Differentially Private Vertical Federated Learning

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Abstract—A successful machine learning (ML) algorithm often relies on a large amount of high-quality data to train well-performed models. Supervised learning approaches, such as deep learning techniques, generate high-quality ML functions for real-life applications, however with large costs and human efforts to label training data. Recent advancements in federated learning (FL) allow multiple data owners/organisations to collaboratively train a machine learning model without sharing raw data. In this light, vertical FL allows organisations to build a global model when the participating organisations have vertically partitioned data. Further, in the vertical FL setting the participating organisation generally requires fewer resources compared to sharing data directly, enabling lightweight and scalable distributed training solutions. However, privacy protection in vertical FL is challenging due to the communication of intermediate outputs and the gradients of model update. This invites adversary entities to infer other organisations’ underlying data. Thus, in this paper, we aim to explore how to protect the privacy of individual organisation data in a differential privacy (DP) setting. We run experiments with different real-world datasets and DP budgets. Our experimental results show that a trade-off point needs to be found to achieve a balance between the vertical FL performance and privacy protection in terms of the amount of perturbation noise.

Index Terms—Differential privacy, clipping, stochastic gradient descent.

I. INTRODUCTION

Artificial intelligence (AI) has gained significant attention because of the achievements of machine learning (ML) and deep learning algorithms that rapidly accelerate research and transform data processing practices in diverse business sectors, including health, agriculture, cybersecurity, and advanced manufacturing [1]–[3]. Training in heterogeneous and potentially massive networks introduces novel challenges that require fundamental innovations in large-scale machine learning, distributed optimisation, and privacy-preserving data analysis [4].

Federated learning (FL) [5] is a new learning paradigm that aims to build a joint ML model based on the data located at multiple sites or owned by different participants. In the model training, information such as gradients are exchanged between participants, but not the raw data. The exchanged information does not reveal any protected private portion of the data belonging to any party.

Figure 1 illustrates the FL process. At first each data owner will receive a generic global model from the aggregation server. Once the initial model is received, each data owner will conduct local training on this model with their data separately and then upload the related gradient information (local model updates) to the aggregation server. The aggregation server then averages the updates sent by data owners into the global model $W = w_1 + w_2 + \cdots + w_n$ and then updates the global model to replace each user’s local model. The above steps repeat until the global model achieves the required performance or the training reaches the maximum iteration number.

In federated learning, privacy protection has become a major concern [4], [6]. Although federated learning protects the private data on each device by exchanging model gradients with the server, instead of raw data, the model communication during the entire training process can still leak sensitive information to a third party, e.g., the reverse engineering of models [7]. Although there are some methods to improve the privacy of data recently, these methods tend to increase the computational burden of the federated network [6]. In order to further protect the security of private data, we need to find new methods to prevent private data from leakage during FL model transmission [6], [9].

Federated learning can be categorised into three groups according to the distribution of data, i.e., horizontal federated learning, vertical federated learning, and federated transfer learning [10]. Horizontal federated learning is suitable in the case that the user features of the two datasets overlap a lot, but the users overlap little. Vertical federated learning is available in the case that the user features of the two datasets overlap little, but the users overlap a lot. In the case that the users and user features of the two datasets both rarely overlap, we can use transfer learning to overcome the lack of training data [11].

Fig. 1. An example federated learning architecture. In order to guarantee the privacy of the data, federated learning only permits all the data owners to exchange the model gradient with the aggregation server. During this process, each data owner trains its own model with the local data, then uploads the local model to the aggregation server. After aggregating all the received models, the server returns the new global model to each data owner.

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In this paper, we consider the privacy issues related to the vertical FL setting. Vertical federated learning is to divide the datasets vertically (by user feature dimension), then select partial data associated with the same set of users but user features are not exactly the same for training. In other words, data in different columns represent the same users. Therefore, vertical federated learning can increase the feature dimension of training data. Figure 2 shows an example of feature separation between data owners in a vertical FL setting.

For example, there are two different institutions, one is a bank and the other one is an e-commerce company. Their user groups contain an intersection set of users. However, because the bank has users’ income and expenditure behaviour and credit rating, while e-commerce keeps users’ browsing and purchasing history, their user features have almost no intersection.

Vertical federated learning is to aggregate these different features in an encrypted manner to enhance the model [12]. At present, many machine learning models such as regression model [13], tree structure model [14, 15], and neural network model [16, 17] have been applied to this federated setting. Thus, protecting the privacy of the training data owned by each participating organisation should be a fundamental requirement in vertical FL, as such training data might be highly sensitive [18].

