Every Query Counts: Analyzing the Privacy Loss of Exploratory Data Analyses

Saskia Nuñez von Voigt¹, Mira Pauli², Johanna Reichert², and Florian Tschorsch¹

¹ Distributed Security Infrastructure Group, Technische Universität Berlin, Straße des 17. Juni 135, 10623 Berlin, Germany
{saskia.nunezvonvoigt,florian.tschorsch}@tu-berlin.de
² anacision GmbH, Albert-Nestler-Straße 19, 76131 Karlsruhe, Germany
{mira.pauli,johanna.reichert}@anacision.de

Abstract. An exploratory data analysis is an essential step for every data analyst to gain insights, evaluate data quality and (if required) select a machine learning model for further processing. While privacy-preserving machine learning is on the rise, more often than not this initial analysis is not counted towards the privacy budget. In this paper, we quantify the privacy loss for basic statistical functions and highlight the importance of taking it into account when calculating the privacy-loss budget of a machine learning approach.

1 Introduction

One of the most prevalent barriers of machine learning involve data management in general and information security and privacy in particular. This is especially relevant for sensitive data sets that, for example, include medical and financial data items. In order to overcome the barriers, the area of privacy-preserving machine learning (PPML) gained attention [2,11]. It is concerned with providing an infrastructure for secure and privacy-preserving data access as well as privacy-preserving model generation.

While PPML reduces the risk of data leaks, particularly the risk of model inversion attacks, one aspect is often overlooked: In order to decide which type of model should be trained and how it should be parametrized, a data analyst performs a preceding exploratory data analysis (EDA). The EDA consists of querying the data for a number of statistics and metrics. The goal is to gain insights on the data quality, as well as the relationships between the variables to initiate data preprocessing before a model is created. To do so, the data analyst has typically full data access and is not restricted in her queries.

In this paper, we evaluate the privacy loss of performing an EDA. To this end, we assume that an analyst obtains differentially-private answers [4] to preserve information privacy. We quantify the privacy loss for basic analysis steps, which can be used to make decisions on how to clean the data, select features, and to select a model. Based on our evaluation, we discuss the implications of the
resulting privacy loss and conclude that an interactive EDA is not feasible in a privacy-preserving setting.

At the same time, we compare the accuracy of an interactive approach with the generation of differentially-private synthetic data. Our results underline that the privacy loss can be mitigated by determining which functions are needed such that they can be answered as correlated queries. The generation of synthetic data is a generalization of this approach. Accordingly, we recommend to develop standardized sets of EDA functions to reduce the privacy loss and/or increase accuracy. In all cases, however, the privacy loss inevitably increases with the amount of information requested and should be considered for EDAs in general.

This paper is organized as follows. In Section 2 and Section 3 we describe our system model and introduce a basic set of EDA functions, respectively. In Section 4 we evaluate the privacy loss and discuss the feasibility of a differentially-private interactive EDA, before concluding this paper in Section 5.

2 Background

2.1 System and Adversary Model

An EDA is typically performed before a machine learning model is created in order to obtain a basic understanding of variable distributions, data quality, and the relationship between variables. By querying this information, a data analyst can determine the necessary steps for data cleaning and a suitable model.

In this paper, we consider the data analyst as an adversary, who should not be able to reveal information about individuals. That is, we assume an interactive query-response setting, which is visualized in Figure 1. The analyst (internal or external) is allowed to query a data set and request aggregated data to perform the EDA and afterwards train a model. In order to mitigate re-identification attacks, noise is added to the results, which satisfy the definition of differential privacy (see below). A privacy budget tracks the privacy loss generated by the queries. It decreases with each query until it is spent and no further queries are answered. The system model captures the privacy-utility trade-off inherent to the notion of information privacy. We believe that the requirement of an EDA is often overlooked when it comes to creating privacy-preserving models.
2.2 Differential Privacy

Differential privacy quantifies the privacy loss regardless of an adversary’s knowledge. It determines the risk of being identified in a database by comparing results of querying the database with and without the individual concerned. The intuition is that the absence/existence of a data subject should have a small impact on the results, which in turn implies that an adversary cannot identify individuals from the result. More formally, a mechanism $\mathcal{K}$ provides $\epsilon$-differential privacy if for all data sets $D_1$ and $D_2$, differing on at most one data subject, and all $S \subseteq \text{Range}(\mathcal{K})$ satisfy

$$P[\mathcal{K}(D_1) \in S] \leq e^\epsilon \cdot P[\mathcal{K}(D_2) \in S].$$ (1)

Differential privacy ensures that the result of an analysis changes by at most a multiplicative factor $e^\epsilon$ when a record is included in the data set or not. For $\epsilon = 0$, the result of an analysis is exactly the same whether a record is included or not and thus provides perfect privacy. With $\epsilon = 0$, however, we cannot obtain meaningful results. In contrast, higher $\epsilon$ provide lower privacy guarantee. It is therefore necessary to find a balance between $\epsilon$ and the accuracy of the results.

