



Saibot: A Differentially Private Data Search Platform

Ze Zhou Huang
Columbia University
zh2408@columbia.edu

Jiaxiang Liu
Columbia University
jl6235@columbia.edu

Daniel Gbenga Alabi
Columbia University
alabid@cs.columbia.edu

Raul Castro Fernandez
University of Chicago
raulcf@uchicago.edu

Eugene Wu
DSI, Columbia University
ewu@cs.columbia.edu

ABSTRACT

Recent data search platforms use ML task-based utility measures rather than metadata-based keywords, to search large dataset corpora. Requesters submit a training dataset, and these platforms search for *augmentations*—join or union-compatible datasets—that, when used to augment the requester’s dataset, most improve model (e.g., linear regression) performance. Although effective, providers that manage personally identifiable data demand differential privacy (DP) guarantees before granting these platforms data access. Unfortunately, making data search differentially private is nontrivial, as a single search can involve training and evaluating datasets hundreds or thousands of times, quickly depleting privacy budgets.

We present *Saibot*, a differentially private data search platform that employs Factorized Privacy Mechanism (FPM), a novel DP mechanism, to calculate sufficient semi-ring statistics for ML over different combinations of datasets. These statistics are privatized once, and can be freely reused for the search. This allows *Saibot* to scale to arbitrary numbers of datasets and requests, while minimizing the amount that DP noise affects search results. We optimize the sensitivity of FPM for common augmentation operations, and analyze its properties with respect to linear regression. Specifically, we develop an unbiased estimator for many-to-many joins, prove its bounds, and develop an optimization to redistribute DP noise to minimize the impact on the model. Our evaluation on a real-world dataset corpus of 329 datasets demonstrates that *Saibot* can return augmentations that achieve model accuracy within 50–90% of non-private search, while the leading alternative DP mechanisms (TPM, APM, shuffling) are several orders of magnitude worse.

PVLDB Reference Format:

Ze Zhou Huang, Jiaxiang Liu, Daniel Gbenga Alabi, Raul Castro Fernandez, and Eugene Wu. Saibot: A Differentially Private Data Search Platform. PVLDB, 16(11): 3057 - 3070, 2023.
doi:10.14778/3611479.3611508

PVLDB Artifact Availability:

The source code, data, and/or other artifacts have been made available at <https://github.com/cudbg/Saibot>.

This work is licensed under the Creative Commons BY-NC-ND 4.0 International License. Visit <https://creativecommons.org/licenses/by-nc-nd/4.0/> to view a copy of this license. For any use beyond those covered by this license, obtain permission by emailing info@vldb.org. Copyright is held by the owner/author(s). Publication rights licensed to the VLDB Endowment.
Proceedings of the VLDB Endowment, Vol. 16, No. 11 ISSN 2150-8097.
doi:10.14778/3611479.3611508

1 INTRODUCTION

Augmenting training data with additional samples or features can significantly enhance ML performance [50]. However, sourcing such data in large corpora—public portals [10, 11], or enterprise data warehouses—is a complex task. To address this, a new form of data search platform [19, 34, 43, 45, 51] is emerging, wherein a requester submits a search request comprising training and testing datasets for augmentation. The platform then finds provider datasets that augment the training dataset in a way that improves *utility* (e.g., ML performance). This involves using a data discovery tool [17, 29] to locate a set of union- or join-compatible tables (*augmentations*), augmenting the training set with each candidate, and then retraining and evaluating the model to assess its *utility*. The augmentations are subsequently ranked by *utility*. Platforms largely differ in the discovery tool procedure, the models they support, and how they accelerate model retraining and evaluation. Recent works [18, 34, 51] suggest that using linear regression as a model proxy provides a good balance of search quality and runtime.

Unfortunately, privacy is a major barrier to sharing for many potential data providers and requesters with sensitive data (e.g., personally identifiable information (PII), and protected health information (PHI)). In these cases, providers are legally obligated to prevent personal data leakage [6, 7, 9]. Rather than prohibit access outright, differential privacy (DP) [22] supports data analysis on sensitive data while bounding the degree of privacy loss based on the budget ϵ set by the data provider. Each query on the dataset adds noise to the results, inversely proportional to the budget consumed; when $\epsilon = 0$, the dataset becomes inaccessible.

Ideally, a differentially private data search platform would let providers and requesters set privacy budgets for their datasets, and enforce these budgets as new datasets and requests arrive. Moreover, since the platform is often a third-party service that may not be trusted by data providers (and the individuals they collect data from), it should not have access to raw data. Unfortunately, integrating DP with data search platforms is non-trivial. To illustrate, Figure 1 shows where existing mechanisms would add noise in a two-level data-sharing architecture that matches many real-world settings. In this architecture, individuals (e.g., patients) generate sensitive data aggregated by providers/requesters (e.g., hospitals), and the search platform further aggregates their datasets.

Global DP (GDP) is a DP definition widely used by private DBMSes [36, 40, 60], where the employed mechanisms add noise after executing, e.g., a query over private data by a trusted central DBMS. However, when applied to data search, previous GDP mechanisms need to “split the budget” across every candidate augmentation on

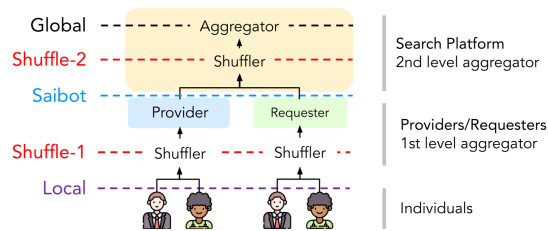


Figure 1: Summary of DP-mechanisms under various trust models in a standard data sharing architecture: Providers/requesters collect data from individuals, and the search platform aggregates data from providers/requesters. At the extremes, mechanisms for local models introduce noise to individual tuples, whereas naive mechanisms for global models add noise to query results through a trusted 2^{nd} -level aggregator. Mechanisms for the shuffle model introduce a shuffler at a point of aggregation (either at the 1^{st} -level (Shuffle-1) or the 2^{nd} -level (Shuffle-2)). In contrast, Saibot adds noise to sufficient statistics computed by providers/requesters.

every request. The budget ends up being so small that the noise drowns any signal in the data. Further, their trust model requires the search platform, acting as the central aggregator, to be trusted, which is challenging since it is a third-party service. To address this, mechanisms for Local DP (LDP) (e.g., randomized response [20, 27]) eliminate the need for a trusted data curator by privatizing individual tuples. Nevertheless, the noise required for these mechanisms can be quite large, potentially compromising data utility [59]. Shuffling [26, 28] is a mechanism for an intermediate trust model that, instead of relying on a trusted central aggregator, requires trust in a shuffler. After privatizing tuples (using mechanisms for LDP), the shuffler shuffles the primary keys of tuples during aggregation to disassociate them from individuals; this "amplifies privacy" by allowing each tuple to have less noise applied. Variation *Shuffle-1* shuffles at the provider/requester level but requires considerable noise for small datasets; *Shuffle-2* shuffles within the search platform but needs to trust the platform. An alternative to shuffling, widely used by federated ML [54, 55, 59, 64], is to let providers/requesters iteratively compute and privatize model gradients locally, and let an untrusted aggregator compute the final model. However, these gradients are specific to a single augmentation's model, so the budget is still split across all candidate augmentations.

Is it possible for a DP search platform to return search results of comparable quality to non-private search, *and* for the platform to scale to many datasets and requests? We are motivated by the recent data search platform Kitana [34], which uses semi-ring aggregation to quickly evaluate a candidate augmentation's *utility* on a linear regression model without materializing the augmented table and fully retraining it. These semi-rings can be computed for each dataset offline, and Kitana only needs these semi-rings to evaluate a candidate augmentation in $\approx 1-5ms$, independent of the dataset size. *Our main observation is that these precomputed semi-rings also serve as ideal intermediates for DP, as they help directly estimate model parameters, can be combined over joins and unions, and can be freely reused once made private.*

This paper presents *Saibot*, a differentially private data search platform for tabular datasets that scales to unlimited datasets and requests, returns results comparable to non-private search, and doesn't need to be trusted. Data providers upload their privatized datasets to the platform. When a requester submits a privatized training dataset, the platform searches for the best combinations of privatized datasets which, when augmented with the requester's dataset, most improve the accuracy of a linear regression model. For the trust model, *Saibot* assumes that the 1^{st} -level aggregators are trusted (unlike the local model) but the 2^{nd} -level aggregators (i.e., search platform) are not (unlike global model). In practice, regulations [6–9] mandate that the 1^{st} -level aggregators (e.g., healthcare providers, schools) securely store individual data. Once *Saibot* identifies predictive augmentations using differentially private proxy models (linear regression), it can directly return the private proxy models, although they may not be complex enough for some requesters. To address this, *Saibot* can be integrated within a larger differentially private federated ML system [55, 57, 59, 64] to train more advanced models, like deep neural networks through differentially private gradient descent, on the identified augmentations.

Our key innovation is a new DP mechanism called *Factorized Privacy Mechanism* (FPM), where each requester or provider computes and privatizes sufficient statistics on their own datasets based on their privacy requirements. These sufficient statistics provide high utility, can be freely reused for ML over different augmentations, and only require the search platform to store privatized datasets. FPM satisfies GDP, but the randomized algorithm is applied by the 1^{st} -level aggregators rather than the 2^{nd} -level ones. Note that FPM has broader applications, not only for the data search but also for more general differentially private factorized learning.

The main algorithmic challenge FPM solves is to design privatized sufficient statistics for ML that are composable to support various join and union augmentations. Previous works have applied DP to sufficient statistics for privatized linear regression [58] and GLM [35, 41], but these sufficient statistics can be used for only a single dataset. Our key insight is to design these sufficient statistics as a semi-ring [30], which includes addition and multiplication operators for union and join. Although sufficient semi-ring statistics have been utilized for ML [52, 53] over joins, we are the first to explore their application in a DP setting. The results of our real-world experiments indicate that FPM is capable of identifying augmentations that achieve an average $r2$ score of $\sim 50-90\%$ compared to non-private searches. Additionally, FPM can support a large data corpus and unlimited requests. In contrast, the other baseline mechanisms achieve $r2$ scores < 0.02 .

To summarize, our contributions are as follows:

- We propose FPM, a novel DP mechanism that privatizes reusable and composable monomials for join/aggregation augmentations. We integrate FPM into *Saibot* to achieve scalability for large volumes of datasets and search requests with high utility.
- We optimize FPM based on the parity of the statistics order. For the special case of tables containing a single feature, we reduce the expected error by a further factor of $\sqrt{2}$.
- We provide a deep analysis of FPM to linear regression models. Specifically, we study the statistical bias introduced in many-to-many joins, and design an unbiased estimator to address this.

- We design an optimization that carefully redistributes noise across sufficient statistics to improve linear regression accuracy.
- We thoroughly evaluate FPM across a real-world data corpus with >300 datasets. Our results show that FPM can accurately identify augmentations that achieve $r2$ scores close to (~ 50 – 90%) those of a non-private search. We further use ablation studies to validate our theoretical analyses and study the sensitivity.

Note: The paper is self-contained. References to appendices can be disregarded or located in the technical report [12].

2 PRIVATE TASK-BASED DATA SEARCH

In this section, we formalize the problem of task-based private data search. We start with an introduction of the non-private problem and current solutions. We then provide the primer of differential privacy, and present the differentially private data search problem.

2.1 Non-Private Task-based Data Search

We provide the background of previous task-based data search problem [19, 43, 45, 51], which is non-private, and previous solutions.

Data Model. We follow the standard relational data model. Relations are denoted as R , attributes as A , and domains as $dom(A)$. R 's schema is represented by $S_R = [A_1, \dots, A_n]$, with tuples labeled as t and attribute values as $t[A]$. For clarity, the schema is included in square brackets following the relation in examples $R[A_1, \dots, A_n]$. The domain of a relation is the Cartesian product of attribute domains: $dom(R) = dom(A_1) \times \dots \times dom(A_n)$. We consider each dataset as a relational table and use these terms interchangeably.

