FedCG: Leverage Conditional GAN for Protecting Privacy and Maintaining Competitive Performance in Federated Learning

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Abstract

Federated learning (FL) aims to protect data privacy by enabling clients to build machine learning models collaboratively without sharing their private data. Recent works demonstrate that information exchanged during FL is subject to gradient-based privacy attacks and, consequently, a variety of privacy-preserving methods have been adopted to thwart such attacks. However, these defensive methods either introduce orders of magnitudes more computational and communication overheads (e.g., with homomorphic encryption) or incur substantial model performance losses in terms of prediction accuracy (e.g., with differential privacy). In this work, we propose FedCG, a novel federated learning method that leverages conditional generative adversarial networks to achieve high-level privacy protection while still maintaining competitive model performance. FedCG decomposes each client’s local network into a private extractor and a public classifier and keeps the extractor local to protect privacy. Instead of exposing extractors, FedCG shares clients’ generators with the server for aggregating clients’ shared knowledge aiming to enhance the performance of each client’s local networks. Extensive experiments demonstrate that FedCG can achieve competitive model performance compared with FL baselines, and privacy analysis shows that FedCG has a high-level privacy-preserving capability.

Introduction

Deep neural networks (DNN) have achieved dramatic success in many areas, including computer vision, natural language processing, and recommendation systems. Their success largely depends upon the availability of a wealthy amount of training data. In many real-world applications, however, training data is typically distributed across different organizations, which are unwilling to share their data because of privacy and regulation concerns directly. To alleviate these concerns, federated learning (FL) (McMahan et al. 2017) is proposed to enable multiple clients to collaboratively build DNN models without sharing clients’ private data.

Despite the privacy-preserving capability introduced by FL, recent works have empirically demonstrated that the classic federated averaging method (FedAvg (McMahan et al. 2017)) and its variants (e.g., FedProx (Li et al. 2020)) are vulnerable to gradient-based privacy attacks such as the deep leakage from gradients (DLG) (Zhu and Han 2020), which is able to reconstruct the original data of clients from publicly shared gradients and parameters. Varieties of technologies have been leveraged to further improve the privacy of FL, the most popular ones are homomorphic encryption (HE) (Gentry et al. 2009, Aono et al. 2017) and differential privacy (DP) (Dwork, Roth et al. 2014). HE provides a high-level security guarantee by encrypting exchanged information among clients. Nonetheless, its extremely high computation and communication cost make it unsuitable to DNN models that typically consist of numerous parameters. While DP imposes a low complexity on FL, it causes precision loss and still suffers from data recovery attacks. To prevent data leakage and still enjoy the benefits of FL, FedSplit (Gupta and Raskar 2018, Gu et al. 2021) combining split learning (Vepakomma et al. 2018) and federated learning proposes to split a client’s network into private and public models, and protect privacy by hiding private model from the server. However, FedSplit experiences a non-negligible performance drop.

In this work, we propose FedCG, a novel federated learning method that leverages conditional generative adversarial networks (Mirza and Osindero 2014) to achieve high-level privacy protection resisting DLG attack while still maintaining competitive model performance compared with baseline FL methods. More specifically, FedCG decomposes each client’s local network into a private extractor and a public classifier, and keeps the extractor local to protect privacy. The novel part of FedCG is that it shares clients’ generators in the place of extractors with the server for aggregating clients’ shared knowledge aiming to enhance model performance. This strategy has two immediate advantages. First, the possibility of clients’ data leakage is significantly reduced because no model that directly contacts with original data is exposed, as compared to FL methods in which the server has full access to clients’ local networks (e.g., FedAVG and FedProx). Second, the server can aggregate clients’ generators and classifiers using knowledge distillation (Hinton, Vinyals, and Dean 2015) without accessing any public data.

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The main contributions of this work are:

- To the best of our knowledge, this work is the first attempt to integrate cGAN into FL aiming to protect clients’ data privacy by hiding local extractors from the server while enabling clients to have competitive model performance by integrating shared knowledge embedded in the global generator.
- Extensive experiments demonstrate that FedCG can achieve competitive performance compared with varieties of baseline FL methods. The privacy analysis proves that FedCG has a high-level privacy-preserving capability against gradient inversion attacks.

