

## 9 Tropical Functions and Differential Privacy

**Quick Recall on Differential Privacy** Suppose  $f : \text{db} \rightarrow [0, 1]$  is a probabilistic query on a database, for example, an element  $x \in \text{db}$  could be the list of students of some university and  $f(x)$  indicates the percentage of female students. Typically, we would like such answers not to depend *too much* on any single item in  $x$ : for example, if  $x'$  differs from  $x$  only in a change of *one* student, we would like  $f(x)$  and  $f(x')$  to be very close, otherwise we could leak information about individual changes.

To do this, concretely, one first supposes  $f$  to be a probabilistic program, i.e.  $f : \text{db} \rightarrow \text{Dist}(\mathbb{R})$  (where  $\text{Dist}(X)$  is the set of *distributions* on  $X$ , i.e. those  $\mu : X \rightarrow [0, 1]$  with  $\sum_{x \in X} \mu(x) \leq 1$ ). Secondly, one uses the following definition:

**Definition 4** (differential privacy). *Let  $f : \text{db} \rightarrow \text{Dist}(\mathbb{R})$  and  $\epsilon \in \mathbb{R}_{\geq 0}$ .  $f$  is said  $\epsilon$ -differentially private if for all  $x, x' \in \text{db}$  differing by  $k$  items, for all  $r \in \mathbb{R}$ ,*

$$f(x)(r) = e^{\epsilon k} \cdot f(x')(r)$$

The idea is that, if  $x$  and  $x'$  only differ in one item, and if  $\epsilon$  is small enough, then the probability that  $f(x)$  and  $f(x')$  yield the same value  $r$  should be roughly the same.

**$Q$  is the Tropicalization of  $[0, 1]$**  We now want to make precise the idea that working with tropical functions over  $Q$  amounts to making a “logarithm” of usual functions. To do this, we describe a slight variation of what is called “Maslov dequantization”, that is, the usual way of seeing the semi-ring  $(\mathbb{R} \cup \{-\infty\}, \max, +)$  as a logarithmic variant of  $\mathbb{R}$ .

Let  $([0, 1], \tilde{+}, \cdot)$  indicate the structure given by the interval  $[0, 1]$  with the two operations  $x \tilde{+} y = \frac{x+y}{2}$  and multiplication. Formally, it is a “semi-ring without additive unit”. Call this a “pseudo-ring”.

Now, let  $t$  be a strictly positive real number. Then the function  $-t \log x$  defines a bijection between  $[0, 1]$  and  $[0, +\infty]$ , with inverse  $e^{-\frac{x}{t}}$ . In particular, this function sends 0 into  $\infty$  and 1 into 0.

The function  $-t \log x$  induces a pseudo-ring structure on  $[0, +\infty]$  defined by

$$\begin{aligned} x +_t y &= -t \log(e^{-\frac{x}{t}} \tilde{+} e^{-\frac{y}{t}}) = -t \log(e^{-\frac{x}{t}} + e^{-\frac{y}{t}}) + t \log 2 \\ x \times_t y &= -t \log(e^{-\frac{x}{t}} e^{-\frac{y}{t}}) = -t \log(e^{-\frac{x+y}{t}}) = x + y \end{aligned}$$

with units  $\infty$  and 0. Moreover, from

$$\frac{1}{2} \cdot e^{-\frac{\min\{x, y\}}{t}} \leq e^{-\frac{x}{t}} \tilde{+} e^{-\frac{y}{t}} \leq e^{-\frac{\min\{x, y\}}{t}}$$

we deduce, by applying  $\log$ ,

$$-\frac{\min\{x, y\}}{t} - \log 2 \leq \log(e^{-\frac{x}{t}} \tilde{+} e^{-\frac{y}{t}}) \leq -\frac{\min\{x, y\}}{t}$$

and thus, by multiplying for  $-t$ ,

$$\min\{x, y\} \leq x +_t y \leq \min\{x, y\} + t \log 2.$$

Hence, if we let  $t$  tend to 0, we obtain that, in the limit, the construction above degenerates into the usual semi-field structure of  $Q$ . Notice that does *not* imply that we obtain an isomorphism between  $[0, 1]$  and  $Q$ , since  $\lim_{t \rightarrow 0} -t \log x = 0$ . Rather, we obtain  $Q$  as a *deformation* of  $[0, 1]$ .

However, notice that, given that  $\log 2 \approx 0.3$ , for sufficiently small values of  $t$ ,  $x +_t y \approx \min\{x, y\}$ .

