

**Theorem** in algorithm RecConcave<sup>1</sup> for privacy parameters  $\epsilon, \delta$ , 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  $r > \frac{16}{3\epsilon\alpha} \ln \left( \frac{|R|}{\beta} \right)$

**proof** by The Algorithmic Foundations of Differential Privacy<sup>2</sup> 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  $e^{-t} = \beta \Rightarrow t = \ln \left( \frac{1}{\beta} \right)$ ,  $\Delta u = 1$  and  $|R_{OPT}| = 1$  we get:

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

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

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

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

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

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

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

alternatively if we want to bound  $|R|$

$$\frac{3\epsilon\alpha r}{16} > \ln \left( \frac{|R|}{\beta} \right) \Rightarrow e^{\frac{3\epsilon\alpha r}{16}} > \frac{|R|}{\beta} \Rightarrow |R| < \beta e^{\frac{3\epsilon\alpha r}{16}} = \beta e^{\frac{3\epsilon\alpha |s|}{32}}$$

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

<sup>2</sup>C.Dwork, A.roth