### Related Work

#### Federated Learning

Federated learning (FL) is a distributed machine learning paradigm that enables clients (devices or organizations) to train a machine learning model collaboratively without exposing clients’ local data. The concept of FL was first proposed by (McMahan et al. 2017). Further, many serious challenges emerge with the development of FL. Particularly, the “naked” FL methods without any privacy protection mechanism are proven to be vulnerable to data recovery attacks such as deep leakage (Zhu and Han 2020) and model inversion (Fredrikson, Jha, and Ristenpart 2015). Therefore, a wealth of technologies have been proposed to improve the privacy of FL. The most popular ones are homomorphic encryption (HE) and differential privacy (DP). However, HE is extremely computationally expensive, while DP suffers from non-negligible precision loss. Another school of FL methods (Gupta and Raskar 2018; Poirot et al. 2019; Gu et al. 2021) tries to strike a balance between privacy and efficiency by splitting a neural network into private and public parts.

#### DLG in Federated Learning

Federated learning is proposed to protect data privacy by keeping private data localized and sharing only model parameters. However, recent research on Deep Leakage from Gradients (DLG) demonstrates (Zhu and Han 2020) that shared gradients can actually leak private training data. Particularly, DLG can achieve pixel-wise level data recovery without any assistance information. A follow-up work (Zhao, Mopuri, and Bilen 2020) shows that label information can also be restored from gradients of the last layer of a client’s model. (Geiping et al. 2020) further extends DLG to more realistic settings where gradients are averaged over several iterations or several images and shows that users’ privacy is not protected in these settings. GRNN (Ren, Deng, and Xie 2021) improves DLG by recovering fake data and labels through a generative model instead of regressing them directly from random initialization.

#### GAN In Federated Learning

Recent research works that utilize GAN in the FL setting focus mainly on two lines of works: One is leveraging GAN to perform data recovery attacks. (Hitaj, Ateniese, and Perez-Cruz 2017) assumes a malicious client that utilizes the shared model as the discriminator to train the generator in a GAN. Then, the trained generator is used to mimic the training samples of the victim client. (Wang et al. 2019b) assumes the server is malicious. The malicious server first learns representations of the victim client’s data through DLG and then leverages these representations to train the generator, which eventually can generate the victim’s private data. Another is to train high-quality GAN across distributed data sources under privacy, efficiency, or heterogeneity constraints. MD-GAN (Hardy, Le Merrer, and Sericola 2019) proposes a system that the server hosts the generator while each client hosts a discriminator. The discriminators communicate with each other in a peer-to-peer fashion for improving computational efficiency. FedGAN (Rasouli, Sun, and Rajagopal 2020) trains a GAN across Non-IID data sources in a communication efficient way, but it may produce biased data. The follow-up work (Mugunthan et al. 2021) is able to generate bias-free synthetic datasets using FedGAN by fine-tuning the federated GAN with synthesized metadata. Fed-TGAN (Zhao et al. 2021) is proposed to learn complex tabular GAN on non-identical clients.

### Proposed Method

#### Problem Formulation

In this work, we consider typical federated learning (FL) setting that includes a central server and $N$ clients holding private datasets $\{X_1, X_2, ..., X_n\}$. These private datasets share the same feature space but have different sample spaces.

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**Overview of FedCG.**

Each client $i$ has a classification network parameterized by $\theta_{C_i}$ and a generator $G_i : \mathcal{Z} \rightarrow \mathbb{R}^d$ parameterized by $\theta_{G_i}$, and a discriminator $D_i : \mathbb{R}^d \rightarrow \mathcal{I}$ parameterized by $\theta_{D_i}$. Where $\mathcal{Z}$ is the Gaussian distribution and $\mathcal{I}$ indicates a single scalar in the range of $[0, 1]$. The training procedure of the cGAN...
is performed locally aiming to train the generator $G_i$ to approximate the extractor $E_i$ such that $G_i(z, y)$ captures the distribution of features extracted by $E_i(x|y))$.

