Momentum Gradient Descent Federated Learning with Local Differential Privacy

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Abstract

Nowadays, the development of information technology is growing rapidly. In the big data era, the privacy of personal information has been more pronounced. The major challenge is to find a way to guarantee that sensitive personal information is not disclosed while data is published and analyzed. Centralized differential privacy is established on the assumption of a trusted third-party data curator. However, this assumption is not always true in reality. As a new privacy preservation model, local differential privacy has relatively strong privacy guarantees. Although federated learning has relatively been a privacy-preserving approach for distributed learning, it still introduces various privacy concerns. To avoid privacy threats and reduce communication costs, in this article, we propose integrating federated learning and local differential privacy with momentum gradient descent to improve the performance of machine learning models.

Keywords: Differential Privacy, Local Differential Privacy, Federated Learning, Momentum, Internet of Things

Chapter 1 gives the introduction. Chapter 2 introduces the related works of local differential privacy and federated learning and IoT application. Chapter 3 introduces the basic knowledge of federated learning and local differential privacy. In Chapter 4, we describe the design of LDP-MGD in detail. Finally, we show experimental results in Chapter 5 and draw a conclusion in Chapter 6.
1 Introduction

Massive volumes of data are constantly being created by people, businesses, research institutions, and other entities as a result of the rapid development of big data analysis technologies and the ongoing expansion of the application fields for Internet cloud computing. They are becoming more and more interested in gathering and analysing user data, whether they are Internet behemoths or other social organisations[1]. Browsers and mobile application software, for instance, continuously gather user terminal data in order to train machine learning models and study user behaviour trends. Social service providers compile data on user lives in order to create correspondingly tailored treatment plans.[2][3].

Collecting user data is a double-edged sword. A third party’s direct collection of user information is not conducive to protecting user privacy. However, if the users information is not accurately collected, it is difficult to obtain feedback and improve the corresponding service quality, which is also not conducive to the public interest. Introducing a privacy protection mechanism in the collection phase to reduce and control the risk of privacy leakage, balance the relationship between privacy protection and data availability, and solve and improve big data analysis problems and mechanisms that do not sacrifice user privacy is of great theoretical and practical significance.

Although as early as 2006, Dwork [4] proposed a strictly provable differential privacy protection technology. However, because a third party is still needed to manage user privacy data, differential privacy has always been a definition of privacy at the level of theoretical research and has not been applied to actual products on a large scale. Therefore, the idea of local differential privacy under the crowdsourcing mode was developed in order to balance the relationship between individual privacy and big data analysis, meet the requirements of differential privacy protection, and improve the privacy and usability of the protection mechanism. Without relying on external data managers to keep personal information safe from leaks while still ensuring that data collectors can accurately infer group statistics from a macro perspective, local differential privacy can directly add noise to private data locally.

As an important branch of differential privacy research, local differential privacy is moving from theoretical research to large-scale practical industry product applications and has gradually become a popular topic in the field of differential privacy protection. Recently, local differential privacy and its combination of research in various fields have resulted in a large number of new achievements emerging.
The pervasive usage of mobile devices in contemporary society has significantly facilitated the development of integrated network ecosystems such as the Internet of Things (IoT). The incorporation of cloud computing into the Internet of Things has achieved significant popularity as a centralised computing solution that facilitates the execution of complex computer tasks or multidimensional activities. Utilizing the cloud allows devices with limited processing capability to expand their service area. Numerous businesses, such as telemedicine, mobile banking, and mobile leasing, have been profoundly impacted by this innovation. Clearly, cloud computing solutions are a kind of centralised computing, which often facilitates the configuration of client-side hardware and software. As the Internet of Things seeks to enhance the quality of life, it has garnered significant interest and appeal in recent years. Numerous intelligent home devices have grown, generating large quantities of data.

Moreover, federated learning is a novel way for protecting the confidentiality of distributed learning. Users own their own data sets, and these data sets are never transferred to the cloud server. Instead, each user learns continually based on personal data and uploads changes to the server to aid the final machine learning model.

Federated learning makes it possible for analysts to share, process, and use locally produced data without having to upload it to a central server. In other words, the information is stored locally, but its value is well-maintained.

