Measurement of Local Differential Privacy Techniques for IoT-based Streaming Data

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***Abstract*—Various Internet of Things (IoT) devices generate complex, dynamically changed, and infinite data streams. Adversaries can cause harm if they can access the user's sensitive raw streaming data. For this reason, protecting the privacy of the data streams is crucial. In this paper, we explore local differential privacy techniques for streaming data. We compare the techniques and report the advantages and limitations. We also present the effect on component (e.g., smoother, perturber) variations of distribution-based local differential privacy. We find that combining distribution-based noise during perturbation provides more flexibility to the interested entity.**

I. Introduction

The number of intelligent systems around us is growing rapidly. Examples of these Internet of Things (IoT) based systems are smart home devices, health monitors, autonomous vehicles, and the smart grid. They collect sensitive data about home activities, health conditions, travel information, power usage, etc. These technical means are constantly growing in power and sophistication. We will see even more rapid development with the widespread deployment of 5G wireless networks, which will provide high-speed data transfer and more precise location information. As these systems scale up, the need for privacy and security increases. Currently, we observe the deficiency to ensure meaningful data privacy guarantees to our citizens, institutions, and infrastructure. Thus, the scientific challenge of data privacy encompasses numerous issues including public safety as well as national security.

Privacy attacks take seemingly innocuous released information and use it to discern private details about individuals or national security [1]. Some attacks focus on identifying if an individual was part of the dataset [2] while others in identifying the sensitive information in the dataset [3] which are more common among biomedical-based systems. Other attacks are dedicated to reconstructing the model and interfering decision-making process [4]. However, there are many cases where the data was stolen before it reached the server or machine learning model. These cyber-security attacks are most common among music and video streaming applications such as Netflix, Hulu, Pandora, Spotify. IoT-based solutions such as Fitbit, Apple Watch, Samsung SmartThings are not an exception to these attacks. Although security mechanisms lack stronger guarantees in these cases, data privacy techniques can help in enforcing better protection.

Data privacy describes the practices which ensure that the data shared by customers is only used for its intended purpose and not used to cause harm. Many systems and platforms generate data that have sensitive properties. Sensitive properties are dependent on the type and purpose of the system. The state of the system can reveal sensitive information. From smart meter data, an intruder can guess sleeping habits, presence or absence from home, presence of a child at home, etc. Smart meter data is considered sensitive data because knowing the real value can be used by intruders to cause harm. Another example of sensitive data is the data collected by health monitoring devices such as blood pressure, sugar levels, heart rate. If someone gets access to them can know what is the health status of the individual and use this data to sell targeted products. These examples show how sensitive data can be used to cause harm, and providing data privacy for sensitive data is crucial.

Differential privacy [5], [6] is considered a de-facto standard for privacy and it provides a strict privacy guarantee. One limitation of differential privacy is that it requires raw data access to a trusted entity. Local differential privacy [7], [8], [9] is a variation of differential privacy technique where it ensures the definition of differential privacy guarantee locally without trusting any entity. In this work, we apply local differential privacy techniques (e.g., variations of RAPPOR [7] based technique, Laplace technique [10], count sketch-based technique) for streaming applications such as IoT. We compare the techniques based on several categories (e.g., distribution-based techniques, randomized response-based techniques, hash-based techniques). We also show the comparison in estimating frequency between differential privacy and local differential privacy. We state the advantages and limitations of using a specific technique. Our goal is to assist the interested party to know which methods would be beneficial for them in what scenario. Moreover, the comparison shows a techniques'

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privacy-utility level compared to others.

We also examine component variations (e.g., smoother, perturber) for the distribution-based noise techniques. The reason for choosing the distribution-based noise technique is that it supports instantaneous reporting of noisy stream data that can be used in different aspects of computation. We show that a combination of different distribution-based noises widens the window for the privacy-utility trade-off.

The main contribution of the paper is as follows:

- We adopt different local differential privacy (LDP) techniques for streaming data and compare among several categories (e.g., distribution-based, randomized response-based, hash-based).
- We vary components (e.g., smoother, perturber, peak value) for distribution-based techniques and show the effect of variations. We also state that combining sequential composition of noise gives more flexibility to the interested parties.
- We show the benefits and limitations of LDP techniques and component variations. It will be helpful for an interested party to identify which settings they want in the privacy-utility trade-off.
- We evaluate comparison among DP technique, all LDP techniques, and component variation experiments using real-world power consumption streaming data from the NREL dataset [11].

The outline of the paper is organized as follows. First, we describe the background knowledge in Section II. We explain the methodology in Section III. We present the evaluation results and comparisons in Section IV. We report the existing related works in Section V. Finally we conclude in Section VI.

