Attribute Inference Attack of Speech Emotion Recognition in Federated Learning Settings

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Abstract—Speech emotion recognition (SER) processes speech signals to detect and characterize expressed perceived emotions. Many SER application systems often acquire and transmit speech data collected at the client-side to remote cloud platforms for inference and decision making. However, speech data carry rich information not only about emotions conveyed in vocal expressions, but also other sensitive demographic traits such as gender, age and language background. Consequently, it is desirable for SER systems to have the ability to classify emotion constructs while preventing unintended/improper inferences of sensitive and demographic information. Federated learning (FL) is a distributed machine learning paradigm that coordinates clients to train a model collaboratively without sharing their local data. This training approach appears secure and can improve privacy for SER. However, recent works have demonstrated that FL approaches are still vulnerable to various privacy attacks like reconstruction attacks and membership inference attacks. Although most of these have focused on computer vision applications, such information leakages exist in the SER systems trained using the FL technique. To assess the information leakage of SER systems trained using FL, we propose an attribute inference attack framework that infers sensitive attribute information of the clients from shared gradients or model parameters, corresponding to the FedSGD and the FedAvg training algorithms, respectively. As a use case, we empirically evaluate our approach for predicting the client’s gender information using three SER benchmark datasets: IEMOCAP, CREMA-D, and MSP-Improv. We show that the attribute inference attack is achievable for SER systems trained using FL. We further identify that most information leakage possibly comes from the first layer in the SER model.

Index Terms—Speech Emotion Recognition, Federated Learning, Adversarial, Machine Learning, Privacy

1 INTRODUCTION

Speech emotion recognition (SER) aims to identify emotional states conveyed in vocal expressions. Speech emotion recognition systems are currently deployed in a wide range of applications such as in smart virtual assistants [1], clinical diagnoses [2], [3], and education [4]. A typical centralized SER system has three parts: data acquisition, data transfer, and emotion classification [5]. Under this framework, the client typically shares the raw speech samples or the acoustic features derived from the speech samples (to obfuscate the actual content of the conversation) to the remote cloud servers for emotion recognition [6]. However, the same speech signal carries rich information about individual traits (e.g., age, gender) and states (e.g., health status), many of which can be deemed sensitive from an application point of view. Attribute inference attacks would aim to reveal an individual’s sensitive attributes (e.g., age and gender) that they did not intend or expect to share [7], [8]. These undesired/unauthorized usages of data may occur when the service provider is not trustworthy (insider attack) or an intruder attacks the cloud system (outsider attack) [9], [10], [11].

Federated learning (FL) is a popular privacy-preserving distributed learning approach that allows clients to train a model collaboratively without sharing their local data [12]. In an FL setting, during the training process, a central server coordinates each client device to locally train a shared model with their private data and only upload their respective model updates to the central server. This machine learning approach reduces information leaks compared to classical centralized machine learning frameworks since personal data do not leave the client device. Therefore, this distributed learning paradigm can be a natural choice for developing real-world multiuser SER applications as sharing raw speech or speech features from users’ devices are vulnerable to attribute inference attacks.

Attacks in Federated Learning: Despite that the model updates are less informative than the raw data samples, recent works have demonstrated that FL also faces a variety of privacy attacks, including membership inference attacks [13] and reconstruction attacks [14], [15]. For instance, recent work has shown that the attacker can efficiently reconstruct a training image from the gradients [14]. More recent works increasingly show that image reconstruction is also achievable through the model parameter updates even without accessing to the raw gradients [15]. On the other hand, prior work has demonstrated that the attacker can perform membership attacks in FL settings to infer whether a particular model update belongs to the private training data of a single participant (if the update is of a single participant) or of any participant (if the update is the aggregate) [13]. Although most existing FL attack works are related to computer vision (CV) domains, it is reasonable to believe that the shared model updates in training the SER model using the FL technique also introduce
information leakage.

