# On the relation between the relative earth mover distance and the variation distance (an exposition)* 

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#### Abstract

Summary. In this note we present a proof that the variation distance up to relabeling is upperbounded by the "relative earth mover distance" (to be defined below). The relative earth mover distance was introduced by Valiant and Valiant [VV11], and was extensively used in their work. The foregoing claim was made in [VV11], but was not used there. The claim appears a special case of [VV15, Fact 1] (i.e., the case of $\tau=0$ ). The proof we present is merely an elaboration of (this special case of) the proof presented by Valiant and Valiant in [VV15, Apdx A].


## 1 Definitions

We start by introducing some definitions and notations.
Definition 1 (Histograms and relative histograms for distributions) For a distribution $p$ : $[n] \rightarrow[0,1]$, the corresponding histogram, denoted $h_{p}:[0,1] \rightarrow \mathbb{N}$, such that $h_{p}(x) \stackrel{\text { def }}{=} \mid\{i \in[n]:$ $p(i)=x\} \mid$ for each $x \in[0,1]$. The corresponding relative histogram, denoted $h_{p}^{R}:[0,1] \rightarrow \mathbb{R}$, satisfies $h_{p}^{R}(x)=h_{p}(x) \cdot x$ for every $x \in[0,1]$.

That is, $h_{p}(x)$ equals the number of elements in $p$ that are assigned probability mass $x$, whereas $h_{p}^{R}(x)$ equals the total probability mass assigned to these elements. Hence, $h_{p}(0)$ may be positive, whereas $h_{p}^{R}(0)$ is always zero.

For a non-negative function $h$, let $S(h) \stackrel{\text { def }}{=}\{x: h(x)>0\}$ denote the support of $h$. Observe that for any distribution $p:[n] \rightarrow[0,1]$ we have that $\sum_{x \in S\left(h_{p}\right)} h_{p}(x)=n$ and $\sum_{x \in S\left(h_{p}^{R}\right)} h_{p}^{R}(x)=1$. Also note that $S\left(h_{p}^{R}\right)=S\left(h_{p}\right) \backslash\{0\}$.

The following definition interprets the distance between non-negative functions $h$ and $h^{\prime}$ as the cost of transforming $h$ into $h^{\prime}$ by moving $m(x, y)$ units from $x$ in $h$ to $y$ in $h^{\prime}$ (for every $x \in S(h)$ and $y \in S\left(h^{\prime}\right)$ ), where the cost of moving a single unit from $x$ to $y$ is either $|x-y|$ or $|\log (x / y)|$ (depending on the distance).

[^0]Definition 2 (Earth-Mover Distance and Relative Earth-Mover Distance) For a pair of non-negative functions $h$ and $h^{\prime}$ over $[0,1]$ such that $\sum_{x \in S(h)} h(x)=\sum_{x \in S\left(h^{\prime}\right)} h^{\prime}(x)$, the earth-mover distance between them, denoted $\operatorname{EMD}\left(h, h^{\prime}\right)$, is the minimum of

$$
\sum_{x \in S(h)} \sum_{y \in S\left(h^{\prime}\right)} m(x, y) \cdot|x-y|
$$

taken over all non-negative functions $m: S(h) \times S\left(h^{\prime}\right) \rightarrow \mathbb{R}$ that satisfy:

- For every $x \in S(h)$, it holds that $\sum_{y \in S(h)} m(x, y)=h(x)$, and
- For every $y \in S\left(h^{\prime}\right)$, it holds that $\sum_{x \in S\left(h^{\prime}\right)} m(x, y)=h^{\prime}(y)$.