II. Preliminaries

Differential privacy (DP), proposed by Dwork [5], provides strong mathematical privacy guarantees. It is defined as follows:

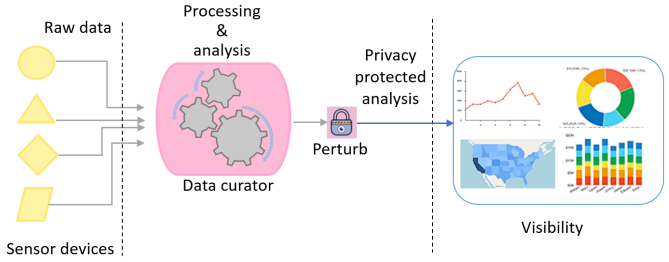
Definition II.1 (ϵ-DP)**.** A randomized mechanism F guarantees ϵ-DP ($\epsilon \geq 0$) for datasets D and D' differing at most one value if and only if F satisfies:

$$Pr[F(D) \in O] \leq e^{\epsilon} Pr[F(D') \in O] \tag{1}$$

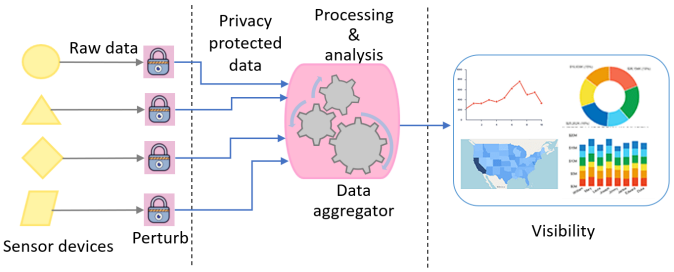
Here, O is the subset of output.

In DP, a data curator first collects the raw data and then performs a targeted analysis. The analysis result is then perturbed and released (Fig. 1a). The limitation of DP is the need for a trusted data curator. Local differential privacy (LDP) is differential privacy in local settings. In LDP, the data is perturbed first before sending it to an aggregator for analysis (Fig. 1b). The advantage of LDP is that there is no need for a trusted data aggregator.

Definition II.2 (ϵ-LDP)**.** A randomized mechanism F guarantees ϵ-LDP ($\epsilon \geq 0$) for any pair of input values v and $v' \in S$ if and only if F satisfies:



(a) Differential privacy (DP)



(b) Local differential privacy (LDP)

Fig. 1: Workflow of stream data analysis under DP and LDP

$$Pr[F(v) \in O] \leq e^{\epsilon} Pr[F(v') \in O] \tag{2}$$

Here, O is the subset of output.

Local differential privacy follows sequential composition [12] property. It states as follows:

Theorem 1. (Sequential composition). If a mechanism F_i provides ϵ_i-LDP, a series of mechanisms on a data stream satisfies $\sum \epsilon_i$.

III. Methodology

In this section, we describe selected local differential privacy algorithms and component variations techniques.

A. Local Differential Privacy (LDP) Techniques

We describe three categories of LDP techniques and the data preprocessing to apply these techniques. Table I shows the overview of selected privacy mechanisms and the dimension of comparison.

1) Distribution-based Techniques: For the distribution-based technique, we follow the DPLM privacy protection approach proposed by Hassan *et al.* [11]. In their approach, they only used the Laplace distribution-based noise mechanism. In our case, we apply four well-known distribution-based noise mechanisms (e.g., Laplace, Gaussian, Exponential, and Gamma). The raw power consumption data of every 10 minutes is perturbed by adding or removing random noise generated from different distributions. In addition, abnormal peaks are preserved to protect specific incidents (e.g., use of specific electronic instruments). The scale of the noise (i.e., sensitivity) is determined by the maximum allowed noise agreement between the utility and user.

TABLE I: Overview of selected privacy mechanisms, dimension of comparison and evaluation metrics. MAPE denotes mean absolute percentage error and MAE denotes mean absolute error (defined in Section IV)

Techniques Category	Comparisons	Evaluation
LDP: Distribution-based	Laplace distribution vs Gaussian distribution vs Exponential distribution vs Gamma distribution	MAPE: Average error between original streaming data and noisy streaming data
LDP: Randomized response-based	Bloom filter based RAPPOR (Bloom) vs Unary encoding based RAPPOR (Memoized) vs Simple one randomization based RAPPOR (Simplified)	MAPE: Average error between original frequency and estimated frequency
LDP: Hash-based	Original vs Count sketch-based	MAE: Average error between original relative frequency and estimated relative frequency
	Original vs Johnson Lindenstrauss random projection-based	Relative Frequency: Histogram of original relative frequency and estimated relative frequency
DP and LDP	DP vs LDP (Laplace) vs LDP (Randomized response-based: Simplified)	MAPE: Average error between original frequency and estimated frequency

Fig. 2: Data stream perturbation (instant reporting)

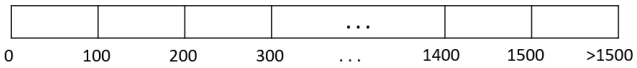


Fig. 3: Histogram bins for encoding

The benefit of using distribution-based noise is that the interested third party can obtain instantaneous perturbed data as shown in Fig. 2. With this data, an interested party can also calculate the frequency estimation (e.g., highest load in which hour), summation value (e.g., user's power consumption for the whole month), and others. The limitation is that we need to choose an optimal peak value (i.e., sensitivity) for the distribution-based noise.

