# Privacy-aware Process Performance Indicators: Framework and Release Mechanisms

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Abstract. Process performance indicators (PPIs) are metrics to quantify the degree with which organizational goals defined based on business processes are fulfilled. They exploit the event logs recorded by information systems during the execution of business processes, thereby providing a basis for process monitoring and subsequent optimization. However, PPIs are often evaluated on processes that involve individuals, which implies an inevitable risk of privacy intrusion. In this paper, we address the demand for privacy protection in the computation of PPIs. We first present a framework that enforces control over the data exploited for process monitoring. We then show how PPIs defined based on the established PPINOT meta-model are instantiated in this framework through a set of data release mechanisms. These mechanisms are designed to provide provable guarantees in terms of differential privacy. We evaluate our framework and the release mechanisms in a series of controlled experiments. We further use a public event log to compare our framework with approaches based on privatization of event logs. The results demonstrate feasibility and shed light on the trade-offs between data utility and privacy guarantees in the computation of PPIs.

Keywords: Performance Indicators · Process Monitoring · Differential Privacy

## 1 Introduction

Many companies improve their operation by applying process-oriented methodologies. In this context, Business Process Management (BPM) provides methods and techniques to aid in the monitoring, analysis, and optimization of business processes [4]. Important means to enable the continuous optimization of processes are *process performance indicators* (PPIs), i.e. numerical measures computed based on data recorded during process execution [3]. PPIs assess whether predefined goals set by the process owner are fulfilled, e.g., related to the mean sojourn time of a business process. Fig. 1 illustrates a simple insurance claim handling process and respective PPIs. Each indicator comprises a definition of a measure, a target value, and an observation period, called scope.

The data used to calculate PPIs often includes personal data. In Fig. 1, such data relates to the knowledge workers handling the claims or the customers who submitted them. Processing of personal data is strictly regulated. The GDPR [7], as an example, prohibits the use of personal data without explicit consent and especially restricts their *secondary use*, i.e., the processing of data beyond the purpose for which they were originally recorded. Process optimization typically represents such a secondary use of

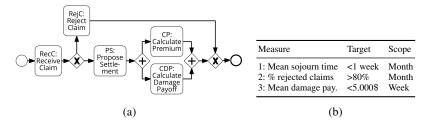


Fig. 1: (a) Model of a claim handling process; (b) PPIs defined on the model.

process execution data [14]. To motivate, why unregulated access to process execution data may be problematic, we turn back to the example model and PPI in Fig. 1b. Assume that data is recorded about three claims handled by Alice with sojourn times of 4, 4, and 5 days; three claims handled by Bob within 2, 6, and 6 days; and three claims handled by Sue lasting for 7, 8, and 8 days. Here, the mean sojourn time of these nine process instances is ~5.5 days and thus fulfils PPI 1 set by management. Yet, considering this data directly would reveal Sue's generally slower processing times, which may be prohibited by privacy regulations. Here, privacy-protected PPI schemes, i.e., techniques that incorporate data anonymization in the computation of PPIs, would allow for the evaluation of PPIs, while protecting the privacy of the recorded individuals in the log file, thus lifting these privacy regulations. Yet, data anonymization commonly leads to a trade-off between the strength of a privacy guarantee and a loss in data utility, thus a privacy-protected PPI scheme needs to minimize the accuracy loss introduced.

Models for privacy-aware computation of traditional aggregates [16,20] have limited applicability for PPIs, though. Since these models do not take into account the highly structured nature of data generated by processes and PPIs defined on them, these methods are not suitable for privatizing PPIs. Approaches for privacy-aware publishing and querying of process execution data [8, 13], in turn, are too coarse-grained. Handling comprehensive execution data, these techniques cannot be tailored to minimize the loss in data utility for a given set of PPIs. Against this background, we identify the research question of how to design a framework for the evaluation of privacy-protected PPIs.

In this paper, we address the above question, by proposing PaPPI, a first framework for **privacy-a**ware evaluation of **PPIs**. It separates trusted and untrusted environments to handle process execution data. They are connected by a dedicated interface that serves as a privacy checkpoint, ensuring  $\epsilon$ -differential privacy [5]. We then instantiate this framework with data release mechanisms for PPIs that are defined based on the established PPINOT meta-model [3]. This way, we enable organizations to compute expressive PPIs without risking privacy violations. Finally, we explore the impact of privacy-aware evaluation of PPIs on their quality. We report on controlled experiments using synthetic data and a case study with a publicly available event log. Our results demonstrate the feasibility of the framework and its instantiation through specific release mechanisms, given that a reasonable amount of process execution data has been recorded.

In the remainder, Section 2 provides background on PPIs and privacy guarantees. Section 3 introduces our framework for privacy-aware evaluation of PPIs, which is

instantiated with specific release mechanisms in Section 4 and evaluated in Section 5. Finally, we review related work in Section 6, before we conclude in Section 7.