**Threat Model:** This work presents a detailed analysis of the attribute inference attack on the SER application trained in a FL setting. We assume that the attack is a white-box attack. The attacker knows all model parameters and hyper-parameters in the FL process, including learning rate, local epochs, local batch size, local sample size, and model architecture. Any adversary that has access to the shared model updates can execute the attack. The attacker’s goal is to infer sensitive attributes of the client using shared model updates (parameters/gradients) of SER applications trained under FL architecture. In this work, we consider gender prediction as the exemplary attribute inference attack task. We show that the adversary can effectively infer a client’s gender attribute while training the SER model in an FL setup; we use the IEMOCAP [16], Crema-D [17], and MSP-Improv [18] datasets for the experiments. To the best of our knowledge, this is the first work to demonstrate that shared model updates that are communicated in FL to train an SER model can cause attribute information leakage (e.g., gender).

## 2 SER Experimental Data Sets

In this work, we use three data sets for developing SER models and threat models. Due to the data imbalance issue in the IEMOCAP corpus, previous works use the most four frequently occurring emotion labels (neutral, sad, happiness, and anger) for training the SER model [19]. In this work, we pick these four emotion classes also because all three corpora contain these labels. Table 1 shows the label distribution of utterances in these corpora. The details of these corpora are below:

### 2.1 IEMOCAP

The IEMOCAP database [16] was collected using multi-modal sensors that capture motion, audio, and video of acted human interactions. The corpus contains 10,039 utterances from ten subjects (half male and half female) targeting expressing categorical emotions. In addition, the utterances are divided into improvised conditions and scripted conditions based on whether the utterance is from a fixed script. We choose to remove data from script conditions as suggested in previous work [19].

### 2.2 CREMA-D

The CREMA-D [17] corpus is a multi-modal database of emotional speech collected from 91 actors, 48 of whom are male, and 43 are female. The set contains 7,442 speech recordings that simulate emotional expressions, including happy, sad, anger, fear, and neutral.

### 2.3 MSP-Improv

The MSP-Improv [18] corpus was created to study naturalistic emotions captured from improvised scenarios. The corpus includes audio and visual data of utterances spoken in natural condition (2,785 utterances), target condition (652 target utterances in an improvised scenario), improvised condition (4,381 utterances from the remainder of the improvised scenarios), and read speech condition (620 utterances). The data is collected from 12 participants (half male and half female). Similar to the IEMOCAP data set, we use the data only from the improvised scenarios.

## 3 Problem Setup

In this section, we describe preliminaries and the problem setup of the attack framework. To improve readability, we summarize the notations adopted in this paper in Table 2.

### 3.1 Federated Learning

Federated learning is an architecture that enables multiple clients to collaboratively train a joint ML model under the coordination of a central server. For example, in a typical FL training round shown in Fig 1, a subset of selected clients receive a global model, which they can locally train with their private data. Afterward, the clients only share their model updates (model parameters/gradient) to the central server. Finally, the server aggregates the model updates to obtain the global model for the next training round. FedSGD and FedAvg are two common approaches to produce the aggregated models in FL [20].

**FedSGD** We define $\theta^t$ as the global model parameter in $t$-th global round. In FedSGD, the $k$-th client locally computes gradient updates $g^t_k$ based on one batch of private training data, and sends the $g^t_k$ to the server. Assuming $K$ clients of $N$ samples participate in the $t$-th round of training where each client is of sample size $n_i$ and learning rate is $\eta$, the server computes the updated global model as:

$$
\theta^{t+1} = \theta^t - \sum_{k=1}^{K} \frac{n_i}{N} g^t_k
$$

**FedAvg** In the FedAvg algorithm, each client locally takes several epochs of model updates using its entire training data set $D_i$ and obtains a local model with parameters $\theta^t_k$. Each client then submits
Fig. 1. The figure shows the training process of a global round in Federated Learning. The server shares a global model with several clients to perform local training with their private data in each global round. Eventually, the clients transfer the model updates (model parameters/gradients) to the central server for aggregating the latest global model.

$$\theta^{t+1} = \frac{1}{N} \sum_{k} n_k \theta_k^t$$ (2)