2) Randomized Response-based Techniques: We consider three randomized response (RR) techniques for our experiment, i.e., simplified RR, memoized RR, bloom RR. In the simplified RR, we consider a simple randomization technique [13] with unary encoding and one randomization technique. The memoized RR consists of a unary encoding technique, permanent randomization with memoization, and instantaneous randomization technique proposed by RAPPOR [7]. We follow the ProTECting [14] algorithm to implement the memoized RR. The bloom RR is similar to memoized RR, except, we use hash-based bloom filter encoding instead of unary encoding. Note that, bloom filter-based technique consists of hash-based encoding and randomized response-based perturbation. In our experiment, we consider it in the randomized response-based category for ease of comparison.

While encoding the numerical data, we consider the histogram representation with 16 bins as shown in Fig. 3. For unary encoding, if the data is 50, the first index will be 1 and the other index value will be 0. If the data is 2550, the last index will be 1.

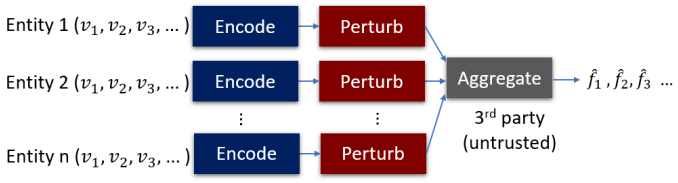


Fig. 4: Randomized response-based technique

An untrusted third party aggregates the perturbed data from different entities at every timestep and report estimated frequency (Fig. 4). The limitation is that we need multiple entity data. Higher the number of entities, we obtain higher accuracy. On the other hand, we get very low accuracy in calculating the estimated frequency for a few entities.

3) Hash-based Techniques: We consider two hash-based techniques. One is the count-sketch technique [15] and the other is the Johnson Lindenstrauss random projection technique [16].

In the count-sketch technique, we consider the whole month's power consumption data and distribute them into

TABLE II: Overview of component variation and dimension of comparison for distribution-based LDP mechanism

Component	Comparisons
Smoother	No smoothing (Noisy) vs Average smoothing vs Median smoothing
Truncated load	With carry-on vs Without carry-on
Peak value	Same peak value vs Time varying peak value
Noise combination	One distribution-based noise vs Sequential composition of two noises

a matrix. We then compress this original load matrix $A \in R^{(m \times n)}$ using a sketch matrix $S \in R^{(n \times s)}$. The resultant matrix will be C = AS where $C \in R^{(m \times s)}$. For the original load matrix, we consider m as the number of days in a specific month and n be the number of loads produced in one day. In our case, n = 144 (i.e., 10 minutes interval data). We vary the size of the sketch matrix column s. Lower the size of s contributes to the more compressed output. The privacy parameter ϵ is calculated following Li *et al.* [15]. Finally, we compute the l2-norm from the resultant matrix C for each day and find the normalized distribution. The advantage of count-sketch is that the communication cost is reduced based on the size of the sketch matrix. One disadvantage is that we can not compute single-point perturbation.

We also consider Johnson Lindenstrauss's random projection technique for streaming data. Each household or entity encode numerical load data to k categorical attributes by utilizing histogram representation where $k = 16$ (Fig. 3). We then follow Bassily and Smith [16] algorithm, and it returns k frequency estimates for a specific time. For streaming data, we can capture frequency estimates for every timestamp or a specific period (i.e., one day). In our case, the number of attribute k can be smaller than the number of households.

B. Our Approach: Component Variations

We describe the component variations for the distribution-based LDP technique. Table II shows the overview of various components and the dimension of comparison. We perform several experiments to understand the impact of different components using the distribution-based noise technique to protect instantaneous load reporting.

First, we consider the most simple case shown in Fig. 2. Streaming values pass through the perturber and noisy streaming values will be produced. For a specific peak value B (i.e., threshold or sensitivity), there are two options for the remainder load $(v_i - B)$ when the current load (v_i) is greater than the peak value. We can truncate the remainder load (i.e., without carry-on) or add the remaining load with the next streaming value v_{i+1} (i.e., with a carry-on).

