

Theorem in algorithm RecConcave¹ for privacy parameters ϵ, δ , promise r database X , domain R , sensitivity-1 utility function u and recursion bound $N = 2$ then: the step 6 will returns a “good interval” in probability at least $1 - \beta$ if $r > \frac{16}{\epsilon\alpha} \ln \left(\frac{\log_2(T)}{\beta} \right)$

Proof notice that when $N = 2$ the recursion call actually calls the *Exponential-Mechanism* and retrieves its answer

we want to make sure that the *Exponential-Mechanism* outputs with high probability a good interval

meaning that

$$\Pr \left[q(S, j) < \frac{3\alpha}{\epsilon} r \right] < \beta$$

by The Algorithmic Foundations of Differential Privacy² Theorem 3.11

$$\Pr \left[q(M_E(x, q, R)) \leq OPT_q(x) - \frac{2\Delta q}{\epsilon} \left(\ln \left(\frac{|R|}{|R_{OPT}|} \right) + t \right) \right] \leq e^{-t}$$

and if we switch $e^{-t} = \beta$ and take the specific parameters used in our case $\Delta u = 1$, $|R| = \log_2(T)$ and $|R_{OPT}| = 1$

we get

$$\Pr \left[q(M_E(x, q, R)) \leq OPT_q(x) - \frac{2}{\epsilon} \ln \left(\frac{\log_2(T)}{\beta} \right) \right] \leq \beta$$

we also know that $\frac{\alpha}{2} r \leq OPT_q(x) \leq r$

if we combine all the above we get that we want

$$\frac{3\alpha}{8} r < \frac{\alpha}{2} r - \frac{2}{\epsilon} \ln \left(\frac{\log_2(T)}{\beta} \right) \Rightarrow r > \frac{16}{\epsilon\alpha} \ln \left(\frac{\log_2(T)}{\beta} \right)$$

Remark we saw that for A_{dist} to run we must have

$$r > \frac{8 \ln \left(\frac{1}{\beta\delta} \right)}{3\epsilon\alpha}$$

notice that this bound will be less than the one above iff $\delta > \frac{\beta^5}{\log_2^6(T)}$

Proof

$$\begin{aligned} \frac{8 \ln \left(\frac{1}{\beta\delta} \right)}{3\epsilon\alpha} &< \frac{16}{\epsilon\alpha} \ln \left(\frac{\log_2(T)}{\beta} \right) \Rightarrow \ln \left(\frac{1}{\beta\delta} \right) < 6 \ln \left(\frac{\log_2(T)}{\beta} \right) \Rightarrow \frac{1}{\beta\delta} < \left(\frac{\log_2(T)}{\beta} \right)^6 \\ &\Rightarrow \delta > \frac{\beta^5}{\log_2^6(T)} \end{aligned}$$

¹A. Beimel, K. Nissim, and U. Stemmer. Private learning and sanitization- Pure vs. Approximate Differential Privacy

²C.Dwork, A.roth