3.2 Problem Definition

Fig. 2 shows the problem setup we investigate in this work. In this study, the *primary task* is SER, models for which are trained using the FL framework, while in the *Adversarial task* the attacker attempts to predict the client’s gender label. We follow a setup in which we have a private-labeled data set $D_p$ from a number of clients, where each client has a feature set $X$ and an emotion label set $y$. We also assume a gender label $z$ associated with each client. This work focuses on the white-box attack, where the attacker knows the model architecture and hyper-parameters like batch size, local epochs, and learning rate. We also assume that the attack does not have access to the private training data. However, the adversary can access to public data sets with a similar data distribution to $D_p$. Similar to the attacking framework proposed in [15], we define two attack scenarios based on two FL algorithms: FedSGD and FedAvg.

**FedSGD** In the FedSGD framework, we assume that the attacker has access to shared gradients $g_k^t$ from the $k$-th client in the $t$-th global training epoch but not the private speech data $X_k$. The attacker attempts to predict the sensitive attribute $z_k$ (e.g. gender label) of the $k$-th client using $g_k^t$.

**FedAvg** In the FedAvg framework, the attacker has access to the global model parameter $\theta^t$ and shared model parameters $\theta_k^t$ from $k$-th client at the $t$-th global training round but not the private speech data $X_k$. The attacker’s goal is to infer the sensitive attribute $z_k$ (e.g. gender label) of the $k$-th client using $\theta^t$ and $\theta_k^t$.

4 Attacking Method

In this section, we describe our proposed method for attribute inference attacks in detail. Our attack focuses on training a classification model using the shared model updates data generated in the FL setting, either the model gradients $g$ or the model parameters $\theta$, to infer the sensitive label $z$ with the help of the FL server. Here is the summary of the steps when IEMOCAP data set is used as $D_p$:

1) **Service provider**: Private training of the SER models using the FL setup using IEMOCAP data set as $D_p$.

2) **Attacker**:
   a) Shadow training of the SER models that mimic the private training setup using a different data set $D_s$, which is a combination of CREMA-D and MSP-Improv.
   b) Collect the shared model updates during the shadow training in step a) to generate the attack data set $D_a$.
   c) Train a gender classification model $M_a$ using $D_a$.
   d) Infer the gender of the clients in $D_p$ using the shared model updates from the private training and $M_a$.

4.1 Private Training

Private training is our target model (SER model) training process to obtain $M_p$. In this paper, the private training is done in the FL setting, where we have a private training data set $D_p$ with emotion labels $y_p$. All the private training data are on the client’s device and not accessible by the central server. The server performs the FL using two algorithms: FedSGD and FedAvg. As described above, only the model gradients or the model parameters are shared with the central aggregator in the FedSGD algorithm and
the FedAvg algorithm, respectively. In this work, we also assume that the attacker cannot access the private training data. However, the shared training updates (either the gradients or the model parameters) are insecure, where the attacker can legitimately or illegitimately obtain this information.

4.2 Shadow Training

The shadow training is first proposed in the membership inference attack [21]. In this paper, we use a similar attack framework in membership inference attacks to construct our attribute inference attack architecture. Specifically, the shadow models $M_{s1}, M_{s2}, ..., M_{sm}$ are trained to mimic the private training model $M_p$. In this paper, the shadow models also aim to classify emotion categories from speech features. To train the shadow models, the attacker typically collects a set of shadow training data sets, where each is similar in format and distribution to the private training data set. While the individual shadow data sets may overlap, the private training data set and the shadow data set shall not overlap. In each experiment, we propose to use one public SER data set (e.g., IEMOCAP) as the private training data set and two other public SER data sets (e.g., CREMA-D and MSP-Improv) as the shadow training data set. The shadow models are to predict emotion categories similar to the private model. Since we are focusing on the white-box attack, we train the shadow models in a similar fashion to the private FL training, where the shadow models have the same model architecture as the private model and are with the same hyper-parameters (e.g., learning rate, local epochs) used in the private training. We use 80% of data in $D_s$ to train each shadow SER model.