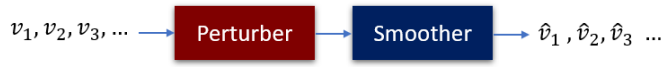


Fig. 5: Data stream perturbation with smoothing

Second, we consider the smoothing component after the perturbation as shown in Fig. 5. Several recent works use smoothing after using distribution-based noise [17], [18], [19]. We consider median smoothing and average smoothing. The smoothing from timestep t is done using the perturbed data from timesteps t, t_{i-1} and t_{i+1}.

Third, we consider two perturbers instead of one. For instance, we consider combining both Laplace and Exponential distribution-based noise instead of just using Laplace distribution-based noise. We combine the noises following the sequential composition property (Theorem 1).

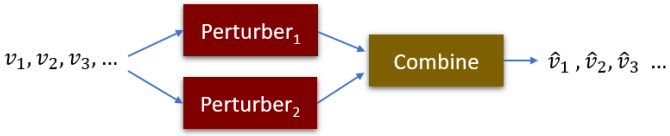


Fig. 6: Sequential composition of multiple distribution-based noises

IV. Result

In this section, we present the quantitative comparison among different local differential privacy-based techniques and component variations. A lower privacy parameter value (ϵ) represents a higher privacy guarantee with lower utility. A higher ϵ value represents a lower privacy guarantee with higher utility.

A. Experimental Setup

We selected NREL DATA [11] for our experiments. This dataset contains residential electricity demand in every 10-minute interval for the whole year of 2010. These data were from randomly selected 200 households located in the midwest region of the US.

We implement the experiments in Python 3.8 with numpy, pandas, mmh3, math, scipy, and sklearn libraries. We conduct experiments on a PC with Intel Core i7-8550U CPU and 16GB RAM. All experiments are repeated five times.

B. Experimental Metrics

We consider five metrics to evaluate our experiments. These are mean absolute percentage error, relative error, mean absolute error, mutual information, and Jensen-Shannon divergence. Here, x is denoted as the expected value and y is denoted as the observed value.

We compute the mean absolute percentage error (MAPE) shown in Equation 3 for two cases. In the first case, we

calculate the histogram comparison between different bins. Here, we consider n as bin size. In the second case, we calculate the discrepancy between every streaming data point. Here, we consider n as the window size of streaming data.

$$MAPE = \frac{\sum_{i=1}^{n} |\frac{y_i - x_i}{x_i}|}{n} \quad (3)$$

We compute the relative error (Equation 4) in the cases where we have the total noisy load value and actual load value of a specific period.

$$Relative\ Error = |\frac{y_i - x_i}{x_i}| * 100\% \quad (4)$$

We compute mean absolute error (MAE) shown in Equation 5 for relative frequency data.

$$MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} \quad (5)$$

Mutual information measures the statistical data utilities. Mutual information between x and y is:

$$Mutual\ Information = \sum_{x,y} p(x,y)\ log \frac{p(x,y)}{p(x)p(y)} \quad (6)$$

Jensen-Shannon (JS) divergence measures similarity between two distribution x and y. Lower JS divergence value denotes higher similarity.

$$JS\ Divergence = \frac{1}{2}KL(x||m) + \frac{1}{2}KL(y||m) \quad (7)$$

where $m = \frac{1}{2}(x + y)$ and $KL()$ denotes Kullback-Leibler divergence [20].

C. Comparison of Different Distribution-based Noise

We evaluate different distribution-based techniques. The description of the selected approaches is depicted in Section III-A1. In Fig. 7, we show the impact of different noise-based distributions varying the privacy parameter ϵ. Gamma distribution shows comparatively lower relative error among them, and Gaussian distribution shows a higher relative error.

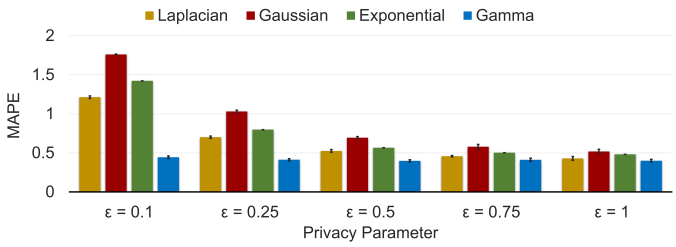


Fig. 7: Comparison of different distribution-based noise varying privacy parameter

The Gaussian mechanism satisfies (ϵ, δ)-differential privacy. Changing the value of δ and ϵ changes the error level as well (Fig. 8). We observe that higher value of δ results in higher utility and lower value of δ results in higher level of privacy.

