Federated Domain-Specific Knowledge Transfer on Large Language Models Using Synthetic Data

Haoran Li*1, Xinyuan Zhao*2, Dadi Guo*3, Hanlin Gu§ 4
Ziqian Zeng⁵, Yuxing Han², Yangqiu Song¹, Lixin Fan⁴, Qiang Yang^{1,4}

¹The Hong Kong University of Science and Technology

²Shenzhen International Graduate School, Tsinghua University, Shenzhen 518055, China

³Center for Data Science, AAIS, Peking University ⁴WeBank, China

⁵South China University of Technology

hlibt@connect.ust.hk

Abstract

As large language models (LLMs) demonstrate unparalleled performance and generalization ability, LLMs are widely used and integrated into various applications. When it comes to sensitive domains, as commonly described in federated learning scenarios, directly using external LLMs on private data is strictly prohibited by stringent data security and privacy regulations. For local clients, the utilization of LLMs to improve the domain-specific small language models (SLMs), characterized by limited computational resources and domain-specific data, has attracted considerable research attention. By observing that LLMs can empower domain-specific SLMs, existing methods predominantly concentrate on leveraging the public data or LLMs to generate more data to transfer knowledge from LLMs to SLMs. However, due to the discrepancies between LLMs' generated data and clients' domain-specific data, these methods cannot yield substantial improvements in the domain-specific tasks. In this paper, we introduce a Federated Domainspecific Knowledge Transfer (FDKT) framework, which enables domain-specific knowledge transfer from LLMs to SLMs while preserving clients' data privacy. The core insight is to leverage LLMs to augment data based on domain-specific few-shot demonstrations, which are synthesized from private domain data using differential privacy. Such synthetic samples share similar data distribution with clients' private data and allow the server LLM to generate particular knowledge to improve clients' SLMs. The extensive experimental results demonstrate that the proposed FDKT framework consistently and greatly improves SLMs' task performance by around 5% with a privacy budget of less than 10, compared to local training on private data.

1 Introduction

Presently, the generative large language models (LLMs) are revolutionizing the existing paradigms in Natural Language Processing (NLP) tasks into a generation pipeline [50, 6, 44, 45]. With the support of extensive training data and careful fine-tuning, LLMs exhibit unparalleled capabilities in comprehension and adherence to instructions, reasoning [30, 61], planning [71, 24] and generalization to unseen tasks [8, 78, 52, 9]. Hence, both research and engineering efforts are made to build LLM-empowered autonomous systems [55, 47, 41, 53] to exploit LLMs as agents for complex tasks. However, for sensitive applications that emphasize the protection of data security and privacy, external LLMs yet cannot be directly utilized due to their inherent privacy vulnerabilities [35, 18].

[§]Corresponding author.

To protect data privacy on sensitive domains, federated learning (FL) [65, 43, 32] has been proposed to collaboratively build machine learning models without compromising on clients' data privacy. Conventionally, for FL, clients (the data holders) train their models locally and optimize their model weights according to all clients' aggregated model weights (FedAvg) [32, 31] coordinated by the server. When it comes to federated LLMs, a few recent works [59, 11, 67, 28] considered data holders with domain-specific small LMs (SLMs), i.e., as the clients and LLMs' service providers as the servers. In addition to aggregating knowledge from other clients, each client can directly learn from the server LLM via knowledge distillation to improve its local SLMs' performance.

This formulation presents an unresolved challenge for clients: their personalized private data, denoted as $D \sim \mathcal{D}$, which follows an unknown distribution \mathcal{D} , is often limited in quantity. A naive solution is to upload the private domain-specific data to the server and allow the LLMs to augment more data which follows \mathcal{D} . However, this approach is not viable due to privacy constraints. Therefore, a series of works aims to improve SLMs with the aid of LLMs without disclosing D. The knowledge distillation method [59] transfers the knowledge from LLMs to SLMs based on the public data D_p . Nevertheless, there is a discrepancy between D_p and D because D_p may not necessarily follow the distribution \mathcal{D} . This difference prevents these methods from effectively improving the SLMs. Other augmentation methods [11] mitigate this discrepancy by utilizing LLMs to generate data according to private labels. Still, the augmented data causes a misalignment with the actual distribution \mathcal{D} .

To address the aforementioned limitations, in this work, we propose a Federated Domain-specific Knowledge Transfer (FDKT) framework. FDKT implements a generative pipeline on private data D by leveraging LLMs to augment the data according to domain-specific examples. These domain-specific examples are generated from the private data distribution $\mathcal D$ with differential privacy (DP) [13] guarantee, resulting in synthetic data. Due to the introduction of DP's noise, the synthetic data may contain artifacts. To address this discrepancy, we further exploit the sever LLM for clustering-based filtering and augmentation to correct the artifacts. The contributions of our proposed FDKT are summarized below:

- FDKT enables domain-specific knowledge transfer from LLMs to SLMs. The client transmits synthetic data conditionally generated on its private data to glean required knowledge from the server-side LLM. The server can then impart the client's domain-oriented knowledge to improve each client's customized task performance.
- FDKT prioritizes privacy. To protect the privacy of clients' sensitive data, FDKT minimizes potential threats by sharing synthetic and differentially private data to the server. Simultaneously, to protect the server's intellectual property, FDKT only requires API-level access to the server LLM without exposing any unnecessary hidden information.
- FDKT is versatile across various model architectures for both the server-side LLM and client-side SLM, hence ensuring comprehensive applicability.
- Experimental results demonstrate that our proposed FDKT can consistently improve individual client SLM's accuracies significantly. Moreover, FDKT effectively facilitates multi-task learning across multiple clients for the one-to-many scenario.

