PEEPLL: Privacy-Enhanced Event Pseudonymisation with Limited Linkability *

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ABSTRACT

Pseudonymisation provides the means to reduce the privacy impact of monitoring, auditing, intrusion detection, and data collection in general on individual subjects. Its application on data records, especially in an environment with additional constraints, like reidentification in the course of incident response, implies assumptions and privacy issues, which contradict the achievement of the desirable privacy level. Proceeding from two real-world scenarios, where personal and identifying data needs to be processed, we identify requirements as well as a system model for pseudonymisation and explicitly state the sustained privacy threats, even when pseudonymisation is applied. With this system and threat model, we derive privacy protection goals together with possible technical realisations, which are implemented and integrated into our event pseudonymisation framework PEEPLL for the context of event processing, like monitoring and auditing of user, process, and network activities. Our framework provides privacy-friendly linkability in order to maintain the possibility for automatic event correlation and evaluation, while at the same time reduces the privacy impact on individuals. Additionally, the pseudonymisation framework is evaluated in order to provide some restrained insights on the impact of assigned paradigms and all necessary new mechanisms on the performance of monitoring and auditing. With this framework, privacy provided by event pseudonymisation can be enhanced by a more rigorous commitment to the concept of personal data minimisation, especially in the context of regulatory requirements like the European General Data Protection Regulation.

CCS CONCEPTS

• Security and privacy → Pseudonymity, anonymity and untraceability; Management and querying of encrypted data; Public key encryption; Hash functions and message authentication codes.

KEYWORDS

personal data minimisation, pseudonym re-usage, privacy protection goals, pseudonymisation framework, indistinguishability, unobservability, limited linkability

1 INTRODUCTION

Monitoring and auditing of user, process, and network activities plays an important role for the security of a system. By leveraging gained information, a security operator can observe unusual Christian Burkert University of Hamburg

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behaviour and possibly detect or even prevent past and ongoing attacks on his system. The success of such an analysis requires as much information about the actions in the system as possible. However, it also has severe privacy implications. Each data record might not only contain directly or indirectly identifying attributes of a person, like names or addresses, but also IP addresses, unique user ids, or account data. Such data is called *personal data* [1, Article 4(1)] or quasi identifier (OIDs) [2] and comprises directly identifying as well as potentially identifying features, i.e., attributes that are by themselves not sufficient to identify individuals but may in combination be used to do so. Analysing such data constitutes a severe impact on the privacy of individuals. It facilitates the creation of user profiles and social networks as well as tracking of user activities, performance, and preferences. In order to reduce that impact, e.g., due to legal obligations, privacy principles for the purpose of de-identification¹ can be applied such as generalisation and supression [5], permutation and aggregation [6], perturbation [7], and pseudonymisation [8]. A pseudonym replaces a QID of a subject in order to prevent or impede its identification, while at the same time maintains the possibility to re-identify the subject by means of a certain secret [8]. This provides linkability of individual data records as well as allows an investigation of incidents with a link to individuals, which both are vital requirements for applications such as intrusion detection and prevention. At the same time, it aims at reducing the impact, which data collection and processing such as auditing or monitoring has on privacy by means of data minimization. Therefore, it is a suitable de-identification technique in the context of event correlation and processing.

However, using pseudonymisation, especially in a distributed setting, as a technique to provide such a privacy-friendly linkability of individual data records is not a panacea for absolute data protection and privacy. Several assumptions have to be made and involved components have to be trusted. Furthermore, pseudonymisation as a tool to de-identify data sets bears a heavy legacy. Recent history has shown, that even properly de-identified data can be re-identified with the right background knowledge and so a connection between data set entries and individuals has been re-established in a long list of examples [3, 9, 10, 11, 12, 13, 14, 15, 16, 17]. These recognitions strongly indicate that it is inherently impossible to achieve full de-identification in general and full privacy via pseudonymisation in specific. If, however, the term privacy is not associated with an underlying assumption of completeness, but rather is taken in a sense of reduction and in the best case in a sense of minimisation of QIDs, as it has been postulated by Sweeney [3] and Ohm [4,

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¹The often used term of *anonymisation* is avoided, since its usage is controversial [3, 4, Kap. II.C.2] and misleading due to the associated expectation of absolute privacy.

Sect. II.C.2] already, pseudonymisation remains a valid tool to enhance the privacy of individuals in the context of event and data processing. Additionally, no other privacy preserving technique can be applied to data records as easily as pseudonymisation, while preserving the correctness of the original data. In this regard, it is necessary to move away from a binary distinction between full privacy on the one hand and no privacy on the other hand, but rather define privacy as an increasing or decreasing non-formalised continuum. In view of these facts, our main contributions can be summarised as follows:

- The explicit formulation of a system and threat model of event and data record pseudonymisation and the highlighting of remaining privacy threats,
- the proposal of privacy protection goals, which do not aim to achieve full privacy, but rather increase privacy by minimisation of personal as well as potentially personal data,
- the design and development of a pseudonymisation framework including technical realisations of all protection goals, and
- a discussion about performance implications and an evaluation of the framework.

The rest of the paper is structured as follows. We provide background on techniques especially important for our framework in Sect. 2 as well as on the system and threat model including possible scenarios of our framwork and derived requirements in Sect. 3. The threat model motivates the proposal of privacy protection goals and a discussion on potential conflicts in Sect. 4 including further details about technical realisations of the privacy protection mechanisms implemented in our event pseudonymisation framework PEEPLL. We survey related work in Sect. 5 and conclude in Sect. 6.

2 BACKGROUND

The following sections briefly introduce topics, which are needed as basic building blocks for the design and implementation of several parts of the pseudonymisation framework.

