. By constraining learning on local client-task datasets such that important parameters are not overwritten across clients and earlier tasks, it may be possible to limit inter-client interference. Similarly, this process may also promote consolidation of salient parameters learned across clients, promoting effective knowledge sharing. Whereas FedWeIT proposes transfer of task-adaptive parameters between clients, we instead propose transfer of task-adaptive importance estimates encoded by $\theta*$ and $F*$.

Fig. 2 summarizes how FedCurv and EWC can be extended to FCL problems. This schematic illustrates the objective of training a local model on $D^t_c$ in a scenario with two clients and two tasks. We formulate the process of learning $D^t_2$ as incorporating the likelihood into the conditional prior of other client-task partitions to give a new posterior. We approximate this term by combining three cases:

- **Case 1: Previous task, same client.** Here, we approximate $p(\theta | D^1_c)$ using $\theta^1_{c,t}$, $F^1_{c,t}$ (EWC; beige in Fig. 2). Because $\theta^1_{c,t}$ is a previous task trained to convergence, we expect $\theta^1_{c,t}$ to be at a local minima.

- **Case 2: Previous task, different client.** Here (shown in green), $p(\theta | D^1_1)$ is an earlier task learned on client 1. To prevent overwriting knowledge from $D^1_1$ while learning $D^2_2$, we also need to account for $\theta^1_{c,1}$, $F^1_{c,1}$ in the local objective.

- **Case 3: Same task, different client.** In this case (FedCurv; shown in blue), when we approximate $p(\theta | D^1_2)$, we use $\theta^1_{c,2}$, $F^1_{c,2}$ from other clients as an MAP and precision estimate. Because task 2 is also being trained on other clients, $\theta^2_{c,2}$ acts as a rough approximation of the MAP where $\theta^2_{c,r} \approx \hat{\theta}^2_{c,r}$ for large $E$.

We leverage Online-EWC to scale the scenario shown in Fig. 2 to a set of clients $C$, each of which learn a series of $T$ tasks. Online-EWC applies Laplace’s approximation to the full posterior rather than each term individually by storing a single FIM estimate $F^*_{c}$ and re-centered MAP estimate $\theta^*_c, F^*_{c}$ [Schwarz et al., 2018]. The online FIM estimate $F^*_{c} := \sum_{k=1}^{t-1} F^k_{c,t}$ is computed as a running sum of Fisher information matrices estimated for each of the $t$ previous $t - 1$ tasks on client $c$. The MAP estimate $\theta^*_c$ in the $r$th round of training can be found by minimizing:

$$- \log p(D_{c,t} | \theta) + \frac{\lambda_1}{2} \sum_{i \in C} \star F_i (\theta - \theta^*_i)^2$$

$$+ \frac{\lambda_2}{2} \sum_{i \in C \setminus C} \hat{F}_i (\theta - \hat{\theta}^t_{i,r-1})^2$$  \hspace{1cm} (4)$$

The first term uses $\lambda_1$ to weight refined estimates $\star F$, $\theta$ from previous tasks, while the second uses $\lambda_2$ to weight rough
Algorithm 1: ELastic Transfer

Input: Client-task datasets \( \{D_{c,t}\}_{c \in C, t \in \{1, \ldots, T\}} \), \( \alpha \), \( \gamma \), epochs-per-round \( E \), rounds-per-task \( R \), Clients \( C \), Number of tasks \( T \)

Output: Optimized global model \( \theta_G \)

\[
\text{for } t \leftarrow 1 \text{ to } T \text{ do}
\]

\[
\begin{align*}
\text{if } t > 1 \text{ then} & \quad \text{for } c \in C \text{ do} & \\
& \quad \text{Update } \theta^t_{c,i} \text{ from previous task} & \\
& \quad \text{Send } \theta^t_{c,i} \text{ to other clients} & \\
& \quad \text{for } r \leftarrow 1 \text{ to } R \text{ do} & \\
& \quad \text{Select available clients } C_r \subseteq C & \\
& \quad \text{for } c \in C_r \text{ do} & \\
& \quad \hat{\theta}^t_c, \hat{F}^t_c \leftarrow \text{TrainLocal}(\theta_G, E) & \\
& \quad \text{minimize } \text{e.q. 4 on device} & \\
& \quad \text{Send } \hat{\theta}^t_c, \hat{F}^t_c \text{ to other clients} & \\
& \quad \theta_G \leftarrow \sum_{c \in C_r} \frac{1}{|C_r|} \hat{\theta}^t_{c,r} & \\
\end{align*}
\]

\text{return } \theta_G

estimates of \( \hat{\theta}, \hat{F} \) currently being optimized across clients. The first term applies case 1 when \( c = i \), and case 3 when \( c \neq i \). The second term handles case 2. We show the training process for optimizing this local loss in Alg. 1. Under this regime, storage requirements are linear in \( |C| \), while communication requirements are quadratic in \( |C| \).

