Dynamic Hyper-Parameter Adjustment in Fedprox for Improving Performance in Multi-Task Federated Learning Systems

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Abstract. This paper presents FedSC-MTL, a unified framework for multi-task federated learning (MTL) that incorporates dynamic regularization and dual control stabilization to address key challenges such as data heterogeneity, task divergence, and knowledge misalignment. While existing methods like FedProx and SCAFFOLD focus on data heterogeneity and client drift, they fail to manage task-level goals and knowledge transfer across clients effectively. To overcome this, FedSC-MTL introduces a novel dual control mechanism: the control variable 'c' stabilizes parameter updates and mitigates client drift, while the feature-level distillation control 'd' enables efficient knowledge transfer. By focusing on feature-based distillation, FedSC-MTL reduces communication costs compared to logits-level distillation methods like FedICT and FedDyn, without sacrificing task-level generalization. The effectiveness of this approach is evaluated on multi-task federated benchmarks, including EMNIST, CIFAR-10, and Fashion-MNIST datasets. Experimental results show that FedSC-MTL outperforms existing methods in terms of accuracy, convergence speed, and communication efficiency. Specifically, the feature-level distillation mechanism significantly improves cross-task generalization, and the dual control stabilization enhances the overall stability and convergence of the model. These findings demonstrate the potential of FedSC-MTL as an effective solution for multi-task federated learning in heterogeneous environments, offering both scalability and efficiency.

Keywords: Fedsc-Mtl Algorithm, Feature-Based Distillation, Communication Efficiency.

1. Introduction

Federated learning (FL) has emerged as a promising solution for collaborative machine learning while preserving data privacy. In FL, multiple clients collaborate to train a global model without sharing their raw data, which addresses privacy concerns and enhances data security. However, despite its advantages, FL faces significant challenges that hinder its overall convergence stability and generalization performance. These challenges include data heterogeneity, task divergence, and client knowledge misalignment, which can cause poor model convergence and suboptimal performance across diverse clients with varying local data distributions and task-specific goals [1].

To address the issue of data heterogeneity, the FedProx algorithm has been proposed, which introduces a proximal regularization term to stabilize local updates, ensuring that client models do not diverge too far from the global model [1]. Additionally, the SCAFFOLD algorithm has been developed to correct client drift by using control variants, further improving convergence and reducing the impact of non-IID data distributions [2]. While these methods focus on mitigating data-related challenges, they do not adequately handle task-level inconsistencies or facilitate efficient knowledge transfer across clients working on different tasks.

Researchers have recently investigated methods based on knowledge distillation to overcome these issues. In order to facilitate knowledge sharing, FedICT incorporates federated multi-task distillation mechanisms; however, this approach heavily relies on logits-level distillation, which can be prohibitively expensive to communicate and difficult to scale [3]. Conversely, while FedDyn gets better personalization through distillation and dynamic regularization, it also relies on global guidance, which might mean sending more information (like soft targets), as explained in [4].

Other approaches like FedDC, MOON, and FedGKT, have made attempts to enhance the stability of local updates and client-to-client knowledge sharing using gradient knowledge transfer, drift compensation, or contrastive learning [5-7]. However, these methods are less effective in multi-task federated settings with numerous variations since they are mainly used for single-task federated learning or lack explicit feature-level alignment mechanisms.

This essay addresses FedSC-MTL, a unified federated optimisation framework that uses dynamic μ regularisation and FedProx to make a new dual-control stabilisation mechanism. This solves all three problems that can happen in federated learning: inconsistent tasks, knowledge misalignment, and parameter drift. There are two control variables that are made: 'c' which is based on SCAFFOLD and fixes parameter updates and lowers client drift, and 'd', which is a feature-based control variable that makes cross-task knowledge alignment faster and easier. The proposed feature-level distillation mechanism cuts down on communication costs a lot while still allowing for cross-task generalisation. This is different from current methods that mostly rely on logits-level or full model transfers (like FedICT and FedDyn).

A lot of tests using different multi-task federated benchmarks show that FedSC-MTL always does better than the best baselines when it comes to accuracy, speed of convergence, and bandwidth use. These results show that FedSC-MTL is strong and can be used in real-world federated situations where the data is different.