2.1 **Pseudonymisation**

The definition of pseudonymisation used throughout this paper is based on the definition given by GDPR [1] in Article 4(5): "pseudonymisation means the processing of personal data in such a manner that the personal data can no longer be attributed to a specific data subject without the use of additional information [...]." As the definition states, some additional information exists, e.g., a mapping table or a function, to attribute a pseudonym to the corresponding identifier, which can be used to revert the process of pseudonymisation. We call this additional information the pseudonym lookup table. Without knowledge about the mapping, a re-identification should be unfeasible without undue effort. The effectiveness of pseudonymisation is significantly determined by the decision, which data items constitute QIDs and therefore need to be covered by pseudonymisation. Note that the process of determining QIDs is higly application-specific. Note further that the literature often calls the mapping "link", which must not be confused with the term "Linkability" explained in Sect. 3.1.2.

2.2 Hash Functions and HMACs

A hash function is a mapping H from an input of arbitrary length to an output of fixed length $n \in \mathbb{N}$, $H : M^* \to M^n$, which is called the hash value or digest of the input. This mapping is considered unique if the following properties hold: 1) *Preimage resistance*: Given the hash value y = H(x), it is infeasible to find the input x equivalent to invert the hash function H. 2) *Second preimage resistance*: Given an input x, it is infeasible to find another input $x' \neq x$ such that H(x') = H(x). 3) *Collision resistance*: It is infeasible to find two arbitrary inputs x and x' with $x \neq x'$ such that H(x') = H(x). Apart from specialised attacks, which target the underlying mathematics and constructions of hash functions, they suffer from simple brute-force attacks. Especially when the preimage space consist of QIDs, preimage resistance cannot be provided by hash functions sufficiently [18].

One solution is the enlargement of the preimage space by adding additional entropy in form of a secret key to the input value. Such a construction is called a keyed hash function. An HMAC is a practical realisation of a keyed hash function. As every Message Authentication Code (MAC), it takes a randomly chosen secret key k of sufficient length and a message m of arbitrary length as input, and outputs Mac(k, m), a so called tag of the message, which is unforgeable as long as the secret key k is not known [19].

2.3 Bloom Filter

Bloom Filters are used to store and query set member information in a space-efficient way by applying hash functions. The filter itself consists of a bit array of fixed length m, initially set to all 0's. Given r differing hash functions $H_i : M^* \to \{0, \ldots, m-1\}, i \in \{1, \ldots, r\}$ mapping inputs to a single bit position in the filter, a new input can be inserted by computing the r hash values for the input and setting the bits at these positions to 1. To test for set membership of an input, the hash values are computed like in the insert step and the resulting positions are looked up in the filter. If all bits at the rpositions are set to 1, the input is a possible member of the set.

The space efficiency comes at the cost of possible false positives. If the union of all member hash values leads to a filter, in which the set bits include all bits of a non-member, the filter would still indicate the set membership for this non-member. On the other hand, a filter, where any bit for the hash values of an input is set to 0, definitely states the non-membership of this input [20].

2.4 1-out-of-N Oblivious Transfer

1-out-of-N Oblivious Transfer (OT) refers to a cryptographic primitive, which is defined as follows: A sender S has N messages M_0, \ldots, M_{N-1} and a receiver \mathcal{R} wants to get the *i*-th message M_i without S learning any information about which message is of interest for \mathcal{R} . Additionally, \mathcal{R} shall not learn any information about any other message $M_j \neq M_i$ than the requested one. A very basic 1-out-of-N OT protocol based on the computational Diffie-Hellman assumption has been proposed by Naor and Pinkas [21] and recently a very efficient one by Chou and Orlandi [22]:

Preliminaries: The protocol uses a hash function *H* and a group \mathbb{Z}_p of prime order *p* with *g* as a generator of that group.

Initialisation (only once, used for all subsequent transfers): 1) S randomly chooses a secret $y \in \mathbb{Z}_p$ and computes $s = g^y$ and $t = s^y$. 2) S sends s as its public key to \mathcal{R} .

Input/Output: \mathcal{R} 's input is the index $i \in \{0, ..., N-1\}$, and \mathcal{S} 's input is the messages $M_0, ..., M_{N-1}$. At the end of the protocol, \mathcal{R} 's output is M_i , while \mathcal{S} learns nothing about i.

Key Derivation (for every index of interest for \mathcal{R} , even in parallel): 1) \mathcal{R} with input *i* randomly chooses a secret $x \in \mathbb{Z}_p$ and computes $r = s^i \cdot g^x$ as well as $k_i = H(s||r||s^x) = H(s||r||g^{y \cdot x})$.² 2) \mathcal{R} sends *r* to S. 3) For all $j \in \{0, ..., N - 1\}$ S computes $k_i = H(s||r||r^y/t^j) = H(s||r||g^{(y \cdot i + x) \cdot y}/g^{y \cdot y \cdot j})$.

Transfer (for every index of interest for \mathcal{R} , even in parallel): 1) For all $j \in \{0, ..., N - 1\}$ S encrypts each M_j by computing $C_j = Enc(k_j, M_j)$ and then sends these encryptions $(C_0, ..., C_{N-1})$ to \mathcal{R} . 2) \mathcal{R} decrypts C_i by computing $M_i = Dec(k_i, C_i)$.

Research on the topic of OT is manifold and fast-paced. There are many variants and so called extension, which try to further improve the security or efficiency. See further [23].

2.5 Secure Indexes

Secure Indexes offer the possibility to search for keywords in encrypted documents by querying specially crafted indexes that maintain the confidentiality of the indexed keywords [24]. Each Secure Index is based on a Bloom Filter (see Sect. 2.3), which encodes the keywords for the corresponding document. Keywords undergo a two-step encoding before they are inserted in the Bloom Filter. 1) A concealment of the keyword by applying a pseudo-random function *f* to both the keyword *w* and a secret key $K = (k_1, \ldots, k_r)$. The output $x = (x_1 = f(w, k_1), \dots, x_r = f(w, k_r))$ is called trapdoor. 2) A personalisation of each trapdoor with the unique document identifier D_{id} by applying the pseudo-random function f again. The result $y = (y_1 = f(x_1, D_{id}), \dots, y_r = f(x_r, D_{id}))$ is called a codeword. Its elements y_i are then inserted into the Bloom Filter. The second step is to achieve different codewords for identical keywords in different documents, which avoids a cross-document analysis of common keywords. The Bloom Filter is stored together with the encrypted document as its Secure Index. To query if a document contains a given keyword, one calculates the trapdoor for this keyword, personalises it with the document id, and checks if the resulting codeword is included in the document's Bloom Filter.

