Federated Adversarial Training with Transformers

Ahmed Aldahdooh 1  Wassim Hamidouche 1  Olivier Déforges 1

Abstract
Federated learning (FL) has emerged to enable global model training over distributed clients’ data while preserving its privacy. However, the global trained model is vulnerable to the evasion attacks especially, the adversarial examples (AEs), carefully crafted samples to yield false classification. Adversarial training (AT) is found to be the most promising approach against evasion attacks and it is widely studied for convolutional neural network (CNN). Recently, vision transformers have been found to be effective in many computer vision tasks. To the best of the authors’ knowledge, there is no work that studied the feasibility of AT in a FL process for vision transformers. This paper investigates such feasibility with different federated model aggregation methods and different vision transformer models with different tokenization and classification head techniques. In order to improve the robust accuracy of the models with the not independent and identically distributed (Non-IID), we propose an extension to FedAvg aggregation method, called FedWAvg. By measuring the similarities between the last layer of the global model and the last layer of the client updates, FedWAvg calculates the weights to aggregate the local models updates. The experiments show that FedWAvg improves the robust accuracy when compared with other state-of-the-art aggregation methods.

1. Introduction
FL (McMahan et al., 2017) is an emerging learning paradigm that aims to train a global model that aggregates its parameters, over many communication rounds, from models that are trained on private data distributed over multiple clients while preserving data privacy. In each communication round, clients are required to only send local model parameters, but not the data, to the server to build the global model by aggregating the local models. Since FL minimizes the risk of sensitive and private data leakage, industry found FL is useful in healthcare (Rieke et al., 2020; Xu et al., 2021), natural language processing (Liu et al., 2021), edge devices and internet of things (IoT) (Lim et al., 2020; Imteaj et al., 2020), wireless communications (Qin et al., 2021; Liu et al., 2020), smart cities (Jiang et al., 2020; Zheng et al., 2021), and for other applications (Yang et al., 2019).

FL, like any emerging technique, has major problems to be tackled before being ready for deployment in real-world applications. Clients’ models drift1 and models convergence are the main challenges of FL on Non-IID data. To resolve these challenges, two approaches are identified. The first one is to optimize the FL aggregation methods such as FedAvg (McMahan et al., 2017), FedProx (Li et al., 2019), FedGate (Haddadpour et al., 2021), q-FFL (Li et al., 2020), Qsparse (Busu et al., 2020), and SCAFFOLD (Karimireddy et al., 2020). For instance, SCAFFOLD (Karimireddy et al., 2020) was shown to have better convergence than FedAvg, and FedProx. The second approach is to carefully choose the model architecture (Shah et al., 2021; Qu et al., 2021). For instance, in (Shah et al., 2021), VGG-9 model (Simonyan & Zisserman, 2015) was found to yield higher performance than Network-in-Network model (Lin et al., 2014) on CIFAR-10 dataset (Krizhevsky & Hinton, 2009). Moreover, in (Qu et al., 2021), vision transformer (ViT) (Dosovitskiy et al., 2021) was shown to be significantly effective than ResNet50 (He et al., 2016) model on Non-IID CIFAR-10 dataset (Krizhevsky & Hinton, 2009).

On the other hand, FL is vulnerable to attacks that may put the model and the data in risk (Kairouz et al., 2021; Jere et al., 2020; Lyu et al., 2020). Attacks happen either during the training phase and it is categorized into poisoning attacks (Tolpegin et al., 2020; Sun et al., 2020) and inference attacks (Mothukuri et al., 2021; Nasr et al., 2020) or during inference/testing time and it is called evasion attacks (Yuan et al., 2019; Akhtar et al., 2021). To defend against evasion attacks, many defense approaches have been proposed in the literature (Akhtar et al., 2021; Aldahdooh et al., 2022). Adversarial training is one of the most effective defense strategies (Bai et al., 2021; Shaham et al., 2018; Madry et al., 2018). It retrain the model by including the AEs in

1The phenomena of model drift is identified when models are learning different representations of a given data.
the training process. In each training iteration, the AEs are generated using the current state of the model. In practice, any algorithm can be used to generate the AEs, such as fast gradient sign attack (FGSM) (Goodfellow et al., 2015), and projected gradient descent (PGD) (Madry et al., 2018).

To the best of authors’ knowledge, there is no paper that investigated the vision transformer models in the federated adversarial training (FAT) settings. Hence, in this paper, we study the feasibility of using vision transformer models in FAT settings and under the IID and the Non-IID data distribution settings (Zhu et al., 2021). We analysed the model convergence and drift in natural and adversarial training on Non-IID data and observed that model convergence, model accuracy, and model robust accuracy are affected by both the model architecture and the aggregation method. In order to enhance the model’s robust accuracy, we introduce an extension to the FedAvg (McMahan et al., 2017) aggregation algorithm in which a weighted average is applied by the global server. The new aggregation method is called FedWAvg. This latter generates the weights by measuring the similarities between the last layer of the global model and the last layer of the client updates. Moreover, we investigate different vision transformer architectures to identify the source of the robustness in the FAT setting. We investigate models with different tokenization techniques such as tokens-to-token ViT (T2T-ViT) (Yuan et al., 2021), and transformer-in-transformer (TNT) (Han et al., 2021) and we investigate different head classification techniques such as second-order cross-covariance pooling of visual tokens (Xie et al., 2021). The experiments using heterogeneous data distributions show that FedWAvg improves the robust accuracy when compared with other state-of-the-art aggregation methods. The main contributions of the paper are:

- Introduce an aggregation method for FAT process, called FedWAvg, to improve the robust accuracy of the global model with Non-IID data distribution. FedWAvg uses the similarities between the last layer of the global model and the last layer of the client updates to calculate the weights for the aggregation.
- Show that the tested state-of-the-art aggregation methods, except the conventional FedAvg algorithm and the proposed FedWAvg, are not convenient for adversarial training with transformers in FL since it decreases the robust accuracy performance of the model.
- Study the relationship between using different tokenization and classification head techniques of the transformers and the robust accuracy of the global model.

