# HideNseek: Federated Lottery Ticket via Server-side Pruning and Sign Supermask

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## Abstract

Federated learning alleviates the privacy risk in distributed learning by transmitting only the local model updates to the central server. However, it faces challenges including statistical heterogeneity of clients' datasets and resource constraints of client devices, which severely impact the training performance and user experience. Prior works have tackled these challenges by combining personalization with model compression schemes including quantization and pruning. However, the pruning is data-dependent and thus must be done on the client side which requires considerable computation cost. Moreover, the pruning normally trains a binary supermask  $\in \{0, 1\}$  which significantly limits the model capacity yet with no computation benefit. Consequently, the training requires high computation cost and a long time to converge while the model performance does not pay off. In this work, we propose HideNseek which employs one-shot data-agnostic pruning at initialization to get a subnetwork based on weights' synaptic saliency. Each client then optimizes a sign supermask  $\in \{-1, +1\}$  multiplied by the unpruned weights to allow faster convergence with the same compression rates as state-of-the-art. Empirical results from three datasets demonstrate that compared to state-of-theart, HideNseek improves inferences accuracies by up to 40.6% while reducing the communication cost and training time by up to 39.7% and 46.8% respectively.

# 1 Introduction

Federated learning [McMahan et al., 2017] improves privacy protection by decoupling the need for a central data repository from learning distributed datasets. Each client uploads its local model trained with local datasets to a central server that maintains a global model. The server updates the global model via aggregating the clients' updates and sends the new model to the clients. These processes are iterated until the model converges or the predefined cycle ends.

While improving privacy protection, this paradigm also faces challenges such as statistical heterogeneity, which refers to the non-IID distribution of the data among clients, impacting the global model convergence if data from different clients are too diverged. Some works address statistical heterogeneity by introducing various learning techniques for personalization [Fallah et al., 2020; Smith et al., 2017; Lin et al., 2020; Gong et al., 2021; Zhu et al., 2021].

Another major challenge faced by federated learning is the resource constraints, which refer to the limited computation capacity and transmission bandwidth of the client devices. The limited resource restricts the model size that can be trained in the client devices and transmitted timely to the server for aggregation. Several recent works have surged to address this challenge by adapting

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training procedures [Li et al., 2020; Reisizadeh et al., 2020] and employing model compression schemes [Diao et al., 2021; Horvath et al., 2021; Bouacida et al., 2021].

Lately, FedMask [Li et al., 2021] tackles both statistical heterogeneity and resource constraints by employing a "masking is training" philosophy based on the lottery ticket hypothesis (LTH) [Frankle and Carbin, 2018]. FedMask prunes the local model to comply with the resource constraints. Then, the client learns a sparse local binary supermask for personalization to alleviate the statistical heterogeneity across clients.

However, exiting methods face several challenges. First, current pruning methods in federated setup are mostly data-dependent and thus have to be performed on the client-side. Hence the client devices with limited resources cannot avoid the considerable computation cost. Second, such pruning methods commonly employ the binary supermask which essentially is unstructured pruning that brings no computational advantage yet limits the model capacity. Consequently, the model performance is limited, yet requires high computation cost and a long convergence period.

Therefore, in this paper, we propose HideNseek, a statistical heterogeneity-aware federated learning framework that provides computation and communication efficiency powered by sign supermask [Zhou et al., 2019]. Specifically, we make the following contributions.

- HideNseek proposes a federated version of LTH with sign optimization for the first time. Compared with the commonly used binary supermask, our approach provides higher accuracy and faster convergence.
- HideNseek performs server-side one-shot pruning at initialization by employing an iterative data-agnostic approach based on synaptic saliency of the weights' signs. As such, HideNseek greatly alleviates the computation burden and communication cost for the clients with limited capacities.
- Empirical results on varied datasets demonstrate that HideNseek outperforms the state-ofthe-art methods in inference accuracy by up to 40.6% while reducing the communication cost and training time by up to 39.7% and 46.8% respectively.

# 2 Background & Objective Formulation

In this section, we begin with the background on federated learning and LTH and formulate the objective of data-agnostic pruning for federated learning.

#### 2.1 Federated Learning

In federated learning, a deep neural network must be learned in a distributed fashion. This is achieved by a central server aggregating copies of the network weights learned among clients on their local datasets. The learning objective is to find weights w that minimize the empirical loss across clients

$$\min_{w} F(w) = \sum_{k=1}^{K} \frac{n_k}{n} \mathcal{L}[f(x_k; w), y_k]$$
(1)

where the network  $f(\cdot; w)$  is a composite function of layers parametrized by vectorized weights  $w \in \mathbb{R}^d$  and  $\mathcal{L}$  is the empirical loss function which measures the ability to approximate the function generating the local dataset  $(x_k, y_k)$  of client k.  $n_k$  is the number of local samples and  $n = \sum_k n_k$  is the total number of samples across all the K clients.