The relative earth-mover distance between $h$ and $h^{\prime}$, denoted $\operatorname{REMD}\left(h, h^{\prime}\right)$, is the minimum of

$$
\sum_{x \in S(h)} \sum_{y \in S\left(h^{\prime}\right)} m(x, y) \cdot|\log (x / y)|
$$

subject to the same constraints on $m$ as for EMD.
The term earth-mover comes from viewing the functions as piles of earth, where for each $x \in S(h)$ there is a pile of size $h(x)$ in location $x$ and similarly for each $y \in S\left(h^{\prime}\right)$ there is a pile of size $h^{\prime}(y)$ in location $y$. The goal is to transform the piles defined by $h$ so as to obtain the piles defined by $h^{\prime}$, with minimum "transportation cost". Specifically, $m(x, y)$ captures the possibly fractional number of units transferred from pile $x$ in $h$ to pile $y$ in $h^{\prime}$. For EMD the transportation cost of a unit from $x$ to $y$ is $|x-y|$ while for REMD it is $|\log (x / y)|$. In what follows, for a pair of distributions $p$ and $q$ over $[n]$ we shall apply EMD to the corresponding pair of histograms $h_{p}$ and $h_{q}$, and apply REMD to the corresponding relative histograms $h_{p}^{R}$ and $h_{q}^{R}$.

Variation distance up to relabeling, as defined next, is a natural notion in the context of testing properties of symmetric distributions (i.e., properties that are invariant under relabeling of the elements of the distribution).

Definition 3 (Variation Distance up to Relabeling) For two distributions $p$ and $q$ over $n$, the variation distance up to relabeling between $p$ and $q$, denoted $\operatorname{VDR}(p, q)$, is the minimum over all permutations $\sigma$ over $[n]$ of

$$
\frac{1}{2} \sum_{i=1}^{n}|p(i)-q(\sigma(i))|
$$

## 2 Proofs

Our goal is to present a proof of the following result.
Theorem 4 (special case of Fact 1 in [VV15]) For every two distributions $p$ and $q$ over $[n]$, it holds that

$$
\operatorname{VDR}(p, q) \leq \operatorname{REMD}\left(h_{p}^{R}, h_{q}^{R}\right)
$$

The proof will consist of two steps (captured by lemmas):

1. $\operatorname{VDR}(p, q)=\frac{1}{2} \cdot \operatorname{EMD}\left(h_{p}, h_{q}\right)$.
2. $\operatorname{EMD}\left(h_{p}, h_{q}\right) \leq 2 \cdot \operatorname{REMD}\left(h_{p}^{R}, h_{q}^{R}\right)$.

Actually, we start with the second step.
Lemma 5 For every two distributions $p$ and $q$ over $[n]$,

$$
\operatorname{EMD}\left(h_{p}, h_{q}\right) \leq 2 \cdot \operatorname{REMD}\left(h_{p}^{R}, h_{q}^{R}\right) .
$$

The following proof shows how to construct, for every transportation function $m^{\prime}$ used for the relative histograms ( $h_{p}^{R}$ and $h_{q}^{R}$ ) a corresponding transportation function $m$ for the corresponding histograms ( $h_{p}$ and $h_{q}$ ) such that the EMD cost of $m$ is at most twice the REMD cost of $m^{\prime}$.
Proof: It will be convenient to consider two distributions, $\widetilde{p}$ and $\widetilde{q}$ that are slight variations of $p$ and $q$, respectively. They are both defined over [2n], where $\widetilde{p}(i)=p(i)$ and $\widetilde{q}(i)=q(i)$ for every $i \in[n]$, and $\widetilde{p}(i)=\widetilde{q}(i)=0$ for every $i \in[2 n] \backslash[n]$. Since $h_{\widetilde{p}}^{R}=h_{p}^{R}$ and $h_{\widetilde{q}}^{R}=h_{q}^{R}$, we have that $\operatorname{REMD}\left(h_{\widetilde{p}}^{R}, h_{\widetilde{q}}^{R}\right)=\operatorname{REMD}\left(h_{p}^{R}, h_{q}^{R}\right)$. As for $h_{\widetilde{p}}$ and $h_{\tilde{q}}$, they agree with $h_{p}$ and $h_{q}$, respectively, everywhere except on 0 , where $h_{\widetilde{p}}(0)=h_{p}(0)+n$ and $h_{\widetilde{q}}(0)=h_{q}(0)+n$, $\operatorname{so} \operatorname{EMD}\left(h_{\widetilde{p}}, h_{\widetilde{q}}\right)=$ $\operatorname{EMD}\left(h_{p}, h_{q}\right)$ as well. Therefore, it suffices to show that $\operatorname{EMD}\left(h_{\widetilde{p}}, h_{\widetilde{q}}\right) \leq 2 \cdot \operatorname{REMD}\left(h_{\widetilde{p}}^{R}, h_{\widetilde{q}}^{R}\right)$.