## 2 Background

We introduce a basic model for event logs (Section 2.1) and process performance indicators (Section 2.2). Finally, we review the concept of differential privacy (Section 2.3).

#### 2.1 Notions and Notations for Event Logs

We consider ordered, finite datasets, each being a set of elements  $X = \{x_1, \dots, x_n\}$  that carry a numeric value and are partially ordered by  $\leq$ .\(^1\) The cardinality of the dataset is denoted as |X| = n. For one of the (potentially many) elements of X that are minimal and maximal according to  $\leq$ , we write X and X, respectively. An interval of the dataset is defined by  $X = (x_{lower}, x_{upper})$  with  $X_{lower}, x_{upper} \in X$  and  $X_{lower} \leq x_{upper}$ . Lifting the notation for minima and maxima to X, we define  $X = x_{lower}$  and  $X = x_{upper}$ .

Our notion of an event log is based on a relational event model [1]. That is, an event schema is defined by a tuple of attributes  $A = (A_1, \ldots, A_n)$ , so that an event is an instance of the schema, i.e., a tuple of attribute values  $e = (a_1, \ldots, a_n)$ . An event schema consists of at least three attributes, the case that identifies the process instance to which an event belongs, the timestamp for the point in time an event has been recorded, and the activity, for which the execution is signalled by an event. The timestamp-ordered list of events corresponding to a single case is called a trace. Such a trace represents the execution of a single process instance. An event log is a set of traces.

#### 2.2 Process Performance Indicators

A key performance indicator (KPI) is a metric that quantifies, to which extent the goals set for an organisation are fulfilled. A process performance indicator (PPI) is a KPI, which is related to a single business process and which is evaluated solely based on the traces recorded during process execution. The Process Performance Indicator Notation (PPINOT) [3] is a meta-model for the definition and evaluation of PPIs. At its core, the PPINOT model relies on the composition of measures, i.e., simple, well-defined functions that enable the definition and automated evaluation of more complex PPIs:

Base measures concern a single instance of a process and include event counts (e.g., to count activity executions), timestamp differences between events, the satisfaction of conditions, or aggregations over the events' attribute values.

Aggregation measures are multi-instance measures that combine values from multiple process instances into a single value. PPINOT includes aggregation measures to calculate the minimum, maximum, mean, and sum of a set of input values.

*Derived measures* are user-defined functions of arbitrary form, applied to a single process instance, or a set thereof.

<sup>&</sup>lt;sup>1</sup> For ease of presentation, we exemplify datasets as sets of integers or real numbers, even though in practice, a dataset may contain multiple elements referring to the same numeric value.

A PPI defined using the PPI meta-model is represented as a function composition tree. Fig. 2 exemplifies such a tree for the PPI 2 of our example from Fig. 1b. It calculates the fraction of rejected insurance claims and received claims. Here, *count* is a base measure; *sum* is an aggregation measure; and the fraction r(x, y) is a derived measure.

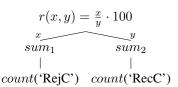


Fig. 2: The function composition tree of PPI 2 in Fig. 1b.

#### 2.3 Differential Privacy

Differential privacy [5] is a privacy guarantee that limits the impact a single element may have on the output of a function f that is computed over a set of elements. Therefore, it limits an adversary to conclude on the set of used input elements (or the presence of a certain input element) from the result of the function. This obfuscation is usually achieved by adding noise, for which the magnitude depends on the sensitivity  $\Delta f$  of function f, i.e., the maximal impact any element  $x \in X$  may have on f(X).

A randomized mechanism K is a randomized function that can be applied to a dataset, with range(K) as the set of possible results. Let  $D_1, D_2$  be two neighbouring datasets, i.e., they differ in exactly one element. The randomized mechanism K provides  $(\epsilon, \delta)$ -differential privacy, if the following inequality holds for the probabilities of the function result falling into a sub-range of all possible results:

$$\forall S \subseteq range(K): P(K(D_1) \in S) \leq e^{\epsilon} P(K(D_2) \in S) + \delta$$

Differential privacy enforces an upper bound on the difference in result probabilities of neighbouring datasets. If  $\delta = 0$ , K is  $\epsilon$ -differentially private (or  $\epsilon$  is omitted altogether). Larger  $\epsilon$  values imply weaker privacy, while the contrary holds true for smaller values.

A specific mechanism to achieve differential privacy is the Laplace mechanism [5]. It adds noise sampled from a Laplace distribution with parameters  $\mu=0$  and  $b=\Delta f/\epsilon$  onto f(X). Due to the symmetric nature of the Laplacian and the exponential falloff, results are expected to lie close to f(X).

The symmetrical monotonous falloff of the Laplace mechanism may yield undesirable results, e.g., if values close to the true result have a disproportionally negative effect on the utility. The *exponential mechanism* [15] avoids this problem, by constructing a probability space based on a function q(D,r), which assigns a score to all results  $r \in range(K)$  based on the input dataset D. Here, a higher score is assigned to more desirable results. The mechanism then chooses a result  $r \in range(K)$  with a probability proportional to  $e^{(\epsilon q(D,r))/(2\Delta q)}$ , where  $\Delta q$  is the sensitivity of the scoring function, i.e., the maximum change in assigned scores possible for two neighbouring datasets.