A prior work [McMahan et al., 2017] provides the widely used FedAvg to solve this objective via distributed SGD. In each communication round t, the central server selects a subset of  $c \ll K$  clients and sends them a copy of the global weights  $w^t$ . The clients modify their local copy of the weights  $w^t_k$  by minimizing the empirical loss on local datasets to obtain  $w^{t+1}_k$  and transmit them back to the server. The server updates the global weights by simply averaging the clients' weights

$$w^{t+1} = \frac{1}{c} \sum_{k=1}^{c} w_k^{t+1}$$
(2)

Several problems arise in a real-world deployment. Firstly, the clients incur communication costs due to weight transmission and computation costs due to local weight optimization. Secondly, the

local datasets are not independent and identically distributed (non-IID) so the global weights must generalize well among clients. Some works have modified their learning objective(s) to address these problems (see Section 6).

## 2.2 Lottery Ticket Hypothesis

LTH [Frankle and Carbin, 2018] is a nascent avenue in machine learning that can tackle the aforementioned issues in federated learning. It states that a randomly initialized neural network contains a subnetwork called a winning ticket when trained in isolation, performs as well as the original network. A more ambitious extension comes from [Ramanujan et al., 2020] which states that a sufficiently overparametrized network contains a winning ticket at a randomly initialized state. Furthermore, this winning ticket can be determined via freezing the weights at random initialization  $w^0$ and pruning a subset of these weights to find a sparse subnetwork. To improve the learning performance, [Chen et al., 2022] suggest applying a transform function  $U \in \mathcal{U}$  to the weights to further minimize the empirical loss. The learning objective is thus

$$\min_{U \in \mathcal{U}, ||m||_0 = S} \mathcal{L}[f(x; U(w^0 \odot m)), y]$$
(3)

where  $m \in \{0, 1\}^d$  is a binary supermask with sparsity level S and the same dimensionality as the weights. The winning ticket is represented as the element-wise multiplication of the weights and the supermask, i.e.,  $w^0 \odot m$ . However, optimizing Eq. (3) is computationally intractable due to the large dimensionality of weights and transformation space  $\mathcal{U}$ . Hence, they propose to decouple the optimization into two stages. The first stage is the pruning phase where a binary supermask must be found to sparsify the model by optimizing the following

$$\hat{m} \in \min_{||m||_0 = S} R(f(x; w^0 \odot m)) \tag{4}$$

where R is a scoring function that measures the ability of the binary supermask m to isolate the winning ticket from the model. The second stage is the training phase where a weight transformation is learned to minimize the empirical loss

$$\hat{U} \in \min_{U \in \mathcal{U}} \mathcal{L}[f(x; U(w^0 \odot \hat{m})), y]$$
(5)

#### 2.3 Objective Formulation

In essence, LTH applies a "masking is training" philosophy where an optimal sparse subnetwork must be learned without modifying the weights. Given the communication and computation efficiency brought by this idea (discussed in subsequent sections), we propose to adopt this hypothesis for the federated setting. However, the weight transformation space  $\mathcal{U}$  is very vast. Following [Chen et al., 2022], we confine the space to sign flipping transformation space  $\mathcal{U}_s \in \mathcal{U}$  where a transformation  $U(w, s) = w \odot s$  element-wise multiplication of the sign supermask  $s \in \{-1, +1\}^d$  to the weights w. The updated learning objective of our work is

$$\min_{m,s} F(m,s) = \sum_{k=1}^{K} \frac{n_k}{n} \mathcal{L}[f(x_k; w^0 \odot m \odot s), y_k]$$
(6)

The subsequent sections elaborate on a federated learning algorithm to solve the above objective.

#### 3 Methodology

#### 3.1 HideNseek

In this work, we propose an efficient federated learning algorithm called HideNseek by solving for federated adaptation of the LTH. Figure 1 depicts an overview of the framework. As mentioned earlier, the learning process can be performed in two phases.

In the first phase, the server first performs pruning-at-initialization to isolate the winning ticket (1). Since the server does not possess training data, a data-agnostic pruning method is applied. Following



Figure 1: Overview of HideNseek framework

[Tanaka et al., 2020], we measure the score of the signs of weights via their synaptic saliency (see Section 3.4), and employ global structured pruning for hardware efficiency.

In the second phase, an optimal weight transformation has to be learned to minimize the empirical loss in a federated manner. In each training step t, the server sends the global sign supermask  $s^t$  to the selected clients ((2)) which initializes a local sign supermask  $s_k^{t+1}$ . The clients then freeze the model weights and optimize the local sign supermask by minimizing the empirical loss using Eq. (6) ((3)). As such, a sign flipping transformation is learned and sent back to the server ((4)). The server then aggregates these local supermasks using Eq. (8) ((5)).

After the training phase, each client multiplies the aggregated sign supermask to its weights to get the final local model (6). Algorithm 1 (in Appendix A) summarizes the processes with highlighted details elaborated in the following paragraphs.