Machine Learning. A ML task M , like linear or logistic regression, aims to fit a good model based on feature-target attribute pairs. A training dataset R_{train} comprises features $X \subset S_R$ and a target attribute $y \in S_R$. The task M has a training function $M.Train(\cdot)$ that inputs R_{train} and outputs a model m that optimally predicts y from X , even for unseen X, y pairs. To assess m , M uses a function $M.Evaluate(\cdot)$ which inputs m and a testing dataset R_{test} , and outputs the model's performance on R_{test} , typically measured by accuracy, which is to be maximized.

Task-based Data Search. Given a data corpus with datasets from different providers, requesters send a request with datasets to augment and a task (e.g., ML). Task-based data search aims to identify a set of augmentable (join/union) datasets that maximize task utility.

To formalize this, let $\mathcal{R} = \{R_1, R_2, \dots\}$ be a data corpus with a set of relations, with each from some provider. Requester sends a request with training and testing dataset (R_{train}, R_{test}) , and chooses a model M . Requester's goal is to train model M on R_{train} and maximize its performance on R_{test} , which we call the task's *utility*.

To improve the *utility*, the requester aims to find a set of provider datasets in \mathcal{R} that can be used to augment their data and enhance model performance. The function $Discover(R, augType)$ is used to find datasets in the data corpus \mathcal{R} that can be joined or unioned with R , given $augType \in \{\bowtie, \cup\}$. The requester wants to try different combinations of subsets of these datasets to augment¹ and find the combination that maximizes *utility*.

¹For simplicity, we consider datasets that can be directly joined or unioned with requester R_{train} . The search space could be further expanded by, e.g., 1^{st} joining provider datasets; our solution can be easily adapted to this larger search space.

Putting everything together, the problem can be formulated as:

PROBLEM 1 (TASK-BASED DATA SEARCH). For request (R_{train}, R_{test}, M) , find the set of datasets $\mathbf{R}_{\cup}, \mathbf{R}_{\bowtie} \subseteq \mathcal{R}$ from data corpus such that

$$\begin{aligned} \mathbf{R}_{\cup}^*, \mathbf{R}_{\bowtie}^* &= \operatorname{argmax}_{\mathbf{R}_{\cup}, \mathbf{R}_{\bowtie}} M.Evaluate(m, R_{testAug}) \\ \text{s.t. } \mathbf{R}_{\cup} &\subseteq Discover(R, \cup), \mathbf{R}_{\bowtie} \subseteq Discover(R, \bowtie), \\ R_{trainAug} &= (R_{train} \cup_{R_1 \in \mathbf{R}_{\cup}} R_1) \bowtie_{R_2 \in \mathbf{R}_{\bowtie}} R_2 \\ R_{testAug} &= R_{test} \bowtie_{R \in \mathbf{R}_{\bowtie}} R \\ m &= M.Train(R_{trainAug}) \end{aligned}$$

Solutions. Current task-based data search platforms [19, 43, 45, 51] follow the architecture illustrated in black in Figure 2. Offline, when providers upload raw datasets to *Data storage*, the platform computes minhashes for data discovery [17, 29], and sketches to accelerate retraining [19, 34, 45, 51]. Online, the platform solves Problem 1 for each request (R_{train}, R_{test}, M) . First, *data discovery* [17, 29] uses the minhashes or sketches to return a set of candidate datasets. *Data search* then identifies a subset that maximizes task utility. The brute-force search evaluates all possible combinations and can be expensive due to retraining costs and the large set of combinations, so approaches use various heuristics and greedy algorithms [19, 43, 51].

Our work primarily builds on Kitana [34], which follows the architecture in Figure 2 and uses specialized sketches for factorized ML. factorized ML trains models over joins without materializing them, which speeds up model retraining and evaluation after any candidate augmentation. This allows Kitana to execute task-based searches much faster, while maintaining competitive task utility. Our insight is that these sketches boost performance and act as the ideal sufficient statistics for DP, as detailed in Section 3.2.

2.2 Differential Privacy Primer

Before delving into our solution to differentially private dataset search, we first introduce differential privacy (DP). We focus on the Gaussian mechanism, a common, straightforward technique offering comparable performance and guarantee with other baselines (e.g., it offers the same approximate DP by shuffling [26]). In practice, our solution can also support pure DP by Laplace mechanism (Section 5.2), where shuffling falls short.

Differential Privacy. DP [22] is a technique used to protect reconstruction, membership, and inference attacks [24] by bounding the information leakage from individual records. DP guarantees that the probability that an algorithm will produce the same output on two datasets that differ by only one record is bounded. Formally:

DEFINITION 1 ((ϵ, δ) -DP). Let f be a randomized algorithm that takes a relation R as input. f is (ϵ, δ) -DP if, for all relations R_1, R_2 that differ by adding or removing a row, and for every set S of outputs from f , the following holds: $\Pr[f(R_1) \in S] \leq e^\epsilon \Pr[f(R_2) \in S] + \delta$, where ϵ and δ are non-negative real numbers (called privacy budget). ϵ controls the level of privacy, and δ controls the level of approximation. For the special case when $\delta = 0$, $(\epsilon, 0)$ -DP is also called pure DP.

DP definitions can be global (GDP) or local (LDP) depending on inputs: GDP applies to randomized algorithms that process an entire relation (as an aggregator) described above. In contrast, LDP

guarantees the differential privacy of algorithms on individual tuples (or relations with a cardinality of 1) before transmitting tuples to any aggregator. As a result, LDP algorithms can function under a weaker trust model, where no aggregator is trusted. However, this often leads to increased noise levels and reduced data utility [63].

There are two important theorems of DP:

THEOREM 1 (ROBUSTNESS TO POST-PROCESSING). *Let f be a randomized algorithm that provides (ϵ, δ) -DP. Let g be an arbitrary function. Then, the composition $g \circ f$ provides (ϵ, δ) -DP.*

THEOREM 2 (SEQUENTIAL COMPOSITION). *Let f_1, \dots, f_n be a sequence of independent algorithms that provide $(\epsilon_1, \delta_1), \dots, (\epsilon_n, \delta_n)$ -DP, respectively. Then, the algorithm that applies each of them in sequence, i.e., $f_n \circ f_{n-1} \dots \circ f_1$, is $(\sum_{i=1}^n \epsilon_i, \sum_{i=1}^n \delta_i)$ -DP.*

To ensure (ϵ, δ) -DP when Q queries need to be executed, the privacy budget (ϵ, δ) can be split among the queries using sequential composition, such as allocating $(\epsilon/Q, \delta/Q)$ for each query. This work employs (basic) sequential composition for simplicity, but it could be further optimized by advanced composition [23].

Gaussian Mechanism. The Gaussian mechanism [21] adds noise to a query function to satisfy (ϵ, δ) -differential privacy. Formally:

THEOREM 3 (GAUSSIAN MECHANISM). *Given $\epsilon, \delta \in (0, 1]$, let query q be a function that takes R as input and outputs a vector of real numbers. The Gaussian mechanism independently adds random noise to each output to satisfy (ϵ, δ) -differential privacy: $q'(R) = q(R) + N(0, \sigma^2)$, where $N(0, \sigma^2)$ denotes a Gaussian distribution with mean 0 and standard deviation $\sigma = \sqrt{2 \ln(1.25/\delta)} \Delta_q / \epsilon$. Δ_q is the ℓ_2 -sensitivity of q defined as: for all possible neighbouring relations R_1, R_2 , Δ_q is the maximum ℓ_2 distance of q outputs $\|q(R_1) - q(R_2)\|_2$.*

Different definitions exist for neighbouring relations (and can be extended to multi-relations). We adopt bounded DP [15], where neighbouring relations R_1, R_2 have identical row numbers, but one row's data differ; our system can be readily adapted for other definitions (e.g., unbounded DP where row numbers differ).

2.3 Private Task-based Data Search

We first lay out the privacy requirements based on the criteria (Section 1) and motivated by real-world use cases. Then, we define the differentially private data search problem, and discuss the challenges and the intuition for solutions.

Trust Model. We adopt a standard two-level aggregator setting illustrated in Figure 3: the 1st-level aggregators are providers/requesters (e.g., hospitals, schools), and the 2nd-level aggregator is the search platform. Individuals share data with their direct 1st-level aggregator, who is trusted (e.g., a hospital collects data from patients and stores them securely). However, they don't trust other non-direct 1st-level aggregators or the 2nd-level aggregators (e.g., patients don't trust other hospitals and the search platform).

Our trust model sits between the global model (by GDP) and local model (by LDP): Previous global model [36, 40, 60] assumes that the central data curator (2nd-level aggregator) is trusted. On the contrary, the local model assumes no trusted aggregators. In contrast to the shuffle model [26, 28] which requires a trusted shuffler at either 1st-(Shuffle-1, similar to ours) or 2nd-level (Shuffle-2, similar to the global model), we don't rely on any trusted shuffler.

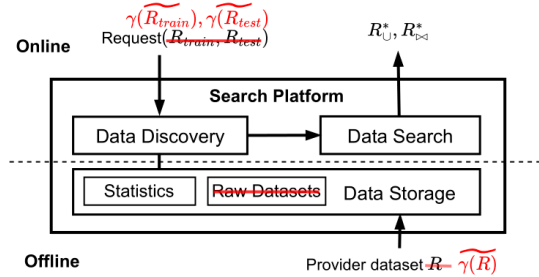


Figure 2: Saibot architecture. Previous data search platforms (black) store raw datasets in data storage, use data discovery to identify augmentable datasets, and search the datasets for task improvement. To ensure privacy, Saibot additionally applies FPM (red) to compute sufficient semi-ring statistics, that are aggregated (γ) and privatized (\sim) before being sent to the search platform. These statistics can support join and union queries to train and evaluate ML as post-processing.

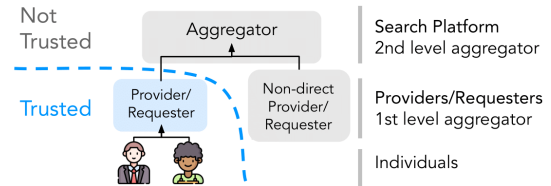


Figure 3: Illustration of Saibot trust model, where individuals only trust the direct 1st-level aggregator, and not any others.

In practice, we believe our trust model fits the structure of many organizations, where individuals solely trust their immediate data aggregator (like a hospital or service provider), but do not trust any other aggregators. Further, regulatory requirements [6, 8] place privacy protection requirements on the 1st-level aggregator.

Privacy Requirement. Providers and requesters hope to disclose datasets to the malicious search platform for augmentation. Each provider or requester sets a DP budget (ϵ, δ) for each of their datasets, which is independent of other datasets and the search platform. As per previous works [46, 61], we assume that each individual contributes to exactly one row of one dataset. In line with prior studies [36, 40, 60], we assume that the schemas and the domains of join keys (as group-by attributes) are public.

The **differentially private task-based data search** problem is then defined as Problem 1, adhering to the above trust model and satisfying the privacy requirements.

EXAMPLE 1. *Fitbit [47], a mobile health app, gathers health data from individuals and is trusted by individuals to handle sensitive information responsibly. To enhance the accuracy of its ML recommender, Fitbit plans to share data with a search platform (as requesters) but also wants to protect sensitive health data. Upon obtaining consent from individuals, Fitbit employs DP to privatize each dataset and uses Saibot to search for valuable augmentations.*

Private task-based data search is particularly challenging because, even for a single request, it requires model retraining over

a combinatorially large space of augmented datasets created by joining and unioning candidate datasets. How to avoid exhausting the requester’s and the providers’ privacy budgets? How can massive datasets and requests be scaled without degrading search quality? Is there a one-time differentially private, yet universally useful intermediate representation [16, 31]?

We draw inspiration from Kitana [34] which uses factorized linear regression to expedite data search. Kitana computes the gram matrix semi-ring (Section 3.1) for each dataset, allowing fast join/union with a candidate dataset and evaluation of the linear regression accuracy. While semi-rings were initially used for performance, they also make an ideal intermediate representation for DP. Thus, in the next section, we design FPM to privatize sufficient semi-ring statistics to support private ML over joins and unions.

3 FACTORIZED PRIVACY MECHANISM

In this section, we introduce Factorized Privacy Mechanism (FPM), which privatizes sufficient semi-ring statistics. We start with the factorized ML background, extend it to monomial semi-ring, present our main mechanism algorithms, and analyze its errors.

3.1 Factorized Machine Learning Primer

We start with the fundamental concepts of annotated relations and aggregation pushdown, then introduce factorized ML [13, 48].