Both above mechanisms assume that  $\Delta f$  and  $\Delta q$  are known beforehand. The *sample-and-aggregate framework* [17] drops this assumption by sampling subsets of the input set and evaluating the given function per sample. The obtained results are then combined using a known differentially private aggregator. If function f can be approximated well on small sub-samples, then the results per sample are close to f(X). By aggregating these approximated results using a differentially private mean, i.e., by computing the mean and adding noise drawn from a Laplacian calibrated with  $\Delta(mean)$ , one achieves a differentially private result for f(X).

# 3 A Framework for Privacy-Aware PPIs

In this section, we introduce a generic framework for the evaluation of privacy-protected PPIs, thereby addressing the research question raised above. Specifically, we discuss design decisions, as well as the underlying assumptions and limitations of the framework.



Fig. 3: Overview of the framework for privacy-aware PPIs.

The evaluation of PPIs is usually conducted on event data recorded and administered by the process owner. As such, we consider a centralized model and assume that the entity collecting and persistently storing the event data is trustworthy. However, as illustrated in Fig. 3, the actual information demand regarding the PPIs is external to this environment. Following existing models for the flow of data in the analysis of information systems, the evaluation of PPIs is conducted in an untrusted environment [2, 14].

Considering the handling of event data in the trusted environment in more detail, the following phases are distinguished. First, the *Data Capture* phase concerns the collection of process-related event data, i.e., whenever an activity has been executed, a respective event is created. Subsequently, the phase of *Primary Use* represents that the captured event data is exploited for the purposes for which it was recorded, which is commonly the proper execution of an individual instance of the process. For example, the recorded events may be used to invoke services, trigger notifications, or schedule tasks for knowledge workers. At the same time, the event data is made persistent, which is modelled as a *Data Storage* phase. The persisted event data may then be used for *Secondary Use*, such as process improvement initiatives conducted by process analysts. Eventually, the event data may be deleted from the persistent storage, in a *Data Deletion* phase. All phases, except the *Secondary Use*, are conducted within the realms of the trusted environment. The *Secondary Use* is part of the untrusted environment, since the data was recorded without having any consent on their use for these applications.

Unlike common primary use of process-related event data, process improvement in general, and the computation of PPIs in particular, aim at generalizing the observations made for individual process instances in some aggregated measures. Thus, in these contexts, the privacy of an involved individual would be compromised, if their contribution to the published aggregate would be revealed to the process analyst. To enable such secondary use without compromising an individual's privacy, we need to prevent a process analyst to assess the impact of a single process instance on the aggregated result. Hence, we consider each trace and the information inferred from it as sensitive information. For example, when a PPI is based on the mean sojourn time of all process instances, we aim to protect the specific sojourn time of each instance.

To achieve this protection, any access to the event data from the untrusted environment must be restricted. Therefore, we propose to design an interface for the evaluation of PPIs, thereby realizing an explicit privacy checkpoint. The interface receives PPI queries stated in PPINOT syntax and answers them while ensuring differential privacy.

To this end, the interface fetches relevant event data from the persistent storage based on the scope of the PPI query, calculates the result, and adds noise to the result, before releasing the result to the process analyst. Any such release reduces a privacy budget, which is chosen based on the desired strength of the privacy guarantee to implement. Since the noise added to the result is calibrated based on the specifics of a PPINOT query and the event data retrieved for evaluating it, we ensure  $\epsilon$ -differential privacy.

By the above, we achieve *plausible deniability*: An analyst cannot distinguish between query results that contain a particular process instance and those that do not.

While access to the event data is restricted, our framework assumes that an analyst has access to models of the respective processes in order to specify the PPIs. Another assumption of our framework is that, for a given time scope, an upper bound for the appearances of an individual in the recorded process instances is known. An individual appearing in n process instances dilutes  $\epsilon$ -differential privacy by at most  $e^{\epsilon n}$ . Knowing an upper bound for n, however, enables mitigation of this effect by changing the privacy parameter  $\epsilon$  accordingly. For our example in Fig. 1, we would need to know the maximal number of claims that can be handled by a knowledge worker within a single month. Lastly, we acknowledge that, while we focus on the evaluation of PPIs, further privacy threats in the trusted environment require additional protection mechanisms [2].

# 4 Release Mechanisms for Privacy-Aware PPIs

In this section, we instantiate the above framework and introduce a specific realization of the interface for the evaluation of PPIs. We first show how the interface leverages the compositional structure of PPIs defined based on the PPINOT meta-model in Section 4.1. We then provide a set of  $\epsilon$ -differentially private release mechanisms in Section 4.2.

