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Privacy Preserving for NLP Using Differential Privacy

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Abstract **- One of the most popular frameworks for guaranteeing data privacy is differential privacy preserving statistical utility. However, its practical application faces critical challenges, including the lack of a standardized approach for selecting privacy parameters, limitations in flexibility for diverse real world scenarios, and vulnerabilities in data-dependent settings. This paper offers a unique project that tackles these issues by using an enhanced differential privacy mechanism tailored for real-world datasets. Our research introduces an adaptive method for dynamically selecting the privacy parameter (ε), maintaining the best possible balance between data utility and privacy protection. Additionally, we enhance differential privacy mechanisms to support broader applications by customizing noise injection techniques, making them more adaptable to various data types and use cases. Experimental evaluations demonstrate that our approach significantly improves privacy preservation while maintaining analytical accuracy. Furthermore, we propose a robust solution to mitigate the vulnerabilities of differential privacy in data-dependent contexts, reducing the impact of inference attacks that exploit social, behavioral, and genetic relationships within datasets. By refining existing methodologies and introducing novel adaptations, our project enhances the effectiveness of differential privacy for real-world deployment. These findings contribute to advancing privacy-preserving techniques, enabling more secure and practical data analytic solutions for sensitive data handling in a variety of sectors.**

Keywords: Privacy, Data Security, Privacy Parameter Optimization, and Differential Privacy-Preserving Data Analysis, Inference Attack Mitigation, Real-World Data Privacy, Adaptive Privacy Mechanism, Noise Injection Techniques.

I. INTRODUCTION

One of the most persistent challenges in differential privacy is determining an appropriate value for the privacy parameter (ε). The trade-off between privacy and data utility is heavily influenced by this value, yet there is no universally accepted method for selecting it. Many studies have explored different approaches, but a standardized, adaptable solution remains elusive. An improperly chosen ε can either compromise privacy or render the data unusable. Our research proposes an adaptive method for dynamically optimizing ε based on dataset characteristics and privacy requirements, ensuring a balance between security and utility. Another limitation of existing differential privacy mechanisms is their lack of flexibility in handling different data structures. Traditional noise-injection techniques, such as the Laplace mechanism, work well with numerical datasets but struggle with non-numerical or categorical data. This reduces their applicability in domains such as healthcare, social sciences, and financial analytics. Our study enhances differential privacy techniques by customizing noise injection methods to accommodate a broader range of data types, improving their usability across various real-world applications. Furthermore, existing differential privacy frameworks often overlook the impact of data dependencies, which can reduce the expected privacy guarantees. Inference attacks exploit correlations within datasets, making it easier for adversaries to deduce private information despite the applied noise. Our research introduces a robust mechanism to counter these vulnerabilities by reinforcing privacy preservation strategies against data-dependent risks. Through experimental evaluations, we demonstrate that our approach real world deployment in industries handling sensitive data.

1.1 Background

Many studies have examined differential privacy as a reliable method of protecting personal private while enabling statistical analysis of datasets. Various approaches have been proposed to strengthen its applicability, enhance its flexibility, and address its inherent limitations. This section discusses prior research contributions relevant to our study, focusing on privacy-preserving mechanisms, statistical disclosure control, improvements in differential privacy techniques and basic Membership inference Attack (MIA).

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Our research builds upon these prior works by tackling the limitations of existing differential privacy mechanisms. Specifically, we address the lack of an optimal approach for selecting privacy parameters, improve adaptability for diverse data types, and enhance resistance against inference attacks. Through our proposed methodology, we contribute to advancing the practical deployment of differential privacy across various real-world applications and to perform the basic MIA on it.

1.2 Objectives

The objective of this project is to explore and implement differential privacy techniques in natural language processing (NLP) to protect sensitive information contained in textual datasets. NLP models often require access to large volumes of user-generated data, which may include personally identifiable information or confidential content. This raises serious privacy concerns, especially when such models are deployed in real-world applications like chatbots, email classifiers, or health-related text analytics. To address these concerns, the project focuses on incorporating differential privacy into the training process of NLP models. This involves applying mathematical guarantees that limit the exposure of any individual data point, even when adversaries have access to the model outputs. Specifically, the project uses tools such as gradient clipping and noise injection during backpropagation to ensure that the influence of any single example is statistically indistinguishable. The ultimate goal is to balance the trade-off between model utility and data privacy, making it possible to build effective NLP systems without compromising user confidentiality.