Though, privacy-preserving techniques, such as differential privacy [19] and secure multiparty computation (SMC) [20], have been explored for horizontal FL settings, however, only a handful of studies have been conducted to explore the suitability of these techniques in vertical FL. Using SMC and differential privacy can boost privacy protection in Federated learning, but such protection often comes with a trade-off between cost and efficiency.

When using SMC, each participating organisation can encrypt the parameters of its model before sending the model to a host organisation (aggregator). Therefore, additional computational resources are required for encryption which will compromise the efficiency of training the model [1, 16]. With differential privacy, noise can be added to the model and data, at the cost of accuracy degradation [9]. Thus, understanding and balancing the trade-off among privacy protection, operating efficiency, and model performance, both theoretically and empirically, are open and challenging problems in privacy-preserving vertical FL systems.

In this paper, we aim to explore how differential privacy can be applied to vertical FL systems. Differential privacy is the current state-of-the-art criterion to provide privacy protection with theoretical guarantees. Under the differential privacy setting, we aim to explore the effect of noise perturbation on model accuracy with different privacy budgets. To conduct experiments, we use several real-world datasets and evaluate the model accuracy under different privacy budgets. Our experimental results show that with differential privacy noise we can trade the performance degradation of the vertical FL model for a certain level of privacy protection with calibrated noise perturbation.

This paper is organised as follows. In Section II we discuss the current literature of vertical federated learning, and provide preliminaries in Section III. We describe the considered vertical FL system in Section IV. We present and discuss the results of our experiments in Section V. Finally, we conclude and point out directions of future research in Section VII.

II. RELATED WORKS

Federated learning is actually a kind of encrypted distributed machine learning technology, in which participants can build a model without disclosing the underlying data [5]. Through the parameter exchange under a secure communication mechanism, a common global model is established. Under such a mechanism, all parties involved can successfully use their data to build a machine learning model collaboratively [4].

The federated setting poses novel challenges to existing privacy-preserving algorithms. Beyond providing rigorous privacy guarantees, it is necessary to develop methods that are computationally cheap, communication efficient, and tolerant to dropped devices all without overly compromising accuracy [2, 8]. Although there are a variety of privacy definitions in federated learning. However, the privacy in federated learning protocols can be considered under two scenarios, (1) the model updates generated at each iteration are private to all data owners other than the central server (trusted), while (2) the model updates are also private to the central server (untrusted or semi-trusted).

The privacy techniques used in federated learning models can be typically categorised as secure multiparty computation and differential privacy. Bonawitz et al. [1] used a secure multiparty computation based aggregation protocol in a horizontal FL model to protect individual model updates from an untrusted central server. Sotthiwat et al. [21] encrypt critical part of model (gradients) parameters to reduce communication cost, while maintaining MPC’s advantages on privacy-preserving without sacrificing accuracy of the learnt global model. Madi et al. [22] secure framework for verifiable FL relying on Homomorphic Encryption and Verifiable Computation. Recently, Kanagavelu et al. [23] proposes a hierarchical model aggregation to reduce the communication cost incurred in MPC enabled Federated Learning.

Due to the popularity, differential privacy is often used to enhance the privacy of each data owner in a federated...
learning settings [9], [24]–[28]. Geyer et al. [24] proposed a federated optimisation algorithm with differential privacy, which is applied to clients to ensure their global differential privacy. Yu et al. [29] efficient FL protocol which protects the privacy of the IoT devices during the training process. McMahan et al. [5] proposed a protocol that applies differential privacy to federated learning and offer global differential privacy. Liu et al. [30] proposed an asynchronous FL model which used local differential privacy to protect the client privacy while reducing communication overhead during the training process. In order to avoid blindly adding unnecessary noise, Andrew et al. [28] designed a pruning scheme based on adaptive gradient to reduce the penetration of noise to the gradient. Though, differential privacy provides efficient privacy solutions compared to SMC techniques, such solutions bring uncertainty into the upload parameters and may harm the training performance.

To achieve stronger privacy guarantees, differential privacy combined with secure multiparty computation is used in federated learning models. Truex et al. [16] proposed a federated learning model which utilises differential privacy with SMC to reduce the growth of noise injection as the number of parties increases without sacrificing privacy while maintaining a predefined rate of trust. Mughunthan et al. [31] a new mechanism that distributed differentially private noise utilization in a multi-party setting for federated learning to reduce gradient leakage.