Let $m^{\prime}$ be a function over $S\left(h_{\widetilde{p}}^{R}\right) \times S\left(h_{\widetilde{q}}^{R}\right)$ that satisfies the constraints stated in Definition 2 for the pair of histograms $h_{\tilde{p}}^{R}$ and $h_{\tilde{q}}^{R}$. We next show that there exists a non-negative function $m$ over $S\left(h_{\widetilde{p}}\right) \times S\left(h_{\widetilde{q}}\right)$ that satisfies the constraints stated in Definition 2 for the pair of histograms $h_{\widetilde{p}}$ and $h_{\widetilde{q}}$, and also satisfies

$$
\begin{equation*}
\sum_{x \in S\left(h_{\widetilde{p}}\right)} \sum_{y \in S\left(h_{\widetilde{q}}\right)} m(x, y) \cdot|x-y| \leq 2 \cdot \sum_{x \in S\left(h_{\tilde{p}}^{R}\right)} \sum_{y \in S\left(h_{\widetilde{q}}^{R}\right)} m^{\prime}(x, y) \cdot|\log (x / y)| \tag{1}
\end{equation*}
$$

Note that the range of $m^{\prime}$ is $[0,1]$, since it is defined over relative histograms, while $m$ is not upper bounded by 1 . However, the constraints on the two functions are related since for every $x \in S\left(h_{\widetilde{p}}^{R}\right)=S\left(h_{\widetilde{p}}\right) \backslash\{0\}$ it is required that $\sum_{y \in S\left(h_{\widetilde{q}}^{R}\right)} m^{\prime}(x, y) / x=h_{\widetilde{p}}(x)=\sum_{y \in S\left(h_{\tilde{q}}\right)} m(x, y)$ and for every $y \in S\left(h_{\widetilde{q}}^{R}\right)=S\left(h_{\widetilde{q}}\right) \backslash\{0\}$ it is required that $\sum_{x \in S\left(h_{\tilde{p}}^{R}\right)} m^{\prime}(x, y) / y=h_{\widetilde{q}}(y)=\sum_{x \in S\left(h_{\widetilde{q}}\right)} m(x, y)$. (Indeed, $m$ is also subjected to constraints on $x=0$ and $y=0$, whereas $m^{\prime}$ is not.)

We now define the function $m$. For each $x \in S\left(h_{\tilde{p}}^{R}\right)$, initialize $m(x, 0)$ to 0 and similarly for each $y \in S\left(h_{\widetilde{q}}\right.$, initialize $m(0, y)$ to 0 . For every pair $(x, y) \in S\left(h_{\widetilde{p}}^{R}\right) \times S\left(h_{\widetilde{q}}^{R}\right)$, if $m^{\prime}(x, y)=0$, then $m(x, y)=0$, and otherwise we do the following.

- If $x>y$, let $m(x, y)$ be set to $m^{\prime}(x, y) / x$ and increase $m(0, y)$ by $m^{x}(0, y) \stackrel{\text { def }}{=} m^{\prime}(x, y) / y-$ $m^{\prime}(x, y) / x>0$. Observe that $m(x, y) \cdot(x-y)=m^{\prime}(x, y) \cdot(1-y / x)=m^{x}(0, y) \cdot y$. Therefore, the contribution to the left-hand-side of Equation (1) is

$$
m(x, y) \cdot(x-y)+m^{x}(0, y) \cdot(y-0)=2 m^{\prime}(x, y) \cdot(1-y / x)<2 m^{\prime}(x, y) \cdot \log (x / y)
$$

where the last inequality is due to the fact that $f(z)=\log z+(1 / z)-1>\ln z+(1 / z)-1$ is positive for all $z>1$.

