

# Variants of Differential Privacy

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## Basic Definitions

The following all admit the Gaussian mechanism with the specified noise variance  $\sigma^2$ .

| Definition                | Gaussian mech.  | Seq. Comp.                                       | Advanced comp.   | Conv. to $(\epsilon, \delta)$ -DP                      |
|---------------------------|---|--|--|--|
| $(\epsilon, \delta)$ -DP  | $\sigma^2 = \frac{2\Delta^2 \log(1.25/\delta)}{\epsilon^2}$ | $(\epsilon_1 + \epsilon_2, \delta_1 + \delta_2)$ | $(2\epsilon\sqrt{2k\log(1/\delta')}, k\delta + \delta')$ | n/a  |
| Moments acct.             | (same as DP)  | (same as DP)                                     | $(4\epsilon\sqrt{2k\log(1/\delta)}, \delta)$             | n/a  |
| $(\alpha, \epsilon)$ -RDP | $\sigma^2 = \frac{\Delta^2 \alpha}{(2\epsilon)}$            | $(\alpha, \epsilon_1 + \epsilon_2)$              | n/a  | $(\epsilon + \frac{\log(1/\delta)}{\alpha-1}, \delta)$ |
| $\rho$ -zCDP              | $\sigma^2 = \frac{\Delta^2}{(2\rho)}$                       | $\rho_1 + \rho_2$                                | n/a  | $(\rho + 2\sqrt{\rho\log(1/\delta)}, \delta)$          |

## tCDP

The *arsinh* mechanism for a query  $q$  with  $L_2$  sensitivity  $\Delta$  provides  $(16\rho, \frac{A}{8\Delta})$ -tCDP:

$$M(x) \leftarrow q(x) + A \operatorname{arsinh}\left(\frac{1}{A} \mathcal{N}\left(\frac{\Delta^2}{2\rho}\right)\right)$$

where  $\operatorname{arsinh}(x) = \log(x + \sqrt{x^2 + 1})$ .

Another way to phrase this (without  $A$ ) is: adding noise sampled from

$$8\Delta\omega \operatorname{arsinh}\left(\frac{1}{8\Delta\omega} \mathcal{N}\left(\frac{8\Delta^2}{\rho}\right)\right)$$

preserves  $(\rho, \omega)$ -tCDP.

## Amplification by Subsampling

Here, we uniformly sample a size- $n$  subset of a size- $N$  dataset. We let  $s = n/N$ .

| Definition                | Sampling bound                               |
|---------------------------|--|
| $(\epsilon, \delta)$ -DP  | $(\log(1 + s(e^\epsilon - 1)), s\delta)$ -DP |
| $(\alpha, \epsilon)$ -RDP | see below                                    |
| $\rho$ -zCDP              | N/A  |
| $(\rho, \omega)$ -tCDP    | $(13s^2\rho, \frac{\log(1/s)}{4\rho})$ -tCDP |

For  $(\alpha, \epsilon(\alpha))$ -RDP, when the Gaussian mechanism is used, a not-quite-tight bound is  $(\alpha, \epsilon'(\alpha))$ , where:

$$\epsilon'(\alpha) = \frac{1}{\alpha - 1} \log \left( 1 + \sum_{j=2}^{\alpha} 2s^j \binom{\alpha}{j} e^{(j-1)\epsilon(j)} \right)$$

The tight bound is available in Wang et al. (2018).

We can loosen the bound slightly more and avoid expressing  $\epsilon$  as a function of  $\alpha$ . By Mironov, proposition 8 (monotonicity of Rényi divergence), we know that for any RDP mechanism and positive integer  $k < \alpha$ ,  $\epsilon(\alpha - k) \leq \epsilon(\alpha)$ . Thus,

$$\epsilon'(\alpha) \leq \frac{1}{\alpha - 1} \log \left( 1 + \sum_{j=2}^{\alpha} 2s^j \binom{\alpha}{j} e^{(j-1)\epsilon(\alpha)} \right)$$

So given an  $(\alpha, \epsilon)$ -RDP mechanism, running the mechanism on a subsampled dataset yields at least  $(\alpha, \epsilon')$ -RDP, where:

$$\epsilon' = \frac{1}{\alpha - 1} \log \left( 1 + \sum_{j=2}^{\alpha} 2s^j \binom{\alpha}{j} e^{(j-1)\epsilon} \right)$$