As illustrated in Figure 1, the workflow of FEDCG goes as follows: in each FL communication round, each client $i$ uploads its $G_i$ and $C_i$ to the server once the local training is completed while keeps the $E_i$ and $D_i$ local to strengthen privacy protection. Then, the server applies knowledge distillation to build a global generator $G_g$ and a global classifier $C_g$. Next, clients download $G_g$ and $C_g$ to replace their corresponding local models and start the next training iteration.

In our FEDCG, clients collaboratively train the global generator and classifier with the help of the central server, while each client leverages the global generator and global classifier to build a personalized local classification network that can perform well on its local test dataset. We will elaborate on this in the following two sections.

**Two-stage Client Update**

The client’s local training procedure involves two stages: classification network update and generative network update. Figure 2 illustrates the two stages while Algorithm 1 describes the detailed procedure.

![Diagram](image)

**Figure 2: Two-stage client update.** (a) Classification network update. (b) Generative network update.

In the classification network update stage (Algo 1 lines 3-9), each client $i$ optimizes its extractor $\theta_{E_i}$ and classifier $\theta_{C_i}$ by minimizing the classification loss:

$$L^{\text{cls}} = \mathbb{E}_{x, y \sim X_i} \Omega(C_i(E_i(x|y; \theta_{E_i}); \theta_{C_i}), y),$$  

(1)

where $\Omega$ is cross-entropy function. In addition, client $i$ also wants to integrate the shared knowledge embedded in the global generator (aggregated in the previous round) into its local extractor. To this end, it freezes the global generator $\theta_{G_g}$ and optimizes its local extractor $\theta_{E_i}$ by minimizing the mean-square-error loss as follows:

$$L^{\text{mse}} = \mathbb{E}_{x, y \sim X_i} |E_i(x|y; \theta_{E_i}) - G_g(z, y; \theta_{G_g})|^2.$$  

(2)

Then, we have the task loss $L^{\text{task}}$, which is the combination of $L^{\text{cls}}$ and $L^{\text{mse}}$, and is formalized by:

$$L^{\text{task}} = L^{\text{cls}} + \gamma L^{\text{mse}},$$  

(3)

where the $\gamma$ is a non-negative hyperparameter that adjusts the balance between the two loss terms. In this work, $\gamma$ gradually increases from 0 to 1 as the global generator becomes more accurate in producing feature representations during training.

In the generative network update stage (Algo 1 lines 10-18), each client $i$ wants to approximate its local generator’s output to the feature representations extracted by its local extractor. To this end, it freezes the parameters $\theta_{E_i}$ of extractor $E_i$ and conducts a cGAN training procedure to train the generator. More specifically, it samples a mini-batch of training data $(x, y)$ and feeds $x$ to the $E_i$ to obtain the “ground-truth” feature representations $\hat{h}$. Then, it randomly generates Gaussian noises $z$ with the same batch size and feeds $(z, y)$ to generator $G_i$ to generate estimated feature representations $\tilde{h}$. Next, it feeds $\hat{h}$ and $\tilde{h}$ to discriminator $D_i$ to calculate discriminator loss $L^{\text{disc}}$ and generator loss $L^{\text{gen}}$ according to (4), and alternatively minimize the two losses to optimize the generator $\theta_{G_i}$ and discriminator $\theta_{D_i}$.

$$L^{\text{disc}} = \mathbb{E}_{x, y \sim X_i} \mathbb{E}_{z \sim \mathcal{Z}} \left[ \log (1 - D_i(E_i(x|y; \theta_{E_i}); \theta_{D_i})) + \log D_i(G_i(z, y; \theta_{G_i}); \theta_{D_i}) \right],$$

(4)

$$L^{\text{gen}} = \mathbb{E}_{x, y \sim X_i} \mathbb{E}_{z \sim \mathcal{Z}} \log (1 - D_i(G_i(z, y; \theta_{G_i}); \theta_{D_i})).$$

Once the local training is completed, each client $i$ sends its generator $\theta_{G_i}$ and classifier $\theta_{C_i}$ to the server for aggregation.