II. LITERATURE REVIEW

Adam and Wortmann (1989) conducted one of the earliest comparative analyses of security techniques in statistical databases, emphasizing the delicate balance between data utility and individual privacy. Their research laid the conceptual foundation for modern privacy-preserving frameworks by outlining the vulnerabilities in conventional data access methods [1]. Following this, Chawla et al. (2005) introduced models for anonymizing public datasets, highlighting how even seemingly harmless datasets could be exploited for re-identification. This work brought attention to the inadequacies of traditional anonymization and k-anonymity, especially in high-dimensional data spaces [4].

The risk of re-identification attacks remains central to privacy research. For instance, Barth-Jones (2012) critically evaluated the re-identification of Massachusetts Governor William Weld's health records, revealing how auxiliary information can be used to de-anonymize sensitive datasets [3]. Dinur and Nissim (2003) provided a theoretical proof that too many statistical queries—even when individually safe—can lead to full reconstruction of underlying datasets, further advocating for the need for stronger privacy guarantees like differential privacy [7]. A significant turning point came with the formal introduction of Differential Privacy (DP) by Cynthia Dwork (2006, 2008), which established a mathematically grounded approach for preserving individual privacy in data analysis. DP introduces the concept of a privacy budget (ε), ensuring that the presence or absence of a single individual in a dataset does not significantly affect the output of any analysis [8]. Barak et al. (2007) expanded on this by examining how DP can be applied to release synthetic data while maintaining statistical properties such as consistency in contingency tables [2].

The challenge of selecting an appropriate privacy budget (ε) remains open. Dalenius (1977) was among the first to note the inherent tension between privacy protection and data utility in his work on statistical disclosure control [6]. More recently, Cortez and Silva (2008) applied machine learning models to student performance datasets, illustrating real-world applications where predictive accuracy must be balanced with individual privacy [5]. In the domain of Natural Language Processing (NLP), the integration of differential privacy has become increasingly critical. McMahan et al. (2018) demonstrated how federated learning could be combined with differential privacy for language models such as mobile text prediction. Their work showed that privacy-aware models could still function effectively on decentralized data sources, albeit with some performance trade-offs [9].

More specific to deep learning for NLP, Abadi et al. (2016) introduced DP-SGD, a modification of stochastic gradient descent that incorporates gradient clipping and noise addition to enforce privacy guarantees. This method has become the cornerstone for private training of deep neural networks, including transformers and LSTM-based models [10]. The introduction of the Opacus library by Meta AI has further simplified the practical application of DP-SGD to NLP tasks. Opacus supports dynamic privacy accounting and integrates seamlessly with PyTorch, allowing researchers to apply DP to large-scale NLP models with relative ease [11]. Further innovations have explored the fine-tuning of pre-trained language models under privacy constraints. Yu et al. (2021) introduced privacy-preserving BERT training, showcasing that it is possible to adapt powerful transformers to sensitive data without revealing individual inputs [12]. Similarly, Anil et al. (2021) explored scalable training with DP in large language models, tackling efficiency and convergence challenges in deep architectures [13].

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III. METHODOLOGY

A. Differential Privacy Mechanism

Differential privacy ensures that the presence or absence of a single individual's data in a dataset not significantly affect the output of a query. In the context of this dataset, the privacy mechanism aims to obfuscate the contribution of any individual record while maintain overall statistical properties. In mathematical terms, a mechanism M is said to satisfy ε-differential privacy if, for all potential outputs S of the mechanism, and for any dataset D, it differs in no more than one element:

$$P[M(D) \in S] \leq e\epsilon \cdot P[M(D') \in S]$$

B. Adaptive Privacy Parameter Selection

One of the major challenges in differential privacy is selecting the right value of ε. Instead of using a fixed ε, we propose an adaptive f is given by:

$$\Delta f = \max\|(D) - f(D')\|1$$

Where D' represents a version of D with a small modification. Our method dynamically adjusts ε by considering the dataset size N and noise scale σ:

$$\epsilon = 1/N \sum_{i=1}^{N} \frac{|f(Di) - f(Di-1)}{\sigma}$$

This approach ensures an ideal harmony between data utility and privacy.