3 REQUIREMENTS & THREAT MODEL

Before discussing privacy threats and protection goals as well as the design and implementation of our pseudonymisation framework to mitigate these threats, the following section introduces principles and requirements for the pseudonymisation framework and the underlying system model including the most important basic terms used throughout the rest of the paper. Consider the following two scenarios, where pseudonymisation of data records is needed:

Scenario 1 An organisation has deployed a distributed security incident detection system consisting of several distributed sensors throughout the whole IT as well as physical infrastructure in order to monitor user activities from several points of view and to detect

intrusion, extrusion, and anomalous activities. All sensor data is being combined at a central data processing unit, which provides abilities to analyse and correlate the data. Most importantly, the data of all sensors has to be archived for a certain amount of time to allow a thorough investigation in cases of security breaches.

Scenario 2 A consortium of several independent medical institutions wants to collect and share medical data on specific rare diseases as well as on their treatment and corresponding results in order to be able to improve the quality level of treatments especially where one institution does not get enough data by itself to achieve statistical relevance. The collection and sharing is not limited to a closed set of medical data but should be able to incorporate data from patients' follow-up examinations over time. Therefore, the data is only useful for research purposes when it is not completely de-identified but maintains the ability to update patients' medical records from different institutions while the disease status is monitored and the treatment is adjusted.

3.1 Requirements

The two scenarios highlight the following requirements, which need to be established in order to protect the privacy of individuals in the context of data collection and sharing.

3.1.1 Personal Data Minimisation. In both scenarios, the collection, storage and processing of data records has severe implications for the privacy of users. To mitigate this effect, the principle of personal data minimisation should be applied and enforced [25]. "By ensuring that no, or no unnecessary, data is collected, the possible privacy impact of a system is limited." [26]. Effective mechanisms for personal data minimisation in these scenarios are Select before you Collect [27], which means the limitation of personal data "to what is necessary in relation to the purposes for which they are processed" [1, Article 5(1)(c)] and Pseudonymisation. Any other form of de-identification is not an option for both scenarios, because separate data items, that are collected, might need to be linked to each other in a way, that allows the attribution to the same subject, even though it is generally unimportant, which identity is behind that subject. Additionally, in case of an investigation in Scenario 1 or a new special treatment possibility for a patient in Scenario 2, the subject might need to be re-identifiable.

3.1.2 Linkability. Monitoring of user, process, and network activities as well as collecting medical records have not an end in themselves, but are rather embedded into a broader evaluation process such as intrusion or anomaly detection or statistical analysis. Linkability [8] provides the context to set individual records in relation and is the basis for correlation and interpretation.

3.1.3 Global Pseudonym Consistency. Both scenarios have the requirement, that all data records, which concern the same subject, must be pseudonymised such that linkability wrt. the subject is maintained regardless of the data source. Otherwise, analysis and statistics of the collected and correlated data are distorted. Such a global consistency requires specific information about already used pseudonyms or a deterministic algorithm.

3.1.4 *Pseudo- vs. Truly-random Pseudonyms.* There are two ways to maintain global pseudonym consistency, both resulting in different

²Prepending the values *s* and *r* to the hash function as salt approximates a random oracle and makes sure that the oracle is local to the protocol session. It further helps against malleability attacks [22].

system models. 1) A pseudonymisation component might derive pseudonyms solely from data records alone and in a deterministic manner. We call this local deterministic or pseudo-random pseudo*nymisation*. This allows the setup of a simple pseudonymisation infrastructure, because each pseudonymisation component can derive pseudonyms for QIDs independently from each other, while at the same time maintain global pseudonym consistency. However, Marx et al. [18] demonstrated, that preimage attacks via brute force to uncover such deterministically derived pseudonyms can be done with reasonable effort due to fairly low cardinalities of typical preimage domains, such as QIDs (e.g. IP addresses, e-mail addresses). Furthermore, the need to re-identify a subject behind a locally and deterministically derived pseudonym, commands the creation, protection, and coordination of additional pseudonym disclosure information. 2) Not susceptible to brute force attacks are pseudonyms, which are not derived from data records, but which are chosen truly randomly. To determine whether a random pseudonym has already been chosen for a given OID, as it is necessary to maintain global pseudonym consistency, a global lookup table between QIDs and the corresponding random pseudonyms has to be consulted. Re-identification of randomly chosen pseudonyms, can be done via this lookup table as well.

3.1.5 Component Separation. All information that potentially threatens the privacy of users is collected decentralised on different independent data sources in both scenarios. For the deployment of a proper pseudonymisation process, it makes most sense to pseudonymise all QIDs independently and as close to the data sources as possible, meaning a one-to-one relation between a data source and a pseudonymisation component. Furthermore and for the sake of personal data minimisation a strict separation of all components of the pseudonymisation process itself should be enforced. On the one hand, data leakage due to a compromise of a pseudonymisation component does not necessarily break the whole pseudonymisation process, due to a separation of knowledge. On the other hand, such a separated pseudonymisation allows the exchange of information between all components taking part in the pseudonymisation process on a so called need-to-know basis. This reduces the exchange and processing of personal data as well as other potentially jeopardising data, such as pseudonym frequencies and temporal information about appearances of pseudonyms for distinct data sources, to an absolute minimum.