Though many of the techniques above proposed for horizontal FL, only few techniques have been proposed for vertical FL scheme. Hardy et al. [32] proposed a vertical federated learning model which uses a distributed logistic regression of Paillier additive homomorphic encryption scheme which can effectively protect privacy and also improve the accuracy of the classifier. In [33], a quasi-Newton method was used for training logistic regression models in a vertical FL scheme to reduce the communication complexities.

Apart from these logistic regression models, few work have been proposed for tree based models [34]–[37]. Cheng et al. [34] proposed a lossless vertical federated learning scheme in which all parties combine user features to train together to improve the accuracy of decision making. Liu et al. [35] proposed a vertical FL scheme, called Federated Forest, which uses a tree based prediction algorithm that largely reduce the communication overhead while improving the prediction efficiency.

Recently, Feng et al. [38] a multiple data owners multi-class vertical FL framework that enables label sharing of each owner with other participants in a privacy-preserving manner. In [39], asynchronous vertical FL frameworks are proposed where the local models are updated by each party in an asynchronous manner and do not require feature sharing between parties.

As we have discussed above, vertical FL frameworks commonly uses SMC technologies such as encryption to ensure secure and private learning. Further, to reduce computational complexities in the SMC techniques, few recent works have utilised differential privacy (DP) into the training process to provide strict privacy guarantees for data of each data provider [34], [41]. However, DP based mechanisms tend to decrease utility in training. Thus, it is important to understand how to add the right amount of noise with out compromising the performance of the vertical FL model.

### III. Background

#### A. Privacy threats in Vertical Federated Learning

Recent studies have demonstrated that federated learning is vulnerable to multiple types of inference attacks, such as membership inference, property inference, and feature inference. However, membership inference is not meaningful in vertical FL as every participating data owner already knows the training sample IDs intrinsically during the sample alignment step. Thus, it is important to investigate other meaningful attacks that are applicable in a VFL setting.

Luo et al. [42] studied the privacy leakage problem in the prediction stage of VFL, by presenting several feature inference attacks based on model predictions. In the proposed attack model, the authors assumed that the adversary can control the trained vertical FL model and the model predictions. The model predictions can leak considerable information about the features held by the data owners, which calls for designing private algorithms to protect the prediction outputs.

Jin et al. [43] proposed a data leakage attack to efficiently recover batch data from the shared aggregated gradients. Their experimental results on vertical FL settings demonstrated their attack can perform large-batch data leakage effectively, thus VFL has a high risk of data leakage from the training gradients compared to its horizontal counterpart. The authors suggested that leveraging fake gradients in the training process can overcome such privacy issues with a negative impact on the model performance.

Weng et al. [44] proposed a reverse multiplication attack for logistic regression based VFL models [34]–[37]. In this attack, the adversary reverse-engineers each multiplication term of the matrix product, so as to infer the target participant’s raw training data. As a countermeasure, the authors proposed to apply differential noise to protect the target participant’s private sensitive data set, but still will be able to infer the information about the data set by training an equivalent model.

Sun et al. [45] studied how to defend against input leakage attacks in Vertical FL. The authors proposed a framework that stimulates a game between an attacker who actively reconstructs raw input from the embedding layer and a defender who aims to prevent input leakage. The framework uses a noise regularisation module, which adds Gaussian noise to the training samples. Their experimental results show the suggested framework can effectively protect the privacy of input data while maintaining a reasonable model utility.

Recently, Fu et al. [46] proposed three different label inference attack methods in the VFL setting: passive model completion, active model completion, and direct label inference attack. In model completion attacks, the attacker needs extra auxiliary labelled data for fine-tuning its local model. Zou et al. [47] proposed to use autoencoder and entropy regularization to hide the true labels as a countermeasure to gradient inversion attacks and label inference attacks.
B. Differential Privacy

Differential privacy (DP) [48] is a privacy definition that guarantees the outcome of a calculation is insensitive to any single record in the data set. Differential privacy requires the output of a data analysis mechanism to be approximately the same if any single record is replaced with a new one. In order to achieve this privacy guarantee, a DP algorithm must contain some form of randomness such that the probability of obtaining a particular outcome \( o \in O \) from database \( D \) is associated with any pair database-outcome \((D, o)\). Formally:

**Definition 1** (Neighbouring databases). Databases \( D, D' \in \mathcal{D} \) over a domain \( \mathcal{D} \) are called neighbouring databases if they differ in exactly one record.