Annotated Relations. The annotated relational model [30] maps $t \in R$ to a commutative semi-ring $(D, +, \times, 0, 1)$, where D is a set, $+$ and \times are commutative binary operators closed over D , and $0/1$ are zero/unit elements. An annotation for $t \in R$ is denoted as $R(t)$. Semi-ring annotation expresses various aggregations. For example, the natural numbers semi-ring expresses count aggregations.

Semi-ring Aggregation Query. Semi-ring aggregation queries can now be reformulated using annotated relations by translating group-by, union, and join operations into addition (+) and multiplication (\times) operations over the semi-ring annotations, respectively.

$$\begin{aligned} (\gamma_A R)(t) &= \sum \{R(t_1) \mid t_1 \in R, t = \pi_A(t_1)\} \\ (R_1 \cup R_2)(t) &= R_1(t) + R_2(t) \\ (R_1 \bowtie R_2)(t) &= R_1(\pi_{S_{R_1}}(t)) \times R_2(\pi_{S_{R_2}}(t)) \end{aligned}$$

(1) The annotation for group-by $\gamma_A R$ is the sum of the annotations within the group. (2) The annotation for union $R_1 \cup R_2$ is the sum of annotations in R_1 and R_2 . (3) The annotation for join $R_1 \bowtie R_2$ is the product of annotations from contributing tuples in R_1 and R_2 .

Aggregation Pushdown. The optimization of factorized ML [13, 53] involves the distribution of aggregations γ (additions) through joins \bowtie (multiplications). For example, consider the query $\gamma_D(R_1[A, B] \bowtie R_2[B, C] \bowtie R_3[C, D])$. Rather than applying γ on the join (which is $O(n^3)$ where n is relation size), γ can be performed on R before \bowtie with S , and this process can be repeated two more times (in $O(n)$):

$$\gamma_D(\gamma_C(\gamma_B(R_1[A, B]) \bowtie R_2[B, C]) \bowtie R_3[C, D])$$

The associativity of additions can be similarly exploited for union:

$$\gamma_A(R_1[A, B] \cup R_2[A, B]) = \gamma_A(R_1[A, B]) \cup \gamma_A(R_2[A, B])$$

Factorized Linear Regression. The fundamental optimization of factorized ML is aggregation pushdown, but different semi-rings are used for different models. We use linear regression as an example.

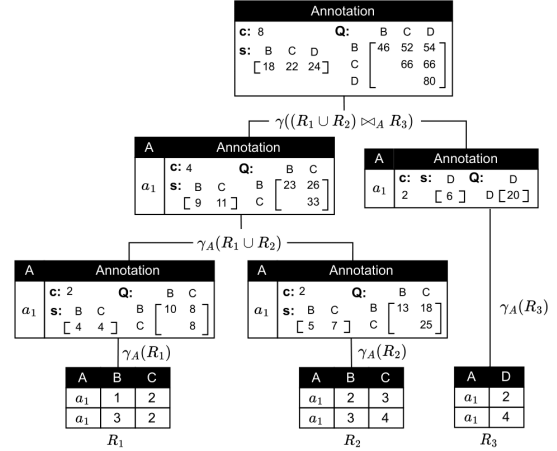


Figure 4: Optimized query plan of $\gamma((R_1 \cup R_2) \bowtie_A R_3)$ for factorized ML. Aggregations are pushed down before joins.

$(R_1 \cup R_2) \bowtie_A R_3$	Aggregated Monomials	Statistics																																																										
<table border="1"> <thead> <tr><th>A</th><th>B</th><th>C</th><th>D</th></tr> </thead> <tbody> <tr><td>a_1</td><td>1</td><td>2</td><td>2</td></tr> <tr><td>a_1</td><td>3</td><td>2</td><td>2</td></tr> <tr><td>a_1</td><td>2</td><td>3</td><td>2</td></tr> <tr><td>a_1</td><td>3</td><td>4</td><td>2</td></tr> <tr><td>a_1</td><td>1</td><td>2</td><td>4</td></tr> <tr><td>a_1</td><td>3</td><td>2</td><td>4</td></tr> <tr><td>a_1</td><td>2</td><td>3</td><td>4</td></tr> <tr><td>a_1</td><td>3</td><td>4</td><td>4</td></tr> </tbody> </table>	A	B	C	D	a_1	1	2	2	a_1	3	2	2	a_1	2	3	2	a_1	3	4	2	a_1	1	2	4	a_1	3	2	4	a_1	2	3	4	a_1	3	4	4	$\sum 1 = 8$ $\sum B = 18$ $\sum C = 22$ $\sum D = 24$ $\sum B^2 = 46$ $\sum BC = 52$ $\sum C^2 = 66$ $\sum BD = 54$ $\sum CD = 66$ $\sum D^2 = 80$ \dots	<table border="1"> <thead> <tr> <th>1-order</th> <th>3-order</th> </tr> </thead> <tbody> <tr><td>$E[B] = 2.25$</td><td>$E[B^3] = 15.75$</td></tr> <tr><td>$E[C] = 2.75$</td><td>$E[B^2C] = 17.24$</td></tr> <tr><td>$E[D] = 3$</td><td>$E[B^2D] = 17$</td></tr> <tr><td>$E[B^2] = 5.75$</td><td>$E[BC^2] = 22.5$</td></tr> <tr><td>$E[BC] = 6.5$</td><td>$E[BCD] = 19.5$</td></tr> <tr><td>$E[C^2] = 8.25$</td><td>$E[BD^2] = 20.5$</td></tr> <tr><td>$E[BD] = 6.75$</td><td>$E[C^3] = 36$</td></tr> <tr><td>$E[CD] = 8.25$</td><td>$E[C^2D] = 27.5$</td></tr> <tr><td>$E[D^2] = 10$</td><td>$E[CD^2] = 24.75$</td></tr> <tr><td>\dots</td><td>\dots</td></tr> </tbody> </table>	1-order	3-order	$E[B] = 2.25$	$E[B^3] = 15.75$	$E[C] = 2.75$	$E[B^2C] = 17.24$	$E[D] = 3$	$E[B^2D] = 17$	$E[B^2] = 5.75$	$E[BC^2] = 22.5$	$E[BC] = 6.5$	$E[BCD] = 19.5$	$E[C^2] = 8.25$	$E[BD^2] = 20.5$	$E[BD] = 6.75$	$E[C^3] = 36$	$E[CD] = 8.25$	$E[C^2D] = 27.5$	$E[D^2] = 10$	$E[CD^2] = 24.75$	\dots	\dots
A	B	C	D																																																									
a_1	1	2	2																																																									
a_1	3	2	2																																																									
a_1	2	3	2																																																									
a_1	3	4	2																																																									
a_1	1	2	4																																																									
a_1	3	2	4																																																									
a_1	2	3	4																																																									
a_1	3	4	4																																																									
1-order	3-order																																																											
$E[B] = 2.25$	$E[B^3] = 15.75$																																																											
$E[C] = 2.75$	$E[B^2C] = 17.24$																																																											
$E[D] = 3$	$E[B^2D] = 17$																																																											
$E[B^2] = 5.75$	$E[BC^2] = 22.5$																																																											
$E[BC] = 6.5$	$E[BCD] = 19.5$																																																											
$E[C^2] = 8.25$	$E[BD^2] = 20.5$																																																											
$E[BD] = 6.75$	$E[C^3] = 36$																																																											
$E[CD] = 8.25$	$E[C^2D] = 27.5$																																																											
$E[D^2] = 10$	$E[CD^2] = 24.75$																																																											
\dots	\dots																																																											

Figure 5: Aggregated monomials and statistics.

We start with an overview of linear regression and its sufficient statistics. Given the training data $\mathbf{X} \in \mathbb{R}^{n \times m}$, and the target variable $\mathbf{y} \in \mathbb{R}^{n \times 1}$, the goal is to find parameters $\theta \in \mathbb{R}^{m \times 1}$ that minimize the square loss $\theta^* = \operatorname{argmin}_{\theta} \|\mathbf{y} - \mathbf{X}\theta\|^2$, yielding a closed-form solution $\theta^* = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$. Including the target variable as a special feature and appending it to \mathbf{X} for $\mathbf{X}' = [\mathbf{X} \mid \mathbf{y}]$, we find that $\mathbf{X}'^T \mathbf{X}' \in \mathbb{R}^{m' \times m'}$, where $m' = m + 1$, is the core sufficient statistics to compute, where each cell represents the sum of products between feature pairs.

We can compute $\mathbf{X}'^T \mathbf{X}'$ over the join $R_{\bowtie} = R_1 \bowtie \dots \bowtie R_k$ by the covariance matrix semi-ring [53]. For m' features, the semi-ring is defined as a triple $(c, \mathbf{s}, \mathbf{Q}) \in (\mathbb{Z}, \mathbb{R}^{m'}, \mathbb{R}^{m' \times m'})$, which contains the count, sums, and sums of pairwise products respectively. The zero and one elements are $\mathbf{0} = (0, \mathbf{0}^m, \mathbf{0}^{m' \times m'})$ and $\mathbf{1} = (1, \mathbf{0}^m, \mathbf{0}^{m' \times m'})$. $+$ and \times between two annotations a and b are defined as:

$$\begin{aligned} a + b &= (c_a + c_b, \mathbf{s}_a + \mathbf{s}_b, \mathbf{Q}_a + \mathbf{Q}_b) \\ a \times b &= (c_a c_b, c_b \mathbf{s}_a + c_a \mathbf{s}_b, c_b \mathbf{Q}_a + c_a \mathbf{Q}_b + \mathbf{s}_a \mathbf{s}_b^T + \mathbf{s}_b \mathbf{s}_a^T) \end{aligned}$$

Then, computing $\mathbf{X}'^T \mathbf{X}'$ is reduced to executing $\gamma(R_1 \bowtie \dots \bowtie R_k)$, where aggregation can be pushed down as discussed before.

EXAMPLE 2. Consider R_1, R_2, R_3 in Figure 4. We aim to train linear regression on $(R_1 \cup R_2) \bowtie_A R_3$ using D as the feature and C as the target variable. The naive solution is to first materialize the union and join results (Figure 5) and then compute $\mathbf{X}'^T \mathbf{X}'$. Using factorized linear regression, we can optimize the query plan (Figure 4) by pushing down aggregations: $\gamma((\gamma_A(R_1) \cup \gamma_A(R_2)) \bowtie_A \gamma_A(R_3))$. This approach

yields the same result as the naive solution, but avoids the costly materialization. We use the aggregates to fit the linear regression:

$$\theta = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y} = \begin{bmatrix} \sum D^2 & \sum D \\ \sum D & \sum 1 \end{bmatrix}^{-1} \begin{bmatrix} \sum CD \\ \sum C \end{bmatrix} = \begin{bmatrix} 80 & 24 \\ 24 & 8 \end{bmatrix}^{-1} \begin{bmatrix} 66 \\ 22 \end{bmatrix}$$

After obtaining the model parameters θ , the model performance can also be evaluated. For square loss, $\sum (y - x^T \theta)^2 = \sum (y^2 - 2\theta^T xy + \theta^T xx^T \theta) = \mathbf{y}^T \mathbf{y} - 2\theta^T \mathbf{X}^T \mathbf{y} + \theta^T \mathbf{X}^T \mathbf{X} \theta$.

3.2 Monomial Semi-ring

This section introduces sufficient statistics as vectors of monoids and extends it with semi-ring operations $+$ and \times . This helps bridge ideas from two communities—semi-rings from the factorized ML literature that train models over joins and unions, but primarily focused on non-private linear regression, and privatized sufficient statistics from the ML literature [35, 41, 58] that approximate generalized linear models, but do not support joins and unions. We are the first to explicitly extend semi-ring from gram matrix (linear regression) to higher order monomial (generalized linear models). This section focuses on the semi-ring design of monomials to support join and union operations *without DP*. In the next section, we introduce FPM, a mechanism to privatize these monomials for DP.

We first define the k -order monomial [35] in sufficient statistics:

DEFINITION 2 (k -ORDER MONOMIAL). Given n random variables f_1, f_2, \dots, f_n , the k -order monomials are of the form $p = f_1^{k_1} f_2^{k_2} \dots f_n^{k_n}$, where k_1, k_2, \dots, k_n are n non-negative integers s.t. $\sum_{i=1}^n k_i = k$.

