A Generative Federated Learning Framework for Differential Privacy

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Abstract—In machine learning, differential privacy and federated learning concepts are gaining more and more importance in an increasingly interconnected world. While the former refers to the sharing of private data characterized by strict security rules to protect individual privacy, the latter refers to distributed learning techniques in which a central server exchanges information with different clients for machine learning purposes. In recent years, many studies have shown the possibility of bypassing the privacy shields of these systems and exploiting the vulnerabilities of machine learning models, making them leak the information with which they have been trained. In this work, we present the 3DGL framework, an alternative to the current federated learning paradigms. Its goal is to share generative models with the 3DGL framework, an alternative to the current federated with which they have been trained. In this work, we present the 3DGL framework, an alternative to the current federated learning paradigms. Its goal is to share generative models with high levels of utility and safety for the individual. We evaluate the 3DGL framework based on DDP-βVAE, showing how the overall system is resilient to the principal attacks in federated learning and improves the performance of distributed learning algorithms.

I. INTRODUCTION

Data privacy is increasingly becoming one of the most relevant issues in the Machine Learning era. While it represents a fundamental right for the individual, it is also considered the most significant limitation for sharing information, especially if sensitive. Furthermore, with the growing popularity of Centralized and Collaborative Learning, several scenarios are characterized by flows of sensitive information to centralized servers, which have made it necessary to find solutions to new threats and possible attacks on privacy.

One of the most adopted solutions has been introduced by Abadi et al. [1] which aimed at improving and measure differential privacy via the introduction of noise during different stages of neural networks training. Even if this approach has proven to introduce considerable benefits in terms of privacy attacks resistance, there are still many open issues related to gradient and data sharing between parties.

More recent works have exploited the ability of Generative Adversarial Networks [12] and Variational Autoencoders [19] to generate synthetic data. Combining them with the concept of differential privacy makes it possible to cope with many privacy information leakage issues.

In our work, we propose a novel paradigm named Decentralized Distributed Deep Generative Learning (3DGL) as an alternative for both Centralized and Collaborative Learning approaches. While the first approach is based on sharing private data between clients and server, and the second on sharing gradients and updates between local models and a central server, our approach aims at sharing data generators trained with strict differential privacy constraints between clients directly. We show how our approach turns out to have high resistance levels to the most famous threats concerning the two aforementioned federated learning techniques.

In this work, we make the following contributions:

- We present DDP-βVAE, a generative model, based on βVAE, which is able to synthesize data preserving high utility levels, and guarantees strict levels of differential privacy.
- We present 3DGL, a federated learning paradigm alternative to Centralized and Collaborative Learning, based on the exchange of generative models and characterized by high levels of security.
- We demonstrate the effectiveness of the 3DGL framework based on DDP-βVAE by identifying, simulating, and evaluating the main scenarios in which it can be exploited and showing the benefits in terms of performance and privacy for each client of the system.

II. RELATED WORK

Differential privacy [2, 7] is a privacy model providing strong guarantees against the disclosure of sensitive information related to individual samples. In this work, we consider (ε, δ)-differential privacy (for simplicity, ε-DP), i.e., the version proposed by Dwork et al. [9]. It is defined as a randomized mechanism $\mathcal{M} : D \rightarrow R$ with domain $D$ and range $R$ which is satisfied if for any two adjacent inputs $d, d' \in D$ and for any subset of outputs $S \subseteq R$ it holds that:

$$Pr[\mathcal{M}(d) \in S] \leq \exp^\varepsilon Pr[\mathcal{M}(d') \in S] + \delta,$$  \hspace{1cm} (1)

where $\varepsilon$ is a privacy budget balancing the Accuracy of the mechanism with sensitive disclosures. The smaller the budget, the higher the privacy guarantees. The $\delta$ parameter relaxes the constraints of $\varepsilon$-DP introduced in [8] by allowing violations with probability $\delta$.