3.1.6 Out of scope. Several other requirements might be important for the process of pseudonymisation. However, only those mentioned in the previous Sects. have been taken into account for the design of the proposed pseudonymisation framework. In particular, the actual process for pseudonym disclosure in order to re-identify a subject behind a pseudonym is open for future work. Furthermore, the problem of authenticity wrt. the origin of the data records will be considered as out of scope. It is up to the pseudonymisation components to ensure, that the processed information is authentic. Other requirements might be the unforgeability or integrity of the pseudonym lookup table, to prevent a malicious altering of the content of the lookup table, the application of group pseudonyms and more generally of identical pseudonyms for multiple QIDs, or the establishment of limited linkability according to a session E. Zimmer et al.

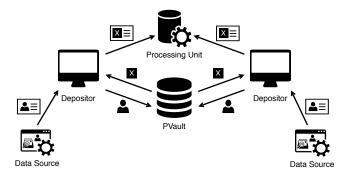


Figure 1: System Model of the Pseudonymisation Framework.

concept. All of these have to be established separately, in case they are mandatory requirements.

3.2 System Model

The identified and discussed requirements result in the following system model for our pseudonymisation framework PEEPLL (see Fig. 1): A data source is emitting some representation of an event or some medical record, which for brevity will be called data record and which possibly contains personal data of a subject. A so called **Depositor** assigned to that data source has the task to replace a QID of a subject, if present, with a pseudonym. For that, it extracts QIDs on a single identifier basis one by one, requests a pseudonym for each QID from a so called Pseudonym Vault (PVault) and upon receiving a response from the PVault, replaces the identifier with the pseudonym. The PVault receives a pseudonym request from a Depositor and might be faced with two situations. First, there already exists a pseudonym for this identifier in the pseudonym lookup table, which can be sent back to the Depositor. And second, there does not exist a pseudonym for this identifier in the pseudonym lookup table and so a new trulyrandom pseudonym must be created and stored in the pseudonym lookup table together with the corresponding QID by the PVault. The pseudonymised data record is then sent from the Depositor to the data collection and correlation unit.

Remarks: The integrity and confidentiality of all communication is protected. The pseudonymisation process is transparent to the data sources and the processing unit. The PVault is needed in order to provide truly-random pseudonyms while at the same time maintain global pseudonym consistency. Communication for the pseudonymisation process only is needed between the Depositors and the PVault, not between the Depositors themselves.³

3.3 Threat Model

PEEPLL does not aim at providing provable privacy against strong external or internal attackers. In fact, there are several threats, which directly undermine the privacy protection mechanisms of PEEPLL, mainly because of their fundamental nature:

³Even though the Depositors provide identical functionality and interact identically with the PVault, they can not be seen as one logical component, because each Depositor should be limited to the scope of its data source.

- A malicious data source can undermine the pseudonymisation process for all locally processed data records.
- A malicious Depositor can 1) create his own local pseudonym lookup table containing all locally processed QIDs and pseudonyms, as well as 2) ignore pseudonym responses or even skip requesting pseudonyms from the PVault and use his own (random or not) pseudonyms.
- A malicious PVault can manipulate the pseudonym lookup of already processed QIDs as well as manipulate the generation function and ignore the requirement of random pseudonyms.

Apart from organisational rules and regulations, there are no protection mechanisms, which could be deployed by PEEPLL in order to prevent these threats. At most, a weak mitigation against these fundamental privacy threats can be achieved by a strict separation of all components and an enforcement to prevent a collution, since it is limiting their scope to the locally accessible data. Nonetheless, from a threat model point of view, these components need to be considered as trusted and a collaboration must be prohibited. Furthermore, recent publications on re-identification of de-identified data strongly indicate, that it is inherently impossible to achieve full privacy via pseudonymisation (see Sect. 1).

However, PEEPLL moves away from a binary distinction between full privacy on the one hand and no privacy on the other hand, but rather sees privacy as well as an opposing threat to privacy as an increasing or decreasing non-formalised continuum. With this association of the term *privacy*, the minimisation of existing identifying and quasi-identifying features in a system exacerbates the privacy threats mentioned above and increases the privacy of individuals. Conversely, the existence of such QIDs including meta data of a pseudonymisation process itself constitutes a threat to privacy, since it aids to re-identify individuals. Thus, the main focus of PEEPLL is the strict minimisation of QIDs, including meta data of the pseudonymisation process itself, such as re-usage patterns of pseudonyms. It tries to maintain the information that really is needed by the data processing unit in order to provide its functionality as well as the information that really is needed for the process of pseudonymisation. The remaining sources of potentially sensitive information shall be eliminated as accurately as possible. In particular, PEEPLL facilitates the minimisation of the following data or the prevention of its utilisation:

- Meta information about the usage count of existing pseudonyms can be inferred by Depositors, which will be prevented by PEEPLL with specifically designed responses of the PVault so that Depositors do not learn such information (see Sect. 4.1).
- The PVault has a global view on all cleartext QIDs prevalent in the whole system. This threat will be addressed in PEEPLL by protecting the confidentiality of all QIDs with respect to the PVault (see Sect. 4.2).
- The PVault can infer usage patterns from pseudonym requests as a form of meta information, which, over time, might provide the ability to infer additional sensitive information. PEEPLL will mitigate this threat by limiting the linkability of data records (see Sect. 4.5) as well as by preventing the PVault from learning any information about which entry of the pseudonym lookup table matches a queried deposit (see Sect. 4.3)
- The collection of pseudonymised data records in general allows the creation of individual profiles over pseudonyms,

which increase in accuracy over time, since all data records related to the same QID are linkable via the corresponding pseudonym. Those profiles, even without being directly linkable to individuals, might on the one hand leak sensitive information and on the other hand illegally be de-pseudonymised, which both have an increasing success probability over time. PEEPLL will mitigate this threat by limiting the linkability of several related data records (see Sect. 4.5).

4 PEEPLL

Pseudonymisation alone does not protect against tracking, profiling, and re-identification via background knowledge attacks [28, 29].⁴ We will consider the following protection goals with respect to the design and implementation of the proposed pseudonymisation framework. Each protection goal aims at reducing the impact on the privacy of individuals. The overall challenge is to preserve the linkability of certain data records to some specifiable extent.

