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On the Quality of Randomized Approximations of Tukey's Depth*

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Abstract. Tukey's depth (or halfspace depth) is a widely used measure of centrality for multivariate data. However, exact computation of Tukey's depth is known to be a hard problem in high dimensions. As a remedy, randomized approximations of Tukey's depth have been proposed. In this paper we explore when such randomized algorithms return a good approximation of Tukey's depth. We study the case when the data are sampled from a log-concave isotropic distribution. We prove that if one requires that the algorithm runs in polynomial time in the dimension, the randomized algorithm correctly approximates the maximal depth 1/2 and depths close to zero. On the other hand, for any point of intermediate depth, any good approximation requires exponential complexity.

Key words. Tukey depth, high-dimensional statistics, data analysis

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1. Introduction.

Ever since Tukey introduced a notion of data depth [50], it has been an important tool of data analysts to measure the centrality of data points in multivariate data. Apart from Tukey's depth (also called halfspace depth), many other depth measures have been developed, such as simplical depth [32, 33], projection depth [34, 52], a notion of "outlyingness" [49, 14], and the zonoid depth [17, 29]. Each of these notions offers distinct stability and computability properties that make it suitable for different applications [38]. For surveys of depth measures and their applications we refer the reader to [37, 1, 18, 42, 40].

Tukey's depth is defined as follows: for $x \in \mathbb{R}^d$ and unit vector $u \in S^{d-1}$ (where S^{d-1} is the unit sphere of $\mathbb{R}^d$ under the euclidean norm), introduce the closed halfspace

$$H(x,u) = \left\{ y \in \mathbb{R}^d \ : \ \langle y,u \rangle \leq \langle x,u \rangle \right\} ,$$

where $\langle \cdot,\cdot \rangle$ is the usual scalar product on $\mathbb{R}^d$. Given a set of n data points $\{x_1,\ldots,x_n\}$ in $\mathbb{R}^d$, for each $x \in \mathbb{R}^d$, define the directional depth

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$$r_n(x,u) = \frac{1}{n}\sum_{i=1}^{n} \mathbb{1}_{x_i \in H(x,u)} \,.$$

For any $x \in \mathbb{R}^d$, its depth in the point set $\{x_1, \ldots, x_n\}$ is defined as

$$d_n(x) = \inf_{u \in S^{d-1}} r_n(x,u) \,.$$

Note that, due to the normalization in our definition, $d_n(x) \in [0,1]$ for all $x \in \mathbb{R}^d$. A point that maximizes Tukey's depth is called a Tukey median. Tukey's depth possesses properties expected of a depth measure. It is affine invariant, it vanishes at infinity, and it is monotone decreasing on rays emanating from the deepest point. It is also robust under a symmetry assumption [15].

A well-known disadvantage of Tukey's depth is that even its approximate computation is known to be an NP-hard problem [2, 5, 24], presenting challenges for applications. While fast algorithms exist for computing the depth of the deepest point in two dimensions [8], the computational complexity grows exponentially with the dimension. In [8], a maximum-depth computation algorithm of complexity $\mathcal{O}(n^{d-1})$ is given.

The curse of dimensionality affects several other depth measures, posing significant challenges in multivariate analysis. To address these challenges, focus has been put on developing approximation algorithms. In [19], the importance of finding such algorithms is presented and MCMC methods are proposed in [48] for approximating the projection depth. In [51], an approximate version of Tukey's depth is introduced and an algorithm with linear time complexity in the dimension is provided, though the proposed version may be a poor approximation of Tukey's depth.

A natural way of approximating Tukey's depth, proposed independently by Dyckerhoff [16] and Cuesta-Albertos and Nieto-Reyes [11], is a randomized version in which the infimum over all possible directions $u \in S^{d-1}$ in the definition of $d_n(x)$ is replaced by the minimum over a number of randomly chosen directions. More precisely, let $U_1, \ldots, U_k$ be independent identically distributed vectors sampled uniformly on the unit sphere S^{d-1} and define the *random Tukey depth* (with respect to the point set $\{x_1, \ldots, x_n\}$) as

$$D_{n,k}(x) = \min_{i=1,\ldots,k} r_n(x, U_i) \,.$$

It is easy to see that for every $x \in \mathbb{R}^d$, $\lim_{k\to\infty} D_{n,k}(x) = d_n(x)$ with probability 1. However, this randomized approach is only useful if the number of random directions k is reasonably small so that computation is feasible. The purpose of this paper is to explore the tradeoff between computational complexity and accuracy. In particular, we may ask how large k has to be in order to guarantee that, for given accuracy and confidence parameters $\epsilon \in (0,1/2)$ and $\delta \in (0,1)$, $|D_{n,k}(x) - d_n(x)| \le \epsilon$ with probability at least $1-\delta$.

It is easy to see that the value of k required to satisfy the property above may be arbitrarily large. To see this, fix $n \ge 4$ even and consider the two-dimensional example in which, for $i = [1,n]$, the points $x_i = (x_{i,1}, x_{i,2})$ are defined by

$$x_{i,1} = \frac{i}{n}\,, \qquad x_{i,2} = a\left(\frac{i}{n}\right)^2,$$

where $a > 0$ is a parameter. We want to evaluate the depth of $x_{n/2}$ in the point set $S = \{x_1, \dots, x_{n/2-1}, x_{n/2+1}, \dots, x_n\}$. Since $x_{n/2}$ lies outside of the convex envelope of S, its depth with regard to the set S is 0. However, to "see" this depth we need to evaluate the depth in a direction u such that

$$\langle x_{n/2-1}, u\rangle > \langle x_{n/2}, u\rangle$$

and

$$\langle x_{n/2+1}, u\rangle > \langle x_{n/2}, u\rangle .$$

An illustration, presented in Figure 1, shows that by choosing a arbitrarily small, the set where u must be sampled to detect the depth of $x_{n/2}$ becomes arbitrarily small, and consequently k must be chosen arbitrarily large to accurately estimate the Tukey depth.

In order to exclude the anomalous behavior of the example above, we assume that the points x_i are drawn randomly from an isotropic log-concave distribution μ. Recall that a distribution μ is log-concave if it is absolutely continuous with respect to the Lebesgue measure, with density f of the form $f(x) = e^{-g(x)}$, where $g : \mathbb{R}^d \to \mathbb{R}$ is a convex function. μ is isotropic if for a random vector X distributed by μ, the covariance matrix $\mathbb{E}(X - \mathbb{E}X)(X - \mathbb{E}X)^T$ is the identity matrix. Examples of log-concave distributions include Gaussian distributions and the uniform distribution on a convex body in $\mathbb{R}^d$.

For random data, one may introduce the "population" counterpart of r_n defined by

$$\overline{r}(x, u) = \mu(H(x, u)) .$$

Similarly, the population versions of the Tukey depth and randomized Tukey depth are defined by

$$\overline{d}(x) = \inf_{u \in S^{d-1}} \overline{r}(x, u) \quad \text{and} \quad \overline{D}_k(x) = \min_{i=1,\dots,k} \overline{r}(x, U_i) .$$

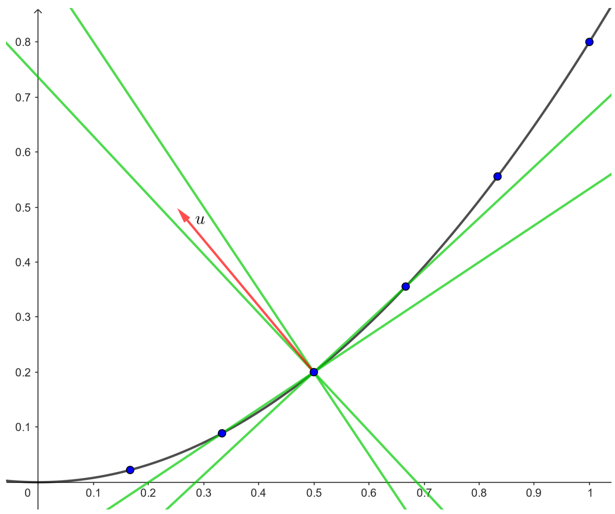

Figure 1. *Illustration of the dataset $x_i = (i/6, 0.8(i/6^2)$ for $i \in [6]$. In green, the lines between which vector u must lie to detect that the depth of x_3 is 0.*

Remark that if μ has a density, then Tukey's depth lies between 0 and 1/2. As was observed in [11] and [10], as long as $n \gg d$, the population versions of the Tukey depth $\overline{d}(x)$ and randomized Tukey depth $\overline{D}_k(x)$ are good approximations of $d_n(x)$ and $D_{n,k}(x)$, respectively. This follows from standard uniform convergence results of empirical process theory based on the VC dimension. The next lemma quantifies this closeness. For completeness we include its proof in the appendix.