2 Preliminaries

2.1 Federated Learning on LLMs

Adapting general-purpose LLMs [64, 77, 44, 58] to downstream tasks typically involves the full fine-tuning of all model parameters. However, this approach can be prohibitively expensive, especially for domain-specific tasks. To mitigate this challenge, Parameter-Efficient Fine-Tuning (PEFT) methods [22, 20, 34, 37, 23] have been proposed. PEFT methods provide a direct solution to the challenges of communication overhead and fine-tuning costs in federated learning for large language models [10, 3]. Several studies have extended PEFT methods in the context of FL for LLMs, including FedPETuning [74], Federated Adapter Tuning [7], Federated Prompt Tuning [75] and FATE-LLM [14]. Specifically, the FedPETuning methods proposed by [74] have demonstrated a significant reduction in communication overhead in the FL setting. Additionally, they found that PEFT methods can effectively reduce local model adaptation costs for clients in FL systems. These methods enable the sharing of LLMs across different tasks while maintaining only a few parameters for each task, thereby reducing the storage requirement.

In addition to PEFT methods, a few recent works [59, 11] explore the transfer learning approach to transfer server LLMs' knowledge into client SLMs. Wang *et al.*[59] propose knowledge distillation based on publicly available data while Deng *et al.*[11] expliot the server LLM to augment data via prompting with general descriptions about domain and label information. However, these works focus on the general knowledge transfer pipeline and fail to exploit rich domain characteristics inside clients' private data due to privacy considerations. In contrast, we propose to transfer the server LLM's knowledge using domain-oriented and privacy-preserving synthetic data that share a similar distribution with clients' private data.

2.2 Differential Privacy

In this section, we introduce the formal definition of Differential Privacy (DP) [13]:

Definition 2.1 (Differential Privacy). A randomized *mechanism* M with domain \mathcal{X} and range \mathcal{R} satisfies (ϵ, δ) -differential privacy if for any two neighboring datasets D_1, D_2 that only differ in one element and for any subsets of output $O \subseteq \mathcal{R}$:

$$Pr[M(D_1) \in O] \le e^{\epsilon} Pr[M(D_2) \in O] + \delta. \tag{1}$$

The definition provided by DP introduces the concept of *plausible deniability* [5] and establishes bounded privacy parameters (ϵ, δ) that serve to quantify the effectiveness of the mechanisms under scrutiny. Regarding deep learning models, DPSGD [1] injects Gaussian noise into the models' gradients so that the trained models are differentially private with respect to their training data. In addition, according to the Post-Processing Theorem [13], for any mapping g, the post-processing $g \circ M$ is also (ϵ, δ) -DP. Thus, the trained models can be safely released for public usage.

2.3 DP-tuned LMs

To enhance data privacy within LMs, a majority of research focusing on privacy-preserving LMs primarily incorporates DPSGD as the foundational component. DPSGD's usage can be summarized into four parts. The first part is DP fine-tuning that fine-tunes LMs on sensitive downstream datasets [15, 48, 54, 70, 36, 38, 25, 69]. Though DP fine-tuning can achieve comparable performance as normal fine-tuning on several NLP tasks, it is time-consuming to train on the downstream datasets. Hence, the second part proposes DP pre-training to pre-train privacy-preserving LMs so that no more fine-tuning is needed for downstream tasks. DP-BART [26] considered text rewriting under LDP [29] to rewrite the input with DP guarantee. The third part focuses on generative LLMs and proposes various DP-based prompt-tuning methods [46, 39, 12, 21] which leverage prompt tricks to protect privacy during LLM interactions. Lastly, the fourth part proposes DP-based synthetic text generation to conditionally sample text from DP-tuned generative LMs [72, 33, 42, 16]. Their experimental findings indicate that language models fine-tuned with synthetic texts can outperform LMs that have been tuned directly with DPSGD in terms of testing performance. In our approach, we suggest enabling clients to share DP-sanitized synthetic texts with the server, thereby facilitating the transfer of client-specific knowledge without compromising data privacy.

3 Federated Domain-Specific Knowledge Transfer

In this section, we present the detailed workflow of our proposed Federated Domain-specific Knowledge Transfer (FDKT). First, we formulate the problem for the 1-to-1 server-client setting based on their capabilities and incentives. Then, from the client's perspective, we show how synthetic and privacy-preserving data are generated. Next, for the server side, we introduce in-context data augmentation with careful selection mechanisms of the augmented data to generate the client's required knowledge. Finally, we extend FDKT to handle multiple clients and train multi-task SLMs across multiple sensitive domains collaboratively. Figure 1 depicts FDKT's whole workflow.

3.1 Problem Formulation

This paper takes both the client's and server's incentives into consideration. The client's goal is to improve its SLM's performance by leveraging the server LLM. From the server's perspective, the server is also reluctant to transfer excessive knowledge or reveal its LLM's hidden aspects to

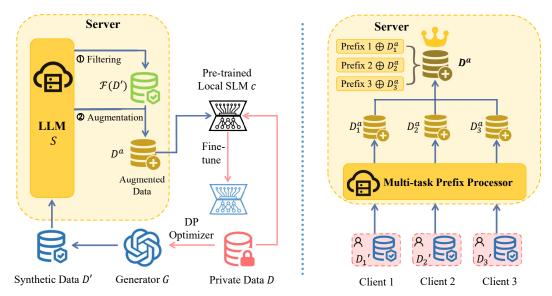


Figure 1: Overview of FDKT's selective knowledge transfer pipeline. The left subfigure illustrates the workflow of FDKT for enhancing individual client performance, while the right subpart depicts how FDKT facilitates federated training across multiple clients for multi-task learning. The yellow region is under the control of the server and the rest part belongs to the client. The rose lines involve interactions with private data D. In contrast, blue lines represent interactions that do not disclose D. In all interactions between FDKT's client and server, only synthetic data D' is exchanged to facilitate knowledge transfer. In the right subpart, the multi-task prefix processor adds task-dependent prefixes to each client's augmented data to train multi-task SLMs.