The core statistics for ML are the expected value of each monomial $E[p]$. For example, 1-order monomials estimate means, 1, 2-order monomials estimate covariance (core sufficient statistics for linear regression), and 1, 2, 3-order monomials estimate skewness. Moreover, a generalized linear model can be approximated by high-order monomials using Taylor series expansions [35].

EXAMPLE 3. Consider the relation in Figure 5 (left) and random variables B, C, D . The 1-order monomials are B, C, D , the 2-order monomials are $B^2, BC, C^2, BD, CD, D^2$, and the 3-order monomials are $B^3, B^2C, B^2D, BC^2, BCD, \dots$. The statistics (right) are the expected monomials when the relation is the population, and can be derived from the aggregated monomials (middle). The 1,2-order statistics are the sufficient statistics for linear regression training (Example 2).

Instead of computing statistics over join and union through costly materialization and subsequent aggregation, factorized linear regression utilizes semi-ring operators for $+$ and \times to push down the aggregation of 1,2-order statistics. We extend this concept by defining operators for a k -order monomial semi-ring, thus generalizing factorized linear regression (2-order monomial semi-ring).

DEFINITION 3 (k -ORDER MONOMIAL SEMI-RING). Given m features f_1, f_2, \dots, f_m , the k -order monomial semi-ring has domain of a vector with size $\frac{1-m^k}{1-m}$ for $m \geq 2$, and $1+k$ for $m=1$. The domain breaks into $k+1$ subvectors $[s_0, s_1, \dots, s_k]$ where s_i is a vector of size m^i . Then, given two semi-ring element $a = [s_0^a, s_1^a, \dots, s_k^a]$ and $b = [s_0^b, s_1^b, \dots, s_k^b]$, let:

$$a + b = [s_0^a + s_0^b, s_1^a + s_1^b, \dots, s_k^a + s_k^b]$$

$$a \times b = [s_0^a \otimes s_0^b, \sum_{i=0}^1 s_i^a \otimes s_{1-i}^b, \dots, \sum_{i=0}^k s_i^a \otimes s_{k-i}^b]$$

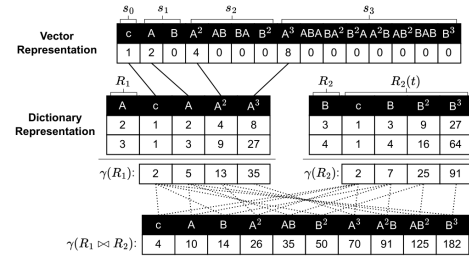


Figure 6: Aggregation of 3-order monomial semi-ring over join: $\gamma(R_1[A] \bowtie R_2[B])$. Each row is one tuple, and we show the vector representation for the first tuple in R_1 . Dictionary representation removes redundancy and sparsity. Dotted lines map the contributing components to aggregated results.

where $\otimes : R^p \times R^q \rightarrow R^{pq}$ is the tensor product defined as: for $\mathbf{a} = [a_1, a_2, \dots, a_p]$ and $\mathbf{b} = [b_1, b_2, \dots, b_q]$, tensor product computes the pairwise product $\mathbf{a} \otimes \mathbf{b} = [a_1 b_1, a_1 b_2, \dots, a_p b_1, a_p b_2, \dots, a_p b_q]$.

The zero element is a vector of all zeroes, and the one element is a vector with non-zero $s_0 = [1]$, but the rest as all zeroes.

Intuitively, each subvector s_k^a holds the k -order monomials with a size m^k , as there are m^k possible permutations with repetition. In order to compute statistics using a k -order monomial semi-ring, we annotate R by assigning to each tuple t its monomials (non-existing features are considered to be all zeroes). Note that, while this vector representation provides a straightforward way to define semi-rings for arbitrary orders, it is inherently inefficient and can be optimized by the dictionary representation discussed next.

Dictionary Representation. Vector representation has redundancies (e.g., $f_1 f_2 = f_2 f_1$) and sparsity (nonexistent features are zeros). Dictionary representations [39] help reduce redundancy: monomials serve as keys to deduplicate, and monomials with zeros are not materialized. We next provide an example of semi-ring operations using the dictionary representation for join-aggregation:

EXAMPLE 4. Consider two relations of a single feature $R_1[A] = [2, 3]$ and $R_2[B] = [3, 4]$, and the aggregation query $\gamma(R_1 \bowtie R_2)$ for 3-order monomial semi-ring. Figure 6 illustrates the annotated relations and the query processing. To start, the aggregations are pushed down by summing each monomial. Next, the monomials are combined according to the multiplication operator for join.

Assuming the join result, R_{\bowtie} , as the population, we can use the aggregated monomials to compute statistics (i.e., the expected monomials). Let $s = \gamma(R_{\bowtie})$ be the aggregated monomial semi-ring. Then, for monomial p : $E[p] = s[p]/s[c]$, where c is the count (0-order monomial). For example, in Figure 6, $E[AB] = s[AB]/s[c] = 35/4 = 8.75$. The aggregated monomials comprise count and sum aggregations over the base tables, which can be efficiently computed by requesters/providers using SQL queries. Further, they serve as an ideal intermediate for DP due to their reusability, as discussed next.

3.3 FPM Mechanism

In this section, we present the Factorized Privacy Mechanism (FPM) which applies the Gaussian mechanism to the aggregated monomials discussed in the previous section to support differentially

private data search (Section 2.3) while maintaining high utility. The primary algorithmic challenge FPM addresses is designing sufficient statistics that are composable (through semi-ring operators) and reusable (as post-processing without additional privacy cost) to support ML across various join and union augmentations.

We make the following simplifications: (1). Features consist only of numerical attributes, and join keys consist only of categorical attributes. Section 3.5 describes preprocessing to support categorical features. (2). Group-by operator γ has been extended to annotate group-by keys without tuples with zero elements (group-by attribute domains are assumed public in Section 2.3). (3). Datasets are preprocessed so that the ℓ_2 norm of the features in each tuple is bounded by a constant value B , following previous works [25, 58].

Algorithms. The FPM mechanism, detailed in Algorithm 1, is applied locally by either the requester or provider before dataset upload to the search platform. It uses as inputs: (1) the relation R to be privatized (2) the join key A^2 , which = *null* if R is only for union, (3) the order of monomials, k , based on the model to support, and (4) the DP budget (ϵ, δ) for R . FPM computes locally aggregated monomials $\gamma(R)$ and applies the Gaussian mechanism to these, with sensitivity optimized based on order parity and feature count (line 2, 7): For even-order monomials, sensitivity is reduced by $\sqrt{2}$, and if there's only one feature, sensitivity is reduced by another $\sqrt{2}$.

THEOREM 4. *FPM is $(\epsilon, \delta) - DP$.*

PROOF SKETCH. FPM applies the Gaussian mechanism [21] to the aggregated monomials for $(\epsilon, \delta) - DP$. Therefore, we only need to show the correctness of Δ . We present simple cases illustrating proof concepts for the union and join of 1 feature (with lower Δ), and the union of 2 features with 1/2-order monomial semiring. These cases are meant to illustrate the key intuitions; full proofs and generalizations are available in Appendix A due to space limits.

• (1 feature, Union, any order) For union, count (0-order monomial) remains unchanged as we consider bounded DP, where the neighbour relation has one tuple modified (instead of removed/added). Let the modified feature value be $a \rightarrow a'$ where both a and a' have a domain of $[-B, B]$. Then, for the i -th monomial, the squared difference is $(a^i - a'^i)^2$. When i is odd, $a^i \in [-B^i, B^i]$, and $(a^i - a'^i)^2 \leq (2B^i)^2$. When i is even, $a^i \in [0, B^i]$, and $(a^i - a'^i)^2 \leq (B^i)^2$.

• (1 feature, Join, any order) For join, the query also groups results by join key A . This can be considered as a histogram [62], where each bin is a join key, and the value is the k -order monomial semiring. The neighbouring relation has two cases: the modified tuple has changed the join key or not. If the join key doesn't change, this is the same as the union case. If the join key changes, there are two bins with a maximum square difference of $\sum_{i=0}^k B^{2i}$ (note that, unlike the union, the counts change). Thus, the sensitivity is bounded by $\sqrt{2 \sum_{i=0}^k B^{2i}}$. Finally, we take the maximum.

• (2 features, Union, 1-order) Let the modified feature value be $(a, b) \rightarrow (a', b')$ where both $a^2 + b^2$ and $a'^2 + b'^2$ are $\leq B^2$. Then, consider the 1-order monomials (a, b) , (a', b') . The squared difference is:

$$(a - a')^2 + (b - b')^2 \leq (2a^2 + 2a'^2) + (2b^2 + 2b'^2) = 4B^2$$

² A could be composite. To support multiple join keys, the DP budget can be split among different key combinations. Additionally, optimization techniques can be applied to take advantage of the correlations between join keys [49].

The sensitivities for higher odd orders are similar.

• (2 features, Union, 2-order) For even-orders, we can obtain a tighter bound. Consider the 2-order monomials (a^2, ab, b^2) , $(a'^2, a'b', b'^2)$. The squared difference is:

$$\begin{aligned} & (a^2 - a'^2)^2 + (ab - a'b')^2 + (b^2 - b'^2)^2 \\ & \leq (a^2 - a'^2)^2 + 2(ab - a'b')^2 + (b^2 - b'^2)^2 \\ & = (a^4 - 2a^2a'^2 + a'^4) + (2a^2b^2 - 4aba'b' + 2a'^2b'^2) + (b^4 - 2b^2b'^2 + b'^4) \\ & = (a^2 + b^2)^2 + (a'^2 + b'^2)^2 - 2(aa' + bb')^2 \leq B^4 + B^4 - 0 = 2B^4 \end{aligned}$$

For higher even orders, we can similarly amplify the monomials by the binomial coefficients (second line) to find a non-negative red term for even-order monomials, resulting in a tighter bound. Extending to joins follows a similar approach as the single feature case, where we consider group-by queries as histograms. \square

Algorithm 1: FPM mechanism

inputs : Relation R , Join Key A , Order k , DP budget (ϵ, δ)
output : Privatized Aggregated Relation \tilde{R}

- 1 **if** $A = \text{null}$ (Union Only) **then**
- 2 $\Delta = \sqrt{\sum_{i=1}^k (\text{if } i \text{ odd: } 4, \text{ elif } \#fea=1: 1, \text{ else: } 2) \cdot B^{2i}}$;
- 3 $\sigma, \tilde{R} = \sqrt{2 \ln(1.25/\delta)} \Delta / \epsilon, \gamma(R)$;
- 4 // add i.i.d. noises to each $1 - k$ order monomial s ;
- 5 $\tilde{R} = \{s : \tilde{R}[s] + e \sim \mathcal{N}(0, \sigma^2) \text{ for } 1 - k \text{ monomial } s\}$;
- 6 **else**
- 7 $\Delta = \max(\sqrt{\sum_{i=1}^k (\text{if } i \text{ odd: } 4, \text{ elif } \#fea=1: 1, \text{ else: } 2) \cdot B^{2i}}, \sqrt{2 \sum_{i=0}^k B^{2i}})$;
- 8 $\sigma, \tilde{R} = \sqrt{2 \ln(1.25/\delta)} \Delta / \epsilon, \gamma_A(R)$;
- 9 **foreach** $a \in \text{dom}(A)$ **do**
- 10 // add i.i.d. noises to each $0 - k$ order monomial s ;
- 11 $\tilde{R}(a) = \{s : \tilde{R}(a)[s] + e \sim \mathcal{N}(0, \sigma^2) \text{ for } 0 - k \text{ monomial } s\}$;
- 12 **return** \tilde{R} ;

3.4 Comparison with Other Mechanisms

We next analyze the error of FPM in estimating the statistics s (expected values of monomials). Generally, the expected errors of s are correlated with the error of the target model parameter β and accuracy; we will study the confidence bound for linear regression parameter in the next section, where the s error is the key factor.

Setting. We consider a data corpus with size n_{corp} (defined as the number of provider datasets) and has received n_{req} requests. To simplify the analysis, we assume that: (1) the search only uses union operations (and we will discuss the extension to join). (2) each dataset has one feature, n tuples, and a DP budget of (ϵ, δ) . The search platform evaluates all possible augmentations, each corresponding to a unique combination of provider datasets.