#### 3.2 Personalization

The output layer of the model cannot be simply optimized for its signs because the weight magnitudes must be scaled for stable training. We thus split our models into feature extractors which constitute all the hidden layers and classifier which is the output layer. The weights are frozen and the sign supermask is learned only for the feature extractor while the weights of the classifier are modifiable, as the optimization of the local data. Aligned with prior works [Zhu et al., 2021], our work further reinforces personalization among clients.

## 3.3 Sign Flipping Transformation

Optimizing the sign supermask is crucial to learning in our algorithm. As such, we handle certain preliminaries to achieve the optimization. As mentioned earlier, a model can be expressed as a composition of layers performing operations of vectorized weights. As an example, let us consider the fully connected layer. Note that the bias term has been omitted for brevity. A fully-connected layer l can be expressed as  $y^{[l]} = (w^{[l]} \odot s^{[l]}) \cdot x^{[l]}$ , where  $y^{[l]} \in \mathbb{R}^i$  is the output,  $x^{[l]} \in \mathbb{R}^j$  is the input, and  $w^{[l]} \in \mathbb{R}^{i \times j}$  is the weights. We thus handle the learning of a sign supermask  $s^{[l]} \in \{-1, +1\}^{i \times j}$  with the same dimensionality as the weights.

However, the traditional SGD optimization cannot be applied to the sign supermasks due to their discrete nature. Hence, we implement a straight-through estimator [Bengio et al., 2013] with a real-valued sign supermask  $\hat{s}^{[l]} \in \mathbb{R}^{i \times j}$ . In the forward pass,  $\hat{s}$  is quantized using the piecewise sign function

$$s_{ij} = \operatorname{sign}(\hat{s}_{ij}) = \begin{cases} +1 & \hat{s}_{ij} \ge 0\\ -1 & \hat{s}_{ij} < 0 \end{cases}$$
(7)

where  $s_{ij}$  is an element in the *i*-th row and *j*-th column of the sign supermask *s*. The gradients of *s* in the backward pass are computed as  $\nabla_s \mathcal{L} = (\nabla_y \mathcal{L} \cdot x^T) \odot w$ . Given that the sign function is not differentiable, directly assigning the gradients from the quantized sign supermask to the real sign supermask (i.e.,  $\nabla_{\hat{s}}\mathcal{L} = \nabla_s\mathcal{L}$ ) would lead to large gradient variance [Courbariaux et al., 2016]. Hence, we employ a hyperbolic tangent function, denoted as  $\tanh(\cdot)$ , for a continuous approximation of the sign function for the backward pass,  $s_{ij} = \tanh(\hat{s}_{ij})$ . This would allow us to compute the gradients of the real sign supermask  $\hat{s}$  from the binary sign supermask *s* as  $\nabla_{\hat{s}}\mathcal{L} = \Psi \odot \nabla_s \mathcal{L}$ , where  $\Psi$  is the gradient matrix of the hyperbolic tangent function with values explicitly calculated as  $\Psi_{ij} = (1 - \hat{s}_{ij}^2)$ .

Since the clients transmit quantized sign supermasks to the server for communication efficiency, we employ the following sign aggregation scheme to obtain the real-valued sign supermask at the server

$$\hat{s} = \operatorname{arctanh}\left(\sum_{k} \frac{n_k}{n} s_k\right) \tag{8}$$

#### 3.4 Server-side Pruning

Another crucial aspect in HideNseek is the pruning phase where the winning ticket must be isolated from the network. Following [Li et al., 2021], we employ one-shot pruning at initialization but perform it on the server-side to reduce the load on the clients. As the server does not contain any training data, we employ a data-agnostic iterative pruning approach [Tanaka et al., 2020] where the prune scores are determined based on the weight's synaptic saliency. Given that the weights are frozen during training the sign supermask, we measure the synaptic saliency of the sign of a given weight in a model with L layers is as follows

$$R_{\rm SF}(s_{ij}^{[l]}) = \left[ \mathbb{1}^{\mathsf{T}} \prod_{h=l+1}^{L} \left| s^{[h]} \odot w^{[h]} \right| \right]_{i} \left| s_{ij}^{[l]} \odot w^{[l]}_{ij} \right| \left[ \prod_{h=1}^{l-1} \left| s^{[h]} \odot w^{[h]} \right| \mathbb{1} \right]_{j}$$
(9)

In essence, the synaptic saliency of a weight's sign is the product of all the weights multiplied by their respective sign supermasks that have the weight's sign within the path from the input to the output layer. To further promote hardware efficiency, we employ global structured pruning by scoring groups of weights by channels in convolutional layers and nodes in fully-connected layers. The prune score for the *i*-th channel or node in a layer as  $||w_i^{[l]} \odot \nabla_s R_{SF,i}^{[l]}||_2$ . Additionally, we keep the first few layers and only prune from the latter layers of the model with a prune rate  $p_r$ .