safeguard intellectual property. Without loss of generality, we start from the one-to-one configuration where there is a server with only one client and we incorporate FDKT to improve the client SLM's performance individually. We assume the client possesses a private local dataset $D=(x_i,y_i)_{i=1}^N$ where N is relatively small and has limited computational resources that can only operate a small-scale LM c in-house. Furthermore, the server owns a powerful LLM S. Since S is small, directly fine-tuning S on S cannot yield satisfactory results. The **threat model** we consider is semi-honest server S aims to infer the private data of client S.

3.2 Client-side Synthetic Data Generation

To acquire domain-specific knowledge for its own task, the client needs to share its task-dependent data with S at first for further knowledge transfer. However, directly transmitting private local data D to the server violates the client's privacy requirement and sharing existing public data cannot acquire c's desired knowledge. Inspired by recent progress on differentially private synthetic text generation [72, 33], we propose to share such synthetic data that are distributed similarly with D to the server. Specifically, we use private data D to fine-tune a pre-trained generative LM with DPSGD. After fine-tuning, we obtain a differentially private generator G. Finally, we can conditionally sample from G to acquire the domain-specific synthetic data.

During fine-tuning, for any $(x,y) \in D$, we concatenate the data pair with task-specific prompts into a coherent string $s = \text{``}\{p_1\} + \{y\} + \{p_2\} + \{x\}\text{''}$ where p_1, p_2 are the prompts and '+' denotes the textual concatenation. For review sentiment classification, given its review x and corresponding rating y, we may construct the string as $s = \text{``Rating: }\{y\}$, Review:\n $\{x\}$ '' for fine-tuning. Then, the language modeling objective is applied with teacher forcing [63] to fine-tune G based on s:

$$L_G(s; \theta_G) = -\sum_{i=1}^{u-1} \log(\Pr(w_i|w_0, w_1, ..., w_{i-1})),$$
 (2)

where $s = "w_0w_1...w_{u-1}"$ is the reformatted string from $(x,y) \in D$ and θ_G is optimized via noise-injected DP optimizers. In addition, the client has the discretion to determine its privacy budget parameters (ϵ, δ) according to its specific privacy requirements. After fine-tuning G, G's outputs are guaranteed to be (ϵ, δ) -DP with respect to the client's private data D.

To generate synthetic data, we adopt sampling-based decoding algorithms to conditionally generate synthetic sample x' given the label y. We repeatedly prompt the generator G with the concatenated string consisting of " $\{p_1\} + \{y\} + \{p_2\}$ " to generate x'. By sampling, we may obtain as many synthetic x' as we want via decoding multiple times.

After generating sufficient synthetic data, we obtain the synthetic dataset $D' = \{(x_i', y_i)\}_{i=1}^{|D'|}$. Then, D' can be safely shared to the server side with the DP guarantee. Such DP-sampled synthetic data have two advantages. First, these conditionally generated synthetic data encompass data distribution similar to that of private data. Hence, knowledge extraction on conditionally generated D' can selectively transfer the client's task-specific knowledge. Second, based on the aforementioned Post-Processing Theorem, synthetic data are sampled from DP-tuned LMs so that the same DP guarantee used for fine-tuning is satisfied.

3.3 Sever-side Knowledge Transfer

To transfer the client's required knowledge, FDKT implements a generative pipeline for data augmentation with careful data selection procedures.

3.3.1 High-quality Data Filtering Mechanism

Even though conditionally generated synthetic data have already been adopted, there are still two weaknesses. First, the quality of synthetic data often deteriorates due to the incorporation of random noise throughout the optimization process of generator G. Second, synthetic data generated from the same prompt tends to exhibit similar semantics, resulting in a significant lack of diversity. Consequently, under a similar distribution, poor-quality samples can be detrimental to data augmentation and model training. In light of the above observations, we propose a simple yet effective data filtering mechanism $\mathcal{F}(\cdot)$ to discard low-quality samples within the same distribution. Our filtering mechanism includes a clustering stage and a selection stage.

In the initial stage, we compute sentence embeddings for all sentences using pre-trained sentence transformers [51]. Subsequently, we apply K-means clustering [19] to these embeddings to group similar sentences. Based on the number of sentences, we manually select the appropriate cluster number so that all samples within the same cluster fit within the server LLM's context length.

For the selection stage, we exploit the LLM S as an evaluator [76, 17, 40] to select high-quality samples within each cluster. Specifically, among each cluster, we design a multiple-choice prompt template that presents the samples as options. We then instruct the server LLM S to select half of the samples with higher quality and filter out the remaining half. We use $\mathcal{F}(D')$ to denote the selected synthetic data after the filtering mechanism.