**Definition 2** (Differential Privacy [19]). A randomised algorithm \( A \) is \((\epsilon, \delta)\)-differentially private if for all neighbouring databases \( D \) and \( D' \), and for all sets \( \mathcal{O} \) outputs, we have

\[
Pr[A(D) \in \mathcal{O}] \leq \exp(\epsilon) \cdot Pr[A(D') \in \mathcal{O}] + \delta, \tag{1}
\]

where \( Pr[\cdot] \) denotes the probability of an event.

We use the term pure differential privacy when \( \delta = 0 \) and the term approximate differential privacy when \( \delta > 0 \), in which case \( \delta \) is typically a negligible value in the order of the inverse of the database size \( |D| \).

Following this definition, adding an additional data point to a dataset must not substantially change the result of the algorithm \( A \). The formula is expressed using probabilities to account for the randomness in \( A \). If one guesses the results of the algorithm \( A \) to be in a set of possible values \( \mathcal{O} \), then adding one data point should not change the probability of being correct by more than \( e^\epsilon \). If this is not the case, then adding the new data point might break the privacy promise because it is noticeable whether the data point was used by the query or not.

The amount of noise necessary to ensure differential privacy for \( A \) depends on the sensitivity of the algorithm \( A \).

**Definition 3** (Sensitivity [19]). The sensitivity \( S(A) \) of algorithm \( A \) describes by how much the outputs can differ if the query is executed on two adjacent databases,

\[
S(A) = \max_{D, D'} ||A(D) - A(D')||_2, \tag{2}
\]

where \( || \cdot ||_2 \) is the L2-norm.

IV. VERTICAL FEDERATED LEARNING MODEL

We now describe the vertical federated learning (VFL) model in detail. As we explained before, the basic idea of FL is to collaboratively train a machine learning model by a group of data owners, where only model updates are shared during the training process and local data never leaves its owner.

In the VFL setting, each data owner holds different features of the same set of samples. Thus, the main goal of VFL is to aggregate these different features in an encrypted state to enhance the performance of the model. Besides the local training organisations, we assume a host organisation that holds the labels of these training samples. During the inference phase, the host organisation is responsible for privately collecting and aggregating intermediate results of all data owners, computing the confidence scores, and sending them back to the local organisations for updating their models.

We define the VFL training process formally for \( n \) data owners as follows and this training process is illustrated in Fig. 3. Let us assume a data set \( \mathcal{D} = \{x, y\} \) with \( \{x\} \) and \( \{y\} \) being a set of feature vectors and the corresponding label data, respectively. We assume the set of feature vectors \( \{x\} \) can be decomposed into \( n \) blocks with \( \{x\} = \{x_i\}_{i=1}^n \) with each block \( \{x_i\} \) held by data owner \( i \). We assume that the set of labels \( y \) is owned by the host organisation. This is a reasonable assumption because the labelled data contains valuable information and is not easy to come by in practice [12].

Following [49], each data owner \( i \) trains a sub-model \( M_i \) which outputs local latent embedding \( E_i \) represented by,

\[
E_i = M_i(w_i, \{x_i\}), \tag{3}
\]

where \( w_i \) is the training parameters of data owner \( i \). Here, \( M_i \) can take different forms of models such as linear and logistic regression, support vector machines, neural networks.

Each party sends the latent embedding \( E_i \) to the host organisation, which concatenates these embeddings into the final embedding \( \mathcal{E}, \mathcal{E} = \text{concat}(E_i)_{i=1}^n \). The host organisation feeds the final embedding into their training model (named top model) \( M \), which outputs the predictions \( \Theta(\mathcal{E}) \) where \( \Theta(\cdot) \) is a non-linear operation such as sigmoid or softmax function. Thus, we can define a classification loss function \( l(\cdot) \) for this training process as,

\[
l(w_1, w_2, \ldots, w_n; \mathcal{D}) = l(\Theta(\mathcal{E}), y). \tag{4}
\]