In the deep learning field, several approaches have been proposed to integrate differential privacy guarantees within training and inferential procedures. To protect the sensitivity
of training data, Abadi et al. [1] designed a Differentially-Private version of the Stochastic Gradient Descent algorithm, i.e., the DP-SGD, for training deep neural networks with non-convex objectives. Papernot et al. [24] address the problem of the implicit storage of sensitive training data within a machine learning model, proposing the PATE framework, which relies on the separation of teacher models, directly trained on disjoint sensitive datasets and not published, and student models, learning from the teachers to predict an output retrieved by noisy voting among them.

Synthetic data generation is another important aspect of differential privacy. Deep generative models, such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs), are powerful tools learning to generate realistic data largely resembling the training datasets. While achieving high data utility, these models do not implement any countermeasure against the disclosure of sensitive data possibly provided during training. Chen et al. [3] introduce a Differentially-Private VAE-based generative model, while a Differentially-Private version of GAN is defined by Xie et al. [33]. Jordan et al. [16] extended the PATE framework to GANs, while Mugunthan et al. [23] applied differential privacy to the InfoGAN model. DP-auto-GAN, a framework for synthetic data generation applicable to unlabeled mixed-type data, has been proposed by Tantipongpipat et al. [29] and it is able to combine the flexibility of GANs with the dimensionality-reduction capabilities of Autoencoders. Torkzadehmahani et al. [31] applied differential privacy to Conditional GANs, relying on the recent Rényi differential privacy model.

Takahashi et al. [28] showed that by customizing the VAE ELBO loss with different divergence terms, the sensitivity of the model to the noise introduced by DP-SGD scales with the batch size. For solving this issue, the authors define a novel training procedure, term-wise DP-SGD, that keeps the VAE sensitivity low when attaching divergence. Acs et al. [2], instead, separated the Differentially-Private data synthesis process in two steps: first they carry out Differentially-Private $K$-means clustering over the sensitive training dataset, and then they train $K$ separate generative models, one for each cluster, achieving higher data utility through the models mixture with respect to a single generative model.

Despite the broad applications of DP optimization algorithms to neural networks, many authors showed that sensitive information leakage could happen if provoked by malicious intent. Different privacy attacks have been developed with the purpose of showing that unintended disclosure of training dataset information is possible. Model inversion, for example, is an attack developed by Fredrikson et al. [11], which tries to find a missing value feature of a dataset row, given all the remaining ones. The attack leverages access to the model, but only in a black-box fashion. The initially proposed attack has two significant drawbacks. The first one is that it can not be used when the unknown features cover an intractably large set, while the second one is that there is no guarantee that the attacks will be effective. Further development of this attack has been proposed by Fredrikson et al. [10]. They extend the attack to a full reconstruction of a dataset example, addressing two major themes: white-box decision tree attacks and black-box reconstruction attacks to facial recognition models.

Another type of privacy threat is known as the Membership Inference attack and has been proposed by Shokri et al. [27]. Given a data record and black-box access to a model, the attacker tries to determine if the record was in the model training dataset. To achieve this objective, they leverage the models different behaviour when they operate with training examples, with respect to first-time seen examples. Their methodology builds different proxy training sets, either mimicking the distribution of the original dataset or using other datasets closely related to the private one, used to train the target model. These datasets are also called shadow datasets. They then built over these $n$ shadows training datasets $n$ different shadows models. A practical example is the shadow dataset created using the target model with inference procedure. Using a kind of Model Inversion, the authors tried to replicate records classified with a high probability. The attack model is then trained to recognize from these different shadow models their behavior over in-sample ad out-sample examples. Membership Inference attacks have also been developed and customized for generative models, as by Hayes et al. [13].

Facing these new challenges, the scientific community tried to develop different strategies to address the risk of privacy leakage. In most contexts, data is centrally stored in a dedicated server for training. If, on the one hand, this setting guarantees high security standards against external unauthorized accesses, on the other, it implies for the uses to share data information and to make it converge in a single point. If this information turns out to be sensitive or in clear, this represents a substantial privacy issue. Collaborative Learning [17] is a practical system that enables multiple clients to jointly learn a model for a given objective without sharing their input datasets. Methods coming from this family, e.g., [26], exploit parallelization and asynchronous execution in stochastic gradient descent-based algorithms. Different clients cooperate, training their models on local private datasets and then sharing weights updates with a central server able to balance the different contributions. This approach is also helpful in the case of possible cooperation between different entities.