Federated learning still poses a number of privacy concerns, however. An adversary may, for instance, undertake an assault to get photos from a face recognition system. Therefore, to accomplish federated learning training that respects privacy, local differential privacy and federated learning must be integrated.

2 Related Work

2.1 Federated Learning

An emerging effective distributed machine learning technique called federated learning makes use of remote resources to cooperatively train a machine learning model. It is often used to resolve concerns about data privacy in machine learning. FL is a distributed machine learning method where a number of users cooperate to train a model without moving the raw data to a single data aggregator[5]. FL not only ensures the security and privacy of the decentralised raw data in order for machine learning training to be carried out successfully using distributed data, but it also ensures the security
and privacy of the decentralised raw data. In FL, the training data consists of the raw data or the data created based on the raw data with security processing. FL only permits the transmission of processed data among the distributed computer resources, hence preventing the transfer of raw data. Distributed computing resources relate to end-users’ mobile devices or numerous businesses’ servers. FL answers the most pressing issues of data privacy, ownership, and localisation [6]. Thus, FL may allow numerous users to train a model while meeting privacy and data security requirements.

Compared to federated learning, conventional centralised machine learning systems aggregate the dispersed raw data created by many devices on a single server with shared data storage, which may raise grave data privacy and security problems [7]. In general, centralised techniques are connected with a variety of issues, including computing power and training time, and most crucially, security and privacy, given that the server has access to all raw data [8].

Recently, federated learning has been used extensively inside the Internet of Things. Lim et al. [9] compiled a thorough review of applications of federated learning in mobile edge networks, covering techniques, comparison, applications, and prospective future research areas. Hao et al. [10] developed a differential improved federated learning approach for artificial industry. To safeguard the privacy of gradients, they use the differential privacy method, which is centralised differential privacy. To guarantee the privacy of each client, we adopt a stronger privacy-preserving method, namely local differential privacy. Moreover, Lu et al. [11] introduced CLONE, a collaborative learning technique on the edges for connected cars that saves training time while ensuring the accuracy of prediction. In contrast to their suggested solution, our proposed framework leverages local differential privacy to safeguard the privacy of uploaded data by inserting noises. Furthermore, Fantacci et al. [12] use FL to safeguard the privacy of mobile edge computing, while Saputra et al. [13] have used FL to estimate the energy consumption for electrical vehicle networks.

### 2.2 Local Differential Privacy

LDP has been frequently used in IoT research. For instance, Xu et al. [14] used deep learning and local differential privacy strategies to secure the privacy of users in edge computing. They created the EdgeSanitizer framework as a new layer of defence against sensitive inference by using a deep learning model to minimise data and obscure the learnt features with noise. Choi et al.
investigated the applicability of LDP to ultra-low-power systems. They used resampling, thresholding, and a privacy budget management algorithm to circumvent the ULPs’ poor resolution and fixed point nature. He et al. addressed two possible privacy concerns produced by the wireless task offloading feature of location privacy and usage pattern privacy by providing a privacy-aware task offloading scheduling method based on a restricted Markov decision process. Their approach enabled a mobile device to achieve the best latency and energy consumption efficiency possible while preserving a certain degree of privacy. Terminal devices created and sent encrypted data to the edge server, which subsequently forwarded the aggregated data to the public cloud data centre. The public cloud centre recovered the aggregated plaintext data using its private key. Their protocol ensured the confidentiality of data on terminal devices and offered source authentication and data integrity. In addition, their plan might reduce communication expenses by half. To safeguard the privacy of enormous amounts of data created by IoT systems, Arachchige et al. developed an LDP method for deep learning called LATENT. The LATENT was built by inserting a randomisation layer between the convolutional module and the fully connected module in order to disturb data before it was released to machine learning services. Wu et al. locally train the GNN model in each user client using the local user-item interaction data to infer the user-item graph. To safeguard user privacy, they employ local differential privacy approaches to local gradients and add randomly chosen things as pseudo-interacted items for anonymity. Moreover, Chamikara et al. use $\alpha - CLDP$ to build a protocol for industrial settings to provide better performance while enforcing stronger privacy levels.