Lemma 1.1. *Let $\delta > 0$. If $X_1, \dots, X_n$ are independent, identically distributed random vectors in $\mathbb{R}^d$, then*

$$\mathbb{P}\left\{\sup_{x\in\mathbb{R}^d} |\overline{d}(x) - d_n(x)| \geq c\sqrt{\frac{d\log(n)}{n}} + \sqrt{\frac{\log(1/\delta)}{2n}}\right\} \leq \delta,$$

where c is a universal constant. Also, given any fixed values of $U_1, \dots, U_k$,

$$\mathbb{P}\left\{\sup_{x\in\mathbb{R}^d} |\overline{D}_k(x) - D_{n,k}(x)| \geq c\sqrt{\frac{\log(n)\min(d,\log(k))}{n}} + \sqrt{\frac{\log(1/\delta)}{2n}}\,\middle|\, U_1, \dots, U_k\right\} \leq \delta.$$

Thanks to Lemma 1.1, in the rest of the paper we restrict our attention to the population quantities $\overline{d}(x)$ and $\overline{D}_k(x)$ and we may forget the data points $X_1, \dots, X_n$. In particular, we are interested in finding out for what points $x \in \mathbb{R}^d$ and $k \geq 0$ the random Tukey depth $\overline{D}_k(x)$ is a good approximation of $\overline{d}(x)$. To this end, we fix an accuracy $\epsilon > 0$ and a confidence level $\delta > 0$ and ask that

$$\overline{D}_k(x) - \overline{d}(x) \leq \epsilon \quad \text{holds with probability at least } 1-\delta. \tag{1.1}$$

(Note that, by definition, $\overline{D}_k(x) \geq \overline{d}(x)$ for all x and k.) The main results of the paper show an interesting trichotomy: for most "shallow" points (i.e., those with $\overline{d}(x) \leq \epsilon$), we have $\overline{D}_k(x) \leq \epsilon$ with probability at least $1-\delta$ even for k of *constant* order, depending only on ϵ and δ. When x has near maximal depth in the sense that $\overline{d}(x) \approx 1/2$ (note that such points may not exist unless the density of μ is symmetric around 0), then for values of k that are slightly larger than a linear function of d, (1.1) holds. However, in sharp contrast with this, for points x of intermediate depth, k needs to be exponentially large in d in order to guarantee (1.1). Hence, roughly speaking, the depth of very shallow and very deep points can be efficiently approximated by the random Tukey depth but for all other points, any reasonable approximation by the random Tukey depth requires exponential complexity.

1.1. Related literature. In [11], various properties of the random Tukey depth are investigated and good experimental behavior is reported. The maximum discrepancy between d_n and its randomized approximation has also been studied in [39]. They establish conditions under which $\sup_{x\in\mathbb{R}^d}(\overline{D}_k(x) - \overline{d}(x)) \to 0$ as $k \to \infty$ and provide bounds for the rate of convergence. As opposed to the global view presented in [39], our aim is to identify the points x for which the random Tukey depth approximates well $\overline{d}(x)$ for values of k that are polynomial in the dimension.

In [4], it is shown that the average depth $\int_{\mathbb{R}^d} \overline{d}(x)d\mu(x)$ is exponentially small in the dimension when μ is log-concave. In [23], the set of "deep points" for a mesure and its weighted empirical counterpart are compared. On a similar line of questions, [7] studies convergence of the empirical level sets when the data points are drawn independently from the same distribution, and [9] studies the quality of other randomized approximations of the Tukey depth for point sets in general position.

1.2. Contributions and outline. As mentioned above, the main results of this paper show that, for isotropic log-concave distributions, the quality of approximation of the random Tukey depth varies dramatically, depending on the depth of the point x.

Most points have a small random Tukey depth. In section 2 we establish results related to shallow points. It follows from [4, Theorem 1.1] (together with the solution of Bourgain's slicing problem in [28]) and Markov's inequality that all but an exponentially small fraction of points are shallow in the sense that, for all $\epsilon > 0$,

$$\mu\Big(\{x \in \mathbb{R}^d : \overline{d}(x) > \epsilon\}\Big) \leq \frac{e^{-cd}}{\epsilon},$$

where $c > 0$ is a universal constant. The main result of section 2 is that, in high dimensions, not only are most points shallow but most points even have a small random Tukey depth for k of *constant* order, only depending on the desired accuracy. In particular, Theorem 2.1 leads to the following.

Corollary 1.2. *Assume that μ is an isotropic log-concave measure on $\mathbb{R}^d$. There exist universal constants $c, \kappa, C > 0$ such that for any $\epsilon, \delta, \gamma > 0$, if*

$$k = \left\lceil \max\left(C, \frac{4}{\epsilon}\log\frac{3}{\gamma}, \frac{2}{c}\log\frac{4}{\delta}\right)\right\rceil,$$

and the dimension d is so large that

$$d \geq \max\left(\left(\frac{3(k+1)}{\gamma}\right)^{1/\kappa}, \frac{64k\log(1/\epsilon)^2}{\pi}\log\frac{3k}{\gamma}, \left(\frac{1}{c}\log\frac{6k}{\delta}\right)^2, \left(\frac{2}{\epsilon}\right)^{\kappa}\right),$$

then, with probability at least $1-\delta$,

$$\mu\Big(\{x \in \mathbb{R}^d : \overline{D}_k(x) > \epsilon\}\Big) < \gamma.$$

Of course, $\overline{D}_k(x) \leq \epsilon$ implies that $\overline{d}(x) \leq \epsilon$ and, in particular, that $\overline{D}_k(x) - \overline{d}(x) \leq \epsilon$. Thus, Corollary 1.2 implies that the random Tukey depth of *most* points (in terms of the measure μ) is a good approximation of the Tukey depth after taking just a constant number of random directions. All of these points are shallow in the sense that $\overline{d}(x) \leq \epsilon$.

It is natural to ask whether the Tukey depth of every shallow point is well approximated by its random version. However, this is false as the following example shows.

Example. Let μ be the uniform distribution on $[-\sqrt{3}, \sqrt{3}]^d$ so that μ is isotropic and log-concave on $\mathbb{R}^d$. If $x = (\sqrt{3}, 0, \ldots, 0)$, then $\overline{d}(x) = 0$, but it is a simple exercise to show that $\overline{D}_k(x) \geq 1/4$ with high probability, unless k is exponentially large in d.

Intermediate depth is hard to approximate. Arguably the most interesting points are those whose depth is in the intermediate range, bounded away from 0 and 1/2. Unfortunately, for all such points, the random Tukey depth is an inefficient approximation of the Tukey depth. In section 3 we show that for all points in this range, the random Tukey depth $\overline{D}_k(x)$ is close to 1/2, with high probability, unless k is exponentially large in the dimension. Hence, in high dimensions, $\overline{D}_k(x)$ fails to efficiently approximate the true depth $\overline{d}(x)$. In particular, Theorem 3.1 leads to the following.

Corollary 1.3. *Assume that μ is an isotropic log-concave measure on $\mathbb{R}^d$ and let $\delta \in (0,1)$. For any $\gamma \in (0,1/2)$, there exists a positive constant $c = c(\gamma)$ such that if $x \in \mathbb{R}^d$ is such that $\overline{d}(x) = \gamma$, then for every $\epsilon < c$, if $k \le (\delta/2)e^{d\epsilon^2/2}$, then, with probability at least $1-\delta$,*

$$\overline{D}_k(x) - \overline{d}(x) \ge \epsilon\,.$$

Points of maximum depth are easy to localize. As mentioned above, if μ has no atoms, the Tukey depth $\overline{d}(x)$ of any $x \in \mathbb{R}^d$ is at most 1/2. If $\overline{d}(x) = 1/2$, then for every $u \in S^{d-1}$, the median of the projection $\langle X, u\rangle$ equals $\langle x, u\rangle$ (where the random vector X is distributed as μ). Such points are quite special and may not exist at all. If there exists an $x \in \mathbb{R}^d$ with $\overline{d}(x) = 1/2$, then the measure μ is called *halfspace symmetric* (see [53, 40]). It is easy to see that if μ is halfspace symmetric and has no atoms, there is a unique $m \in \mathbb{R}^d$ with $\overline{d}(m) = 1/2$. Then m is the unique *Tukey median* of μ. Centrally symmetric measures are halfspace symmetric though the converse does not hold in general. Remarkably, if μ is the uniform distribution over a convex body and it is halfspace symmetric, then it is also centrally symmetric; see Funk [21], Schneider [47], and Rousseeuw and Struyf [43], who independently proved a more general result, stating that an atomless distribution is halfspace symmetric if and only if it is angularly symmetric. See [40] for further discussion.