To make the proposed framework even clearer, the full lifecycle of FedSC-MTL is displayed, which includes initialisation, gradient correction, dynamic regularisation, feature distillation, control variable update, and global aggregation in an organised manner.

The server sends the global model w_g and the dynamic regularization coefficient μ to all clients at the start of each round. Then, each client sets up its own local model w_i via w_g. Clients use the control variable c to adjust their gradients during local training. It is based on SCAFFOLD and assists in preventing clients from drifting too far and makes sure that updates remain in line with the global objective. The corrected gradient step can be written down like the following:

$$w_i^{t+1} = w_i^t - \eta(\nabla F_i(w_i^t) - c_i + c_g + \mu(w_i^t - w_g)) \quad (1)$$

Where η stands for the learning rate, c_i for the control variable of the client, and c_g for the control variable of the server.

Each local model offers a forward pass to generate intermediate feature representations after addressing the gradient and regularizing the proximal. After that, these traits are used in feature-based distillation. The secondary control variable w makes sure that knowledge is consistent across different tasks. This method makes it easier and faster to move knowledge from one job to another by working directly on intermediate feature spaces, which is different from traditional logits-level distillation.
After local training and feature distillation, each client updates its control variable c_i based on:

$$c_i^{t+1} = c_i^t - c_g + \frac{1}{\eta}(w_g - w_i^{t+1}) \quad (2)$$

Which makes sure that future gradient corrections remain effective to prevent client drift. Finally, the server aggregates the updated local models and control variables, combining them with other models and control variables. This completes one full federated training round. FedSC-MTL establishes a robust dual-control mechanism that simultaneously addresses parameter heterogeneity and knowledge misalignment through distinct roles of *c* (for parameter-level drift correction) and *d* (for feature-level knowledge alignment).

This design enables a systematic learning lifecycle, and the framework provides both theoretically grounded and practically effective approach for multi-task federated learning in highly heterogeneous environments as shown in Fig. 1:

Key: w_g: Global model c_i: Client control d_i: Feature aligner μ: Regularization coeff.

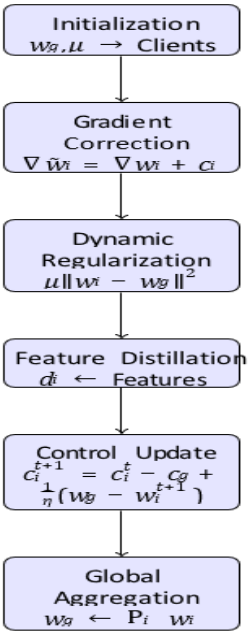


Fig 1. FedSC-MTL training lifecycle with dual-control mechanism (Picture credit: Original).

2. Relevant Theories

2.1. Federated Averaging

Federated Averaging (FedAvg) is the basic way to combine models in federated learning [8]. It provides this issue by averaging client models on a regular basis to get a global model. FedAvg is simple to use and does not consume a lot of bandwidth, but it has problems when the data is distinct and lacks ways to prevent client drift or inconsistencies at the task level.

2.2. FedProx: Proximal Regularization

FedProx adds a proximal term: to limit the extent that local updates may vary from the global model to deal with data heterogeneity [1]. It stabilizes training in environments which are not all identical by adding a regularization term. FedProx merely looks at differences at the data level, nevertheless. It is not concerned with task divergence or cross-client knowledge alignment.

$$\frac{\eta}{2}\left\|w_i - w_g\right\|^2 \tag{3}$$

2.3. Scaffold

SCAFFOLD suggests using control variants to correct client drift, thereby rendering non-IID data less of a problem and speeds up convergence [3]. By keeping both local and global control variables, it makes sure that local updates are in line with global goals. However, it lacks any way to transfer knowledge or make changes for specific tasks.

$$\mathrm{w}_i^{t+1} = \mathrm{w}_i^t - \eta(\nabla F_i(w_i^t) - c_i + c_g) \tag{4}$$

