

# Filling in the Gaps in Raphael's Idea

## 1 Preliminaries

We consider the usual Hilbert finite normed vector space  $(\mathbb{R}^n, \ell_2)$ ,  $n \in \mathbb{N}_{>0}$ ,  $\ell_2$  the classical euclidean norm. We denote a unit ball in  $\mathbb{R}^n$  with  $B$  and unit sphere in  $\mathbb{R}^n$  of radius  $r$  as  $S$ . We only denote the radius  $r$  explicitly as in  $B_r$  and  $S_r$ , when  $r$  is different than 1. We denote the set of real symmetric matrices of size  $n$  by  $\mathbb{S}^n$ , and the set of linear functions in  $\mathbb{R}^n$  by  $\mathcal{L}(\mathbb{R}^n)$ . We denote the ellipsoid described by the matrix  $P \in \mathbb{S}^n$  as  $E_P$ . We denote the homothety of ratio  $\lambda$  by  $\mathcal{H}_\lambda$ .

For the rest of the write-up, we denote the set of indices of the modes as  $M = \{1, 2, \dots, m\}$ , where  $m \in \mathbb{N}_{>0}$  is the number of the modes. We denote the joint spectral radius of the set of matrices  $\{A_1, A_2, \dots, A_m\}$  by  $\rho$ . Let us consider  $X = S \times M$  the Cartesian product of the unit sphere  $S$  with  $M$ . Every element of  $X$  can be written as  $x = (s_x, k_x)$  with  $s_x \in S$  and  $k_x \in M$ . For notational simplicity, we drop the subscript  $x$  whenever it is clear from the context.

We define the projections:

$$\pi_S : S \times M \rightarrow S, (s, k) \mapsto s$$

$$\pi_M : S \times M \rightarrow M, (s, k) \mapsto k.$$

It is well-known that  $S$  is a  $n - 1$  embedded submanifold of  $\mathbb{R}^n$ , and can thus be seen as an image of an atlas (collection) of smooth maps  $\phi_i : U \rightarrow S$ ,  $U \in \mathbb{R}^n$  called charts. It has the topology inherited from its ambient space  $\mathbb{R}^n$ . If  $\mathbb{R}^n$  is provided with a  $\sigma$ -algebra  $\Sigma$ , this parametrization also induces a  $\sigma$ -algebra on  $S$ ,  $\Sigma_S$ . Hence, a measure  $\mu$  on the measurable space  $(\mathbb{R}^n, \Sigma)$  defines a measure  $\mu_S$  on the measurable space  $(S, \Sigma_S)$ . This measure can be seen as push-forward  $\phi_{i*}(\mu)$  of  $\mu$  by the charts, i.e.,  $\phi_{i*}(\mu)(A) = \mu(\phi_i^{-1}(A))$  for any  $A \in \Sigma_S$ . In particular, with the classical Borel  $\sigma$ -algebra and Lebesgue measure in  $\mathbb{R}^n$ , we obtain a  $\sigma$ -algebra  $\mathcal{B}_S$  with  $A \in \mathcal{B}_S$  if and only if the sector  $tA$ ,  $t \in [0, 1]$  is in  $\mathcal{B}_{\mathbb{R}^n}$ ; and the classical spherical measure commonly

denoted by  $\sigma^{n-1}$  and defined by

$$\forall A \in \mathcal{B}_S, \sigma(A) = \frac{\lambda(tA)}{\lambda(B)}.$$

We can notice that  $\sigma^{n-1}(S) = 1$ .

We assume now that  $S$  is provided with a  $\sigma$ -algebra  $\Sigma_S$  and  $M$  with the classical  $\sigma$ -algebra associated to finite sets:  $\Sigma_M = \wp(M)$ , where  $\wp(M)$  is the power set of  $M$ .

We consider an unsigned finite spherical measure  $\mu_S$  on  $(S, \Sigma_S)$  and an unsigned finite measure<sup>1</sup>  $\mu_M$  on  $(M, \Sigma_M)$  with  $\text{supp}(\mu_M) = M$ . In other words,  $\forall k \in M, \mu_M(\{k\}) > 0$ .