3.3.2 In-context Data Augmentation

Currently, LLMs are extensively employed for in-context data augmentation, and the superior quality of the augmented data has been thoroughly investigated [60, 57, 56, 62]. Therefore, we propose to randomly sample a few selected synthetic data points from $\mathcal{F}(D')$ as demonstrations and exploit the server-side LLM S to generate similar samples of better quality to further rectify errors introduced by random noise from G. To conduct in-context data augmentation, we first need to prepare the augmentation prompt I consisting of the task instruction and few-shot demonstrations sampled from the filtered synthetic data $\mathcal{F}(D')$ as described in Sec 3.3.1. Then, the augmented data can be represented as:

$$D^{a} = \{(x,y)|x \sim S(x|I), y \sim S(y|x,I)\},\tag{3}$$

where S(x|I) denotes that x is generated from S conditioned on the augmentation prompt I. By utilizing few-shot demonstrations, the server LLM S can perform in-context learning to augment new data points based on its knowledge. Such newly augmented data, D^a , not only enhance the diversity of the private dataset D while preserving a similar distribution but also maintain better data quality than synthetic data since LLM S is more capable than the generator G. Consequently, D^a can effectively improve the generalization abilities of client SLMs.

3.4 Local SLM Fine-tuning

After the server sends back its augmented dataset D^a , we can integrate augmented pairs (x,y) with private data. During training, we can directly apply language modeling objective to fine-tune the client SLM c to maximize c's conditional generation probability $\Pr(y|x)$ similar as Equation 2. During inference, for any given query x, we use greedy decoding to decode the SLM c's response.

3.5 Extending FDKT to One-to-many Scenario with Multiple Clients

In addition to the one-to-one server-client configuration for the client SLM's own improvement, in this section, we extend FDKT to support the one-to-many scenarios with diverse tasks from multiple clients. This extension enables individual clients to train multi-task SLMs to handle other clients' tasks simultaneously.

As depicted in the right subpart of Figure 1, following the one-to-one configuration, client i transfers its synthetic data D_i' to the server. Then, the server LLM S performs in-context data augmentation based on the filtered data $\mathcal{F}(D_i')$ to generate the augmented data D_i^a . To facilitate multi-task training for various clients, the server maintains a multi-task prefix processor which assigns a task-specific prefix for each D_i^a . Depending on clients' tasks, prefixes can be different across different clients and are prepended to the input x in each data pair (x,y) within D_i^a . Following this, the server aggregates all D_i^a to form the final augmented data D^a for multi-task training. In the final step, the server dispatches both D^a and all prefixes back to clients for fine-tuning local SLMs with language modeling objectives. During inference, by inserting the appropriate prefixes at the beginning of inputs, the tuned SLM can be utilized for designated tasks.

4 Experiments

To evaluate the effectiveness of the proposed FDKT, we conduct comprehensive experiments, and the details of our experiments are introduced below.

4.1 Experimental Setups

Datasets. Following prior works [72, 33], we conduct our experiments on the Yelp dataset [73] for review rating prediction. We sample our experimented data from three domains of the Yelp dataset, including *Shopping*, *Art*, and *Health*. For each review, we retain its review text and rating. Beyond review classification, we also include the AGNews [73] dataset to predict the news topic.

Data Split. In each domain of *Shopping*, *Art*, and *Health*, we filter 5,000 samples and enforce a uniform distribution across all 5 categories to establish balanced datasets. For *AGNews*, we sample 5,000 records that are distributed uniformly over 4 topic labels. We randomly select 1,000 non-overlapped data points for each subset as testing data to report evaluation results.

FDKT details. For each domain, we first use generator G to sample 20,000 synthetic samples and apply the filter \mathcal{F} to select 7,000 samples. We then augment 30,000 examples based on $\mathcal{F}(D')$. For generator G's privacy budgets, we fix $\epsilon = 8$ and $\delta = 1\text{e-}5$.

Evaluated Models. Our evaluated models include different model architectures for both local SLMs and server-side LLMs. For local models, we use DP-tuned GPT- 2_{large} [49] as our generator G to generate synthetic data and use pre-trained T5_{large} [50] as the client SLM c. We follow [50] to consider the rating prediction as a seq2seq task. For server-side LLMs S, we use Llama- 3_{8B} [2] for main experiments. In addition, we also report FDKT's performance over a wide range of opensource LLMs including Mistral_{7B} [27], Llama- 2_{7B} [58],Qwen_{7B} and Qwen_{14B} [4].

Evaluation Metrics. To evaluate SLMs' performance, we perform greedy decoding on the testing data and use regular expressions to extract the generated labels. All extraction failures are regarded as incorrect predictions. We report the *Exact Acc* that calculates the exact prediction accuracy for ground truth labels. In addition, since our Yelp reviews have 5-scale ratings, we aggregate the five rating labels into three sentiment categories: positive, neutral, and negative and report *Rough Acc* as the accuracy for these 3 labels. Specifically, ratings of 1-2 stars are classified as negative, 3 stars as neutral, and 4-5 stars as positive. Throughout our experiments, we report both accuracies in %.

Mothod	Aı	rts	Hea	alth	Shopping		AGNews
Method	Exact	Rough	Exact	Rough	Exact	Rough	Exact
Local FT	54.66 _{±4.57}	$70.22_{\pm 4.99}$	55.82 _{±1.93}	81.30 _{±0.39}	$ 50.08_{\pm 2.21} $	$70.30_{\pm 3.28}$	$73.57_{\pm 7.62}$
Syn FT	$52.57_{\pm 3.29}$	$64.73_{\pm 4.80}$	$52.28_{\pm 5.97}$	$72.76_{\pm 7.33}$	$47.82_{\pm 3.73}$	$65.72_{\pm 5.18}$	$74.45_{\pm 8.85}$
Syn FT+ \mathcal{F}	$55.72_{\pm 3.16}$	$72.68_{\pm 2.88}$	$55.72_{\pm 3.15}$	$75.96_{\pm 3.66}$	$50.86_{\pm 3.26}$	$67.98_{\pm 4.60}$	$76.95_{\pm 3.70}$
Gen KT	$60.10_{\pm 0.83}$	$79.20_{\pm 2.04}$	$54.17_{\pm 3.36}$	$82.13_{\pm 0.05}$	$53.80_{\pm 2.67}$	$74.55_{\pm 2.59}$	$86.97_{\pm 2.51}$
FDKT	$ 62.87_{\pm 2.45} $	$80.97_{\pm 1.30}$	$56.43_{\pm 1.53}$	$82.23_{\pm 0.33}$	$56.13_{\pm 0.57}$	$78.43_{\pm 0.45}$	$87.83_{\pm 1.53}$