2. Related Works

Our main focus is the federated adversarial training, hence, the related work of vision transformers is discussed in App. A.

2.1. Aggregation methods in FL

McMahan et al. (McMahan et al., 2017) were the first to introduce the concept of federated averaging aggregation (FedAvg). It provides communication-efficient performance since it allows the clients to perform multiple local steps before sending their updates. On the other hand, FedAvg performance on Non-IID is questionable since it causes clients to drift from each other which yields slow global model convergence. To address this issue, other algorithms were introduced (Li et al., 2019; Wang et al., 2020; Karimireddy et al., 2020; Haddadpour et al., 2021; Basu et al., 2020; Mohri et al., 2019; Li et al., 2020). In (Li et al., 2019), FedProx aggregation brings an additional $L_2$-regularization term in the client loss function to maintain the difference between the client model and the global model. To control the regularization, a control parameter $\mu$ is set. The regularization term almost has no effect if $\mu$ is too small, moreover, if $\mu$ is large, the client update will be too limited to the previous round and will cause slow convergence. Hence, careful tuning is required for the regularization term. FedNova (Wang et al., 2020) came to solve the issue when the number of local steps of the clients are different. Firstly, it normalizes and scales the client updates according to their number of local steps before updating the global model. Stochastic controlled averaging (SCAFFOLD) (Karimireddy et al., 2020) algorithm uses variance reduction technique (Schmidt et al., 2017; Johnson & Zhang, 2013; Defazio et al., 2014) to correct for the client drift. In SCAFFOLD, control terms are identified for the server and clients to estimate the update direction of the global model and of each client. The difference between these update directions is used to estimate the client drift which will be added to the client updates. FedGate (Haddadpour et al., 2021) adopts the idea of local gradient tracking that ensures that each client uses an estimate of the global gradient direction to update its model. Compared to SCAFFOLD, FedGate is much simpler and no extra control parameters are required. In (Basu et al., 2020), Qsparse algorithm is introduced which updates the client updates by combining quantization, aggressive sparsification, and local computation along with error compensation, by keeping track of the difference between the true and compressed gradients. Agnostic federated learning (AFL) (Mohri et al., 2019) and q-FFL (Li et al., 2020) adopted a fair federated learning (FFL) concept. The former uses a minimax optimization scheme to optimize for the performance of the single worst device, while the latter employs fair distribution of the model performance across clients. All the aforementioned FL algorithms are server-based FL paradigms that produce a global model. In the literature, another paradigm exists that can be seen as an intermediate paradigm between the server-based FL and the local model training paradigm. This paradigm is called personalized FL that produces an additional personalized model, beside
the global model, to balance between the local task-specific and the task-general models. In our investigation, we focus on server-based paradigm, and we refer to (Kulkarni et al., 2020; Tan et al., 2021) for more information about personalized FL.

Most of the aforementioned server-based algorithms are not investigated for vision transformer models under the AT settings.

2.2. Federated adversarial training (FAT)

AT is a way to reduce the threat of evasion attacks, i.e. attacks during the inference time. AT retrains the model by including the AEs in the training process and aims at solving min-max optimization problem Eq. (1) (Shaham et al., 2018; Madry et al., 2018).

\[
\min_{\theta} \rho(\theta), \rho(\theta) = \mathbb{E}_{(x,y) \sim \mathcal{D}}[\max_{\epsilon} \mathcal{L}(\theta, x + \epsilon, y)]
\]

where,
- \(\mathcal{D}\) and \((x, y)\): data distribution \(\mathcal{D}\) over pairs of examples \(x \in \mathbb{R}^d\) and its labels \(y \in \text{classes}\).
- \(\theta \in \mathbb{R}^p\): is the set of model parameters of the neural network of the standard classification task.
- \(\mathcal{L}(\theta, x, y)\): is the loss function for the neural network.
- \(\epsilon\): is the allowed \(l_p\)-ball perturbation around \(x\).
- \(\mathbb{E}_{(x,y) \sim \mathcal{D}}[\mathcal{L}(\theta, x, y)]\): is the risk of the neural network model, i.e. the risk of the prediction function.

The inner maximization problem finds the worst-case AEs for the neural network model, while the outer minimization problem finds the model parameters that minimize the adversarial loss given by the inner maximization problem.

The AT is well investigated in the literature for the centralized training and for CNNs (Bai et al., 2021). Under FL settings, there are very limited studies that investigate AT. In (Shah et al., 2021), Shah et al. tried to mitigate the performance impact of AT in FL setting. Compared to centralized learning, it is observed that there is a drop in both natural and adversarial accuracies when AT is used in the FL setting.

Hence, Shah et al. (Shah et al., 2021) proposed an adaptive algorithm to calculate the number of the local epochs \(E\) to mitigate the model drift. This algorithm is not applicable if we need to perform only one local epoch in the training. On the other hand, the work in (Zizzo et al., 2020) evaluated the vulnerability of Byzantine resilient defenses in the FAT setting. They mainly showed that Byzantine resilient defenses, such as Krum (Blanchard et al., 2017), cause significant drop in adversarial performance. The work in (Chen et al., 2021a) used randomized smoothing techniques into FAT to build certifiable-robust FAT. In (Hong et al., 2021), a novel learning setting that propagates adversarial robustness from high resource clients, i.e. clients can afford AT, to those low-resource clients. It transfers robustness through carefully designed batch-normalization statistics. To achieve that, the server requires to access the client parameters which violates the rules of secure aggregation. All the aforementioned works investigated the FAT setting using CNNs and vision transformers models are never investigated in FAT setting.