We note that for any log-concave measure, $1/e \le \sup_{x\in\mathbb{R}^d} \overline{d}(x) \le 1/2$ (see [40, Theorem 3]).

If $m \in \mathbb{R}^d$ is such that $\overline{d}(m) = 1/2$, then clearly $\overline{D}_k(m) = 1/2$ for all $k \ge 1$. In section 4 we show that, for values of k that are only polynomial in d, points with $\overline{D}_k(x) \approx 1/2$ must be close to m. Hence, selecting points of high random Tukey depth efficiently estimates the Tukey median for halfspace symmetric isotropic log-concave distributions. More precisely, Theorem 4.1 combined with Lemma 1.1 leads to the following.

Corollary 1.4. *Assume that μ is an isotropic log-concave, halfspace symmetric measure on $\mathbb{R}^d$ and let m be its unique Tukey median. Let $X_1, \dots, X_n$ be independent random vectors distributed as μ. Let $m_{n,k} \in \mathbb{R}^d$ be an empirical random Tukey median, that is, $m_{n,k}$ is such that $D_{n,k}(m_{n,k}) = \max_{x\in R^d} D_{n,k}(x)$. There exist universal constants $c, C > 0$ such that for any $\delta \in (0,1)$ and $\gamma \in (0,c)$, if $n \ge Cd/\gamma^2$ and*

$$k \ge c\,(d\log d + \log(1/\delta))\,,$$

then $\|m_{n,k} - m\| \le C\gamma\sqrt{d}$ with probability at least $1-\delta$.

By taking γ of the order of $1/\sqrt{d}$, the corollary above shows that, as long as $n \gg d^2$, it suffices to take $O(d\log d)$ random directions so that the empirical random Tukey median is within a distance of constant order of the Tukey median. Note that, due to the "thin-shell" property of log-concave measures (see, e.g., [20]), the measure μ is concentrated around a sphere of radius $\sqrt{d}$ centered at the Tukey median m and hence localizing m to within a constant distance is a nontrivial estimate.

One may even take γ to be smaller order than $1/\sqrt{d}$ and get a better precision with the same value of k. However, for better precision, one requires the sample size n to be larger.

At first glance, the statements of Theorems 3.1 and 4.1 might seem contradictory. Indeed, the former states that the random Tukey depth of points of intermediate depth concentrates around $1/2$ while the latter states that, in the halfspace symmetric case, it is possible to localize the Tukey median using the points of high random Tukey depth. Theorem 3.1 states that the random Tukey depth is larger than $1/2-c$ for a (potentially small) constant c. In the meantime, meaningful information is extracted from Theorem 4.1 when points of depth at least $1/2-1/\sqrt{d}$ are considered. This suggests that even though a random Tukey depth of a point of intermediate depth concentrates around $1/2$, it is still below $1/2-1/\sqrt{d}$ and this allows localization of the Tukey median.

One may wonder whether the Tukey median can be localized by maximizing the random Tukey depth for general (not only halfspace symmetric) log-concave distributions. While we cannot rule out this property, its proof would require new ideas as by Theorem 3.1, even if the Tukey median has depth smaller than $1/2$, intermediate points have a random Tukey depth concentrating around $1/2$.

2. Random Tukey depth of typical points.

In this section we show that for isotropic log-concave distributions, in high dimensions, a constant number k of random directions suffice to make the random Tukey depth $\overline{D}_k$ small for most points. In other words, the curse of dimensionality is avoided in a strong sense. In particular, we prove the following theorem, which implies Corollary 1.2 in a straightforward manner.

Theorem 2.1. *Assume that μ is an isotropic log-concave measure on $\mathbb{R}^d$. There exist universal constants $c,\kappa>0$ such that the following holds. Let $\epsilon>0$ and suppose that d is so large that $d^{-\kappa}\le\epsilon/2$. Then for every $k\le cd^{\kappa}$,*

$$\mu\left(\{x\in\mathbb{R}^d:\overline{D}_k(x)>\epsilon\}\right)\le(1-\epsilon/4)^k+(k+1)d^{-\kappa}+ke^{\frac{-d\pi}{64k\log(1/\epsilon)^2}}$$

with probability at least $1-ke^{-ck}-(k+1)e^{-c\sqrt{d}}$ over the choice of directions $U_1,\dots,U_k$.

Our main tool is the following extension of Klartag's celebrated central limit theorem for convex bodies [25]. Let $G_{d,k}$ denote the Grassmannian of all k-dimensional subspaces of $\mathbb{R}^d$ and let $\sigma_{d,k}$ be the unique rotationally invariant probability measure on $G_{d,k}$.

Proposition 2.2 (Klartag [26]). *Let the random vector X take values in $\mathbb{R}^d$ and assume that X has an isotropic log-concave distribution. Let S_k be a random k-dimensional subspace of $\mathbb{R}^d$ drawn from the distribution $\sigma_{d,k}$. There exist universal constants $c,\kappa>0$ such that the following holds: if $k\le cd^{\kappa}$, then with probability at least $1-e^{-c\sqrt{d}}$, for every measurable set $A\subset S_k$,*

$$|\mathbb{P}\{\pi_k(X)\in A\}-\mathbb{P}\{N\in A\}|\le d^{-\kappa},$$

where N is a k-dimensional normal vector in S_k with zero mean and identity covariance matrix, and π_k is the orthogonal projection on S_k.

Proof of Theorem 2.1. First note that the random subspace of $\mathbb{R}^d$ spanned by the independent uniform vectors $U_1, \dots, U_k$ has a rotation-invariant distribution and therefore it is distributed by $\sigma_{d,k}$ over the Grassmannian $G_{d,k}$.

For any $u \in S^{d-1}$, define $q(\epsilon, u)$ as the ϵ-quantile of the distribution of $\langle X, u\rangle$, that is,

$$\mu(\{x : \langle x, u\rangle \le q(\epsilon, u)\}) = \epsilon\,.$$

Observe that, by Proposition 2.2 (applied with $k = 1$) and the union bound, with probability at least $1 - ke^{-c\sqrt{d}}$,

$$\text{for all } i = 1, \dots, k, \quad q(\epsilon, U_i) \ge \Phi^{-1}(\epsilon/2)$$

whenever d is so large that $d^{-\kappa} \le \epsilon/2$, where $\Phi(z) = \int_{-\infty}^{z} (2\pi)^{-1/2} e^{-t^2/2} dt$ denotes the standard Gaussian cumulative distribution function.

Then, with probability at least $1 - ke^{-c\sqrt{d}}$,

$$\begin{aligned}
\mu\left(\left\{x : \overline{D}_k(x) > \epsilon\right\}\right) &= \mu\left(\left\{x : \min_{i=1,\dots,k} \mu(H(x, U_i)) > \epsilon\right\}\right) \\
&= \mu\left(\{x : \langle x, U_i\rangle > q(\epsilon, U_i) \text{ for all } i = 1, \dots, k\}\right) \\
&\le \mu\left(\left\{x : \langle x, U_i\rangle > \Phi^{-1}(\epsilon/2) \text{ for all } i = 1, \dots, k\right\}\right).
\end{aligned}$$

If the U_i were orthogonal, we could now use Proposition 2.2. This is not the case but almost. In order to handle this issue, we perform Gram–Schmidt orthogonalization defined, recursively, by $V_1 = U_1$ and, for $i = 2, \dots, k$,

$$R_i = \sum_{j=1}^{i-1} \langle U_i, V_j\rangle V_j \quad \text{and} \quad V_i = \frac{U_i - R_i}{\|U_i - R_i\|}\,.$$

Then $V_1, \dots, V_k$ are orthonormal vectors, spanning the same subspace as $U_1, \dots, U_k$.

Now, we may write

$$\begin{aligned}
&\mu\left(\left\{x : \overline{D}_k(x) > \epsilon\right\}\right) \\
&\quad \le \mu\left(\left\{x : \langle x, U_i\rangle > \Phi^{-1}(\epsilon/2) \text{ for all } i = 1, \dots, k\right\}\right) \\
&\quad \le \mu\left(\left\{x : \langle x, V_i\rangle > \Phi^{-1}(\epsilon/4) \text{ for all } i = 1, \dots, k\right\}\right) \\
&\qquad + \mu\left(\left\{x : \langle x, U_i - V_i\rangle > \Phi^{-1}(\epsilon/2) - \Phi^{-1}(\epsilon/4) \text{ for some } i = 1, \dots, k\right\}\right) \\
&\quad \le \mu\left(\left\{x : \langle x, V_i\rangle > \Phi^{-1}(\epsilon/4) \text{ for all } i = 1, \dots, k\right\}\right) \\
&\qquad + \sum_{i=2}^{k} \mu\left(\left\{x : \langle x, U_i - V_i\rangle > \frac{\sqrt{2\pi}}{4\log(1/\epsilon)}\right\}\right),
\end{aligned} \tag{2.1}$$

where the last inequality follows from the union bound and Lemma 2.3 below.