4.1 Re-use Indistinguishability

Definition 4.1

The information about whether or how often a pseudonym has been used before by any Depositor is only known to the PVault. Especially, a Depositor should not be able to distinguish whether or not a pseudonym has been used before by any other Depositor.

A pre-requisite of this protection goal is the separation of pseudonym creation from querying existing or new pseudonyms, which confirms the importance of the distributed environment already established by the system model. From a technical point of view to protect the Re-use Indistinguishability, the PVault is responding to a pseudonym request of a Depositor in such a way, that both cases, the generation of a new pseudonym and the finding of a matching entry in the pseudonym lookup table, look identical and thus are indistinguishable to the Depositor. This approach, however, is not applicable to every configuration of PEEPLL. See Sect. 4.3.2 for more details.

4.2 Deposit Confidentiality

Definition 4.2

The QID, which is to be replaced with a pseudonym by a Depositor, is only known to that Depositor itself. Neither the PVault nor any other Depositor shall learn any information about the underlying QID from a pseudonym request or a deposit, except another Depositor is processing the same QID as well.

PEEPLL utilises HMACs by equipping all Depositors with a shared secret k not known to the PVault. Given k and a *QID*, which is to be pseudonymised, a Depositor converts the plain *QID* into a lookup token $T_{QID} = Mac(k, QID)$ calculated by the tag-generation function of the HMAC. This lookup token will later be used to recognize a possibly corresponding existing pseudonym P_{QID} without relying on information about the *QID* itself – therefore establishing *Deposit Confidentiality*. Furthermore, because all Depositors use the same shared secret k, the lookup

⁴See also Sect. 1 and Sect. 3.3.

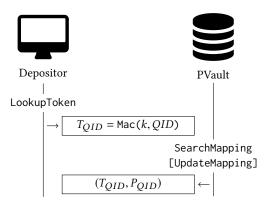


Figure 2: Interaction between a Depositor and the PVault in the HMAC-based approach.

token of *QID* stays consistent across the whole system, which preserves the requirement of *Global Pseudonym Consistency*. The Depositor sends a pseudonym request containing T_{QID} to the PVault owning the global pseudonym lookup table *PM*, which is a set of pairs of existing lookup tokens and corresponding pseudonyms { $(T_{QID_1}, P_{QID_1}), \ldots, (T_{QID_n}, P_{QID_n})$ } for already processed QIDs. The PVault searches *PM* for a matching entry (T_{QID}, P_{QID}) of the lookup token and the corresponding pseudonym connected to *QID*. In case such a matching pair in *PM* does not exist yet, the PVault has to generate a new pseudonym P_{QID} , store it together with the lookup token in *PM* and respond the Depositor with P_{QID} . The Depositor replaces the *QID* with the received pseudonym P_{QID} and carries on. Compare Fig. 2.

The secret key, which is shared among all Depositors but not with the PVault, adds entropy to the hashing process, which is necessary since the PVault could otherwise easily brute-force the actual QID (see Sect. 2.2). In PEEPLL it is generated and distributed to all Depositors once at the very beginning of the deployment. Such a brute-force attack is still possible, in cases where Depositors get hold of foreign deposits not related to their currently processed QID. This can happen when protection mechanisms for *Matching Pseudonym Unobservability* (see Sect. 4.3) are deployed as well. Since all Depositors know the secret key, the additional entropy is truncated. We refer to this problem as *Weak Deposit Confidentiality* and discuss a solution in Sect. 4.4.3.

4.3 Matching Pseudonym Unobservability

Definition 4.3

Which pseudonym from the pseudonym lookup table actually matches a specific data item requested by a Depositor is only known to the Depositor itself. In other words, the PVault does not learn any information about which entry of the pseudonym lookup table matches a queried deposit. simple form, this protection goal can be achieved by sending the whole pseudonym lookup table to each Depositor who requests a pseudonym. In this way, the PVault does not learn which entry is of real interest. However, besides the need of a great amount of bandwidth, this approach raises two problems.

4.3.1 *Privacy Issue.* All existing data items as well as their corresponding pseudonyms will become known to the requesting Depositor, which contradicts the principle of *Personal Data Minimisation* and the limitation of the scope of one Depositor. PEEPLL balances this conflict and additionally saves bandwidth by limiting the number of returned pseudonym lookup table entries, while at the same time assures, that this number is truly greater than one.⁵

A Depositor converts the data item *E* into a lookup token T_E and sends a pseudonym request containing T_E to the PVault owning the global pseudonym lookup table PM. The lookup token creation is returning a filter or mask, which can be applied to the pseudonym lookup table PM by the PVault and which matches both the entry of real interest as well as other irrelevant entries. In particular, the lookup token T_E created by a Depositor for a specific data item E consists of a Bloom Filter (see Sect. 2.3), which not only contains the data item E, but also a blinding of b randomly chosen bits. The blinding accomplishes an artificial false positive rate, which influences the probability, that more than one entry matches a given lookup token, while searching the pseudonym lookup table *PM*. The false positive rate can be controlled via the number of blinding bits *b* (see Sect. 4.4.2). The PVault applies the lookup token to PM and returns a set of all matching pairs of pseudonyms and the corresponding data items. The Depositor itself searches the set for a matching pair (E_j, P_{E_j}) , where $E_j = E$, replaces the data item *E* with the pseudonym P_{E_i} and carries on.

4.3.2 New Data Item Issue. The second problem relates to the case of a new data item of real interest, which does not exist in the pseudonym lookup table yet. In this case, the returned set only contains irrelevant entries, which will and must be sorted out by the Depositor. Eventually, the Depositor has to request the creation of a new pseudonym from the PVault, thereby thwarting Re-use Indistinguishability and also Matching Pseudonym Unobservability, since the creation request unambiguously references the data item of real interest. This can only partially be fixed by forcing the creation of dummy pseudonyms. After each pseudonym request and its corresponding response, the Depositor must send a pseudonym creation request, which either contains the data item of real interest, when only irrelevant pseudonym lookup table entries have been sent back from the PVault, or which contains a dummy data item otherwise. Re-use Indistinguishability will still be violated, since the Depositor can distinguish meaningful from irrelevant responses. This problem remains open for future work.