Table 1: Evaluation results for the one-to-one scenario where there is one server and one client. Syn $FT+\mathcal{F}$ refers to fine-tuning on the filtered synthetic data. Exact and Rough denote the exact and rough accuracy, respectively. Except Local FT, for all other methods, we fine-tune client SLMs on both private data and generated data. All results are reported in %.

Training details. Unless otherwise specified, we optimize *Local FT* for 100 epochs and train SLMs of *Syn FT*, *Gen KT* and FDKT for 20 epochs to report the evaluation results. For full experimental details, please refer to Appendix A.

4.2 Baselines

We consider the following three baselines to compare our proposed FDKT:

- •Local FT: Local FT refers to the local fine-tuning baseline that directly fine-tunes the client SLM c on private data D without any additional data.
- •Syn FT: Syn FT denotes synthetic fine-tuning [72, 33] that fine-tunes c on the combination of synthetic data D' and the client's private data D.
- •Syn FT+ \mathcal{F} : Syn FT+ \mathcal{F} applies the data filtering mechanism \mathcal{F} on the synthetic data D' as mentioned in Section 3.3.1. Then, the client SLM c is fine-tuned on the combination of filtered data $\mathcal{F}(D')$ and the client's private data D.
- •Gen KT: Gen KT represents the general knowledge transfer pipeline [59, 11, 66] that leverages LLM S's knowledge on its pre-training data and performs zero-shot data augmentation by only providing necessary descriptions about private data D's tasks' and labels' information. We use D^g to denote Gen KT's augmented data. The client SLM c is fine-tuned on the combination of D^g and D.

4.3 Experimental Results

4.3.1 Evaluation on the One-to-one Scenario

We explore the effectiveness of FDKT in multiple domains in terms of improvement in individual domains' local SLMs. Within each domain, we conduct a comparative evaluation of FDKT against Local FT, Syn FT and Gen KT for both exact and rough accuracy. We generate 20,000 synthetic samples D' and retain 7,000 samples for $\mathcal{F}(D')$. Then, we exploit server LLM S to augment 30,000 samples as D^a . To ensure fair comparisons, we randomly sample from D' to set |D'|=7,000 and we also set $|D^g|=30,000$ for Gen KT. During training, we mix private data with generated data.

The evaluation results are shown in Table 1, where we train clients' SLMs over 5 random seeds and report their mean accuracies and sample standard deviation. The results imply the following findings:

- 1): FDKT consistently achieves superior performance across all evaluated domains with less variance. Both Syn FT and Gen KT under-perform Local FT occasionally for Health and Shopping domain. Instead, FDKT always outperforms Local FT and other baselines over the 4 domains, achieving the highest results in both exact and rough accuracies. For example, in the domains of Arts and Shopping, although we train the Local FT for 100 epochs to optimize its performance, FDKT outperforms Local FT by 5% and 7% in Exact Acc and Rough Acc, respectively. For AGNews, FDKT even gains 14% improvement over Local FT. The consistent improvements suggest that FDKT is capable of enhancing the task-specific performance of the client SLM c.
- 2): Synthetic data fail to improve client SLMs' task-specific performance. Our results indicate that Syn FT and Syn FT+ \mathcal{F} offer only marginal improvements over Local FT and sometimes even worsen

Mothod	FT Data	A	rts	He	alth	Shopping		AGNews
Method		Exact	Rough	Exact	Rough	Exact	Rough	Exact
Gen KT FDKT	D^g D^a	32.50 42.20	53.10 62.00	39.70 52.40	59.70 77.90	31.40 44.90	47.20 66.60	65.30 75.60

Table 2: Evaluation of the quality of data generated by Gen KT and FDKT with 30,000 augmented data. FT Data denotes the data used for fine-tuning client SLMs. All results are reported in %.

Private Data #	Augmented Data #	Exact Ac Local FT	ec (%) FDKT	Rough A Local FT	cc (%) FDKT
200	1,200	46.50	50.20	72.50	74.20
500	3,000	47.50	51.10	72.60	76.90
1,000	6,000	47.00	51.80	75.40	77.00
2,000	12,000	51.30	58.70	77.10	79.40
5,000	30,000	55.82	56.43	81.30	82.23

Table 3: Evaluation results with different numbers of private data for the Health domain.

SLMs' performance. Moreover, $Syn\ FT$ leads to unstable performance with higher variance. Such high variance is likely to be caused by the generator G's injected noise.

3): Our filtering mechanism \mathcal{F} can effectively mitigate synthetic data D''s negative impacts. Due to compromised data quality and homogeneous data distribution, $Syn\ FT$ frequently leads to the worst performance even though the SLMs are fine-tuned on D'+D. After adding the filter mechanism \mathcal{F} , $Syn\ FT+\mathcal{F}$ fine-tuned on $\mathcal{F}(D')+D$ leads to better accuracies with smaller variance. Such improvements emphasize \mathcal{F} 's effectiveness in enhancing synthetic data quality, making it a valuable component for our FDKT's pipeline.