As $\langle x, V_1\rangle, \dots, \langle x, V_k\rangle$ are coordinates of the orthogonal projection of x on the random subspace spanned by $U_1, \dots, U_k$, we may use Proposition 2.2 to bound the first term on the right-hand side of (2.1). Let $N_1, \dots, N_k$ be independent standard normal random variables. Then by Proposition 2.2, with probability at least $1 - e^{-c\sqrt{d}}$,

$$\begin{aligned}
&\mu\left(\{x : \langle x, V_i\rangle > \Phi^{-1}(\epsilon/4) \text{ for all } i = 1,\dots,k\}\right)\\
&\quad \le \mathbb{P}\{N_i > \Phi^{-1}(\epsilon/4) \text{ for all } i = 1,\dots,k\} + d^{-\kappa}\\
&\quad = \mathbb{P}\{N_1 > \Phi^{-1}(\epsilon/4)\}^k + d^{-\kappa}\\
&\quad = (1-\epsilon/4)^k + d^{-\kappa}.
\end{aligned}$$

It remains to bound the second term on the right-hand side of (2.1). Once again, we use Proposition 2.2. By rotational invariance, for $i \in [2,k]$, the distribution of $(U_i - V_i)/\|U_i - V_i\|$ is uniform on S^{d-1} and therefore the distribution of

$$\mu\left(\left\{x : \langle x, U_i - V_i\rangle > \frac{\sqrt{2\pi}}{4\log(1/\epsilon)}\right\}\right)$$

is the same as that of

$$\mu\left(\left\{x : \langle x, W\rangle > \frac{\sqrt{2\pi}}{4\log(1/\epsilon)\|U_i - V_i\|}\right\}\right)$$

(if $\epsilon \le 1/2$), where W is uniformly distributed on S^{d-1}. By Lemma 2.4 below, with probability at least $1 - ke^{-ck}$,

$$\max_{i=1,\dots,k} \|U_i - V_i\| \le \sqrt{4k/d}.$$

Combining this with Proposition 2.2, we have that, with probability at least $1 - ke^{-ck} - ke^{-c\sqrt{d}}$,

$$\begin{aligned}
\sum_{i=2}^{k} \mu\left(\left\{x : \langle x, U_i - V_i\rangle > \frac{\sqrt{2\pi}}{4\log(1/\epsilon)}\right\}\right) &\le kd^{-\kappa} + k\mathbb{P}\left\{N > \frac{\sqrt{2\pi}}{4\log(1/\epsilon)}\sqrt{\frac{d}{4k}}\right\}\\
&\le kd^{-\kappa} + ke^{\frac{-d\pi}{64k\log(1/\epsilon)^2}}.
\end{aligned}$$

In the proof of Theorem 2.1, we have used the following two lemmas. The proof of the first lemma may be found in the appendix.

Lemma 2.3. *For the standard Gaussian cumulative distribution Φ function and $0 < \epsilon < e^{-2}$,*

$$\Phi^{-1}(\epsilon/2) - \Phi^{-1}(\epsilon/4) \ge \frac{\sqrt{2\pi}}{4\log(1/\epsilon)}.$$

Lemma 2.4. *For every $i = 1,\dots,k$, with probability at least $1 - e^{-ck}$,*

$$\|U_i - V_i\| \le \sqrt{\frac{4k}{d}},$$

where c is a universal constant, possibly different than the previous constant c.

Proof. Note that, since $\|R_i\|^2 = \langle U_i, R_i\rangle$,

$$\langle U_i, V_i\rangle = \frac{1-\langle U_i, R_i\rangle}{\|U_i - R_i\|} = \sqrt{1-\|R_i\|^2} \geq 1 - \|R_i\|^2$$

and therefore

$$\|U_i - V_i\|^2 = 2(1-\langle U_i, V_i\rangle) \leq 2\|R_i\|^2 = 2\sum_{j=1}^{i-1}\langle U_i, V_j\rangle^2 .$$

We may write $U_i = Z_i/\|Z_i\|$, where Z_i is a Gaussian vector in $\mathbb{R}^d$ with zero mean and identity covariance matrix. Since Z_i is independent of $V_1,\dots,V_{i-1}$ and the V_j are orthonormal, $\sum_{j=1}^{i-1}\langle Z_i, V_j\rangle^2$ is a χ^2 random variable with $i-1$ degrees of freedom. Thus, $\|U_i - V_i\|^2 = 2A/B$ is the doubled ratio of a $\chi^2(i-1)$ random variable A and a $\chi^2(d)$ random variable B (which are not independent). Then, with probability at least $1-e^{-ck}$,

$$\|U_i - V_i\|^2 \leq \frac{4k}{d} .$$

To see this, we may use standard tail bounds for the χ^2 distribution (see, e.g., [3]). Indeed,

$$\mathbb{P}\left\{\frac{A}{B} \geq \frac{4k}{d}\right\} \leq \mathbb{P}\{A \geq 2k\} + \mathbb{P}\{B \leq d/2\} .$$

Using $d \geq k$, both terms may be bounded by e^{-ck} using the inequality of Remark 2.11 in [3]. ∎

3. Estimating intermediate depth is costly.

In this section we prove that, even though the random Tukey depth is small for most points $x \in \mathbb{R}^d$ (according to the measure μ), whenever the depth $\overline{d}(x)$ of a point is not small, its random Tukey depth $\overline{D}_k(x)$ is close to $1/2$, unless k is exponentially large in d. This implies that for points whose depth is bounded away from $1/2$, the random Tukey depth is a poor approximation of $\overline{d}(x)$.

The main result of the section is the following theorem that immediately implies Corollary 1.3 stated in section 1.

Theorem 3.1. *Assume that μ is an isotropic log-concave measure on $\mathbb{R}^d$ and let $0<\gamma<1/2$. Let $x \in \mathbb{R}^d$ be such that $\overline{d}(x) = \gamma$ and let $\epsilon > 0$. Then*

$$\mathbb{P}\left\{\overline{D}_k(x) \leq \frac{1}{2} - C_\gamma \epsilon \log^2\left(\frac{1}{\epsilon}\right)\right\} \leq 2ke^{-(d-1)\epsilon^2/2} ,$$

where $C_\gamma > 0$ is a constant depending only on γ.

Proof. Without loss of generality, we may assume that the origin has maximal depth, that is, $\overline{d}(0) = \sup_{x\in\mathbb{R}^d}\overline{d}(x)$. Fix $x \in \mathbb{R}^d$ with $\overline{d}(x) = \gamma$, and note that $\overline{d}(0) \geq \gamma$.

The main tool of this proof is Lévy's isoperimetric inequality ([46], [31]; see also [30]). It states that if the random vector U is uniformly distributed on the sphere S^{d-1} and A is Borel-measurable set such that $\mathbb{P}\{U \in A\} \geq 1/2$, then for any $\epsilon > 0$,

$$\mathbb{P}\left\{\inf_{v\in A}\|U - v\| \geq \epsilon\right\} \leq 2e^{-(d-1)\epsilon^2/2} . \qquad (3.1)$$

Lévy's inequality may be used to prove concentration inequalities for smooth functions of the random vector U. Our goal is to prove that the measure $\mu(H(x,U))$ of the random halfspace $H(x,U)$ is concentrated around its median $1/2$.

In order to prove smoothness of the function $\mu(H(x,u))$ (as a function of $u \in S^{d-1}$), fix $u, v \in S^{d-1}$, $u \neq v$. Consider the two-dimensional cone spanned by the segments (x,u) and (x,v) defined by

$$C(x,u,v) = \left\{x + au + bv : \ a, b \in \mathbb{R}^+\right\} .$$

Denote by $\mathcal{H}$ the only two-dimensional affine space containing $x,\ x+u,\ x+v$.