Without loss of generality, the collaborative training problem can be formulated as,

\[
\min_W (W, \mathcal{D}) \triangleq l(\Theta(\mathcal{E}), y) + \lambda \sum_{i=1}^n \gamma(w_i), \tag{5}
\]

where \( W = [w_1, w_2, \ldots, w_n] \), \( \lambda \) is the hyperparameter, and \( \gamma(\cdot) \) is the regularizer. Finally, the host organisation calculates
Theorem 1. A machine learning algorithm \( \mathcal{A} \) based on stochastic gradient descent computes a gradient estimate in each of \( T \) training iterations. The data used to compute the estimate is sampled using a probability \( p \). The sensitivity of the estimate is bounded by a constant \( d \) and we can add Gaussian noise sampled from \( N(0, \sigma^2 d^2) \) to the gradient estimate in each iteration. To compute the weights (training parameters) \( w_{j+1} \) of the next iteration \( j+1 \), the estimate is subtracted from the current weights \( w_j \) of a given iteration \( j \). Thus, if there exists constants \( c_1 \) and \( c_2 \), then the algorithm \( \mathcal{A} \) is \((\varepsilon, \delta)\)-differentially private for any \( \varepsilon < c_1 \sigma^2T \) with \( \delta > 0 \) and the standard deviation of noise is characterized by:

\[
\sigma \leq c_2 p\sqrt{T \log(1/\delta)}/\varepsilon.
\]

Following [26], this can be adapted to a VFL setting. In each iteration of FL, the data of each data owner \( i \) is sampled with a probability of \( p \). This ensures that the number of sampled records can differ across iterations. To bound the sensitivity of the gradient estimate, we can bound the size \( s \) that an individual local model update \( w_i \) can have. Thus, this can be implemented by checking the \( L_2 \) norm of \( w_i \), i.e.,

\[
\tilde{w}_i \begin{cases} 
  w_i & \text{if } ||w_i||_2 \leq s \\
  w_i \times \frac{s}{||w_i||_2} & \text{otherwise}
\end{cases}
\]

For a neural network model with \( K \) layers, the overall limit \( s \) can be computed as,

\[
s = \sqrt{\sum_{k=1}^{K} s_k},
\]

where \( s_k \) is the limit of the \( L_2 \)-norm in the \( k \)-th layer.

If the set of sampled data is denoted by \( C \), then we can estimate the gradient as,

\[
\mathbb{E}_g(C) = \frac{\sum_{j \in C} m_j x_j}{\sum_{j \in C} m_j},
\]

where the number of data points \( m_j \) reflects the importance of the selected data sample in iteration \( j \). Assuming \( N = \sum_{j \in C} m_j \) is the number of records in the current sample, we can estimate the \( L_2 \)-norm of estimated gradients as,

\[
||\mathbb{E}_g(C)||_2 = \left( \frac{\sum_{j \in C} m_j x_j^2}{\sum_{j \in C} m_j} \right)^{1/2} = \frac{\sum_{j \in C} m_j}{N} \left( \frac{x_j^2}{m_j} \right)^{1/2} \leq \frac{\sum_{j \in C} m_j}{N} \left( \frac{||x_j||_2}{m_j} \right)^{1/2} \leq \frac{\sum_{j \in C} m_j}{N} s = s.
\]

This can be expanded into the calculation of sensitivity bounds of gradient estimates as,

\[
S(\mathbb{E}_g) = \max_{C,D} ||\mathbb{E}_g(C) - \mathbb{E}_g(C \cup D)||_2 \\
\leq \max_{C,D} ||\mathbb{E}_g(C)||_2 + ||\mathbb{E}_g(C \cup D)||_2 = \max_{C,D} ||\mathbb{E}_g(C)||_2 + ||\mathbb{E}_g(C \cup D)||_2 = \max_{C,D} ||\mathbb{E}_g(C)||_2 + \max_{D} ||\mathbb{E}_g(C \cup D)||_2 = \max_{C,D} ||\mathbb{E}_g(C)||_2 + ||\mathbb{E}_g(C \cup D)||_2.
\]
TABLE I
OVERVIEW OF THE DATA SETS USED IN THE EXPERIMENTS.

| Dataset        | Domain   | Number of records | Number of Attributes | Classification       |
|----------------|----------|-------------------|----------------------|----------------------|
| Adult          | Census   | 32,561            | 9                    | Binary classification|
| Sport          | Sport    | 9,120             | 5,625                | Binary classification|
| Energy         | Energy   | 768               | 10                   | Multi-output Regression|
| Boston-Housing | Product  | 506               | 12                   | Regression           |
| California-Housing | Product | 20,640          | 8                    | Regression           |

V. EXPERIMENTAL EVALUATION

In this section, we present our experimental results to demonstrate the usefulness of applying differential privacy in a vertical federated learning (FL) setting. We first describe the datasets and parameters we used for the experiments. Then, we discuss our experimental results.