4.3.2 Evaluation on the Quality of Generated Data

Besides studying whether FDKT is beneficial for client SLMs' performance, in this section, we compared the quality of data generated by $Gen\ KT$ and FDKT. Instead of fine-tuning the SLMs based on mixed private data and generated data, we fine-tune SLMs based only on the generated data for each method. To make a fair comparison, we set $|D^g| = |D^a| = 30,000$.

Table 2 displays client SLMs' performance fine-tuned exclusively on generated data. According to the results in Table 1 where private data is also trained, our FDKT only yields about $1\sim2\%$ accuracy improvement over *Gen KT*. However, in the absence of D, our FDKT can outperform *Gen KT* by more than 10%. This substantial improvement suggests that FDKT's augmented data more closely matches the distribution of private data.

4.3.3 Evaluation on Extreme Data Scarcity

In this section, we show our FDKT's effectiveness in tackling clients' data scarcity issues. We experiment on Yelp's Health domain with |D| = 200, 500, 1,000, 2,000 and 5,000. For each D, we set $|D^a|$ = $6 \times |D|$ and fine-tune SLMs for the same iterations mentioned in Section 4.1. For example, when |D| = 1,000, we Fine-tune *Local FT* for 500 epochs and FDKT for 100 epochs.

Table 3 depicts evaluation results on $Local\ FT$ and FDKT for various |D|. Both exact and rough accuracies verify that FDKT is effective even when the private data is extremely scarce.

4.3.4 Evaluation on the One-to-many Scenario

Besides the one-to-one configuration, we also study FDKT's effectiveness over multiple clients for multi-task learning. For simplicity, we focus on two distinct domains including Shopping and AGNews. Following the experimental settings in Section 4.1, each of them serves as a separate client engaged in different tasks. We merge both domains' 30,000 augmented data samples to obtain $|D^a|=60,000$ and use their testing data to report in-domain and out-domain results for *Local FT* and FDKT. The term "in-domain" indicates that the SLM is fine-tuned and tested on the same domain, while "out-domain" refers to testing on the SLM fine-tuned by a different domain.

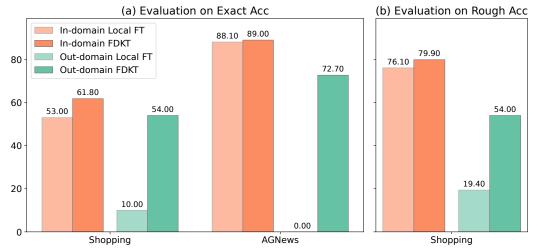


Figure 2: Evaluation of FDKT for the one-to-many scenario. In-domain Local FT denotes the SLM is fine-tuned and evaluated within the same domain and Out-domain FDKT refers to the SLM fine-tuned on one domain's private data mixed with augmented data D^a and tested on another domain.

Figure 2 depicts evaluated in-domain and out-domain results for the two clients. The huge performance gap between *Out-domain Local FT* and *Out-domain FDKT* indicates FDKT's effectiveness in improving clients' SLMs multi-task ability to handle other clients' tasks. Moreover, after comparing *In-domain Local FT* with *In-domain FDKT*, we observe that FDKT's multi-task learning also improves clients' own task performance.

4.3.5 Other Experiments

Evaluation over Multiple LLMs Beyond different domains, we also extend the evaluation of FDKT's effectiveness to encompass various server-side LLMs. To maintain consistency in our assessment, we experiment on the *Shopping* domain and set $D^a = 30,000$ to report accuracies of client SLMs fine-tuned on $D^a + D$. Our evaluation includes several open-source LLMs of different model sizes and versions, including Mistral [27], Llama-2 [58], and Qwen v1.5 [4].

The results of this evaluation are summarized in
Table 4, where we present Exact Acc and Rough

LLM Name	Exact Acc	Rough Acc
Mistral-7b	58.30	79.00
Llama2-7b-chat	55.00	74.00
Llama3-8b-instruct	56.13	78.43
Qwen-7b-Chat	54.80	76.10
Qwen-14b-Chat	53.60	76.10

Table 4: Evaluation of FDKT's performance over different LLMs within the "Shopping" domain.

Acc across these different LLMs. The results suggest that FDKT integrated with different LLMs consistently surpasses Local FT over more than 5%. Moreover, FDKT's performance is highly correlated with the server LLM S's capabilities. FDKT can also benefit from S's improved utility.

Case Studies. We perform case studies including an error analysis about FDKT's D^a and compare a few data samples from D,D', D^a and D^g . Detailed results can be found in Appendix B.

Ablation Studies. We also evaluate our FDKT's performance with varied privacy budgets and numbers of augmented data. Details can be found in Appendix C.

5 Conclusion

In this paper, we explore the federated transfer learning scenarios involving server-side LLMs and client-side SLMs. Upon identifying the limitations of differentially private synthetic data and general knowledge transfer pipelines, we present the Federated Domain-specific Knowledge Transfer (FDKT) framework. Instead of directly transferring clients' data to the server which may lead to privacy leakage, we propose to share synthetic data sampled from the differentially private generator G that distributes similarly as the private data. Then, we propose a data filtering mechanism based on server

LLM's data quality evaluation to enhance data quality and discard noisy data compromised by DP. Finally, the server can perform in-context data augmentation and send back the augmented data for selective knowledge transfer. Consequently, without any expert annotation, we realize the oriented federated knowledge transfer to improve clients' local SLMs' task-specific performance. For future work, we aim to expand our framework to incorporate more clients with diverse tasks to train a multi-task SLM collaboratively, potentially increasing the robustness and utility of clients' SLMs.