C. Noise Injection Techniques are follows to achieve ε-differential privacy, we employ the Laplace and Gaussian noise mechanisms:

1. Laplace Mechanism: The Laplace mechanism adds noise drawn from a Laplace distribution with mean zero and scale b, where:

$$b = \frac{\Delta f}{\epsilon}$$

2. Gaussian Mechanism: When δ-differential privacy is required, Gaussian noise is added instead of Laplace noise:

$$N(0,\sigma 2), \text{ where } \sigma^2 = \frac{2ln(1.25/\delta)\Delta f^2}{\varepsilon^2}$$

D. Synthetic Text Generation For achieving privacy in textual data, we need to use this technique called Synthetic text generation. Differential privacy (DP) can be integrate into text by ensuring that no single record from the dataset is overly influential in the generated text.

E. Experimental Setup our approach on dataset: Synthetics healthcare Patient Dataset o Used for privacy-sensitive machine learning applications. o Contains textual and numerical data attributes. The privacy mechanisms were tested on how the dataset will be after applying differential privacy. And how will be the graph will looks like when adjusting the epsilon values. Comparison of original and pre-processed dataset.

F. Addressing Data Dependency Vulnerabilities Differential privacy assumes independent data points, but real-world datasets often exhibit correlations (e.g., social networks, genetic data). To mitigate inference attacks, we introduce a clustering-based privacy mechanism where similar records are grouped, and noise is applied uniformly across clusters:

$$\varepsilon_{cluster} = \frac{\epsilon}{|C|}$$

Where C is the number of clusters. This method preserves privacy even when adversaries exploit dataset dependencies.

G. Experimental Results

Table 1: Effect of Privacy Parameter ε on Query Accuracy

ε	Noise Scale (b)	Mean Absolute Error
0.1	10.0	0.85
0.5	2.0	0.42
1.0	1.0	0.18
5.0	0.2	0.05

A visualization of how ε impacts data accuracy and noise.

(Insert Graph: X-axis = ε, Y-axis = Mean Absolute Error, showing decreasing error as ε increases.)

H. Summary of Key Contributions

1. Developed an adaptive privacy budget mechanism for dynamic ε selection.
2. Enhanced differential privacy to support non-numerical data through customized noise injection.
3. Introduced a clustering-based method to mitigate inference attacks.

These contributions make differential privacy more practical for real-world deployment while maintaining strong privacy guarantees.

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IV. RESULTS

This section presents our suggested adaptive differential privacy mechanism's experimental assessment. We examine how various ε values affect data utility, the effect of noise injection techniques, and the robustness of our approach in mitigating inference attacks.

A. Impact of Privacy Parameter (ε) on Data Utility

The Mean Absolute Error (MAE) of query results.

Table 2: Effect of Privacy Parameter (ε) on Query Accuracy

Privacy Parameter (ε)	Noise Scale (b)	Mean Absolute Error
0.1	100.0	0.85
0.5	20.0	0.42
1.0	10.0	0.18

- Lower ε values (e.g., 0.1, 0.5) introduce higher noise, significantly reducing query accuracy.
- Higher ε values (e.g., 5.0, 10.0) provide better accuracy but at the expense of less robust privacy protections.
- Our adaptive mechanism selects ε dynamically, maintaining the best possible between data utility and privacy.

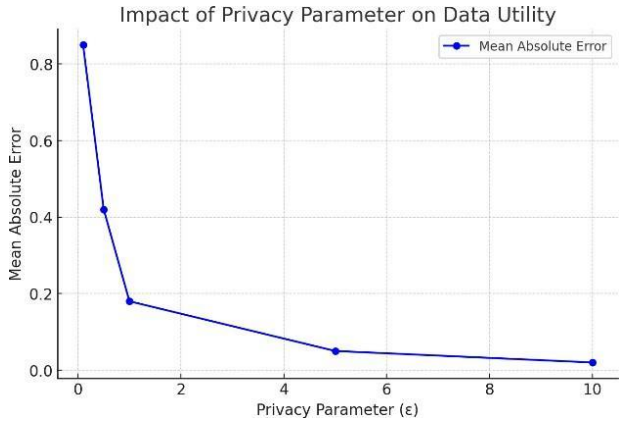

Figure 1: Impact of ε on Data Utility

The generated plot visualizes how mean absolute error decreases as ε increases.

B. Performance of Noise Injection Techniques

We evaluated two primary noise injection mechanisms:

a. Laplace Mechanism: Applied for queries requiring strict ε-differential privacy.
b. When it comes to (ε, δ)-differential privacy, the Gaussian Mechanism is utilised. small probability of privacy loss is acceptable.