Metrics. The goal is to evaluate, for each augmentation, the expected ℓ_2 error of the privatized set of monomials \tilde{s} : $E[\|s - \tilde{s}\|_2]$.

Mechanisms. We compare FPM with standard DP mechanisms used in various existing trust models:

- For Saibot's trust model (Section 2.3), FPM (Algorithm 1) privatizes local aggregates independently for each dataset, and combines the aggregates with factorized ML.

- For the local model, the Per-tuple Privacy Mechanism (TPM)³ applies Algorithm 1 to privatize each tuple [63].
- For the global model, the Aggregate Privacy Mechanism (APM)⁴ first computes the union result R_U after augmentation, and then applies Algorithm 1 to $\gamma(R_U)$ [58]. To ensure $(\epsilon, \delta) - DP$ for all $n_{req}(2^{n_{corp}} - 1)$ augmentations, the DP budget has to be split.
- For the shuffle model, shuffling [26] privatizes each tuple, similar to TPM, but applies Laplace mechanism with the amplified privacy budget. These tuples are shuffled either at the 1^{st} - (SF-1) or 2^{nd} -level (SF-2); akin to APM, SF-2 requires budget splits.

PROPOSITION 5. *For the estimation of each augmentation (assuming that the number of augmented datasets and the order of s are small constants), FPM/SF-1 has expected ℓ_2 error of $\tilde{O}(\Delta/n\epsilon)$, while TPM has an error of $\tilde{O}(\Delta/\sqrt{n\epsilon})$ and APM/SF-2 has an error of $\tilde{O}(n_{req}2^{n_{corp}}\Delta/n\epsilon)$, where $\tilde{O}(\cdot)$ hides at most a logarithmic term.*

The proof is in Appendix B.

Remark. Proposition 5 highlights prior mechanisms' limitations: APM/SF-2 are competitive only for small corpora and quickly exhaust budget for larger requests/corpus sizes due to budget split for all possible augmentations, and require trust in centralized aggregators/shufflers. TPM adds excessive noise to each tuple, requiring quadratically more tuples to achieve the same level of error as FPM. Although SF-1 can theoretically match FPM's complexity with privacy amplification, it's significant only for large numbers of tuples. For instance, given $\epsilon=1$ and $\delta=10^{-6}$, ϵ is amplified when n reaches ~ 650 [26, 28]. However, small n needs amplification most, where SF-1 provides much larger errors than FPM (Section 5.2).

3.5 Differentially Private Data Search Platform

In this section, we discuss *SaiBOT*, a data search platform that integrates FPM to ensure differential privacy.

Provider. The architecture of the *SaiBOT*, which uses FPM for DP, is illustrated in Figure 2. For each dataset R data provider owns, the supported operation (\bowtie / \cup^5 or \cup -only) is decided. If join is supported, the join key A must also be specified. FPM is then applied locally to R to privatize the sufficient statistics $\gamma(R)$, which are then uploaded to *SaiBOT*. As *SaiBOT* is not trusted, *data storage* only stores privatized statistics, but not raw data. All operations over $\gamma(R)$ are post-processing without additional DP costs.

Requester. The requester has model type M and R_{train} , and wants to improve accuracy on R_{test} . The requester computes and submits to *SaiBOT* the privatized sufficient statistics $\gamma(R_{train})$ and $\gamma(R_{test})$. *Data discovery* returns a set of joinable or unionable relations R from *data storage*. Then, *Data search* applies greedy algorithm (following Kitana [34]): in each iteration, it evaluates each candidate and adds the one that most improves the model accuracy. *SaiBOT* is agnostic to the search algorithm, and others [19, 56] can also be used.

Data Discovery. Previous data discovery systems [17, 29] leverage MinHash sketches, column type and data distribution statistics; *SaiBOT* supports all of them. Specifically, for categorical attributes,

³An alternative is to apply Gaussian mechanism to raw tuples and then compute monomial semi-ring; this, however, results in an even larger error.

⁴There are other alternatives like perturbing objectives and gradients; however they are similarly limited by the combinatorially large number of models to train.

⁵Any dataset supports join also supports union by aggregating out the join key.

we utilize minhash sketches, computed from public domains, to measure set similarity. For numerical attributes, we rely on public schemas for column names and types.

Preprocessing. Before applying FPM, requesters and providers can locally preprocess datasets to enhance utility and robustness. For instance, datasets may have categorical features not directly supported by the proxy model (linear regression). Standard one-hot encoding can be applied, treating the encoded features as numerical for privatization by FPM. *SaiBOT* also applies two steps to boost DP robustness. First, it removes outliers (>1.5 std from the mean), which typically improves model performance and reduces the tuple ℓ_2 norms, enhancing DP noise robustness [42]. Second, all DP mechanisms (including ours) degrade with increasing dimensionality due to the increased tuple ℓ_2 norms. Thus, *SaiBOT* applies dimensionality reduction [44] to retain the top K principal components ($K=1$ works best in our experiments), and rescales tuples to bound max ℓ_2 norm $\leq B$. These steps are applied to all datasets and DP baselines in our real-world experiments (Section 5.1).

Supporting Varied Privacy Needs. A unique benefit of *SaiBOT*'s design is that it can adapt to different privacy needs. In cases where pure DP ($\delta=0$) is required, FPM can be modified to apply Laplace mechanisms [22]. In situations where individuals don't trust providers or requesters, FPM can be reduced to LPM to privatize individual tuples. Conversely, shuffling only guarantees approximate DP and GPM always requires a trusted centralized aggregator.

ML training after data search. After *SaiBOT* finds predictive augmentations using a differentially private proxy model (linear regression), the model could be directly returned to requesters. However, requesters may need more complex model M , and the training shall also satisfy DP. To achieve this, *SaiBOT* can be integrated within a larger differentially private federated ML system [55, 57, 59, 64], where *SaiBOT* first locates augmentations, and then the ML systems use the augmented dataset to train sophisticated models, such as deep neural networks, via differentially private gradient descent.

Scope. While *SaiBOT* can employ FPM to support a wide range of models [52] and approximate GLM [41], this paper focuses on linear regression [53] because it's widely used and is adopted by previous data search [18, 34, 51]. Next, we dive deep into linear regression to analyze the task utility and propose further optimizations.

4 DIVING DEEP INTO LINEAR REGRESSION

This section examines the ML task *utility* FPM provides and suggests optimizations for linear regression. We start with the assumption of linear regression on many-to-many join (as opposed to one-to-one [32, 57]), which is challenging due to unexpected duplication and independence. We then propose an unbiased estimator. Next, we explore the confidence bounds for the linear regression parameters and propose optimizations to tighten the bound further.

4.1 Linear Regression on Many-to-Many Join

Linear regression assumes a noisy linear relationship between the features and target variable: $\mathbf{y} = \mathbf{X}\beta + \mathbf{e}$, where \mathbf{e} is the error term. This is consistent with our assumption so far if $R_{\bowtie} = R_1 \bowtie \dots R_k$ is the population, and let us use the monomial semi-ring to compute the expected s . However, when many-to-many joins

are involved, R_{\bowtie} often doesn't represent the population as joins generate Cartesian products for each matching key. This leads to (1) duplicated tuples (the same \mathbf{y} values are repeated) and (2) unexpected *independence* between features from different relations with the same join key, leading to biased estimation.

Our analysis focuses on an easy-to-explain case inspired by vertical federated ML [32, 57], where we want to train linear regression over relation R . However, R is not directly observable, and each party can only access a projection $\pi(R)$. Multiple $\pi(R)$ may have many-to-many relationships on the common attribute (join key) instead of the one-to-one relationships studied by federated ML. The objective is to train linear regression on R collectively.

Unbiased Estimator. Given R of cardinality n , suppose there are two parties holding different projections $\pi_{F_1}(R)$ and $\pi_{F_2}(R)$, and the goal is to compute the 2-order monomial semi-ring $\gamma(\pi_{F_1 \cup F_2}(R))$. However, factorized ML is trained on $R_{\bowtie} = \pi_{F_1, J}(R) \bowtie \pi_{F_2, J}(R)$ with join key $J = F_1 \cap F_2$; R_{\bowtie} is likely to differ from $\pi_{F_1 \cup F_2}(R)$ (unless J is primary key), resulting in bias. To address this, we propose an unbiased estimator for s based on $s' = \gamma(R_{\bowtie})$.

PROPOSITION 6 (UNBIASED ESTIMATOR OF s OVER R). *We make the simplifying assumption that J is uniformly distributed (if $d = |\text{dom}(J)|$, each $j \in J$ appears n/d times in R) and is not correlated with any other attribute. Let $s' = \gamma(R_{\bowtie})$. Then,*

$$\hat{s} = \begin{cases} f_1 f_2 = \frac{1-n}{1-d} \frac{s'[f_1 f_2]}{s'[c]} + \frac{n-d}{1-d} \frac{s'[f_1]}{s'[c]} \frac{s'[f_2]}{s'[c]} \\ \quad \text{for } f_1 \in F_1 - J, f_2 \in F_2 - J \\ p = s'[p]/s'[c] \quad \text{for any other monomial } p \end{cases}$$

\hat{s} is an unbiased estimator of monomial semi-ring $s = \gamma(\pi_{F_1 \cup F_2}(R))$.

The proof is in Appendix C. We assume vertical partitions of R , but real-world datasets may also be horizontally partitioned; the estimators could be refined for these cases. Our analysis studies the base case, and the unbiased estimator can be recursively applied for multiple joins and unions. Note that the estimators are post-processing steps without compromising DP.

4.2 Simple Linear Regression Analysis

Building on the assumption in the previous section, this section studies the confidence bound of factorized linear regression. Compared to [58], our analysis focuses on simple linear regression with one feature, under less stringent assumptions; this scenario is sufficient to show FPM's advantages over other mechanisms, and motivates optimization. We first consider a single relation case, then extend to union and join. We'll begin with defining the confidence bound, which will be used to evaluate the utility of private estimators.

DEFINITION 4 (CONFIDENCE BOUND). *Given parameter θ , the $(1-p)$ confidence bound $C_{\theta}^{\hat{\theta}}(p)$ for an private estimator $\hat{\theta}$ is:*

$$C_{\theta}^{\hat{\theta}}(p) = \inf \{ b : \mathbb{P}[|\hat{\theta} - \theta| \leq b] \geq 1 - p \}$$

where $\hat{\theta}$ is the non-private estimator.

We consider relation $R[x, y]$ with one feature x , target variable y , and cardinality n . We want to train $y = \beta_x \cdot x + \beta_0$, and focus on the parameter β_x ; β_x has an optimal non-privitized estimator $\hat{\beta}_x = \frac{E[xy] - E[x]E[y]}{E[x^2] - E[x]^2} = \frac{\widehat{\sigma}_{xy}}{\widehat{\sigma}_x^2}$, where $\widehat{\sigma}_{xy}$ and $\widehat{\sigma}_x^2$ are polynomials

that can be derived from aggregated 2-order monomials $\gamma(R)$. We apply FPM to compute the privatized 2-order $\gamma(R)$ and study the confidence bound of the privatized estimator $\tilde{\beta}_x$. Note that more familiar error definitions like mean-squared-error can be upper bounded, roughly, by the square of the confidence bound.

THEOREM 4.1 (CONFIDENCE BOUND OF $\tilde{\beta}_x$). *For every p where $\tau_1 < 1$ holds, the $(1-p)$ confidence bound for $\tilde{\beta}_x$ is:*

$$C_{\tilde{\beta}_x}^{\hat{\beta}_x}(p) \leq \tau_2 + \frac{\tau_1}{1 - \tau_1} (\hat{\beta}_x + \tau_2)$$

where $\tilde{\beta}_x$ ($\hat{\beta}_x$) is the private (non-private) estimate of β_x . Let B_1 and B_2 be the $(1-p)$ confidence bounds for $\widehat{\sigma}_x^2$ and $\widehat{\sigma}_{xy}^2$ respectively. Then $\tau_1 = B_1/\widehat{\sigma}_x^2$ and $\tau_2 = B_2/\widehat{\sigma}_x^2$ are both $O\left(\frac{B^4 \ln(1/\delta) \ln(1/p)}{\epsilon^2 n \widehat{\sigma}_x^2}\right)$. The probability is taken over the randomness of FPM.