**Server Aggregation**

The server utilizes knowledge distillation (KD) [Lin et al. 2020] to perform the aggregation. One major advantage of FEDCG over existing KD methods in FL is that FEDCG does not require the server to access any public data in order to perform distillation.

**Algorithm 1: Two-stage Client Update**

**Input:** clients’ datasets $\{X_i\}_{i=1}^n$; clients’ extractors, classifiers, generators and discriminators: $\{E_i(\cdot; \theta_{E_i}), C_i(\cdot; \theta_{C_i}), G_i(\cdot; \theta_{G_i}), D_i(\cdot; \theta_{D_i})\}_{i=1}^n$; global generator $\{G_g(\cdot; \theta_{G_g})$ and global classifier $C_g(\cdot; \theta_{C_g})$; learning rate $\eta_1, \eta_2$; local training epoch $T$

1. Clients receive $\theta_{G_g}$ and $\theta_{C_g}$ from the server.
2. for each client $i = 1, \ldots, N$ in parallel do
3. $\theta_{C_i} \leftarrow \theta_{C_g};$
4. for $t \in \{1, \ldots, T\}$ do
5. for all $x, y \in X_i$ do
6. sample $z$ from $N(0, 1)$
7. $\theta_{E_i, C_i} \leftarrow \theta_{E_i, C_i} - \eta_1 \nabla_{\theta_{E_i, C_i}} L^{\text{task}}(x, y, z)$
8. end for
9. $\theta_{C_i} \leftarrow \theta_{C_g};$
10. for $t \in \{1, \ldots, T\}$ do
11. for all $x, y \in X_i$ do
12. sample $z$ from $N(0, 1)$
13. $\theta_{D_i} \leftarrow \theta_{D_i} - \eta_2 \nabla_{\theta_{D_i}} L^{\text{disc}}(x, y, z)$
14. $\theta_{G_i} \leftarrow \theta_{G_i} - \eta_2 \nabla_{\theta_{G_i}} L^{\text{gen}}(y, z)$
15. end for
16. end for
17. end for
18. end for each
19. Client $i$ sends $\theta_{G_i}$ and $\theta_{C_i}$ to server.
Figure 3: Server aggregation. The server generates Gaussian noise $z$ and class label $y$ as the inputs of clients’ $\{G_i, \theta_{G_i}\}_{i=1}^n$ and global $G_g$, and it optimizes $\theta_{C_g}$ and $\theta_{C_g}^g$ by minimizing the KL divergence between the distribution ensembled from $\{C_i\}_{i=1}^n$ and the one outputted from $C_g$.

Figure 3 illustrates the server aggregation while Algorithm 2 describes the detailed procedure. When the server receives generators $\{G_i\}_{i=1}^n$ and classifiers $\{C_i\}_{i=1}^n$ uploaded by clients, it initializes parameters of the global generator $\theta_{G_g}$ and global classifier $\theta_{C_g}$ by weighted averaging $\{\theta_{G_i}\}_{i=1}^n$ and $\{\theta_{C_i}\}_{i=1}^n$. For distillation (Algo 2 line 3-6), the server first generates a mini-batch of training data $(z, y)$, where labels $y$ are sampled from uniform distribution $U(0, c)$ and noises $z$ are sampled from Gaussian distribution $N(0, 1)$. Then, according to (5) it feeds $(z, y)$ to all generators and calculates two class probability distributions $P_c(y, z)$ and $P_s(y, z)$, the former is ensembled from clients’ classifiers while the latter is from the global classifier. Next, the server optimizes the global classifier $\theta_{C_g}$ and generator $\theta_{G_g}$ by minimizing the KL divergence between the two distributions, according to (6).

$$P_c(y, z) = \sigma \left( \frac{1}{n} \sum_{i=1}^{n} |X_i| C_i(G_i(y, z; \theta_{G_i}); \theta_{C_i}) \right),$$

$$P_s(y, z) = \sigma \left( C_g(G_g(y, z; \theta_{G_g}); \theta_{C_g}) \right),$$

$$\mathcal{L}_{KL} = \mathbb{E}_{y \sim U} \mathbb{E}_{z \sim N} \text{KL}(P_c(y, z), P_s(y, z)),$$

where $| \cdot |$ denotes the size of data set, KL indicates Kullback–Leibler divergence and $\sigma$ is the softmax function. Once the server aggregation is completed, the server dispatches the global generator $\theta_{G_g}$ and global classifier $\theta_{C_g}$ to all clients.