- If $x<y$, let $m(x, y)$ be set to $m^{\prime}(x, y) / y$ and increase $m(x, 0)$ by $m^{y}(x, 0) \stackrel{\text { def }}{=} m^{\prime}(x, y) / x-$ $m^{\prime}(x, y) / y>0$. Similarly to the previous case, $m(x, y) \cdot(y-x)=m^{y}(x, 0) \cdot x$, and the contribution to the left-hand-side of Equation (1) is

$$
m(x, y) \cdot(y-x)+m^{y}(x, 0) \cdot(x-0)=2 m^{\prime}(x, y) \cdot(1-x / y)<2 m^{\prime}(x, y) \cdot \log (y / x) .
$$

- If $x=y$, let $m(x, y)=m^{\prime}(x, y) / x\left(=m^{\prime}(x, y) / y\right)$. In this case both $m(x, y) \cdot|x-y|=0$ and $m^{\prime}(x, y) \cdot|\log (x / y)|=0$.
Finally, we set $m(0,0)=h_{\widetilde{p}}(0)-\sum_{y \in S\left(h_{\widetilde{q}}^{R}\right)} m(0, y)$. To see that $m(0,0) \geq 0$, note that since $h_{\widetilde{p}}(0) \geq n$ while

$$
\sum_{y \in S\left(h_{\tilde{q}}^{R}\right)} m(0, y)=\sum_{y \in S\left(h_{\tilde{q}}^{R}\right)} \sum_{x \in S\left(h_{\tilde{p}}^{R}\right) \cap(y, 1]} m^{x}(0, y)=\sum_{y \in S\left(h_{\tilde{q}}^{R}\right)} \sum_{x \in S\left(h_{\bar{p}}^{R}\right) \cap(y, 1]} m^{\prime}(x, y) / y \leq n .
$$

By combining the contribution of all pairs $x, y$ as defined above, Equation (1) holds.
It remains to verify that $m$ satisfies the constraints in Definition 2. For each $x \in S\left(h_{\widetilde{p}}\right) \backslash\{0\}$,

$$
\begin{aligned}
\sum_{y \in S\left(h_{\widetilde{q})}\right.} m(x, y) & =m(x, 0)+\sum_{y \in S\left(h_{\widetilde{q}}\right) \cap(0, x]} m(x, y)+\sum_{y \in S\left(h_{\widetilde{q}}\right) \cap(x, 1]} m(x, y) \\
& =\sum_{y \in S\left(h_{\tilde{q}}^{R}\right) \cap(x, 1]} m^{y}(x, 0)+\sum_{y \in S\left(h_{\widetilde{q}}^{R}\right) \cap(0, x]} m(x, y)+\sum_{y \in S\left(h_{\widetilde{q}}^{R}\right) \cap(x, 1]} m(x, y) \\
& =\sum_{y \in S\left(h_{\tilde{q}}^{R}\right) \cap(x, 1]}\left(\frac{1}{x}-\frac{1}{y}\right) \cdot m^{\prime}(x, y)+\sum_{y \in S\left(h_{\widetilde{q}}^{R}\right) \cap(0, x]} \frac{m^{\prime}(x, y)}{x}+\sum_{y \in S\left(h_{\widetilde{q}}^{R}\right) \cap(x, 1]} \frac{m^{\prime}(x, y)}{y} \\
& =\sum_{y \in S\left(h_{\widetilde{q}}^{R}\right)} \frac{m^{\prime}(x, y)}{x}=h_{\widetilde{p}}(x) .
\end{aligned}
$$