4 Experiments

4.1 Dataset and Centralized Baseline

We use Socially-Aware Navigation (SAN) as a proof-of-concept HRI domain. In SAN tasks, robots position themselves appropriately by learning social norms and expectations of humans in the environment. We use the SocNav1 benchmark for evaluating socially-aware robot navigation models [Manso et al., 2020b]. This dataset contains 9280 annotated examples gathered from 12 participants using a desktop-based tool. Participants were presented a static social scenario including humans, robots, and objects, and were instructed to "assess the robot's behavior in terms of the disturbance caused to humans" on a scale from 0 to 100.

The SocNav1 authors developed a graph neural network (GNN) architecture for learning SocNav1 scenes [Manso et al., 2020a]. We replicated their GNN comparison to (1) determine suitable hyperparameters, and (2) establish a centralized learning baseline assuming standard train/validation/test partition on a server. A Graph Convolutional Network implemented via Deep Graph Library (GCN+DGL) with \( \alpha = 5e^{-3}, \gamma = 1e^{-4} \), and a mini-batch size of 32 performed the best (test MSE=0.0296). We use this configuration in all following decentralized learning experiments.

4.2 FCL Evaluation

We simulate the learning scenario in Fig. 1 with three clients and four tasks by assigning annotations from each of the 12 SocNav1 participants to a distinct client-task dataset. Because participants rated a varying number of scenes (Fig. 3) this simulates non-iid local dataset imbalances. Because participants also rate a common subset of scenes and demonstrate rating variability (avg \( \pm 14 \) points on 100 point scale), this also simulates non-iid concept shift. We increase the training dataset size via a dataset augmentation approach suggested by the SocNav1 authors.

In experiment one, compare existing FCL methods with respect to our decentralized learning desiderata. We compare 10 methods combining CL and FL strategies (reported as CL-FL, or baseline). We assess adaptation quality via average MSE (AMSE), a CL metric that records test MSE at the end of training on each task. We assess adaptation time via FWT, a CL metric that records average test MSE on future tasks that have not been encountered yet in training. Low FWT demonstrates zero-shot transfer, or generalization, to data from new participants, which means that the method will quickly adapt to new individuals. We also record BWT, which measures the test set performance difference between earlier tasks and the current one. High BWT suggests that earlier task performance has deteriorated, indicating inter-client interference may have occurred. Finally, we measure model overhead via the number of static (S) and trainable (T) parameters required by each method. We set \( E = 1, R = 75 \), and include all clients in each round of training.

In experiment two, we measure how AMSE changes as a function of training dataset size. If a method demonstrates lower AMSE as dataset size increases, this suggests (1) strong adaptation time (i.e. high sample efficiency) and
Table 1: Comparison of existing FCL methods.

| Algorithm          | Evaluation Metrics | Parameters | S | T |
|--------------------|--------------------|------------|---|---|
|                    | AMSE  | BWT   | FWT   | S  | T |
| Baselines          |        |       |       |    |   |
| SIIE               | 0.0216 | 0.0109 | 0.4175 | 0 | 36.724 |
| FedAvg-SGD         | 0.0426 | -0.0031 | 0.0483 | 0 | 7.681 |
| FedProx-SGD        | 0.0431 | -0.0024 | 0.0508 | 7.681 | 7.681 |
| Regularization     |        |       |       |    |   |
| Local-EWC          | 0.0497 | 0.0134 | 0.0719 | 61.448 | 7.681 |
| FedAvg-EWC         | 0.0410 | 0.0090 | 0.0466 | 61.448 | 7.681 |
| FedProx-EWC        | 0.0419 | -0.0019 | 0.0495 | 69.129 | 7.681 |
| Architectural      |        |       |       |    |   |
| Local-APD          | 0.0521 | 0.1139 | 0.1838 | 0 | 39.176 |
| FedAvg-APD         | 0.0480 | 0.2230 | 0.5101 | 0 | 39.176 |
| FedProx-APD        | 0.0495 | 0.1625 | 0.2263 | 7.424 | 39.176 |
| FedWeIT            | 0.0959 | 0.2259 | 0.6610 | 89.100 | 39.272 |

Table 2: Comparison of Elastic Transfer with other FL-CL methods.