A. Datasets

We used four different datasets in our experiments. We summarize their basic facts in Table I. In each of these datasets, we used 20% records for testing and the remaining for training.

The adult dataset contains records of individuals from 1994 US Census, and is used to predict if an individual’s annual income exceeds 50,000, which can be viewed as a binary classification problem. We use daily and sports activities dataset [51] that comprises motion sensor data of 19 daily and sports activities, each performed by 8 subjects (4 female, 4 male, between the ages 20 and 30) in 5 minutes. This dataset contains 9,120 samples and 5,625 attributes. This dataset is also used for formulating a classification problem.

We also used an energy dataset [52] which contains eight attributes (or features, denoted by X1...X8) and two responses (or outcomes, denoted by y1 and y2) of energy usage of 768 different building shapes. Here, the eight features used are relative compactness, surface area, etc. The two responses are heating load and cooling load. The aim is to use the eight features to predict each of the two real-valued responses, thus making this dataset be used for formulating a regression problem.

The last two dataset we used in our experiments are the Boston-Housing dataset [53] and the California-Housing dataset [54]. We used both of these dataset to predict the median house values which can be viewed as a univariate regression problem. The Boston-Housing dataset contains 506 records each with the features of capita crime rate by town, proportion of residential land zoned for lots over 25,000 square feet, proportion of non-retail business acres per town, Charles River dummy variable (= 1 if tract bounds river; 0 otherwise), Nitric Oxides concentration (parts per 10 million), average number of rooms per dwelling, proportion of owner-occupied units built prior to 1940, weighted distances to five Boston employment centres, index of accessibility to radial highways, full-value property-tax rate per USD 10,000, pupil-teacher ratio by town, and lower status of the population.

The California-Housing dataset was derived from the 1990 U.S. census, using one row per census block group. A block group is the smallest geographical unit for which the U.S. Census Bureau publishes sample data (a block group typically has a population of 600 to 3,000 people). This dataset contains features of median income in block group, median house age in block group, average number of rooms per household, average number of bedrooms per household, block group population, average number of household members, block group latitude, and block group longitude.

B. Parameter settings

In our experiments, we assumed 3, 4, and 5 data owners with one host organisation holding the labels. For each of the data set, we split the number of attributes equally among the data owners.

We adopt a classic multilayer perceptron (MLP) network consisting of three hidden layers with 48, 96 and 196 neurons, respectively. The second layer is chosen as the cut/splitting layer, where the size of the forward output of each bottom model will be 32 and the input size of the top model will be 96. We adopt an SGD optimizer and the learning rate is set to 0.0002. We set the number of training epochs (iterations) to 100 and used batch processing with a batch size of 100.

Following Definition 2, we applied Gaussian noise with $\delta$ to 0.001 to local model parameters (model weights) of each data owner before sending these parameters to the host organisation. We consider sequential composition over training cycles where differential privacy noise is added to model weights. To prevent gradients from explosion due to noise addition, we used gradient clipping with a clipping threshold. We set the clipping threshold to the 80th percentile of the gradient norms of the first 50 iterations. Figure 4 shows the
clipping threshold for Adult and Energy datasets. We set the privacy budget ($\epsilon$) value to 1, 1.5, 2, 5, 10, 50, and 100.

For performance evaluation, we used test accuracy, test loss, and mean square error as metrics. As baselines, we selected two approaches. First, we adopted a centralized learning setting without adding any differential noise. This baseline provides the conventional learning setting where a single data owner holds the training data and their labels. As the second baseline approach, we used the federated learning setting without adding any differential noise in the model parameters. This baseline shows the best utility that can be achieved for each dataset in our VFL setting.

We implemented all approaches in Python 3.7 and we used TensorFlow to implement our deep learning model [55]. All experiments were performed on a 64-bit Intel Core i9 chip, with eight cores running 16 threads at speeds of up to 2.4GHz, along with 64 GBytes of memory, and running on Windows 10. To facilitate repeatability, the data sets and the programs will be made available to the readers.

