

**Due date: March 25, 2025**

**Problem 1: High Dimensional Cubes? Spheres!** As you may have known, high-dimensional geometry is *very* weird. Many phenomena that we take for granted break down as we move into higher dimensional spaces.

- (i) Consider the difference between the  $d$ -dimensional unit cube  $C^d = [-1/2, 1/2]^d$  and the  $d$ -dimensional unit ball  $B^d = \{x \in \mathbb{R}^d : \|x\|_2 \leq 1\}$ . Show by example that for small  $d$ ,  $C^d$  is entirely contained in  $B^d$ , but as  $d$  increases, argue that the vertices of  $C^d$  lie far outside the unit ball  $B^d$ . Part (ii) shows things are much crazier than just this!
- (ii) The *Weak Law of Large Numbers* says if you have independent and identically distributed (i.i.d.) random variables  $X_1, X_2, \dots$ , then as  $n \rightarrow \infty$ , the mean  $Y_n = \sum_{i=1}^n X_i/n$  converges to  $\mathbb{E}X_1$ , and the larger  $n$  is, the more likely  $Y_n$  will be *close* (this is formally called *convergence in probability*) to  $\mathbb{E}X_1$ . For example if you flip a fair coin 10 times, you may find it unsurprising to get  $0.4 \cdot 10 = 4$  heads. However, if you flip the coin 1000 times and observe only  $0.4 \cdot 1000 = 400$  heads, you may start to think that the coin is biased, even though the fraction of heads remains 0.4.

Consider randomly sampling a point  $X = (X_1, \dots, X_n)$  in  $C^d$  by sampling each  $X_i$  uniformly from  $[-1/2, 1/2]$ . Then  $\mathbb{E}X_i^2 = \int_{-0.5}^{0.5} x^2 dx = 1/12$ . What do you suspect

$$S_n = \sqrt{X_1^2 + \dots + X_n^2}$$

to converge to, as  $n \rightarrow \infty$ ? How large is this value compared to the radius of  $B^d$ ? Argue (informally) that in high-dimensions, (i) the unit cube is essentially *almost* just a sphere (state its radius) and (ii) *almost all* volume of  $C^d$  lies outside of  $B^d$ .

**Solution.**

- (i) Clearly, when  $d = 1$ , the line segment  $[-1/2, 1/2]$  (the 1-dimensional unit cube) is entirely contained in  $[-1, 1]$  (the 1-dimensional unit ball). Likewise,  $[-1/2, 1/2]^2$  is entirely contained in the 2-D unit ball  $\{(x, y) : \sqrt{x^2 + y^2} = 1\}$ .

However, consider what happens when  $d$  is large: one of the vertices is of form  $(1/2, 1/2, \dots, 1/2)$ , whose Euclidean distance to the origin is  $\sqrt{(1/2)^2 + \dots + (1/2)^2} = \sqrt{d}/2$ . For  $d > 4$ ,  $\sqrt{d}/2 > 1$ , and so this vertex lies outside  $B^d$ . For a drastic example, consider  $d = 100$ , in which case each vertex of the  $d$ -cube is of distance  $\sqrt{100}/2 = 5$  from the origin — five times the radius of the unit ball!

- (ii) The *Weak Law of Large Numbers* (WLLN) states that if each  $X_i^2$  satisfies  $\mathbb{E}X_i^2 = 1/12$ , then  $\sum_{i=1}^n X_i^2/n$  converges (formally, *converges in probability*, a special notion of convergence which you can disregard for the purpose of this problem) to  $1/12$  as  $n \rightarrow \infty$ . Hence  $\sum_{i=1}^n X_i^2 \rightarrow n/12$ , and  $S_n \rightarrow \sqrt{n}/\sqrt{12}$ .

The intuition (of *convergence in probability*) is that when  $n$  is *very* large, the distribution of  $S_n$  is highly concentrated around  $\sqrt{n}/\sqrt{12}$ . As you can see, this is an ever-growing

quantity, so we obtain two results: (i) most masses of a high-dimensional cube essentially concentrates around a thin spherical shell, and (ii) the radius of this spherical shell is much larger than 1, the radius of the unit ball, as  $n$  gets large.

*To prove this result rigorously, you'll need knowledge in (graduate-level) real analysis and measure theory (MATH 631), and/or measure-theoretic probability theory (MATH 641). This example is taken (informally) from Example 2.2.5 of the famous Durrett PTE5. I thought it'd be a cool part of the HW :3*

**Problem 2:** Let  $X$  be a matrix. Describe a relationship between the eigenvalues and singular values of  $A = X^T X$ .