2.3 Differential Privacy based Federated Learning

In the training phase, DP-based FL techniques are often committed to capturing the trade-off between privacy and convergence performance. The study presented offered a FL algorithm keeping client confidentiality in mind. This method can produce excellent training performance at a given degree of privacy, particularly when a substantial number of customers are involved. The research given provides an alternate solution that employs both differential privacy and secure multiparty computing to mitigate differential attacks. However, none of the two previous efforts on DP-based FL design included privacy protection during the parameter uploading step, meaning that the clients’ private information might be captured by unseen adversaries when training results are sent to the server. Moreover, these two
papers lacked theoretical examination of the FL system, such as the tradeoffs between privacy, convergence performance, and convergence rate, and only presented empirical conclusions based on simulations. Augenstein et al. [23] propose a generative model for federated learning with variable privacy. They alter the server’s settings, and all users trust the server by default. Instead, we safeguard the privacy of sensitive users on the server. Wei et al. [24] offer a NbAFL strategy that meets Global DP in global data under a given amount of noise disturbance by adjusting the variances of Gaussian noises. Many optimisation techniques, such as [25], [26], [27] are used to improve the machine learning process in FL. According to the authors’ understanding, the majority of works on differential privacy techniques in federated learning emphasise centralised differential privacy rather than local differential privacy.

Existing FL solutions often employ gradient descent (GD) to minimise the loss function. GD is a one-step algorithm in which the next iteration is solely determined by the current gradient. It is possible to increase the convergence rate of GD by including more prior iterations. [28]. Momentum gradient descent (MGD) may thereby speed convergence by adding the last iteration, known as the momentum term. The work in [29] provided a theoretical justification for why, under the assumption of strong convexity, MGD accelerates convergence relative to GD. Further research in [30] established the prerequisites for global convergence of MGD. Yuan et al. [31] also discuss the difference between the adjacent mini-batch gradient to improve the performance further.

This work proposes a novel federated learning architecture using momentum gradient descent paired with local differential privacy (LDP-MGD) in response to the aforesaid finding. In the suggested approach, we include the momentum term into the FL local update and use it to conduct local iterations. On the basis of the MNIST and Cifar-10 datasets, we quantitatively examine and assess the performance of the suggested model. The findings of the experiment indicate that LDP-MGD converges quicker than FL and has superior performance.

3 Preliminaries

3.1 Federated Learning

The parameter server federated learning architecture uses the central server to transfer and aggregate models to train excellent global models to achieve the goal of federated learning[6]. The workflow of this architecture can be summarized as follows. First, initialize the parameter server. The parameter
server sends the initialization model to all clients participating in federated learning and selects some clients to participate in this round of algorithm iteration. The selected client uses local data to perform local model optimization processing. After the local optimization is completed, the client sends updated model parameters to the parameter server. The parameter server receives the updated model parameters calculated by each client participating in this round of training to update the public model and then repeats the above process until the general model converges.

The following is the fundamental pattern for federated learning training. The central server manages the training process by repeating the steps outlined below until learning is complete.

Step 1: Initialization. After startup, all clients download the current model and model parameters from the server.

Step 2: Local training. All active clients create model parameters or model updates by conducting a training programme against a private local dataset. They calculate training gradients and provide the server locally learned ML parameters.

Step 3: Aggregation. The client (device) sends model parameters or model changes to the server for aggregation. This stage is also an integration point for several other technologies, such as secure aggregation to enhance privacy, lossy compression of aggregation to enhance communication efficiency, and noise addition and update clipping for differential privacy.

Step 4: Parameters broadcasting. The server notifies the clients with the aggregated parameters.

Step 5: Model update. To update the global shared model, the server generates an aggregate update using the local model parameters or model updates of the clients participating in the current round.

In the application of the Internet of Things, the Internet of Things contains many sensors and devices used to collect and transmit data, such as autonomous vehicles and wearable devices. As the storage and computing capabilities of these devices increase, the demand for data has increased, and the requirements for applications have also increased. For example, the development of a safer and more reliable self-driving car may require data or models related to pedestrian behavior, data or models related to traffic signals and routes, and the latest data or models of street building maps. However, due to the privacy of data and the limited connectivity of devices, it may be difficult to aggregate these data models and build a global model. The proposal of federated learning can help break the situation of data isolation to train models, effectively adapt to the changes of these systems while maintaining user privacy, and provide technical support for
the establishment of more stable and efficient IoT applications.