C. Results and Discussion

Figures 5 to 9 show the accuracy and loss results for different datasets. As can be seen from those figures, the model accuracy is affected by the added differential privacy noise. When the models are perturbed with large amount of noise (e.g. $\epsilon < 10$), the overall accuracy of the model is lower compared to the VFL setting without DP noise. This is due to the fact that the perturbed forward output will make the loss function value biased. Therefore, the fundamental relationship between the convergence bound and the privacy level needs to be characterised to achieve configurable trade-off requirements.

As expected, when the local model parameters are perturbed with less amount of noise, the training of the VFL setting tends to achieve similar classification accuracy as the centralized learning setting. Also, we noted that the results in terms of the loss of trained models do not change much after 20 epoch cycles for some datasets.

VI. RECOMMENDATIONS AND FUTURE DIRECTIONS

Federated learning is an active and ongoing area of research. Due to the growing interest in federated applications, some recent work has begun to address some of the challenges that are unique in the vertical federated settings. Several critical open questions are yet to be explored. In this section, we outline a few promising research directions surrounding the previously discussed privacy challenges and introduce additional challenges regarding dataset characteristics.

A. Privacy attacks and possible defences

As we discussed in Section III, VFL systems are vulnerable to different privacy attacks [42]-[44], [46]. Among those attacks, label inference attacks are powerful against VFL on real-world, large-scale datasets. Protecting the privacy of the labels owned by the host organisation should be a fundamental guarantee provided by VFL, as the labels might be highly sensitive. For example, in a medical application, the labels might indicate whether a person has a certain kind of disease. However, as shown by Fu et al. [46] the bottom model structure and the gradient update mechanism of VFL can be exploited by a malicious data owner to infer the privately owned labels.

Defences, such as gradient compression and noisy gradients, are possible countermeasures that can effectively mitigate the threat of a direct label inference attack. However, such mechanisms are ineffective against passive and active label inference attacks because an adversary can fine-tune the bottom model with an additional classification layer for label inference using...
a small amount of auxiliary labelled data. Thus, this calls for new defence strategies designed for VFL systems.

B. Vertical Federated Unlearning

Recent legislation and regulations in the EU and US have established a new data privacy right called “the right to erasure” (e.g., in the EU’s General Data Protection Regulation [1]) or “the right to delete” (e.g., in the California Consumer Privacy Act [2]). This privacy right of “data erasure” states that under many circumstances, a user can request an organization to erase his/her data entry from a database, even after data collection and analysis. Such a strong level of privacy protection can make a user utterly invisible in a data life cycle, thus safeguarding fundamental human rights such as freedom of association and freedom from discrimination.

In the context of FL, “data erasure” means that the learning should be partially undone by forgetting the training data of a given local client. Such a reverse learning operation is recently referred to as “federated unlearning” [56]. However, existing work on federated unlearning treats HFL only. Its extension to VFL is unclear and non-trivial. More specifically, erasing one data sample from HFL is one thing, but forgetting some attributes of multiple samples or even an entire data silo from
VFL is another story.

C. Ethical Concerns

The paradigm of VFL opens up new avenues of data collection from a variety of sources for a host organization. However, the bright future of big data and AI analytics using VFL also raises ethical concerns. Take insurance pricing as an example; although direct discrimination is prohibited by legislation and regulations, indirect discrimination is a grey area because the pricing models and algorithms are usually opaque and not accessible. More specifically, when applying VFL to pricing insurance contracts, would it be ethical and fair to use the consumer data of grocery/online shopping, fitness levels from gym surveys or wearable trackers, income/taxation/employment information, membership status in various groups, and household energy usage patterns from smart meters? If yes, would it be acceptable to further dip into the consumer data of prescription medications, social media posts/images/videos, vehicle GPS trajectories, Youtube watching lists, or web browsing history? Where is the boundary of data usage in VFL for insurance underwriting and other applications? In practice, we believe multi-disciplinary research is needed to investigate VFL’s discrimination and fairness issues for various business use cases to reduce the risk of harm to consumers in terms of exclusion and prejudice.
VII. CONCLUSION

Recent advancements in federated learning (FL) allow multiple data owners/organisations to collaboratively train a machine learning model without sharing their raw data. In this paper, we explore how differential privacy can be used in a vertical federated learning setting. It is a widely adopted method to add DP noise to the output in the process of gradient iteration, so as to achieve the goal of privacy protection. We can further add noise to the data to enhance privacy protection. However, DP comes at a cost of sacrificing the performance of the model. Hence, a reasonable trade-off point needs to be found to determine the appropriate amount of additive DP noise, while maintaining a useful model.

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