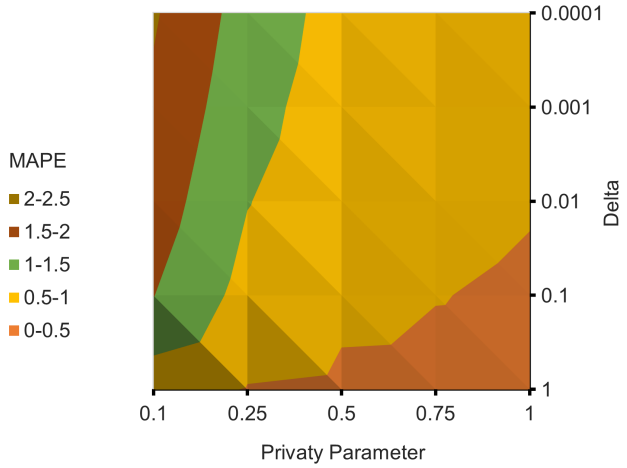


Fig. 8: Gaussian noise label varying Delta (δ) and privacy parameter

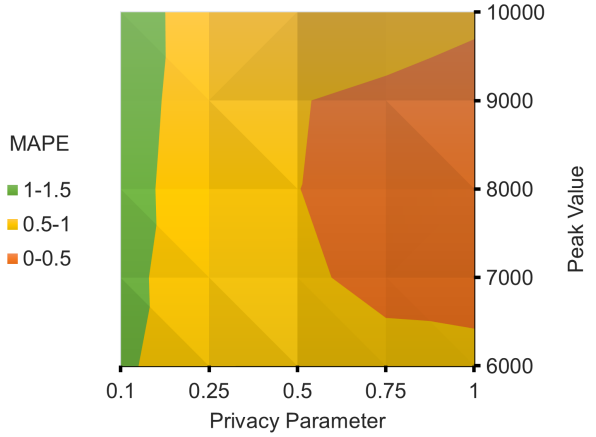


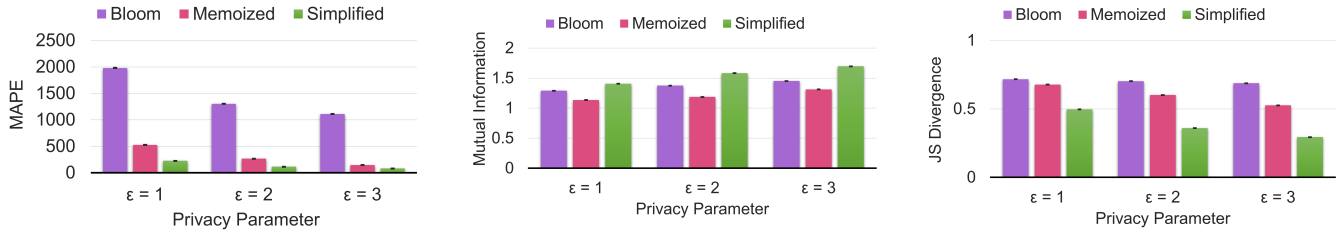
Fig. 9: Laplace noise label varying peak value and privacy parameter

Choosing the optimal peak value (i.e., cutoff) is also an important factor. We observe that higher peak value results in a higher error as the higher sensitivity introduces a high amount of noise (Fig. 9). On the other hand, a lower peak value also results in a higher error as noisy load values are cut off at the peak point and the remainder is transmitted to the next stream. In the NREL dataset, the maximum load value is 14,777, and the 99.94 percentile load value is 8,000.

For distribution-based comparison (Fig. 7), we consider peak value of 8,000 for all distributions and $\delta = 0.01$ for Gaussian distribution.

D. Comparison on RAPPOR Variations for Frequency Estimation

We show the comparison of three variations of RAPPOR techniques (i.e., simplified, memoized, and bloom) on streaming data in Fig. 10. We show the performance based on three metrics: MAPE, mutual information [21], and JS



(a) MAPE (b) Mutual Information (c) Johnson Shannon Divergence

Fig. 10: Evalution of the RAPPOR techniques

divergence [22]. The simplified technique shows higher utility with lower MAPE, higher mutual information, and lower JS divergence than other techniques. The reason behind the high utility is that each data only gets perturbed for one time. On the other hand, the bloom technique shows higher privacy with higher MAPE and JS divergence values. Both bloom and memoized use perturbation twice. However, in the bloom technique, the extra level of privacy comes from hash-based bloom filter encoding.

E. Results using Count Sketch Approach

Section III-A3 describes the approach we adopt for protecting streaming data privacy using the count-sketch technique. We observe that the mean absolute error and compression ratio vary with the privacy parameter (Fig. 11). In our experiment, the column of the original matrix is 144. When we choose sketch matrix column 26, the compressed output matrix is 5.5 times smaller with the ϵ value of 0.5 and mean absolute error (MAE) value of 0.0029. Increasing sketch matrix column results in lower privacy (i.e., higher ϵ value) and higher utility (i.e., lower MAE value).