3.2 Local Differential Privacy

The centralised differential privacy technology relates to two data protection frameworks: interactive and non-interactive frameworks, in which a third party gathers all user data and answers to user questions. In the interactive framework, when a data analyst submits a related query, the data collector provides appropriate privacy processing on the query result based on the query request, such as adding noise to fulfil differential privacy needs. In the non-interactive framework, the data collector releases beforehand statistical information about the data set that complies with differential privacy. After the data analyst performs a query, the response will be delivered straight from the public statistical data. In local differential privacy, there are interactive and non-interactive data protection schemes, however local differential privacy relies on untrusted third-party data collectors. Consequently, the definitions of these two protection frameworks vary from those of centralised differential privacy.

Local differential privacy is a solution to the problem of untrusted third parties collecting private data. Its primary purpose is to guarantee that the collector cannot gather or hold correct personal information, and it may also deduce statistical information about user groups. Specifically, the user employs differential privacy technology to locally scramble the original data, and then transmits the resulting noisy data to the collector. Local differential privacy secures user privacy and prevents privacy data governance concerns posed by data collectors in this manner.

During the data collecting phase, the local differential privacy model takes into account the danger of data collectors stealing or leaking user private. Each each user analyses the data in privacy before transmitting it to a third-party data collector. The data collector will next conduct statistical analysis on the acquired data in order to provide effective findings. There is a guarantee that personal private information will not be shared during statistics data analysis. The following is the formal definition of local differential privacy:

Definition 1 (Local Differential Privacy) Given n users, where each user corresponds to one record, given a algorithm A, its domain D(A) and
range $R(A)$, if for any two records $x$ and $x'$ ($x, x' \in D(A)$), algorithm $A$ obtains the same output result $x^*$ ($x^* \in R(A)$), then $A$ satisfies $(\epsilon, \delta)$-local differential privacy, where $\epsilon \geq 0$ and $0 \leq \delta \leq 1$,

$$Pr[A(x) = x^*] \leq \exp(\epsilon) Pr[A(x') = x^*] + \delta$$

From definition 1, we can see that by controlling the similarity of any two records' outputs, local differential privacy ensures algorithm $A$ satisfies $\epsilon$-local differential privacy. In a nutshell, given an output of algorithm $A$, it is almost not possible to tell which record its input is. In local differential privacy, the stage of privacy processing is shifted from the data collector to each user. Hence, it does not need the intervention of the trusted third party, and it also avoids the privacy attack that the untrusted third-party data collector may bring. Definition 1 theoretically guarantees that the algorithm satisfies $(\epsilon, \delta)$-local differential privacy, while it is realized through a disturbance mechanism.

Similar to a centralised arrangement, LDP regulates plausible deniability for any two values such that the $A$ satisfies $(\epsilon, \delta)$-LDP. Given the result of the privacy algorithm, it is almost difficult to determine the input data’s value. In a centralised context, the idea of a neighbour dataset defines the algorithm $A$ ‘s privacy. It is necessary for a reliable data collector to gather data and give analysis findings in secret. Each participant may individually manage his or her data in the Local setting; specifically, the privacy procedure is passed from the data collector to the individual participant. Consequently, LDP prevents privacy threats from an untrusted data collector.

3.2.1 Gaussian noise

In this case, rather than scaling the noise to the $\ell_1$ sensitivity $\Delta f$, we instead scale to the $\ell_2$ sensitivity:

**Definition 2 ($\ell_2$-sensitivity)** The $\ell_2$-sensitivity of a function $f : \mathbb{N}|\mathcal{X}| \rightarrow \mathbb{R}^k$ is:

$$\Delta_2(f) = \max_{x, y \in \mathcal{X}} \frac{1}{\|x-y\|_1=1} \|f(x) - f(y)\|_2$$