The proof and extension to multi-features can be found in Appendix D. Theorem 4.1 demonstrates that the private estimator $\tilde{\beta}_x$ is asymptotically close to the non-private $\hat{\beta}_x$. The key factors in reducing the discrepancy are τ_1, τ_2 . APM and SF-2 have combinatorially large τ_1, τ_2 due to the budget splits. TPM requires quadratically more data than FPM to achieve the same level of τ_1, τ_2 .

Algorithm 2: FPM-OPT algorithm for Join

inputs : Relation R , Join Key A , Order k , DP budget (ϵ, δ)
output : Privatized Annotated Relation \tilde{R}

- 1 **foreach** $i \in \{0, \dots, k\}$ **do**
- 2 $\Delta, \epsilon', \delta' = (\text{if } i \text{ odd: } 2, \text{ else: } \sqrt{2}) \cdot B^i, \epsilon/(k+1), \delta/(k+1)$;
- 3 $\sigma, \tilde{R} = \sqrt{2 \ln(1.25/\delta')} \Delta / \epsilon', \gamma_A(R)$;
- 4 **foreach** $a \in \text{dom}(A)$ **do**
- 5 // add i.i.d. noises to each i order monomial s ;
- 6 $\tilde{R}(a) = \{s : \tilde{R}(a)[s] + e \sim \mathcal{N}(0, \sigma^2) \text{ for } i \text{ monomial } s\}$;
- 7 **return** \tilde{R} ;

4.3 Optimization: Better Noise Allocation

In Section 4.2, we analyzed the linear regression confidence bounds. We propose to adjust noise allocation to improve the bounds further.

First, previous work (e.g., [15]) has shown that β_x is usually the parameter of interest instead of β_0 for linear regression over the union. In this case, we suggest each provider adding noises directly to $\sigma_x^2, \sigma_{xy}^2$, rather than monomials x^2, xy, x, y . This reduces τ_1 and τ_2 by a factor of $O(B^2 \sqrt{\ln(1/\delta) \ln(1/p)} / \epsilon)$ (Appendix E).

Second, optimizing joins is more difficult as we add noise locally to monomials to circumvent combinatorially large DP costs. However, we can reduce τ_1, τ_2 by $O(B^2)$ through smart budget allocation (Appendix E). Our insight is that lower-order monomials are multiplied by more monomials than higher-order ones. For example, in Figure 6, 0-order monomials are multiplied by 0, 1, 2, 3-order ones, while 3-order monomials only multiply with 0-order ones. Hence, we shall decrease the noise to lower-order ones. FPM-OPT in Algorithm 2 achieves this by dividing the DP budget across orders; lower order monomials have lower sensitivity and thus fewer noises.

5 EVALUATION

We evaluate FPM on NYC Open Data [11] corpus of 329 datasets for an end-to-end dataset search. We then use ablation studies via synthetic datasets to validate our theoretical analyses.

5.1 Real-world Experiments

Data and Workload. We construct a large data corpus of 329 NYC Open Data [11] datasets. Since prior DP mechanisms need to know the number of requests up front, we create a workload of 5 requests using the following random datasets:

- **Regents** [4] contains 2014-17 regents exams data.
- **ELA** [1] contains 2013-18 Early Learning Assessment (ELA) data.
- **Gender** [3] contains 2013-16 ELA data by grades and gender.
- **Grad** [5] contains 2016-17 graduation outcomes.
- **Math** [2] contains 2013-18 Math grades.

For each request, we look for a single dataset to join/union with the requested dataset. We turn off data discovery so every dataset in the platform is considered. By default, each dataset has DP budget ($\epsilon = 1, \delta = 10^{-6}$). We report the final r_2 score evaluated non-privately. For reliability, we run each request 10 times.

Baselines. We consider different DP mechanisms. **Non-P** doesn't use DP and provides r_2 upper bound. **FPM** applies Algorithm 2 to each dataset. **APM** (Aggregate Privacy Mechanism), following Wang [58], applies Algorithm 2 to the augmented dataset to privatize the aggregated sufficient statistics (and requires a trusted search platform). We use attribute max-frequency from Flex [36] to bound join sensitivity. Note that APM requires budget splits across all augmentations. **TPM** (Per-tuple Privacy Mechanism) applies Algorithm 2 to each tuple and uses half the ϵ to perturb the join key with generalized random response [37]. **SF** is similar to TPM, but applies the Laplace mechanism to each tuple with an amplified budget then shuffles [26, 28]. Since SF doesn't support joins (by 2^{nd} -level aggregator), we only shuffle each dataset locally by 1^{st} -level aggregators. In each case, we use a failure mechanism that reports $r_2 = 0$ if the privatized $\mathbf{X}^T \mathbf{X}$ is not positive definite [15].

Results. Figure 7 shows the non-private r_2 of 10 runs of private data search for the 5 requests. FPM dominates the DP alternatives and is ~ 50 – 90% of the non-DP case. FPM's performance depends on dataset cardinality: the *Gender* dataset contains on average ~ 40 tuples per join key (compared to >100 tuples per join key in other datasets) and is more vulnerable to noise.

We next vary the number of datasets by sampling $n_{corp} \in \{10, 50, 100, 300\}$ datasets and rerunning each baseline over the smaller corpus. Figure 8 reports the median r_2 . For a small corpus ($n_{corp} = 10$), APM outperforms FPM because it imputes noise to the aggregated statistics across join key values and there are fewer budget splits, while FPM has to add noise to the individual statistics for each join key. TPM and SF have low r_2 due to high noise.

Finally, we vary the number of requests ($n_{req} \in \{1, 10, 50, 100\}$) by sending the same request n_{req} times, and report median r_2 . Figure 9 shows that each baseline is almost invariant to n_{req} , and FPM dominates. In theory, APM is worse for more requests but is already poor due to the large dataset corpus.

5.2 Synthetic Dataset Experiments

We next validate our theoretical analysis of linear regression using synthetic data, and conduct ablation tests to study the impact of various parameters (number of tuples n , DP budget ϵ, δ , corpus size n_{corp} , number of requests n_{req} and join key domain size d).

5.2.1 Setup. We generate datasets by first creating a symmetric positive-definite matrix (`make_spd_matrix` in *sklearn*) as the covariance $\mathbf{X}^T \mathbf{X}$. We then sample from a multivariate normal distribution with this covariance to create a relation. To ensure the ℓ_2 norms of tuples $\leq B=5$, we resample for any tuples that exceed this limit.

By default, for union, we generate relations with $n = 1000$ tuples and 3 numerical attributes $[y, x_1, x_2]$. For join, we generate relations with $n = 10000$ tuples and include a categorical join key J uniformly distributed with a domain size of $d = 100$. We construct two vertical partitions with projections $[y, x_1, J]$ and $[x_2, J]$, respectively. We start with $n_{corp} = 2$ datasets, $n_{req} = 1$ request.

We will report the ℓ_2 distance to the non-private sufficient statistics (s error) and regression parameter (β error) as metrics. Each experiment will be repeated 100 times, and we will present the medians (dots), as well as the 25^{th} and 75^{th} percentiles (error bars).

5.2.2 DP for Union. Baselines include APM, TPM (same as in Section 5.1), SF-1, which shuffles tuples locally, SF-2, which shuffles the unioned dataset, and FPM using Algorithm 1 rather than Algorithm 2 (which is for join).

First, we vary $n \in \{10, 100, 500, 1K, 10K\}$. Figure 10a and Figure 10b report s and β errors. Since there are $n_{corp}=2$ datasets, APM and FPM perform similarly. In contrast, TPM requires quadratically more data to achieve the same s errors, consistent with our analysis in Section 3.4. SF's amplification is not significant for small n , when it's needed most, and both variants have high s errors. β error eventually converges to 0 for all baselines, but FPM does so at a comparable rate to APM ($n=500$ vs. $10K$ for the others).

Figure 10c shows that β error naturally correlates with s error, and higher s error increases the chance of failure (β error $=\infty$). The remaining results will focus on β error, as it is of interest.

Next, we vary the DP budget $\epsilon=0.1$ or $\delta=0$ (pure DP). The results are shown in Figure 10d and Figure 10e, respectively. For $\epsilon=0.1$, the plot shifts right due to a smaller budget. In the case of pure DP with $\delta=0$, FPM, APM and TPM can adapt to it by applying Laplace mechanism, achieving similar performance. In contrast, SF-1 and SF-2 fail as only approximate DP is supported.

Figure 10f and Figure 10g vary the number of datasets and requests $n_{corp}, n_{req} \in \{1, 5, 10, 50, 100\}$, respectively. FPM's β error is flat. TPM, SF-1 and SF-2 frequently fail due to high noise, while APM only performed well when $n_{corp} \leq 5$ or $n_{req} \leq 10$. **APM is hence unsuitable for large data corpora.**

Figure 10h reports linear regression optimization benefit in Section 4.3. For a two-attribute dataset $R[y, x]$, while FPM adds noise to monomials (x, y, x^2, y^2, xy) , FPM-OPT adds noise to polynomials $(\sigma_x^2, \sigma_{xy}^2)$ because we only care about β_x . We find that FPM-OPT reduces the β error and failure likelihood, especially for $n < 100$.

5.2.3 DP for Join. We evaluate different DP mechanisms over the join. Baselines include FPM-OPT, which uses a smart allocation strategy to reduce the noise of lower order statistics, as discussed in Section 4.3. SF-2 doesn't support joins, so it is not reported.

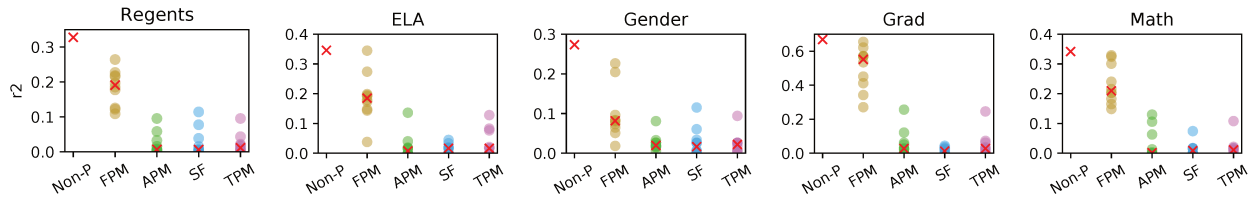


Figure 7: Utility (non-privatized r^2) of the returned combinations of datasets searched by different baselines over 10 runs, with the median indicated by a red cross. **FPM** exhibits significantly better utility than the other baselines.

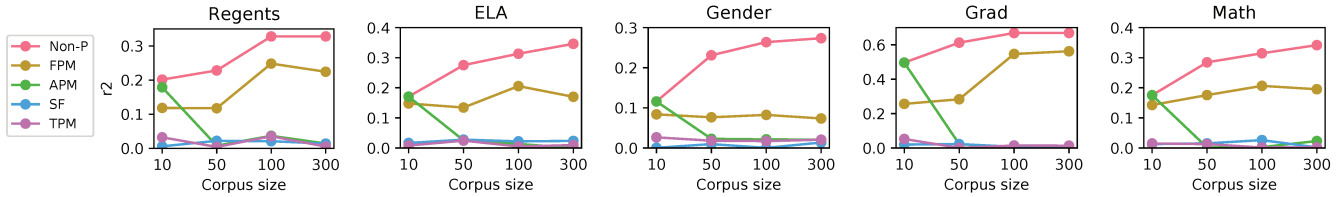


Figure 8: Utility of the returned combinations of datasets searched by different baselines when varying the corpus size n_{corp} . **FPM** is scalable for large corpus, while **APM** only performs well for small n_{corp} .