4.3 Attack Model

In this work, we compose the attack training data set $D_a$ using the shared model updates which are generated during the shadow training experiments. Given a shared model update $g'_k$ from k-th client in the shadow training process, we record the gender of the k-th client $z_k$ as the label of $g'_k$. We then use $D_a$ to train the attack model $M_a$ to infer the gender attribute $z$. Finally, we define the attack training data under two FL learning scenarios:

**FedSGD** In the FedSGD framework, the attacker can directly take the gradient updates as the attack training input. In other words, the attack model takes the gradients $g'_k$ as the input data to train the attack model in predicting the gender label $z_k$. The attacker model attempts to minimize the following cross-entropy loss with parameters $\psi$:

$$\min_\psi L(M_a(g'_k; \psi), z_k)$$

**FedAvg** Herein, only the global model parameters $\theta^t$ and the updated model parameters $\theta^t_k$ from the k-th client are accessible by the attacker but not the raw gradients. Thus, we derive a pseudo gradient that is similar to previous work in [15] as the attack model’s input data. Specifically, we assume that the global model undergoes $T$ times of local updates at the k-th client, where $T$ is the product between the local training epoch and the number of mini-batches within a local training epoch. Thus, we can define the following with the pseudo gradients $g''_k$ and the learning rate $\eta$:

$$\theta^t_k = \theta^t - T \eta \cdot g''_k$$

Eventually, we can define the pseudo gradients $g''_k$ as:

$$g''_k = \frac{1}{T \eta} (\theta^t - \theta^t_k)$$

Consequently, we aim to train the attack model with parameters $\psi$ to minimize the following cross entropy loss function:

$$\min_\psi L(M_a(g''_k; \psi), z_k)$$

More specifically, our proposed attacker model is similar to the membership inference attack model in [22]. The attack model
Fig. 4. The architecture of our proposed attack model. The model updates (raw gradients in FedSGD; pseudo gradients in FedAvg) are the input features to train the attack model. The CNN feature extractor uses the weight update matrix to compute the hidden representation, which combines with bias updates. Finally, we use the combined attack feature representation to infer the gender attribute.

consists of CNN feature extractors and classifiers as shown in Fig. 4. $\nabla W_i$ and $\nabla b_i$ represent the weight updates and the bias updates in the $i$-th layer of $g$, respectively. Each layer’s weight updates (generated from the FL training) is first fed into a three-layer CNN feature extractor to compute the hidden representation. We then flatten the output from the CNN feature extractor and concatenate it with the layer’s bias updates. We then pass this combined representation to the MLP classifier to predict gender. We use a fusion layer to combine the predictions from the individual layer classifiers; the fusion method used in this work is a weighted average function. We determine the importance of each layer’s gender prediction output based on the size of the shared updates. Finally, we evaluate the performance of the attack model using the shared model updates generated in the private FL setting where the attack model’s goal is to infer the gender labels of clients in the private training data set.

5 Experiments

In this section, we describe our experimental setup including data processing, data setup, and training details. The implementation of this paper is at https://github.com/usc-sail/fed-ser-leakage.

5.1 Data Preprocessing

To investigate the effectiveness of the proposed attack framework, we train our SER models on a variety of speech representations. We first generate the Emo-Base feature set using the OpenSMILE toolkit [23] for each utterance. In addition to the knowledge-based speech feature set, we propose to evaluate our framework on SUPERB (Speech Processing Universal PERformance Benchmark) [24], which is designed to provide a standard and comprehensive testbed for pre-trained models on various downstream speech tasks. We compute the deep speech representations from the pre-trained models that are available in SUPERB including APC [25], Vq-APC [26], Tera [27], NPC [28], and DeCoAR 2.0 [29]. We further compute the global average of the last layer’s hidden state as the final feature from the pre-trained model’s output. Using the last hidden state is suggested in prior works for downstream tasks [25], [28], [29], [30]. In summary, the feature sizes are 988 in Emo-Base; 512 in APC, Vq-APC, and NPC; 768 in Tera and DeCoAR 2.0.