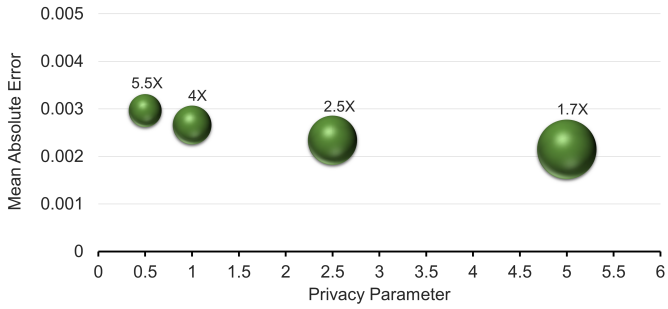


Fig. 11: Evaluation of sketch based techniques varying privacy parameters

F. Results using JLRR Approach

We consider 200 households data at a specific timestamp for evaluating Johnson-Lindenstrauss Randomized response (JLRR) method. We show relative frequency estimation result in Fig. 12. When the original frequency estimate is very high, the JLRR shows a lower estimate than the original one. Among other cases, JLRR shows slightly higher estimate than the original, in about 67% of the cases.

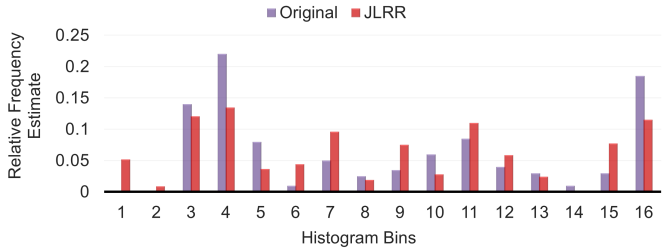


Fig. 12: Evaluation of Johnson Lindenstrauss randomized response (JLRR) approach

G. Results on DP vs LDP Techniques

We compare the DP technique and two LDP techniques, i.e., distribution-based (Laplace), randomized response-based (simplified) in Fig. 13. For the DP, we use Diffprivlib [23] library from IBM. In this case, we consider the data lower than the 75 percentile and ignore the outliers. In DP, we compute the original frequency from 200 households and add noise before release. We observe that the DP shows higher utility with very low MAPE. However, a trusted aggregator is needed for the DP technique. In LDP techniques, 200 households add noise (distribution-based noise or perturbation noise) before sending their data to an aggregator who estimates the frequency. Randomized response-based LDP incurs a higher error than distribution-based LDP.

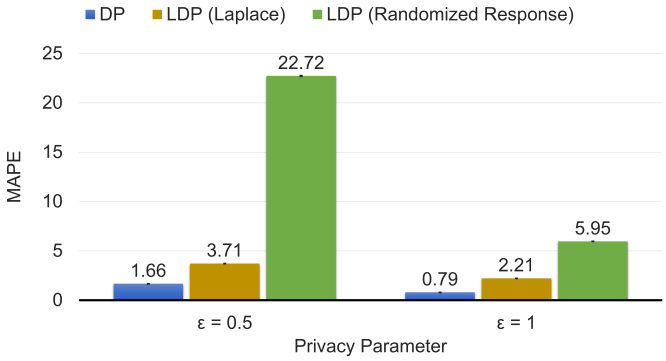


Fig. 13: Comparison of differential privacy (DP) and local differential privacy (LDP) techniques varying privacy parameter

H. Impact of Varying Components

We consider instantaneous load reporting for one household for one month with load values generated in 10 minutes time intervals. We protect the specific event (i.e., higher load value) of the household using the optimal peak value with Laplace distribution-based technique. If load at a specific time is higher than a chosen peak value, then consider sending load value as peak value and add the noise depending on sensitivity. The remainder of the load can be either added to the next reading (i.e., w/ carry on) or the remainder is simply ignored (i.e., w/o carry on).

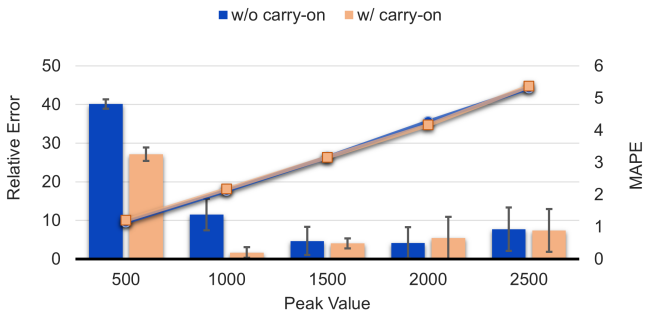


Fig. 14: Results on varying peak value. "w/o carry-on" denotes without carry-on and "w/ carry-on" denotes with carry-on truncated load value in next streaming data

We vary peak value and examine the impact on w/ carry-on and w/o carry-on in Fig. 14. The bars show relative error (error between the original sum of load and the noisy sum of load for the first month) and lines show MAPE (average error among noisy load and the original load of every timestamp). We observe the best lowest error relative error of 1.67 when the peak is 1000 for w/ carry. For the w/o carry option, the best relative error is 4.19 when the peak is 2000. Lower peak value contributes to additional loss of load for w/o carry-on option. Therefore, the relative error is much higher for w/o carry-on than w/carry-on. MAPE is similar for both cases for varying peak values.

