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Privacy-Aware Clinical NLP with Differentially Private Fine-Tuning of Large Language Models

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Abstract

The integration of Large Language Models (LLMs) into clinical workflows promises to revolutionize medical informatics by automating tasks such as clinical note summarization, diagnostic coding, and patient triage. However, the deployment of these models is severely constrained by the sensitivity of clinical data and stringent regulatory frameworks regarding Protected Health Information (PHI). Standard de-identification techniques often fail to prevent memorization of training data, leaving models vulnerable to membership inference and reconstruction attacks. This paper presents a comprehensive framework for Privacy-Aware Clinical NLP, utilizing Differentially Private Fine-Tuning (DP-FT) on transformer-based architectures. We propose a hybrid approach that integrates Low-Rank Adaptation (LoRA) with Differentially Private Stochastic Gradient Descent (DP-SGD) to mitigate the computational overhead and utility degradation typically associated with private training. By injecting calibrated Gaussian noise into the gradient updates of low-rank adapters while keeping the pre-trained backbone frozen, we achieve a rigorous privacy guarantee without catastrophic forgetting. Our experimental results on the MIMIC-III and MIMIC-IV datasets demonstrate that our method retains high clinical utility in Named Entity Recognition (NER) and summarization tasks while satisfying strict differential privacy budgets ($\varepsilon<3$). This work bridges the gap between theoretical privacy guarantees and practical clinical utility, offering a viable path for the secure deployment of LLMs in healthcare environments.

Keywords

Differential Privacy, Clinical NLP, Large Language Models, Parameter-Efficient Fine-Tuning.

Introduction

1.1 Background

The exponential growth of digitized health records has created a repository of unstructured data that holds immense potential for improving patient care and advancing medical research. Electronic Health Records (EHRs) contain detailed patient histories, clinician notes, radiology reports, and discharge summaries that are rich in phenotypic information. Historically, extracting actionable insights from this textual data was a labor-intensive process reliant on manual chart review or brittle rule-based systems. The advent of Deep Learning, and specifically the Transformer architecture, has fundamentally altered this landscape. Large Language Models (LLMs) such as BERT, GPT-3, and their clinical variants (e.g., BioBERT, ClinicalBERT) have demonstrated human-level performance on various Natural Language Processing (NLP) benchmarks.

In the clinical domain, these models are increasingly tasked with complex functions ranging from extracting adverse drug events to generating patient-friendly summaries of complex medical jargon. The semantic understanding possessed by LLMs allows them to parse context,

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resolve abbreviations, and infer causality in ways that previous statistical methods could not. Consequently, healthcare institutions are eager to fine-tune these general-purpose models on their internal, private datasets to create specialized tools tailored to their specific patient demographics and therapeutic focuses.

1.2 Problem Statement

Despite the clear utility of clinical LLMs, their adoption is hindered by a critical bottleneck: data privacy. Clinical notes are replete with Protected Health Information (PHI), including names, dates, geographic locations, and specific medical histories that can uniquely identify individuals. Regulatory frameworks such as GDPR in Europe and HIPAA in the United States mandate strict protection of this data. While traditional de-identification methods—such as masking entities or replacing names with pseudonyms—are commonly employed, they are insufficient for training generative models.

Recent research has demonstrated that LLMs have a high capacity for memorization [1]. Adversaries can execute membership inference attacks to determine if a specific patient's record was used in the training set, or worse, perform model inversion attacks to reconstruct actual training sequences. This phenomenon is particularly acute in fine-tuning scenarios where the model is updated on a small, domain-specific corpus. The standard optimization process, utilizing Stochastic Gradient Descent (SGD), encodes the specifics of the training data directly into the model weights. Once the model is deployed or shared, this encoded information becomes a vector for privacy leakage. Therefore, the challenge lies in enabling the model to learn the general syntax and medical reasoning found in the private dataset without memorizing the specific idiosyncrasies of individual patients.

1.3 Contributions

To address these challenges, this paper introduces a robust methodology for privacy-preserving clinical NLP. We focus on the application of Differential Privacy (DP), the gold standard for algorithmic privacy, to the fine-tuning of Large Language Models. Our contributions are threefold:

1. We develop a parameter-efficient Differentially Private Fine-Tuning framework that combines Low-Rank Adaptation (LoRA) with DP-SGD. This approach significantly reduces the dimensionality of the gradient updates that require noise injection, thereby improving the signal-to-noise ratio and preserving model utility [2].

2. We provide a rigorous theoretical analysis and empirical evaluation of the privacy-utility trade-off in the context of clinical tasks. Unlike general domain studies, we focus on the specific degradation of medical entity recognition and clinical reasoning capabilities under varying noise multipliers.