| Algorithm          | Evaluation Metrics | Parameters | S | T |
|--------------------|--------------------|------------|---|---|
|                    | AMSE  | BWT   | FWT   | S  | T |
| FedAvg-SGD         | 0.0191 | 0.0088 | 0.0369 | 0 | 7.681 |
| FedProx-SGD        | 0.0408 | 0.0093 | 0.3711 | 7.681 | 7.681 |
| FedCurv-SGD        | 0.0378 | 0.0092 | 0.0382 | 20.043 | 7.681 |
| FedAvg-EWC         | 0.0386 | 0.0128 | 0.0373 | 61.448 | 7.681 |
| Elastic Transfer   |        |       |       |    |   |
| λ = 0.5e^-2, λ2 = 5e^-1, λ3 = 5e^-1 | 0.0363 | 0.0083 | 0.0352 | 115.215 | 7.681 |
| 5e^-2, 5e^-1, 5e^-1 | 0.0396 | 0.0062 | 0.0400 | 115.215 | 7.681 |

5 Conclusion and Future Work
In this work, we introduced decentralized learning methods to improve privacy in decentralized robot learning scenarios. We outline four key priorities that would be balanced in HRI personalization scenarios and evaluate existing approaches with respect to these criteria using a social navigation benchmark. We also develop a new regularization-based FCL method – Elastic Transfer. Our evaluation shows that Elastic Transfer improves adaptation quality, adaptation time, and knowledge sharing on this dataset. Importantly, our evaluation also shows that decentralized learning can improve privacy while still maintaining acceptable performance compared to centralized alternatives.

There are several opportunities to expand this work. Federated Continual Learning serves as an extensible decentralized learning framework that can be applied in other HRI domains. Based on our promising evaluation of Elastic Transfer, future work can extend this approach to new machine learning domains, and evaluate it thoroughly on a series of broader benchmarks. We also see opportunities to further reduce communication overhead by leveraging similar reformulations introduced by FedCurv and Online-EWC. We hope that this work will inspire further assessment and development of privacy-preserving methods for personalization in human-robot interaction.
References

[Butler et al., 2015] Daniel J Butler, Justin Huang, Franziska Roesner, and Maya Cakmak. The privacy-utility trade-off for remotely teleoperated robots. In Proceedings of the tenth annual ACM/IEEE international conference on human-robot interaction, pages 27–34, 2015.

[Churamani et al., 2020] Nikhil Churamani, Sinan Kalkan, and Hatice Gunes. Continual learning for affective robotics: Why, what and how? Age, 30:40, 2020.

[Hodson, 2014] Hal Hodson. The first family robot, 2014.

[Huszár, 2017] Ferenc Huszár. On quadratic penalties in elastic weight consolidation. arXiv preprint arXiv:1712.03847, 2017.

[Kirkpatrick et al., 2017] James Kirkpatrick, Razvan Pascanu, Neil Rabinowitz, Joel Veness, Guillaume Desjardins, Andrei A Rusu, Kieran Milan, John Quan, Tiago Ramalho, Agnieszka Grabska-Barwinska, et al. Overcoming catastrophic forgetting in neural networks. Proceedings of the national academy of sciences, 114(13):3521–3526, 2017.

[Leite et al., 2013] Iolanda Leite, Carlos Martinho, and Ana Paiva. Social robots for long-term interaction: a survey. International Journal of Social Robotics, 5(2):291–308, 2013.

[Lesort et al., 2020] Timothée Lesort, Vincenzo Lomonaco, Andrei Stoian, Davide Maltoni, David Filliat, and Natalia Díaz-Rodríguez. Continual learning for robotics: Definition, framework, learning strategies, opportunities and challenges. Information Fusion, 58:52–68, 2020.

[Li and Hoiem, 2017] Zhizhong Li and Derek Hoiem. Learning without forgetting. IEEE transactions on pattern analysis and machine intelligence, 40(12):2935–2947, 2017.

[Li et al., 2018] Tian Li, Anit Kumar Sahu, Manzil Zaheer, Maziar Sanjabi, Ameet Talwalkar, and Virginia Smith. Federated optimization in heterogeneous networks. arXiv preprint arXiv:1812.06127, 2018.

[Liu et al., 2019] Boyi Liu, Lujia Wang, and Ming Liu. Lifelong federated reinforcement learning: a learning architecture for navigation in cloud robotic systems. IEEE Robotics and Automation Letters, 4(4):4555–4562, 2019.

[MacKay, 1992] David JC MacKay. A practical bayesian framework for backpropagation networks. Neural computation, 4(3):448–472, 1992.

