Decentralized Learning with Average Difference Aggregation for Proactive Online Social Care

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Abstract

The Internet and the Web are being increasingly used in proactive social care to provide people, especially the vulnerable, with a better life and services, and their derived social services generate enormous data. However, privacy concerns require the strict protection of a user’s data which leads to a dilemma between pursuing better intelligent services and privacy preservation. To solve this dilemma, this paper develops a decentralized learning framework to enable proactive social care equipped with artificial intelligence and data protection. The proposed learning framework trains a secure local model for each user using their own datasets. Each user’s device only shares its local model’s parameters with the central model server without exposing any data, and the server integrates multiple users’ models to learn a global data-free model. To improve the generalizability of the global model, we further propose a novel model aggregation algorithm, namely the average difference descent aggregation (AvgDiffAgg for short). In particular, to evaluate the effectiveness of the learning algorithm, we use a case study on the early detection and prevention of suicidal ideation, and the experiment results on four datasets derived from social media demonstrate the effectiveness of the proposed learning method.

Keywords— Decentralized learning; online social care; model aggregation; average difference descent

1 Introduction

Proactive care is a kind of public service for healthcare and community assistance by connecting health organizations, social workers, and targeted patients. Traditional care service is based on face-to-face interaction in a certain place between general practitioners or social workers and people in need. Recently, with the help of online communication such as social networking services and private chatting, a new form of proactive online social service for mental health care has become available to online communities. Proactive social care provides people with early warning and support information to detect and relieve their mental disorders and social-related issues before their condition worsens.

Proactive social care for patients with mental disorders, especially depression and suicidality, is one of the most crucial services of social care in the modern society and has attracted worldwide attention. Mental health plays an important role in an individual’s state of well-being. Mental health issues, such as depression, anxiety and post-traumatic stress disorder, have an adverse impact on people’s daily life and health status. Untreated severe mental disorders could lead to suicidal ideation. According to WHO
reports, around 300 million people suffer from depression\(^1\), and about 900,000 people commit suicide worldwide every year\(^2\). Moreover, these figures continue to increase in every country across the world.

The traditional way to treat a mental health condition is psychological treatment, such as cognitive behavior therapy and interpersonal psychotherapy. This treatment relies heavily on health professionals such as general practitioners and psychiatrists. But current health services are not adequate to ensure effective treatment for such a huge number of potential sufferers. Furthermore, it is difficult to identify mental health issues at an early stage and take preventative action.

With the advances in the Web and mobile technology, mental health services are now using mobile devices to monitor a patient’s health status and provide a platform for private communication within online communities to express mental stress. Conversation is one of the simplest and most effective ways to relieve an individual’s mental disorders and even suicidal ideation. Online text-based communication helps people to express their feelings and sufferings in their daily life and work, providing psycholinguistic clues for early detection. It also provides a possible channel for volunteers and social workers to respond to risky social posts and address a sufferer’s mental health issues through supportive comments.

There are many online platforms, forums and applications for chatting, peer support and early prevention, for instance, HealthfulChat, an online peer health support community, containing several chat rooms for mental health such as anxiety, bipolar and depression\(^3\); ReachOut Forums\(^4\), an anonymous space for 14 to 25 year old Australians to share stories and receive support online discussion; Turn2Me\(^5\), a lifeline web space for sharing and discussing personal issues; and Ibobbly, a mobile health intervention application \cite{29}. Some services offered on these websites are delivered by mental health professionals. These services help people reach out and engage in conversations and consultation through the online communities.

Text-based chatting services such as SMS services, mobile APPs, Web applications, and social networking services could also be helpful in promoting mental wellbeing when integrated with mental health care services. Several works have studied the text-based synchronous conversations for mental health intervention \cite{9}. Other works, especially those on early detection, focus on social networks for recognizing depression \cite{30}, detecting stress \cite{19}, and social network mental disorders \cite{28}. These early detection strategies are preliminary for proactive online social care services for social support.