Assuming that local gradients have been trimmed, LDP is fulfilled by introducing a Gaussian noise component $G_i$. Consider that the variance of Gaussian noise in each dimension is proportional to $C^2$, i.e., $G_i \sim \mathcal{N}(0, C^2 \sigma_i^2 I_d)$ for some $\sigma_i^2 > 0$, where $I_d$ is the $d \times d$ identity matrix. Denote the noisy gradient as $\hat{\Delta}_i$, so the Gaussian LDP mechanism can be represented as $\hat{\Delta}_i = \Delta_i + G_i = \Delta_i + \mathcal{N}(0, C^2 \sigma_i^2 I_d)$. The noise provided for privacy is of
the same sort as other sources of noise; moreover, the sum of two Gaussians is a Gaussian, thus the impacts of the privacy mechanism on the statistical analysis may be simpler to comprehend and adjust for.

4 Proposed model

4.1 System overview

Each device uses its local data to locally descend the current model and then uses the local differential privacy mechanism to perturb the true gradient. The server collects the updated gradients and updates the model. Repeat these steps until the desired goal is met.

Step 1: The client downloads the initial model from the cloud server. Each client $i$ who participates in the federated learning mission inspection and is willing to download the initial models, which are uploaded by the admin and can be obtained on the cloud server.

Step 2: The client extracts the features on their device and use $\theta_{i-1}^t, d_i^t$ in round $t$ to calculate the gradient $\Delta L(\theta_{t-1}; x_i)$. The client can then use the collected data to start training the model.

Step 3: Before the client uploads the gradient to the server, we add noise to these calculated gradients using the local differential privacy mechanism to get perturbed gradient $A(\Delta(\theta_{t-1}; x_i))$. 

Figure 1: System Design
Step 4: Clients upload perturbed gradient to the cloud server.
Step 5: The cloud server aggregates and calculates the gradient, then update the model.

4.2 Algorithm

The local loss function of node $i$ is indicated by $L_i(\theta)$, which is defined only on $D_i$ when FL solutions are used. The learning issue is to minimise $L(\theta)$ based on the model supplied, and it may be stated as follows:

$$\theta^* \triangleq \arg \min \ L(\theta)$$  \hspace{1cm} (1)

Then we define the global loss function $L(\theta)$ on $D$ as follows, where $\theta$ denotes the model parameter:

Definition 3 (Global loss function) Given the loss function $L_i(\theta)$ of edge node $i$, we define the global loss function over all distributed datasets as follows

$$L(\theta) \triangleq \frac{\sum_{i=1}^{N} |D_i|L_i(\theta)}{|D|}$$  \hspace{1cm} (2)

The momentum gradient descent algorithm (MGD) is an enhanced version of the gradient descent algorithm (GD) that is designed to accelerate the learning process. In the GD, the update change of parameters is computed by $\eta \nabla L(\theta_{t-1})$, which is proportional exclusively to the model gradients. As seen in Figure 4, the update route of the GD oscillates because its update direction is constantly gradient descent. In the MGD, the update change of parameters consists of $\eta \nabla L(\theta_{t-1})$ and $\gamma(\theta_{t-2} - \theta_{t-1})$ which is the momentum term utilised to effectively dampen oscillations induced by the GD. The momentum term corrects the parameter update direction such that the MGD method requires less iterations to achieve the optimum point than the gradient descent approach. In Figure 3, the momentum term corrects the direction of parameter update so that the number of MGD iterations required to achieve the optimum point is fewer than that of the GD, demonstrating that the MGD’s ability to dampen oscillation results in a quicker convergence rate.
MGD adds the momentum term as an upgrade to GD, and we give its update rules as follows:

\[
d_t = \gamma d_{t-1} + \nabla L(\theta_{t-1}) \quad (3)
\]
\[
\theta_t = \theta_{t-1} - \eta d_t; \quad (4)
\]

where \(d_t\) which has the same dimension as \(\theta_t\), is the momentum term, \(\gamma\) is the momentum attenuation factor, \(\eta\) is the learning step size and \(t\) is the iteration index. Since MGD enhances the convergence rate of GD, we want to apply MGD to the local update stages of FL and believe that LDP-MGD can accelerate the convergence rate for federated networks.

Using a clipping approach, we can verify that \(|\theta_i| \leq C\), where \(\theta_i\) represents the unperturbed training parameters from the \(i\)-th client without perturbation and \(C\) is a clipping threshold for bounding \(\theta_i\).