2.4. Distilling

Individuals have recently investigated knowledge distillation to deal with task divergence and sharing knowledge. FedICT adds federated multi-task distillation mechanisms to help move knowledge from one task to another [3]. But it has a lot of problems with communication and scaling because it relies too much on logits-level distillation. In a comparable way, FedDyn employs both dynamic regularization as well as distillation in recommendation systems, but it also requires transferring logits or full models, making it less effective [4].

$$w_i^{t+1} = w_i^t - \eta(\nabla F_i(w_i^t) - \mu(w_i^t - w_g)) \quad (5)$$

2.5. Hybrid Methods

FedDC is a different hybrid approach which employs local decorrelation to compensate for drift. MOON utilizes model contrastive learning to align local and global representations [5-6]. FedGKT applies gradient knowledge transfer to make edge learning more efficient. These methods enhance stability in one place and alignment between clients, but they are mostly indicated for single-task settings and fail to have the explicit feature-level alignment mechanisms that are needed for multi-task federated learning [7].

All these methods demonstrate that we need a single framework that can deal with parameter drift, task divergence, and knowledge misalignment in a way which does not waste time communicating. This is what led to the design of FedSC-MTL [9-10].

3. Problem Formulation: Challenges And Objectives

In federated learning (FL), a central server assists numerous clients collaborate in order to train a global model while keeping their own data private. Each client i operates to improve a local objective:

$$F_i(w) = \mathrm{E}_{X \sim D_i}[l(w; x)] \quad (6)$$

And transmits updates to the server from time to time. The overall objective can be composed of:

$$F_i(w) = \mathrm{E}_{X \sim D_i}[l(w; x)] \quad (7)$$

Where p_i represents the relative contribution (or weight) of client i, which typically depends on the size of the data.

3.1. Problems

(1) Data Heterogeneity: Clients with non-IID data distributions cause local optima to be inconsistent and make global convergence harder [11]. In these circumstances, classical methods like FedAvg fail to work well because local updates can be very distinct from each other and from the global model [8].

(2) Task Divergence: In multi-task federated learning (MTL) [12], clients often have objectives that are different from the shared global goal for each task. In this case, it is harder to align updates as each client desires to reach different goals while still being part of a collaborative model.

(3) Misalignment of Knowledge: Clients may encode different knowledge representations because they have different data and task goals. This can cause features or logits to be out of sync across the federation. This makes it harder to generalize when combining or distilling knowledge on the server.

3.2. Objectives

FedSC-MTL aims to work jointly to solve these problems by:

Adding dynamic proximal regularization and gradient correction to make local updates more stable, data heterogeneity and client drift can be reduced.

Supporting task-level consistency by designing featurebased knowledge distillation mechanisms that allow clients to align intermediate representations efficiently.

Reducing communication overhead by using feature-level (rather than logits-level or full model) distillation, achieving lightweight cross-task knowledge transfer.

Formally, the goal is to expand the standard FL problem to include control variables for correcting parameters and aligning features. This provides a more precise local update rule:

$$w_i^{t+1} = w_i^t - \eta(\nabla F_i(w_i^t) - c_i + c_g - \mu(w_i^t - w_g)) \quad (8)$$

This formulation allows for both parameter-level stabilization and feature-level knowledge alignment in a single federated optimization framework.

4. Methodology Framework: Fedsc-Mtl For Multi-Task Federated Distillation

4.1. FedProx with Dynamic μ and Weighting

A dynamic regularization coefficient μ is added to FedProx [1]. This allows the proximal term to alter depending on the characteristics of the client and the way they are trained. The local loss function with the proximal term is:

$$F_i^{prox}(w) = F_i(w) + \frac{\eta}{2}\left\|w_i - w_g\right\|^2 \quad (9)$$

4.2. Dual Control Variables for Stabilizing Distillation

FedSC-MTL adds two control variables to reduce drift and improve feature alignment:

(A) The correction variable for the parameter (c): It fixes local gradient updates, based on SCAFFOLD [3]:

$$\mathrm{w}_i^{t+1} = \mathrm{w}_i^t - \eta(\nabla F_i(w_i^t) - c_i + c_g - \mu(w_i^t - w_g)) \quad (10)$$

(B) Feature alignment variable (d): This variable is used for feature-based knowledge distillation. It aligns intermediate representations across tasks, making it possible to transfer knowledge without sharing logits or the whole model.