Most people are willing to post their issues on the social platforms because of the convenience of communication. However, if their data were collected to analyze their personal profile for commercial purposes, they would be unwilling to share their feelings online. Additionally, their personal information could be stolen and used illegally by the adversaries if the data were not stored securely. Moreover, it is possible that these online users could become victims of stalking or internet fraud. Thus, to enable effective proactive online social care, it is necessary to protect a user’s sensitive data while providing mental health care services.

We propose a data protection framework by decentralized learning and model aggregation for intelligent proactive social care which can be integrated into any type of communication services, such as social networks, online forums and especially private chatting. The significance of this work is to optimize the learning from distributed clients under the framework of data protection without collecting the raw data of users which can help to facilitate mental health care services and protect user’s privacy. This solution comprises four key features, i.e., language representation, data protection, mental health detection, and effectiveness stratification of supportive responses, to empower intelligent proactive social care for mental health. We develop deep neural networks to learn the representation of text for language understanding, and study two tasks to enable proactive online social care under the framework of data protection.

This paper contributes to the literature in the following three ways:

\(^1\)WHO fact sheets about mental disorders, available at \url{https://www.who.int/news-room/fact-sheets/detail/mental-disorders}

\(^2\)Suicide rates, Global Health Observatory (GHO) data, available at \url{http://www.who.int/gho/mental_health/suicide_rates/en/}

\(^3\)Available at \url{http://www.who.int/gho/mental_health/chat-rooms.html}

\(^4\)https://au.reachout.com

\(^5\)https://turn2me.org/
We propose a decentralized learning framework with data protection for proactive social care by introducing a third party data-free model server and by implementing a proactive social service and data collection separately.

To improve model aggregation in the learning framework, we proposed a two-step optimization and average difference descent for global model updates.

To evaluate our decentralized framework and improved model aggregation algorithm, a case study on suicidal ideation detection and effectiveness stratification as services of proactive social care is conducted, resulting in better performance than the baselines.

The structure of this paper is as follows. Related work are reviewed in Section 2. Our proposed learning framework is introduced in Section 3 together with an improved optimization algorithm and privacy analysis. In Section 4, an experimental evaluation is conducted under the settings of proposed framework for proactive social care. A conclusion is drawn in Section 5 together with a brief discussion.

2 Related Work

This paper is related to mental health care, such as the detection of depression or suicidality and conversation treatment, distributed machine learning techniques such as parameter server and federated learning, and privacy-preserving machine learning.

2.1 Mental Health Care

A large body of research focuses on mental health to provide proactive care for those who need it, especially the detection of mental health issues such as stressor events [18], depression [3], and suicidality [23]. Shuai et al. used a machine learning based model to perform multi-source learning for mental disorder detection in social media [28]. Tsugawa et al. extracted features from a user’s Twitter activities and detected that the user was suffering from depression [30]. Nguyen et al. performed affective and content analysis through a comparison between depression communities as the clinical group and normal communities as the control group [21]. Lin et al. proposed a hybrid method of factor graph and convolutional neural network to detect psychological stress through tweet content and user interaction [19].

Severe mental disorders could turn to suicidality. Suicidal risk has been studied from the perspective of interaction between clinicians and patients [31], and knowledge discovery and detection using online social content [11]. De Choudhury et al. investigated the transition of mental health to suicidality in online social communities [4]. Ren et al. proposed a complex emotion model for suicidal intention detection in blogs [26]. Ji et al. proposed an improved model aggregation method to detect suicidal ideation in a distributed manner [10].

2.2 Distributed Machine Learning

Distributed machine learning is a core technology to solve large-scale machine learning in the application of big data. Specific problems include data parallelism and model parallelism. The parameter server is a powerful tool to tackle the distributed machine learning problems with scalability [16] and efficient communication [17]. With the popularization of deep learning techniques, many studies turned to distributed deep learning, such work as synchronous stochastic gradient descent [2] and the distributed deep learning platform from the Apache Incubator project called SINGA [24].