**Solution.** From SVD, one can write  $X = U\Sigma V^T$ . Since  $U, V$  are orthogonal (orthonormal) matrices and  $\Sigma$  diagonal,

$$(X^T X) = (U\Sigma V^T)(U\Sigma V^T) = V\Sigma^T U^T U\Sigma V^T = V(\Sigma^T \Sigma)V^T = V\Sigma^2 V^T. \quad (*)$$

On the other hand, since  $A$  is symmetric positive semidefinite, its eigen-decomposition also admits  $A = (V')^T \Lambda (V')$  where  $(V')$  is orthogonal and  $\Lambda$  diagonal. Relating this with (\*),  $\Lambda = \Sigma^2$ , so for each  $i$ ,  $\lambda_i = \sigma_i^2$ .

**Problem 3:** Let  $S$  be a set of  $n$  points in  $\mathbb{R}^2$ . A point  $x \in \mathbb{R}^2$  is called a *center point* if any half-plane containing  $x$  contains at least  $\lfloor n/3 \rfloor$  points of  $S$ . It is known that a center point always exists.

- (i) Describe an  $O(n^2 \log n)$ -time algorithm to compute a center point of  $S$ . You can assume that the intersection of  $m$  halfplanes can be computed in  $O(m \log m)$  time. (In fact, the run time can be improved to  $O(n^2)$ .)
- (ii) Describe an  $O(n)$  time randomized algorithm that compute an approximate center point  $\tilde{x}$  of  $S$  with probability at least  $1/2$ , i.e., any halfplane containing  $\tilde{x}$  contains at least  $n/4$  points of  $S$ .

**Solution.**

- (i) We consider half-planes defined by lines that go through any two points in  $S$ . Some half-planes defined as such split  $S$  “nicely” into two roughly equal subsets and they impose no constraints on where a center point can be. However, if some half-plane splits  $S$  into two subsets where one subset has  $< \lfloor n/3 \rfloor$  points, then we know that *any* center point *must* lie on the other half.

Therefore, a high-level algorithm can be defined as follows:

- Iterate through all half-planes defined by two points in  $S$ .
- Initialize constraints  $\mathcal{H} = \{\}$ .
- For each of them, check if either side has  $< \lfloor n/3 \rfloor$  points. If so, add the *other* side  $H$  to  $\mathcal{H}$ .

- Return any point  $p \in \bigcap_{H \in \mathcal{H}} H$ .

Such a point is guaranteed to exist by the known result on existence of a center point.

The algorithm can be efficiently implemented using angular sweep. We first maintain the pairwise angle between any  $s_1, s_2 \in S$ , and for each point  $s$ , sort all other points by their relative angles to  $s$ . This step takes  $\mathcal{O}(n^2 \log n)$  and allows us to efficiently collect all points on a certain side of a given half-plane, as the task now reduces to checking whether the relative angle falls within a certain 180-degree range.

There are  $n(n-1)/2 = \mathcal{O}(n^2)$  pairs of points in  $S$ , leading to at most  $\mathcal{O}(n^2)$  half-planes added to  $\mathcal{H}$ . Computing their intersection by assumption takes  $\mathcal{O}(n^2 \log(n^2)) = \mathcal{O}(n^2 \log n)$  time, as desired.

(ii) (From Nick Maroulis) We use  $\epsilon$ -approximation. The algorithm is as follows:

- Choose a subset  $R \subset S$  of a suitable constant size  $c$ ;
- Compute the center point  $\hat{x}$  of  $R$  by brute force or by (i);
- Return  $\hat{x}$ .

Any half-plane containing a true center point contains  $n/3$  points of  $S$ . Our goal here is to find a point where any half-plan containing  $\hat{x}$  contains at least  $n/4$  points. Hence we allow the sampling to have an error of  $n/12$ . In other words, we need

$$\left| \frac{|H \cap R|}{|R|} - \frac{|H \cap S|}{|S|} \right| < \frac{1}{12} \quad \text{for all half-planes } H.$$

Recall the  $\epsilon$ -approximation theorem. We apply it here with  $\delta = 1/2$  and  $\epsilon = 1/12$ . Observe there is no dependency on  $n = |S|$ , but rather on the VC-dimension of the collection of half-planes in  $\mathbb{R}^2$ , which is constantly 3. So, without going over the  $\epsilon - \delta$  notations, there will be a sufficiently large *constant* size  $c$  that achieves our objective.