## 3.5 State of the Art

FedMask [Li et al., 2021] is the closest in spirit to our work. However, its pruning method is datadependent, and hence, have to be performed on client devices, resulting in increased computational load on the resource-constrained clients. Additionally, its weight transformation space is confined to the binary supermasking  $U_b \in U$ , where a local binary supermask  $m_k \in \{0, 1\}$  is learned in the training stage in contrast to the binary sign supermask. Effectively, FedMask further performs unstructured pruning during the training stage with no communication or computation advantage. Contrarily, HideNseek maintains all the weights after the pruning stage allowing for a greater model capacity.

# 4 Experimental Setup

## 4.1 Datasets & Models

We evaluate HideNseek on two applications, including image classification and human activity recognition, using the EMNIST [Caldas et al., 2018] and HAR [Anguita et al., 2013] datasets,

respectively. EMNIST is a handwritten character recognition task involving  $28 \times 28$  grayscale images belonging to 62 classes (upper and lower case letters and digits) already partitioned according to the writers. Thus, each writer is considered a client. The HAR dataset consists of sensor data (flattened into an 1152-valued vector) generated by users performing six possible actions (i.e., classes). To further study the impact of statistical heterogeneity on the performance, we follow prior works [Zhu et al., 2021] and simulate Non-IID data on MNIST [LeCun et al., 1998] dataset via Dirichlet sampling  $Dir(\alpha)$ , where a smaller value of  $\alpha$  denotes greater heterogeneity (see Figure 5 in Appendix B). We employ the VGG9 and multilayer perceptron (MLP) for the image classification and activity recognition tasks, respectively, with model configurations (see Table 5 in Appendix C). We enable pruning for the last four convolutional layers in VGG9 and the first two hidden layers in MLP.

# 4.2 System Implementation

We implement HideNseek and baselines with PyTorch (v1.8.0) [Paszke et al., 2019] on a server equipped with a single Nvidia RTX 3090 GPU. We experiment with a total of K clients set to 160 and 320 for MNIST and EMNIST datasets and 30 for the HAR dataset. We randomly sample  $\rho = 10\%$  of participating clients that perform E = 5 local epochs during each communication round with a total of 300 rounds for MNIST and EMNIST and EMNIST and 200 rounds for HAR. Weights and sign supermasks are initialized using Kaiming uniform [He et al., 2015] and uniform distribution U(-1, 1) respectively. We perform one-shot pruning for 100 iterations in HideNseek (according to [Tanaka et al., 2020]) and one epoch for FedMask and Signed on the last four layers of the VGG9 and the first two hidden layers of the MLP with the pruning rate  $p_r = 0.8$  (80% of the weights are kept). We employ the SGD optimizer with a learning rate  $\eta = 0.001$  for FedAvg, FedMask and Signed,  $\eta = 0.01$  for BNNAvg and  $\eta = 10$  for HideNseek, and momentum  $\mu = 0.9$  for all algorithms chosen empirically. We repeat every experiment thrice with different seeds for reproducibility.

#### 4.3 Baselines

We evaluate HideNseek by comparing its performance against several baselines. We include **Fe-dAvg** [McMahan et al., 2017] to realize the performance of the model when trained at full capacity. **FedMask** [Li et al., 2021] is the closest in spirit to our work and state-of-the-art when it comes to applying LTH for the federated setting with client-side pruning and learning binary supermasks. We also borrow their **BNNAvg** baseline which applies FedAvg to train binarized neural networks (BNN) [Courbariaux et al., 2016] with the weights and activations quantized by their signs. We also implement an extension of FedMask we call **Signed** where we replace binary supermask with sign supermask and change their binarizing function from sigmoid to tanh.

## 5 Results

## 5.1 Training performance

We first compare the training performance by reporting the inference accuracies in Table 1 between HideNseek and the baselines. The inference accuracies were measured by taking a weighted average of the client's inference accuracies based on their local test data, which are weighted based on the number of test samples in their local dataset. While HideNseek performs expectedly worse than the FedAvg which trains the full model and serves as the upper bound in training performance, HideNseek in general, outperforms FedMask, Signed and BNNAvg across tasks. It is worthwhile to mention that the performance improvements are significant for HAR and MNIST datasets with lower heterogeneity at  $\alpha = \{1, 10\}$  with inference accuracies higher by 24.1-40.6% for HideNseek compared to FedMask. HideNseek performance gradually degrades for MNIST ( $\alpha = 0.1$ ) with higher heterogeneity and EMNIST with a large number of classes. This finding can be attributed to the fact that HideNseek employs a shared global feature extractor among the baselines that utilize pruning. While it is challenging to learn generalized features among clients, the performance is still approximate to both FedMask and Signed which learn a more personalized feature extractor. Yet, HideNseek scores higher than FedMask by 2.09% and 19.62% for EMNIST and MNIST( $\alpha = 0.1$ ).