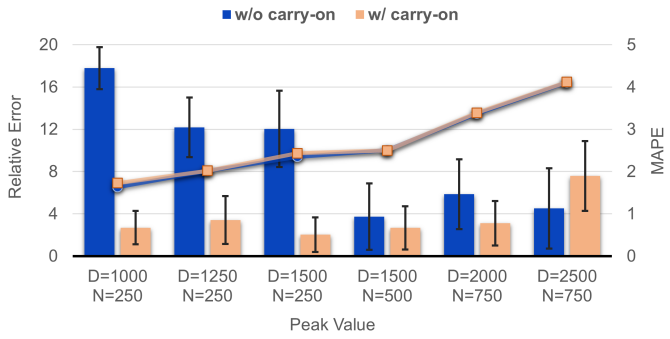


Fig. 15: Results on varying peak value at day (D) and night (N)

Afterward, we consider different peak values for day and night and see the impact on w/ carry on and w/o carry on in Fig. 15. We observe the lowest error relative error of 2.02 when peak value at night is 250 and peak value at other time is 1500 for w/ carry. For the w/o carry option, the best relative error is 3.75 when the peak value at night is 500 and the peak value at other times is 1500. For w/o carry-on option, choosing a different peak value for night shows a lower error value than a single peak value. For w/ carry-on option, constant peak shows better performance. MAPE is similar for both cases for varying peaks as well.

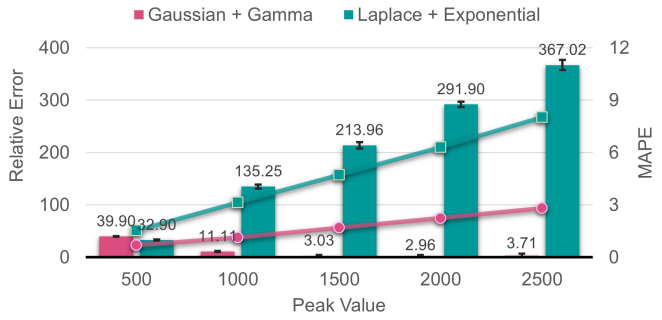


Fig. 16: Sequential composition of distribution-based noises varying peak value

We also try the sequential combination of two distribution-based noises. We consider the ϵ value of 0.5 for both noise distribution and use the sequential combination to get 1-differential privacy. Here we choose $\delta = 1$ for Gaussian distribution-based noise. We observe that the combination of Gamma distribution and Gaussian distribution shows lower relative error and MAPE value. On the other hand, the combination of Laplace and Exponential distribution provides higher relative error and MAPE value. Furthermore, composition technique widens the choice of privacy and utility level to the user compared to using only one distribution-based noise. If the user requires more privacy levels, Laplace and Exponential combination can be a better option. On the other hand, Gamma and Gaussian combination provides more utility.

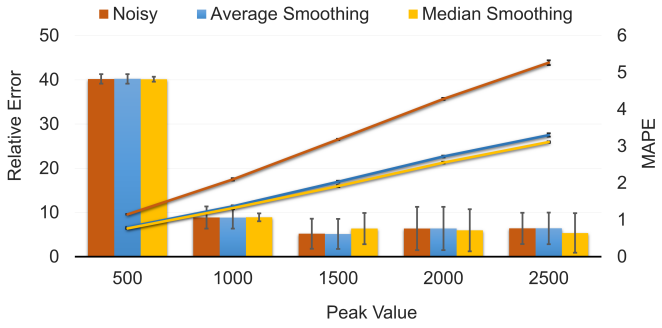


Fig. 17: Result on two smoothing techniques varying peak value

We also explore average smoothing, median smoothing, and no smoothing (i.e., noisy) in Fig. 17. We do not observe

any significant difference in terms of relative error among these smoothing techniques. However, we see the difference in terms of MAPE. Both average and median smoothing show significantly lower MAPE values. Among them, median smoothing shows a slightly lower MAPE value than average smoothing.

Note that, in all component-based experiments, we consider privacy parameter $\epsilon = 1$.

I. Summary of Findings

Here, we provide the summary of findings that we observe from selected differential privacy, local differential privacy techniques, and component variations.