[Manso et al., 2020a] Luis J Manso, Ronit R Jorvekar, Diego R Faria, Pablo Bustos, and Pilar Bachiller. Graph neural networks for human-aware social navigation. In Workshop of Physical Agents, pages 167–179. Springer, 2020.

[Manso et al., 2020b] Luis J Manso, Pedro Nuñez, Luis V Calderita, Diego R Faria, and Pilar Bachiller. Socnav1: A dataset to benchmark and learn social navigation conventions. Data, 5(1):7, 2020.

[Mansour et al., 2020] Yishay Mansour, Mehryar Mohri, Jae Ro, and Ananda Theertha Suresh. Three approaches for personalization with applications to federated learning, 2020.

[Pandey and Gelin, 2018] Amit Kumar Pandey and Rodolphe Gelin. A mass-produced sociable humanoid robot: Pepper: The first machine of its kind. IEEE Robotics & Automation Magazine, 25(3):40–48, 2018.

[Parisi et al., 2019] German I Parisi, Ronald Kemker, Jose L Part, Christopher Kanan, and Stefan Wermter. Continual lifelong learning with neural networks: A review. Neural Networks, 113:54–71, 2019.

[Rudovic et al., 2021] Ognjen Rudovic, Nicolas Tobis, Sebastian Kaltwang, Björn Schuller, Daniel Rueckert, Jeffrey F Cohn, and Rosalind W Picard. Personalized federated deep learning for pain estimation from face images. 2021.

[Schwarz et al., 2018] Jonathan Schwarz, Wojciech Czarnecki, Jelena Luketina, Agnieszka Grabska-Barwinska, Yee Whye Teh, Razvan Pascanu, and Raia Hadsell. Progress & compress: A scalable framework for continual learning. In International Conference on Machine Learning, pages 4528–4537. PMLR, 2018.

[Shoham et al., 2019] Neta Shoham, Tomer Avidor, Aviv Keren, Nadav Israel, Daniel Benditks, Liron Mor-Yosef, and Itai Zeitak. Overcoming forgetting in federated learning on non-iid data. arXiv preprint arXiv:1910.07796, 2019.

[Tan et al., 2021] Alysa Ziying Tan, Han Yu, Lizhen Cui, and Qiang Yang. Towards personalized federated learning, 2021.

[Tjomsland et al., 2020] Jonas Tjomsland, Sinan Kalkan, and Hatice Gunes. Mind your manners! a dataset and a continual learning approach for assessing social appropriateness of robot actions. arXiv preprint arXiv:2007.12506, 2020.

[Xianjia et al., 2021] Yu Xianjia, Jorge Pena Queralta, Jukka Heikkonen, and Tomi Westerlund. Federated learning in robotic and autonomous systems. arXiv preprint arXiv:2104.10141, 2021.

[Yoon et al., 2019] Jaehong Yoon, Saehoon Kim, Eunho Yang, and Sung Ju Hwang. Scalable and order-robust continual learning with additive parameter decomposition. arXiv preprint arXiv:1902.09432, 2019.

[Yoon et al., 2021] Jaehong Yoon, Wonjong Jeong, Gwoong Lee, Eunho Yang, and Sung Ju Hwang. Federated continual learning with weighted inter-client transfer. In International Conference on Machine Learning, pages 12073–12086. PMLR, 2021.
In this technical appendix, we include additional details about our experiment setup (Section A) and results (Section B). The accompanying folder also includes code with our experiment setup and implementation.

A Experiment Details

A.1 Setup

We assign one SocNav1 participant to each of the 12 local-client task partitions, and split each data into a 70/15/15 train, validation, and test set (Table 3). We conducted the same dataset augmentation procedure as the SocNav1 authors recommend [Manso et al., 2020a]. We use the best performance difference between the corresponding set of test datasets $Tr^{(i)}$ available to the algorithm during each task, and columns denote the corresponding set of test datasets $Tr^{(j)}$ (Fig. 5).

\[
\begin{array}{c|ccc}
T & T^{(1)} & T^{(2)} & T^{(3)} \\
\hline
T^{(1)} & R^{(1,1)} & R^{(1,2)} & R^{(1,3)} \\
T^{(2)} & R^{(2,1)} & R^{(2,2)} & R^{(2,3)} \\
T^{(3)} & R^{(3,1)} & R^{(3,2)} & R^{(3,3)} \\
\end{array}
\]

Figure 5: Train-test accuracy matrix $P$.