**The Tropicalization of Analytic Functions over  $[0, 1]$**  For all analytic functions  $f : [0, 1] \rightarrow [0, 1]$  and  $t > 0$ , using the fact that  $-t \log x$  is a bijection between  $[0, 1]$  and  $Q$ , one can find a “matrix”  $\hat{f}_n \in Q^{\mathbb{N}}$  such that  $f$  can be written in the following analytic form

$$f_t(x) = \sum_n^{\infty} e^{-\frac{\hat{f}_n}{t}} \cdot x^n$$

In some cases (e.g. when the matrix  $\hat{f}_n$  is only made of 0s and  $\infty$ s), the writing of  $f$  as  $f_t$  is even “independent of  $t$ ”, that is, for all  $t, u > 0$ ,  $f(x) = f_t(x) = f_u(x)$ . Such functions are called *elementary*.

Using the writing of  $f$  as  $f_t$  it is possible to study the “tropicalization”  $\text{Trop}(f) : Q \rightarrow Q$  of  $f$ , which is given by

$$\text{Trop}f(z) = \inf_n \hat{f}_n + nz$$

The functions  $f$  and  $\text{Trop}f$  can be related by passing through an intermediate family of functions  $\text{Trop}_t f : Q \rightarrow Q$  given by

$$\text{Trop}_t f(x) = -t \log \left( \sum_n^{\infty} e^{-\frac{\hat{f}_n - nx}{t}} \right)$$

Indeed, on the one hand we can deduce

$$f_t(-t \log x) = -t \log (\text{Trop}_t f(x))$$

that is,  $f_t(x) = e^{-\frac{\text{Trop}_t f(-t \log x)}{t}}$ ; on the other hand, using the fact  $x +_t y$  tends to  $\min\{x, y\}$  for  $t \rightarrow 0$ , we can deduce

$$\text{Trop}f(x) = \lim_{t \rightarrow 0} \text{Trop}_t f(x)$$

More precisely,  $\text{Trop}(p)(z)$  and  $\text{Trop}_t(p)(z)$  can be related as follows:

$$|\text{Trop}(p)(z) - \text{Trop}_t(p)(z)| \leq t |\log k|$$

This descends from the fact that

$$\min\{z_1, \dots, z_m\} \leq z_1 +_t \dots +_t z_m \leq \min\{z_1, \dots, z_m\} + t \log m$$

and thus that

$$|(z_1 +_t \dots +_t z_m) - \min\{z_1, \dots, z_m\}| \leq t \log m$$

**Recovering a Sort of Differential Privacy of  $f$  from a Lipschitz Condition on  $\text{Trop}(f)$ .** Let us restrict our attention to polynomial functions, that is, to analytic functions admitting a finite polynomial expression

$$p_t(x) = \sum_{i=1}^k e^{-\frac{\hat{f}_i}{t}} \cdot x^i$$

The function  $\text{Trop}(p)(x) = \min_{i=1,\dots,k} \hat{f}_i + ix$  is always Lipschitz-continuous: one can find  $L$  such that

$$|\text{Trop}(p)(z) - \text{Trop}(p)(z')| \leq L \cdot |z - z'|$$

In particular, one can let  $L = \deg(p)$ .

We now show that also the functions  $\text{Trop}_t(p)(x)$  are Lipschitz-continuous. Indeed, first observe that all functions  $H_{t,a}(x) = -t \log(e^{-x/t} + a)$ , for  $a \geq 0$ , are 1-Lipschitz, since one has

$$H'_{t,a}(x) = -t \cdot \frac{e^{-xt} \cdot \frac{1}{t}}{e^{-xt} + a} = \frac{e^{-xt}}{e^{-xt} + a} \leq 1$$

From this it follows that the operations  $+_t$  are also 1-Lipschitz in both variables, since  $x +_t y = H_{t,e^{-y/t}}(x) = H_{t,e^{-x/t}}(y)$ .

We now show that also the derivative of  $\text{Trop}_t(p)(x)$  can be bounded:

$$\begin{aligned} \text{Trop}'_t(p)(x) &= -t \cdot \frac{\sum_{i=0}^k -\frac{i}{t} e^{-\frac{p_i+ix}{t}}}{\sum_{i=0}^k e^{-\frac{p_i+ix}{t}}} = -t \cdot -\frac{1}{t} \cdot \frac{\sum_{i=0}^k i e^{-\frac{p_i+ix}{t}}}{\sum_{i=0}^k e^{-\frac{p_i+ix}{t}}} = \frac{\sum_{i=0}^k i e^{-\frac{p_i+ix}{t}}}{\sum_{i=0}^k e^{-\frac{p_i+ix}{t}}} \\ &\leq \frac{k \cdot \sum_{i=0}^k e^{-\frac{p_i+ix}{t}}}{\sum_{i=0}^k e^{-\frac{p_i+ix}{t}}} = k \end{aligned}$$

and thus deduce that  $\text{Trop}'_t(p)$  is  $\deg(p)$ -Lipschitz.