We also define $P_{\mathcal{H}}$ as the orthogonal projection onto $\mathcal{H}$. Denoting by $\widetilde{\mu} = P_{\mathcal{H}} \# \mu$ the pushforward of μ by $P_{\mathcal{H}}$, and $\widetilde{H}(x,u) = P_{\mathcal{H}}(H(x,u))$, we have

$$\mu(H(x,u)) = \widetilde{\mu}\left(\widetilde{H}(x,u)\right).$$

Thus, after projecting on the plane $\mathcal{H}$, it suffices to control

$$\begin{aligned} |\mu(H(x,u)) - \mu(H(x,v))| &= \left|\widetilde{\mu}\left(\widetilde{H}(x,u)\right) - \widetilde{\mu}\left(\widetilde{H}(x,v)\right)\right| \\ &= \left|\widetilde{\mu}\left(C(x,u^\perp,v^\perp)\right) - \widetilde{\mu}\left(C(x,-u^\perp,-v^\perp)\right)\right| \\ &\leq \widetilde{\mu}\left(C(x,u^\perp,v^\perp)\right) + \widetilde{\mu}\left(C(x,-u^\perp,-v^\perp)\right), \end{aligned} \tag{3.2}$$

that is, the measure of two cones in a two-dimensional affine space. Here, given an arbitrary orientation to the plane $\mathcal{H}$, $u^\perp$ and $v^\perp$ are the only unit vectors orthogonal to u and v, respectively, in $\mathcal{H}$ such that $u^\perp$ and $v^\perp$ are rotated 90 degrees counterclockwise from u and v (see Figure 2).

Since the measure $\widetilde{\mu}$ is itself an isotropic log-concave measure (see [45, section 3], [41]), the problem becomes two-dimensional. Next, we show that neither $\|x\|$ nor $|m_v|$ are too large, where m_v denotes the median of the random variable $\langle X, v\rangle$. (Note that m_v is uniquely defined since $\langle X, v\rangle$ is log-concave and therefore has a unimodal density.)

In the appendix we gather some useful facts on log-concave densities. In particular, Lemma A.4 shows that any one-dimensional log-concave density with unit variance is upper bounded by an exponential function centered at the median of the log-concave density. Since $\overline{d}(0) \leq \overline{r}(0,v)$ for all $v \in S^{d-1}$, Lemma A.4 used with both v and $-v$ implies that there exist universal constants $c_1, c_2 > 0$ such that

$$\overline{d}(0) \leq c_1 e^{-c_2|m_v|}.$$

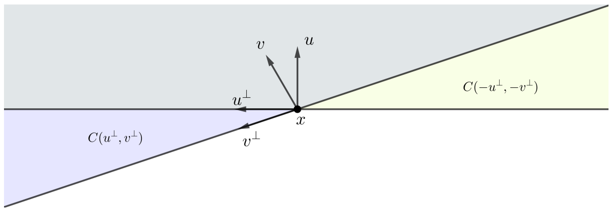

Figure 2. *Illustration of the cones $C(x,u^\perp,v^\perp)$ and $C(x,-u^\perp,-v^\perp)$.*

Since $\overline{d}(0) \geq \gamma$, we have

$$c_2|m_v| \leq \log(c_1/\gamma). \tag{3.3}$$

Moreover, since $\overline{d}(x) = \gamma$, the same argument leads to

$$\gamma \leq c_1 e^{-c_2|\langle x,v\rangle - m_v|}.$$

For $x \neq 0$, we use the above with $v = x/\|x\|$ and the inequality $|a-b| \geq |a| - |b|$ to yield

$$c_2\|x\| \leq \log(c_1/\gamma) + c_2|m_{x/\|x\|}|,$$

which, put together with (3.3), implies

$$\|x\| \leq c\log(c_1/\gamma) \tag{3.4}$$

for a positive constant c. In particular, $\|P_{\mathcal{H}}(x)\| \leq c\log(c_1/\gamma)$. We use this inequality to control the measure of halfspaces around x. Using Lemma A.4 we can uniformly upper bound the measure of every halfspace around the median by

$$\widetilde{\mu}\left(\widetilde{H}(m_v v - tv, v)\right) \leq c_1 e^{-c_2 t}$$

for $t \geq 0$. Now using (3.3) and (3.4), we may uniformly bound the measure of halfspaces around x. In particular, there exist constants $c_\gamma, c'_\gamma > 0$ such that for all $t \geq 0$ and $u \in S^1$,

$$\widetilde{\mu}\left(\widetilde{H}(x - tu, u)\right) \leq c_\gamma e^{-c'_\gamma t}. \tag{3.5}$$

Next we use the fact that an isotropic log-concave density in $\mathbb{R}^2$ is upper bounded by a universal constant. Obtaining upper bounds for log-concave densities is an important problem in high-dimensional geometry. In particular, the so-called *isotropic constant* of a log-concave density f is defined by

$$L_f := \sqrt{\sup_{x\in\mathbb{R}^d} f(x)}\sqrt[4]{\det(\mathrm{Cov}(X))},$$

where X is a random variable with densitiy f. It has a deep connection to Bourgain's "slicing problem" and the Kannan–Lovász–Simonovits conjecture (see, e.g., [35, 27]). Here we only need the simple fact that in a fixed dimension ($d = 2$ in our case) one has $\sup_f L_f \leq K$ for a constant K, where the supremum is taken over all possible log-concave density functions. For an isotropic log-concave density, $L_f = \sqrt{\sup f}$, so indeed there exists an universal constant K which upper bounds any log-concave isotropic density in dimension 2.

Now we are ready to derive upper bounds for the right-hand side of (3.2). To this end, we decompose the cone $C(x, u^\perp, v^\perp)$ into two parts. For any $t > 0$ we may write

$$\widetilde{\mu}\left(C(x,u^\perp,v^\perp)\right) \leq \widetilde{\mu}\left(C(x,u^\perp,v^\perp)\cap B(x,t)\right) + \widetilde{\mu}\left(C(x,u^\perp,v^\perp)\cap \widetilde{H}(x-tu,u)\right),$$

where $B(x,t)$ denotes the closed ball of radius t centered at x. Thus, from (3.5) and the upper bound on the density, we obtain

$$\widetilde{\mu}\left(C(x,u^{\perp},v^{\perp})\right) \le K\pi t^2\theta + c_\gamma e^{-c'_\gamma t},$$

where $\theta \in [0,\pi]$ denotes the angle formed by vectors u and v. We use a similar argument to get the saqme control on $C(x,-u^{\perp},-v^{\perp})$. Choosing $t = \log(1/\theta)/c'_\gamma$, (3.2) implies

$$|\mu(H(x,u)) - \mu(H(x,v))| \le C'_\gamma \theta \log^2\left(\frac{1}{\theta}\right)$$

for a constant C'_γ depending only on γ. Since $\theta \le \frac{\pi}{2}\|u-v\|$, we conclude that there exists a positive constant C_γ such that

$$|\mu(H(x,u)) - \mu(H(x,v))| \le C_\gamma \|u-v\| \log^2\left(\frac{1}{\|u-v\|}\right). \tag{3.6}$$

Now we are prepared to use Lévy's isoperimetric inequality. Choosing $A = \{v \in S^{d-1} : \mu(H(x,v)) \ge 1/2\}$, we clearly have $\mathbb{P}\{U \in A\} = 1/2$ and therefore by (3.1)

$$\mathbb{P}\left\{\inf_{v\in A}\|U-v\| \ge \epsilon\right\} \le 2e^{-(d-1)\epsilon^2/2}.$$

But for any $u \in S^{d-1}$ such that $\inf_{v\in A}\|u-v\| < \epsilon$, (3.6) implies that

$$\mu(H(x,u)) > \frac{1}{2} - C_\gamma \epsilon \log^2\left(\frac{1}{\epsilon}\right),$$

so

$$\mathbb{P}\left\{\mu(H(x,U)) \le \frac{1}{2} - C_\gamma\epsilon\log^2\left(\frac{1}{\epsilon}\right)\right\} \le 2e^{-(d-1)\epsilon^2/2}.$$

Since $\overline{D}_k(x) = \min_{i=1,\dots,k}\mu(H(x,U_i))$ for $U_1,\dots,U_k$ independently sampled uniformly on S^{d-1}, the union bound yields

$$\mathbb{P}\left\{\overline{D}_k(x) \le \frac{1}{2} - C_\gamma\epsilon\log^2\left(\frac{1}{\epsilon}\right)\right\} \le 2ke^{-(d-1)\epsilon^2/2},$$

concluding the proof. ∎

4. Detection and localization of Tukey's median.

As explained in the introduction, a measure μ is called halfspace symmetric if there exists a point $m \in \mathbb{R}^d$ with $\overline{d}(m) = 1/2$. Such a point is necessarily unique if μ has a density. Since it maximizes Tukey's depth, it is the Tukey median. Clearly, for all $k \ge 1$, the random Tukey depth of the Tukey median equals $\overline{D}_k(m) = 1/2$. For $k > d$, if $\overline{D}_k(x) = 1/2$, then x is almost surely the Tukey median, and therefore $1/2$ is trivially an exact estimate of the Tukey depth of m. Here we show that, for any positive γ bounded by some constant, already for values of k that are of the order of $d\log d$, all points that are at least a distance of order $\gamma\sqrt{d}$ away from m have a random Tukey depth less than $1/2-\gamma$, with high probability. This result implies that the Tukey median of isotropic log-concave, halfspace symmetric distributions are efficiently estimated by the random Tukey median, as stated in Corollary 1.4.