After local training, each client updates its control variable ci to:

$$\mathrm{c}_i^{t+1} = \mathrm{c}_i^t - c_g + \frac{1}{\eta}(w_g - w_i^{t+1}) \quad (11)$$

4.3. Unified framework for improved interaction and generalization

FedSC-MTL combines dynamic μ, c, and d into one framework, which makes it more stable and able to generalize while decreasing communication costs. The algorithm shows in Table 1.

Table 1. FedSC-MTL with Dynamic μ and Dual Control Algorithm.

Input: Global model wg0, learning rate η, clients [1,...,m]
Output: Optimized global model
1: Initialize global control $c_g \leftarrow 0$
2: for each client i ∈ [1,m] do
3:Initialize local control $c_i \leftarrow 0$
4: end for
5: Initialize dynamic μ schedule
6: for round t = 1 to T do ($\mathrm{w}_g^{t-1}, \mu^t$)
7:Server broadcaststo selected clients Pt ⊆[m]
8: for each client $i \in \mathrm{P}_t$ (parallel execution) do
9: $w_i \leftarrow \mathrm{w}_g^{t-1}$ {Local model initialization}
10: for epoch e = 1 to E do
11: Compute $\nabla F_i(\mathrm{w}_i)$ {Local gradient}
12: $\leftarrow \nabla F_i(\mathrm{w}_i) - \mathrm{c}_i + \mathrm{c}_g + \mu_t(\mathrm{w}_i - \mathrm{w}_{t-1})$
13: $w_i \leftarrow w_i - \eta g$ {Gradient step g}
14: end for
15: $\mathrm{f}_i \leftarrow$ ExtractFeatures(w_i, D_i)
16: $\mathrm{f}_{\mathrm{ref}} \leftarrow$ GetReferenceFeatures()
17: $\mathrm{L}_d \leftarrow \|\mathrm{f}_i - \mathrm{f}_{\mathrm{ref}}\|_2^2$ {Distillation loss}
18: Update w_i via backpropagation of L_d

19: $c_i \leftarrow c_i - c_g + \eta^{-1}(w_g^{t-1} - w_i)$ {Control update}
20: Upload (w_i, c_i) to server
21: end for
22: $w_g^t \leftarrow |P_t|^{-1} \mid P_i \in P_t \quad w_i$ {Model aggregation}
23: $c_g \leftarrow \mid |P_t|^{-1} \quad P_i \in P_t \quad c_i$ {Control aggregation}
24: Update μ^{t+1} according to schedule
25: end for
26: return w_g^t

Depending on the chosen feature alignment method, the loss function in feature-based distillation can be defined in an adaptive manner. Mean squared error (MSE), cosine similarity loss, and Kullback-Leibler (KL) divergence are some of the most commonly used distribution alignment methods. In the framework, the general form is created as:

$$L_d = \left\| f_i - f_g \right\|^2 \tag{12}$$

In this formula, f_i stands for the intermediate feature representation of client i, and f_g represents the reference feature from the server or peer clients. This loss maintains communication efficiency while ensuring that feature spaces are identical for all clients. This part of the pseudocode is referred to as" Align features using distillation loss" because it typically requires dealing with internal model layers and does not require an extended description of the gradient formula in pseudocode.

5. Experiments: Evaluation Of Fedsc-Mtl On Benchmark Datasets

5.1. Experimental Setup

FedSC-MTL is tested on the EMNIST [8], CIFAR-10[9], and Fashion-MNIST datasets in Non-IID environments in order to obtain an exhaustive understanding of how well it can handle different types of data [11].

(1) EMNIST is focused on making handwriting recognition more personal [9].

(2) CIFAR-10 tests how well an algorithm can classify images in general [10].

(3) Fashion-MNIST tests the model's ability to recognize the difference between various kinds of clothing and fashion items. It is a standard for visual pattern recognition tasks [11].