We denote the product  $\sigma$ -algebra  $\Sigma_S \otimes \Sigma_M$  engendered by  $\Sigma_S$  and  $\Sigma_M$ :  $\Sigma = \sigma(\pi_S^{-1}(\Sigma_S), \pi_M^{-1}(\Sigma_M))$ . On this set, we define the product measure  $\mu = \mu_S \otimes \mu_M$  which is an unsigned finite measure on  $X$ .

## 2 Optimization Problem

We are interested in solving the following optimization problem for a given  $\gamma \in (0, 1)$ :

$$\begin{aligned} & \text{find} && P \\ & \text{subject to} && (A_i s)^T P (A_i s) \leq \gamma^2 s^T P s, \quad \forall i = \{1, 2, \dots, m\}, \forall s \in S, \\ & && P \succ 0. \end{aligned} \quad (1)$$

Note that if  $P$  is a solution to (1), then so is  $\alpha P$  for any  $\alpha \in \mathbb{R}_{>0}$ . Therefore, we can rewrite (1) as the following optimization problem:

$$\begin{aligned} & \text{find} && P \\ & \text{subject to} && (A_k s)^T P (A_k s) \leq \gamma^2 s^T P s, \quad \forall i = \{1, 2, \dots, m\}, \forall s \in S, \\ & && P \succeq I. \end{aligned} \quad (2)$$

We define the linear isomorphism  $\Phi$  as the natural mapping  $\Phi : \mathbb{R}^{\frac{n(n+1)}{2}} \rightarrow \mathbb{S}^n$ . Using this mapping, for a fixed  $\gamma \in (0, 1]$  we can rewrite (2) as:

$$\begin{aligned} & \text{find} && p \\ & \text{subject to} && f(p, x) \leq 0, \forall x \in X. \end{aligned} \quad (3)$$

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<sup>1</sup> Recall that the support of a measure  $\mu$  defined on a measurable space  $(X, \Sigma)$  is  $\text{supp}(\mu) = \{A \in \Sigma | \mu(A) > 0\}$

where  $f(p, x) = \max(f_1(p, x), f_2(p))$ , and

$$\begin{aligned} f_1(p, x) &:= (A_k s)^T \Phi(p) (A_k s) - \gamma^2 s^T \Phi(p) s \\ f_2(p) &:= \lambda_{\max}(\Phi(-p)) + 1. \end{aligned}$$

**Proposition 2.1.** *The optimization problem (3) is convex.*

*Proof.* The function  $f_1(p, x)$  is clearly convex in  $p$  for a fixed  $x \in X$ . The function  $\lambda_{\max} : \mathbb{S}^n \rightarrow \mathbb{R}$  maps a symmetric positive matrix to its maximum eigenvalue. It is well-known that the function  $\lambda_{\max}$  is a convex function of  $P$ . [?]. This means that,  $p \mapsto \Phi(\lambda_{\max}(p))$  is convex in  $p$ . Moreover, maximum of convex functions is also convex, which shows that  $f(p, x)$  is convex in  $p$ .  $\square$

Note that the optimization problem (3) has infinitely many constraints. We next consider the following optimization problem where we sample  $N$  constraints of (3) independently and identically with the probability measure  $\mathbb{P}(A) = \frac{\mu(A)}{\mu(X)}$ ,  $\forall A \in \Sigma$ , where  $N \geq d + 1$ , and  $d := \frac{n(n+1)}{2}$ . We denote this sampling by  $\omega := \{x_1, x_2, \dots, x_N\} \subset X$ , and obtain the following convex optimization problem  $\text{Opt}(\omega)$ :

$$\begin{aligned} &\text{find} && p \\ &\text{subject to} && f(p, x) \leq 0, \forall x \in \omega. \end{aligned} \tag{4}$$

Let  $p^*(\omega)$  be the solution of  $\text{Opt}(\omega)$ . We are interested in the probability of  $p^*(\omega)$  violating at least one constraint in the original problem (3). Therefore, we define constraint violation property next.