It does not matter if the QIDs, which need to be pseudonymised, can be processed as plaintexts or if they need to be concealed in order to protect the Deposit Confidentiality. Because of this, in the following, they are denoted as data item E. In its most

⁵It must be highlighted, that this approach achieves Matching Pseudonym Unobservability, but does not achieve Deposit Confidentiality, even when the confidentiality of data items is protected by the approach explained in Sect. 4.2, since a Depositor getting hold of foreign deposits is able to brute-force the HMACs. For a solution of this Weak Deposit Confidentiality see Sect. 4.4.3

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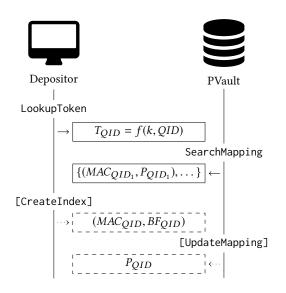


Figure 3: Interaction between a Depositor and the PVault in the Secure-Index--based approach.

4.4 Combined Deposit Confidentiality and Matching Pseudonym Unobservability

In order to protect both the Deposit Confidentiality and Matching Pseudonym Unobservability simultaneously, the concept of 1-outof-N OT (see Sect. 2.4) in conjunction with HMACs as utilised in Sect. 4.2 seems to be a natural solution. However, OT is not easily applicable to our context for two reasons. First, it assumes, that the database is of fixed length and its entries can be accessed by specific indices known to the Depositor. But the pseudonym lookup table of the PVault is constantly changing and its entries as well as their indices are not known to the Depositor. Second, OT involves heavy computation or heavy communication or both. At the end of the OT protocol, the sender delivers the whole database (specifically encrypted) to the receiver, which is not suitable to our setting. For this reason, the mechanisms explained in Sect. 4.2 and Sect. 4.3 are combined in PEEPLL as an alternative to OT. Additionally, certain optimisations are applied, which provide a more tailored solution and which closely relate to the concept of Secure Indexes (see Sect. 2.5). The concept of OT still does provide a viable solution to the problem of Weak Deposit Confidentiality, so its application in PEEPLL is discussed in Sect. 4.4.3.

4.4.1 Secure Indexes paired with HMACs. Given the shared secret k, a Depositor creates a Bloom Filter as lookup token $T_{QID} = BF(k, QID)$ for the data item QID. The Bloom Filter is constructed by deriving a set of r secret keys (k_1, \dots, k_r) from k, randomly picking a subset of r/2 keys and repeatedly applying a pseudorandom function to the QID for each k_i in the subset, determining which bits in the Bloom Filter are set (see Sect. 2.3). Using only half of the keys during lookup introduces an indeterminism to mitigate query profiling as discussed by Goh [24] (compare Sect. 4.4.2). The lookup token then is sent to the PVault, who owns the pseudonym lookup table PM, which is a set of triples each consisting of a Bloom Filter, a HMAC, and a corresponding

pseudonym for already processed QIDs. The PVault returns a set $\{(HMAC_{QID_j}, P_{QID_j}) | (BF_{QID_j}, HMAC_{QID_j}, P_{QID_j}) \in PM \land T_{QID} \subset BF_{QID_j}\}$ of all pairs of HMACs and pseudonyms whose respective Bloom Filter is a superset of T_{QID} . The expected number of elements of the set is influenced by the false positive rate introduced by the blinding injected into the Bloom Filters of the pseudonym lookup table (see Sect. 4.4.2).

In order for a Depositor to recognize the proper pseudonym in the received result set, the locally computed $HMAC_{OID}$ = Mac(k, QID) is compared to the received *HMACs*. If no match is found, the Depositor takes the HMACOID and creates a Bloom Filter similar to the one created as lookup token with the exception that all r keys are used instead of a subset, and adds a blinding of *b* bits to the Bloom Filter by setting *b* randomly chosen bits to 1. The blinding accomplishes an artificial false positive rate, which influences the probability, that more than one triple matches a given lookup token while searching the pseudonym lookup table PM. The false positive rate can be controlled via the number *b* of blinded bits. The result is a pair (HMAC_{OID}, BF_{OID}) of the HMAC and Bloom Filter, which correspond to the QID. This is sent to the PVault, who updates the PM with the resulting pair BFOID, HMACOID and a newly generated pseudonym P_{QID} , which is finally returned to the Depositor. This interaction is shown in Fig. 3.

Note: The presented approach protects *Re-use Indistinguishability* and *Matching Pseudonym Unobservability* only in those cases, where the Depositor finds a matching HMAC in the result set from the PVault. For further details, see Sect. 4.3.2.

4.4.2 False Positive Rates. Given an observed event rate r, the defined retention period p and an aspired false positive rate fp, the number of unique words can be approximated as n = r * p * c, where c is a constant to account for the expected number of identifiers per event. According to Goh [24], Bloom Filters should be parameterized with a number of hash functions $k = -\log_2 fp$ and a Bloom Filter size of $m = n * k/\ln 2$.

Since we employ Goh's extension proposal for a heuristic, that obfuscates query duplicates by sending only a partial trapdoor, the effective false positive rate is elevated. Instead of using the full trapdoor of length k, a random sample of size k' = k/2 is drawn from the full trapdoor. Consequently, the resulting false positive rate is given as $fp' = 2^{-k'} = 2^{-k/2} = \sqrt{2^{-k}} = \sqrt{fp}$. To compensate for the effect of partial trapdoor building on the effective false positive rate, the number of hash functions is chosen as $k^* = -2 \log_2 fp$, where fp is the desired false positive rate.