If different subjects possess a small amount of data and want to collaborate, nondisclosure policies and other reasons could become a barrier. Federates Learning instead allows for cooperation without information disclosure. This approach received the endorsement of big tech companies [21], but recent works raised doubts about its safety.

Hitaj et al. [15] have proposed a GAN-based attack in the context of Collaborative Learning. The attack focuses on the possibility of separately learning a task from $n$ different private datasets sharing weights and parameters updates. The attacker forces other participants to share their private knowledge (thus improving the reconstruction of dataset elements performed by a GAN), simply adding fake examples.
Fig. 1. The architecture of DDP-\(\beta\)VAE. Given a \(k\) classes (with \(k=1\) in case of regression, for instance) private dataset, we create \(k\) sub-datasets, one for each class. Then, for each sub-dataset, we train a \(\beta\)VAE with \(\varepsilon\)-DP. Finally, we collect each decoder obtaining the DDP-\(\beta\)VAE Generator, and we feed it with Gaussian noise to produce a \(k\) classes synthetic dataset.

III. METHOD

A. Model

Starting from the aforementioned works \([1, 28, 5]\) we introduce DDP-\(\beta\)VAE, a distributed DP \(\beta\)VAE to generate private and synthetic data with high utility levels. The idea is to start from \(\beta\)VAE implementation \([14]\) but, instead of tuning \(\beta\) with values greater than 1 to force disentanglement in latent space, as theoretically supported by Burgess et al. \([4]\), we search for \(\beta\) values in range \((0, 1)\). This choice is aimed at discouraging disentanglement in latent space, increasing reconstruction capabilities, preventing vanishing Kullback-Leibler Divergences (KLD) loss, and forcing latent distributions to increase Rényi divergence \([32]\) with respect to multivariate normal distribution. We optimize the DDP-\(\beta\)VAE weights through the \(\varepsilon\)-DP version of adam \([18]\) keeping constant and strict privacy levels among experiments, i.e., \(\varepsilon=1.9, \delta=10^{-4}\), Rényi-DP (RDP)=8 \([22]\).

As shown in Figure 1, given a dataset containing private or sensitive information, we divide it into \(k\) sub-datasets according to the class labels (in case of no class labels, e.g., regressions, we keep the entire dataset as it is). For each sub-dataset, we build and train a dedicated \(\beta\)VAE with \(\varepsilon\)-DP balancing batch dimension and noise multiplier to keep constant DP levels. After the training phase, we keep only the obtained DDP-\(\beta\)VAE decoders. We argue that a system composed of \(k\) independent \(\varepsilon\)-DP generative models is itself \(\varepsilon\)-DP.

B. Metrics & Pipeline

In order to quantify the goodness and the DP preservation, we define a pipeline to evaluate the trained data generators. For each sub-dataset, given its dimension \(D\), we sample from its corresponding DDP-\(\beta\)VAE decoder a synthetic samples amount \(D_s \gg D\), and then we combine all the generated data into a synthetic and private dataset. An open issue in generative deep learning is to quantify the optimal amount of generated data so that it achieves the best performance on real data. Our solution consists of iteratively evaluating batches of synthetic data over the real data used to train the generators, finding the optimal samples amount, and then evaluating it on external data.

In the experiments presented in the next section, we evaluate the performance of Logistic Regression over different classification tasks. In this work, we have focused on this family of problems, but the approach can be easily extended to different tasks, and the performance evaluation can be carried out via different models. We are also interested into an evaluation of the quality of generated samples with respect to data used to learn the latent distribution. For this purpose, we generate a number of synthetic samples equal to the number of real records and set up an adversarial attack to distinguish between real and fake. According to the idea presented by Xu et al. \([34]\), we implement a Logistic Regression as a discriminator, and we evaluate the performance of the model with 10-fold cross-validation.

We want to measure the quality of the distribution of generated synthetic samples with respect to real data and have metrics to compare different generators. Thus, we evaluate the averaged Accuracy, the F1 score and the area under the ROC curve (AUC) and compute the KLD between the two datasets features: given the same performance of synthetic samples over real data and the same \(\varepsilon\)-DP, we prefer the generator with lower averaged Accuracy and AUC, and the higher KLD.