Another similar technique is called federated learning [20], which is an on-device solution to decouple the training procedures from data collection. The method uses an iterative averaging model that can perform distributed training and learn efficiently from decentralized data to achieve the goal of preserving privacy. To improve communication efficiency, Konečný et al. proposed structured updates and sketched updates to reduce uplink communication costs [14]. Geyer et al. proposed differential privacy preserving techniques on the client side to balance performance and privacy [6].
2.3 Privacy Preserving

Privacy preserving techniques fall into three categories depending on whether privacy is preserved in the input data, the model, or the output results [27]. Abadi et al. developed deep learning techniques within the framework of differential privacy [1]. The privacy of the input data is referred to as local differential privacy [12], in which users randomize data before submitting it to an untrusted center.

3 Methodology

In this section, we propose a decentralized learning framework with model aggregation that enables data protection for proactive social care. It is designed with a third-party model server and a two-step optimization strategy to decouple model training and data collecting. In particular, the datasets are located on decentralized clients, e.g. a physical electronic devices or an isolated software container, and won’t be exposed to the central model server which will reduce the risk of privacy abuse and leakage. Further, we undertake a privacy analysis.

3.1 Decentralized Learning Framework

We proposed a decentralized learning framework for proactive social care by secure local training on local client devices and model aggregation. It is powered by a communication server with a chatting service for user data transmission and a third-party service provider, i.e., a mental health care service provider in this paper, for the communication of model parameters. The framework is illustrated in Figure 1. The user data is stored on client devices and the data server. Data accessing for the communication server is protected by a secure connection. The third-party service provider has no permission to access the accurate user data. It can only access to the locally trained model in accordance with the rules of the communication interface. In this way, the communication service is separated from third-party proactive social care, providing third-party applications with an approach to making inferences without accessing the raw data.

The learning principle of this framework is quite similar to fast adaptive meta-learning [5,22], zero-data learning [15], and knowledge transferring [25], that is, it learns a well-generalized global model in the data-free model server by aggregating the information learned from distributed clients.

The workflow of the decentralized learning framework is illustrated in Figure 2. First, the model server chooses a learning model as the client model for each client to perform specific tasks on devices. In this paper, we take two proactive social care tasks into consideration, i.e., text-based suicidality detection and social comment categorization. The first task aims to provide an early detection and warning system. The second task makes it easier for target users to access more effective responses. These two tasks are typically regarded as binary classification and multi-class classification problems, respectively. Deep
neural networks, such as convolutional neural networks (CNNs) [13] for text and long short-term memory networks (LSTM) [8] are chosen as the classification model for clients to learn the language features in user generated content. In this illustration, CNN is used as an example. After parameter initialization, the model parameters are sent to the selected online clients to perform local training using the data of each user. Then, the locally trained models are sent back to the model server for model aggregation and updating. The intuitive way to undertake model aggregation is model averaging. We propose a novel approach to aggregating a client model to optimize the global model, called Average Difference Aggregation or AvgDiffAgg for short. The objective function and our proposed two-step optimization is introduced in detail in Section 3.2 and 3.3. A round of training consists of local training on devices, parameter sending, and model aggregation on the model server. The learning framework with data protection works through an iterative update through client and server communication.

3.2 Objective Function

In the decentralized setting, it is necessary to train the deep learning method by using each user’s own data. However, one user’s data is inadequate for training a deep learning model. To solve this problem, the global model in our proposed framework aims to provide a good initialization to every user so that they can fine-tune a personalized deep learning model with their own data.

