

Qrlew: automatic differential privacy for SQL queries

Anonymous submission

Abstract

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Useful links

PPAI

Last year papers: <https://aaai-ppai23.github.io/#sp2> This year program: <https://ppai-workshop.github.io/>

Comparable open-source projects

- Paszke et al. 2017 - Automatic differentiation in PyTorch <https://openreview.net/pdf?id=BJJsrmfCZ>
- Frostig et al. 2018 - Compiling machine learning programs via high-level tracing <https://mlsys.org/Conferences/2019/doc/2018/146.pdf>

Comparable DP SQL papers

- Lessons Learned: Surveying the Practicality of Differential Privacy in the Industry (Garrido et al. 2022)
- Tumult Analytics: a robust, easy-to-use, scalable, and expressive framework for differential privacy (Berghel et al. 2022)
- Differentially Private SQL with Bounded User Contribution (Wilson et al. 2019)
- CHORUS: a Programming Framework for Building Scalable Differential Privacy Mechanisms (Johnson et al. 2020)
- Towards Practical Differential Privacy for SQL Queries (Johnson, Near, and Song 2018)

Introduction

In recent years, the importance of safeguarding privacy when dealing with personal data has continuously increased. Traditional anonymization techniques have proven vulnerable to re-identification, as demonstrated by numerous works (Archie et al. 2018; Dwork et al. 2017; Narayanan and Shmatikov 2008; Sweeney, Abu, and Winn 2013). The total cost of data breaches has also significantly increased (IBM

2023). And governments have introduced stricter data protection laws. Yet, the collection, sharing, and utilization of data hold the potential to generate significant value across various industries, including healthcare, finance, transportation, and energy distribution.

To realize these benefits while managing privacy risks, researchers have turned to *differential privacy (DP)* (Wood et al. 2018; Dwork, Roth et al. 2014), which has become the gold standard in academia since its introduction by Dwork et al. in 2006 (Dwork et al. 2006) due to its provable and automatic privacy guarantees.

Despite the availability of open-source tools, DP adoption remains limited. One of the reasons for this lack of adoption is the relative complexity of the existing tools considered the utility of the results. *Qrlew* has been designed to solve this problem, by providing the following features:

Leverages existing infrastructure *Qrlew* rewrites a SQL query into a *differentially private* equivalent.

Is fully automated *Qrlew* can rewrite a large class of queries into *differentially private* ones.

Leverages synthetic data using jointly *differentially private* mechanisms and *differentially private* Synthetic Data

This In summary, our main contributions are as follows:

General architecture

Paul on compilation

Victoria on DP mech and DP test

Comparison to other systems

Known limitations

Qrlew relies on the random number generator of the SQL engine used. It is usually not a cryptographic noise.

Qrlew uses the floating-point numbers of the host SQL engine, therefore our system is liable to the vulnerabilities described in

Thank you for reading these instructions carefully. We look forward to receiving your electronic files!

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