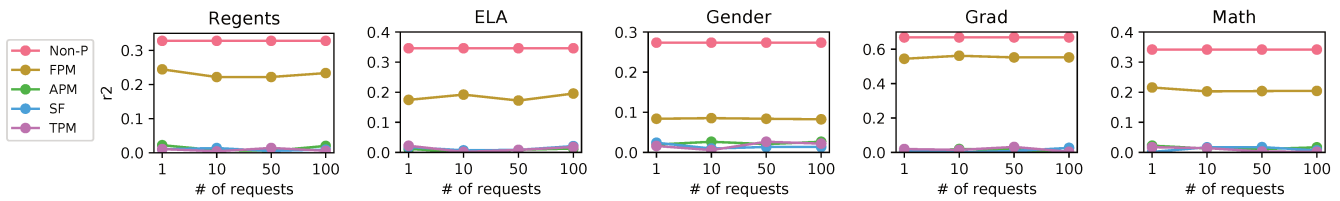


Figure 9: Utility of the returned combinations of datasets searched by different baselines when varying the number of requests n_{req} . **FPM** consistently performs well, while the others either suffer from large noises (**TPM**, **SF**) or budget splits (**APM**).

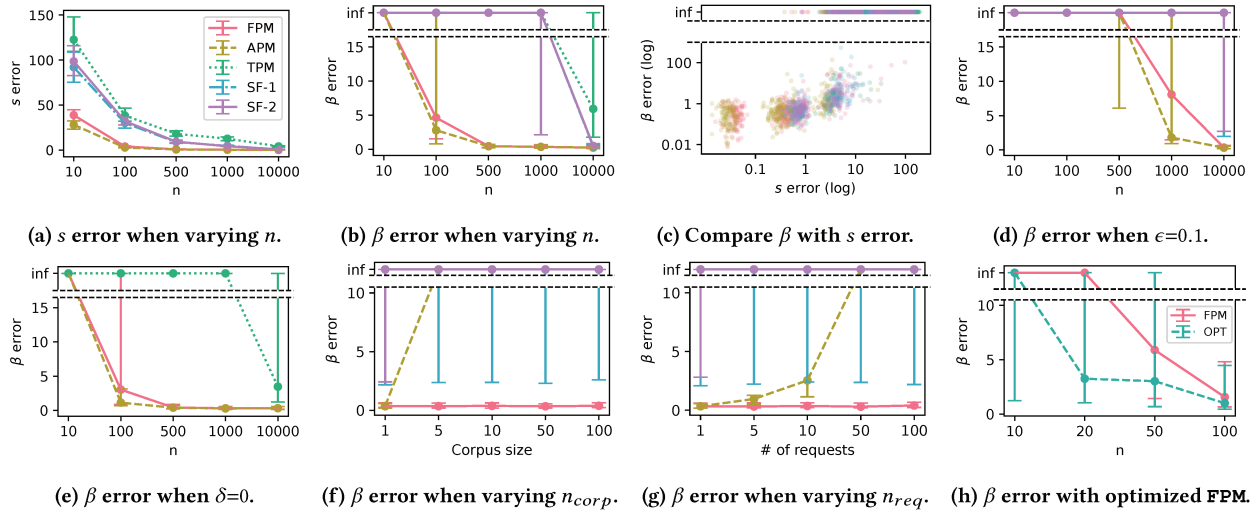


Figure 10: Ablation tests for unions: (a). (b). All baselines show reduced s and β errors as n increases, with **FPM** and **APM** exhibiting the least error; (c). Larger s error results in higher β errors and a greater risk of failure; (d). For $\epsilon = 0.1$, the β error plot shifts to the right; (e). For pure DP with $\delta = 0$, **FPM** can adjust to it and offer comparable utility, while **SF** fails; (f). (g). **FPM** is scalable for large corpora with large numbers of requests, while **APM** deteriorates significantly when $n_{corp} > 5$ or $n_{req} > 10$; (h). For simple linear regression when only β_x is of interest, **FPM-OPT** reduces the β errors and failure risk, particularly for small n .

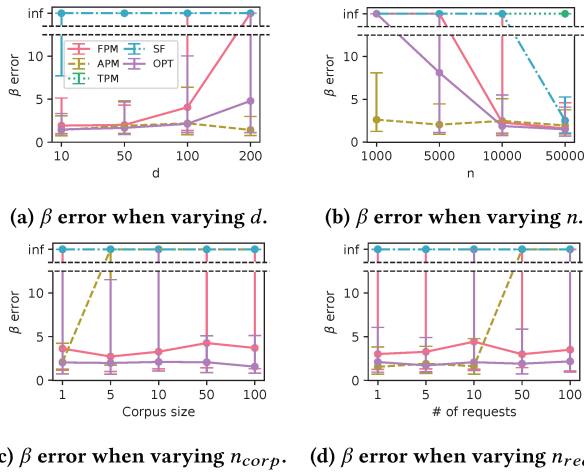


Figure 11: Ablation tests for joins: (a,b). FPM, FPM-OPT and APM provide low error when varying d and n , while TPM and SF are dominated by high noises (c,d). FPM, FPM-OPT show scalability for large repositories with numerous requests, whereas APM has high errors when $n_{corp} > 5$ or $n_{req} > 10$.

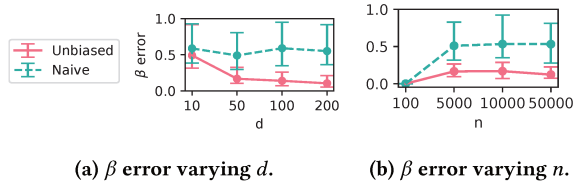


Figure 12: β error for naive and unbiased estimators over join. The unbiased estimator dominates the naive one.

We use $n_{corp} = 2$ datasets: we fix cardinality $n = 10K$ but vary join key domain size $d \in \{10, 50, 100, 200\}$, then fix $d = 100$ but vary $n \in \{100, 5K, 10K, 50K\}$. The results are shown in Figure 11a and Figure 11b, respectively. FPM, FPM-OPT and APM have low β error, while TPM and SF have high failure rates. FPM-OPT outperforms FPM due to better noise allocation. APM outperforms FPM and FPM-OPT at large d or small n because APM adds noise directly to the aggregated statistics across join keys, resulting in a smaller amount of noise. In contrast, FPM adds noise for each join key value. However, for large n , FPM and FPM-OPT outperform APM because it has high sensitivity due to high join fanouts [36].

Figure 11c and Figure 11d respectively vary the number of datasets and requests: $n_{corp}, n_{req} \in \{1, 5, 10, 50, 100\}$. Both TPM and SF have high failure rates, and FPM-OPT outperforms FPM. FPM and FPM-OPT scale to arbitrary numbers of datasets and requests, while APM is restricted to $n_{corp} \leq 5$ or $n_{req} \leq 10$.

5.2.4 Join Unbiased estimator. Here, we compare the β error of the unbiased estimator proposed in Section 4.1 to the naive estimator over many-to-many joins. We first fix the number of tuples $n = 10K$ but vary join key domain size $d \in \{10, 50, 100, 200\}$, then fix $d = 100$ but vary $n \in \{100, 5K, 10K, 50K\}$, and report the results in Figure 12a and Figure 12b respectively. As d increases, the

errors of the unbiased estimator converge to 0, while the biased estimator diverges as it fails to account for many-to-many join. When $n = 100$, the naive estimator achieves similar performance, as each join key has only one tuple (so one-to-one join without bias). However, increasing n introduces duplications and independence (for many-to-many join). The unbiased estimator reduces the noise and performs better than the naive estimator.

6 RELATED WORKS

Dataset search. Traditional data discovery focuses on augmentable (i.e., joinable or unionable) datasets [17, 29], whereas recent dataset search platforms [19, 43, 45, 51] are based on data augmentation for ML tasks. However, none addresses privacy concerns.

Differential Privacy for Databases. Differentially private databases can query over multiple tables [36, 40, 60]. They apply DP mechanisms to query results over joins and unions. Notably, join poses a significant DP challenge due to the exponential sensitivity growth along the join path. FPM may offer a solution by decomposing join query into smaller, bounded-sensitivity statistics.

Federated ML. These methods let each untrusted party compute and privatize their local gradients for horizontal [54, 55, 59, 64] or vertical [32, 57] federated ML, which are then combined to train the final model. However, the gradient is specific to training a single model. In contrast, data search repeatedly trains new models to evaluate candidate augmentations, requiring budget splits.

Differentially Private Sufficient Statistics. Previous works use sufficient statistics [35] for generalized linear models and apply perturbations [41] to guarantee DP. For linear regression, sufficient statistics perturbation, particularly with regularization, outperforms other GDP mechanisms including objective perturbation and noisy SGD [14, 58]. However, they only consider ML on a single dataset.

Factorized ML. Factorized ML decomposes ML models into semi-ring queries, designs algebraic operators to combine them, and achieves asymptotically lower time complexity. They support models like ridge regression [53], random forests [33], SVM [38], and factorization machine [52]. None are differentially private.

7 CONCLUSIONS

SaiBOT is a differentially private data search platform that searches large corpora to find datasets to improve ML performance via augmentation. *SaiBOT* employs FPM, a novel mechanism that privatizes sufficient semi-ring statistics. In a deep study of linear regression, we propose an unbiased estimator for many-to-many joins, prove parameter bounds under augmentations, and propose an optimization to allocate DP budget better. On a >300 dataset corpus, FPM achieves an r^2 score ($\sim 50-90\%$) of non-private search, while other mechanisms report negligible r^2 scores < 0.02 .

ACKNOWLEDGMENTS

This work was supported by the NSF under Grant No. 1845638, 2008295, 2106197, 2103794, 2312991, Columbia Data Science Institute’s Avanesian PhD fellowship, Simons Foundation (965342, D.A.) as part of the Junior Fellowship from the Simons Society of Fellows, as well as support from Amazon and Adobe. We are grateful to anonymous reviewers for helpful feedbacks.