Training a deep learning model is a non-convex optimization task with many local optimal solutions or optimal points in the solution manifold. To address the local optimal problem in deep learning model training, there is an empirical assumption that if the initialization point of the model parameters is close to the global optimal point, arriving at the global optimal point or gaining a “better” local optimal point is more likely if the model is fine-tuned. Here, “better” is compared to the average results with randomly selected initialization points. Therefore, the optimal initialization point $\theta$ should be

$$\arg \min_\theta L = \arg \min_\theta \sum_{k=1}^n \frac{1}{n} L(\theta, \theta_k)$$

(1)

where $\theta_k$ is the optimal parameter solution for the $k$-th user, and $L$ is the loss function for measuring the distance between initialization point $\theta$ and each user’s optimal point $\theta_k$.

The procedure of finding the optimal global parameters is illustrated in Fig. 3. The central body of this illustration shows how the server weights are updated to optimal weights. The subfigure in the upper left corner shows how the local weights are composed as the gradient. The brown arrow in the form of the average difference between the model weights acts as the gradient. The optimization objective on the server side minimizes the average or expectation of the Euclidean distance between the server weight and the user weights. To facilitate this calculation, the loss function can be re-written as

$$L = \sum_{k=1}^n \frac{1}{2n} [L(\theta, \theta_k)]^2$$

(2)
where $L(\cdot, \cdot)$ is specified to Euclidean distance between two sets of weights, and $m$ is the number of users or local devices.

Figure 3: Finding the nearest global weight to all the optimal local weights. The blue arrows show the model updating towards the optimum parameter $\theta^*$. The brown arrow $\nabla$ acts as the “gradient”.

### 3.3 Two-step Optimization

In Equation 2, the global model parameter $\theta$ and the $k$-th client model parameter $\theta_k$ are two correlated parameters that both need to be optimized. To solve this optimization problem, we propose a two-step optimization algorithm that uses gradient descent to simultaneously approach optimal $\theta$ and $\theta_k$. Specifically, optimization is an iterative procedure and each iteration $t$ includes two steps that aim to separately update $\theta$ and $\theta_k$.

In the first step of each iteration, we clip the value of each user’s parameters $\theta_k$, and update the global initialization point $\theta$ with the gradient derived from Equation 2 as:

$$\frac{\partial L}{\partial \theta} = \frac{1}{n} \sum_{k=1}^{n} (\theta_t - \theta^*_k),$$

where $(\theta_t - \theta^*_k)$ is the difference between the initialization point and the optimal point for the $k$-th user. In each iteration, we update the global initialization point with the average difference for all users, corresponding to Algorithm 1 in this paper.

$$\theta_{t+1} \leftarrow \theta_t - \epsilon \frac{1}{n} \sum_{k=1}^{n} (\theta_t - \theta^*_t)$$

In practice, we can randomly sample part of the users in each iteration to estimate the “average difference” so that we can reduce computation and avoid overfitting. As the estimation of $\theta$ only requires part of the users’ parameters, the proposed optimization framework is robust for the scenario in which some users are disconnected during the training procedure.

In the second step of any iteration, the global initialization parameters $\theta$ are fixed, and then we can fine-tune each user’s $\theta_k$ with gradient descent by using the user’s own data $D_k$:

$$\theta^k = O(\theta, D_k, F_k)$$

where $O$ is an operator that iteratively updates the $\theta$ for a certain number of epochs, and $F_k$ is an arbitrary deep learning function applied on the local model of the $k$-th client.

Once the local model’s optimal parameters $\theta^k$ have been learned from the local model, they are sent to the centralized server to estimate the average difference which contributes to updating the global initialization parameters $\theta_{t+1}$.
3.4 Privacy Analysis

The proposed algorithm comprises four steps: model initialization, local training, model upload, and model aggregation. In the model initialization and local training steps, random parameters are downloaded from the server and users do not need to upload their personal data to the server, therefore private information is not released in either step. The model upload step exchanges the user-trained parameters $\theta$, which only relate to the trained model rather than a particular user. The trained model is effectively a black box to the server, and the server cannot deduce any personal related information from $\theta$. The last step, model aggregation, calculates the aggregation of the models of all the users, and as no user information is exchanged in this step, no private information is disclosed. Therefore, communication between the central server and users does not breach privacy. With only the parameters of the local training at different timestamps, the server can only infer the gradient from the aggregated errors of users. User data are not revealed to the central server, nor can user data be inferred by the central server. Thus, privacy is ensured when uploading the model.