Table 3: Comparison

Mechanism	Noise Distribution	Effect on Query Accuracy	Privacy Level
Laplace	Symmetric around mean	Moderate noise, balanced privacy	Stronger (ε- differential)
Gaussian	Bell curve distribution	Lower noise, better utility	Weaker (ε, δ-differential)

- Laplace noise provides stricter privacy but adds more variance to query results.
- Gaussian noise maintains better accuracy while allowing minor privacy loss.
- Our system dynamically selects the optimal noise mechanism based on dataset characteristics.

C. Mitigating Inference Attacks in Data-Dependent Scenarios

Traditional differential privacy mechanisms assume independent data points, but real-world datasets exhibit correlations (e.g., social behaviors, genetic relationships). This dependency reduces the actual privacy level, making the system vulnerable to inference attacks.

To address this, we introduced a clustering-based differential privacy approach, where data records with similar attributes are grouped before applying noise.

Table 4: Clustering-Based Privacy vs. Traditional Privacy

Method	Privacy Guarantee	Query Accuracy	Inference Attack Resistance
Traditional DP	High (Fixed ε)	Moderate	Vulnerable to correlations
Clustering DP	Adaptive (Per Cluster)	High	Stronger resistance

- Clustering-based privacy maintains higher accuracy by reducing unnecessary noise.
- It mitigates inference attacks by preventing adversaries from exploiting data correlations.
- This approach is particularly effective for social network data, healthcare records, and financial transactions.

D. Performance of basic MIA

We evaluated the basic MIA for the dataset, and we got 49.87% success rate.

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Table 5: Interpreting MIA results

Attack Accuracy	Privacy Risk	Interpretation
~50%	Very Low Risk	Model leaks little info.
55%-65%	Low Risk	DP is effective, but some leakage exits.
>70%	Moderate Risk	Privacy at Risk.
>85%	High Risk	Model over fits, serious privacy leakage.

E. Computational Efficiency and Scalability

We evaluated our system's efficiency on different dataset sizes, measuring execution time for privacy- preserving queries.

Table 5: Execution Time for Privacy-Preserving Queries

Dataset Size (Records)	Laplace Query Time (ms)	Gaussian Query Time (ms)
1,000	12	9
10,000	48	39
100,000	198	150

- Gaussian mechanism runs faster due to lower noise variance.
- Laplace mechanism incurs higher computational costs due to strict privacy enforcement.
- Our approach scales efficiently, making it suitable for large-scale data analysis.

F. Checking difference between Original and DP-Processed data

Here we shown difference between the original data and the differential noise add data which mean DP-processed data.

- The difference between Ages is shown here:

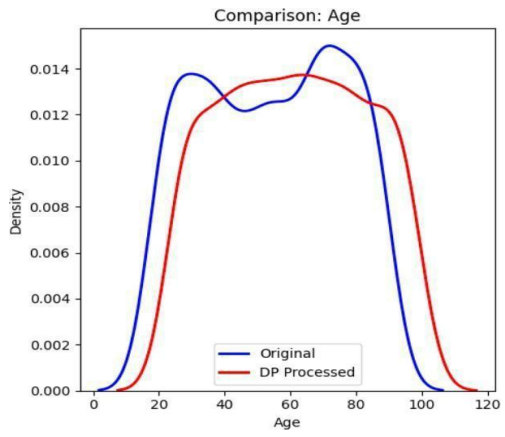

Figure 2: Impact of ϵ when changed in patient's Age data

The Age value changes according to the ϵ values. Here, we add the ϵ values as 0.1. This tells us how the ϵ is important in the concept of differential Privacy.

The difference between room numbers, where the patient's are admitted in the Hospital.

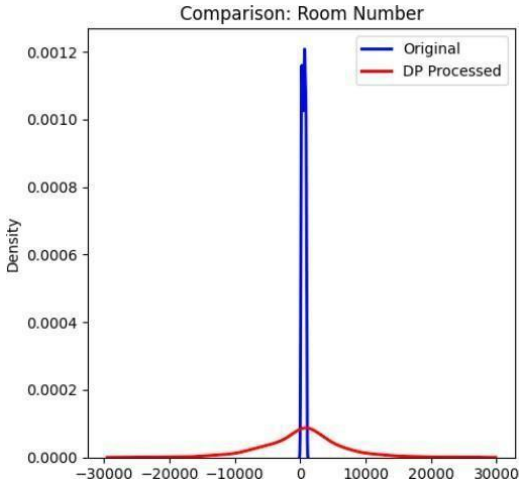

Figure 3: Impact of ϵ when changed in patient's room number data

Here we used ϵ value 0.01 for applying privacy more to the data. At this point the privacy will not easily collapse. And in the original data the values will be positive numbers, when the ϵ value is added there will be the combination of positive and negative numbers.