**Constraint violation probability [2]** The constraint violation probability is defined as:

$$\mathcal{V}^*(\omega) = \begin{cases} \mathbb{P}\{x \in X : f(p^*(\omega), x) > 0\} & \text{if } \omega \in X^{N*}, \\ 1, & \text{otherwise} \end{cases}$$

where  $X^{N*} := \{\omega \in X^N : \text{the solution of } \text{Opt}(\omega) \text{ exists}\}$ . Note that, since we have  $\mathbb{P}(A) = \frac{\mu(A)}{\mu(X)}$ , we can rewrite this as:

$$\mathcal{V}^*(\omega) = \begin{cases} \frac{\mu\{x \in X : f(p^*(\omega), x) > 0\}}{\mu(X)} & \text{if } \omega \in X^{N*}, \\ 1, & \text{otherwise} \end{cases}$$

We make the following assumptions on the problem  $\text{Opt}(\omega)$ :

1. Uniqueness of solution: Note that this can be enforced by adding a tie-break rule of at most  $\frac{n(n-1)}{2}$  convex conditions discriminating our solutions.
2. Nondegeneracy: with probability 1, there is no redundancy in the constraint obtained from the sampling.

The following theorem from [2] explicitly gives a relationship between  $V^*(\omega)$  and  $N, n$ .

**Theorem 2.2** (from [2]). *Consider the optimization problem  $\text{Opt}(\omega)$  given in (4). Let Assumption 1 and Assumption 2 hold. Then, for all  $\epsilon \in (0, 1)$  the following holds:*

$$\mathbb{P}^N\{\{\mathcal{V}^*(\omega) \leq \epsilon\} \cap X^{N*}\} \geq 1 - \sum_{j=0}^d \binom{N}{j} \epsilon^j (1 - \epsilon)^{N-j}.$$

Note that  $\epsilon = 1 - I_\beta^{-1}(N - d, d + 1)$  and can be interpreted as the ratio of the measure of points in  $X$  that might violate at least one of the constraints in (2) to the measure of all points in  $X$ .

We now state our main theorem, which is based on Theorem 2.2 and devote the next section to proving it step by step. We denote by  $\gamma^*$ , the optimum value of the following optimization problem:

$$\begin{aligned} \min_{P, \gamma} \quad & \gamma \\ \text{subject to} \quad & (A_i s)^T P (A_i s) \leq \gamma^2 s^T P s, \quad \forall i = \{1, 2, \dots, m\}, \forall s \in S, \\ & P \succ 0. \end{aligned} \quad (5)$$

**Theorem 2.3** (Main Theorem). *For any  $\eta > 0$ , given  $N \geq n + 1$  and  $\beta \in [0, 1)$ , we can compute  $\delta < \infty$  such that with probability at least  $\beta$ ,  $\rho \leq \delta(1 + \eta)\gamma^*$ . Moreover, as  $N \rightarrow \infty$ ,  $\delta \rightarrow 1$ .*

### 3 Relating the measure of bad sets

For a given sampling  $\omega \in X^{N*}$ , let  $V := \{x \in X : f(p^*(\omega), x) > 0\}$ , i.e., the set of points for which at least one constraint is violated, and  $V_S, V_M$  be its projections on  $S$  and  $M$ , respectively.

**Lemma 3.1.**  $\mu_S(V_S) \leq \frac{\mu(V)}{m_1}$ , where  $m_1 = \min\{\mu_M(\{k\}), k \in M\}$ .

*Proof.* Let  $A \subset X$ ,  $A_S = \pi_S(A)$  and  $A_M = \pi_M(A)$ . We notice that  $\Sigma_M$  is the disjoint union of its  $2^m$  elements  $\{B_i, i \in \{1, 2, \dots, 2^m\}\}$ . Then  $A$  is the disjoint union  $A = \sqcup_{1 \leq i \leq 2^m} (A_i, B_i)$  where  $A_i = \pi_M^{-1}(B_i) \in S$ . We notice that  $A_S = \sqcup_{1 \leq i \leq 2^m} A_i$ , and