As none of these steps releases any personal information and limited access to personal data is granted to only those who need it for processing, we can safely claim that privacy concerns and cyber-security risks are reduced with our proposed general data protection learning method.

In addition, a randomization mechanism as introduced in [6] could be added to this framework during server and client communication to achieve the requirements of differential privacy. A white noise with a mean of 0 and the standard deviation of $\sigma$, it is added to the client parameters after local training on the client devices. For the simplicity of notation, it is written in the form of the following equation by adding the randomization to Equation 4.

$$
\theta_{t+1} \leftarrow \theta_t - \frac{1}{n} \sum_{k=1}^{m} (\theta_t - \theta_{t+1}^{k} + N(0, \sigma^2)) \quad (6)
$$

4 Experimental Evaluation

In this section, we introduce the architecture of proactive social care in online communities. Two tasks for proactive service, i.e., suicidal ideation detection and social response categorization are studied. Datasets and baselines are introduced as well as a series of comparative experiments.

4.1 Proactive Social Care

Proactive social care provides many kinds of care services for targeted users. In this paper, we focus on mental health care in online communities for people who have a wide range of mental health issues. Under the learning framework, we produce two types of services, i.e., mental health detection and effectiveness stratification of social comments. We use suicidal ideation detection as the case study to demonstrate the application of proactive mental health detection. Suicide gestures and attempts are included in F60.3 – Emotionally unstable personality disorder of ICD-10 code from WHO\(^6\). Suicide is the most severe consequence of mental disorders. Post-schizophrenic depressive states may increase the risk of suicide\(^7\). For effectiveness stratification, it provides an evaluation and ranking of people’s comments and can be used for easy access to more persuasive comments. The architecture of proactive social care for mental health is illustrated in Figure 4. We focus on the content from mental health discussion including the user’s original post and the other user’s comment on it. The proactive mental health care service is empowered by deep neural networks to learn language representation for early detection on posts and effectiveness stratification on comments.

\(^{6}\)http://apps.who.int/classifications/apps/icd/icd10online2003/fr-icd.htm?gx60.htm+

\(^{7}\)According to the ICD-10 code F20.4 – Post-schizophrenic depression, available at http://apps.who.int/classifications/apps/icd/icd10online2003/fr-icd.htm?gx60.htm+. 
4.2 Datasets

We collected data from two social websites – Reddit and Twitter. Table 1 lists the basic information of three datasets containing user posts derived from these platforms. For the task of effectiveness stratification, a dataset containing comment text is collected from Reddit.

| Datasets   | # of users | # of posts/tweets |
|------------|------------|-------------------|
| Reddit I   | 99         | 39,600            |
| Reddit II  | 260        | 9,052             |
| Twitter    | 102        | 10,200            |

Reddit Dataset. We obtained two datasets from the website Reddit, which is ranked No. 6 on the list of top websites worldwide by Alexa\(^8\) world wide as of June 2018. As a social website, Reddit aggregates a variety of topics for online discussions and each discussion community with an interest in a particular discussion is called a “subreddit”. There are a wide range of topics for online discussion, including social events and personal experience.

The first aim of this work is to detect an individual’s intent from social texts that involve suicidal ideation for early warning in proactive social care. A suicide-related subreddit called “SuicideWatch”\(^9\), and two other subreddits not related to suicide, “popular”\(^10\) and “AskReddit”\(^11\) are taken as the source of content with a total of 39,600 posts collected. Of these posts, there are 48.16% of them containing suicidal ideation. We call this dataset as Reddit I.