Similarly, for each $y \in S\left(h_{\widetilde{q}}\right) \backslash\{0\}$,

$$
\begin{aligned}
\sum_{x \in S\left(h_{\overparen{p}}\right)} m(x, y) & =m(0, y)+\sum_{x \in S\left(h_{\widetilde{p}}\right) \cap(0, y]} m(x, y)+\sum_{x \in S\left(h_{\widetilde{p}}\right) \cap(y, 1]} m(x, y) \\
& =\sum_{x \in S\left(h_{\tilde{q}}^{R}\right) \cap(y, 1]} m^{x}(0, y)+\sum_{x \in S\left(h_{\widetilde{q}}^{R}\right) \cap(0, y]} m(x, y)+\sum_{x \in S\left(h_{\widetilde{\widetilde{R}}}^{R}\right) \cap(y, 1]} m(x, y) \\
& =\sum_{x \in S\left(h_{\tilde{q}}^{R}\right) \cap(y, 1]}\left(\frac{1}{y}-\frac{1}{x}\right) \cdot m^{\prime}(x, y)+\sum_{x \in S\left(h_{\widetilde{q}}^{R}\right) \cap(0, y]} \frac{m^{\prime}(x, y)}{y}+\sum_{x \in S\left(h_{\widetilde{q}}^{R}\right) \cap(y, 1]} \frac{m^{\prime}(x, y)}{x} \\
& =\sum_{x \in S\left(h_{\widetilde{p}}^{R}\right)} \frac{m^{\prime}(x, y)}{y}=h_{\widetilde{q}}(y) .
\end{aligned}
$$

We defined $m(0,0)$ such that $\sum_{y \in S\left(h_{\widetilde{q}}\right)} m(0, y)=m(0,0)+\sum_{y \in S\left(h_{\widetilde{q}}^{R}\right)} m(0, y)=h_{\widetilde{p}}(0)$, and

$$
\sum_{x \in S\left(h_{\widetilde{p}}\right)} m(x, 0)=\sum_{x \in S\left(h_{\widetilde{p}}\right)} \sum_{y \in \widetilde{q}} m(x, y)-\sum_{x \in S\left(h_{\widetilde{p}}\right)} \sum_{y \in S\left(h_{\widetilde{q}}\right) \backslash\{0\}} m(x, y)=2 n-\sum_{y \in S\left(h_{\widetilde{q}}\right)} h_{\widetilde{q}}(y)=h_{\widetilde{q}}(0),
$$

and the proof is completed.

Lemma 6 For every two distributions $p$ and $q$ over $[n]$,

$$
\operatorname{VDR}(p, q)=\frac{1}{2} \cdot \operatorname{EMD}\left(h_{p}, h_{q}\right) .
$$

Intuitively, there is a one-to-one correspondence between integer-valued transportation functions $m$ as in Definition 2 and the relabeling permutations $\sigma$ used in Definition 3. The core of the following proof is showing that integer-value transportation functions $m$ obtain the minimum for EMD.

Proof: Consider a constrained version of the earth-mover distance in which we also require that $m(x, y)$ is an integer for every $x \in S\left(h_{p}\right)$ and $y \in S\left(h_{q}\right)$, and denote this distance measure by IEMD. Using the definition of VDR and IEMD, one can verify that $\operatorname{VDR}(q, p)=\frac{1}{2} \cdot \operatorname{IEMD}\left(h_{p}, h_{q}\right)$, since there is a correspondence between the permutation $\sigma$ used in Definition 3 and the integer movement in EMD. (The factor of $1 / 2$ is due to the fact that the variation distance between distributions equals half the $L_{1}$-norm between them.)

It therefore remains to prove that $\operatorname{EMD}\left(h_{p}, h_{q}\right)=\operatorname{IEMD}\left(h_{p}, h_{q}\right)$; that is, the function $m$ that obtains the minimum of the EMD objective function has integer values. To this end, we define a specific integer-valued function $m$ (based on a simple iterative assignment procedure), and show that it is optimal.