$$\mu_S(A_S) = \sum_{1 \leq i \leq 2^m} \mu_S(A_i).$$

We have

$$\begin{aligned} \mu(A) = \mu(\sqcup_{1 \leq i \leq 2^m} (A_i, B_i)) &= \sum_{1 \leq i \leq 2^m} \mu((A_i, B_i)) \\ &= \sum_{1 \leq i \leq 2^m} \mu_S \otimes \mu_M((A_i, B_i)) \\ &= \sum_{1 \leq i \leq 2^m} \mu_S(A_i) \mu_M(B_i). \end{aligned}$$

Let  $m_1$  be the minimum value of  $\mu_M$  on its atoms:  $m_1 = \min\{\mu_M(\{k\}), k \in M\}$  (recall that  $m_1 > 0$ ). Then since  $\forall i, \mu_M(B_i) \geq m_1$ , we have

$$\mu_S(A_S) \leq \frac{\mu(A)}{m_1}. \quad (6)$$

This proves our statement by taking  $A = V_S$ .  $\square$

**Corollary 3.2.** *When the modes are sampled from the set  $M$  uniformly random,*

$$\mu_S(V_S) \leq m \mu(V).$$

We consider the linear transformation mapping  $S$  to  $E_P$  that denoted by  $L \in \mathcal{L}(\mathbb{R}^n)$ . Note that since  $P \in \mathbb{S}^n$ , it can be written in its Choleski form  $P = UDU^{-1}$ , where  $D$  diagonal matrix of its eigenvalues, and  $U \in O_n(\mathbb{R})$ . We define  $D^{1/2}$  the positive square root of  $D$  as the matrix  $\text{diag}(\sqrt{d_1}, \dots, \sqrt{d_n})$ . Then, the positive square root of  $P$  is  $VD^{1/2}V$ . This means that,  $L = P^{1/2}$ . For the rest of the write-up, we denote

$$V' := \Pi_S(L^{-1}(V_S)),$$

and show how to upper bound  $\sigma^{n-1}(V')$  in terms of  $\mu(V)$ .

**Lemma 3.3.** *Let  $\psi$  a smooth change of coordinates in  $\mathbb{R}^n$  and  $\mathcal{D} \subset S$ , whose image under  $\psi$  is  $\mathcal{D}' \subset \psi(S)$ . Let  $\mu_S$  be a positive spherical measure induced*

by a measure  $\mu$  on  $\mathbb{R}^n$ . Let  $\Sigma_E$  and  $\mu_E$  be the  $\sigma$ -algebra and the measure induced from  $\Sigma_S$  and  $\mu_S$  on the ellipsoid  $E = \psi(S)$ . Then

$$\mu_E(\psi(V_S)) = |\det(\psi)|\mu_S(V_S), \quad (7)$$

where  $\psi \in \mathcal{L}(\mathbb{R}^n)$ .

*Proof.* We have  $\mu_S(\mathcal{D}) = \int_{x \in \mathcal{D}} \mathbb{1}_{\mathcal{D}}(x) d\mu_S(x)$ ,  $\mu_S = \{\phi_{i*}(\mu)\}_i$  and

$$\mu(\mathcal{D}') = \int_{y \in \mathcal{D}'} \mathbb{1}_{\mathcal{D}'}(y) d\mu(y) = \int_{x \in \mathcal{D}} \mathbb{1}_{x \in \mathcal{D}} |\det J(\phi(x))| d\mu(x).$$

This gives

$$\mu_E(\mathcal{D}') = \int_{y \in \mathcal{D}'} \mathbb{1}_{\mathcal{D}'}(y) d\mu_E(y) = \int_{x \in \mathcal{D}} \mathbb{1}_{x \in \mathcal{D}} |\det J(\psi(x))| d\mu_S(x).$$