To monitor all this together, we define the Turing Logistic Divergence (TLD) between the real and the synthetic populations as:

\[
TLD(r, s) = \left( \frac{KLD(r, s)}{\text{Accuracy}} \right)^{1-AUC},
\]

which maps the input evaluations into a \([0, +\infty)\) interval, and has to be interpreted as the ability of the generator to
synthetic data that is not linearly distinguishable from the real population while maintaining different features distributions properties. We would choose the generator with higher TLD, given the same performances on the main task.

C. Resilience to Privacy Attacks

According to the families of attacks to privacy presented in the previous section, Tiwald et al. [30] argue that in a generative setting like ours, there is no possibility to retain statistical information related to original dataset individuals because sampling from multivariate distributions breaks the 1:1 relationship between real and synthetic samples. Moreover, learning latent representations through DP optimizer further validate their thesis and allows us to consider DP generative approaches resilient to Model Inversion attacks. In fact, trying to reverse a generator having a set of generated samples would make the attacker able to obtain the sampled noise from which the synthetic sample has been created, and thus nothing related to real sensitive data. Concerning Membership Inference attacks, in our approach, each generator is characterized by $\varepsilon = 1.9$ which is corresponding, according to Rahman et al. [25], to a full level of resilience from this attacks family. Having defined the DDP-$\beta$VAE model, the evaluation metrics and its properties of DP resilience, we can now apply them in a federated learning scenario.

D. 3DGL

Federated learning represents the most adopted technique to share and exploit information from isolated endpoints and make it available for Machine Learning purposes through a central server. The main challenge for this procedures relies on privacy preservation, which has been taken into account in different works [3, 35, 20]. Actually, we can distinguish the overall architectures in two families, i.e., the Centralized Learning and the Collaborative Learning [36].

In a Centralized Learning scenario, there are K Clients connected to a Global Server (e.g., a cloud server) which is able to directly collect data in a single location and then train the model on the combined datasets. This approach is probably the most effective if the goal is to obtain extremely performing models, but has several drawbacks related to privacy preservation. However, in many contexts, the data collected could be very sensitive and attributable to private information that users would not want to share.

In Collaborative Learning, instead, each participant Client has its own mirror model to train, and collaborates with the party by sharing only a portion of the parameters updates. This allows to create a network of exchange that is much more privacy-friendly compared with Centralized Learning, mainly because users have not to share their own information, and for higher resilience to Model Inversion attacks.

Hitaj et al. [15] have disclosed the idea behind GAN-based attacks to Collaborative Learning, and even the Collaborative Learning has demonstrated a massive security breach in this framework topology: in fact, it has been shown that even with the application of strong $\varepsilon$-DP constraints, an attacker masked as Client can exploit GANs to map epochs parameters changes from a victim, to reconstruct the samples that have lead to these updates with quite accurate confidence.

In order to overcome this issue, we propose the Decentralized Distributed Deep Generative Learning (3DGL) framework as an alternative to the aforementioned two federated learning paradigms. As shown in Figure 2, the core idea relies on the type of information to share among Clients and the Global Server: while in the first two scenarios, the users exchange personal data and updating parameters, respectively, in 3DGL, we want the users to share $\varepsilon$-DP Data Generators trained on their own private personal data. In this way, the Global Server would act as a collector of Local Generator Models. The idea is to make available to all the Clients all the collected Generators, named from now on as Generators Pool. In this...
scenario, as for the Collaborative Learning, the Clients have only to subscribe to a protocol defining the Local Generator Model characteristics, train it on their Private Dataset and send it to the Global Server to get access to the Generators Pool. It is important to underline the flexibility of this paradigm from the Client perspective: in fact, while in both Centralized and Collaborative Learning, a participant has to adhere to the task to which for which data or updates are collected, e.g., recommendations, in this setting, each Client is left free to exploit the Generators Pool in the way it deems most appropriate, which in our opinion would be very useful in a vast range of cases, e.g., when the Clients are composed by hospitals of private clinics.