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A More on Training Details

A.1 Hyper-parameters

Synthetic data generator G. To train the generator G with private data D, we use a DP-AdamW optimizer based on the modified Opacus package [68, 36] with lr = 1e-5. We follow [38] to freeze the token embeddings during the training process. We set the virtual batch size to 64, the actual batch size equal to 4 and the epoch to 100. For DP settings, we set the target $\delta = 1\text{e-5}$, $\epsilon = 8$ and max_grad_norm = 1. To sample from G, we use sampling-based decoding with top_k = 50, top_p = 90 and temperature = 1.

Client-side SLM c. To train the encoder-decoder client SLM c, we use the AdamW optimizer with lr = 1e-4 and warm_up_step = 40. We set the virtual batch size to 64, the actual batch size equal to 4 and the epoch to 20. During inference, we use greedy decoding to decode the labels given the input texts.

Server-side LLM *S*. To perform data augmentation, we use sampling-based batch decoding. We set the batch size to 8, temperature=0.6, and top_p=0.9.

A.2 Other Details

Computational Resources. During our experiment, we use 2 Nvidia A100 80GB graphic cards to run our codes and it takes around 30 days of GPU hours to complete all experiments.

Full Prompt Templates. Table 8 lists prompt template examples with few-shot demonstrations for data augmentation and data filtering.

Dataset Licenses. We use the Yelp dataset under Apache License, Version 2.0, and the AGNews data under Custom (non-commercial) license.

Data filtering. We use the K-means algorithm for text clustering and choose all-mpnet-base-v2* as the text embedding model. We decide the number of cluster centers so that each cluster has an average of 20 text data points. Then using the prompt in the second row of Table 8, we ask the LLM to remove semantically redundant or ambiguous data, and leave behind high-quality, representative data. Finally, we use regular expressions to retrieve the text indexes selected by the LLM.

B Case Studies

B.1 Error Analysis

In this section, we use the confusion matrix to analyze the limitations of augmented data. Specifically, we use 30,000 augmented data generated by Llama- 3_{8B} for the Arts domain to finetune an SLM, then test it on 5,000 private training data and calculate the confusion matrix for 5 categories. The confusion matrix is shown in Table 5. The number at index i,j represents the count of samples where the true label is i and the predicted value is j.

From the table, we can observe that among the misclassified data, the model is most inclined to

			P	redictio	on	
		1	2	3	4	5
	1	844	147	5	1	3
Ground	2	384	574	32	7	3
Truth	3	117	507	275	86	15
Trum	4	14	115	194	467	210
	5	9	19	23	195	754

Table 5: Confusion matrix for error analysis.

categorize neutral reviews whose label is 3, as 2 (2 indicates that the review is weakly negative). Subsequently, it tends to misclassify data points that belong to rating 2 as 1. We go through the augmented data and find that the data labeled as 2 and 3 tends to contain both positive and negative opinions. Therefore, we suspect that SLMs fine-tuned solely on the augmented data are overly sensitive to the negative aspects of the reviews.

^{*}https://huggingface.co/sentence-transformers/all-mpnet-base-v2

Method	ET Data		Health		
Method	FT Data	ϵ	Exact (%)	Rough (%)	
Local FT	D	-	55.82	81.30	
FDKT	$D^a + D$	1	57.30	81.90	
FDKT	$D^a + D$	4	59.90	81.50	
FDKT	$D^a + D$	8	57.20	81.80	
FDKT	$D^a + D$	32	58.30	81.10	
FDKT	$D^a + D$	256	59.00	82.20	

Table 6: Evaluation of FDKT's performance with varied privacy budget ϵ .

Method	FT Data	Augmented Data #	Shopping		
Methou	r i Data	Augmenteu Data #	Exact (%)	Rough (%)	
Local FT	D	0	50.08	70.30	
FDKT	$D^a + D$	1,000	50.00	67.60	
FDKT	$D^a + D$	5,000	58.00	76.20	
FDKT	$D^a + D$	1,0000	59.50	79.60	
FDKT	$D^a + D$	2,0000	58.20	80.40	
FDKT	$D^a + D$	3,0000	56.13	78.43	

Table 7: Evaluation of FDKT's performance with a varied number of augmented data.

B.2 Examples of Generated Data

In this section, we conduct case studies to compare the generated data with original private data. We select two samples from the Health domain for synthetic data D' with different privacy budgets, Gen KT data D^g , FDKT's augmented data D^a and private data D to compare their data quality intuitively.

Table 9 lists a few representative cases for each data source. For synthetic data, with a small $\epsilon=1$, despite strict privacy protection, the generated reviews are contradictory and may not align with the corresponding ratings. By increasing ϵ , obvious improvements in the synthetic data quality can be observed. In terms of Gen KT's data D^g , we can easily observe that the generated negative reviews frequently contain repetitive phrases like "I'm extremely disappointed with my experience at this health business." and "I wouldn't recommend this." Such repetitions imply that reviews augmented based only on the label information suffer from a lack of diversity and result in poor quality. Instead, our FDKT's augmented data D^a not only improves the quality of synthetic data D' but also exhibits an increased data diversity due to the given in-context examples. Still, if we compare D^a with the client's private data D, it is evident that reviews in D are longer and more descriptive than reviews in D^a . Consequently, FDKT's augmented data quality is still inferior to that of the original private data. This observation on cases intuitively explains why SLMs fine-tuned on D^a underperform SLMs fine-tuned on D, even though D^a has a much larger size.