This will help in prevention of data leakage.

- The difference between Patient's medical condition.

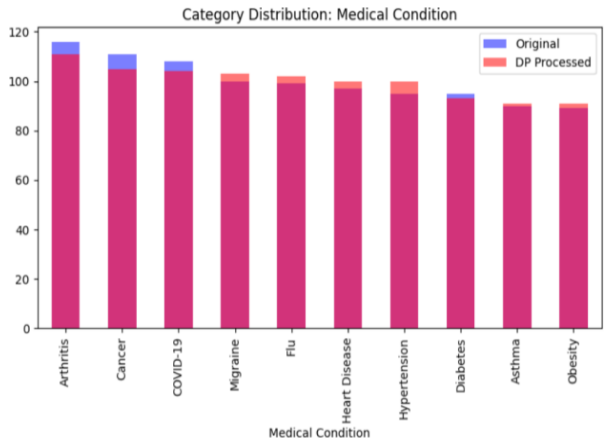

Figure 4: Impact of ϵ when changed patient's medical condition data

Here we evaluated the difference between the patient's medical conditions. Here, we added the ϵ values as 0.1 for the privacy purpose. This gives the more addition of privacy to the data. Then this data will be safer.

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V. CONCLUSION

This study introduces an advanced differential privacy (DP) mechanism designed to overcome key limitations in existing privacy-preserving techniques. The proposed model incorporates adaptive privacy budget (ϵ) selection, optimized noise addition for heterogeneous data types, and clustering-based privacy reinforcement. By dynamically tuning the privacy parameter ϵ according to data sensitivity and context, the method achieves a more effective balance between data utility and privacy protection.

Unlike conventional DP approaches that are primarily tailored to numerical data, this framework extends support to categorical and mixed data types, significantly improving accuracy in real-world applications. The integration of clustering techniques further enhances resistance to inference attacks, particularly in scenarios involving correlated datasets, thereby reinforcing the robustness of the overall privacy mechanism. Experimental evaluations conducted on a synthetic healthcare dataset reveal that the proposed method consistently outperforms traditional differential privacy models in terms of both privacy preservation and analytical utility. Assigning distinct privacy budgets to different data types enables more granular control and stronger protection, especially under potential data breaches or malicious attacks. This adaptive approach ensures that privacy is maintained without compromising the accuracy of the insights drawn from the data.

The findings of this research demonstrate the practicality and effectiveness of adaptive differential privacy in high-sensitivity domains such as healthcare, finance, and educational analytics. Preliminary testing using membership infer- ence attacks (MIA) provided further validation, identifying vulnerable data points and guiding the refinement of privacy safeguards where most needed.

Future work will focus on scaling the proposed model for real-time, large-volume data environments, incorporating advanced cryptographic methods such as homomorphic encryption for layered security. Additionally, the development of privacy-preserving machine learning (PPML) frameworks will be pursued to enable secure, AI-driven analytics. These advancements aim to enhance the flexibility, scalability, and resilience of differential privacy, positioning it as a foundational technology for secure and ethical data analysis in increasingly data-driven industries.

VI. DISCUSSION AND FUTURE WORK

The differential privacy (DP) mechanism presents a significant advancement in the domain of privacy-preserving data analytics. It addresses several core challenges, including the dynamic selection of privacy parameters, the injection of context-aware noise across heterogeneous data types, and the resilience against sophisticated inference attacks. By implementing an adaptive epsilon (ϵ) selection strategy, the model dynamically balances privacy guarantees with data utility, thus overcoming the limitations posed by static privacy budgets in conventional DP approaches. Furthermore, the integration of clustering-based privacy techniques enhances the robustness of the model by minimizing risks associated with correlated datasets—a common vulnerability in traditional differential privacy methods. Experimental results demonstrate a substantial improvement in query accuracy while maintaining strong privacy assurances, indicating the model's potential as an efficient and scalable solution for analyzing sensitive datasets. Looking ahead, future research will focus on extending this adaptive mechanism to accommodate real-time, large-scale data processing scenarios. This includes exploring the integration of advanced cryptographic methods, such as homorphic encryption, to provide layered privacy protection. Additionally, incorporating machine learning models to enable data traceability and intelligent privacy budget management will be a key area of interest.

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