Another dataset from Reddit, referred as Reddit II, contains a total of 9,052 posts from a total of 260 selected users in the Reddit community.

Twitter Dataset. The third dataset was collected from the social website Twitter. A keyword filtering technique was applied to collect the original tweets. The filtering terms included words such as

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\(^8\)https://www.alexa.com/topsites
\(^9\)http://reddit.com/r/SuicideWatch
\(^10\)http://reddit.com/r/popular
\(^11\)http://reddit.com/r/AskReddit
as “suicide”, “die”, and “death”, and suicide-related phrases, such as “end my life” and “kill myself”. Then, we manually checked and labeled the posts. Tweets containing keywords but without suicidal ideation were put in the control group. This Twitter dataset contains a total of 10,200 tweets, of which 5.8% of tweets contained suicidal intention in the text.

Reddit Comments. We collected comments from all the users in the Reddit II dataset for effectiveness stratification. Each comment had a score given by the users who had viewed the comment and clicked the “like” button in the online forum. We scaled the scores of the comments into five classes according to the score distribution. The number of comments on different posts varies. Most posts contain less than 40 comments.

Dataset Partitioning. To mimic the distributed training on the client, we partitioned the data using independently identical distribution (I.I.D.). First, a shuffle is applied to the entire dataset and it is partitioned into several users with a certain number of examples. There are 99 users and 102 users in the Reddit dataset and the Twitter dataset, respectively. Users of Reddit and Twitter had 400 posts and 100 tweets, respectively.

4.3 Settings and Baselines

To evaluate our model, three decentralized baselines with model aggregation, i.e., NonAgg, FullbatchAgg and AverageAgg (where Agg stands for Aggregation), and the centralized method without data protection and model aggregation training on all the collected user data, referred to as Centralized, are used for comparative experiments.

These three baselines for learning with data protection are described as follows:

1. NonAgg: a simple baseline without data sharing or model aggregation by training separate local data-preserving models on different devices for each user.
2. FullbatchAgg: assembles an overall aggregation on the full batch of all users for only a single gradient descent step on each local device.
3. AverageAgg: samples a fraction of users for model aggregation using weighted averaging.

The FullbatchAgg is a special case of AverageAgg where the epoch of local training equals 1 and the fraction of users equals 1.

For the learning models of clients, two popular deep neural models, i.e., CNN [13] and LSTM [8], were used. First, we embedded the input sentence into a 100-dimension word vector to get the distributed representation of text. The word embedding was then placed into three convolutional layers. The learned features of the convolution layers are concatenated together to get the final representation of the text. Lastly, a fully connected layer was used as a classifier in the last layer to produce the prediction. For the LSTM model, we used the same settings for the word embedding and a 64-dimension LSTM hidden unit was used in the recurrent network.

4.4 Suicidal Ideation Detection

We firstly conduct experiments on suicidal ideation detection. To test the performance of our proposed learning framework and two-step optimization, we performed an empirical evaluation by comparing our method with two other types of methods: those without model aggregation and those with model aggregation.

Accuracy-privacy Balance. First, we evaluated the trade-off between prediction accuracy and privacy preservation by comparing our AvgDiffAgg with a data protection method NonAgg and a centralized learning method. The results of classification accuracy for the three datasets are illustrated in Figure 5. The bar chart shows that our proposed method achieves a larger increase in testing accuracy than the rigorous data protection method NonAgg when using CNN and LSTM as the classifier. The centralized training method has the best performance according to the results as it has an advantage over NonAgg and AvgDiffAgg because it learns from the entire dataset. However, it violates the data protection rule and may cause user privacy concerns. Overall, our proposed method can balance the prediction accuracy and privacy preservation.
Comparison between LDPs with model aggregation. To further the evaluation, we compared our method with two baselines in terms of average testing accuracy and the average of area under the receiver operation curve (AUROC). The results are shown in Figure 7. We used the same hyperparameter settings using the same number of training rounds of 10. The local batchsize was 10, and the local training epochs were 5. For AverageAgg and our AvgDiffAgg, the fraction of users was both set to 0.1. As we can see from these figures, our proposed method achieves the best scores when using both CNN and LSTM as the classifier.