3. Methodology

3.1. Weighted Averaging Aggregation for Adversarial Training

3.1.1. Preliminaries

Let \(D = \{(x, y)\}\) represent the global dataset of \(n\) samples and assume there are \(K\) clients indexed by \(k\), where \(k = \{1, 2, \ldots, K\}\). The local dataset of client \(k\) is denoted as \(D_k = \{(x_k, y_k)\}\) with \(n_k\) samples. We use \(\theta_l\) and \(\theta_l^k\) to denote the global model and the local model parameters of client \(k\) in communication round \(t\) respectively, where \(t = 1, 2, \ldots, T\) and \(T\) is the total number of communication rounds. Therefore, \(\theta_t\) is the output of the FL process at communication round \(t\). In FedAvg (McMahan et al., 2017), the output of the FL process is computed as follows:

\[
\theta_t = \sum_{k=1}^{K} \frac{w_k}{n} \theta_l^k, \quad \text{where}, w_k = \frac{n_k}{n}
\]

If all clients have the same number of samples, it means that the averaging weights are evenly divided by the clients regardless of whether the data is independent and identically distributed (IID) or Non-IID.

FL and AT strategies result in the following challenges. 1) **Accuracy drop:** In natural FL process, it was shown (Shah et al., 2021; Zizzo et al., 2020) that the model accuracy slightly decreases with IID and remarkably decreases with Non-IID. FAT increases the model’s adversarial accuracy in the price of model accuracy. 2) **Overfitting:** It was shown in (Kurakin et al., 2017) that AT suffers from label leaking which causes adversarially trained models to perform better on AEs than on clean examples and unseen adversarial. 3) When we use vision transformer models under natural and adversarial FL settings, we believe that the state-of-the-art aggregation algorithms that reduce the client drift with the Non-IID data split will not yield better performance than FedAvg. It was found in (Qu et al., 2021) that ViTs have significantly better convergence than CNNs with the Non-IID which significantly reduces the model drift problem that state-of-the-art aggregation methods try to solve.

3.1.2. The Weighted Averaging Aggregation

In order to enhance the robust accuracy of the vision transformer models under FAT settings, specially with Non-IID data distribution, we use the similarities between the last layer of the global model and the clients to generate the
weights for the aggregation method. Denote \( g_k \) and \( l_k \) as the last layer parameters of the global server and of client \( k \) respectively. First, in each communication round \( t \), calculate the cosine similarity \( c_k \) between the \( g \) and \( l_k \). Then, calculate the weights according to the similarities using the softmax function with a scale factor \( q \):

\[
c_k = \frac{g \cdot l_k}{\|g\|_2 \|l_k\|_2}, \quad w_k = \frac{\exp(q c_k)}{\sum_{j=1}^K \exp(q c_j)}
\]

We calculate the similarities and the weights according to Eq. (3) in natural and adversarial FL using FedAvg and FedProx as illustrated in Fig. 1. We have noted the following observations:

**With IID data partitioning.** The weights of the natural and adversarial FL are close to the weights that are used in FedAvg and FedProx aggregation methods which is \( \frac{1}{K} = 0.2 \).

**With Non-IID data partitioning.** In the natural training, depending on the model architecture, the weights can be close to \( \frac{1}{K} \) as with T2T-ViT model as shown in Fig. 9 in App. B, while the weights are not close to \( \frac{1}{K} \) in the first \( t \) rounds with the TNT model. On the other hand, in the FAT settings, the weights are far from \( \frac{1}{K} \) in the first \( t \) rounds. The difference in the weights are higher in the highly heterogeneous data partitions.

We, then, investigated the impact of using the weights in Eq. (3) to aggregate the global server model in enhancing the robust accuracy of the FAT process. Applying Eq. (3) in the FAT setting will push the global model in the direction of a model that has high similarity to the global model. Algorithm 1 shows the whole process of the FAT with FedWAvg aggregation method.

First, the server initializes the global model parameters \( \theta_0 \) and sends it to \( m \) clients randomly selected from the \( K \) clients. Then, each client, in parallel, perform AT process in which \( n_{adv} \) samples from batch \( b \) are transformed to its adversarial version using the PGD attack and then each client updates its model parameters according to the gradient of the computed loss and sends them back to the server. Finally, the server performs the aggregation with the weights that are generated using the proposed FedWAvg procedure as shown in Algorithm 1. The server repeats the aforementioned steps for \( T \) communication rounds.

Using the cosine similarity in the proposed FedWAvg aggregation is inspired by the works in (Okuno et al., 2018; Wan & Chen, 2021; Mao et al., 2021a; Dong et al., 2021). Theorem 5.1 in (Okuno et al., 2018) implies that the dot product of two neural networks can approximate any similarity measure. A special case of the latter theorem has emerged in (Wan & Chen, 2021), in which the dot product is used to generate the weights for the attention-based attack-adaptive aggregation model to defend against model attacks. In (Mao et al., 2021a), Mao et al. used the contrastive loss as a supervision objective (Chen et al., 2020), which is a self-supervised representation learning approach, to reverse the attack process by finding an additive perturbation to repair the AE. Lin and Song won the 4th in the “Adversarial Attacks on ML Defense Models” Competition (Dong et al., 2021). They proposed the random real target (RRT) attack method to improve the efficiency of AE by applying a new sampling strategy that uses the cosine similarity for the initial perturbed points of the AE.

### 3.2. Vision Transformer Models

Considering the model architecture is one of the approaches to optimise the FL process. This paper is the first paper, to the best of the authors’ knowledge, that investigates the
4. Experiments

4.1. Experiment Setup

We developed our code on the top of the FedTorch (Hadadpour et al., 2021) library. It is an open-source Python package for distributed and federated training of machine learning models.

**Dataset.** In our experiments, we use CIFAR-10 (Krizhevsky & Hinton, 2009) dataset to investigate different visual transformer models under the FAT environment. CIFAR-10 is a collection of images that is usually used in computer vision tasks. It is 32 × 32 RGB images of ten classes: airplanes, birds, cats, deer, dogs, frogs, horses, ships, and trucks. It contains 60000 images, 50000 for training and 10000 for testing. The training images are processed by resizing to 224 × 224, random cropping with padding equals to 28, and random horizontal flipping. The 10000-image test dataset is used as a global test dataset.