Theorem 4.1. *Assume that μ is an isotropic log-concave, halfspace symmetric measure on $\mathbb{R}^d$ and let m be the Tukey median. Let $\delta > 0$ and let $\gamma, r > 0$ be such that $r \geq 8\sqrt{2}e^4\gamma$ and $r \leq \min(e^{-4}/3, 8e^4\gamma\sqrt{d/2})$. There exists a universal constant $C > 0$ such that if*

$$k \geq C\left(d\log\frac{r}{\gamma} + \log(1/\delta)\right)\frac{\gamma\sqrt{d}}{r}e^{C\gamma^2 d/r^2},$$

then

$$\mathbb{P}\left\{\sup_{x\in\mathbb{R}^d:\|x-m\|\geq r}\overline{D}_k(x) \geq \frac{1}{2} - \gamma\right\} \leq \delta.$$

In particular, by taking $r = 8e^4\gamma\sqrt{d/2}$, there exist universal constants $c, C > 0$ such that for all $\gamma \leq c$, if

$$k \geq C\left(d\log d + \log(1/\delta)\right),$$

then

$$\mathbb{P}\left\{\sup_{x\in\mathbb{R}^d:\|x-m\|\geq C\gamma\sqrt{d}}\overline{D}_k(x) \geq \frac{1}{2} - \gamma\right\} \leq \delta.$$

Proof. Without loss of generality, we may assume that $m = 0$, that is, $\overline{d}(0) = 1/2$.

The outline of the proof is as follows. First, we show that for a fixed $x \in \mathbb{R}^d$ of norm r, we have $\overline{D}_k(x) \leq \frac{1}{2} - 2\gamma$ with high probability.

Then we use an ϵ-net argument to extend the control to the sphere $r \cdot S^{d-1}$. To this end, we need to establish a certain regularity of the function $x \mapsto \overline{D}_k(x)$. We then use a monotonicity argument to extend the control to all points outside of the ball of radius r.

Recall that f denotes the density of the measure μ and the random vector X has distribution μ. For any direction $u \in S^{d-1}$, we denote by $\Phi_u(t) = \mathbb{P}\{\langle X, u\rangle \leq t\}$ the cumulative distribution function of the projection of X in direction u.

Fix $x \in r \cdot S^{d-1}$. Since $\overline{D}_k(x) = \min_{i=1,\dots,k}\Phi_{U_i}(\langle x, U_i\rangle)$,

$$\mathbb{P}\left\{\overline{D}_k(x) \geq \frac{1}{2} - 2\gamma\right\} = \mathbb{P}\left\{\Phi_U(\langle x, U\rangle) \geq \frac{1}{2} - 2\gamma\right\}^k. \tag{4.1}$$

Next we bound the probability on the right-hand side. Since $\overline{d}(0) = 1/2$, for all $u \in S^{d-1}$, $\Phi_u(0) = 1/2$. Clearly, the function $t \mapsto \Phi_u(t)$ is nondecreasing, as it is a cumulative distribution function. Since projections of an isotropic log-concave measure are also log-concave and isotropic (see [45, section 3] and [41]). Lemma A.2 in the appendix implies that for all $t \in [-e^{-4}/3, e^{-4}/3]$,

$$\Phi_u'(t) \geq e^{-4}/4,$$

and therefore, for all such t, we have

$$\left|\Phi_u(t) - \frac{1}{2}\right| \geq \frac{e^{-4}}{4}|t|.$$

Since $\|x\| = r \le e^{-4}/3$, we have $|\langle x, U_i\rangle| \le e^{-4}/3$ and hence

$$\mathbb{P}\left\{\Phi_U(\langle x, U\rangle \ge \frac{1}{2} - 2\gamma\right\} \le \mathbb{P}\left\{\frac{1}{4e^4}\langle x, U\rangle \ge -2\gamma\right\}$$
$$= 1 - \mathbb{P}\left\{\langle \frac{1}{r}x, U\rangle \ge \frac{8e^4\gamma}{r}\right\}.$$

Since $\|\frac{1}{r}x\| = 1$, the probability on the right-hand side corresponds to the (normalized) measure of a spherical cap of height $h = 8e^4\gamma/r$. Thus, we may further bound the expression on the right-hand side by applying a lower bound for the measure of a spherical cap. In [6, Lemma 2.1b], such a lower bound is provided for $\sqrt{2/d} \le h \le 1$, which is guaranteed by our condition on r. We obtain

$$\mathbb{P}\left\{\Phi_U(\langle x, U\rangle \ge \frac{1}{2} - 2\gamma\right\} \le 1 - \frac{1}{6h\sqrt{d}}(1-h^2)^{\frac{d-1}{2}}.$$

Hence, by (4.1) we have that for any x with $\|x\| = r \in [8\sqrt{2}e^4\gamma, e^{-4}/3]$,

$$\begin{aligned} \mathbb{P}\left\{\overline{D}_k(x) \ge \frac{1}{2} - 2\gamma\right\} &\le \left(1 - \frac{1}{6h\sqrt{d}}(1-h^2)^{\frac{d-1}{2}}\right)^k \\ &\le \left(1 - \frac{1}{6h\sqrt{d}}e^{-h^2(d-1)}\right)^k \quad (\text{since } 1-x \ge e^{-2x} \text{ for } x \in (0,1/2)) \\ &\le \exp\left(-\frac{k}{6h\sqrt{d}}e^{-h^2(d-1)}\right) \quad (\text{since } 1-x \le e^{-x} \text{ for } x \ge 0). \end{aligned} \tag{4.2}$$

It remains to extend this inequality for a fixed x to a uniform control over all $\|x\| \ge r$. To this end, we need to establish the regularity of the function $x \mapsto \overline{D}_k(x)$.

Since $\|u\| = 1$, the mapping $x \mapsto \langle x, u\rangle$ is 1-Lipschitz. Φ_u is the cumulative distribution function of an isotropic, one-dimensional, log-concave measure, and therefore its derivative is a log-concave density with variance 1. As stipulated in Lemma A.3 in the appendix, such a density is upper bounded by $e^{7.1}$. Hence, for any $u \in S^{d-1}$, $x \mapsto \Phi_u(\langle x, u\rangle)$ is $e^{7.1}$-Lipschitz. Furthermore, since the minimum of Lipschitz functions is Lipschitz, $x \mapsto \overline{D}_k(x)$ is also $e^{7.1}$-Lipschitz.

For $\epsilon > 0$, an ϵ-net of the sphere $r \cdot S^{d-1}$ is a subset N of $r \cdot S^{d-1}$ of minimal size such that for all $x \in r \cdot S^{d-1}$ there exists $y \in N$ with $\|x - y\| \le \epsilon$. It is well known (see, e.g., [36]) that for all $\epsilon > 0$, $r \cdot S^{d-1}$ has an ϵ-net N_ϵ of size at most $|N_\epsilon| \le (\frac{2r}{\epsilon} + 1)^d$. Using the fact that $\overline{D}_k(x)$ is $e^{7.1}$-Lipschitz, by taking $\epsilon = e^{-7.1}\gamma$, using (4.2) and the union bound, we have

$$\mathbb{P}\left\{\sup_{x \in \mathbb{R}^d : \|x\| = r} \overline{D}_k(x) \ge \frac{1}{2} - \gamma\right\} \le \left(\frac{2re^{7.1}}{\gamma} + 1\right)^d \exp\left(-\frac{k}{6h\sqrt{d}}e^{-h^2(d-1)}\right). \tag{4.3}$$

It remains to extend the inequality to include all points outside $r \cdot S^{d-1}$. To this end, it suffices to show that for any $a \ge 1$,

$$\overline{D}_k(ax) \le \overline{D}_k(x).$$

To see this, note that the deepest point 0 has depth 1/2, so every closed halfspace with 0 on its boundary has measure 1/2. Hence, $\mu(H(x,u)) < 1/2$ if and only if $0 \notin H(x,u)$, which is equivalent to $\langle x,u\rangle < 0$. In the event

$$\left\{ \sup_{x\in\mathbb{R}^d:\|x\|=r} \overline{D}_k(x) < \frac{1}{2} - \gamma \right\},$$

for every $x \in r \cdot S^{d-1}$ there exists an $i \in [k]$ such that $\mu(H(x,U_i)) < 1/2$. This implies that for such an i, $\langle x,U_i\rangle < 0$, so for any $a \geq 1$, we have $\langle ax,U_i\rangle \leq \langle x,U_i\rangle$. Since $\mu(H(x,U_i)) = \Phi_{U_i}(\langle x,U_i\rangle)$ and Φ_{U_i} is nondecreasing, we have

$$\mu(H(ax,U_i)) \leq \mu(H(x,U_i)),$$

leading to $\overline{D}_k(ax) \leq \overline{D}_k(x)$ as desired. This extends (4.3) to the inequality

$$\mathbb{P}\left\{ \sup_{x\in\mathbb{R}^d:\|x\|\geq r} \overline{D}_k(x) \geq \frac{1}{2} - \gamma \right\} \leq \left(\frac{2re^{7.1}}{\gamma} + 1 \right)^d \exp\left(-\frac{k}{6h\sqrt{d}} e^{-h^2(d-1)} \right).$$