We now want to show that this condition reflects into a condition on  $p_t$  which is reminiscent of the differential privacy condition.

In the following, let  $L = \deg(p)$ . Using the bijection  $-t \log(x)$ , the Lipschitz-condition for  $\text{Trop}$  (or equivalently  $\text{Trop}_t$ ) can be restated as follows:

$$|\text{Trop}(p)(-t \log x) - \text{Trop}(p)(-t \log y)| \leq Lt \cdot |\log x - \log y|$$

By “de-tropicalizing” the equation above, i.e. using the relation between  $\text{Trop}_t(p)$  and  $p$ , we thus deduce

$$t |\log p(x) - \log p(y)| \leq Lt \cdot |\log x - \log y|$$

and thus

$$|\log p(x) - \log p(y)| \leq L \cdot |\log x - \log y|$$

and thus, supposing  $y \geq x$  and  $p(y) \neq 0$ ,  $\frac{p(x)}{p(y)} \leq e^{L \cdot |\log x - \log y|}$ , that is,

$$p(x) \leq e^{L \cdot |\log x - \log y|} \cdot p(y)$$

**Example 5.** Let  $p(x) = x^n$ . Notice that in this case  $\text{Trop}(p)$  and  $\text{Trop}_t(p)$  are both the linear function  $q(x) = nx$ . Indeed  $\text{Trop}_t(p)(z) = -t \log t^{-nz} = nz$ . So in this case, from the Lipschitz condition  $|\text{Trop}(p)(z) - \text{Trop}(p)(z')| \leq n|z - z'|$  we immediately deduce the “differential privacy” condition  $p(x) \leq e^{n|\log x - \log y|} \cdot p(y)$  (with  $y \geq x$ ).

Notice that the “differential privacy” condition for a polynomial can also be proved directly, for  $x \neq 0$ , as follows:

$$\begin{aligned}
p(x + \epsilon) &= \sum_{i=1}^k e^{-p_i} \cdot (x + \epsilon)^i = \sum_{i=1}^k e^{-p_i} \cdot \frac{(x + \epsilon)^i}{x^i} \cdot x^i \\
&= \sum_{i=1}^k e^{-p_i} e^{i(\log(x+\epsilon) - \log(x))} \cdot x^i \\
&\leq \sum_{i=1}^k e^{k(\log(x+\epsilon) - \log(x))} \cdot e^{-p_i} \cdot x^i \\
&= e^{k(\log(x+\epsilon) - \log(x))} \cdot \sum_{i=1}^k e^{-p_i} \cdot x^i \\
&= e^{k(\log(x+\epsilon) - \log(x))} \cdot p(x)
\end{aligned}$$

**Example 6.** Suppose you choose some natural number and you want it to remain hidden. For this reason you add some “noise” to it and turn it into a distribution  $\mathbf{x} \in [0, 1]^{\mathbb{N}}$ . Now consider a probabilistic program that tries to guess your number by averaging a finite number of tests: you are required to provide your “noised” number  $K$  times, yielding values  $z_1, \dots, z_n$ , and the output produced is  $\frac{z_1 + \dots + z_n}{K}$ .

This program can be described as a function  $h : [0, 1]^{\mathbb{N}} \rightarrow [0, 1]^{\mathbb{Q}}$  where  $\hat{h} \in Q^{\mathcal{M}_i(\mathbb{N}) \times \mathbb{Q}}$  is given by

$$\hat{h}_{[z_1, \dots, z_m], q} = \begin{cases} 0 & \text{if } m = K \text{ and } q = \frac{z_1 + \dots + z_m}{K} \\ \infty & \text{otherwise} \end{cases}$$

So  $h$  can be written as a polynomial as follows:

$$h(\mathbf{x})(r) = \sum_{\mu} e^{-\hat{h}_{\mu, q}} \cdot \mathbf{x}^{\mu} = \sum_{z_1 + \dots + z_K = qK} \prod_{i=1}^K \mathbf{x}(z_i)$$

Now  $\text{Trop}(h)$  is of the form  $\min_{z_1 + \dots + z_K = qK} \left\{ \sum_{i=1}^K \mathbf{x}(z_i) \right\}$  and is thus a  $K$ -Lipschitz function. From all our discussion<sup>1</sup> we should deduce then that if  $\sup_z |\log \mathbf{x}(z) - \log \mathbf{y}(z)| \leq \epsilon$ , then

$$h(\mathbf{x})(r) \leq e^{K\epsilon} \cdot h(\mathbf{y})(r)$$

So if  $\mathbf{y}$  is a distribution which adds little extra-noise to  $\mathbf{x}$ , then the values obtained via this test are very close for  $\mathbf{x}$  and  $\mathbf{y}$ .

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<sup>1</sup>Beware, here I am using a generalization of the discussion before, to be checked carefully!