Learning curve. We drew the learning curve to visualize the performance of FullbatchAgg, AverageAgg, and our AvgDiffAgg as shown in Fig. 6. The training loss for our method decreased more rapidly than AverageAgg. The test accuracy of our method was higher than AverageAgg during the first 20 rounds of training and better still, between rounds 50 and 60. In the other rounds, the testing accuracy was similar. The training curve was smoother for the FullbatchAgg because it uses the full batch of users during aggregation at each iteration, while the other two methods use a random selection of users for model aggregation.

4.5 Effectiveness Stratification of Supporting Words

Conversation is one of the most effective ways to provide supportive words to the vulnerable people with mental health issues and even suicidal ideation. Gilat et al. [7], compared the responses to suicidal
messages from trained volunteers and lay individuals, and found that trained volunteers employ more emotion-based strategies and more therapeutic-like cognitive-focused strategies than lay individuals who rely more on self-disclosure. The effectiveness stratification of supportive words evaluates social workers’ responses in a given social care case, and it can help social workers to improve their conversational skill and compose better supportive words to persuade potential victims to relieve their mental health issue or give up a suicide attempt.

In this section, we applied our AvgDiffAgg method to evaluate the potential effectiveness of social comments according to the score of each comment received from other users in a supervised way. We performed the experiments by training a CNN model and an LSTM model on the entire dataset with 10-fold cross validation. The average testing accuracy for the CNN and LSTM was 36.27% and 35.33%, respectively. These levels of accuracy are treated as the upper bound of the methods with data protection. The experiments using FullbatchAgg, AverageAgg and AvgDiffAgg were then performed 10 trials. The performance of different methods based on CNN and LSTM were then compared in terms of average testing accuracy. The experiment settings for these three methods were the same as the previous experiments, except for the fraction of users. For FullbatchAgg, this was always 1, and for the other two methods, it was set to 0.1. The results are shown in Table 2. Methods without data protection had higher accuracy than methods with data protection. Of the methods with data protection, our proposed method using CNN as the classifier was slightly better than AverageAgg. When using an LSTM as the classifier, the testing accuracy of our method was more than 2% higher than AverageAgg.
Table 2: Comparison of accuracy on predicting comment scores as effectiveness stratification

| Methods        | Avg. Acc. |     |
|----------------|-----------|-----|
|                | CNN       | LSTM|
| FullbatchAgg   | 30.49%    | 31.67%|
| AverageAgg     | 31.16%    | 32.80%|
| AvgDiffAgg     | **31.35%**| **35.08%**|

5 Conclusions

Third-party intelligent web information systems could pave the way for effective social support and improve proactive online social care services from broad perspectives. To relieve the privacy concerns in relation to personal data, especially the private chatting, this paper develops data-protected proactive social care by using a decentralized learning framework with secure local model training, data-free global model training, and novel model aggregation. In particular, the proposed global model aggregation strategy updates the model parameters with the average difference descent that is inferred from a newly developed loss function customized for the proactive social service application scenario. The experiment evaluation on two tasks of suicidal ideation detection and effective stratification of social comments shows the effectiveness of the learning framework and the model aggregation algorithm.

Due to the highly sensitive nature of collecting real-world private data, this work mimics the real-world private chatting scenarios by using the public online data. The contents in the mimic dataset and the real-world private chatting dataset share similar characteristics and patterns that enable the proposed method to be a very promising solution to the development of new mental health care services with data protection. In future work, we will further research confidentiality concerns and propose new methods with an efficient communication mechanism between the server and clients, while ensuring a comparable accuracy.

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