We compute AMSE over tasks as $\frac{1}{T} \sum_{t=1}^{T} \sum_{j=1}^{N} (P_{i,j} - P_{i,j})$. We compute BWT by measuring the performance difference between the previous task and the current task such that:

\[
BWT = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} (P_{i,j} - P_{i,j})}{N(N-1)}
\]

(5)

Because we measure BWT in the context of MSE, negative BWT indicates performance is improving over tasks. We compute FWT via the mean of the grey elements in Fig. 5 such that:

\[
FWT = \frac{\sum_{i=1}^{j-1} \sum_{j=1}^{N} P_{i,j}}{N(N-1)}
\]

(6)

A.2 Evaluation

We compute AMSE, BWT, and FWT as specified in [Lesort et al., 2020]). We compute the training-test performance matrix $P$, where rows denote training datasets $Tr^{(i)}$ and columns denote the corresponding set of test datasets $Tr^{(j)}$ (Fig. 5).

A.3 Network Architecture

We use the same Graph Convolutional Network + Deep Graph Library (GCN+DGL) architecture reported in [Manso et al., 2020a]. We conducted a randomized grid search of the number of network layers, hidden layer size, weight decay, and mini-batch size in a centralized learning evaluation with standard train, validation, and test sets. We use the best performing architecture with 8 layers and 32 hidden units per layer in decentralized experiments.

A.4 Hyper-parameters

All experiments use $\alpha = 5e^{-3}$, $\gamma = 1e^{-4}$, and a mini-batch size of 32 samples. An Adam optimizer with learning rate decay was used, where the $\alpha$ is reduced by a factor of 2 for every 5 consecutive epochs with no validation loss decrease. Training continues at the minimum learning rate of $1e^{-5}$ rather than using early stopping to synchronize training among clients. We set $\mu = 5e^{-2}$ for FedProx, $\lambda = 5e^{-2}$ for EWC, $\lambda_1 = 1e^{-2}$, $1e^{-3}$ and $\lambda_2 = 1e^{-4}$ for FedWeIT. These FedWeIT hyper-parameters were determined by a grid search over the three hyperparameter options on a centralized learning benchmark.

B Additional Results

Table 4 shows the full results of experiment three evaluating elastic transfer with different hyper-parameter combinations.

| Algorithm          | Evaluation Metrics | Parameters | S | T |
|--------------------|--------------------|------------|---|---|
|                    | AMSE               | BWT        | FWT |   |
| FedAvg-SGD         | 0.0391             | 0.0120     | 0.0380 |
| FedProx-SGD        | 0.0408             | 0.0108     | 0.0407 |
| FedCurv-SGD        | 0.0378             | 0.0092     | 0.0382 |
| FedAvg-EWC         | 0.0386             | 0.0128     | 0.0373 |
| Elastic Transfer   |                    |            |     |   |
| $\lambda_1$        | 5e^{-1}            | 0.0408     | 0.0120 |
| $\lambda_2$        | 5e^{-1}            | 0.0389     | 0.0108 |
| $\lambda_3$        | 5e^{-2}            | 0.0383     | 0.0107 |
|                    | 5e^{-2}            | 0.0392     | 0.0114 |
|                    |                    |            |     |   |
|                    | 5e^{-2}            | 0.0385     | 0.0115 |
|                    |                    |            |     |   |
|                    | 5e^{-1}            | 0.0369     | 0.0124 |
|                    | 5e^{-2}            | 0.0389     | 0.0103 |
|                    |                    |            |     |   |
|                    | 5e^{-2}            | 0.0391     | 0.0085 |
|                    |                    |            |     |   |
|                    | 5e^{-1}            | 0.0396     | 0.0062 |
|                    | 5e^{-2}            | 0.0402     | 0.0115 |
|                    |                    |            |     |   |
|                    | 5e^{-2}            | 0.0390     | 0.0080 |
|                    | 5e^{-2}            | 0.0390     | 0.0091 |
|                    |                    |            |     |   |
|                    | 5e^{-1}            | 0.0384     | 0.0115 |
|                    | 5e^{-2}            | 0.0391     | 0.0086 |
|                    |                    |            |     |   |
|                    | 5e^{-2}            | 0.0386     | 0.0128 |
|                    |                    |            |     |   |
|                    | 5e^{-1}            | 0.0388     | 0.0122 |
|                    | 5e^{-2}            | 0.0363     | 0.0083 |
|                    |                    |            |     |   |
|                    | 0                  | 0.0392     | 0.0118 |
|                    | 5e^{-2}            | 0.0374     | 0.0108 |
|                    |                    |            |     |   |
|                    | 0                  | 0.0374     | 0.0101 |
|                    | 5e^{-2}            | 0.0378     | 0.0092 |
|                    |                    |            |     |   |
|                    | 0                  | 0.0388     | 0.0122 |

Table 4: Results of full set of hyperparameter combinations evaluated in experiment three.