

Theorem in algorithm RecConcave¹ for privacy parameters ϵ, δ , promise r database X , domain R and sensitivity-1 utility function u :
if we use *Exponential – Mechanism* instead of A_{dist} (at step 9) it will return the highest scored value $OPT_u(x)$, in probability at least $1 - \beta$ if $r > \frac{16}{3\epsilon\alpha} \ln \left(\frac{\log_2(|\mathcal{R}|)}{\beta} \right)$

proof by The Algorithmic Foundations of Differential Privacy² Theorem 3.11

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

if we set $e^{-t} = \beta \Rightarrow t = \ln \left(\frac{1}{\beta} \right)$, $\Delta u = 1$, $|R| = \log(|\mathcal{R}|)$ and $|R_{OPT}| = 1$ we get:

$$Pr \left[u(M_E(x, u, R)) \leq OPT_u(x) - \frac{2}{\epsilon} \left(\ln(\log(|\mathcal{R}|)) + \ln \left(\frac{1}{\beta} \right) \right) \right] =$$

$$Pr \left[u(M_E(x, u, R)) \leq OPT_u(x) - \frac{2}{\epsilon} \ln \left(\frac{\log_2(|\mathcal{R}|)}{\beta} \right) \right] \leq \beta$$

we want the gap to be at least $\frac{2}{\epsilon} \ln \left(\frac{\log_2(|\mathcal{R}|)}{\beta} \right)$

from the other hand in RecConcave we know that the gap is at least $\frac{3\alpha}{8}r$
if we combine the two we get

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

and in the case of median $r = \frac{|s|}{2}$ so the bound on the sample size is

$$|s| > \frac{32}{3\epsilon\alpha} \ln \left(\frac{\log_2(|\mathcal{R}|)}{\beta} \right)$$

alternatively if we want to bound $|R|$

$$\frac{3\epsilon\alpha r}{16} > \ln \left(\frac{\log_2(|\mathcal{R}|)}{\beta} \right) \Rightarrow e^{\frac{3\epsilon\alpha r}{16}} > \frac{\log_2(|\mathcal{R}|)}{\beta}$$

$$\Rightarrow \log_2(|\mathcal{R}|) < \beta e^{\frac{3\epsilon\alpha r}{16}} = \beta e^{\frac{3\epsilon\alpha |s|}{32}}$$

$$\Rightarrow |\mathcal{R}| < 2^{\beta e^{\frac{3\epsilon\alpha |s|}{32}}}$$

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

²C.Dwork, A.roth