Initially, $m(x, y)=0$ for every $x \in S\left(h_{p}\right)$ and $y \in S\left(h_{q}\right)$. We also initialize $s(x)=h_{p}(x)$ for every $x \in S\left(h_{p}\right)$, and $d(y)=h_{q}(y)$ for every $y \in S\left(h_{q}\right)$. (Intuitively, $s(x)$ is the supply of $x$, and $d(y)$ is the demand of $y$.) Note that $\sum_{x \in S\left(h_{p}\right)} s(x)=n=\sum_{y \in S\left(h_{q}\right)} d(y)$. In each iteration, we consider the smallest $x \in S\left(h_{p}\right)$ for which $s(x)>0$ and the smallest $y \in S\left(h_{q}\right)$ for which $d(y)>0$, set $m(x, y)=\min \{s(x), d(y)\}$ and reduce both $s(x)$ and $d(y)$ by $m(x, y)$. Hence, all intermediate values of $m$ (as well as $s$ and $d$ ) are integers. (We note that an equivalent definition of $m$ can be obtained by considering the mapping $\sigma$ from $[n]$ to $[n]$ that maps the $i^{\text {th }}$ smallest $p$-value to the $i^{\text {th }}$ smallest $q$-value. $)^{1}$ By its construction, the function $m$ satisfies the constraints of Definition 2 .

To verify that the resulting function $m$ is an optimal setting for EMD, consider any other non-negative function $\ell$ over $S\left(h_{p}\right) \times S\left(h_{q}\right)$ that satisfies the constraints of Definition 2. Actually, among all such functions $\ell$ consider only those that agree with $m$ on the longest prefix of pairs $(x, y)$ according to the lexicographical order on pairs, and let $\left(x^{*}, y^{*}\right)$ be the first pair on which $\ell$ and $m$ differ; that is, $\ell\left(x^{*}, y^{*}\right) \neq m\left(x^{*}, y^{*}\right)$ whereas $\ell(x, y)=m(x, y)$ for every $(x, y)<\left(x^{*}, y^{*}\right)$. Furthermore, among all such functions $\ell$, select one for which $\left|\ell\left(x^{*}, y^{*}\right)-m\left(x^{*}, y^{*}\right)\right|$ is minimal. We shall show that $\ell=m$.

Assume towards the contradiction that $\ell \neq m$, and let $\left(x^{*}, y^{*}\right)$ be as above. We first prove that $\ell\left(x^{*}, y^{*}\right)<m\left(x^{*}, y^{*}\right)$. Towards this end, we consider the supply of $x^{*}$ and the demand of $y^{*}$ just before $m\left(x^{*}, y^{*}\right)$ is determined; that is, $s\left(x^{*}\right)=h_{p}\left(x^{*}\right)-\sum_{y<y^{*}} m\left(x^{*}, y\right)$ and $d\left(y^{*}\right)=$ $h_{q}\left(y^{*}\right)-\sum_{x<x^{*}} m\left(x, y^{*}\right)$. Recalling that $m\left(x^{*}, y^{*}\right)=\min \left(s\left(x^{*}\right), d\left(y^{*}\right)\right)$, we note that if $\ell\left(x^{*}, y^{*}\right)>$ $m\left(x^{*}, y^{*}\right)=s\left(x^{*}\right)$, then $\sum_{y \leq y^{*}} \ell\left(x^{*}, y\right)=\sum_{y<y^{*}} m\left(x^{*}, y\right)+\ell\left(x^{*}, y^{*}\right)>h_{p}\left(x^{*}\right)$, which means that $\ell$ violates a constraint of Definition 2. A similar contradiction is obtained by assuming that $\ell\left(x^{*}, y^{*}\right)>$ $m\left(x^{*}, y^{*}\right)=d\left(y^{*}\right)$, when in this case we get $\sum_{x \leq x^{*}} \ell\left(x, y^{*}\right)>h_{q}\left(x^{*}\right)$.