We apply z-normalization to the speech features within each speaker. Since there are only 10 speakers in the IEMOCAP data set and 12 speakers in the MSP-Improv data set, we further divide each speaker’s data in these two data sets into 10 parts of equal size. This division is to create more clients for the FL training. Each divided speaker data is the local training data on a client. In the CREMA-D data set, each speaker is a unique client in the FL training. We leave 20% of speakers as the test data. Then, we repeat the experiments 5 times with test folds of different speakers. Finally, we report the average results of the 5-fold experiments.

5.2 Data setup

We simulate the experiments using different private training data sets. For instance, in the case of the IEMOCAP data set being the private training data set $D_p$, the MSP-Improv data set and CREMA-D data set are combined to train shadow models $M_s_1, ..., M_s_m$. In our experiments, we set $m = 5$. Next, we compose the attack training data set using the shared model updates generated from the FL shadow training process and use it to train the attack model $M_a$. In the above example, we evaluate the performance of $M_a$ using the model updates generated in the
The private training data sets are CREMA-D (FedSGD: 68.20%; FedAvg: 68.24%). We can observe that the deep speech representation, which consists of 3 CNN layers with filter numbers of \{16, 32, 64\}, significantly improves the SER task performance compared to prior works \cite{31, 32} that use spectrograms or MFCCs. In addition, we can observe that the knowledge-based model updates, which are for improving the global SER model, to infer the client’s gender information.

### 5.3 Model and training Details

In this work, we use the multilayer perceptron (MLP) as the SER model architecture. The model consists of 2 dense layers with layer sizes of \{256, 128\}. We choose ReLU as the activation function and the dropout rate as 0.2. We implement both FedSGD and FedAvg algorithms in training the SER model. Only 10% of the clients participate in each global round. 80% of the data at a client is for local training, and the rest 20% is for validation. We set the local training batch size as 20. Specifically, we set the learning rate as 0.0005 and the local training epoch as 1 in the FedAvg algorithm. On the other hand, we set the learning rate as 0.05 in the FedSGD algorithm for faster convergence. The total global training epochs are 200 in both FL scenarios. In the shadow training, the attacker designs the shadow model with the same architecture and trains the shadow models with the same hyperparameters used in the private FL training. The attacker collects the shared model updates and then uses these data to train the attack model in predicting gender label \(z\). We set the learning rate as 0.0001 in training the attack model. The CNN feature extractor consists of 3 CNN layers with filter numbers of \{16, 32, 64\} and filter size of \((5, 5)\). Maxpooling is also applied after each CNN layer. We choose ReLU as the activation function and the dropout rate as 0.2 in the attack model.

## 6 RESULTS

In this section, we present SER results on different private data sets. We also show results of the attack model in predicting gender labels of the clients in the private data set.

### 6.1 Speech Emotion Recognition using FL

The emotion prediction results of FL training on different private training data sets are shown in Table 3. We report the SER prediction results in accuracy (Acc) scores and unweighted average recall (UAR) scores. We can observe that the knowledge-based feature set, Emo-Base, performs comparably in the SER task to prior works \cite{11, 12} that use spectrograms or MFCCs. In addition, we can observe that the deep speech representation, Tera, yields the best UAR scores in prediction emotions when the private training data sets are CREMA-D (FedSGD: 68.20%; FedAvg: 67.35%) and MSP-Improv (FedSGD: 51.97%; FedAvg: 51.27%). APC feature set produces the best UAR scores when the private training data is IEMOCAP (FedSGD: 63.51%). Our results show that the SER task performs better when the training data sets are IEMOCAP and CREMA-D. In summary, these results suggest that our SER models, trained within a FL architecture, produce reasonable predictions for the SER task.

### 6.2 Attribute Inference Attack

We report the UAR score of the gender prediction task is reported. The attack frameworks are simulated in two FL scenarios. Bold indicates the best attack performance in one data combination.
Speeh features: We observe that this attribute inference attack is highly achievable regardless of the speech representation (UAR scores are all above 70%) used for the SER task. It is also interesting to note that the attack model yields the best overall performance in predicting gender labels when the deep speech representations, such as APC and Tera, are the input data to the SER task but not the knowledge-based feature set, Emo-Base. Noticeably, these deep speech representations also provide the best overall emotion prediction performance as shown in Table 3. Typically, deep speech representations are more generalized feature embeddings for downstream speech applications. Besides the knowledge-based feature set, Tera and APC, we find that other deep speech representations can also generate shared model updates in the FL, which can leak significant attribute information about the client like gender.