#### 4.1 Using Function Composition Trees for Privacy Protection

Our idea is to exploit the compositional nature of PPIs defined in the PPINOT meta-model for privacy protection. Instead of adding noise to the final query result, we introduce noise, with smaller magnitude, at the inner functions of a PPI. Such a compositional approach still guarantees  $\epsilon$ -differential privacy of the result. At the same time, it enables us to minimize the overall introduced error. Hence, data utility is preserved to a higher degree, which leads to more useful process analysis, under the same privacy guarantees.

We aim to protect the privacy of individuals, of whom personal data is materialized in a trace. Hence, the results of single-instance measures (base or derived measures) shall be protected. However, common PPIs assess the general performance of process execution by aggregating these results in multi-instance measures (aggregation or derived measures), so that guarantees in terms of differential privacy may be given for these measures. This raises the question of selecting a subset of the multi-instance measures for privatization. On the one hand, this selection shall ensure that the results of *all* aforementioned single-instance measures are protected. On the other hand, the selection shall be *minimal* to keep the introduced noise to the absolutely necessary magnitude.

We capture the above intuition with the notion of an admissible set of measures of a PPI. Let  $(F, \rho)$  be the function composition tree of a PPI, with F as the set of measures

and  $\rho: F \to 2^F$  as the function assigning child measures to measures. With  $\rho^*$  as the transitive closure of  $\rho$ , a set of measures  $F' \subseteq F$  is admissible, if it:

- contains only multi-instance measures:  $f \in F'$  implies that  $f \in \text{dom}(\rho)$ ;
- covers all trace-based measures:  $\forall f \in (F \setminus \text{dom}(\rho)) : \exists f' \in F' : f \in \rho^*(f');$
- is minimal:  $\forall F'' \subset F' : \exists f \in (F \setminus \text{dom}(\rho)) : \forall f'' \in F'' : f \notin \rho^*(f'')$ .

The first condition of an admissable set applies, as differential privacy may only be used for the aggregation of multiple inputs, thus single-instance measures cannot be privatized with the given privacy framework. The second condition ensures, that the selected set of functions privatizes all single-instance derived or base measures, that directly access trace information. Finally, the third condition ensures, that only the minimum amount of noise to achieve  $\epsilon$ -differential privacy is added onto the intermediate results.

The function composition tree in Fig. 2 has two sets of admissible measures,  $\{r\}$  and  $\{sum_1, sum_2\}$ , which both cover the single-instance measures count(RejC') and count(RecC'). In contrast, the set  $\{sum_1\}$  is not admissible, as count(RecC') is not covered (second constraint). Likewise, selecting both base measures or  $\{r, sum_1, sum_2\}$  is not admissible, as this would violate the first and third constraint, respectively.

Once a set of admissible measures is selected, the evaluation of the PPI is adapted by incorporating a release mechanism, as defined next, for the chosen measures.

## 4.2 Release Mechanisms for Multi-Instance Measures

The design of a release mechanism for a specific multi-instance measure is influenced by (i) the ability to assess the domain of input values over which the measure is evaluated, and (ii) the ability to assess the sensitivity of the measure. As for the first aspect, the PPI interface of our framework, see Section 3, can rely on an estimation of the respective domain. Here, a simple estimation is based on the minimal and maximal values,  $\underline{X}$  and  $\overline{X}$ , of the dataset X used as input for the measure (i.e., the result of the child measures). The bounds may be extended by constant offsets to account for the fact that the dataset X is merely a sample of an unknown domain. The sensitivity of the measure, in turn, depends on the semantics of the measure. While for the aggregation functions of PPINOT, this sensitivity may be estimated, it is unknown in the general case of derived measures.

Against this background, this section first introduces three release mechanisms for aggregation measures: an instantiation of the Laplace mechanism; an interval-based mechanism based on the traditional exponential mechanism; and a threshold-sensitive mechanism that extends the interval-based one to preserve the significance of a measure related to a threshold. Finally, we discuss how derived measures, in the absence of an estimate of their sensitivity, can be privatized using a sample-and-aggregate strategy.

Laplace Mechanism for Aggregation Measures. Privatization of an aggregation measure can be based on the addition of Laplace noise to the actual result. As mentioned, this requires to estimate the sensitivity  $\Delta f$  of the given aggregation function, i.e., the maximal impact any element  $x \in X$  may have on f(X). For the aggregation functions of the PPINOT meta-model, the sensitivity is derived as  $\Delta(min) = \Delta(max) = |\overline{X} - \underline{X}|$ ,  $\Delta(sum) = \overline{X}$  and  $\Delta(mean) = |\overline{X} - \underline{X}|/|X|$ . Based thereon, noise from a Laplacian (with parameters  $\mu = 0$  and  $b = \Delta f/\epsilon$ , see Section 2.3) is added to f(X).