Privacy Analysis

In the literature, there are a variety of data recovery methods, among which DLG (Zhu and Han 2020) is able to achieve exact pixel-wise level data revealing. In this work, we consider the server malicious, and it utilizes DLG to recover original data from a victim client. We evaluate the privacy-preserving capability of FedCG by comparing the quality of image data recovered in FedCG, FedAVG and FedSplit.

Algorithm 2: Server Aggregation

**Input:** size of data set $|X|_{i=1}^n$; clients’ generators and classifiers $\{G_i; \theta_{G_i}, C_i; \theta_{C_i}\}_{i=1}^n$; learning rate $\eta$; training iteration $T$, sample batch size $B$.

1. Server receives $\{\theta_{G_i}\}_{i=1}^n$ and $\{\theta_{C_i}\}_{i=1}^n$ from all clients.
2. $\{\theta_{G_g}, \theta_{C_g}\} = \sum_{i=1}^n \frac{|X_i|}{|X|} \{\theta_{G_i}, \theta_{C_i}\}$
3. for $t \in \{1, ..., T\}$ do
4. Sample $(z, y)$, where $z \sim N(0, 1)$ and $y \sim U(0, c)$.
5. $\{\theta_{G_g}, \theta_{C_g}\} \leftarrow \{\theta_{G_g}, \theta_{C_g}\} - \eta \nabla_{\theta_{G_g}, \theta_{C_g}} \mathcal{L}_{KL}(y, z)$
6. end for
7. Server sends $\theta_{G_g}$ and $\theta_{C_g}$ to all clients.

FedAVG is the representative of FL methods that share the full classification network while FedSplit represents FL methods that share only the public classifier. (7) shows the DLG loss $\mathcal{L}^{dlg}$ for the malicious server recovering the real data of victim client $i$.

$$\mathcal{L}^{dlg} = ||\nabla_{\theta} \mathcal{L}^{cls}(x_i) - \nabla_{\theta} \mathcal{L}^{cls}(\bar{x})||^2,$$  

where $x_i$ is the real data of victim client $i$ while $\bar{x}$ is the variable to be trained to approximate $x_i$ by minimizing DLG loss $\mathcal{L}^{dlg}$, which is the distance between $\nabla_{\theta} \mathcal{L}^{cls}(x_i)$ and $\nabla_{\theta} \mathcal{L}^{cls}(\bar{x})$. The Former is observed gradients of $\mathcal{L}^{cls}$ (see [1]) w.r.t. model parameters $\theta$ for the real data $x_i$, while the latter is estimated gradients for $\bar{x}$. For FedAVG, the server knows the full network of client $i$, thus $\theta := \theta_{G_i}, \theta_{C_i}$. While for FedSplit, the server only knows the classifier, and thus $\theta := \theta_{C_i}$. Although subsequent research works on DLG generally employs cosine similarity as the loss function, the image reconstruction quality of MSE is more satisfactory for LeNet networks (Geiping et al. 2020).

Similar to FedSplit, FedCG hides private extractors from the server for protecting privacy. Nonetheless, FedCG shares clients’ generators with the server for aggregating shared knowledge. Thus, FedCG has auxiliary information on extractors’ output distribution estimated by generators. We define the DLG loss for FedCG as follows:

$$\mathcal{L}^{dlg}_{\text{FedCG}} = \mathcal{L}_{KL}(\bar{E}(\tilde{x}, c) - \mu^c)^2 + \alpha \sum_c (||\text{mean}(\tilde{E}(\tilde{x}, c)) - \mu^c||^2 + ||\text{var}(\tilde{E}(\tilde{x}, c)) - \sigma^c||^2),$$

where $\tilde{E}$ is the estimated extractor whose parameters are not known by the server, and thus it is randomly initialized. The second optimization term of $\mathcal{L}^{dlg}_{\text{FedCG}}$ aligns the statistical information of features between the estimated extractor $\tilde{E}$ of the server and the shared generator of victim client $G_i$. $\mu^c$ and $\sigma^c$ are the mean and standard deviation on each channel $c$ of features generated by $G_i$. We will quantitatively measure privacy-preserving capabilities of FedAVG, FedSplit and FedCG according to (7) and (8) in the next section.