REFERENCES

- [1] [n.d.]. 2013 - 2018 School ELA REsults. <https://data.cityofnewyork.us/Education/2013-2018-School-ELA-REsults/qkpp-pb18>.
- [2] [n.d.]. 2013 -2018 School Math Results. <https://data.cityofnewyork.us/Education/2013-2018-School-Math-Results/m27t-h3h>.
- [3] [n.d.]. 2013-16 School ELA Data Files By Grade - Gender. <https://data.cityofnewyork.us/Education/2013-16-School-ELA-Data-Files-By-Grade-Gender/436j-ja87>.
- [4] [n.d.]. 2014-15 To 2016-17 School- Level NYC Regents Report For All Vari-ables. <https://data.cityofnewyork.us/Education/2014-15-To-2016-17-School-Level-NYC-Regents-Report/csp5-2ne9/>.
- [5] [n.d.]. 2016-2017 Graduation Outcomes School. <https://data.cityofnewyork.us/Education/2016-2017-Graduation-Outcomes-School/nb39-jx2v>.
- [6] [n.d.]. California Consumer Privacy Act. <https://oag.ca.gov/privacy/ccpa>.
- [7] [n.d.]. The Family Educational Rights and Privacy Act (FERPA). <https://studentprivacy.ed.gov/>.
- [8] [n.d.]. Health Insurance Portability and Accountability Act of 1996 (HIPAA). <https://www.cdc.gov/php/publications/topic/hipaa.html>.
- [9] 2018. 2018 reform of EU data protection rules. https://ec.europa.eu/commission/sites/beta-political/files/data-protection-factsheet-changes_en.pdf.
- [10] 2022. CMS Data. <https://data.cms.gov/>.
- [11] 2022. NYC Open Data. <https://opendata.cityofnewyork.us/>.
- [12] 2023. (Technical Report) Saibot: A Differentially Private Data Search Platform. https://anonymous.4open.science/r/Saibot-B387/tech/saibot_tech.pdf.
- [13] Mahmoud Abo Khamis, Hung Q Ngo, and Atri Rudra. 2016. FAQ: questions asked frequently. In *Proceedings of the 35th ACM SIGMOD-SIGACT-SIGAI Symposium on Principles of Database Systems*. 13–28.
- [14] Daniel Alabi and Salil Vadhan. 2022. Hypothesis Testing for Differentially Private Linear Regression. In *Advances in Neural Information Processing Systems*, Vol. 35. 14196–14209. https://proceedings.neurips.cc/paper_files/paper/2022/file/5bc3356efa1753fff7e8d6628e71b22-Paper-Conference.pdf
- [15] Daniel Gbenga Alabi. 2022. *The Algorithmic Foundations of Private Computational Social Science*. Ph.D. Dissertation. Harvard University.
- [16] Avrim Blum, Katrina Ligett, and Aaron Roth. 2013. A learning theory approach to noninteractive database privacy. *Journal of the ACM (JACM)* 60, 2 (2013), 1–25.
- [17] Sonia Castelo, Rémi Rampin, Aécio Santos, Aline Bessa, Fernando Chirigati, and Juliana Freire. 2021. Auctus: a dataset search engine for data discovery and augmentation. *Proceedings of the VLDB Endowment* 14, 12 (2021), 2791–2794.
- [18] Xiaojun Chen, Guowen Yuan, Feiping Nie, and Joshua Zhexue Huang. 2017. Semi-supervised Feature Selection via Rescaled Linear Regression.. In *IJCAI*, Vol. 2017. 1525–1531.
- [19] Nadia Chepurko, Ryan Marcus, Emanuel Zraggen, Raul Castro Fernandez, Tim Kraska, and David Karger. 2020. ARDA: automatic relational data augmentation for machine learning. *arXiv preprint arXiv:2003.09758* (2020).
- [20] Bolin Ding, Janardhan Kulkarni, and Sergey Yekhanin. 2017. Collecting telemetry data privately. *Advances in Neural Information Processing Systems* 30 (2017).
- [21] Cynthia Dwork, Krishnaram Kenthapadi, Frank McSherry, Ilya Mironov, and Moni Naor. 2006. Our data, ourselves: Privacy via distributed noise generation. In *Annual international conference on the theory and applications of cryptographic techniques*. Springer, 486–503.
- [22] Cynthia Dwork, Frank McSherry, Kobbi Nissim, and Adam Smith. 2006. Calibrating noise to sensitivity in private data analysis. In *Theory of Cryptography: Third Theory of Cryptography Conference, TCC 2006, New York, NY, USA, March 4-7, 2006. Proceedings 3*. Springer, 265–284.
- [23] Cynthia Dwork, Guy N Rothblum, and Salil Vadhan. 2010. Boosting and differential privacy. In *2010 IEEE 51st Annual Symposium on Foundations of Computer Science*. IEEE, 51–60.
- [24] Cynthia Dwork, Adam Smith, Thomas Steinke, and Jonathan Ullman. 2017. Exposed! a survey of attacks on private data. *Annual Review of Statistics and Its Application* 4 (2017), 61–84.
- [25] Cynthia Dwork, Kunal Talwar, Abhradeep Thakurta, and Li Zhang. 2014. Analyze gauss: optimal bounds for privacy-preserving principal component analysis. In *Proceedings of the forty-sixth annual ACM symposium on Theory of computing*. 11–20.
- [26] Úlfar Erlingsson, Vitaly Feldman, Ilya Mironov, Ananth Raghunathan, Kunal Talwar, and Abhradeep Thakurta. 2019. Amplification by shuffling: From local to central differential privacy via anonymity. In *Proceedings of the Thirtieth Annual ACM-SIAM Symposium on Discrete Algorithms*. SIAM, 2468–2479.
- [27] Úlfar Erlingsson, Vasily Pihur, and Aleksandra Korolova. 2014. Rappor: Randomized aggregatable privacy-preserving ordinal response. In *Proceedings of the 2014 ACM SIGSAC conference on computer and communications security*. 1054–1067.
- [28] Vitaly Feldman, Audra McMillan, and Kunal Talwar. 2022. Hiding among the clones: A simple and nearly optimal analysis of privacy amplification by shuffling. In *2021 IEEE 62nd Annual Symposium on Foundations of Computer Science (FOCS)*. IEEE, 954–964.
- [29] Raul Castro Fernandez, Ziawasch Abedjan, Famiem Koko, Gina Yuan, Samuel Madden, and Michael Stonebraker. 2018. Aurum: A data discovery system. In *2018 IEEE 34th International Conference on Data Engineering (ICDE)*. IEEE, 1001–1012.
- [30] Todd J Green, Grigoris Karvounarakis, and Val Tannen. 2007. Provenance semirings. In *Proceedings of the twenty-sixth ACM SIGMOD-SIGACT-SIGART symposium on Principles of database systems*. 31–40.
- [31] Moritz Hardt and Guy N Rothblum. 2010. A multiplicative weights mechanism for privacy-preserving data analysis. In *2010 IEEE 51st annual symposium on foundations of computer science*. IEEE, 61–70.
- [32] Stephen Hardy, Wilko Henecka, Hamish Ivey-Law, Richard Nock, Giorgio Patrini, Guillaume Smith, and Brian Thorne. 2017. Private federated learning on vertically partitioned data via entity resolution and additively homomorphic encryption. *arXiv preprint arXiv:1711.10677* (2017).
- [33] Zezhou Huang, Rathijit Sen, Jiaxiang Liu, and Eugene Wu. 2022. (Technical Report) JoinBoost: In-Database Tree-Models In Action. https://anonymous.4open.science/r/JoinBoost-FBC4/technical/JoinBoost_tech.pdf.
- [34] Zezhou Huang, Pranav Subramaniam, Raul Castro Fernandez, and Eugene Wu. 2023. Kitana: Efficient Data Augmentation Search for AutoML. [arXiv:2305.10419 \[cs.DB\]](https://arxiv.org/abs/2305.10419)
- [35] Jonathan Huggins, Ryan P Adams, and Tamara Broderick. 2017. PASS-GLM: polynomial approximate sufficient statistics for scalable Bayesian GLM inference. *Advances in Neural Information Processing Systems* 30 (2017).
- [36] Noah Johnson, Joseph P Near, and Dawn Song. 2018. Towards practical differential privacy for SQL queries. *Proceedings of the VLDB Endowment* 11, 5 (2018), 526–539.
- [37] Peter Kairouz, Keith Bonawitz, and Daniel Ramage. 2016. Discrete distribution estimation under local privacy. In *International Conference on Machine Learning*. PMLR, 2436–2444.
- [38] Mahmoud Abo Khamis, Ryan R Curtin, Benjamin Moseley, Hung Q Ngo, Xuan-Long Nguyen, Dan Olteanu, and Maximilian Schleich. 2020. Functional Aggregate Queries with Additive Inequalities. *ACM Transactions on Database Systems (TODS)* 45, 4 (2020), 1–41.
- [39] Mahmoud Abo Khamis, Hung Q Ngo, XuanLong Nguyen, Dan Olteanu, and Maximilian Schleich. 2018. AC/DC: in-database learning thunderstruck. In *Proceedings of the second workshop on data management for end-to-end machine learning*. 1–10.
- [40] Ios Kotsogiannis, Yuchao Tao, Xi He, Maryam Fanaeepour, Ashwin Machanavajjhala, Michael Hay, and Gerome Miklau. 2019. Privatesql: a differentially private sql query engine. *Proceedings of the VLDB Endowment* 12, 11 (2019), 1371–1384.
- [41] Tejas Kulkarni, Joonas Jälkö, Antti Koskela, Samuel Kaski, and Antti Honkela. 2021. Differentially private bayesian inference for generalized linear models. In *International Conference on Machine Learning*. PMLR, 5838–5849.
- [42] Jaewoo Lee and Chris Clifton. 2011. How much is enough? choosing ϵ for differential privacy. In *Information Security: 14th International Conference, ISC 2011, Xi'an, China, October 26-29, 2011. Proceedings 14*. Springer, 325–340.
- [43] Yifan Li, Xiaohui Yu, and Nick Koudas. 2021. Data acquisition for improving machine learning models. *Proceedings of the VLDB Endowment* 14, 10 (2021), 1832–1844.
- [44] Andrzej Maćkiewicz and Waldemar Ratajczak. 1993. Principal components analysis (PCA). *Computers & Geosciences* 19, 3 (1993), 303–342.
- [45] Fatemeh Nargesian, Abolfazl Asudeh, and HV Jagadish. 2022. Responsible Data Integration: Next-generation Challenges. In *Proceedings of the 2022 International Conference on Management of Data*. 2458–2464.
- [46] Joseph P Near, Xi He, et al. 2021. Differential Privacy for Databases. *Foundations and Trends® in Databases* 11, 2 (2021), 109–225.
- [47] Ted North. 2019. Google, Fitbit, and the Sale of Our Private Health Data. <https://www.fitbit.com/global/us/home>.
- [48] Dan Olteanu and Jakub Závodný. 2015. Size bounds for factorised representations of query results. *ACM Transactions on Database Systems (TODS)* 40, 1 (2015), 1–44.
- [49] Wahbeh Qardaji, Weining Yang, and Ninghui Li. 2014. Privview: practical differentially private release of marginal contingency tables. In *Proceedings of the 2014 ACM SIGMOD international conference on Management of data*. 1435–1446.
- [50] Nithya Sambasivan, Shivani Kapania, Hannah Highfill, Diana Akrong, Praveen Paritosh, and Lora M Aroyo. 2021. “Everyone wants to do the model work, not the data work”: Data Cascades in High-Stakes AI. In *proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–15.
- [51] Aécio Santos, Aline Bessa, Christopher Musco, and Juliana Freire. 2022. A sketch-based index for correlated dataset search. In *2022 IEEE 38th International Conference on Data Engineering (ICDE)*. IEEE, 2928–2941.
- [52] Maximilian Schleich, Dan Olteanu, Mahmoud Abo Khamis, Hung Q Ngo, and XuanLong Nguyen. 2019. A layered aggregate engine for analytics workloads. In *Proceedings of the 2019 International Conference on Management of Data*. 1642–1659.
- [53] Maximilian Schleich, Dan Olteanu, and Radu Ciucanu. 2016. Learning linear regression models over factorized joins. In *Proceedings of the 2016 International Conference on Management of Data*. 3–18.

- [54] Reza Shokri and Vitaly Shmatikov. 2015. Privacy-preserving deep learning. In *Proceedings of the 22nd ACM SIGSAC conference on computer and communications security*. 1310–1321.
- [55] Stacey Truex, Ling Liu, Ka-Ho Chow, Mehmet Emre Gursoy, and Wenqi Wei. 2020. LDP-Fed: Federated learning with local differential privacy. In *Proceedings of the Third ACM International Workshop on Edge Systems, Analytics and Networking*. 61–66.
- [56] Haleh Vafaie, Ibrahim F Imam, et al. 1994. Feature selection methods: genetic algorithms vs. greedy-like search. In *Proceedings of the international conference on fuzzy and intelligent control systems*, Vol. 51. 28.
- [57] Chang Wang, Jian Liang, Mingkai Huang, Bing Bai, Kun Bai, and Hao Li. 2020. Hybrid differentially private federated learning on vertically partitioned data. *arXiv preprint arXiv:2009.02763* (2020).
- [58] Yu-Xiang Wang. 2018. Revisiting differentially private linear regression: optimal and adaptive prediction & estimation in unbounded domain. *arXiv preprint arXiv:1803.02596* (2018).
- [59] Kang Wei, Jun Li, Ming Ding, Chuan Ma, Howard H Yang, Farhad Farokhi, Shi Jin, Tony QS Quek, and H Vincent Poor. 2020. Federated learning with differential privacy: Algorithms and performance analysis. *IEEE Transactions on Information Forensics and Security* 15 (2020), 3454–3469.
- [60] Royce J Wilson, Celia Yuxin Zhang, William Lam, Damien Desfontaines, Daniel Simmons-Marengo, and Bryant Gipson. 2019. Differentially private SQL with bounded user contribution. *arXiv preprint arXiv:1909.01917* (2019).
- [61] Genqiang Wu, Xianyao Xia, and Yeping He. 2017. Achieving Dalenius’ Goal of Data Privacy with Practical Assumptions. *arXiv preprint arXiv:1703.07474* (2017).
- [62] Jia Xu, Zhenjie Zhang, Xiaokui Xiao, Yin Yang, Ge Yu, and Marianne Winslett. 2013. Differentially private histogram publication. *The VLDB journal* 22 (2013), 797–822.
- [63] Mengmeng Yang, Lingjuan Lyu, Jun Zhao, Tianqing Zhu, and Kwok-Yan Lam. 2020. Local differential privacy and its applications: A comprehensive survey. *arXiv preprint arXiv:2008.03686* (2020).
- [64] Yang Zhao, Jun Zhao, Mengmeng Yang, Teng Wang, Ning Wang, Lingjuan Lyu, Dusit Niyato, and Kwok-Yan Lam. 2020. Local differential privacy-based federated learning for internet of things. *IEEE Internet of Things Journal* 8, 11 (2020), 8836–8853.