**Models.** As mentioned earlier in Sec. 2, we investigate the vision transformer models with three different embedding methods and three different classification head methods. Fig. 4 in App. A.2 illustrates the models’ architectures. For ViT embedding, we use ViT-S-16 and ViT-B-16 models. For T2T-ViT embedding, we use T2T-ViT-14 and finally, for TNT embedding, we use TNT-S model. It was found in (Aldahdooh et al., 2021) that some small vision transformer architectures, such as ViT-S and and TNT-S, have gained more robustness than larger architectures. For these four models, three classification head methods are used; the first uses the class [CLS] token only, the second uses the visual [VIS] tokens only, and the third uses both the [CLS] and the [VIS] tokens. In total we tested 12 vision transformer models.

**Federated adversarial training (FAT) setting.** Following the setup of (Qu et al., 2021), we assume that we have a server and $K = 5$ available clients and each client will use the Madry’s AT procedure with adversarial ratio of 0.5, i.e. for each batch in each training epoch 50% of the clean samples are replaced with adversarial samples. For the PGD attack, we set the perturbation budget to $\epsilon = 8/255$, the step size to $\alpha = 2/255$, and the steps to $s = 7$. We investigate three data partitioning methods. The first one is the IID setting in which the training data is evenly distributed over the clients. The second one is the Non-IID(4) in which each client is assigned with data from 4 classes only. While the third partitioning method is Non-IID(2) in which each client is assigned with data from 2 classes only.

**Algorithm 1 FedWAvg Algorithm.** Weighted Averaging Aggregation for Adversarial Training

**Input:** The $K$ clients are indexed by $k$, $C$ is the client fraction, the $T$ communication rounds are indexed by $t$, $B$ is the local minibatch size, $E$ is the number of local epochs, and $\eta$ is the learning rate, PGD Attack $A_{s,\epsilon,\alpha}$: where $s, \epsilon, \alpha$ are number of PGD steps, perturbation ball size, step size, $r$ is the adversarial ratio, $q$ is the scale factor.

**Output:** The global model $\theta$.

**On Server:**

1: Initialize $\theta_0$
2: for each round $t = 1, 2, \ldots, T$ do
3: \hspace{1cm} $m \leftarrow \max(1, CK)$
4: \hspace{1cm} $S_t \leftarrow$ (random set of $m$ clients)
5: \hspace{1cm} for each client $k \in S_t$ in parallel do
6: \hspace{2cm} $\theta_{t+1}^k \leftarrow$ ClientUpdate($k, \theta_t$)
7: \hspace{1cm} end for
8: $\theta_{t+1} \leftarrow$ FedWAvg($\theta_t, \{\theta_{t+1}^k\}_{k \in S_t}$)
9: end for
10: return $\theta_{t+1}$

**ClientUpdate($k, \theta$):**

- $B \leftarrow$ split the training data into batches of size $B$
- for each local epoch $i$ from 1 to $E$ do
- \hspace{1cm} for batch $b \in B$ do
- \hspace{2cm} $n_{adv} \leftarrow r \cdot B$ \hspace{1cm} $0 \leq r \leq 1$
- \hspace{2cm} $b_{adv} \leftarrow$ (random set of $b$ of $n_{adv}$ samples)
- \hspace{2cm} $b_{nat} \leftarrow$ (set of $B - n_{adv}$ samples)
- \hspace{2cm} $b \leftarrow A_{s,\epsilon,\alpha} (b_{adv})$
- \hspace{2cm} $b \leftarrow b_{nat} \cup b_{adv}$
- \hspace{2cm} $\theta \leftarrow \theta - \eta \nabla \mathcal{L}(\theta; b)$
- \hspace{1cm} end for
- \hspace{1cm} end for
- \hspace{1cm} return $\theta$

**FedWAvg($G, \{L_i\}_{i=1}^n$):**

- $g \leftarrow$ parameters of last layer of $G$
- for $i = 1$ to $n$ in parallel do
- \hspace{1cm} $l_i \leftarrow$ parameters of last layer of $L_i$
- \hspace{1cm} $c_i \leftarrow \frac{\|g(L_i)\|_2}{\sum_{j=1}^n \|g(L_j)\|_2}$ \hspace{1cm} cosine Similarity
- \hspace{1cm} $w_i \leftarrow \frac{\exp(c_i)}{\sum_{j=1}^n \exp(c_j)}$ \hspace{1cm} softmax
- \hspace{1cm} end for
- \hspace{1cm} $G \leftarrow \sum_{i=1}^n w_i L_i$
- \hspace{1cm} return $G$

**FL aggregation methods.** As mentioned earlier in Section 2, we investigate the server-based FL paradigms that produce a global model. Hence, we compare the proposed FedWAvg algorithm with other four state-of-the-art algorithms: FedAvg, FedProx, FedGate, and SCAFFOLD. For FedProx, the proximal control parameter $\mu$ is set to 0.1 as tuned in (Qu et al., 2021).

**Training configuration.** The server first initializes the model with the weights from the pre-trained model that is trained using ImageNet dataset. Due to the GPU limited memory, we set the batch size to 24. The stochastic gradient
descent (SGD) algorithm is used as optimizer with the momentum set to 0.9. In NT, the learning rate is set to 0.03 as tuned in (Qu et al., 2021), while in adversarial training (AT), the learning rate is set to 0.1. The learning rate is decreased in every epoch by 3.5% in the NT and by 5% in the AT. It was shown that ViT model converges faster than ResNet-50, hence, we set the number of communication rounds $T$ to 50 (Qu et al., 2021). Moreover, on highly heterogeneous data partitions (Qu et al., 2021), it is recommended to set the local epochs $E$ to small number ($\leq 5$), and in our experiments we set $E$ to one local epoch.