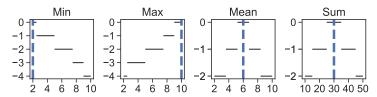


Fig. 4: Intervals and scores for the aggregation functions for dataset  $X = \{2, 3, 7, 8, 10\}$ .

Since the sensitivity  $\Delta f$  directly influences the magnitude of added noise, for mean measures, this mechanism potentially leaks information about the number |X| of process instances (and hence, individuals) within the given scope. An adversary may conclude on the difference  $|\overline{X} - \underline{X}|$  based on the magnitude of noise from another PPI incorporating a min or max measure and, based thereon, derive |X| from the magnitude of noise in a PPI with a mean measure. However, in practice, |X| may be revealed explicitly to enable a process analyst to assess the statistical reliability of the PPI result.

Interval-based Mechanism for Aggregation Measures. The drawback of the Laplace mechanism to privatize aggregation measures is the inherently high sensitivity, which scales linearly with the domain of input values. Our idea, therefore, is to group similar result values into intervals and score them using the exponential mechanism. This way, we obtain a release mechanism with a score function sensitivity  $\Delta q=1$ , which ultimately leads to a smaller magnitude of noise for large domains of input values.

To realize this idea, our interval-based release mechanisms consists of three phases:

- (1) *Interval creation:* We partition the domain and the range of the aggregation function into a set of intervals.
- (2) *Interval probability construction:* Scores are assigned to these intervals, which are then converted to result probabilities.
- (3) *Result sampling:* Using these probabilities, an interval is chosen as the output interval, from which the result value is sampled.

The *interval creation* is based on the range of the aggregation function, given as  $range(f(X)) = (\underline{X}, \overline{X})$  for  $f \in \{min, max, mean\}$  and  $range(f(X)) = (\underline{X} \cdot |X|, \overline{X} \cdot |X|)$  for f = sum. This range is split into non-overlapping intervals  $I = \{I_0, \ldots, I_n\}$ , with  $I_0 \cap \ldots \cap I_n = \emptyset$  and  $I_0 \cup \ldots \cup I_n = range(f(X))$ . Let  $\tau(x_i, x_j) = (x_i + x_j)/2$  be the mean of  $x_i, x_j$  and let  $I_f$  be the interval containing the result value, i.e.  $f(X) \in I_f$ . For mean and sum, the range of f(X) is divided into evenly spaced intervals of size  $\Delta f$ , so that  $f(X) = \tau(I_f, \overline{I_f})$  is the mean of its containing interval. For min and max, the range of f(X) is divided into n intervals of different size, for which the boundaries are the means of neighbouring values  $\tau(x_i, x_{i+1})$  with  $x_i, x_{i+1} \in X$ .

Fig. 4 exemplifies the intervals for a dataset  $X = \{2, 3, 7, 8, 10\}$ . For min and max, the interval boundaries are 2.5, 5, 7.5, and 9. For mean and sum, the intervals have size  $\Delta f = 1.6$  and  $\Delta f = 10$ , and are centred around mean(X) = 6 and sum(X) = 30.

The interval probability construction relies on a scoring function that assigns higher scores to intervals that are closer to the interval containing f(X). Let  $I_1, \ldots, I_n$  be the intervals in the order induced by  $\leq$  over their boundaries, and let  $1 \leq k \leq n$  be the index of interval  $I_f$  containing the result value. Then, the score for each interval  $I_i$  is defined as q(i) = -|k-i|, as illustrated in Fig. 4 for the example. Here, intervals, that lie closer

to f(X), denoted by the blue dashed lines, are scored higher, than those further away. Since each interval  $I_i$  corresponds to a set of potential result values, we incorporate the size of this set in the probability computation. Hence, the probability for  $I_i$  is defined as:

$$P(I_i) = \frac{|I_i| \cdot e^{(\epsilon \cdot q(i)/2 \cdot \Delta_q)}}{\sum_{1 < j < n} |I_j| \cdot e^{(\epsilon \cdot q(j)/2 \cdot \Delta_q)}}$$

*Result sampling* chooses one interval based on their probabilities. From this interval one specific value is drawn based on a uniform distribution over all interval values.

Threshold-Sensitive Mechanism for Aggregation Measures. The interval-based mechanism is problematic, if a PPI is tested against a threshold, as often done in practice. Consider the dataset X and assume that the sum function is the root of a PPI's function composition tree, i.e., f(X) = 30 as shown in Fig. 4. Assume that it is important whether the PPI is less or equal than 30. Then, adding noise may change the actual interpretation of the PPI, since the release mechanism will sometimes publish values larger than 30.

To mitigate this effect, we present a threshold-sensitive release mechanism that extends the previous mechanism in terms of *interval creation* and *interval probability construction*. Let  $\chi$  be a Boolean function formalizing a threshold, e.g.,  $\chi(x) = x \leq 30$ . Then, the Boolean predicate  $\phi(x, f(X), \chi) \Leftrightarrow \chi(x) \equiv \chi(f(X))$  describes, whether the possible result value  $x \in range(f(X))$  leads to the same outcome of  $\chi$  as the true result f(X). For our example,  $\phi(20, 30, \chi)$  holds true  $(20 \leq 30 \text{ and } 30 \leq 30)$ , whereas  $\phi(40, 30, \chi)$  is false  $(40 \nleq 30, \text{ but } 30 \leq 30)$ .