To the best of our judgment, we retain the 3DGL framework to have the highest privacy levels among the three approaches. In fact, it preserves all the advantages of Collaborative Learning, i.e., Model Inversion attacks resilience and no sharing of private data in clear, but is also resilient by nature to GAN-based attacks to Collaborative Learning. Moreover, having that Local Generator Models satisfy strict ε-DP requirements, we argue that 3DGL also keeps the current state of the art of Membership Inference attacks resilience.

In our research, we have implemented 3DGL framework with the previously defined DDP-βVAE in order to demonstrate its effectiveness, to identify the main use cases, and to evaluate them from the user perspective.

IV. EXPERIMENTS & RESULTS

In this section, we present the results of two different experiment pools. In the first pool, we use DDP-βVAE to generate a set of synthetic datasets. Among these, we choose the synthetic dataset that maximizes the performance on the training set, we evaluate it on an external test dataset, and we compare its performance with those we would obtain by evaluating the test starting from real data only. We also perform the adversarial evaluation explained in the previous section to quantify the ability of DDP-βVAE to generate samples hard to distinguish from the population on which it has been trained. In the second pool, we evaluate the performance of 3DGL on a real scenario simulation. We emulate a system composed by 10 Clients, in which each one builds her own generator as in Figure 1 and shares it with the party through a Global Server and receives the Generators Pool.

We test both the experiment pools over 5 different datasets from the UCI Machine Learning Repository [6], i.e., Titanic, Breast Cancer Wisconsin (Diagnostic), Mushroom, Adult and Wine Quality datasets.

A. DDP-βVAE Evaluation

For each dataset, after a cleaning and normalization step, we apply a stratified split into train and testing set, containing 90% and 10% of data, respectively. Then, as shown in Table II, we build a customized DDP-βVAE keeping constant the ε-DP constraints, i.e., ε = 1.9, δ = 10^{-4}, RDP=8.

First, we train a Logistic Regression over the training set and evaluate it over the testing set. Then, we train the DDP-βVAE model over the training set. At this point, we sample an arbitrary huge amount of samples, and we evaluate it increasingly. Starting from a small batch, e.g. 200 synthetic samples, we train a Logistic Regression and evaluate the performance on the training set. We repeat this step enlarging the amount of

### Table I

| Dataset       | Encoder | Latent Space | Decoder |
|---------------|---------|--------------|---------|
| Titanic       | Dense(64, tanh) | Dense(32, tanh) | Dense(32, tanh) |
| Breast Cancer | Dense(64, tanh) | Dense(32, tanh) | Dense(32, tanh) |
| Mushrooms     | Dense(64, tanh) | Dense(32, tanh) | Dense(32, tanh) |
| Adult         | Dense(128, tanh) | Dense(64, tanh) | Dense(128, tanh) |
| Wine Quality  | Dense(64, tanh) | Dense(32, tanh) | Dense(64, tanh) |

### Table II

| Dataset   | Accuracy | F1 | AUC |
|-----------|----------|----|-----|
| Titanic   | 74.04    | 76.34 | 80.84 |
| Breast Cancer | 97.67    | 96.51 | 98.30 |
| Mushrooms | 94.96    | 93.73 | 97.99 |
| Adult     | 82.05    | 79.97 | 85.53 |
| Wine Quality | 97.74    | 98.31 | 96.64 |

### Table III

| Dataset       | Accuracy | F1 | AUC | KLD | TLD |
|---------------|----------|----|-----|-----|-----|
| Titanic       | 54.00    | 55.61 | 57.23 | 342.06 | 15.79 |
| Breast Cancer | 52.69    | 55.06 | 53.88 | 2126.03 | 6.13 |
| Mushrooms     | 57.40    | 55.98 | 60.83 | 1226.03 | 20.15 |
| Adult         | 64.53    | 65.55 | 68.37 | 3358.17 | 14.98 |
| Wine Quality  | 57.69    | 60.85 | 64.61 | 191.81 | 7.81 |
generated samples until the Logistic Regression performance starts to degrade, and finally, we save the most performing model and synthetic dataset. In the end, we compare its performance on the testing set with the one obtained with the Logistic Regression trained on the private local data and evaluated over the testing set. As shown in Table II, DDP-βVAE achieves very interesting generation performance: on average, the models trained on synthetic datasets change their Accuracy, F1 score and AUC by only -0.32%, +5.16% and -1.12% with respect to the same models trained on real data, respectively. We will deeply discuss these results in the next section.

