2022 IEEE/ACM International Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE)

Dementia Care in Federated Learning

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Abstract— **Data privacy is the main concern when using machine learning methods to solve dementia care problems. This paper makes the first attempt to deploy a human robot interaction model for dementia care in federated learning settings so that the privacy for persons with dementia (PwDs) can be retained. Numerical experiments of deploying the human-robot interaction model for cognitive therapy in the federated setting is conducted to show the feasibility of the federated learning setting. The simulated experiments in the case study shows the influence of different factors, i.e., client local training speed, the number of clients, homogenous and/or heterogenous patients.**

I. Introduction

The recent development of machine learning models for dementia such as a cognitive therapy model via a reinforcement learning method [1, 2], an Alzheimer's Disease diagnosis model [3] and a conversational strategy model [4] demonstrates the capability of the emerging machine learning methods on solving problems for dementia. However, privacy protection of users' sensitive data prevents machine learning models to be trained efficiently and accurately. For example, the cognitive therapy model [1] can be trained in about 15 years if a social robot can interact with a PwD 3 times a day and 30 minutes at each time to train the model.

The rapid evolution of computer software and hardware technologies makes the federated learning technologies via edge computing devices (i.e., social robots or other mobile devices) applicable [5]. The federated learning is a decentralized setting of the existing machine learning method. It applies on-device AI, information and communication technologies, and edge computing/IoT to train a global model on decentralized data. Specifically, the global model is trained by updating and exchanging model parameters learned from the decentralized raw data by different clients. The raw data contains the users' privacy information and does not need to be shared, but these model parameters learned from the raw data do not include sensitive information of users. Therefore, privacy is preserved in the federated learning framework.

***CHASE'22*, November 17-19, 2022, Washington, DC, USA**

ACM ISBN 978-1-4503-9476-5/22/11.
http://doi.org/10.1145/3551455.3564706

To fill the gap between an existing human-robot interaction model for dementia care [1] and its application limitations due to data privacy and learning inefficiency, this paper deploys the model in federated learning settings, where different social robots can interact with different PwDs simultaneously and can train a global model collaboratively.

II. Methodology

The human-robot interaction model for cognitive therapy is trained by a reinforcement learning method, i.e., Q-learning, enabling sufficient adaptivity. The PwD is modelled by a number of Markov transition matrices [1], whose dimension represents the number of different mental states S. The elements in the matrix represents the transition probability between different states. The social robot is an agent and can take actions A, i.e., different prompts for conversations and different stimulations for diversions. Q is the value function that computes the accumulated rewards for an action taken in a given state. Q-value is updated at each learning iteration. The goal of the agent is to take actions that maximize the Q attainable from future states to the reward for achieving its current state.

Deploying the human-robot interaction model in federated settings should at least include homes, PwDs, social robots, a cloud server and a communication channel as shown in Fig. 1.

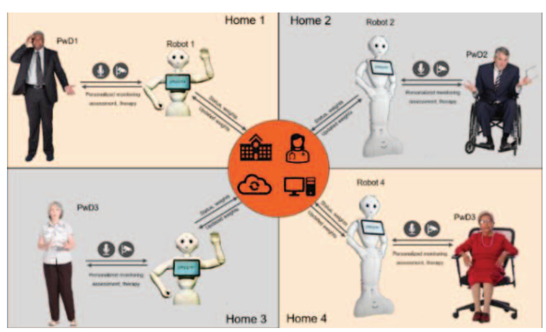

Figure 1. A federated learning setting to deploy human-robot interaction model for dementia care.

Specifically, the agent i as a client learns a Q value after n_i epochs by interacting with its PwD at the x-th federated learning iteration. The Q value is denoted as $Q_x^{(i)}$. Then the value function at the (x+1)-th iteration is updated as the aggregation of all Q values from the x-th iteration as $Q_{x+1} = \sum_i \frac{n_i}{\sum n_i} Q_x^{(i)}$. Therefore, a global model can be trained as $Q_x \rightarrow Q_{x+1}$. Note that in the design of actual setting, an epoch has 30 episodes, each of which is terminated if the PwD need to stop or the threshold (i.e., 50 conversation rounds) is hit or the 15 pictures for the reminiscence therapy are all applied. The agent i can learn faster than the agent i+1 if $n_i > n_{i+1}$.