1) Local Update: The process of local update at each client is performed by:

\[
d_i^t = \gamma d_{i}^{t-1} + \nabla L(\theta_{i}^{t-1}), \quad (5)
\]
\[
\theta_{i}^t = \theta_{i}^{t-1} - \eta d_i^{t-1} \quad (6)
\]

2) Global Aggregation: The aggregation rules are presented as follows:

\[
d_t = \frac{\sum_{i=1}^{N} |D_i| d_i^t}{|D|}, \quad (7)
\]
\[
\theta_t = \frac{\sum_{i=1}^{N} |D_i| \theta_i^t}{|D|}, \quad (8)
\]
where true gradient is perturbed by local differential privacy mechanism.

**Algorithm 1:** Local Differential Privacy based Federated Momentum Gradient Descent Algorithm

1. Server executes;
2. Server initializes the parameter as $\theta_0, d_0$;
3. for $t$ from 1 to maximal iteration number do
   4. Server sends $\theta_{t-1}, d_{t-1}$ to users in group $G_t$;
   5. for each user $i$ in Group $G_t$ do
      6. UserUpdate($i, \Delta L$);
   7. Server computes the average of the gradient of group $G_t$ and updates the parameter $\theta_t^i \leftarrow \theta_{t-1}^i, d_t^i \leftarrow d_{t-1}^i$ where
      8. $d_t^i = \gamma d_{t-1}^i + \nabla L(\theta_{t-1}^i),$
   9. $\theta_t^i = \theta_{t-1}^i - \eta d_{t-1}^i$;
   10. if $\theta_t^i$ and $\theta_{t-1}^i$ are close enough then
       11. break;
12. Clip the local parameters: $\theta_t^{(i)}(t) = \theta_t^{(i)} / \max\left(1, \frac{\|\theta_t^{(i)}\|}{C}\right)$ $t \rightarrow t + 1$
13. UserUpdate($i, \Delta L$);
14. Compute the actual gradient $\Delta L(\theta_{t-1}; x_i)$, where $x_i$ is user $i$’s data;
15. Use a privacy-compliant local differential technique $A$ to calculate the noisy gradient $A(\Delta(\theta_{t-1}; x_i));$

Algorithm 1 outlines our proposed LDP-MGD for training an effective model with a $(\epsilon, \delta)$-LDP requirement. The server broadcasts the needed privacy level parameters $(\epsilon, \delta)$ and the initiate global parameters $\theta_0, d_0$ to clients at the beginning of this algorithm. Throughout the procedure, $N$ active clients train the parameters using local databases and predetermined termination circumstances. After local training is complete, the $i$-th client will add noises to the taught parameters $\theta_t^i$, and upload the noised parameters to the server for aggregation. The server then aggregates the local parameters to update the global parameters. Based on the obtained global parameters $d_t, \theta_t$, each client will estimate the accuracy using local testing databases and initiate the next cycle of the training process. The FL process concludes when the aggregation time reaches a predetermined value $T$, at which point the algorithm provides the loss and precision.

Then we discuss the privacy preservation performance of the LDP-MGD. Compared to conventional FL, the local perturbations on each client before
to uploading to the server will make it more difficult for malicious adversaries to deduce the information at the $i$-th client based on its uploaded parameters. The LDP-MGD learning problem to determine the best model parameter.

5 Experiment

5.1 Experiment Settings

The experiment is based on the algorithm. The basic parameters of the system, such as the data sampling rate, the number of clients participating in federated learning, the batch size of model training, and the number of epochs, are tested and verified on the impact of the overall system performance and convergence speed, and the system is determined. The basic parameters can better coordinate the performance and efficiency of the system. In order to further improve the security of the system and add local differential privacy, the experiment tested the impact of privacy on the availability of data, that is, the impact on the performance of the system.

In this section, we evaluate the performance of our proposed method, LDP-MGD using multi-layer perception (MLP) on real-world datasets. We conduct the experiments by varying the momentum $m$, the privacy budget $\epsilon$ and the number of chosen clients $N$, and the number of epochs $T$.