At this point, we build a dataset composed by the private local data and the same amount of synthetic samples, and we perform an adversarial attack with a Logistic Regression aimed at distinguishing real and fake samples, similar to what is proposed by Xu et al. [34]. As shown in Table III, the models have discriminating difficulties and are able to achieve, on average, an Accuracy equal to 57.26%, which is not so far from the random guessing. Moreover, from the average F1 score and AUC, 58.61% and 60.98% respectively, we notice that even by changing the decision threshold, the models would not increase by more than a few percentage units the overall accuracies. It is interesting to observe the different DDP-βVAE behaviours according to the generated features: in fact, we notice an unexpected huge variance in the Kullback-Leibler Divergences, which is accountable to the different DDP-βVAE hyperparameters, as shown in Table I. Nevertheless, we deem it desirable to have a synthetic dataset with a high KLD and low Accuracy on the adversarial attack given its high performances on the test: this would mean that the generators have sampled fake instances which are informative, different from the real distribution but still difficult to distinguish. In the last columns of Table III we show the proposed Turing Logistic Divergence metric. Despite in this set of experiments its values are not comparable among datasets due to the domain not restricted in the [0,1] range, we retain it a good measurement to choose the best generator given the same Accuracy level over the test: in fact, having a high TLD on the same dataset would mean that the generator is able to produce samples which are at the same time different and not linearly distinguishable from real data, which can also be interpreted as the ability to generate more secure instances with respect to Membership Inference attacks.

B. 3DGL Evaluation

For this experiments pool, we simulate a scenario with a Global Server and 10 Clients, each one producing and sharing a DDP-βVAE trained on their private local data with the same ε-DP constraints of the previous experiments, i.e., $\epsilon = 1.9$, $\delta = 10^{-4}$, RDP=8, and the same structures reported in Table I. For each dataset, after a cleaning and normalization step, we apply a stratified split into train and testing set, containing 90% and 10% of data, respectively. At this point, we apply a further stratified split over the training set to obtain 10 different and not overlapping sub-training folds, which would represent the private local data of the 10 Clients. From now on, we will...
The results of 3DGL evaluated over local private data. For each metric, the Real column represents the average of the Clients scores obtained by Logistic Regressions evaluated via 10-fold cross-validation over local private data. The Synth(Fold-Fold) column represents the average of the Clients scores obtained by Logistic Regressions trained over the optimal synthetic datasets, i.e., the set of synthetic samples that maximizes the performance over the local private data. In the last row, for each metric, is reported the average of the differences between Synth(Fold-Fold) and Real columns.

| Dataset   | Accuracy | F1 | AUC  |
|-----------|----------|----|------|
| Real Synth(Fold-Fold) | Real Synth(Fold-Fold) | Real Synth(Fold-Fold) |
| Titanic   | 77.28    | 77.13 | 55.34 | 62.50 | 76.42 | 79.21 |
| Breast Cancer | 92.20    | 97.52 | 95.29 | 98.06 | 98.51 | 98.89 |
| Mushrooms | 93.86    | 94.11 | 93.48 | 93.87 | 96.62 | 96.42 |
| Adult     | 10.03    | 79.61 | 51.74 | 52.65 | 83.80 | 80.52 |
| Wine Quality | 96.39    | 98.68 | 92.25 | 97.45 | 99.47 | 99.48 |
|           | +1.06    | +7.29 | -     | -0.12 |    |

The results of 3DGL evaluated over external data. For each metric, the Real column represents the average of the Clients scores obtained by Logistic Regressions trained with local private data. The Synth(Fold-Test) column represents the average of the Clients scores obtained by Logistic Regressions trained over the optimal synthetic datasets for the local private data, i.e., the set of synthetic samples that maximizes the performance over the local private data. The Synth(Test-Test) column represents, instead, the average of the Clients scores obtained by Logistic Regressions trained over the optimal synthetic datasets for external data, i.e., the set of synthetic samples that maximizes the performance over the external data. In the last row, for each metric, is reported the average of the differences between Synth(Fold-Test) and Real columns, and the average of the differences between Synth(Test-Test) and Real columns.