In particular, if  $\psi \in \mathcal{L}(\mathbb{R}^n)$ , then  $\forall x \in \mathbb{R}^n$ ,  $\det(J(\psi(x))) = \det(\psi)$  and

$$\mu_E(\mathcal{D}') = \int_{y \in \mathcal{D}'} \mathbb{1}_{\mathcal{D}'}(y) d\mu_E(y) = |\det(\psi)| \int_{x \in \mathcal{D}} \mathbb{1}_{x \in \mathcal{D}} d\mu_S(x).$$

This proves the statement of the lemma when  $\mathcal{D} = V_S$ .  $\square$

**Definition** Let  $X$  be a Hilbert space,  $A$  a nonempty subset of  $X$  and  $\psi : A \rightarrow X$ . Then  $\psi$  is called firmly nonexpansive if

$$\forall x, y \in A, \|\psi(x) - \psi(y)\|^2 + \|(\text{Id} - \psi)(x) - (\text{Id} - \psi)(y)\|^2 \leq \|x - y\|^2,$$

where  $\text{Id}$  denotes the identity function from  $X$  to  $X$ .

**Theorem 3.4** (from [1]). *Let  $C$  be a nonempty closed convex subset of  $X$ , then the convex projector on  $C$ ,  $\Pi_C$ , is firmly nonexpansive.*

**Corollary 3.5.**

$$\|\Pi_C(x) - \Pi_C(y)\| \leq \|x - y\| \quad \forall x, y \in C. \quad (8)$$

**Lemma 3.6.**

$$\mu_S(\Pi_S(L^{-1}(V_S))) \leq \det(L^{-1}) \left( \frac{1}{\lambda_{\min}(L^{-1})} \right)^n \mu_S(V_S). \quad (9)$$

*Proof.* Note that the mapping  $\Pi_S$  can be seen as the composition of the  $\Pi_{S_r}$  for some  $r > 0$ , and  $\mathcal{H}_{\frac{1}{r}}$ . Let  $E' := L^{-1}(S)$ , then when  $r < \min_{x \in E'} \|x\| = \lambda_{\min}(L^{-1})$  we have

$$\Pi_{S_{\lambda_{\min}}}(x) = \Pi_{B_{\lambda_{\min}}}(x) \quad \forall x \in E'.$$

This shows that the restriction of  $\Pi_{S_{\lambda_{\min}}}$  to  $E'$  is a convex projector.

Then by Corollary 3.5

$$\|\Pi_{S_{\lambda_{\min}}}(x) - \Pi_{S_{\lambda_{\min}}}(y)\| \leq \|x - y\|, \quad \forall x, y \in E'. \quad (10)$$

This shows that 1 is a Lipschitz constant of the function  $\Pi_{S_{\lambda_{\min}}}$  on  $E'$ .

By composing  $\Pi_{S_{\lambda_{\min}}}$  with  $\mathcal{H}_{\frac{1}{\lambda_{\min}}}$ , we obtain  $\Pi_S$ . Since the Lipschitz constant of composition of two functions can be bounded by the multiplication of Lipschitz constants of each function, the Lipschitz constant of  $\Pi_S$  on  $E'$  is  $\frac{1}{\lambda_{\min}}$ , which means that:

$$\|\Pi_S(x) - \Pi_S(y)\| \leq \frac{1}{\lambda_{\min}} \|x - y\|, \quad \forall x, y \in E'. \quad (11)$$

Note that, the inequality in (11) is an equality when  $x$  is in the eigenspace of  $\lambda_{\min}$  and  $y = -x$ .

Recall that for any smooth Lipschitz function  $\phi$  with Lipschitz constant,  $\text{Lip}(\phi)$ , we have for all  $x$ ,  $|\det(J(\phi(x)))| \leq \text{Lip}(\phi)^n$ . Combining this with (11) and Lemma 3.6, we get the statement of the lemma.  $\square$

**Theorem 3.7.**  $\sigma^{n-1}(V') \leq m\epsilon \sqrt{\frac{\lambda_{\max}(P)^n}{\det(P)}}$ , where  $\mu(V) = \epsilon$ .