The datasets The MNIST and Fashion MNIST are used for experiments. The MNIST dataset \[32\] includes 60,000 training image samples and 10,000 test image samples. Each sample is a 28x28 grayscale picture with handwritten digits 0 through 9. Adjust the size of the number and centre it inside the picture with a set size. MNIST is also a typical data set for testing machine learning methods. It carries the normal complexity encountered by IoT applications.

Fashion MNIST \[33\] is a dataset of article photos from Zalando, comprising of a training set of 60,000 samples and a test set of 10,000 examples. Each example consists of a 28x28 grayscale picture with a label from one of ten classes.

Each picture has a height of 28 pixels and a width of 28 pixels, for a total of 784 pixels. Each pixel is assigned a single pixel value that indicates the brightness or darkness of that pixel, with higher values suggesting a darker colour. This pixel value is an integer between 0 and 255. Both the training data set and the test data set have 785 columns.

Our model employs an MLP network with one hidden layer and 256 hidden units. ReLU units and a softmax of 10 courses are used. The learning rate for the network optimizer is set at 0.005. Then, we assess our MLP
for the multi-class classification problem using the conventional MNIST and Fashion MNIST datasets, with each client having 800 locally stored training samples.

5.2 Experimental Results

5.2.1 Performance Evaluation of Various Momentum

In Figure 3, we show the experimental results show how different values of momentum, $m$ from 0 to 1, affect the convergence curves of the loss function. The numbers of clients is $N = 30$, the global epochs $E = 20$ and the privacy budget is $\epsilon = 50$ and $\delta = 0.01$. These two figures show the change of final loss function value after 20 epochs in MNIST and Fashion MNIST datasets, respectively. Compared with traditional FL ($m = 0$), the convergence performance of LDP-MGD is improved. We observe that when $m \leq 0.9$, the value of the loss function decreases monotonically with $m$, so the convergence rate of LDP-MGD increases with $m$. However, when $m = 0.99$, the value of the loss function starts to increase. At the same time, there is a gradual deterioration of convergence performance, and it may not remain convergent. Therefore, applying momentum gradient descent can reduce the time of convergence. It will increase the convergence speed. The larger momentum leads to a shorter operating time. However, if the value of momentum is too large, it will decrease the performance of the proposed method and may cause unnecessary problems. This observation is also verified by the following results.
In Figure 4, we plot the accuracy with various momentum $m = 0, m = 0.5, m = 0.9$ and $m = 0.99$ respectively on MNIST and Fashion MNIST datasets.

Figure 4: The comparison of accuracy with various momentum $m = 0, m = 0.5, m = 0.9$ and $m = 0.99$ respectively.

In Figure 4, we plot the accuracy with various momentum $m = 0, m = 0.5, m = 0.9$ and $m = 0.99$. The numbers of clients is $N = 30$, the global epochs $E = 20$ and the privacy budget is $\epsilon = 50$ and $\delta = 0.01$. We can see from Figure 4, applying momentum leads to better results. However, though larger momentum may accelerate the process of convergence and elevate the accuracy sometimes, in some cases, it may take more time for the model to converge, eventually harming the overall accuracy or even degrading the performance of the model. Note when $m = 0.5$, the model remains a relatively high accuracy and also the stability and robustness. Therefore, we have to carefully choose the momentum that is not too large or small.
Figure 5: The comparison of value of loss function with various momentum $m = 0$, $m = 0.5$, $m = 0.9$ and $m = 0.99$ respectively on MNIST and Fashion MNIST datasets.

In Figure 5, we plot the loss function with various momentum $m = 0$, $m = 0.5$, $m = 0.9$ and $m = 0.99$. The numbers of clients is $N = 30$, the global epochs $E = 20$ and the privacy budget is $\epsilon = 50$ and $\delta = 0.01$. We can see from Figure 5, applying momentum will accelerate the convergence and improve the performance. Note that when $m = 0.99$, the value of loss function is poorer comparing to the case when $m = 0.9$. That is the same situation when momentum is too large, cause the whole model’s performance starts to degrade. Therefore, we need to carefully choose momentum $m$ in order to improve the performance but also make sure not to harm our model. We choose momentum $m = 0.5$ in following experiments since it has the overall best performance between various momentum.
5.2.2 Performance Evaluation of Various Privacy Budget

Figure 6: The comparison of accuracy with various privacy budget $\epsilon = 10, \epsilon = 50, \epsilon = 100$ and $\epsilon = 1000$ respectively on MNIST and Fashion MNIST datasets.