Any mechanism guaranteeing differential privacy is robust under composition [10]. If we apply the mechanisms $\mathcal{K}_i$, each providing $\epsilon_i$-differential privacy, several times to the same data, the sequence of queries gives $\epsilon$-differential privacy with $\epsilon = \sum_i \epsilon_i$. In other words, the maximum privacy loss is bounded by the privacy budget $\epsilon$, which in turn is reduced by $\epsilon_i$ for each query. As soon as the budget is spent, no further queries are answered. The parallel application of mechanisms $\mathcal{K}_i$ for $D_i$, an arbitrary disjoint subset of the input domain $D$, each providing $\epsilon_i$-differential privacy, gives $\epsilon$-differential privacy with $\epsilon = \max(\epsilon_i)$.

In an EDA, a data analyst queries interactively, i.e., we assume random queries that are unknown in advance. Therefore, we apply the differential privacy mechanism for each query and calculate the required privacy budget $\epsilon$ according the composition theorems.

To satisfy differential privacy for numeric queries, commonly random noise drawn from a Laplace distribution is added to the numerical output $f(X)$ [4]. The magnitude of noise is calibrated according to the sensitivity of a function. The sensitivity $\Delta f$ is the maximum difference that an output can change by removing or adding a record. For example, a simple counting query, i.e., how many rows have a specific variable value, has $\Delta f = 1$. Differential privacy is then provided by $f(X) + \text{Lap}(\Delta f / \epsilon)$.

3 Exploratory Data Analysis

An EDA is an essential step in any data science application. Generally, an EDA includes different methods and can be an exhaustive analysis within itself. Moreover, the process is not standardized and depends on the objective of the analysis.

In the following, we select some basic statistical functions that serve as the "least common denominator", which we derived from literature as well as our
Table 1: Privacy loss for statistical functions of a basic EDA.

| Statistical function | Information | Numerical (NUM) | Categorical (CAT) | Privacy loss |
|----------------------|-------------|-----------------|-------------------|--------------|
| distribution (DIST)  | range, $Q_1, Q_2, Q_3$ | value counts | $\epsilon_i \cdot (5 \cdot n + c)$ |
| missing values (MISS)| count       | value counts    | $\epsilon_i \cdot n$ |
| outliers (OUTL)      | count outside cut-off | value counts | $\epsilon_i \cdot n$ |
| correlation (CORR)   | Spearman’s correlation | Cramer’s V | $\epsilon_i \cdot (\frac{Q_3}{Q_1}) + (\frac{Q_1}{Q_3})$ |

own practice in the field. The selected statistical functions for this basic EDA are listed in Table 1. Even if we limit our EDA to certain functions, we still assume that the queries performed by the analyst are not known in advance and are sent interactively depending on the results. Since some analyses depend on the data type, we differentiate functions between categorical and numerical variables.

**Distribution.** The distribution of the data is important to understand the data. For numerical variables, the range and quantiles provide information about the validity of the data and a sense of the range of the data. For categorical variables, a data analyst retrieves the unique variable values, especially the number of observations of each variable value. Variables with a discrete uniform distribution, for example, are not suitable to identify meaningful patterns. Variables that show this behavior need to be cleaned or removed for the training process.

**Missing Values.** The number of missing values indicates whether steps for data cleaning are necessary. There are different options such as case deletions or imputation with a vast body of literature discussing these options and their implications for later analysis steps [1].

**Outliers.** Machine learning models can be influenced by outliers, thus an analyst should be aware of their presence in the data set. There are many sophisticated tools to detect outliers, that mostly come with a high degree of privacy loss. Therefore, we resort to a simple box plot approach, where the cutoff point for outliers is defined as the upper and lower quantiles ($Q_1$ and $Q_3$) and a tolerance of $1.5 \cdot (Q_3 - Q_1)$ [6]. We then count all values that lie above or below that cutoff point. In this univariate outlier detection context, categorical variables are not covered, as rare values have already become visible from the distribution.