C Ablation Studies

C.1 FDKT with Different Privacy Budgets

In this section, we study privacy budgets' influence on FDKT's performance. Table 6 lists FDKT's performance with $\epsilon = 1, 4, 8, 32, 256$, where $\epsilon = 1$ indicates the strictest privacy protection and $\epsilon = 256$ fails to provide meaningful protection. The results suggest that under small ϵ , FDKT leads to similar evaluation performance. For example, when $\epsilon = 4$, FDKT's performance is even better than FDKT's results with $\epsilon = 8, 32$. Though strict privacy budgets compromise the synthetic data quality, our in-context augmented data can rectify the errors injected by DP.

C.2 FDKT with Varied Numbers of Augmented Data

Following the experimental settings mentioned in Section 4.1, we control the number of augmented data to study FDKT's performance under varied $|D^a|$ on the Shopping domain.

Tasks	Prompts
Data Augmentation	I will give you some customer feedback on {'sub_domain'} related purchases. These reviews gradually shift from negative to positive from 1 star to 5 stars. 1 star represents the worst, 2 stars are better than 1 star, but still indicate a negative review. 3 stars represent a neutral review. 4 stars indicate a positive review, but less positive than 5 stars. 5 stars represent perfection. Please generate more similar samples for each rating star as shown in the following format, bearing in mind that the generated results should not copy or resemble the examples, and should be {'sub_domain'}-related and align with the rating stars. The examples are delimited by '*******
	- <rating>: {'label_1'} stars. - <review>: {'input_1'}. \n\n ******</review></rating>
	- <rating>: {'label_2'} stars <review>: {'input_2'}. \n\n</review></rating>
Data Filtering	I will give you some customer review text samples with their rating stars, these samples are indexed starting from 0, the samples are delimited by '******* 0 <rating>: {'label_1'} stars <review>: {'input_1'}. \n\n ******* 1 <rating>: {'label_2'} stars <review>: {'input_2'}. \n\n</review></rating></review></rating>
	These reviews gradually shift from negative to positive from 1 star to 5 stars. 1 star represents the worst, 2 stars are better than 1 star, but still indicate a negative review. 3 stars represent a neutral review. 4 stars indicate a positive review, but less positive than 5 stars. 5 stars represent perfection. Please filter out text that does not belong to customer reviews or does not meet the rating stars, and leave review texts that meet the labels. You should also filter out text that is too similar to other samples and keep the most representative ones. Your answer should begin with 'The eligible samples:\n\n' and the indexes of the texts you choose, use spaces to separate the indexes and do not provide duplicate indices or indices that exceed the maximum index of samples.

Table 8: Prompt templates used for our experiments.

Table 7 illustrates that the performance of FDKT begins to improve and then diminishes as the volume of augmented data ($|D^a|$) increases. This phenomenon suggests that simply increasing the quantity of augmented data is not the optimal strategy. Therefore, clients can choose a reasonable amount of augmented data to download from the server. For instance, 10,000 units of data may be sufficient for shopping data.

Example Source	Content
Synthetic data D' with $\epsilon = 1$	(1) If you are a doctor you can do this. It is very difficult, and if you can't you should not try this. When it starts to feel like a job, you can leave. (Rating: 1 star)
	(2) The first day I got my appointment I felt so bad that my first visit was cancelled. The front desk staff is very friendly and helpful. My initial concerns were about the appointment being cancelled after the office visit. The doctor is very nice and attentive. I feel my first appointment was a waste of my time. (Rating: 1 star)
Synthetic data D' with $\epsilon = 32$	(1) Dr. David was wonderful with my children's needs. He took an interest in their mental health, and was a great help to me and my children. I can't wait for our next visit! (Rating: 5 stars)
	(2) The staff is so nice. They are always friendly and attentive and the place is clean and safe. I was worried about a little something but everything was good. (Rating: 3 stars)
Gen KT data D^g	(1) I was extremely disappointed with my experience at this health business. The staff seemed overwhelmed and unfriendly, and the equipment was outdated and in disrepair. I left feeling frustrated and unsure if I would ever return. Overall, I would not recommend this business to anyone looking for a positive and effective health experience. (Rating: 1 star)
	(2) I'm extremely disappointed with my experience at this health business. As someone who's trying to make positive lifestyle changes, I was expecting personalized guidance and support. Instead, I felt like I was just another number in a crowded room. The trainer was unprofessional and seemed put off when I asked questions. The facilities were also dirty and outdated. I wouldn't recommend this place to anyone. (Rating: 1 star)
Augmented data D^a	(1) Dr. David was wonderful with my children's needs. He took an interest in their mental health, and was a great help to me and my children. I can't wait for our next visit! (Rating: 5 stars)
	(2) I had a mixed experience at this dentist office. The hygienist was nice and did a good job cleaning my teeth, but the dentist was rushed and didn't take the time to explain what he was doing. The office was also quite noisy and chaotic. (Rating: 2 stars)
Private data D	(1) If you want to relax and enjoy some "me" time this is the place to go! If you are ok with being naked in front of other people then this is the place to go there are multiple soaking tubs with different temps. The massage is great as well as the body scrub! I loved being able to relax in the sauna and other amenities that were included while I waited for my massage. (Rating: 4 stars)
	(2) I love their food that you can get to go. The food is not properly labeled as far as how much it will cost. I guess it comes with the territory. it doesn't help that most of them do not speak any English so that is hard for somebody that doesn't speak complete Spanish. I would probably come here more if it seemed like they were customer-friendly. They are there to do a job and get it done. (Rating: 3 stars)

Table 9: Case studies of synthetic data, augmented data and original private data on the Health domain.