In Figure 6, we plot the accuracy with various privacy budget $\epsilon = 10, \epsilon = 50, \epsilon = 100$ and $\epsilon = 1000$. The numbers of clients is $N = 30$, the global epochs $E = 20$ and the momentum is $m = 0.5$ and $\delta = 0.01$. We can see from Figure 6, accuracy in LDP-MGD are increasing as we relax the privacy guarantees, that is increasing $\epsilon$. That is very intuitive since the more strict of privacy guarantee, the larger noise is added to the data, causing the accuracy decreases.
Figure 7: The comparison of value of loss function with various momentum $\epsilon = 10, \epsilon = 50, \epsilon = 100$ and $\epsilon = 1000$ respectively on MNIST and Fashion MNIST datasets

In Figure 7, we plot the loss function with various privacy budget $\epsilon = 10, \epsilon = 50, \epsilon = 100$ and $\epsilon = 1000$. The numbers of clients is $N = 30$, the global epochs $E = 20$ and the momentum is $m = 0.5$ and $\delta = 0.01$. As shown in Figure 7, loss in LDP-MGD decreased as we relax the privacy guarantees, that is increasing $\epsilon$. Larger $\epsilon$ leads to looser privacy requirement. Though it has higher accuracy and lower value of loss function when $\epsilon$ is large compared to the situation when $\epsilon$ is small, it provides less protect of personal information and privacy guarantee. Therefore, we need to choose the value of privacy budget according to our needs for different levels of privacy protection.
5.2.3 Performance Evaluation of Various Numbers of Clients

In Figure 8, we plot the accuracy with various numbers of clients $N = 10$, $N = 30$, $N = 50$ and $N = 100$ respectively on MNIST and Fashion MNIST datasets.

As shown in Figure 8, the accuracy goes up as we increase the number of clients. This is because additional clients not only contribute bigger training datasets, but also reduce the standard deviation of additive noises as a result of aggregation. Therefore, more clients lead to higher accuracy.
In Figure 9, we plot the value of loss function with various numbers of clients $N = 10, N = 30, N = 50$ and $N = 100$ respectively on MNIST and Fashion MNIST datasets. The local epochs $E = 20$ and the momentum is $m = 0.5$ and the privacy budget is $\epsilon = 50, \delta = 0.01$. As shown in Figure 9, the loss goes down as we decrease the number of clients. The results are in line with previous experiments. We come to the conclusion that more clients leads to lower value of loss.

5.2.4 Performance Evaluation of Various Global Epochs

As we can see from the above experimental results, we show the trend of accuracy increase with larger global epochs and stabilize thereafter. It also suggests that the ideal number of global epochs rises almost proportionally to $\epsilon$.

6 Conclusions

In the big data era, personal data is highly sensitive, and how to protect the privacy information from disclosure is a major challenge. Local differential privacy, which differs from centralized differential privacy breaks the assumption of trusted third-party data collectors in centralized differential privacy and conducts privacy processing on the user side. In this paper, we have proposed LDP-MGD, which performs MGD in the local update step with local differential privacy to solve the distributed machine learning problem. We integrate local differential privacy mechanisms and momentum gradient

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**Figure 9**: The comparison of value of loss function with various number of clients $N = 10, N = 30, N = 50$ and $N = 100$ respectively on MNIST and Fashion MNIST datasets.
descent with federated learning to create the LDP-MGD algorithm. Finally, based on the MNIST and Fashion MNIST datasets, our simulation results have confirmed the accelerated convergent speed of LDP-MGD compared to the traditional method. We demonstrate a tradeoff between convergence performance and layers of privacy protection. In other words, higher convergence performance results in a lower protection level (when $\epsilon$ goes up, the accuracy goes down). Therefore, our findings are useful for the design of momentum-combined FL systems with varying convergence performance and privacy level tradeoff requirements. performance and privacy levels.
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