*Proof.* By taking  $\mu_S$  as the uniform spherical measure  $\sigma^{n-1}$ , and combining Corollary 3.2 with Lemma 3.6 we get the statement of the theorem.  $\square$

## 4 Relating $\epsilon$ to $\delta$

We denote  $\epsilon' := \frac{\epsilon}{2} \sqrt{\frac{\lambda_{\max}(P)^n}{\det(P)}}$ , where the additional factor  $\frac{1}{2}$  follows from the homogeneity of the dynamics. In this section, we show how to relate  $\epsilon'$  to  $\delta$  in the statement of the Theorem 2.3. We start by a few definitions that will help us along the way.

**Spherical Cap** We define the *spherical cap* on  $S$  for a given hyperplane  $c^T x = k$  as:

$$\mathcal{C}_{c,k} := \{x \in S : c^T x > k\}.$$

**Proposition 4.1.** *Let  $d$  be a distance on  $\mathbb{R}^n$ . The distance between a set  $X \subset \mathbb{R}^n$  and a point  $p \in \mathbb{R}^n$  is  $d(X, p) := \inf_{x \in X} d(x, p)$ . Then if  $X$  is compact, we have:*

$$d(X, p) = \min_{x \in X} d(x, p).$$

*Proof.* This is due to the fact that the function  $d$  is continuous and therefore attains its minimum on the compact set  $X$ .  $\square$

**Proposition 4.2** (see e.g. [?]). *The distance between the point  $x = 0$  and the hyperplane  $c^T x = k$  is  $\frac{|k|}{\|c\|}$ .*

**Lemma 4.3.** *Consider the boundary of the compact convex set*

$$X := \bigcap_{i \in I} \{x : c_i^T x \leq k_i\},$$

*denoted by  $\partial X$ , then:*

$$d(\partial X, 0) = \min_{i \in I} \frac{|k_i|}{\|c_i\|}.$$

*Proof.* Due to Proposition 4.2 we have:

$$d(\partial X, 0) = \inf_{i \in I} d(\{x : c_i^T x = k_i\}, 0) = \inf_{i \in I} \frac{|k_i|}{\|c_i\|}. \quad (12)$$

Note that due to Proposition 4.1, the  $\inf_{x \in \partial X} d(x, 0)$  is attained by a point  $x^* \in \partial X$  due to compactness of  $\partial X$ . Hence, there exists an  $i \in I$  such that  $c_i^T x^* = k_i$  and this leads to:  $\inf_{i \in I} \frac{|k_i|}{\|c_i\|} = \min_{i \in I} \frac{|k_i|}{\|c_i\|}$ .  $\square$

We define the function  $\Delta : 2^S \rightarrow [0, 1]$  as:

$$\Delta(X) = \sup\{r : B_r \subseteq \text{convhull}(S \setminus X)\}. \quad (13)$$

**Lemma 4.4.** *Given a set  $X \subseteq S$ , let  $\text{convhull}(S \setminus X) := B \cap \mathcal{P}$ , where  $\mathcal{P} := \bigcap_{i \in I} \{x : c_i^T x \leq k_i\}$ . Then we have:*

$$\Delta(X) = \min_{i \in I} \frac{|k_i|}{\|c_i\|}.$$

*Proof.*

$$\begin{aligned} \Delta(X) &= \sup\{r : B_r \subseteq \text{convhull}(S \setminus X)\} \\ &= \min(d(\partial \mathcal{P}, 0), d(S, 0)) \\ &= \min\left(\min_{i \in I} \frac{|k_i|}{\|c_i\|}, 1\right) \quad \text{due to Lemma 4.3.} \end{aligned} \quad (14)$$