Using this predicate, we adapt the intervals  $I=I_1,\ldots,I_n$  obtained during *interval creation*, so that interval boundaries coincide with changes in  $\phi$ . Let  $B(\phi)$  be the boundary values of  $\phi$ , i.e., the values  $x \in range(f(X))$  with  $\lim_{y < x, y \to x} \phi(y, f(X), \chi) \neq \lim_{y > x, y \to x} \phi(y, f(X), \chi)$ . For our example, we arrive at  $B(\phi) = \{30\}$ . Based thereon, we split each interval  $I_i$  containing a boundary value  $b \in B(\phi)$  into two new intervals  $(I_i, b), (b, \overline{I_i})$ . Hence, each interval contains only values that share the outcome of the Boolean function  $\chi$ . In our example, the interval (25, 35) is split into (25, 30) and (30, 35), as shown in Fig. 5.

Finally, the scoring function used for interval probability construction is adapted. Let d(i) be the minimal inter-interval-distance of interval  $I_i$  to any other interval  $I_j$  with  $\phi(x,f(X),\chi)\neq\phi(y,f(X),\chi)$  for all  $\underline{I_i}\leq x\leq \overline{I_i}$  and  $\underline{I_j}\leq y\leq \overline{I_j}$ . As before, let k be the index of interval  $I_f$  containing the result value. Then, scores assigned to intervals that preserve the outcome of the Boolean function  $\chi$  remain unchanged. For all other intervals  $I_i$ , the score is reduced by  $\xi\cdot d(i)$ , i.e., by the distance to the closest interval preserving the outcome multiplied by a falloff factor  $\xi\in\mathbb{N}$ . The adapted scoring function is defined as:

$$q(i) = \begin{cases} -|k-i| & \text{if } \phi(x,f(X),\chi) \text{ for all } \underline{I_i} \leq x \leq \overline{I_i}, \\ -|k-i| - \xi \cdot d(i) & \text{otherwise.} \end{cases}$$

Fig. 5 illustrates the adapted scores for our running example, using  $\xi = 3$ . The scores of the right-most three intervals are reduced, as all of their values lead to a different outcome compared to the true result, f(X) = 30, when testing against  $\chi(x) = x \le 30$ .

We obtain d(4)=1, d(5)=2, and d(6)=3 for those intervals, given that the third interval (25,30) is the closest one retaining  $\phi$  to any of those three. Thus, we arrive at q(4)=-4, q(5)=-8, and q(6)=-12. As the largest possible change in scores assigned to a possible result value in neighbouring input sets is never larger than  $\xi$  and as the interval sizes are determined based on  $\Delta f$ , we conclude that  $\Delta q=\xi$ .

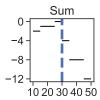


Fig. 5: Adapted intervals and scores.

Sample-and-aggregate Mechanism for Derived Measures. Since the sensitivity of a derived multi-instance measures is unknown in the general case, the above mechanisms are not applicable. However, many derived measures may be approximated using small samples, since their range is often independent of the domain of their input values. Functions that compute a normalized result are an example of this class of measures. For instance, the derived measure that denotes the root of the function composition tree of the example in Fig. 2 yields a percentage, i.e., it is normalized to 0% to 100%. For such measures, the sample-and-aggregate-framework mentioned in Section 2.3 may be instantiated. That is, the actual result f(X) is computed on n partitions of X. The obtained results per sample are then aggregated using a differentially private mean function to achieve privatization of the derived measure.

## 5 Experimental Evaluation

To assess the feasability and utility of the proposed approach, we realized the PPI interface on top of an existing PPINOT implementation.<sup>2</sup> We conducted controlled experiments using synthetic data (Section 5.1) and a case study with the *Sepsis Cases* log (Section 5.2). The latter compares the proposed tree-based privatization with the direct evaluation of PPIs on logs that have been anonymized with the PRIPEL framework [10] beforehand. Our implementation and evaluation scripts are publicly available.<sup>3</sup>

# **5.1** Controlled Experiments

In a first series of experiments, we assessed the impact of different properties of the dataset X used as input. Specifically, we consider the impact of the estimation of the domain of input values, its size and underlying value distribution, and the privacy parameter  $\epsilon$ . We sampled sets of 10, 50, 100, and 200 random values from a Gaussian distribution, a Pareto distribution, and a Poisson distribution. We chose these distributions, as they are often observed in event data recorded by business processes. We performed 200 runs per experiment. Unless noted otherwise, the input domain is estimated using the minimal and maximal element of X, the dataset comprises 200 values drawn from a Gaussian distribution, and the privacy parameter is set as  $\epsilon = 0.1$ .