**FedSGD and FedAvg:** We find that this attribute information leakage exists in both these FL learning algorithms. Increasingly, we discover that the attack model has higher chances to predict the client’s gender information when we train the private SER model using the FedSGD algorithm. Thus, as we observe from the Table 4, the attack model performs better when we train the SER model using the FedSGD algorithm. As a straightforward defense is to train the global SER model using the FedAvg algorithm. An additional benefit of using the FedAvg is that it significantly reduces the communication overhead during training. The client can transfer the shared model updates after $T$ times of local training instead of each local mini-batch. The primary reason of why the attack model performs worse in the FedAvg scenario is that the averaged model differences contain less information about the training samples than the raw gradients as shown in [15].

### 7 Mitigation Possibilities

There are protection schemes such as cryptography solutions [33], [34] and the use of trusted execution environments [35], [36] for secure aggregation. However, cryptography solutions have a significant performance overhead and they are not scalable to systems with many edge devices. Trusted Execution Environments such as Intel SGX [37] provide private environments for data privacy and computational integrity. However, they are not available on all the data centers. In this section, we present an analysis of potential factors related to the attribute information leakage in the FL of the SER model. We aim to investigate a few mitigation strategies based on these possible information leakage factors. Note that all of these proposed mitigation strategies are software-based solutions with low performance overhead. These methods do not need any special system support.

#### 7.1 FedSGD and FedAvg

As we observe from the Table 4, the attack model performs better when we train the SER model using the FedSGD algorithm. Thus, a straightforward defense is to train the global SER model using the FedAvg algorithm. An additional benefit of using the FedAvg is that it significantly reduces the communication overhead during training. The client can transfer the shared model updates after $T$ times of local training instead of each local mini-batch. The primary reason of why the attack model performs worse in the FedAvg scenario is that the averaged model differences contain less information about the training samples than the raw gradients as shown in [15].

### TABLE 5

Prediction results of the attribute inference attack model using shared updates between different layers in the SER model. The unweighted average recall (UAR) scores of the gender prediction task are reported. The attack frameworks are simulated in two FL scenarios.

| $D_p$    | $D_s$     | Feature   | FedSGD $\n\n\begin{align*} & VW_1 + Vb_1 & VW_2 + Vb_2 & VW_3 + Vb_3 \end{align*}$ | FedAvg $\n\n\begin{align*} & VW_1 + Vb_1 & VW_2 + Vb_2 & VW_3 + Vb_3 \end{align*}$ |
|----------|-----------|-----------|--------------------------|--------------------------|
| IEMOCAP  | MSP-Improv | Emo-Base  | 91.43% | 48.13% | 54.48% | 83.21% | 42.39% | 56.83% |
| CreMA-D  |           | APC       | 91.63% | 53.15% | 52.70% | 91.37% | 49.62% | 55.03% |
|         |           | Vq-APC    | 83.12% | 52.23% | 54.78% | 85.40% | 55.47% | 55.92% |
|         |           | NPC       | 89.07% | 55.61% | 53.57% | 80.14% | 53.19% | 54.06% |
|         | DeCoAR 2.0| Tera      | 88.64% | 54.61% | 55.90% | 85.18% | 55.76% | 55.67% |
| CreMA-D  |           | Emo-Base  | 78.01% | 53.28% | 55.00% | 82.45% | 50.23% | 56.25% |
|         | MSP-Improv| APC       | 81.50% | 50.09% | 55.31% | 77.71% | 55.51% | 55.16% |
|         |           | Vq-APC    | 78.93% | 52.33% | 58.18% | 71.34% | 52.36% | 60.49% |
|         |           | NPC       | 74.09% | 55.03% | 55.20% | 74.81% | 50.34% | 59.04% |
|         | DeCoAR 2.0| Tera      | 73.62% | 53.87% | 54.11% | 75.62% | 50.76% | 55.16% |
| MSP-Improv| IEMOCAP  | Emo-Base  | 86.26% | 45.40% | 59.45% | 90.18% | 45.22% | 56.59% |
|         | CreMA-D   | APC       | 94.11% | 49.46% | 55.84% | 93.70% | 49.21% | 51.11% |
|         |           | Vq-APC    | 90.49% | 53.18% | 55.64% | 83.03% | 53.02% | 54.76% |
|         |           | NPC       | 94.90% | 50.96% | 55.88% | 87.21% | 51.96% | 53.65% |
|         | DeCoAR 2.0| Tera      | 90.02% | 53.17% | 57.48% | 85.12% | 51.64% | 53.87% |