4.2. Results and Discussions

FedWAvg convergence. Fig. 2 shows the accuracy and robust accuracy of TNT-CLS model in the FL and FAT processes, respectively, with different aggregation methods. Similar figures with loss values for other models are in App. C. In federated natural training with IID and Non-IID(4) data distributions as shown in Fig. 2a and Fig. 2b, we notice that all the aggregation methods yield a fast convergence roughly from round 2. Unlike other methods, FedProx needs more rounds to reach a comparable accuracy performance to other methods. FedWAvg shows comparable and stable convergence behavior to other methods. While with Non-IID(2) data distribution as shown in Fig. 2c, FedWAvg shows comparable convergence, better for some models, to FedAvg. FedProx shows slow convergence while FedGate and SCAFFOLD show unstable convergence.

In FAT with IID data distribution as shown in Fig. 2d, FedWAvg shows comparable convergence to other methods while FedProx shows slow convergence. With Non-IID(4) and Non-IID(2) data distributions as shown in Fig. 2e and Fig. 2f, FedGate and SCAFFOLD show unstable convergence for the accuracy and show slow convergence for the robust accuracy. Moreover, FedProx shows slow convergence for robust accuracy, while FedWAvg shows comparable or better convergence than FedAvg for robust accuracy. Moreover, we calculate the model drift using singular vector canonical correlation analysis (SV-CCA) (Raghu et al., 2017), as shown in Fig. 3, between client 1 and client 4 (top), between client 1 and the server (middle), and between client 4 and the server (bottom) for layer 1 and layer 9 of TNT-CLS model. In Fig. 3a, the SV-CCA is calculated using clean samples, while in Fig. 3b the SV-CCA is calculated using the adversarial samples. Similar figures for other models are given in App. D. We found that at layer 1, the drift between the clients and the server is decreasing during the training and all methods show comparable behavior. While at layer 9, the drift behavior of FedGate and SCAFFOLD is not stable as in FedAvg and FedWAvg.

Accuracy and robust accuracy with FedWAvg. For CNNs, the aggregation methods for FL are mainly developed and tested in the natural federated learning process. In this work we test the state-of-the-art aggregation methods in
the FAT process for transformers. Tab. 1, Tab. 2, and Tab. 3 show the best accuracy for the natural federated learning and the best robust accuracy and the corresponding accuracy for the FAT with IID, Non-IID(4), and Non-IID(2) data distributions.

In federated natural training with IID and Non-IID(4), all aggregation methods including FedWAVg yield comparable model accuracy, while with Non-IID(2), FedProx, FedGate, and SCAFFOLD achieve less model accuracy compared to FedAvg. On the other hand, FedWAVg achieves better accuracy than FedAvg for models like T2T-ViT-VIS and TNT-CLS, and achieves comparable accuracy for models like T2T-ViT-CLS+VIS.

For the FAT process, we demonstrate the performance of the FedWAvg with the Non-IID data partitioning. With Non-IID(4), we notice that FedWAvg always yields better robust accuracy than FedProx, FedGate, and SCAFFOLD. Compared to FedAvg, we notice that FedWAvg yields better robust accuracy like in TNT-CLS-VIS and ViT-B, comparable robust accuracy like in ViT-CLS, and lower robust accuracy than FedAvg like in T2T-ViT-CLS. While with Non-IID(2), FedWAvg yields better robust accuracy than other aggregation methods with all models except with FedAvg in TNT-VIS model.

Robustness and tokenization. Tokenization played an important role in the FL and the FAT processes. As shown in Tab. 1, Tab. 2, and Tab. 3, tokens-to-token method has positive role in enhancing the models’ accuracy in NT and AT process when compared with size-comparable vision transformer ViT-S and TNT-S, while it has negative role in enhancing models’ robust accuracies. Tokens-to-token method shows its ability to represent training samples with local and global features that helps enhancing the model accuracy. The main reason for the low robust accuracy is as mentioned in (Aldahdooh et al., 2021); the energy spectrum of the perturbation that is generated using PGD for the T2T-ViT model is not spread across all frequencies which makes T2T-ViT not robust against the PGD attack. On the other hand, image patches in ViT-S and mapping local pixel dependencies of image patches in TNT models don’t help with Non-IID data partitioning. With Non-IID(4), ViT-S and TNT show comparable performance that decrease model’s accuracy and increase the model’s robust accuracy. While with Non-IID(2) ViT shows better model’s accuracy in NT and in AT process. As a conclusion, you can select the tokenization method according to the priority you give to accuracy and robust accuracy.

Robustness and classification head. The role of the classification head type appears during the NT process with Non-IID(2) data partitioning. We notice, as shown in Tab. 3, that using VIS tokens only for the classification head notably decreases model’s accuracy, while using CLS token only for the classification head significantly enhance the model’s accuracy. Compared to using CLS token, combining both configurations, i.e. CLS+VIS, may yield better model’s accuracy like in TNT with FedAvg, or may yield lower model’s accuracy like in T2T-ViT with FedWAvg.

Moreover, the role of the classification head type appears during the AT process with IID and Non-IID data partitioning. With the IID data distribution, as shown in Tab. 1, using CLS token for the classification head enhances the model’s accuracy and the model’s robust accuracy in TNT models, while using VIS tokens for the classification head decreases the model’s robust accuracy in T2T-ViT models. With the Non-IID, the preference of one classification head type is not clear. Finally, we can conclude that avoid using VIS
Table 1. Models accuracy under NT and models (accuracy, robust accuracy) under AT in FL with IID. The first and the second best robust accuracy are marked.

| Token Model | FedAvg | FedProx | FedGate | SCAFFOLD | FedWAvg(0) | FedWAvg(1) |
|-------------|--------|---------|---------|----------|------------|------------|
| CLS         | 97.35  | 79.41   | 79.41   | 79.41    | 79.41      | 79.41      |
| VIS         | 97.35  | 79.41   | 79.41   | 79.41    | 79.41      | 79.41      |
| VIS+CLS     | 97.35  | 79.41   | 79.41   | 79.41    | 79.41      | 79.41      |
| AT           | 97.35  | 79.41   | 79.41   | 79.41    | 79.41      | 79.41      |
| AT+CLS      | 97.35  | 79.41   | 79.41   | 79.41    | 79.41      | 79.41      |