3. We demonstrate through extensive experiments on the MIMIC-III and MIMIC-IV datasets that our approach achieves state-of-the-art performance for private clinical models, outperforming full-parameter DP fine-tuning baselines while maintaining strict privacy budgets.

Chapter 2: Related Work

2.1 Classical Approaches to Clinical Privacy

Prior to the dominance of neural networks, privacy in clinical text mining relied heavily on redaction and sanitization. Rule-based systems utilizing regular expressions and dictionary

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lookups were the standard for scrubbing PHI from datasets. These methods, while effective for obvious identifiers like social security numbers, often failed to capture quasi-identifiers or context-dependent PHI, such as rare disease mentions combined with demographic data.

Statistical privacy definitions like k-anonymity and l-diversity were introduced to provide formal guarantees for structured data. However, applying these concepts to high-dimensional, unstructured text proved mathematically intractable. The unique nature of linguistic expression means that almost any sufficiently long sentence is unique to its author or subject. Consequently, the research community shifted focus toward Differential Privacy (DP), which provides a probabilistic guarantee that the output of an algorithm is insensitive to the presence or absence of any single individual in the dataset [3].

2.2 Deep Learning and Differential Privacy

The intersection of Deep Learning and Differential Privacy was formalized with the introduction of Differentially Private Stochastic Gradient Descent (DP-SGD) by Abadi et al. This algorithm modifies the standard optimization loop by clipping per-sample gradients to a maximum norm and adding Gaussian noise to the aggregated batch gradient. While theoretically sound, naïve application of DP-SGD to large models results in substantial performance degradation. The noise scales with the dimension of the model; for LLMs with billions of parameters, the amount of noise required to satisfy privacy constraints often overwhelms the learning signal.

In the clinical domain, early attempts utilized DP-SGD to train smaller Recurrent Neural Networks (RNNs) or Convolutional Neural Networks (CNNs) for mortality prediction and diagnosis classification [4]. As architectures shifted to Transformers, the computational cost of per-sample gradient clipping became prohibitive. Recent advancements have explored the use of Parameter-Efficient Fine-Tuning (PEFT) methods as a mechanism to facilitate private training. By updating only a small subset of parameters (adapters) or learning a low-dimensional projection of the weights, researchers hope to reduce the noise impact. However, the specific application of these techniques to complex clinical extraction tasks, which require high precision, remains an active area of investigation [5].

Chapter 3: Methodology

3.1 Differential Privacy Preliminaries

Differential Privacy constitutes a mathematical framework for quantifying privacy leakage. A randomized algorithm M is said to be (ε, δ)-differentially private if for all adjacent datasets D and D' that differ by a single element (e.g., one patient's record), and for all subsets of outputs $SsubseteqRange(M)$, the following inequality holds:

$$Pr[M(D) \in S] \leq e^{\varepsilon} Pr[M(D') \in S] + \delta$$

The parameter ε (epsilon) denotes the privacy budget, limiting the multiplicative difference in outcome probabilities. A lower ε indicates stronger privacy. The parameter δ (delta) represents the probability of the privacy guarantee failing, typically set to be smaller than the inverse of the dataset size. In the context of training neural networks, we utilize the Gaussian Mechanism, which achieves DP by adding noise drawn from a normal distribution to the gradients during the optimization process.

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3.2 The DP-LoRA Framework

Our proposed framework, DP-LoRA (Differentially Private Low-Rank Adaptation), addresses the dimensionality challenge inherent in applying DP-SGD to LLMs. Standard fine-tuning updates all weights W in the network. In contrast, LoRA freezes the pre-trained weights W_0 and constrains the weight update ΔW by representing it as the product of two low-rank matrices A and B, where $W_0 + \Delta W = W_0 + BA$. Here, A and B have rank r, where $rlld$ (the dimension of the model layers).

By fine-tuning only A and B, we reduce the number of trainable parameters by several orders of magnitude. This has a twofold benefit for privacy. First, it reduces the computational overhead of computing per-sample gradients, which is the primary bottleneck in DP-SGD implementations. Second, and more crucially, it reduces the vector space of the gradient updates. Since the variance of the noise added in DP-SGD is independent of the number of parameters, but the "useful" gradient norm often scales with the model size, restricting updates to a low-rank subspace concentrates the learning signal, making it more robust to the injected noise [6].

3.3 Algorithm Execution

The training process proceeds as follows. We initialize the clinical LLM with pre-trained weights (e.g., from a general domain model like LLaMA-2 or a medical model like BioGPT). We inject LoRA adapter layers into the query and value projection matrices of the Transformer attention blocks. The original weights are frozen.