**Data Set:** In general, we find that this attribute inference attack is possible with all data set combinations used in this work. However, the attack model appears to have slightly better gender prediction performance when the private training data sets are either the IEMOCAP or the MSP-Impro. This is probably because the CREMA-D data set consists of more unique speakers, creating more diverse FL training updates.

**Summary:** The experimental results above demonstrate that our proposed attack framework is robust to infer gender information of the clients involved in the FL without accessing the client’s private speech feature data but the shared model updates (raw gradients or pseudo gradients). Consequently, even though the speech feature samples are not accessible by the attacker in FL when training the global SER model, the attribute information about a client can leak through the model updates.
weaker using training the SER model using the FedAvg, the attacks are much.

prediction performance decreases significantly when using the model updates between the feature input and first dense layer consistently predict the client’s gender label using only the shared model updates from different layers in the SER model.

From Table 5, we can observe that the attack model can con-
sistently predict the client’s gender label using only the shared model updates from different layers in the SER model.

The deep models appear to internally capture many uncorrelated properties (like gender) associated with the clients in the FL can leak through the shared updates when training the SER model.

The layer position of shared model updates

As suggested in the previous works [38], [39], most information leakage is related to the early layers in a machine learning model. To evaluate this in our attack scenario, we measure the gender prediction performance of the individual classifier without fusion. Table 5 shows the gender prediction performance by using the shared model updates from different layers in the SER model.

From Table 5, we can observe that the attack model can consistently predict the client’s gender label using only the shared model updates between the feature input and first dense layer (\(W^b_1\) and \(V^b_1\)) of the classifier model. However, the gender prediction performance decreases significantly when using the shared model updates between the first to second dense layer (\(W^b_2\) and \(V^b_2\)) or between the second to the output layer (\(W^b_3\) and \(V^b_3\)) of the model. The gender prediction accuracy is in the range of 45% – 55% using \(VW_2\) and \(Vb_2\) in most of the experiment setups following the FedSGD, and this performance increases to 50% – 60% when using input \(VW_3\) and \(Vb_3\). When training the SER model using the FedAvg, the attacks are much weaker using \(VW_3 + Vb_3\) or \(VW_2 + Vb_2\). Thus, we can conclude that the earlier layer’s shared updates leak more information about the client’s gender attribute when training the SER model using FL.

7.3 Dropout

Another possible defense is to employ higher dropout [40], a popular regularization technique used to mitigate overfitting in neural networks. Dropout randomly deactivates activations between neurons, with a probability between 0 and 1. Random deactivations may weaken the attack model because the adversary observes fewer gradients corresponding to the active neurons. We evaluate this assumption by increasing the dropout value to 0.4 and 0.6 after the first dense layer of the MLP classifier. We only increase the dropout rate associated with the first dense layer, since we have shown that this attribute information leakage comes mostly from \(VW_1\) and \(Vb_1\). Table 6 shows the UAR scores of the SER task and the inference attack task using the shared model updates, for different dropout values. Increasing dropout value can remove features that is relevant for our primary application, thus decreasing the performance of the SER task. However, our attacks become stronger with increased randomness of dropout applied to the SER model, which is similar to the results shown in [13]. Our assumption is that there are many shared features which are both informative of emotion and gender. Therefore, removing non-important features for the SER task also eliminates irrelevant features for the gender prediction, while the remaining features are more informative about the gender information.