| Dataset   | Accuracy | F1 | AUC  |
|-----------|----------|----|------|
| Real Synth(Fold-Test) | Real Synth(Fold-Test) | Real Synth(Fold-Test) |
| Titanic   | 73.28    | 74.81 | 76.34 | 59.88 | 64.71 | 67.37 |
| Breast Cancer | 93.84    | 97.54 | 96.51 | 95.33 | 97.98 | 97.30 |
| Mushrooms | 93.85    | 94.20 | 94.10 | 93.40 | 93.93 | 93.72 |
| Adult     | 81.18    | 79.55 | 80.99 | 51.87 | 52.27 | 54.48 |
| Wine Quality | 95.67    | 97.99 | 98.12 | 90.29 | 95.88 | 96.15 |
|           | +1.26    | +1.65 | 66.80 | +7.65 | -0.86 | -0.16 |

As shown in Figure 3, we have identified three main scenarios in which 3DGL would be involved. By keeping in mind that the task choice is due to the Client, the image at the left represents the case in which she wants to evaluate the Generators Pool performance over her own population. We guess that the availability of generators coming from other private data sources would be beneficial to improve the predictive capabilities of the Client’s own population. We ran a set of experiments in which we iteratively and uniformly sample from each element of the Generators Pool to build larger synthetic datasets. Then, we evaluated over local private data each obtained dataset with a Logistic Regression and saved the best model according to the best amount of generated samples. We compared its performance with the one obtained from a Logistic Regression evaluated on the private local data via 10-fold cross-validation.

The results shown in Table IV demonstrate that on average, each Client is able to improve the performance over her own population: in fact, we notice an average improvement of Accuracy and F1 score of +1.06% and +7.29%, respectively, while recording a very limited degradation of the AUC, i.e., -0.12%.

In the second and third scenarios, shown in Figure 3 in the middle and right images, respectively, the Clients goal is to evaluate the external data in the most accurate way. In both cases, each Client generates synthetic datasets in the same way as the previous scenario: in the first case, which is probably the most common one, the external data would not be exploitable to select the best number of generated samples, and thus each Client has to choose it according to her own private data, like in the previous experiments pool. In the second case, instead, she has the possibility to access external data and exploit it to generate the optimal number of synthetic samples to have the highest performance on data coming from the external population. Also in these two cases, we use Logistic Regression to select the best synthetic datasets and to evaluate their information on the external data. For each Client, we compared the results obtained from these two applications with the ones obtained by using Logistic Regression trained only on private local data and evaluated over the external data.

In Table V are reported the performance of these two experiments pools. For each evaluation metric, as in Figure 3, the second and the third columns, i.e., Synth(Fold-Test) and Synth(Test-Test), represent the second and the third scenarios, respectively. In both cases, we notice that the information generated from the Generators Pool makes the models able to improve their average performance over external data with respect to the same models trained on local private data. As expected, the biggest improvements are achieved in the third scenario, i.e., when the Clients have the possibility to build the synthetic dataset having information about the external population: in this case, we observe an average improvement refer to the testing set as external data, i.e., the only set which has not been learned by a generator into the Generators Pool.

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among the tested datasets of +1.65% over Accuracy and +7.65% over the F1 score, despite a minimal degradation over the AUC of -0.16%. In our opinion, the most interesting and significant results come from the second scenario, in which each Client has generated the synthetic dataset according to her own private data and without any knowledge about the external population. In this case, we observe an average improvement of +1.26% and +6.80% over Accuracy and F1 score, respectively, with a minor reduction over AUC of -0.86% with respect to the same models trained over individual local private data.

In the next section, we will further discuss the results obtained so far. However, we can assert that, from an exclusively quantitative point of view, the 3DGL paradigm is on average able to improve Clients performance, concerning the one reached exploiting only local private data, and regardless of the type of scenario in which it is applied.

V. DISCUSSION

Concerning the first part of the experiments, we assert that DDP-\(\beta\)VAE is able to generate synthetic data characterized by high utility levels notwithstanding the strict levels of \(\varepsilon\)-DP imposed on the model.