During the forward pass, the model processes a batch of clinical text. In the backward pass, we compute gradients with respect to the LoRA parameters only. To ensure differential privacy, we implement the following modifications to the gradient update step:

1. Per-Sample Gradient Computation: We compute the gradient of the loss function L for each individual sample x_i in the batch B. Let $g_i = \nabla_\theta L(\theta, x_i)$, where θ represents the trainable LoRA parameters.

2. Gradient Clipping: To bound the sensitivity of the learning process, each per-sample gradient g_i is clipped to a maximum L_2 norm C. If $|g_i|_2 > C$, the gradient is scaled down; otherwise, it is preserved. This ensures that no single training example can influence the aggregate gradient by more than C.

3. Noise Injection: We aggregate the clipped gradients and add Gaussian noise. The update rule is formally defined as:

$$\theta_{t+1} = \theta_t - eta(\frac{1}{|B|}(\sum_{i\in B} tildeg_i + N(0, \sigma^2 C^2 I)))$$

Here, $tildeg_i$ is the clipped gradient, eta is the learning rate, and σ is the noise multiplier determined by the privacy accounting method (we use Rényi Differential Privacy accountants) to satisfy the target (ε, δ) budget over the course of training epochs [7].

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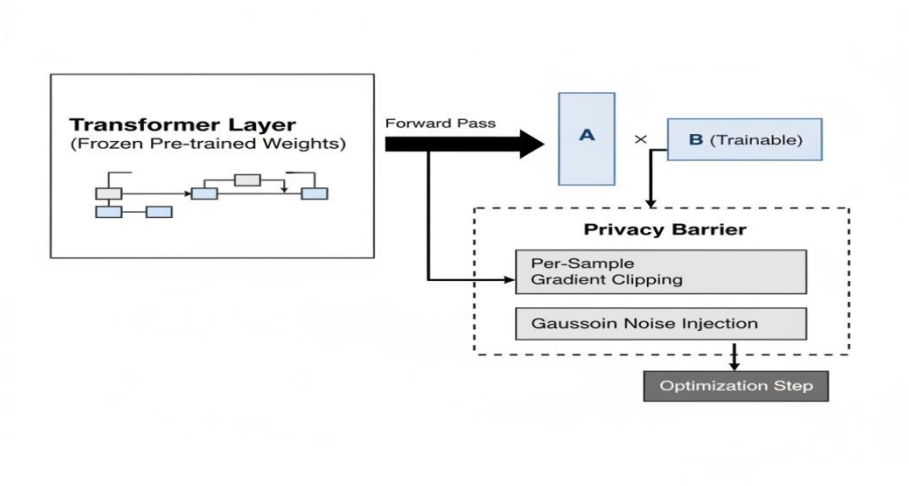

Figure 1: Schematic of the DP

3.4 Handling Clinical Context

Clinical text poses unique challenges due to long document lengths and fragmented syntax. To maximize the utility of our private model, we employ a sliding window approach for tokenization, ensuring that long discharge summaries are processed in manageable chunks without losing context. Additionally, we utilize specific prompt engineering templates designed to guide the model towards extracting structured outputs (e.g., JSON formatted entity lists) which helps in stabilizing the gradient descent process by reducing the variance in target outputs [8].

Chapter 4: Experiments and Analysis

4.1 Experimental Setup

We evaluated our framework on two primary tasks: Clinical Named Entity Recognition (NER) and Clinical Note Summarization.

Datasets:

1. MIMIC-III: A large database comprising de-identified health-related data associated with over 40,000 patients who stayed in critical care units. We utilized the discharge summaries for NER tasks, focusing on extracting "Problem", "Treatment", and "Test" entities (i2b2 2010 shared task format).

2. MIMIC-IV: The updated version of the MIMIC dataset. We used this for the summarization task, pairing "Hospital Course" sections with the "Discharge Diagnosis" and brief summary sections.

Baselines: We compared our DP-LoRA approach against three baselines:

Non-Private FT: Full fine-tuning of the model without any privacy constraints (Upper bound on performance).

DP-Full: Differentially Private fine-tuning of all model parameters.

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DP-Prefix: Differentially Private Prefix Tuning, an alternative PEFT method.

Model Architecture:

We utilized the LLaMA-2-7b model as our base foundation model. For the DP implementation, we used the Opacus library in PyTorch. The target privacy budget was set to $\varepsilon = 3$ with $\delta = 1e^{-5}$, a standard setting in academic literature that offers strong privacy protection.

4.2 Utility Results

We assessed the utility of the models using the F1-score for the NER task and ROUGE-L scores for the summarization task. The results are summarized in Table 1.