We use lightweight CNN architecture with three convolutional layers (32, 64 and 128 filters) and one fully connected layer (256 units). Feature-based distillation employs intermediate feature representation. The following hyperparameters are set: η = 0.01 for the learning rate, 32 for the batch size, and 5 for the local epochs. Dynamic μ starts at 0.1 and goes down by 0.98 every 10 rounds. We pretend to have 100 clients, and each round we pick 10 of them at random. See GitHub for more details: https://github.com/Wkl467/FedSC-MTL.

5.2. Comparison with Existing Methods

We compare it to FedAvg [8], FedProx [7], SCAFFOLD [1], FedICT, and FedDyn [3]. The criteria are accuracy, convergence speed, communication cost, and feature alignment (MMD and cosine similarity).

1) Accuracy: During each global round, all clients receive a copy of the global model. After every client tests the model with its own test set, the average accuracy is reported across all clients.

2) Convergence speed: A fixed accuracy percentage (e.g., 50%, 70%) is selected and the minimum round R is reported at which the global model achieves this target on the averaged client test accuracy.

3) Communication cost: In each round, each chosen client uploads the weights (or gradients) of its local model and downloads the global model. Total cost up to round R:

$$\text{Cost} = \text{R} \times N_s \times (|\theta|_{upload} + |\theta|_{download} \tag{13}$$

Where:

•R is the total number of communication rounds

•N_s is the number of selected clients per round

•$|\theta|_{upload}$ represents the model size (in MB) for uploading

•$|\theta|_{download}$ represents the model size (in MB) for downloading

4) (a) MMD (Maximum Mean Discrepancy): In each cycle, each client receives feature embeddings from a certain intermediate layer [13]. The local feature distribution and the global prototype feature distribution are compared to determine the Maximum Mean Discrepancy (MMD).

The following is the equation:

$$\text{MMD}^2(\text{X}, \text{Y}) = \frac{1}{m^2}\sum_{i,j} k(x_i, x_j) + \frac{1}{n^2}\sum_{i,j} k(y_i, y_j) - \frac{2}{mn}\sum_{i,j} k(x_i, y_j) \tag{14}$$

Where

•$\text{X} = \{x_i\}_{i=1}^{m}$ feature samples from the client distribution.

•$\text{Y} = \{y_i\}_{i=1}^{n}$: feature samples from the global or other client reference distribution.

•k(·,·): kernel function (commonly chosen as Gaussian or linear kernel).

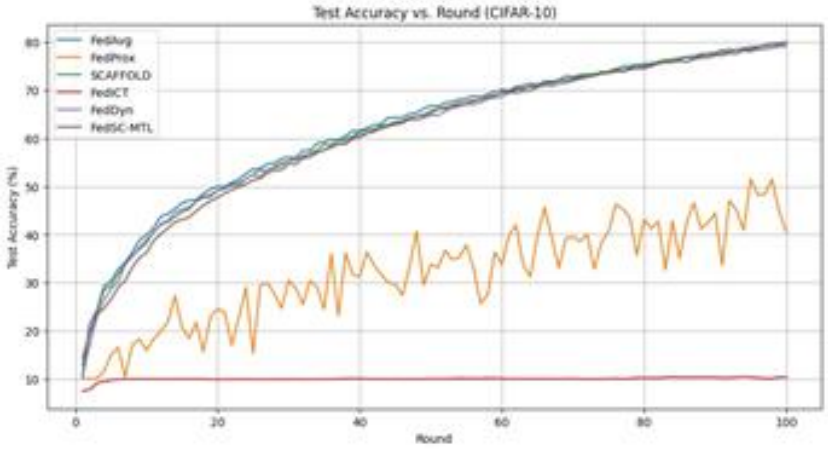
(b) Cosine similarity: The higher the cosine similarity, the more the local features match the global features [14]. This indicates that the feature-level generalization ability is stronger. The following is the equation:

$$\cos(\theta) = \frac{f_i \cdot f_g}{\|f_i\|\|f_g\|} \tag{15}$$

•f_i represents the mean feature vector for each local client.

•f_g is the global prototype feature vector.