**Correlation.** The results of the correlation between variables mainly contribute to feature selection, where certain variables may be excluded from the model or combined with each other. Correlated variables are problematic for the interpretation of a model [14]. Furthermore, the relationship between independent variables may imply that dimensionality reduction methods can be applied to the data set to improve model performance. Based on this motivation, we include Spearman’s correlation matrix for numerical data and a Cramer’s V for categorical variables in our basic set of EDA functions.
4 Privacy loss and Accuracy Impact Assessment

In Table 1 we quantify the privacy loss of the functions of our basic EDA. The privacy budget required to compute the respective functions is cumulated by the privacy loss of each query. It depends on the privacy loss per query \( \epsilon_i \), the number of categorical variables \( c \), and the number of numerical variables \( n \).

For the numerical distribution a data analyst queries the \( \min \), \( \max \), \( Q_1 \), \( Q_2 \), and \( Q_3 \). In other words, to obtain the information an analyst needs to query the data five times. Since each record is contained in each variable, an analyst spends \( 5 \cdot \epsilon_i \cdot n \) of its privacy budget for this statistical function. The categorical distribution can be investigated by the counts per variable value that are queried only once per variable and the required budget increases by \( \epsilon_i \) and \( c \).

The missing values as well as the outliers of categorical variables are visible from the value counts. Therefore, the privacy budget only increases by the numerical variables for both the missing values and the outliers.

We quantify the relationship between two variables using Spearman’s correlation for numerical and Cramer’s V for categorical variables. Since both measures are symmetrical, the privacy budget increases by the number of permutations

4.1 Privacy Loss

We determine the privacy budget for some data sets from the UCI Machine Learning Repository\(^3\). The data sets differ in size and number of variables. Common values for \( \epsilon \) comprise 0.01, 0.1, 1, \( \ln(2) \), or \( \ln(3) \) \(^5\). Therefore we fixed the privacy guarantee for each query to \( \epsilon_i = 0.01 \), as this is the smallest value.

\(^3\)http://archive.ics.uci.edu/ml
Figure 2 shows the cumulative privacy loss by conducting all statistical functions from our basic EDA. We observe an increasing and high privacy loss. For computing all functions, the adult data set requires the smallest privacy budget. The prime cause of this difference is the small number of variables in total. Indeed, the magic04 data set has less variables in total but more numerical variables. Since an analyst sends an additional query for numerical variables to determine the missing values or outliers, the privacy loss increases and is thus higher than for categorical variables.

The correlation leads to the highest privacy loss, since the budget increases by the binomial coefficient \( \binom{n}{2} \) and \( \binom{c}{2} \).

Note that the privacy budget increases linearly with the number of queries. With a lower privacy guarantee, i.e., \( \epsilon_i > 0.01 \), the total privacy budget would exceed the privacy budget of \( \epsilon = 3 \), which yields a 20 times higher chance \( e^3 \) to be compromised. With a smaller \( \epsilon_i \), we can reduce the privacy loss and therefore the total required privacy budget. However, this leads to an accuracy loss.

### 4.2 Accuracy

Due to the order of queried information the answers of our queries cannot be re-used. In order to reduce the privacy budget, numerous approaches aggregate queries and determine correlations between queries \([7,9,12,13]\). This allows estimating results from other noisy answers without spending its privacy budget. The results of these mechanisms can also be treated as differentially-private synthetic data that support the original working method of a data analyst.

In this section, we evaluate the accuracy of a differentially-private EDA and compare the interactive setting with differentially-private synthetic data sets. For data sets with numeric variables, we remove some values from a variable to have a numerical variable with 10% missing values.

We generate synthetic data sets using the correlated mode of DataSynthesizer\(^4\) that learns a Bayesian network with a degree of four. For comparison, we generate synthetic data with the same privacy budget that is required to investigate the correlation in an interactive setting. For example for the adult synthetic data set we set \( \epsilon = 51 \cdot 0.01 = 0.51 \).

We measure the accuracy of our basic EDA using the relative error of each query. Figure 3 reports the relative error for each statistical function visualized as box plot containing the relative error for each query. Overall, the synthetic data sets have a smaller relative error compared to the interactive setting. However, the relative error of the synthetic data sets for the numerical correlation is higher compared to the interactive setting. For the data set magic04 (Figure 3c), we observe a similar effect for the outliers. The high error occurs in the synthetic data sets due to the high range of some numerical variables. Remarkably, we obtain a high error for outliers for the interactive setting. This demonstrates that the relative error for the variables varies.