**Input Boundary Estimation.** First, we compare the boundary estimation using the minimal and maximal elements in X with extensions of these boundaries by 15% and

 $<sup>^2\; \</sup>texttt{https://mvnrepository.com/artifact/es.us.isa.ppinot/ppinot-model}$ 

 $<sup>^{3}\; \</sup>verb"github.com/Martin-Bauer/privacy-aware-ppinot"$ 

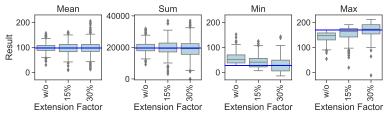


Fig. 6: Impact of the input boundary estimation on the results.

30% at either boundary. The results for the interval-based mechanism, see Fig. 6, show that an extension of the domain increases the introduced magnitude of noise for all functions due to an increase in sensitivity. These observations are confirmed for the Laplace mechanism. Yet, for min and max, there is a shift of the expected result towards the true result f(X) (denoted by the blue line). The reason is that, without the extension, f(X) coincides with boundary values of X. The extension increases the size of the interval containing f(X), which increases the probability of this interval to be chosen.

Input Size and Distribution. For the Laplace and interval-based mechanisms, we identify a dependency of  $\Delta f$  on the input size for mean functions. This dependency coincides with smaller noise magnitudes for larger input sizes, as illustrated in Fig. 7.

These trends were confirmed for the interval-based mechanism for min and max. Here, the increased number of intervals and a more fine-grained differentiation between result values leads to higher utility, i.e., the expected result is close to the actual one. Yet, the trends are only visible for distributions with small inter-value distances, such as the Gaussian. For the Pareto- and Poisson-distributions, there was a significant reduction in utility for larger inputs using max. These distributions

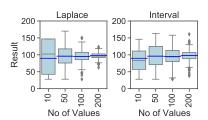


Fig. 7: Impact of the cardinality of the dataset X on the results for mean.

preserve most of their probability mass on the smaller values, This inadvertently results in the creation of disproportionally large intervals and the same output probability for large portions of the output space.

**Epsilon.** The results obtained when changing the privacy parameter  $\epsilon$  are shown in Fig. 8a for mean. Both the Laplace and interval-based mechanism show a similar increase in the introduced noise. The Laplace mechanism yields better results for larger  $\epsilon$ .

For min and max, however, the interval-based mechanism clearly outperforms the Laplace mechanism for all values of  $\epsilon$ , see Fig. 8b for the maximum function. Here, the large sensitivity for the Laplace mechanism completely obfuscates the actual result f(X), rendering the mechanism inappropriate for these functions.

**Threshold-sensitive Mechanism.** For the extension of the interval-based mechanism that aims to preserve the significance for thresholds, the general trends remain unaffected. However, the threshold-sensitive mechanism shifts large portions of the probability mass of the output space, as shown in Fig. 9. Here, the threshold to preserve is  $\phi(x): x < f(X) \pm y$ , with y being 100 for sum and 10 for the other aggregation functions. For

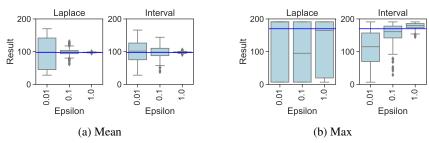


Fig. 8: Sensitivity of mean and maximum function towards  $\epsilon$ .

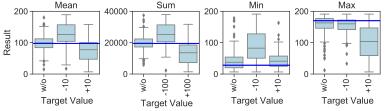


Fig. 9: Results for the threshold-sensitive mechanism using differing result thresholds.

comparison, the results for the interval-based mechanism without threshold preservation are also given. There is a clear shift in output probabilities, depending on which values preserve the same properties as f(X). Note that the results should not be interpreted in absolute terms, but serve as a binary indicator regarding the threshold.

**Derived Measures.** The sample-and-aggregate mechanism for derived measures mirrored the trends of the Laplace mechanism for mean. This is expected since the mechanism is based on the privatized mean. Yet, due to the use of m buckets of size n, the magnitude of noise is larger. The mechanism requires m times as many values in X to achieve the same sensitivity as the mechanism for the mean. Since the mean is computed using n values per bucket, the result estimation is accurate only for large datasets.

## 5.2 Case Study: Process for Sepsis Cases

To explore how the presented mechanisms perform in a real-world application, we conducted a study using the Sepsis Cases log. As part of that, we compare our approach to a state-of-the-art privatization approach for event logs. That is, we evaluated the same PPIs non-anonymously using logs that have been anonymized with PRIPEL [10]. The PPIs used in our case study were created based on criteria and guidelines presented in [12,21] and are listed in Table 1, together with the employed mechanism used for privatization. Some concern the lengths of stays and treatments for patients (PPI 1-4), wile others target the adherence to treatment guidelines (PPI 5-6). To illustrate the behaviour of our release mechanism, we calculated each PPI 10 times using  $\epsilon=0.1$  and report aggregate values. While results for all PPIs are available online, due to space constraints, we here focus on PPI 1 and PPI 6, see Fig. 10 and Fig. 11, respectively.