Having shown that $\ell\left(x^{*}, y^{*}\right)<m\left(x^{*}, y^{*}\right)$. we now derive a function $\ell^{\prime}$ that violates the "minimality" of $\ell$. Specifically, $\ell\left(x^{*}, y^{*}\right)<m\left(x^{*}, y^{*}\right)$ (combined with $\ell(x, y)=m(x, y)$ for every $\left.(x, y)<\left(x^{*}, y^{*}\right)\right)$ implies that there exists $x^{\prime}>x^{*}$ such that $\ell\left(x^{\prime}, y^{*}\right)>m\left(x^{\prime}, y^{*}\right)$ and $y^{\prime}>y^{*}$ such that $\ell\left(x^{*}, y^{\prime}\right)>m\left(x^{*}, y^{\prime}\right)$. Letting $c=\min \left(m(x, y)-\ell\left(x^{*}, y^{*}\right), \ell\left(x^{\prime}, y^{*}\right), \ell\left(x^{*}, y^{\prime}\right)\right)>0$, define

[^1]$\ell^{\prime}$ as equal to $\ell$ on all pairs except for the following four pairs that satisfy $\ell^{\prime}\left(x^{*}, y^{*}\right)=\ell\left(x^{*}, y^{*}\right)+c$, $\ell^{\prime}\left(x^{\prime}, y^{*}\right)=\ell\left(x^{\prime}, y^{*}\right)-c, \ell^{\prime}\left(x^{*}, y^{\prime}\right)=\ell\left(x^{*}, y^{\prime}\right)-c$, and $\ell^{\prime}\left(x^{\prime}, y^{\prime}\right)=\ell\left(x^{\prime}, y^{\prime}\right)+c$. Then, $\ell^{\prime}$ preserves the constraints of Definition 2, but $\ell^{\prime}(x, y)=\ell(x, y)=m(x, y)$ for every $(x, y)<\left(x^{*}, y^{*}\right)$ and $\left|\ell^{\prime}\left(x^{*}, y^{*}\right)-m\left(x^{*}, y^{*}\right)\right|=\left|\ell\left(x^{*}, y^{*}\right)-m\left(x^{*}, y^{*}\right)\right|-c$, in contradiction to the choice of $\ell$, since $c>0$.

## 3 Comments

As noted in [VV11], there exist distributions $p$ and $q$ for which $\operatorname{VDR}\left(h_{p}, h_{q}\right) \ll \operatorname{REMD}\left(h_{p}^{R}, h_{q}^{R}\right)$. The source of this phenomenon is the unbounded cost of transportation under the REMD (i.e., transforming a unit of mass from $x$ to $y \operatorname{costs}|\log (x / y)|)$. For example, for any $\epsilon \in[0,0.5]$, consider the pair $(p, q)$ such that $p$ is uniform over [n] (i.e., $p(i)=1 / n$ for every $i \in[n])$ and $q$ is extremely concentrated on a single point in the sense that $q(n)=1-\epsilon$ and $q(i)=\epsilon /(n-1)$ for every $i \in[n-1]$. Then, the variation distance between $p$ and $q$ is $\frac{n-1}{n}-\epsilon$, but the REMD is at least $\frac{n-1}{n} \cdot \log (1 / \epsilon)$.

This phenomenon is reflected in the proof of Lemma 5 at the point we used the inequality $1-(1 / z)<\log z$ for $z>1$. This inequality becomes more crude when $z$ grows.

## References

[VV11] G. Valiant and P. Valiant. Estimating the unseen: an $n / \log (n)$-sample estimator for entropy and support size, shown optimal via new CLTs. In Proceedings of the Fourty-Third Annual ACM Symposium on the Theory of Computing (STOC), pages 685-694, 2011. See ECCC TR10-180 for the algorithm, and TR10-179 for the lower bound.
[VV15] G. Valiant and P. Valiant. Instance optimal learning. CoRR, abs/1504.05321, 2015.


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[^1]:    ${ }^{1}$ That is, letting $\pi_{p}$ and $\pi_{q}$ be permutations over [ $n$ ] such that $p\left(\pi_{p}(i)\right) \leq p\left(\pi_{p}(i+1)\right)$ and $q\left(\pi_{q}(i)\right) \leq q\left(\pi_{q}(i+1)\right)$ for every $i \in[n-1]$, define $\sigma\left(\pi_{p}(i)\right)=\pi_{q}(i)$ for every $i \in[n]$.