Experiments

In this section, we compare the performance of our proposed FedCG against FL baselines and evaluate the privacy-preserving capability of FedCG.
Experiment Settings

Model Backbone
LeNet5 (LeCun et al. 2015) is used as the backbone network for image classification tasks in FL system. The first 2 convolutional layers of LeNet are regarded as private extractor, while the latter 3 fully connected layers are regarded as public classifier. The generative adversarial network architecture is a modified version of DCGAN (Radford, Metz, and Chintala 2015), in which the size and stride of convolution kernels are adjusted to match the output dimensions of the extractor and generator.

Datasets
We evaluate model performance of clients on 5 image datasets: FMNIST (Xiao, Rasul, and Vollgraf 2017), CIFAR10 (Krizhevsky, Hinton et al. 2009), Digit5 (Peng et al. 2019), Office-Caltech10 (Gong et al. 2012), and DomainNet (Peng et al. 2019). Figure 4 shows some samples of the 5 datasets. FMNIST and CIFAR10 simulate the independent identical distributed (IID) setting. Digit5, Office-Caltech10, and DomainNet comprise data from multiple domains, and thus they naturally form the Non-IID setting. DomainNet has images across 345 categories, from which we pick the top 10 categories with the most samples for experiments. To keep the image resolution consistent across all experiments, we resize all images in all datasets to 32 x 32.

Baselines
We chose 5 FL baselines from two categories of FL methods. The first category includes FEDAVG (McMahan et al. 2017), FEDPROX (Li et al. 2020) and FEDDF (Lin et al. 2020), in which clients share their full networks with the server. The second one includes FEDSPLIT (Gu et al. 2021) and FEDGEN (Zhu, Hong, and Zhou 2021), in which clients share only their public classifiers. More specifically, FEDAVG is the most widely used FL method. FEDPROX introduces a proximal term in the local objective to regularize the local model training. FEDDF utilizes knowledge distillation to aggregate local models on the server leveraging unlabeled public data. FEDSPLIT shares only the public classifier of the local classification network to protect privacy. FEDGEN employs knowledge distillation to train a global generator, which in turn helps clients train local models. In this work, we implement FEDGEN based on FEDSPLIT, in which only the public classifiers of local networks are shared. We also consider the local classification network trained solely based on local data as a baseline and denote it as LOCAL.

Configurations
We perform 100 global communication rounds and 20 local epochs, and each local epoch adopts a mini-batch of 16. All experiments use the Adam optimizer with a learning rate of 3e-4 and a weight decay of 1e-4. For FEDPROX, we tried proximal term factor in the range of {0.001, 0.01, 0.1, 1} and picked the best one. FEDGEN, FEDDF and FEDCG perform 2000 iterations in the server for model fusion with a batch size of 16.

We consider each domain as a client for Digit5, Office-Caltech10 and DomainNet except that MNIST and Painting are held out as distillation data for FEDDF. We consider 4- and 8-client scenarios for CIFAR10 and consider a 4-client scenario for FMNIST. For these two datasets, 32000 training samples are held out as distillation data for FEDDF. For FMNIST, CIFAR10, and Digit5, we randomly sample 2000 images for each client as the local training set. For Office-Caltech10 and DomainNet, 50% of the original data of each domain is used as the local training set. We use validation and test datasets on clients to report the best test accuracy over 5 different random seeds. We also leverage diversity loss from (Mao et al. 2019) to improve the stability of the generator and adopt early stopping to avoid overfitting.