Looking at Table II we notice that the Accuracy changes range from -2.08% over the Adult dataset to +2.30% over the Titanic dataset. We did not expect to improve the performance over the testing set, especially because we build the synthetic dataset used for the evaluation according to the best score over the local private data. We suppose that the combination of low \(\beta\) values with the noise produced by the DP-adam optimizer could have led the DDP-\(\beta\)VAE to constraint the latent space information so that, in some cases, it is able to sample likely instances belonging to a distribution which is similar regarding certain features, and completely different regarding others. This would also explain the high levels of the KLD between the real and the synthetic distributions associated with the low discrimination capabilities reported in Table III, which is a good property for synthetic data.

Another interesting aspect regards the DDP-\(\beta\)VAE improvements over the F1 score. In fact, in some cases, we have observed important positive variations with respect to the models trained on local private data, regardless of the Accuracy variation, which, for instance, for the Adult dataset turns out to be negative. In our experiments, we have generated a number of samples that is balanced among the classes, and this is, in our opinion, the main reason why we observe such improvements over the F1 score. Although it is beyond the scope of this paper, it would be interesting to investigate this phenomenon by replicating the exact class equilibrium within real data or by looking for the optimal balance to maximize performance on a task. In our experiments, we assumed that we do not know the class balance a priori.

Concerning the second part of the experiments, i.e., the testing of the 3DGL paradigm, we argue that, on average, our proposal would bring benefits for all the parties, as shown in Table IV and in Table V. From a performance point of view, the general behaviour of the three proposed scenarios is consistent with that of the DDP-\(\beta\)VAE just described.

The improvements are on average greater due to the lower amount of data available to the various Clients, compared to having a single generator trained starting from all the data of the Clients, as in the previous experiments. We also have good reasons to believe that, following the deep learning paradigm according to which the more data, the greater the performance, as the number of Clients participating in the party increases, there can be ample and further span for improvement. Furthermore, in our simulation, we used data from the same population split in a stratified manner among the Clients. On the one hand, this choice may have benefited the utility of the data generated. On the other, we believe that it has limited its generality and that the presence of heterogeneous sources would greatly benefit the entire system.

The 3DGL paradigm presented in this work is designed to be replicated and adapted to any generative model, as long as it meets the proposed \(\varepsilon\)-DP requirements. Likewise, the entire system is easily extendable to other types of data as well as tasks. 3DGL is not intended to be a replacement for Centralized or Collaborative Learning, which will indeed preserve and will continue to preserve advantages in environments where privacy is not an issue. The idea behind this work is to propose an effective alternative with a higher level of security that can be applied in everyday contexts as well as in situations that require high levels of confidentiality.

From our point of view, in a world that continues to increase the level of challenges to be overcome and that changes rapidly and unexpectedly, sharing information is a fundamental objective in order to make the most of modern technologies, but it is necessary that is done with the highest and most stringent levels of security and with ethical purposes. It is with this objective that we have decided to undertake this research path, thinking about how much hospitals, clinics, schools and many other realities can benefit from a sharing of information that preserves the confidentiality of even highly private or sensitive data.

VI. CONCLUSION

In this work, we presented and formalized 3DGL, a generative federated learning framework with high privacy levels, and DDP-\(\beta\)VAE, the distributed generative model with differential privacy with which it was implemented and tested. We have shown the effectiveness of DDP-\(\beta\)VAE in generating synthetic datasets characterized by high levels of both \(\varepsilon\)-differential privacy and utility. Subsequently, we proposed the 3DGL framework, a valid alternative to Centralized and Collaborative Learning, based on the exchange of generative models, and effective even in situations where very high levels of confidentiality are required. Finally, we demonstrated through a simulation the effectiveness of this federated learning paradigm from the point of view of the clients, managing to obtain improvements in the differential privacy scenario. We believe that this work can be applied, extended and adapted in many real domains and that, if properly exploited, it can help to
break down the barriers that currently appear to be the greatest obstacle to shared knowledge. In conclusion, although there are still many open issues that link the world of machine learning to that of security, we hope that this work can be a step forward in a path towards a more efficient, shared, and safer world.

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