For PPIs 1 to 3, we were able to reconstruct the general trends of the non-privatized analysis (exemplified for PPI 1 in Fig. 10). Yet, we also observed specific months with high result variances. For PPI 1 and 2 (mean functions), the variance stems from the

ID	Measure	Target Value	s Scope	Mechanism
1:	Avg waiting time until admission	<24 hours	Monthly	Mean - Interval
2:	Avg length of stay	<30 days	Monthly	Mean - Interval
3:	Max length of stay	<35 days	Monthly	Max - Interval
4:	Returning patient within 28 days	<5%	Monthly	Sum - Laplace
5:	Antibiotics within one hour	>95%	Monthly	Sum - Laplace
6:	Lactic acid test within three hours	>95%	Monthly	Sum - Laplace

Table 1: PPIs defined for the Sepsis Cases log.

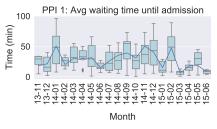




Fig. 10: Evaluation Results for PPI1, only PaPPI (left), and PaPPI and PRIPEL (right).

large domain of input values, resulting in higher sensitivities. For PPI 3 (max function), variances were relatively small, except for one month, which represents a notable outlier.

The results obtained with our framework are in sharp contrast to those achieved when privatizing the event log with PRIPEL before computing the PPIs in a regular manner. As shown in Fig. 10 (right), the latter approach accumulates an error over the recorded time period. The steadily increasing deviation from the true value is caused by traces that represent outlier behaviour, which was artificially created by PRIPEL.

PPIs 4 to 6 were calculated using privatized *sum* functions. Due to the relatively low number of traces recorded per month, the application of the sample-and-aggregate-framework for the calculation of the final percentage value led to worse results. Here, the buckets contained not enough values to approximate the true result well. However, using privatized *sum* functions, the results for PPIs 4 to 6 fol-

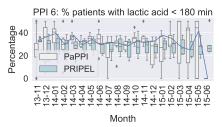


Fig. 11: Evaluation Results of PPI6

low the general trends of the true values, see Fig. 11 for PPI 6. Similarly, also the computation based on logs privatized with PRIPEL yields comparable results. In months, in which few traces are selected for a PPI, e.g., at the beginning and end of the covered time period, the variance is notably larger for our proposed framework, an effect that is avoided by the approach based on event log privatization.

Turning to research question RQ3, our results provide evidence that the proposed framework enables the computation of privacy-aware PPIs that mirror the general trends of their true values. Only for time periods, in which the PPI computation is based solely on a few traces, our framework does not yield sensible results. Thus, given a sufficiently large number of traces as the basis for the evaluation of PPIs, we can expect our framework to retain the trends.

#### 6 Related Work

For a general overview of privacy-preserving data mining, as mentioned in Section 1, we refer to [16] and [20]. However, data anonymization commonly leads to a trade-off between the strength of a privacy guarantee and a loss in data utility. This calls for anonymization schemes that minimize the accuracy loss of PPI queries, so that management may still assess the fulfilment of operational goals, while the privacy of involved individuals is protected.

To define PPIs, it was suggested to rely on ontology-based systems [24] or resort to predicate logic to enable formal verification [18]. In this work, we followed the PPINOT meta-model, which is very expressive due to its compositional approach. The compositionality is also the reason why we opted for the adoption of differential privacy in our approach. Other privacy models include k-anonymity [22] and its derivatives [9,11], which statically mask recorded data points. Yet, since the evaluation of PPIs is driven by queries and processes continuously record data, these techniques are not suitable.

In the context of data-driven business process analysis, the re-identification risk related to event data was highlighted empirically in [23]. To mitigate this risk, various directions have been followed, including the addition of noise to occurrence frequencies of activities in event logs [13], transformations of logs to ensure k-anonymity or t-closeness before publishing them [8, 19], and the adoption of secure multi-party computation [6]. However, since these approaches focus on the control-flow perspective of processes, they cannot be employed for the privacy-aware evaluation of PPIs in the general case.

## 7 Conclusion

In this paper, we proposed the first approach to privacy-aware evaluation of process performance indicators based on event logs recorded during the execution of business processes. We presented a generic framework that includes an explicit interface to serve as the single point of access for PPI evaluation. In addition, for PPIs that are defined following the PPINOT meta-model, we showed how to design release mechanisms that ensure  $\epsilon$ -differential privacy. We evaluated our mechanisms on both synthetic data and in a case study using the Sepsis Cases log. The results highlight the feasibility of our approach, given that a sufficiently large number of process executions is available.

In future work, we aim to extend the evaluation of the mechanisms, in order to recommend which functions to privatize, for a given function tree. This would aid process analysts in receiving PPI results, with minimal quality loss.

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