$\square$



**Lemma 4.5.**  $\Delta(\mathcal{C}_{c,k_1}) < \Delta(\mathcal{C}_{c,k_2})$  when  $k_1 < k_2$ .

*Proof.*

$$\Delta(\mathcal{C}_{c,k}) = \text{convhull}(\mathcal{S} \setminus \mathcal{C}_{c,k}) = \text{convhull}(\mathcal{S} \setminus \{x \in \mathcal{S} : c^T x > k\}) = \{x \in \mathcal{B} : c^T x \leq k\}.$$

Due to Lemma 4.4, we have  $\Delta(X) = \frac{|k|}{\|c\|}$ . Then since  $\frac{|k_1|}{\|c\|} < \frac{|k_2|}{\|c\|}$  when  $k_1 < k_2$ , the result of the lemma follows.  $\square$

**Lemma 4.6.**  $\sigma^{n-1}(\mathcal{C}_{c,k_1}) < \sigma^{n-1}(\mathcal{C}_{c,k_2})$ , for  $k_1 > k_2$ .

*Proof.*  $\text{convhull}(\mathcal{S} \setminus \{x \in \mathcal{S} : c^T x > k_1\}) \subseteq \text{convhull}(\mathcal{S} \setminus \{x \in \mathcal{S} : c^T x > k_2\})$ , for  $k_1 > k_2$ .  $\square$

Now we are ready to present the following lemma which is the key to proving our main result.

**Lemma 4.7.** For any set  $X \subseteq \mathcal{S}$ , there exists  $c$  and  $k$  such that  $\mathcal{C}_{c,k}$  satisfies:

$$\mathcal{C}_{c,k} \subseteq X,$$

and

$$\Delta(\mathcal{C}_{c,k}) = \Delta(X). \quad (15)$$

*Proof.* As discussed previously, we can represent  $\text{convhull}(\mathcal{S} \setminus X)$  as

$$\text{convhull}(\mathcal{S} \setminus X) = \bigcap_{i \in I} \{x \in \mathcal{B} : c_i^T x \leq k_i\}.$$

Note that when  $X = \emptyset$ , the statement of the lemma trivially holds since we can always find a  $c$  and  $k$  such that  $\mathcal{C}_{c,k} = \emptyset$ , hence we assume  $X \neq \emptyset$  for the rest of the proof. This implies  $I \neq \emptyset$ . Then due to Lemma 4.4, there exists  $\ell \in I$  such that  $\Delta(X) = \frac{|k_\ell|}{\|c_\ell\|}$ . Now, consider the spherical cap  $\mathcal{C}_{c_\ell, k_\ell}$ . Note that again due to Lemma 4.4, we have  $\Delta(\mathcal{C}_{c_\ell, k_\ell}) = \frac{|k_\ell|}{\|c_\ell\|} = \Delta(X)$ .

We next show  $\mathcal{C}_{c_\ell, k_\ell} \subseteq X$ . We prove this by contradiction. Assume  $x \in \mathcal{C}_{c_\ell, k_\ell}$  and  $x \notin X$ . Note that, if  $x \notin X$ , then  $x \in \mathcal{S} \setminus X \subseteq \text{convhull}(\mathcal{S} \setminus X)$ . Since  $x \in \mathcal{C}_{c_\ell, k_\ell}$  we have  $c_\ell^T x > k_\ell$ , but due to the fact that  $x \in \text{convhull}(\mathcal{S} \setminus X)$ , we also have  $c_\ell^T x \leq k_\ell$ , which leads to a contradiction. Therefore,  $\mathcal{C}_{c_\ell, k_\ell} \subseteq X$ .  $\square$

We now prove our main result.

**Theorem 4.8.** Let  $X_{\epsilon'} = \{X \subset \mathcal{S} : \sigma^{n-1}(X) = \epsilon'\}$ . Then, for any  $\epsilon' \in (0, 1)$ , the function  $\Delta(X)$  attains its minimum over  $X_{\epsilon'}$  when  $X$  is a spherical cap.