Experiment Results

Performance Evaluation
We evaluate FEDCG’s performance by first comparing its averaged clients’ accuracy with those of 6 baselines in 6 scenarios. Table 1 reports the results. It shows that FEDCG achieves the best accuracy in 4 out of 6 scenarios, demonstrating its competitive performance. More specifically, FEDCG achieves the best accuracy in all 3 non-IID scenarios. In particular, it outperforms the next-best-performing FEDPROX by 4.35% on Office. In IID scenarios, FEDAVG, FEDPROX and FEDDF have an edge in that they aggregate full local networks trained directly from original local data while there is no negative transfer effect caused by data heterogeneity (Wang et al. 2019). As a result, they perform better than FEDCG overall, on CIFAR10 particularly. However, they are vulnerable to DLG attacks, as we will discuss in the next section.

Figure 4: We demonstrate the competitive performance of FEDCG on 5 datasets: Digit5 is a collection of 5 benchmarks for digit recognition, namely MNIST, Synthetic Digits, MNIST-M, SVHN, and USPS. Office-Caltech10 contains 10 Office Supplies from 4 domains: Amazon, DSLR, Webcam, and Caltech. DomainNet comprises of 6 domains: Painting, Clipart, Infograph, Quickdraw, Real and Sketch. FMNIST and CIFAR10 are widely used image datasets.
| Method      | FMNIST (4) | CIFAR10 (4) | CIFAR10 (8) | Digit5 (4) | Office (4) | Domainnet (5) |
|------------|------------|-------------|-------------|------------|------------|----------------|
| LOCAL      | 79.66±0.55 | 40.90±0.92  | 40.65±0.84  | 83.09±0.42 | 60.61±0.78 | 48.33±0.27     |
| FedAvg     | 82.97±0.67 | 47.23±0.25  | 49.61±0.65  | 83.73±0.55 | 62.76±0.76 | 49.11±0.47     |
| FedProx    | 83.61±0.64 | 49.19±0.89  | 50.76±0.26  | 83.92±0.85 | 62.99±1.07 | 49.32±0.53     |
| FedDF      | 83.20±0.57 | 47.88±0.62  | 50.43±0.49  | 84.48±0.28 | *           | 49.21±0.42     |
| FedSplit   | 81.95±0.43 | 44.67±0.64  | 46.00±0.78  | 82.96±0.42 | 62.71±0.88 | 48.61±0.49     |
| FedGen     | 81.66±0.46 | 44.98±0.49  | 45.57±0.59  | 82.55±0.65 | 62.70±1.05 | 47.86±0.64     |
| FedCG (ours)| 83.81±0.28 | 47.52±0.68  | 49.15±0.48  | 84.82±0.40 | 67.34±0.83 | 49.90±0.18     |

Table 1: Comparison of FedCG with baselines in terms of top-1 test accuracy. Results reported in **bold** are the best performance. * indicates no results is measured. The number in the parentheses indicates the number of clients.

Because the objective of FedCG is to improve the performance of each client’s personalized local network validating on local test data, we further compare the accuracy gains between FedCG and 5 FL baselines over the LOCAL. Figure 5 shows the results. In IID scenarios, all FL methods outperform LOCAL on all clients by large margins, as shown in Figures 5(a) and 5(b). Particularly, FedCG performs best on FMNIST (4) while FedProx performs best on CIFAR10 (8). In non-IID scenarios, while no FL method can beat LOCAL on every client across all 3 non-IID datasets, FedCG achieves the best result such that it outperforms LOCAL on 12 out of 13 clients, as shown in Figure 5(e).

5(d) and 5(e) FedAvg, FedProx and FedDF are not excel in non-IID scenarios as they are in IID scenarios because the average-based global model may be far from client’s local optima [Li et al. 2021]. Besides, the distillation dataset leveraged by FedDF is from a different domain than those of clients, which may have negative impacts on the performance of aggregated global model.