We further compare the training performances by plotting the inference accuracies against the communication round. In the case of HAR dataset in Figure 2(a) and MNIST dataset in Figure 3,

Algorithm	EMNIST	MNIST			HAR
	Non-IID	$\alpha = 0.1$	$\alpha = 1$	$\alpha = 10$	Non-IID
FedAvg	$94.41 \pm 0.06$	$98.81 \pm 0.10$	$99.23 \pm 0.05$	$99.38 \pm 0.05$	$93.37 \pm 0.22$
BNNAvg	$29.09 \pm 1.27$	$51.80 \pm 0.45$	$54.39\pm0.16$	$64.62\pm0.15$	$66.50 \pm 0.57$
FedMask	$67.09 \pm 0.23$	$57.73 \pm 0.21$	$67.46 \pm 0.40$	$84.41\pm0.12$	$81.93\pm0.55$
Signed	$69.99\pm0.76$	$59.45 \pm 0.26$	$72.17\pm0.19$	$86.69\pm0.12$	$76.30 \pm 1.04$
HideNseek	$\textbf{69.18} \pm \textbf{5.58}$	$\textbf{77.35} \pm \textbf{0.81}$	$\textbf{94.97} \pm \textbf{0.64}$	$\textbf{96.69} \pm \textbf{0.56}$	$\textbf{90.60} \pm \textbf{0.30}$

Table 1: Inferences accuracies of baselines and HideNseek on different datasets.



Figure 2: Performance on Non-IID EMNIST and HAR datasets.



Figure 3: Performance on MNIST with different data heterogeneities.

HideNseek converges faster than FedMask, Signed and BNNAvg. Whereas HideNseek experiences higher volatility in training compared to the baselines in EMNIST dataset in Figure 2(b) and to some extent in MNIST dataset with higher heterogeneity at  $\alpha = 0.1$  in Figure 3(a). Both of which again point to the difficulty in training a shared global sign supermask under heterogeneous conditions.

#### 5.2 Communication Cost

We then compare the communication cost for each client by measuring the upload and download sizes in MB for each client during each communication round as shown in Table 2. First, BNNAvg with binary parameters is four times smaller than FedAvg because 1 byte is the smallest element size to represent a parameter in PyTorch. FedMask and Signed have a lower upload cost compared to BNNAvg due to client-side pruning. HideNseek further reduces the download cost thanks to serverside pruning. Furthermore, prune scores are more granular in HideNseek compared to FedMask and Signed. This leads to smaller subnetworks since we drop all weights with scores equal to the threshold (see line 15 in Algorithm 1). Overall, HideNseek demonstrates a reduction in communication cost compared to the second-best performance (FedMask) by 20.9-39.7% times across all tasks.

Algorithm	EMNIST		MNIST		HAR	
	upload	download	upload	download	upload	download
FedAvg	4.53	4.53	4.33	4.33	1.44	1.44
BNNAvg	1.07	1.07	1.07	1.07	0.36	0.36
FedMask	0.74	1.07	0.70	1.07	0.27	0.36
Signed	0.74	1.07	0.70	1.07	0.27	0.36
HideNseek	0.70	0.70	0.70	0.70	0.19	0.19

Table 2: Communication cost in MB for each client in a communication round

Table 3: Training times in seconds of baselines and HideNseek measure on Nvidia RTX 3090.

Algorithm	EMNIST	MNIST	HAR
FedAvg	$475.61 \pm 0.54$	$587.43\pm0.50$	$49.31\pm0.15$
BNNAvg	$580.64\pm0.42$	$693.76 \pm 1.82$	$61.10\pm0.42$
FedMask	$1150.77 \pm 5.53$	$1200.71 \pm 3.86$	$83.52\pm0.12$
Signed	$979.90 \pm 1.78$	$908.93 \pm 3.46$	$76.34\pm0.48$
HideNseek	$\textbf{612.33} \pm \textbf{2.35}$	$\textbf{705.16} \pm \textbf{2.61}$	$\textbf{64.44} \pm \textbf{0.72}$

# 5.3 Computation Cost

We report the computation cost by measuring the total training time on a single Nvidia RTX 3090 GPU (Table 3). FedAvg is the fastest primarily because of that it does not utilize any latent weights, such as the masks in the case of Signed, FedMask and HideNseek. Even BNNAvg is slower than FedAvg since the quantization must be performed at runtime and there is no built-in optimization in PyTorch when dealing with 1-bit parameters. Still, HideNseek has lower training time compared to FedMask and Signed because these baselines require the client-side one-shot pruning each time a new client participates in the training. Additionally, FedMask is more computationally expensive as it employs sparsity regularization term. Overall, HideNseek demonstrates a reduction in computation costs compared to FedMask by 22.8-46.8% across all tasks.