Although the methodology shown in this section is simulation-algorithm-oriented, we discussed the design of this work for a field study in the future. Specifically, a social robot is designed to Q&A conversation regularly with its PwD to review some old pictures for a reminiscence therapy to the PwD. During the conversation, the social robot can ask questions with different difficulty level, can comfort the PwD, can repeat the questions and can identify the emotional and mental states of the PwD after each conversation round with the assistance of different build-in sensors and machine learning models, e.g., ECG sensor, machine vision camera and facial expression recognition model. The human-robot interaction model is to learn an optimal conversational strategy that the social robot can use to talk with its PwD so that the PwD can be stimulated to talk more and be in a positive manner more. N social robots can interact with their PwDs independently to train their own models and the robot i has a training speed of n_i, $i \in [1,2,\ldots, N]$, n_i equaling to one means that the robot can train 3×30 minutes per day. After ten days (i.e., an epoch with n_i=1), N social robots can update their model parameters, i.e., conversation strategy, to a cloud server. The could server can aggregate their model parameters and announce a new set of a global model parameters based on the aggregation to all social robots. The new global model parameters can be utilized as an initial point for all social robots to train their own models in the next ten days. The cloud server can keep the global model parameters updated until the parameters converge to a level of interest.

To deploy the human robot interaction model in federated learning setting, this work conducted four simulated experiments with different parameters. Let the number of clients be N. The PwDs in the federated setting modelled by similar (resp. different) Markovian transition matrices are called homogenous (resp. heterogenous) patients. The machine learning model trained by one social robot without federated learning is regarded as a benchmark experiment i.e., (N = 1, n_1 = 1). The parameters of the four experiments in an order are (N = 2, n_1 = n_2 = 2, homogenous), (N = 2, n_1 = 1, n_2 = 3, homogenous), (N = 3, n_1 = n_2 = n_3 = 1, heterogenous), and (N = 2, n_1 = n_2 = 1, heterogenous), respectively. The results are shown in the following.

III. Results and Discussion

Global model convergent time for all experiments, a local model convergent time for the benchmark experiment, the Q-value sum indicating the maximum reward value of machine learning models are shown in Table 1. The model with the largest Q-value sum provides an optimal policy, i.e., the best conversational strategy.

As shown in Table 1., the QVS values are the same in E_1, E_2, and BE since the patient models in E_1, E_2 are homogeneous to that in BE. Therefore, the global model deployed in this federating learning setting can provide the optimal policy as the benchmark experiment. The global model convergent time (1400 days) in E_1 is the same as that of each robot in E_1 since the training speed for each robot in E_1 are the same. This time is ¼ of the convergent time (5600 days) in BE since there are two clients in E_1 and each of which has a faster training speed than that of the only robot in BE. The global model convergent time in E_2 is around 1400 days, which is the average between the two robots and is similar to that in E_1. The two robots in E_2 have almost the same convergent time but robot 2 uses a little less time since it has a faster training speed.

The convergent time in E_3 is about 1/3 of that in BE since there are three clients in E_3, each of which has the same training speed with robot 1 in BE. However, QVS in E_3 is lower than that in BE since the patient models in E_3 is heterogenous to that in BE. The global model trained in E_4 only has a QVS of 10000 since the patient models applied in E_4 has the largest heterogeneity. We used the global model trained in E_4 as a pretrained model, and let a single client to learn the model on a patient who is heterogenous to those in E_4 and homogeneous to BE, then the client takes about 1500 days to obtain the optimal policy as in BE starting from the pretrained model. Therefore, it is shown that the global model deployed in federated learning can be a good pretrained model

TABLE 1. The Results of Traing the Global Model in Federated Learning Setting

	Robot 1	Robot 2	Robot 3	QVS
E_1	1400 days	1400 days	~	12000
E_2	1450 days	1300 days	~	12000
E_3	2000 days	2000 days	2000 days	11800
E_4	1500 days	1500 days	~	10000
BE	5600 days	~	~	12000

E_i is the experiment i, BE is the bench mark experiment
Robot i represents the convergent time of robot i
QVS is the Q-value sum

IV. Conclusion

This paper makes the first attempt to deploy a human robot interaction model for dementia care in federated learning settings so that the privacy for persons with dementia (PwDs) can be retained. Different factors of federated learning setting are investigated. In homogeneous patients' settings, increase the number of clients and the training speed of each client can increase the global model convergent time. In heterogeneous patients' settings, the global model is not optimal but can serve as a good pretrained model for optimization.

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