8 Conclusion

In this paper, we investigated attribute inference attacks on speech emotion recognition models trained within federated learning scenarios of shared gradient (FedSGD) and shared model (FedAvg). Our results show that unintended, and potentially private, properties (like gender) associated with the clients in the FL can leak through the shared updates when training the SER model. The deep models appear to internally capture many uncorrelated features with the tasks they are being trained for. Consequently, the attribute inference attacks are potentially powerful in this setting because the shared training updates carry significant potentially sensitive information about a (training) client. Our results suggest that the attacks are stronger in training the global SER model using the FedSGD algorithm than the FedAvg algorithm. We also show that the shared updates between the input and first dense layer leaks most information in this attribute inference attack. We further empirically demonstrate that defense strategies like dropout are not effective in mitigating this information leakage. These results motivate future work on defenses using the adversarial training technique to unlearn the sensitive attribute. Some of

### Table 6

| \(D_p\) | \(D_s\) | Feature | SER Model | Attack Model |
|---|---|---|---|---|
| | | Dropout=0.2 | Dropout=0.4 | Dropout=0.6 |
| | | Dropout=0.2 | Dropout=0.4 | Dropout=0.6 |
| IEMOCAP | MSP-Improv | Emo-Base | 61.19% | 60.50% | 60.60% | 83.21% | 88.64% | 86.63% |
| | | APC | 62.33% | 62.49% | 59.52% | 91.37% | 89.86% | 90.01% |
| | | Vq-APC | 61.88% | 61.93% | 59.43% | 85.40% | 85.96% | 81.73% |
| | | NPC | 58.20% | 58.31% | 56.35% | 80.14% | 88.87% | 86.38% |
| | | DeCoAR 2.0 | 64.40% | 64.73% | 60.14% | 85.18% | 87.39% | 94.86% |
| | | Tera | 63.24% | 62.88% | 61.63% | 87.70% | 91.83% | 89.17% |
| CREMA-D | IEMOCAP | Emo-Base | 65.34% | 63.28% | 63.92% | 82.45% | 85.74% | 82.19% |
| | | APC | 67.13% | 64.81% | 63.39% | 77.71% | 86.11% | 82.12% |
| | | Vq-APC | 66.45% | 65.72% | 63.63% | 71.34% | 77.51% | 78.71% |
| | | NPC | 63.44% | 62.25% | 60.78% | 74.81% | 70.91% | 76.45% |
| | | DeCoAR 2.0 | 67.06% | 65.89% | 64.12% | 75.62% | 70.96% | 73.66% |
| | | Tera | 67.35% | 66.79% | 64.42% | 84.47% | 85.23% | 88.25% |
| MSP-Improv | IEMOCAP | Emo-Base | 46.23% | 46.92% | 46.15% | 90.18% | 89.63% | 88.56% |
| | | APC | 49.61% | 49.97% | 48.00% | 93.70% | 94.51% | 96.68% |
| | | Vq-APC | 50.43% | 50.36% | 48.59% | 83.03% | 90.20% | 92.02% |
| | | NPC | 45.87% | 45.63% | 43.08% | 87.21% | 91.51% | 86.93% |
| | | DeCoAR 2.0 | 50.02% | 50.62% | 49.62% | 85.12% | 93.79% | 90.72% |
| | | Tera | 51.27% | 51.50% | 49.65% | 83.59% | 92.94% | 81.55% |
the limitations of our study include the relatively small number of clients and data sets even by combining three widely used SER test-beds. In addition, our work considers that attacker has access to each client’s model updates, but this can be mitigated by aggregating shared updates from several clients in a local aggregator before transferring them to the central aggregator. In the future, we aim to build our SER model using more complex model structures, e.g., RNN+classifier. We also wish to apply the defense mechanism, such as adversarial training shown in [31], to train the SER model in the FL set up. Finally, we wish to evaluate the membership inference attack within similar experimental settings.

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