\(^4\) Available for download at [https://github.com/DataResponsibly/DataSynthesizer](https://github.com/DataResponsibly/DataSynthesizer)
4.3 Discussion

The results show that even basic investigations of an EDA require a high privacy budget in an interactive setting. Therefore, an interactive analysis with both acceptable accuracy and an acceptable privacy guarantee is not possible.

Non-interactive mechanisms, such as differentially-private synthetic data sets, can be used to increase accuracy and/or reduce the privacy budget. Notably, the synthetic data set can be used directly to train a model without dividing the privacy budget among EDA and model generation. However, the expressiveness of non-interactive mechanisms is limited to the correlations used for generating the output. Therefore, these mechanisms are not applicable for an interactive setting with random or unknown queries [3].

In an EDA, information is queried interactively, where one query depends on the results of previous queries. Grouping or limiting the queries to certain statistics, a differentially-private EDA might become feasible, though. We therefore appeal to data analysts to agree on widely applicable statistics that show the information necessary for model generation. With our basic EDA, we made a first attempt to create such a collection of statistics. A standardized set of statistical functions used in an EDA could be optimized to balance the privacy-utility trade-off.
5 Conclusion

In this paper we demonstrate the increase of the privacy loss and thus the required budget for an interactive differentially-private analysis. We argue that the EDA should be considered in privacy-preserving models, as it is an essential step in machine learning. In order to address the privacy-utility trade-off, we propose to agree on standardized sets of EDA functions and use the remaining privacy budget for model creation.

Acknowledgement This work was supported by the Federal Ministry of Education and Research of Germany (project number 16KIS0909).

References

1. Acuna, E., Rodriguez, C.: The treatment of missing values and its effect on classifier accuracy. In: Classification, clustering, and data mining applications, pp. 639–647. Springer
2. Al-Rubaie, M., Chang, J.M.: Privacy-preserving machine learning: Threats and solutions. IEEE Secur. Priv. 17(2), 49–58
3. Dankar, F.K., Emam, K.E.: Practicing differential privacy in health care: A review. Trans. Data Priv. 6(1), 35–67
4. Dwork, C.: Differential privacy. In: ICALP’06: 33rd International Colloquium on Automata, Languages and Programming, pp. 1–12
5. Dwork, C.: Differential privacy: A survey of results. In: TAMC’08: 5th International Conference on Theory and Applications of Models of Computation. Lecture Notes in Computer Science, vol. 4978, pp. 1–19. Springer
6. Laurikkala, J., Juhola, M., Kentala, E., Lavrac, N., Miksch, S., Kavsek, B.: Informal identification of outliers in medical data. In: Fifth international workshop on intelligent data analysis in medicine and pharmacology, vol. 1, pp. 20–24
7. Leoni, D.: Non-interactive differential privacy: a survey. In: WOD’12: International Workshop on Open Data, pp. 40–52. ACM
8. Li, C., Hay, M., Rastogi, V., Miklau, G., McGregor, A.: Optimizing linear counting queries under differential privacy. In: PODS’10: 29th ACM Symposium on Principles of Database Systems, pp. 123–134
9. Li, C., Miklau, G.: An adaptive mechanism for accurate query answering under differential privacy. Proc. VLDB Endow. 5(6), 514–525
10. McSherry, F., Talwar, K.: Mechanism design via differential privacy. In: FOCS’07: Proceedings of the 48th Annual IEEE Symposium on Foundations of Computer Science, pp. 94–103
11. Mohassel, P., Zhang, Y.: Secureml: A system for scalable privacy-preserving machine learning. In: SP’17: IEEE Symposium on Security and Privacy, pp. 19–38
12. Roth, A., Roughgarden, T.: Interactive privacy via the median mechanism. In: STOC’10: 42nd ACM Symposium on Theory of Computing, pp. 765–774
13. Yaroslavtsev, G., Cormode, G., Procopiuc, C.M., Srivastava, D.: Accurate and efficient private release of data cubes and contingency tables. In: ICDE’13: 29th IEEE International Conference on Data Engineering, pp. 745–756
14. Zuur, A.F., Ieno, E.N., Elphick, C.S.: A protocol for data exploration to avoid common statistical problems. Methods in ecology and evolution 1(1), 3–14