*Proof.* We prove this via contradiction. Assume that  $X^* \in X_{\epsilon'}$ ,  $X^*$  is not a spherical cap and  $\arg \min_{X \in X_{\epsilon'}} (\Delta(X)) = X^*$ . Due to Lemma 4.7 we can construct a spherical cap  $\mathcal{C}_{c,k}$  such that  $\mathcal{C}_{c,k} \subseteq X^*$  and  $\mathcal{C}_{c,k} = \Delta(X^*)$ . Note that, we further have  $\mathcal{C}_{c,k} \subset X^*$ , since  $X^*$  is assumed not to be a spherical cap. This means that  $\sigma^{n-1}(\mathcal{C}_{c,k}) < \epsilon'$ .

Then, the spherical cap  $\mathcal{C}_{c,\tilde{k}}$  with  $\sigma^{n-1}(\mathcal{C}_{c,\tilde{k}}) = \epsilon'$ , satisfies  $\tilde{k} < k$ , due to Lemma 4.6. This implies  $\Delta(\mathcal{C}_{c,\tilde{k}}) < \Delta(\mathcal{C}_{c,k}) = \Delta(X^*)$  due to Lemma 4.5. Therefore,  $\Delta(\mathcal{C}_{c,\tilde{k}}) < \Delta(X^*)$ . This is a contradiction since we initially assumed that  $\Delta(X)$  attains its minimum over  $X_{\epsilon'}$  at  $X^*$ .  $\square$

**Theorem 4.9.** *Given a spherical cap  $\mathcal{C}_{c,k} \subseteq S$  such that  $\sigma^{n-1}(\mathcal{C}_{c,k}) = \epsilon'$ ,*

$$\Delta(\mathcal{C}_{c,k}) = \sqrt{(1 - \alpha)},$$

where  $\alpha := I^{-1} \left( \frac{\epsilon' \Gamma(\frac{d}{2})}{\pi^{d/2}}, \frac{d-1}{2}, \frac{1}{2} \right)$  and  $\Gamma(x) = \int_0^\infty t^{x-1} e^{-t} dt$ . Here  $I^{-1}$  is the inverse incomplete beta function, i.e.,  $I^{-1}(y, a, b) = x$  where  $I_x(a, b) = y$ .

*Proof.* Let  $h := 1 - \Delta(\mathcal{C}_{c,k})$ . It is well known [3] that the area of the spherical cap  $\mathcal{C}_{c,k} \subseteq S$  is given by the equation:

$$\epsilon' = \sigma^{n-1}(\mathcal{C}_{c,k}) = \frac{\pi^{d/2}}{\Gamma[\frac{d}{2}]} I_{2h-h^2} \left( \frac{d-1}{2}, \frac{1}{2} \right), \quad (16)$$

where  $I$  is the incomplete beta function. From this, we get the following set of equations:

$$\begin{aligned} \frac{\epsilon' \Gamma[\frac{d}{2}]}{\pi^{d/2}} &= I_{2h-h^2} \left( \frac{d-1}{2}, \frac{1}{2} \right) \\ 2h - h^2 &= I^{-1} \left( \frac{\epsilon' \Gamma(\frac{d}{2})}{\pi^{d/2}}, \frac{d-1}{2}, \frac{1}{2} \right) \\ 2h - h^2 &= \alpha \\ h^2 - 2h + \alpha &= 0. \end{aligned} \quad (17)$$

From (17), we get  $h = 1 \pm \sqrt{(1 - \alpha)}$ . Since  $h \leq 1$ , we conclude that  $\Delta(\mathcal{C}_{c,k}) = \sqrt{(1 - \alpha)}$ . Note that,  $\Delta(\mathcal{C}_{c,k})$  only depends on  $\epsilon$  for fixed  $n$ .  $\square$

**Corollary 4.10.** *When  $N \rightarrow \infty$ ,  $\Delta(X) \rightarrow 1$ .*

*Proof.* To be proved:  $\epsilon \rightarrow 0$ .

Then by our assumption  $\frac{\lambda_{\max}}{\lambda_{\min}}$  is bounded so  $\epsilon'$  tends to 0. By continuity and monotonicity of  $I^{-1}$  in its first parameter,  $\Delta$  tends to 1.  $\square$

## References

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