Table 2. Models accuracy under NT and models (accuracy, robust accuracy) under AT in FL with Non-IID (4). The first and the second best robust accuracy are marked.

| Token Model | FedAvg | FedProx | FedGate | SCAFFOLD | FedWAvg(0) | FedWAvg(1) |
|-------------|--------|---------|---------|----------|------------|------------|
| CLS         | 96.37  | 78.45   | 78.45   | 78.45    | 78.45      | 78.45      |
| VIS         | 96.37  | 78.45   | 78.45   | 78.45    | 78.45      | 78.45      |
| VIS+CLS     | 96.37  | 78.45   | 78.45   | 78.45    | 78.45      | 78.45      |
| AT           | 96.37  | 78.45   | 78.45   | 78.45    | 78.45      | 78.45      |
| AT+CLS      | 96.37  | 78.45   | 78.45   | 78.45    | 78.45      | 78.45      |

Table 3. Models accuracy under NT and models (accuracy, robust accuracy) under AT in FL with Non-IID (2). The first and the second best robust accuracy are marked.

| Token Model | FedAvg | FedProx | FedGate | SCAFFOLD | FedWAvg(0) | FedWAvg(1) |
|-------------|--------|---------|---------|----------|------------|------------|
| CLS         | 95.38  | 77.49   | 77.49   | 77.49    | 77.49      | 77.49      |
| VIS         | 95.38  | 77.49   | 77.49   | 77.49    | 77.49      | 77.49      |
| VIS+CLS     | 95.38  | 77.49   | 77.49   | 77.49    | 77.49      | 77.49      |
| AT           | 95.38  | 77.49   | 77.49   | 77.49    | 77.49      | 77.49      |
| AT+CLS      | 95.38  | 77.49   | 77.49   | 77.49    | 77.49      | 77.49      |

ViT-S and ViT-B. We notice that the ViT-B significantly enhances the model accuracy and fails in enhancing the robust accuracy with IID and Non-IID (4). While with Non-IID, ViT-B achieves comparable robust accuracy to ViT-S. Hence, we recommend, for high heterogeneous data partitioning, to use ViT model with large number of attention blocks.

5. Conclusion

In this work, we studied the feasibility of AT in a FL process for vision transformers. Vision transformer models that have different tokenization and classification head techniques were investigated with different federated model aggregation methods. We found that the state-of-the-art aggregation methods decrease the robust accuracy of the model compared to FedAvg with Non-IID. Hence, we proposed an extension to the FedAvg algorithm, called FedWAvg, to improve the robust accuracy of the model. We showed that FedWAvg improved the robust accuracy with highly heterogeneous data and has comparable convergence and drift behavior compared to FedAvg. Moreover, we showed that choosing the tokenization method depends on the system's goal of either enhancing the model's accuracy or enhancing the model’s robust accuracy. Finally we showed that it is recommended to avoid using visual tokens alone for the classification head.
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A. Vision Transformers

In this section, we briefly show the related work that belongs to transformers and then we show the different models that we consider in our experiments, as described in Fig. 4.

A.1. Related work

Transformer (Vaswani et al., 2017) was first introduced for natural language processing (NLP) tasks. It adopts the self-attention mechanism to learn the model. Transformer and its variants maintain state-of-the-art performance for different NLP tasks. Recently, transformers were found to be effective for different computer vision tasks, such as, image processing (Chen et al., 2021b), video processing (Cao et al., 2021), and image classification (Dosovitskiy et al., 2021). Dosovitskiy et al. (Dosovitskiy et al., 2021) was the first to build an image classification model, vision transformer (ViT), that uses the vanilla transformer encoder blocks. ViT and its variants establish the state-of-the-art performance especially if it is trained with significantly large-scale datasets, such as JFT-300M (Sun et al., 2017; Dosovitskiy et al., 2021). Using transfer learning, ViT models can be downgraded to smaller datasets, such as ImageNet-1k (Deng et al., 2009), and achieves performance comparable to or better than state-of-the-art CNNs models. Recently, in (Qu et al., 2021), Qu et al. investigated the feasibility of using ViTs in the FL settings and observed that ViTs significantly accelerate convergence and reach a better global model, especially when dealing with heterogeneous data.

ViT has the capability to learn the global context of the input image, while it is not effectively capable to learn local features as CNNs and that’s why ViT requires large-scale dataset for training to maintain the state-of-the-art performance. Hence, many efforts have been done to mitigate this obstacle (Dosovitskiy et al., 2021; Yuan et al., 2021; Han et al., 2021; Xie et al., 2021). One approach is the embedding based approach in which the way of generating the embedded patches to be passed to the transformer encoder is changed. In (Dosovitskiy et al., 2021), ViT-Res is introduced which replaces the input image patches with the flattened ResNet-50 feature maps to generate the embedded patches. While in (Yuan et al., 2021), tokens-to-token ViT (T2T-ViT) replaces input image patches with a tokens-to-token (T2T) transformation. The T2T module progressively structurizes the image into tokens by recursively aggregating neighboring tokens into one token. The features that are learned by the T2T module are, then, passed to the transformer encoder. In (Han et al., 2021), Han et al. suggested to model both patch-level and pixel-level representations and proposed transformer-in-transformer (TNT) architecture. It stacks multiple TNT blocks that each has an inner transformer and an outer transformer. The inner transformer block further divides the image patch to sub-patches to extract local features from pixel embeddings. The output of the inner transformer block is merged with the patch embeddings to be the input of the outer transformer block. Other architectures exist in the literature like convolutional vision transformer (CVT) (Wu et al., 2021) and conditional position encoding vision transformer (CPVT) (Chu et al., 2021). Another approach to mitigate the ViT obstacle is to customize the classification head of the model. ViT only uses the class token for the classification while second-order vision transformer (So-ViT) (Xie et al., 2021) uses visual tokens along with the class token. So-ViT proposes a second-order cross-covariance pooling of visual tokens to be combined with the class token for final classification. Moreover the work in (Mao et al., 2021b) considered only the visual tokens.