- Gamma distribution-based technique shows comparatively lower relative error (i.e., lower privacy), and gaussian distribution shows a higher relative error (Fig. 7).
- Privacy parameter (ϵ), peak value, delta (δ) control the privacy-utility trade-off (Fig. 8 and Fig. 9).
- Bloom filter-based randomized response technique provides high user privacy (i.e., low utility) among selected three randomized response techniques (Fig. 10).
- For the count sketch-based technique, the privacy compression ratio controls the privacy-utility trade-off (Fig. 11).
- Differential privacy provides comparatively lower relative error (i.e., lower privacy) than local differential privacy techniques (Fig. 13).
- Relative error is much higher for without carry-on than with carry-on approach (Fig. 14).
- For without carry-on option, choosing a different peak value for day and night shows higher utility than choosing a single peak value (Fig. 15).
- Composition of Laplace and Exponential provides more privacy level. On the other hand, Gamma and Gaussian combination provides more utility options (Fig. 16).
- Both average and median smoothing lower error value (i.e., MAPE). Among them, median smoothing shows a slightly lower MAPE value than average smoothing (Fig. 17).

V. Related work

Several research works have been proposed using differential privacy and local differential privacy in academia and industry to protect streaming data from IoT devices and other edge devices.

Thorve *et al*. [24] propose a Laplace-based differential privacy technique for streaming data. One year's load data was clustered based on power energy level, then Laplace noise is added in each cluster and finally, the private time-series representation of each cluster are released. Robinson *et al*. [25] propose CASTLEGUARD that guarantees k-anonymity, l-diversity, and differential privacy at the same time. It uses Laplace distribution-based noise for perturbation and clustering to satisfy k-anonymity.

RAPPOR [7], [26] is proposed by Google that achieve ϵ-LDP when a user reports a value infinite times using randomized response technique. They consider bloom filter encoding with two rounds of randomization (e.g., permanent randomization and instantaneous randomization). Among them, permanent randomization guarantees Longitudinal Privacy. ProTECting [14] also follows two round of randomization RAPPOR technique. During encoding, they apply unary encoding instead of bloom filter encoding. They use smart meter data to estimate the frequency and show that ProTECting achieves better performance than RAPPOR. PrivApprox [27] also use a randomization technique. However, they introduce sampling at the client-side for low-latency approximation before the randomization technique and also implement transmitting answers using a proxy for anonymization and unlinkability.

Adding distribution-based noise is another technique to provide privacy to streaming data. PeGaSus [18] takes a stream data and perturb the data using Laplace noise. It also utilizes a grouper module that partitions the streaming data to apply smoothing on the perturbed data. Hassan *et al*. [10] propose instantaneous data reporting with peak value preservation using Laplace noise. Fang *et al*. [28] propose local differential private streaming (LDPS) protocol for numerical and categorical attributes. LDPS satisfy local differential privacy and sliding window-based w-event privacy. For mean estimation, Duchi's [29] method and Laplace mechanism are considered. For frequency estimation, RAPPOR [7] technique is considered.

Bassily *et al*. [16] propose a succinct histogram protocol based on a random matrix project technique following Johnson-Lindenstrauss Lemma. Count sketch [30], [31] based implementation is another technique which is used by Apple [32]. Li *et al*. [15] propose a DiffSketch framework that uses a hash-based sketch matrix to reduce communication cost with a marginal decrease in accuracy metric.

Several techniques propose an optimized threshold optimization technique for streaming data. Perrier *et al*. [33] consider finding a more realistic threshold (i.e., peak value) based on a 99.5 percentile value as a threshold from a time lag. They also consider a binary tree algorithm to reduce the scale of the noise level. Wang *et al*. [19] propose to release a real-time data stream under differential privacy based ToPS and local differential privacy based ToPL. They also formulate an Exponential Mechanism-based optimization algorithm to choose an optimal threshold.

Several existing works show the theoretical comparison of LDP techniques [34], [35]. We compare the quantitative measure of the privacy-utility tradeoff for streaming data. Additionally, the existing works on distribution-based noise mainly focus on using one type of noise (e.g., Laplace). In this paper, we show that combining more noise provides the entity (e.g., user) and third party some flexibility in determining how much noise is preferred in the noisy streaming data.

VI. Conclusion

We present various privacy-preserving local differential privacy algorithms for streaming data. We compare these techniques and show their limitations and benefits. To get frequency estimation, if an entity agrees to release only aggregated streaming data (e.g., streaming data generated in one month), the count sketch-based technique is an excellent choice due to lower communication costs. If an entity agrees to release noisy streaming data in every timestep, the bloom filter-based RAPPOR technique provides a higher privacy guarantee.

We also vary different components for distribution-based noise for instant noisy reporting of the streaming data and present when they can be useful. The smoothing technique after the perturbation is beneficial if the third party is interested in examining every timestamp noisy streaming data. Combining different noise-based techniques also offers a wide range of options for data privacy-utility tradeoff.

As future work, we plan to show demonstrations of local differential privacy techniques from physical devices. Also, we plan in using perturbed data in different machine learning algorithms.

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