We have measured this relation in the deployed implementation displayed in Fig. 4. It shows the average number of deposits with matching Bloom Filters dependent on the false positive rate fp' for a fixed number of pre-added deposits. Obviously our approach can only give probabilistic guarantees for the number of false positives and as a consequence of this for the protection goal of Matching Pseudonym Unobservability.

4.4.3 Solving Weak Deposit Confidentiality. The presented approach still raises a special challenge. The entries of the pseudonym lookup table consist of pairs of confidential QIDs and corresponding pseudonyms, with the mandatory requirement, that the technical realisation to protect the *Deposit Confidentiality* is of deterministic

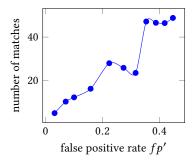


Figure 4: Average number of matching Bloom Filters dependent on the false positive rate measured by adding deposits to a prefilled PVault (100 records).

nature. This determinism assures, that a QID always results in the same concealed data item (the HMAC of a QID), which is sent to the PVault as a pseudonym request and stored in the pseudonym lookup table for future reference. This determinism additionally assures, that a Depositor, who receives a set of deposits as a response to its pseudonym request, which potentially contains deposits from earlier pseudonym requests as well as from other Depositors, and which should remain confidential even to this Depositor (see Definition 4.2), is able to recognise the one deposit, which matches the actual QID of real interest. However, this determinism makes all deposits, or more precisely their HMACs, that are returned to the Depositor, susceptible to brute-force attacks by that Depositor, because the additional entropy added to the HMACs is known to the Depositor and so is useless as protection mechanism against an enumeration of all possible QIDs. As a result, the deposits, which are to be sent to the Depositor as a response to a pseudonym request, have to be processed in a way, that conceals all deposits except the one of real interest for the Depositor, before leaving the PVault.

A perfectly valid solution is the application of 1-out-of-N OT as explained in Sect. 2.4 with some adjustments to overcome its two major obstacles for our setting. 1) The first obstacle concerns the missing fixed indices, which would need to be used to pinpoint a specific entry of the pseudonym lookup table on the side of a Depositor playing the receiver of the OT protocol. A resolution is the utilisation of the HMACs themselves, which are part of the lookup tokens, as keys or indices of a hash map storing the corresponding entries of the pseudonym lookup table. As this again would deliver the HMACs of foreign deposits to a Depositor, who can easily brute-force them, the HMACs as indices of the hash map are hashed a second time together with the OT specific entry key formerly denoted as k_j for all $j \in \{0, ..., N - 1\}$ with N being the number of all entries: $OT-INDEX_{OID_i}$ = $Mac(k_i, HMAC_{OID_i})$. The Depositor who requests the pseudonym for a specific QID can calculate the OT-key k_{OID} , which is used to decrypt the requested deposit out of the received set of encrypted deposits. This OT-key also allows the Depositor to compute the correct OT-INDEXOID and so identify the requested deposit in the received set. 2) The second obstacle concerns the computational as well as the communication overhead introduced by the OT protocol. This obstacle can at least be mitigated by not using the whole pseudonym lookup table as input for the sender (PVault), but

limiting the number of inputs to the ones requested by the Depositor via the Bloom Filter. This denotes a trade-off between achievable security of OT and the performance of the pseudonymisation framework.

4.5 Limited Linkability

Definition 4.4

The linkability of data records concerning the same QID should only be maintained for a specified and limited period.

Limiting the linkability constitutes a trade-off between the requirements of *Personal Data Minimisation* and *Linkability*. This trade-off has to be optimised by adjusting variables to control the limitation, which is a highly application-specific process. Technical mechanisms to achieve *Limited Linkability* are realised in PEEPLL by limiting the time period in which reuses are possible as well as by limiting the re-uses.

4.5.1 Temporal Limitation by Global Epochs. Temporally limiting the linkability of pseudonyms is realised in PEEPLL by introducing epochs, at whose beginning all pseudonyms are changed. The PVault is enforcing the limitation by simply deleting the existing pseudonym lookup table. On the Depositor's side, temporal limitation is achieved by combining the QID with an epoch specific tag t_i in a way, that the PVault cannot link lookups for $QID \circ t_i$ and $QID \circ t_i$, where $i \neq j$, to the same QID. For that, PEEPLL utilises HMACs in the same way as they are use in order to achieve Deposit Confidentiality. The epoch specific tag t_i for epoch i is deterministically derived from the secret key k that is shared among all Depositors as a master secret. Given this epoch tag and a QID, which is to be pseudonymised, the combination $QID \circ t_i$ is derived by converting the plain data item into a lookup token $T_{OID_{t_i}}$ = Mac(t_i , QID). A major advantage of this approach is the possibility, that it can be enforced by both the Depositor and the PVault in such a way that no re-usage is possible beyond limitation if at least one party complies. We will refer to this two-sided enforcement as anytrust.

4.5.2 Budget Limitation. By limiting the linkability of data records by a budget, it is not possible to re-use a pre-existing pseudonym mapping after the budget sum of prior re-uses has exceeded the maximum privacy budget. The individual budgets are either simply 1 or a weight that is sensitive to the context and the impact of a pseudonym re-use on the privacy of a subject. In its most simple form, the privacy budget accumulates the number of re-uses of a pseudonym. Such an approach can be achieved by introducing usage counters for each pseudonym on the PVault. If the counter for a pseudonym exceeds the upper bound, the existing entry in the pseudonym lookup table is deleted or hidden, which triggers the creation of a new pseudonym for this QID on its next request. In order to prevent the revelation of the actually matching pseudonym by the budget accounting to the PVault when enforcing Matching Pseudonym Unobservability, the costs for the current request is added to all pseudonyms that match the lookup including the irrelevant matches. As a consequence, the budget counter associated to a pseudonym on the PVault would only be a fuzzy account and an upper bound of its actual budget.