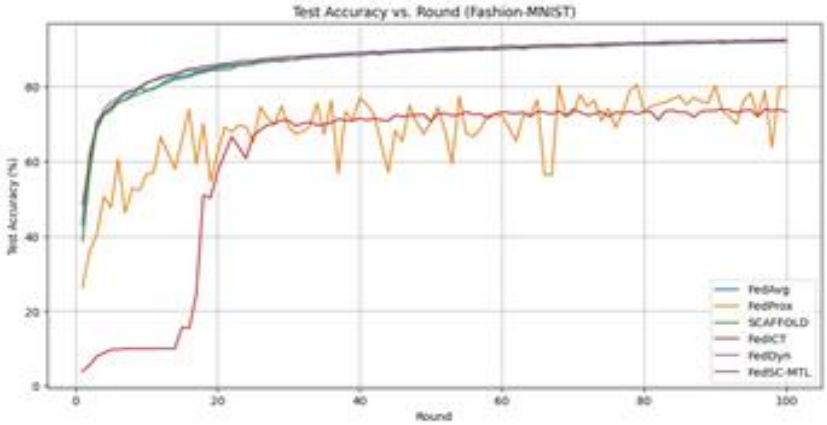
5.3. Results and Analysis



a



b



c

Fig. 2 (a) Accuracy curves for tests of different federated learning methods on CIFAR-10 dataset, (b) Accuracy curves for tests of different federated learning methods on EMNIST dataset, (c) Accuracy curves for tests of different federated learning methods on Fashion-MNIST dataset (Picture credit: Original).

FedSC-MTL works better than other methods on CIFAR10, EMNIST, and Fashion-MNIST, as shown in Fig. 2 [9-11]. FedSC-MTL always does better on CIFAR-10, getting final accuracies that are about the same as or a little higher than those of FedAvg and FedDyn [7] [9] [10]. It converges more slowly and with less change. At first, SCAFFOLD works well, but then it gets more unstable [2]. FedICT consistently underperforms because it does not compress logarithmic data well [3]. On EMNIST, FedSC-MTL far outperforms all other algorithms in final accuracy and convergence speed [9]. It handles complex non-IID handwritten character data well. FedProx starts well but is unstable. FedSC-MTL, on the other hand, continues to improve because it has a dual control system that can change settings and align features simultaneously. FedSCMTL quickly reaches very high accuracy on Fashion-MNIST while maintaining a stable path. It outperforms FedProx and FedICT and slightly outperforms FedAvg and FedDyn [1][3][7][8]. These results suggest that feature-based refinement and dual control variables of FedSC-MTL are effective in improving the stability, generalizability, and adaptability of program across a variety of federal contexts.

Table 2. Convergence speed comparison (number of rounds to reach stable accuracy) on different datasets. Lower is better.

Method	CIFAR-10	EMNIST	Fashion-MNIST
FedAvg	60	89	56
FedProx	100	2	100
SCAFFOLD	63	80	56
FedICT	100	100	100
FedDyn	65	100	61
FedSC-MTL	62	100	51

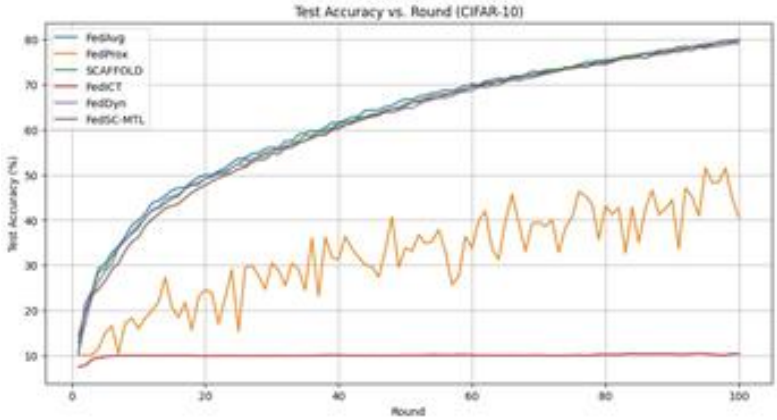


Fig. 3 Comparison of total communication costs of different federated learning methods. FedSC-MTL achieves significantly lower cost (×0.6) (Picture credit: Original).