Recalling that $h = 8e^4\gamma/r$ and that r is bounded, this implies the announced statement. ∎

Appendix A. In this section, we compile several properties of one-dimensional, isotropic, log-concave densities. For a survey on log-concave densities, see [44]. Before stating our results, we briefly explain why we only prove results for continuous log-concave densities and why the results directly extend to noncontinuous log-concave probability densities. If a function g is convex on $\mathbb{R}$, then there exists $a, b \in \mathbb{R} \cup \{-\infty, +\infty\}$ such that g is continuous on (a,b) and $g = +\infty$ on $(-\infty, a) \cup (b, +\infty)$. But, for any $\epsilon > 0$, there exists a continuous convex function $\bar{g}$, which coincides with g on $(a+\epsilon, b-\epsilon)$, and that is such that the measure of density $e^{-\bar{g}(t)}$ has total mass and variance in $(1-\epsilon, 1+\epsilon)$. Using this fact alone is enough to directly adapt the following proofs to any log-concave isotropic probability density.

A.1. Lower bounds for log-concave densities.

Lemma A.1. *Let $f(t) = e^{-g(t)}$ be a log-concave probability density on $\mathbb{R}$ having variance* 1 *and let m denote its (unique) median. Then*

$$e^{-g(m)} \geq \frac{e^{-4}}{2}.$$

Proof. Without loss of generality, we may assume that $m = 0$ and g takes its minimum on $\mathbb{R}^-$. Following the remark at the top of the appendix, we also assume that g is continuous.

If $g(0) \leq 0$, the result is obvious, so suppose $g(0) > 0$. Since g is convex, by taking its minimum on $\mathbb{R}^-$ it is nondecreasing on $\mathbb{R}^+$. By continuity, there exists $L > 0$ such that $g(L) = 2g(0)$.

From the convexity of g we have that $g'(L) \geq \frac{g(0)}{L}$, and therefore for all $t \geq L$,

$$g(t) \geq g(L) + \frac{g(0)}{L}(t-L) \geq \frac{g(0)}{L}t. \tag{A.1}$$

Since $\int_{\mathbb{R}} f(x)dx = 1$ and 0 is the median,

$$\frac{1}{2} = \int_0^L e^{-g(t)}dt + \int_L^\infty e^{-g(t)}dt\,.$$

Using (A.1),

$$\int_L^\infty e^{-g(t)}dt \le \int_L^\infty e^{-g(0)t/L}dt = \frac{L}{g(0)}e^{-g(0)}\,.$$

Because g is nondecreasing on $\mathbb{R}^+$,

$$\int_0^L e^{-g(t)}dt \le e^{-g(0)}L\,,$$

leading to

$$\frac{1}{2} \le \frac{L}{g(0)}e^{-g(0)} + e^{-g(0)}L = e^{-g(0)}L\left(1 + \frac{1}{g(0)}\right)\,. \tag{A.2}$$

Now we use the fact that the variance equals 1, that is,

$$1 = \int_{-\infty}^{+\infty} t^2 e^{-g(t)}dt - \left(\int_{-\infty}^{\infty} te^{-g(t)}dt\right)^2\,.$$

Since the difference between the expectation and the median of any distribution is at most the standard deviation, we have $|\int_{-\infty}^{\infty} te^{-g(t)}dt| \le 1$. Moreover, since g is increasing on $\mathbb{R}^+$, for all $t \in [0, L]$ we have $g(t) \le 2g(0)$, and therefore $1 \ge \int_0^\infty t^2 e^{-g(t)}dt - 1$ implies

$$2 \ge \int_0^L t^2 e^{-2g(0)}dt = \frac{L^3}{3}e^{-2g(0)}\,. \tag{A.3}$$

From (A.2) we have

$$e^{-2g(0)}L^3 e^{-g(0)}\left(1 + \frac{1}{g(0)}\right)^3 \ge \frac{1}{8}\,.$$

Hence, by plugging the inequality into (A.3), we get

$$e^{-g(0)}\left(1 + \frac{1}{g(0)}\right)^3 \ge \frac{1}{48}\,. \tag{A.4}$$

Note that the function $h : t \mapsto e^{-t}(1 + \frac{1}{t})^3$ is nonincreasing on $\mathbb{R}^+$. To conclude, observe the following:

- If $g(0) \le 4.5$, then $e^{-g(0)} \ge \frac{e^{-4}}{2}$.
- If $g(0) > 4.5$, then

  $$h(g(0)) < \frac{1}{48},$$

  contradicting (A.4). ∎

The next result shows that an isotropic log-concave density is in fact bounded from below by a universal constant on an interval around the median.

Lemma A.2. *Let $f(t)=e^{-g(t)}$ be a log-concave probability density on $\mathbb{R}$ having variance* 1 *and median $m=0$. Then for all $t\in[-\frac{1}{3e^4},\frac{1}{3e^4}]$,*

$$f(t)\geq\frac{1}{4e^4}\,.$$

Proof. Denote $\alpha=1/(3e^4)$ and suppose that there exists $t\in[-\alpha,\alpha]$ such that $f(t)<1/(4e^4)$. Since log-concave densities are unimodal, on $[-\alpha,\alpha]$ the density f reaches its minimum on an endpoint of the interval. Without any loss of generality, assume that

$$e^{-g(\alpha)}<\frac{1}{4e^4}\,,$$

that is,

$$g(\alpha)>4+\log(4)\,.$$

By the convexity of g, for all $t\geq\alpha$,

$$g(t)\geq\frac{g(\alpha)-g(0)}{\alpha}(t-\alpha)+g(\alpha)\,.$$

Since by Lemma A.1, $g(0)\leq 4+\log(2)$, we get that for all $t\geq\alpha$

$$g(t)\geq\frac{\log(2)}{\alpha}(t-\alpha)+\log(4e^4)\,.$$

It follows that

$$\int_\alpha^\infty e^{-g(t)}dt\leq\frac{1}{4e^4}\cdot\frac{\alpha}{\log(2)}\,.$$

We also prove in Lemma A.3 below that $\sup_{t\in\mathbb{R}}e^{-g(t)}\leq e^4$, so

$$\int_0^\alpha e^{-g(t)}dt\leq\alpha e^4\,.$$

Using the fact that 0 is the median, we get

$$1=\frac{1}{2}+\int_{\mathbb{R}^+}e^{-g(t)}dt\leq\frac{1}{2}+\alpha\left(e^4+\frac{1}{4e^4}\frac{1}{\log(2)}\right)\,.$$

But

$$\alpha\left(e^4+\frac{1}{4e^4}\frac{1}{\log(2)}\right)<\frac{1}{2}\,,$$

which is a contradiction. This concludes the proof. ■

A.2. Upper bounds for log-concave densities.

Lemma A.3. *Let $f(t)=e^{-g(t)}$ be a log-concave probability density on $\mathbb{R}$ having variance* 1*. Then*

$$\sup_{t\in\mathbb{R}}e^{-g(t)}\leq e^{7.1}.$$

Proof. Without loss of generality, we may assume that $g(0) = \inf_{t\in\mathbb{R}} g(t)$ and $\int_0^\infty t^2 e^{-g(t)}dt \geq 1/2$. Following the remark at the top of the appendix, we also assume that g is continuous.