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4.6 Achievable Protection Goals

In the preceding section, we have introduced technical means for several of our protection goals, namely *Re-use Indistinguishability, Deposit Confidentiality, Matching Pseudonym Unobservability, Combined Deposit Confidentiality and Matching Pseudonym Unobservability as well as Limited Linkability. However, some of these technical means lead to violations of other protection goals. Especially, our approaches for achieving <i>Matching Pseudonym Unobservability* are built in such a way that the protection goal of *Re-use Indistinguishability* is not achieved. Finding solutions which accomplish these combinations of protection goals should be seen as an open challenge.

5 RELATED WORK

The concept of pseudonymisation and *Limited Linkability* of pseudonymous data has attracted some interest in concrete research fields, especially vehicular ad hoc networks (VANETs) and mobile communication.

Petit et al. [30] survey different strategies for pseudonym creation in VANETs and highlight changing pseudonyms as a vital requirement in the lifecycle of a pseudonym. The risk of enabling an attacker to create mobility patterns of drivers has to be balanced with the linkability required for operational tasks like collision detection. However, in opposition to VANETs, where one vehicle uses a pseudonym, our scenario has the requirement of *Global Pseudonym Consistency* for data receiving different pseudonyms coming from different data sources, so that the given strategies are not applicable.

Arapinis et al. [31] examine the handling of pseudonym updates in mobile communication networks, namely the strategy of reallocating temporary identifiers (TMSI) in the 3GPP standard. They find that current implementations of the standard miss reasonable reallocation strategies and therefor enable user tracking for long time periods over different areas and independent of the amount of user activity. We try to prevent similar tracking approaches in our scenario by limiting the linkability as given in Sect. 4.5.

Recently Florian et al. [32] proposed a pseudonymisation and pseudonym change approach utilizing the blockchain technique to achieve a complete decentralisation and resistance against sybil attacks. While this approach is of interest for pseudonymous authentication challenges, e.g. in the vehicular communication, it is not suitable for our scenario of multiple data sources requesting pseudonyms for different data items.

In intrusion detection research pseudonymisation has been widely examined to balance automatic anomaly detection requirements with privacy requirements.

In 1997, Sobirey et al. [33] discussed the impact, which the collection and analysis of audit events might have on users' privacy and presented pseudonymisation as a viable way to protect the privacy interests of employees and users of computer systems in general against the upcoming trend of automatic intrusion detection and operating system auditing. They describe the distributed intrusion detection system *AID* which uses deterministic encryption to provide consistent pseudonyms for different agents in their system. However, they do not discuss the consequences of *Global*

Pseudonym Consistency in a distributed system as well as issues with *Limited Linkability*.

Büschkes and Kesdogan [34] describe the conflicting interests of an IDS operator and the monitored users in detail. They demand the concepts of data avoidance and data minimization. They propose a pseudonym-based solution, which requires a central trusted third party knowing the user identities for pseudonym generation. To minimize the impact of user profiling they introduce the concept of group reference pseudonyms referencing user groups instead of single users. Our approach uses *Component Separation* to prevent the central component from learning user identities.

Biskup and Flegel [35, 36] substitute identifying features in audit event messages with transaction pseudonyms, which are derived via Shamir's secret sharing from a longer-living pseudonym. If the number of audit events concerning the same identity, i.e. the number of issued secret shares, exceeds a defined threshold, an auditor can recover the pseudonym from the observed shares. The correlation of pseudonyms generated by different pseudonymisation components, as we try to achieve with PEEPLL, is stated as an open issue.

6 CONCLUSION AND OUTLOOK

This paper works out sustained privacy threats to the pseudonymisation of data records due to the existence of identifying and quasiidentifying data as well as meta data of the pseudonymisation process itself, proposes four privacy protection goals, and presents privacy enhancements for the application of pseudonymisation of data records in form of a framework. We first provided the motivation based on two real-world scenarios, where identifying and quasi-identifying material needs to be processed and the privacy of the affected subjects can be restored by utilising pseudonymisation. Based on these scenarios, we identified three important requirements for our event pseudonymisation, namely Global Pseudonym Consistency, Component Separation, as well as Linkability, and formalised our setting with a concrete system and threat model in Sect. 3. This includes an explanation of operational limits to the achievable level of privacy by event pseudonymisation, which lead to the formulation of the four privacy protection goals Re-use Indistinguishability, Deposit Confidentiality, Matching Pseudonym Unobservability, and Limited Linkability in Sect. 4. An important observation is the sometimes contrary nature of these protection goals and the resulting conflicts and obstacles, which arise when two or more of these protection goals shall be achieved. For each protection goal, the technical realisation in PEEPLL as well as potential performance consequences were explained as well. Assuming all components of our framework act compliantly to their protocol (honest-but-curious), the framework provides the following properties:

- Pseudonymisation with Global Pseudonym Consistency,
- Enforcing *Limited Linkability* (temporal and budget)
- Protection of Deposit Confidentiality,
- Protection of Matching Pseudonym Unobservability
- Protection of *Re-use Indistinguishability*, but only in combination with *Deposit Confidentiality*, not with *Matching Pseudonym Unobservability*.

Practical scenarios for the application of our framework are not limited to the ones mentioned in Sect. 3, but those were the focus of our development. PEEPLL will be applied to those scenarios in the context of two of our research projects, where the requirement of data analysis and monitoring meets strict privacy regulations. The first context is the privacy respecting detection and prevention of insider attacks, which embraces extensive monitoring of employee activities and so attacks from one of the pseudonymisation components themself (PVault, Depositors) have to be taken into account. The second context is the collection and processing of medical patient data, which deals with highly privacy relevant records on the one hand, and the need to analyse detailed information from patients' disease processes on the other hand.

Future work will be conducted on the integration of a pseudonym re-identification (pseudonym disclosure) process and potential side effects on the achievement of the privacy protection goals. Further aspects comprise the *Weak Deposit Confidentiality*, the enforcement of *anytrust* in the context of *Budget Limitation*, and the simultaneous protection of *Re-use Indistinguishability* and *Matching Pseudonym Unobservability*.

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