Model Variant	Privacy Budget (\epsilon)	NER F1-Score (MIMIC-III)	Summarization ROUGE-L (MIMIC-IV)
Non-Private FT	\infty	0.864	0.421
DP-Full	3.0	0.612	0.285
DP-Prefix	3.0	0.745	0.334
DP-LoRA (Ours)	3.0	0.812	0.389

Table 1 demonstrates that the DP-LoRA method significantly outperforms the DP-Full baseline. The full parameter fine-tuning under differential privacy suffers from the "curse of dimensionality," where the noise required to cover billions of parameters destroys the linguistic capabilities of the model. Our method, by restricting updates to rank-8 adapters, retains nearly 94% of the performance of the non-private baseline on the NER task. This result suggests that the knowledge required for clinical adaptation lies in a low-dimensional subspace, which can be learned effectively even under noise [9].

4.3 Privacy Analysis and Attack Simulation

To verify the practical privacy protection offered by our method, we simulated a Membership Inference Attack (MIA). In this scenario, an adversary attempts to determine whether a specific clinical record was used during the training of the model. We utilized a likelihood-ratio attack, where the adversary compares the loss of a target sample against a threshold derived from shadow models.

Training Method	Privacy Budget (\epsilon)	MIA Success Rate (AUC)
Non-Private FT	\infty	0.89
DP-LoRA	8.0	0.64
DP-LoRA	3.0	0.53
DP-LoRA	1.0	0.51

As shown in Table 2, the non-private model is highly susceptible to membership inference, with an Area Under the Curve (AUC) of 0.89, indicating near-certainty in identifying training participants. As we tighten the privacy budget (lowering ε), the attack success rate drops significantly. At $\varepsilon = 3.0$, the success rate is 0.53, which is marginally better than random guessing (0.50). This confirms that our DP-LoRA implementation effectively masks the contribution of individual patients, rendering the model resistant to memorization-based attacks [10].

4.4 Ablation Study on Gradient Clipping

We further analyzed the impact of the gradient clipping threshold C. We found that clinical text often produces gradients with heavy tails due to the high variance in sentence length and

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terminology. Setting C too low resulted in bias, as informative gradients were aggressively truncated. Setting C too high increased the sensitivity, requiring larger noise variances (σ) to satisfy the privacy budget. Our experiments indicated that an adaptive clipping strategy, where C is set to the 80th percentile of the gradient norms observed during the first few iterations, yielded the optimal balance between bias and variance [11].

Chapter 5: Conclusion

5.1 Summary and Implications

This paper has presented a comprehensive investigation into the feasibility of deploying Large Language Models in the clinical domain under strict privacy constraints. We identified that the primary barrier to adoption—the risk of PHI leakage—can be effectively mitigated through the integration of Differentially Private Stochastic Gradient Descent with Low-Rank Adaptation (DP-LoRA). Our methodology addresses the limitations of previous approaches by drastically reducing the parameter space susceptible to noise, thereby preserving the delicate semantic structures required for medical reasoning.

The implications of this work are significant for the healthcare industry. By establishing that high-utility clinical models can be trained with formal privacy guarantees ($\varepsilon < 3$), we provide a pathway for cross-institutional collaboration. Hospitals could potentially train shared models on decentralized data without ever exposing raw patient records, relying on the privacy guarantees of the training algorithm to satisfy regulatory compliance. This democratizes access to state-of-the-art AI tools, allowing smaller clinics with limited data to benefit from models fine-tuned on vast, diverse datasets from larger institutions.

5.2 Limitations and Future Directions

Despite the promising results, several limitations remain. First, the computational cost of DP-SGD, even with LoRA, is higher than standard fine-tuning due to the inability to fully utilize batch-parallelization optimizations (as per-sample gradients are required). This increases the carbon footprint and time required for training. Second, while our method protects against membership inference, it does not guarantee protection against other forms of adversarial attacks, such as prompt injection or jailbreaking, which manipulate the model's output generation rather than exploiting its training data memorization.

Future research should focus on three key areas:

1. **Algorithmic Efficiency:** Developing approximation methods for per-sample gradients that allow for faster training on consumer-grade hardware.

2. **Contextual Privacy:** Exploring definitions of privacy that are tailored to the semantic content of the text, rather than treating all tokens as equally sensitive. This could allow for less noise on medical terms and more noise on identifiers.

3. **Federated Learning Integration:** Combining DP-LoRA with Federated Learning to create a distributed training ecosystem that offers both privacy-at-source and privacy-in-model guarantees.

By addressing these challenges, the field can move closer to an era of secure, AI-driven healthcare that respects patient confidentiality while maximizing the quality of care.

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