# 5.4 Active Clients

We now evaluate the impact of the number of active clients per communication round on the training performance. Table 4 demonstrates the inference accuracies among clients on the MNIST ( $\alpha = 1$ ) with different numbers of active clients  $K = \{10, 20, 40\}$ . While most baselines experience an improvement in accuracy with more active clients, HideNseek experiences a minor drop of 3.92% in performance when K quadruples. Still, HideNseek demonstrates better performance compared to BNNAvg, FedMask and Signed by a significant margin. This signifies the scalability and partly backs up the robustness of heterogeneity demonstrated in Figure 3.

## 5.5 Pruning Rate

From the results discussed above, it is evident that the VGG9 model is overparametrized for the MNIST dataset proven by the high inference accuracies of FedAvg and HideNseek. Hence, we tried a drastically more aggressive pruning rate of  $p_r = 0.2$  compared to previous experiments where  $p_r = 0.8$ . As shown in Figure 4, the drop in performance is very marginal in the less heterogeneous datasets  $\alpha = \{1, 10\}$ , while there is a significant drop in the more heterogeneous dataset  $\alpha = 0.1$ . This demonstrates that the computation and communication advantage of HnS over baselines is larger than the prior results without a noticeable accuracy drop in some cases when using a high prune rate.

# 6 Related Work

**Statistical Heterogeneity.** After the seminal work on federated learning [McMahan et al., 2017], immediate advancements sought to tackle the problem of statistical heterogeneity in federated learning by adapting personalization schemes. PerFedAvg [Fallah et al., 2020] integrates a model-agnostic meta-learning approach into FedAvg for personalization. MOCHA [Smith et al., 2017] introduces federated multi-task learning where each client is considered as a task. A plethora of

			*
Algorithm	K=10	K=20	K=40
FedAvg	$99.23 \pm 0.05$	$99.19\pm0.05$	$99.25 \pm 0.07$
BNNAvg	$54.39 \pm 0.16$	$58.17 \pm 0.16$	$61.78 \pm 0.24$
FedMask	$67.46 \pm 0.40$	$69.51 \pm 0.22$	$72.31\pm0.05$
Signed	$72.17 \pm 0.19$	$73.02 \pm 0.15$	$73.48\pm0.01$
HideNseek	$\textbf{94.97} \pm \textbf{0.64}$	$\textbf{93.40} \pm \textbf{0.61}$	$\textbf{91.05} \pm \textbf{0.87}$

Table 4: Inference accuracies when varying the number of active clients per communication round.



Figure 4: Performance on MNIST with different pruning rates.

works [Lin et al., 2020; Gong et al., 2021; Zhu et al., 2021] has also applied knowledge distillation to learn a global surrogate model which teaches the clients' local models. [Li et al., 2021] performs personalization by allowing each client to learn a local binary supermask. In contrast, we employ personalization by globally sharing all hidden layers of the model while fine-tuning the final layer to the clients' local data. This allows HideNseek to stably train the model by modifying weight magnitudes for a small subset of the weights while quantizing the updates transmitted for all the hidden layers. As such, HideNseek reduces the communication cost while maintaining better ability in terms of learning data with varied heterogeneities as shown in Figure 3.

**Communication and Computation Cost.** Another significant issue in federated learning is the increased communication and computation cost on client devices when optimizing and transmitting the weights. FedProx [Li et al., 2020] alleviates this issue via allowing training preemption and partial updates, and FedPAQ [Reisizadeh et al., 2020] allows periodic averaging and quantizing model updates. Several works have also introduced variations of pruning and dropout [Diao et al., 2021; Horvath et al., 2021; Bouacida et al., 2021] for model compression. For example, FedMask applies LTH [Frankle and Carbin, 2018] by performing one-shot pruning at the client-side and learning a local binary supermask that is quantized during communication. However, the binary supermask learned is essentially unstructured pruning with no computational advantage and limits model capacity. We thus replace the binary supermask with a sign supermask for faster convergence and employ data-agnostic pruning at the server to reduce computational load on the client.

# 7 Conclusion & Future Work

In this work, we have introduced HideNseek which applies the lottery ticket hypothesis under the federated setting by optimizing the signs of a synaptically salient subnetwork of the model. To further reduce computation load on the client, we perform one-shot pruning at initialization on the server-side using the data-agnostic approach and optimize a sign supermask that is quantized when transmitting model updates. Empirical results suggest that HideNseek demonstrates better inference accuracy than the state-of-the-art in general while considerably reducing the communication cost and training time. Nevertheless, an imminent challenge faced is that the memory cost incurred by employing straight-through-estimators is substantial. Therefore, in the future, we will explore the efficacy brought by employing a binary optimizer [Helwegen et al., 2019] that only modifies signs of weights without the need for latent parameters like the sign supermasks.

# 8 Broader Impact

In this work, we propose an algorithm in the field of federated learning which originated from the need to develop deep learning applications in the wake of recent advances in data protection regulations such as the GDPR [Viorescu et al., 2017]. Furthermore, we explore an approach to reduce communication and computation costs on battery-powered mobile devices to reduce environmental impact. While our work demonstrates energy-saving implications from a theoretical standpoint, we hope future works will further delve into system optimization geared towards energy conservation.