Privacy Evaluation. We calculate Peak Signal-to-Noise Ratio (PSNR) to measure the similarity between original images and images recovered from DLG. PSNR is an objective standard for image evaluation, and it is defined as
The two images. We also apply differential privacy (DP) to higher the PSNR score, the higher the similarity between RGB image fluctuation over MSE between two images. The logarithm of the ratio of the squared maximum value of the ground-truth image and the recovered one using DLG. Compared to FEDAVG, FEDSPLIT and FEDCG could achieve competitive accuracies for all three datasets. However, native FEDAVG has much higher risk of leaking data information (high PSNR value), which can also be observed in Figure 6 where the reconstructed images from FEDAVG looks very similar to the originals. Although the data privacy could be better protected by introducing DP to FEDAVG, there is a significant drop (over 20%) in the model performance. On the other hand, FEDSPLIT and FEDCG effectively protect the data privacy (low PSNR value). This is also evidenced by the reconstructed images in Figure 6 where no clear patterns of the reconstructed images could be observed. While achieving similar privacy protection level, FEDCG demonstrates better model accuracy than FEDSPLIT for all three datasets by at least 2%.

Table 2 compares FEDAVG, FEDSPLIT and FEDCG in terms of model performance and privacy-preserving capability. The numerical number in the parentheses indicates the noise level $\sigma^2$.

| Dataset  | Metric          | FEDAVG | FEDAVG (0.001) | FEDAVG (0.1) | FEDSPLIT | FEDCG |
|----------|-----------------|--------|----------------|--------------|----------|-------|
| CIFAR10  | Accuracy(%)     | 47.23  | 37.5           | 35.4         | 44.67    | 47.52 |
|          | PSNR(dB)        | 24.14  | 20.30          | 6.81         | 6.23     | 8.99  |
| DIGIT    | Accuracy(%)     | 83.73  | 68.6           | 64.3         | 82.96    | 84.82 |
|          | PSNR(dB)        | 26.82  | 20.20          | 6.32         | 5.47     | 7.85  |
| OFFICE   | Accuracy(%)     | 62.76  | 40.6           | 32.7         | 62.71    | 67.34 |
|          | PSNR(dB)        | 23.14  | 18.78          | 6.38         | 5.61     | 7.57  |

Figure 6: Reconstructed images using DLG attack in FEDAVG, FEDSPLIT and FEDCG. From the first row to the last row, images are taken from CIFAR10, DIGIT5 and OFFICE respectively. PSNR is reported under each restored images.

The logarithm of the ratio of the squared maximum value of RGB image fluctuation over MSE between two images. The higher the PSNR score, the higher the similarity between the two images. We also apply differential privacy (DP) to FEDAVG by adding Gaussian noises to shared gradients. We experiment with two noise levels, $\sigma^2 = 0.1$ and $\sigma^2 = 0.001$.

Table 2 compares FEDCG with FEDSPLIT and FEDAVG in terms of model performance measured by accuracy and privacy-preserving capability measured by PSNR between the ground-truth image and the recovered one using DLG. Compared to FEDAVG, FEDSPLIT and FEDCG could achieve competitive accuracies for all three datasets. However, native FEDAVG has much higher risk of leaking data information (high PSNR value), which can also be observed in Figure 6 where the reconstructed images from FEDAVG looks very similar to the originals. Although the data privacy could be better protected by introducing DP to FEDAVG, there is a significant drop (over 20%) in the model performance. On the other hand, FEDSPLIT and FEDCG effectively protect the data privacy (low PSNR value). This is also evidenced by the reconstructed images in Figure 6 where no clear patterns of the reconstructed images could be observed. While achieving similar privacy protection level, FEDCG demonstrates better model accuracy than FEDSPLIT for all three datasets by at least 2%.

### Conclusion

We propose FEDCG, a novel federated learning method that leverages conditional GAN to protect data privacy while maintaining competitive model performance. FEDCG decomposes each client’s local network into a private extractor and a public classifier, and keeps the extractor local to protect privacy. It shares clients’ generators with the server to aggregate shared knowledge aiming to enhance the performance of clients’ local networks. Experiments show that FEDCG has a high-level privacy-preserving capability and can achieve competitive model performance. Future works include extending FEDCG to deeper neural networks for investigating the effectiveness of FEDCG further and providing theoretical analysis on the privacy guarantee of FEDCG.

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