A.2. Vision Transformer Models

ViT’s encoder receives as input a 1D sequence of token embeddings. The image $x \in \mathbb{R}^{H \times W \times C}$ is reshaped into a sequence of flattened 2D image patches $x_p \in \mathbb{R}^{N \times (P^2 \times C)}$, where $H$, $W$, $C$, $P$, and $N$ are image height, image width, number of image channels, patch width and height, and $N = \frac{HW}{P^2}$ is the number of patches, respectively. To prepare the patch embeddings, Eq. (4), the flattened patches are mapped to $D$ dimensions with a trainable linear projection since the transformer encoder uses constant latent vector size $D$ for all the layers. To maintain the positional information, Eq. (4), position embeddings are added to the patch embeddings using the standard learnable 1D position embeddings. The basic component in the transformer-based neural networks (NNs) is the attention blocks. The standard transformer encoder in ViT stacks $L$ layers of attention blocks. The attention block consists of two sub-layers; the first is the multiheaded self-attention (MSA), Eq. (5), and the second is a simple multi-layer perceptron (MLP) layer, Eq. (6), also called position-wise fully connected feed-forward network (FFN). Layernorm (LN) is applied before every sub-layer, and residual connections are applied after each sub-layer. MLP consists of two linear transformation layers and a nonlinear activation function, Gaussian error linear units (GELU) (Hendrycks & Gimpel, 2016), in between. For classification head, ViT adds $[CLS]$ token to the sequence of embedded patches $(z_0^l = x_{\text{class}})$. The $[CLS]$ token at the transformer’s output $z^L_0$ will be used for image representation, Eq. (7).

$$z_0 = [x_{\text{class}}; x_p^1 E; x_p^2 E; \ldots; x_p^N E] + \mathbf{E}_{\text{pos}},$$

$$\mathbf{E} \in \mathbb{R}^{(P^2 \times C) \times D}, \quad \mathbf{E}_{\text{pos}} \in \mathbb{R}^{(N+1) \times D}$$

$$z'_l = MSA(LN(z_{l-1})) + z_{l-1}, \quad l = 1 \ldots L$$

$$z_l = MLP(LN(z'_l)) + z'_l, \quad l = 1 \ldots L$$

$$y = LN(z^L_L)$$

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Other patch embeddings methods. As discussed earlier in App. A.1, T2T-ViT replaces input image patches with a tokens-to-token (T2T) transformation (Yuan et al., 2021). The T2T module progressively structurizes the image into tokens by recursively aggregating neighboring tokens into one token. The features that are learned by the T2T module are, then, passed to the transformer encoder. While TNT (Han et al., 2021) models both patch-level and pixel-level representations. It stacks multiple TNT blocks that each has an inner transformer and an outer transformer. The inner transformer block further divides the image patch to sub-patches to extract local features from pixel embeddings. The output of the inner transformer block is merged with the patch embeddings to be the input of the outer transformer block.

Other classification head methods. In order to improve vision transformer robustness, the work (Mao et al., 2021b) suggested a classification head that depends on the visual tokens \( [z_1^{L}, ..., z_N^{L}] \) not on the \([CLS] \) token \( z_0^{L} \). The proposed classification head performs average pooling of the visual tokens. While the work in (Xie et al., 2021) proposed a classification head that depends on class and visual tokens as illustrated in Fig. 5 in order to improve the network accuracy.

In summary, we investigate the vision transformer models with three different embedding methods and three different classification head methods. Fig. 4 illustrates the models’ ar-

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**Figure 4.** Tested Vision Transformers’ Architectures for Federated Adversarial Training. The left part shows the main blocks of the transformer. 1) The embedded patches block. 2) the Attention block, and 3) the classification head block. For the embedding patches, we consider three methods, in green blocks, a) image patches, tokens-to-token, and sub-patches for image patches. For the Attention block, we consider the multi-head attention mechanism. For the classification head block, we consider using the CLS token, VIS tokens, and both.

**Figure 5.** The classification head that is proposed in (Xie et al., 2021) that uses the second-order cross-covariance pooling of visual tokens. FC: fully connected layer.
chitectures. For ViT embedding, we use ViT-S-16 and ViT-B-16 models. For T2T-ViT embedding, we use T2T-ViT-14 and finally, for TNT embedding, we use the TNT-S model. For these four models, three classification heads are used; the first uses the class [CLS] token only, the second uses the visual [VIS] tokens only, and the third uses both the [CLS] and the [VIS] tokens. In total we tested 12 vision transformer models.

B. More figures cosine similarity weights

More figures to show the calculated cosine similarity weights for some of the tested models are shown in Figs. 6 to 10.

C. More figures for FedWAvg convergence

More figures to show the convergence of FedWAvg and some of the tested state-of-the-art are shown in Figs. 11 to 13. Other figures that shows the convergence and the loss are shown in Figs. 14 to 16. Moreover, Figs. 17 and 19 show the convergence during the training and the testing.

D. More figures for model drift

Figs. 20 to 25 show more model drift for some of the tested models.
Figure 6. The calculated weights using cosine similarity, Eq. (3) during the federated training process using ViT-S model and IID partitioning. a) for the natural training, and b) for the adversarial training.

Figure 7. The calculated weights using cosine similarity, Eq. (3) during the federated training process using ViT-S model and Non-IID partitioning (each client has 4 classes). a) for the natural training, and b) for the adversarial training.