# References

- Davide Anguita, Alessandro Ghio, Luca Oneto, Xavier Parra Perez, and Jorge Luis Reyes Ortiz. A public domain dataset for human activity recognition using smartphones. In *Proceedings of the 21th international European symposium on artificial neural networks, computational intelligence and machine learning*, 2013.
- Yoshua Bengio, Nicholas Léonard, and Aaron Courville. Estimating or propagating gradients through stochastic neurons for conditional computation. *arXiv preprint arXiv:1308.3432*, 2013.
- Nader Bouacida, Jiahui Hou, Hui Zang, and Xin Liu. Adaptive federated dropout: Improving communication efficiency and generalization for federated learning. In *IEEE INFOCOM 2021 - IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, 2021.
- Sebastian Caldas, Sai Meher Karthik Duddu, Peter Wu, Tian Li, Jakub Konečný, H Brendan McMahan, Virginia Smith, and Ameet Talwalkar. Leaf: A benchmark for federated settings. arXiv preprint arXiv:1812.01097, 2018.
- Xiaohan Chen, Jason Zhang, and Zhangyang Wang. Peek-a-boo: What (more) is disguised in a randomly weighted neural network, and how to find it efficiently. In *International Conference on Learning Representations*, 2022.
- Matthieu Courbariaux, Itay Hubara, Daniel Soudry, Ran El-Yaniv, and Yoshua Bengio. Binarized neural networks: Training deep neural networks with weights and activations constrained to+ 1 or-1. *arXiv preprint arXiv:1602.02830*, 2016.
- Enmao Diao, Jie Ding, and Vahid Tarokh. HeteroFL: Computation and Communication Efficient Federated Learning for Heterogeneous Clients. In *International Conference on Learning Representations*, 2021.
- Alireza Fallah, Aryan Mokhtari, and Asuman Ozdaglar. Personalized federated learning with theoretical guarantees: A model-agnostic meta-learning approach. Advances in Neural Information Processing Systems, 33, 2020.
- Jonathan Frankle and Michael Carbin. The lottery ticket hypothesis: Finding sparse, trainable neural networks. *arXiv preprint arXiv:1803.03635*, 2018.
- Xuan Gong, Abhishek Sharma, Srikrishna Karanam, Ziyan Wu, Terrence Chen, David Doermann, and Arun Innanje. Ensemble attention distillation for privacy-preserving federated learning. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, 2021.
- Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Delving deep into rectifiers: Surpassing human-level performance on imagenet classification. In *Proceedings of the IEEE international conference on computer vision*, pages 1026–1034, 2015.
- Koen Helwegen, James Widdicombe, Lukas Geiger, Zechun Liu, Kwang-Ting Cheng, and Roeland Nusselder. Latent weights do not exist: Rethinking binarized neural network optimization. *Advances in neural information processing systems*, 32, 2019.
- Samuel Horvath, Stefanos Laskaridis, Mario Almeida, Ilias Leontiadis, Stylianos Venieris, and Nicholas Lane. Fjord: Fair and accurate federated learning under heterogeneous targets with ordered dropout. Advances in Neural Information Processing Systems, 34, 2021.
- Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11), 1998.
- Ang Li, Jingwei Sun, Xiao Zeng, Mi Zhang, Hai Li, and Yiran Chen. Fedmask: Joint computation and communication-efficient personalized federated learning via heterogeneous masking. In *Proceedings of the 19th ACM Conference on Embedded Networked Sensor Systems*, pages 42–55, 2021.
- Tian Li, Anit Kumar Sahu, Manzil Zaheer, Maziar Sanjabi, Ameet Talwalkar, and Virginia Smith. Federated optimization in heterogeneous networks. In *Proceedings of Machine Learning and Systems*, volume 2, pages 429–450, 2020.

- Tao Lin, Lingjing Kong, Sebastian U Stich, and Martin Jaggi. Ensemble distillation for robust model fusion in federated learning. volume 33, pages 2351–2363, 2020.
- Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, and Blaise Aguera y Arcas. Communication-Efficient Learning of Deep Networks from Decentralized Data. In *Proceedings* of the 20th International Conference on Artificial Intelligence and Statistics, 2017.
- Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. Pytorch: An imperative style, highperformance deep learning library. Advances in neural information processing systems, 32, 2019.
- Vivek Ramanujan, Mitchell Wortsman, Aniruddha Kembhavi, Ali Farhadi, and Mohammad Rastegari. What's hidden in a randomly weighted neural network? In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2020.
- Amirhossein Reisizadeh, Aryan Mokhtari, Hamed Hassani, Ali Jadbabaie, and Ramtin Pedarsani. Fedpaq: A communication-efficient federated learning method with periodic averaging and quantization. In *International Conference on Artificial Intelligence and Statistics*, pages 2021–2031. PMLR, 2020.
- Virginia Smith, Chao-Kai Chiang, Maziar Sanjabi, and Ameet S Talwalkar. Federated multi-task learning. Advances in neural information processing systems, 30, 2017.
- Hidenori Tanaka, Daniel Kunin, Daniel L Yamins, and Surya Ganguli. Pruning neural networks without any data by iteratively conserving synaptic flow. 33:6377–6389, 2020.
- Razvan Viorescu et al. 2018 reform of eu data protection rules. *European Journal of Law and Public Administration*, 4(2):27–39, 2017.
- Hattie Zhou, Janice Lan, Rosanne Liu, and Jason Yosinski. Deconstructing lottery tickets: Zeros, signs, and the supermask. *Advances in neural information processing systems*, 32, 2019.
- Zhuangdi Zhu, Junyuan Hong, and Jiayu Zhou. Data-free knowledge distillation for heterogeneous federated learning. In *International Conference on Machine Learning*, pages 12878–12889. PMLR, 2021.