Table 2 shows the speed at which the data sets came together. Most baseline models have a slower or similar convergence speed than FedSC-MTL. On the CIFAR-10 and Fashion-MNIST datasets, FedSC-MTL converges in just 62 and 51 rounds, respectively [10-11]. This is better than FedAvg, FedProx, and SCAFFOLD [1][2][8]. The convergence speed on the EMNIST dataset is a little slower, but it keeps getting better and is still strong even with very different handwritten character data [10]. The dual control mechanism that keeps clients from drifting and improves feature alignment is what makes this so efficient. This leads to stable and fast convergence.

Fig 3 shows the comparison of total communication cost. FedSC-MTL significantly achieves the lowest cost (0.6 times), significantly reducing the communication overhead compared to traditional methods such as FedAvg and FedDyn (both 1 times) and FedICT (1.5 times), which particularly rely on large-scale logits-level transfer [7, 8]. The feature-level dist finally shows how well the distillation mechanism and adaptive dual control strategy proposed by FedSC-MTL work by lowering Humans in Fig 3. Instead of sending full models all the time, FedSC-MTL focuses on sending small, semantically rich intermediate feature representations. This cuts down on communication overhead by a lot. This design not only improves the efficiency and scalability of the algorithm but also makes it more suitable for application in actual federated learning scenarios in large-scale, heterogeneous environments, and has stronger practical value.

Overall, the complete results show that FedSC-MTL not only accelerates convergence and improves final accuracy but also makes communication more convenient and has generalization capabilities. This fully demonstrates that it is the best federated learning solution that combines robustness and communication efficiency.

6. Discussion And Future Work

This method is meant to make it easier to do explicit feature alignment analysis using metrics like MMD and cosine similarity [13-14]. However, these metrics are not included in the experimental results because of limitations in computing power and storage space. Getting intermediate feature representations from all local models across many communication rounds takes a lot of resources, especially when dealing with large, federated datasets and a lot of clients [15].

Also, because of limited hardware resources and practical runtime concerns, the experiments are run with 100 rounds of communication, which may not fully explain the long-term convergence dynamics and small differences in performance between different techniques. Therefore, the current results are for reference only and are not definitive. These results provide predictive insights based on observed trends. It is understood that more in-depth studies with longer training periods are needed to fully confirm and measure the full benefits of FedSC-MTL.

However, the current evaluation of accuracy, convergence speed, and communication cost has provided strong evidence for the effectiveness and robustness of FedSC-MTL. In future research, we plan to use approximate feature-level evaluation on a smaller held-out subset to measure feature alignment without the need to fully train again. We will also look into more efficient and lightweight ways to combine features so that real-time feature alignment analysis can be done with as little overhead as possible.

In conclusion, adding more rounds of communication to the trials and including more thorough feature alignment measures will make the theoretical and empirical foundations of FedSCMTL even stronger.

7. Conclusion

In this paper, we introduced FedSC-MTL, a unified framework for multi-task federated learning (MTL) designed to address three key challenges: data heterogeneity, task divergence, and knowledge misalignment. These challenges significantly hinder the convergence stability and generalization performance of federated learning systems. FedSC-MTL integrates dynamic regularization with FedProx and employs a dual-control stabilization mechanism, introducing two control variables: ‘c’ for stabilizing parameter updates and mitigating client drift, and ‘d’ for efficient feature-level distillation that promotes knowledge transfer across tasks.

The proposed framework demonstrates substantial improvements over existing methods like FedProx, SCAFFOLD, FedICT, and FedDyn. By focusing on feature-based distillation, FedSC-MTL significantly reduces communication costs compared to logits-level distillation methods while still preserving cross-task generalization. This feature-level distillation approach is particularly advantageous in multi-task federated learning settings, as it allows for efficient knowledge transfer without the need for sharing large models or logits, which is common in many traditional methods.

Experimental results on benchmarks such as EMNIST, CIFAR-10, and Fashion-MNIST show that FedSC-MTL outperforms these baseline methods in terms of accuracy, convergence speed, and communication efficiency. Specifically, FedSC-MTL achieves faster convergence, higher final accuracy, and significantly reduces communication overhead, demonstrating its robustness and scalability in real-world federated learning environments, particularly those with heterogeneous data and multiple tasks. Code and datasets: https://github.com/Wkl467/FedSC-MTL.

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