First note that if $g(0) \geq 0$, then there's nothing to prove, so suppose that $g(0) < 0$. By the intermediate value theorem there exists $L > 0$ such that $g(L/2) = g(0)/2$. Since g is convex and $\int_{\mathbb{R}} \exp(-g(t))dt = 1$, we have

$$\frac{L}{2} e^{-g(0)/2} \leq 1\,. \tag{A.5}$$

Since g has a nondecreasing derivative, for all $t \geq L/2$,

$$g'(t) \geq -\frac{g(0)}{2} \cdot \frac{2}{L} = -\frac{g(0)}{L}\,.$$

Then for all $t \geq L/2$, $g(t) \geq g(L/2) - \frac{g(0)}{L}(t - L/2) \geq g(0) - \frac{g(0)}{L}(t-L)$, which implies

$$\int_{L/2}^\infty t^2 e^{-g(t)}dt \leq e^{-2g(0)} \int_{L/2}^\infty t^2 e^{\frac{g(0)}{L}t}dt\,.$$

Since for $c > 0$

$$\int_{L/2}^\infty t^2 e^{-ct}dt = \left(\frac{L^2}{4c} + \frac{L}{c^2} + \frac{2}{c^3}\right) e^{-cL/2},$$

taking $c = -g(0)/L$, which is positive,

$$\int_{L/2}^\infty t^2 e^{-g(t)}dt \; \leq \left(\frac{-L^3}{4g(0)} + \frac{L^3}{g(0)^2} - \frac{2L^3}{g(0)^3}\right) e^{-3g(0)/2}\,. \tag{A.6}$$

Next we establish a lower bound for $\int_{L/2}^\infty t^2 e^{-g(t)}dt$. The fact that the second moment on $\mathbb{R}^+$ is greater than $1/2$ implies

$$\int_{L/2}^\infty t^2 e^{-g(t)}dt \geq \frac{1}{2} - \int_0^{L/2} t^2 e^{-g(t)}dt\,.$$

It is immediate from the fact that g reaches its minimum in 0 that

$$\int_0^{L/2} t^2 e^{-g(t)}dt \leq \frac{L^3}{24} e^{-g(0)}\,,$$

leading to

$$\int_{L/2}^\infty t^2 e^{-g(t)}dt \geq \frac{1}{2} - \frac{L^3}{24} e^{-g(0)}\,. \tag{A.7}$$

Comparing (A.6) and (A.7), we obtain

$$\frac{1}{2} - \frac{L^3}{24} e^{-g(0)} \leq L^3 \left(\frac{-1}{4g(0)} + \frac{1}{g(0)^2} - \frac{2}{g(0)^3}\right) e^{-3g(0)/2}\,,$$

leading to

$$\frac{1}{2} \leq L^3 \left(\frac{e^{g(0)/2}}{24} - \frac{1}{4g(0)} + \frac{1}{g(0)^2} - \frac{2}{g(0)^3} \right) e^{-3g(0)/2} . \tag{A.8}$$

From (A.5) we have $L^3 e^{-3g(0)/2} \leq 8$, which, plugged into (A.8), yields

$$1 \leq 16 \left(\frac{e^{g(0)/2}}{24} - \frac{1}{4g(0)} + \frac{1}{g(0)^2} - \frac{2}{g(0)^3} \right) .$$

And so

$$1 \leq \frac{2}{3} e^{g(0)/2} - \frac{4}{g(0)} + \frac{16}{g(0)^2} - \frac{32}{g(0)^3} . \tag{A.9}$$

The function $h : t \mapsto \frac{2}{3}e^{t/2} - \frac{4}{t} + \frac{16}{t^2} - \frac{32}{t^3}$ is nondecreasing on $\mathbb{R}^-$. To conclude the proof, note that if $g(0) \geq -7.1$, then $e^{-g(0)} \leq e^{7.1}$. Otherwise, if $g(0) < -7.1$, then, since h is nondecreasing,

$$h(g(0)) \leq h(-7.1) \leq 0.99 < 1 ,$$

which contradicts (A.9). ■

It is known (see, e.g., [12]) that for any log-concave density f on $\mathbb{R}^d$, there exist positive constants α, β such that $f(x) \leq e^{-\alpha\|x\|+\beta}$ for all $x \in \mathbb{R}^d$. The next lemma shows that for isotropic log-concave densities on $\mathbb{R}$ with median at 0, one may choose α and β independently of f.

Lemma A.4. *Let $f(t) = e^{-g(t)}$ be a log-concave probability density on $\mathbb{R}$ having variance 1 and median $m = 0$. Then there exist universal constants $\alpha, \beta > 0$ such that for all $t \in \mathbb{R}$,*

$$f(t) \leq \alpha e^{-\beta|t|} .$$

Proof. By Lemma A.1 we have $e^{-g(0)} \geq e^{-4}/2$. The log-concavity of the density implies that on any given interval, the minimum is reached at one of the endpoints of the interval. Thus,

$$\int_0^{2e^4} e^{-g(t)} dt \geq 2e^4 \min\left(e^{-g(2e^4)}, e^{-4}/2\right) .$$

Since 0 is the median of f, $2e^4 \min(e^{-g(2e^4)}, e^{-4}/2) \leq 1/2$. Thus,

$$e^{-g(2e^4)} \leq \frac{e^{-4}}{4} . \tag{A.10}$$

A mirror argument proves that $e^{-g(-2e^4)} \leq \frac{e^{-4}}{4}$. By Lemma A.1, $g(0) \leq \log(2) + 4$ and (A.10) implies $g(2e^4) \geq \log(4) + 4$. Using the convexity of g yields that for all $t \geq 2e^4$,

$$g(t) \geq 4 + \log(4) + (t - 2e^4)\frac{\log(2)}{2e^4} ,$$

so, using Lemma A.3, which states that $g(0) \geq -7.1$, for all $t \in \mathbb{R}^+$,

$$g(t) \geq -7.1 + (t - 2e^4)\frac{\log(2)}{2e^4} .$$

A identical argument on $\mathbb{R}^-$ concludes the proof of the Lemma. ■

A.3. Proof of Lemma 1.1.

Proof. To prove the first inequality, observe that

$$\begin{aligned}\sup_{x\in\mathbb{R}^d}|\bar{d}(x)-d_n(x)| &= \sup_{x\in\mathbb{R}^d}\left|\inf_{u\in S^{d-1}}\mu(H(x,u)) - \inf_{u\in S^{d-1}}\frac{1}{n}\sum_{i=1}^n \mathbb{1}_{X_i\in H(x,u)}\right| \\ &\le \sup_{x\in\mathbb{R}^d}\sup_{u\in S^{d-1}}\left|\mu(H(x,u)) - \frac{1}{n}\sum_{i=1}^n \mathbb{1}_{X_i\in H(x,u)}\right| .\end{aligned}$$

The first inequality of the lemma follows from the Vapnik–Chervonenkis inequality (see, e.g., [13, Theorem 12.5]) and the fact that the VC dimension of the class of all halfspaces $H(x,u)$ equals $d+1$.

The second inequality is proved similarly, combining it with a simple union bound that gives a better bound when $\log(k) \ll d$. ∎

A.4. Proof of Lemma 2.3.

Proof. Because Φ is convex, increasing on $\mathbb{R}^-$, and $\Phi(\mathbb{R}^-) = [0,1/2]$, then Φ^{-1} is concave on $[0,1/2]$. Thus

$$\frac{\Phi^{-1}(\epsilon/2) - \Phi^{-1}(\epsilon/4)}{\epsilon/4} \ge (\Phi^{-1})'(\epsilon/2) .$$

Using the fact that $(\Phi^{-1})' = 1/(\Phi'(\Phi^{-1}))$ and $\Phi'(t) = \frac{1}{\sqrt{2\pi}}e^{-t^2/2}$,

$$\Phi^{-1}(\epsilon/2) - \Phi^{-1}(\epsilon/4) \ge \frac{\epsilon}{4}\sqrt{2\pi}e^{\Phi^{-1}(\epsilon/2)^2/2} . \tag{A.11}$$

By Gordon's inequality for the Mills' ratio [22], for $t \le 0$,

$$\Phi(t) \ge -\frac{1}{\sqrt{2\pi}}\frac{t}{t^2+1}e^{-t^2/2} ,$$

and therefore

$$t \ge \Phi^{-1}\left(-\frac{1}{\sqrt{2\pi}}\frac{t}{t^2+1}e^{-t^2/2}\right) ,$$

leading, for $t < -1$, to

$$t \ge \Phi^{-1}\left(-\frac{e^{-t^2/2}}{10t}\right) . \tag{A.12}$$

Choosing $t_\epsilon = -\sqrt{2\log(1/\epsilon)}\sqrt{1-\frac{\log\log(1/\epsilon)}{\log(1/\epsilon)}}$ for $\epsilon < e^{-2}$ and noting that

$$-\frac{e^{-t_\epsilon^2/2}}{10t_\epsilon} \ge \epsilon/2,$$

(A.12) implies that

$$-\sqrt{2\log(1/\epsilon)}\sqrt{1-\frac{\log\log(1/\epsilon)}{\log(1/\epsilon)}} \geq \Phi^{-1}(\epsilon/2)\,.$$

Plugging this inequality into (A.11),

$$\Phi^{-1}(\epsilon/2)-\Phi^{-1}(\epsilon/4) \geq \frac{\sqrt{2\pi}}{4\log(1/\epsilon)}\,,$$

proving Lemma (2.3). ■

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