# A Algorithm

Algorithm 1 summarizes the training procedure of HideNseek. Note that 1 in line 15 is a threshold function (as opposed to the identity matrix in Equation 9).

# Algorithm 1: HideNseek

1 Procedure ServerRuns: **Input:** set of K clients  $S \leftarrow \{C_1, C_2, \ldots, C_K\}$  with data  $(x_k, y_k)$  on k-th client device randomly initialize DNN with weights  $w^0$ 2 initialize the global sign mask  $s^0$  with signs of  $w^0$ 3  $w^0 \leftarrow ServerPruning(w^0, s^0)$  // one-shot pruning (1) in Figure 1 4 for each round  $t = 1, 2, \ldots, T$  do 5  $c \leftarrow \max(K \times \rho, 1)$  // select c active clients from K available 6 clients with random sampling rate  $\rho$  $S_t \leftarrow \{C_1, C_2, \dots, C_c\}$  // selected clients 7 for  $C_k \in S_t$  in parallel do 8  $| s_k^{t+1} \leftarrow ClientUpdate(C_k, s^t \odot s_k^t) // (2)$  and (4) in Figure 1 9  $s^{+1} \leftarrow aggregate(\{s^{t+1}_1, \dots, s^{t+1}_c\})$  // using Eq. (8) (5) in Figure 1) 10 11 Function ServerPruning(w, s): // No. of iterations set to recommended value following [Tanaka  $% \mathcal{T}_{\mathrm{A}}$ et al., 2020]  $\begin{array}{l} \text{for each round } e = 1, 2, \dots 100 \text{ do} \\ S_{SF,i}^{[l]} \leftarrow \| w_i^{[l]} \odot \nabla_s R_{SF,i}^{[l]} \|_2 \\ \tau \leftarrow p_r \text{ percentile score in } S_{SF} \end{array}$ 12 13 14  $m_i^{[l]} \leftarrow \mathbb{1}(S_{SF,i}^{[l]} > \tau)$  $w_i^{[l]} \leftarrow w_i^{[l]} \odot m_i^{[l]}$ 15 16 return w17 18 Function  $ClientUpdate(C_k, s_k^{t-1})$ : // ( performs (3) in Figure 1)  $\hat{s}_k^t \leftarrow \text{initialize real-valued sign mask from } s_k^{t-1}$ 19  $\mathcal{B} \leftarrow$  split local data into batches 20 for batch  $(x_b, y_b) \in \mathcal{B}$  do 21  $\hat{s}_k^t \leftarrow \hat{s}_k^t - \eta \nabla_{\hat{s}_k^t} \mathcal{L}[f(x_b; w^0 \odot \operatorname{sign}(\hat{s}_k^t)), y_b] // \eta$  is the learning rate 22  $s_k^t \leftarrow \operatorname{sign}(\hat{s}_k^t)$  // binarize the real-valued sign mask 23 return  $s_k^t$ 24

# **B** Simulating Non-IID Data

Figure 5 depicts the effect of the parameter  $\alpha$  on the label distribution among clients when employing Dirichlet sampling to partition MNIST dataset in Non-IID manner.

# C Model Configurations

The model configurations employed in this work are depicted in Table 5. For VGG9, each ConvBlock(N) is composed a convolutional layer with N channels with size 3, a BatchNorm layer followed by ReLU activation. Each MaxPool2d layer has a kernel size and stride length of 2. The number of nodes in the final fully connected layer are 62 or 10 depending on EMNIST or MNIST dataset.



Figure 5: Label distribution among 20 clients for MNIST dataset with dirichlet sampling at different  $\alpha$ .

VGG9	MLP
ConvBlock(32)	Linear(300)
MaxPool2d	ReLU
ConvBlock(64)	Liner(100)
MaxPool2d	ReLU
ConvBlock(128)	Linear(6)
ConvBlock(128)	
MaxPool2d	
ConvBlock(256)	
ConvBlock(256)	
MaxPool2d	
Flatten	
Linear(62 or 10)	

Table 5: Model configurations.