

Corrigendum

Corrigendum to “A Comprehensive Survey on Local Differential Privacy”

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In the article titled “A Comprehensive Survey on Local Differential Privacy” [1], the authors identified a number of errors in the communication cost and computation cost as well as pros and cons columns of Table 4. These errors were

introduced during the preparation of the manuscript and do not impact the conclusions. The corrected Table 4 is as follows:

TABLE 4: Comparisons of frequency oracle mechanisms for frequency estimation under LDP.

Method	Encode	Randomness	Asymptotic bound error	Candidate	Communication cost	Computation cost	Pros and cons
k -RR [35] GRR [36]	Direct	Local	$O(k\sqrt{k}/\epsilon\sqrt{n})$	Known	P: $O(1)$ S: $O(n)$	P: $O(1)$ S: $O(n+k)$	Pros: no encoding, predigest the process; lower candidate size can achieve higher utility; cons: low utility in low privacy regime
O-RR [35]	Unary (bloom filter)	Local	$O(k\sqrt{k}/\epsilon\sqrt{n})$	Unknown	P: $O(h)$ S: $O(nh)$	P: $O(k)$ S: linear regression	Pros: open candidate; cons: low utility in low privacy regime, high computation cost due to regression
RAPPOR [7]	Unary (bloom filter)	Local	$O(k/\epsilon\sqrt{n})$	Known	P: $O(h)$ S: $O(nh)$	P: $O(k)$ S: LASSO and linear regression	Pros: lower error, lower storage cost, support big candidate; cons: consider bloom filter parameter settings, high computation cost due to regression
k -RAPPOR (basic one-time) [7]	Unary	Local	$O(k/\epsilon\sqrt{n})$	Known	P: $\Theta(k)$ S: $O(nk)$	P: $O(k)$ S: $O(n+k+\frac{nk}{\epsilon^{7/2}})$	Pros: lower error, lower storage overhead, simpler and faster implement; cons: consider parameter settings of bloom filter

TABLE 4: Continued.

Method	Encode	Randomness	Asymptotic bound error	Candidate	Communication cost	Computation cost	Pros and cons
OUE [36]	Unary	Local	$O(k/\varepsilon\sqrt{n})$	Known	P: $\Theta(k)$ S: $O(nk)$	P: $O(k)$ S: $O(n + k + \frac{nk}{\varepsilon^2})$	Pros: lower error, lower storage cost, lower computation cost and easier to implement; cons: larger candidate lead to higher communication cost
O-RAPPOR [35]	Unary (bloom filter)	Local	$O(k/\varepsilon\sqrt{n})$	Unknown	P: $\Theta(h)$ S: $O(nh)$	P: $O(k)$ S: linear regression	Pros: open candidate, higher utility, lower storage overhead; cons: need consider parameter settings of bloom filter
k -Subset [41, 42]	Direct	Local	$O(k/\varepsilon\sqrt{n})$	Known	P: $\Theta(k)$ S: $O(nk)$	P: $O(k)$ S: $O(n + k + \frac{nk}{\varepsilon^2})$	Pros: better sample complexity and higher utility; cons: higher communication and computation cost due to set output
RMP(SHist) [37]	Binary	Public (shared matrix)	$O(\sqrt{\log k}/\varepsilon\sqrt{n})$	Known	P: $O(1)$ S: $O(n)$	P: $O(k)$ S: $O(nk)$	Pros: lower communication cost; cons: Unstable query accuracy due to the noise from RMP matrix
HRR [10, 38]	Binary	Public (shared matrix)	$O(\sqrt{\log k}/\varepsilon\sqrt{n})$	Known	P: $O(1)$ S: $O(n)$	P: $O(k)$ S: $O(nk)$	Pros: lower communication cost; cons: unable query accuracy due to the noise from RMP matrix
BLH [36]	Binary	Local and public	$O(\sqrt{\log k}/\varepsilon\sqrt{n})$	Known	P: $O(1)$ S: $\Theta(\log(n))$	P: $O(k)$ S: $O(nk)$	Pros: lower communication cost; cons: higher computation overhead due to the Hashing
OLH [36]	Binary	Local and public	$O(\sqrt{\log k}/\varepsilon\sqrt{n})$	Unknown	P: $O(1)$ S: $\Theta(\log(n))$	P: $O(k)$ S: $O(nk)$	Pros: higher utility in the setting big candidate size, lower communication cost; cons: higher computation overhead due to the Hashing
HR [39]	Binary	Local	$O(k/\varepsilon\sqrt{n})$	Known	P: $O(\log(k))$ S: $(O(n\log(k)))$	P: $O(k)$ S: $O(n + k)$	Pros: obtain efficient computation complexity due to fast walsh-hadamard transform; cons: unstable accuracy due to the noise from encoding

References

- [1] X. Xiong, S. Liu, D. Li, Z. Cai, and X. Niu, "A Comprehensive Survey on Local Differential Privacy," *Security and Communication Networks*, vol. 2020, Article ID 8829523, 29 pages, 2020.