Figure 8. The calculated weights using cosine similarity, Eq. (3) during the federated training process using ViT-S model and Non-IID partitioning (each client has 2 classes). a) for the natural training, and b) for the adversarial training.
Figure 9. The calculated weights using cosine similarity, Eq. (3) during the federated training process using T2T-ViT-14-VIS model and Non-IID partitioning (each client has 4 classes). a) for the natural training, and b) for the adversarial training.

Figure 10. The calculated weights using cosine similarity, Eq. (3) during the federated training process using TNT-S-CLS+VIS model and Non-IID partitioning (each client has 4 classes). a) for the natural training, and b) for the adversarial training.
Figure 11. The accuracy and robust accuracy of ViT-S-CLS model in the FAT process for different aggregation methods. The accuracies against the communication rounds under the NT process using IID, Non-IID(4), and Non-IID(2) are shown in (a), (b), and (c) respectively. The accuracies (top) and the robust accuracies (bottom) against the communication rounds under the AT process using IID, Non-IID(4), and Non-IID(2) are shown in (d), (e), and (f) respectively.

Figure 12. The accuracy and robust accuracy of T2T-ViT-CLS model in the FAT process for different aggregation methods. The accuracies against the communication rounds under the NT process using IID, Non-IID(4), and Non-IID(2) are shown in (a), (b), and (c) respectively. The accuracies (top) and the robust accuracies (bottom) against the communication rounds under the AT process using IID, Non-IID(4), and Non-IID(2) are shown in (d), (e), and (f) respectively.
**Figure 13.** The accuracy and robust accuracy of TNT-CLS+VIS model in the FAT process for different aggregation methods. The accuracies against the communication rounds under the NT process using IID, Non-IID(4), and Non-IID(2) are shown in a), b), and c) respectively. The accuracies (top) and the robust accuracies (bottom) against the communication rounds under the AT process using IID, Non-IID(4), and Non-IID(2) are shown in d), e), and f) respectively.

**Figure 14.** The accuracy and the robust accuracy of TNT-CLS+VIS model with loss values in the FAT process for different aggregation methods. The accuracies (top) and the robust accuracies (bottom) against the communication rounds under the AT process using Non-IID(4), and Non-IID(2) are shown in a), and b) respectively.
Figure 15. The accuracy and the robust accuracy of ViT-CLS model with loss values in the FAT process for different aggregation methods. The accuracies (top) and the robust accuracies (bottom) against the communication rounds under the AT process using Non-IID(4), and Non-IID(2) are shown in a), and b) respectively.

Figure 16. The accuracy and the robust accuracy of T2T-ViT-CLS model with loss values in the FAT process for different aggregation methods. The accuracies (top) and the robust accuracies (bottom) against the communication rounds under the AT process using Non-IID(4), and Non-IID(2) are shown in a), and b) respectively.
Figure 17. The accuracy in training (dashed) and testing (solid) of ViT-CLS model with loss values in the FAT process for different aggregation methods. The accuracies against the communication rounds under the AT process using Non-IID(4), and Non-IID(2) are shown in a), and b) respectively. For better visualization dashed line is shifted for one round forward.

Figure 18. The accuracy in training (dashed) and testing (solid) of T2T-ViT-VIS model with loss values in the FAT process for different aggregation methods. The accuracies against the communication rounds under the AT process using Non-IID(4), and Non-IID(2) are shown in a), and b) respectively. For better visualization dashed line is shifted for one round forward.

Figure 19. The accuracy in training (dashed) and testing (solid) of TNT-CLS+VIS model with loss values in the FAT process for different aggregation methods. The accuracies against the communication rounds under the AT process using Non-IID(4), and Non-IID(2) are shown in a), and b) respectively. For better visualization dashed line is shifted for one round forward.
Figure 20. The SV-CCA for the first and the ninth layer of server, client 1, and client 4 models against communication rounds under FAT process using ViT-CLS model with Non-IID(4). a) using clean test samples and b) using adversarial test samples. The top row shows the SV-CCA between client 1 and client 2, the middle row shows the SV-CCA between the server and client 1, and the bottom row shows the SV-CCA between the server and client 4.

Figure 21. The SV-CCA for the first and the ninth layer of server, client 1, and client 4 models against communication rounds under FAT process using ViT-CLS model with Non-IID(2). a) using clean test samples and b) using adversarial test samples. The top row shows the SV-CCA between client 1 and client 2, the middle row shows the SV-CCA between the server and client 1, and the bottom row shows the SV-CCA between the server and client 4.
Figure 22. The SV-CCA for the first and the ninth layer of server, client 1, and client 4 models against communication rounds under FAT process using T2T-ViT-VIS model with Non-IID(4). a) using clean test samples and b) using adversarial test samples. The top row shows the SV-CCA between client 1 and client 2, the middle row shows the SV-CCA between the server and client 1, and the bottom row shows the SV-CCA between the server and client 4.

Figure 23. The SV-CCA for the first and the ninth layer of server, client 1, and client 4 models against communication rounds under FAT process using T2T-ViT-VIS model with Non-IID(2). a) using clean test samples and b) using adversarial test samples. The top row shows the SV-CCA between client 1 and client 2, the middle row shows the SV-CCA between the server and client 1, and the bottom row shows the SV-CCA between the server and client 4.
Figure 24. The SV-CCA for the first and the ninth layer of server, client 1, and client 4 models against communication rounds under FAT process using TNT-CLS-VIS model with Non-IID(4). a) using clean test samples and b) using adversarial test samples. The top row shows the SV-CCA between client 1 and client 2, the middle row shows the SV-CCA between the server and client 1, and the bottom row shows the SV-CCA between the server and client 4.

Figure 25. The SV-CCA for the first and the ninth layer of server, client 1, and client 4 models against communication rounds under FAT process using TNT-CLS-VIS model with Non-IID(2). a) using clean test samples and b) using adversarial test samples. The top row shows the SV-CCA between client 1 and client 2, the middle row shows the SV-CCA between the server and client 1, and the bottom row shows the SV-CCA between the server and client 4.