

Chapter 25

Distances Defined by Zonoids

The goals of this chapter are to:

- Introduce \mathfrak{N} -distances defined by zonoids,
- Explain the connections between \mathfrak{N} -distances and zonoids.

Notation introduced in this chapter:

Notation	Description
$h(K, u)$	Support function of a convex body
$K_1 \oplus K_2$	Minkowski sum of sets K_1 and K_2
S^{d-1}	Unit sphere in \mathbb{R}^d

25.1 Introduction

Suppose that \mathfrak{X} is a metric space with the distance ρ . It is well known (Schoenberg 1938) that \mathfrak{X} is isometric to a subspace of a Hilbert space if and only if ρ^2 is a negative definite kernel. The so-called \mathfrak{N} -distance (Klebanov 2005) is a variant of a construction of a distance on a space of measures on \mathfrak{X} such that \mathfrak{N}^2 is a negative definite kernel. Such a construction is possible if and only if ρ^2 is a strongly negative definite kernel on \mathfrak{X} .

In this chapter, we show that the supporting function of any zonoid in \mathbb{R}^d is a negative definite first-degree homogeneous function. The inverse is also true. If the support of a generating measure of a zonoid coincides with the unit sphere, then the supporting function is strongly negative definite, and therefore it generates a distance on the space of Borel probability measures on \mathbb{R}^d .

25.2 Main Notions and Definitions

Here we review some known definitions and facts from stochastic geometry.¹

Let \mathfrak{C} (resp. \mathfrak{C}') be the system of all compact convex sets (resp. nonempty compact convex sets) in \mathbb{R}^d . A set $K \in \mathfrak{C}'$ is called a convex body if $K \in \mathfrak{C}'$; then for each $u \in S^{d-1}$ there is exactly one number $h(K, u)$ such that the hyperplane

$$\{x \in \mathbb{R}^d : \langle x, u \rangle - h(K, u) = 0\} \quad (25.2.1)$$

intersects K , and $\langle x, u \rangle - h(K, u) \leq 0$ for each $x \in K$. This hyperplane is called the *support hyperplane*, and the function $h(K, u)$, $u \in S^{d-1}$ (where S^{d-1} is the unit sphere), is the *support function* (restricted to S^{d-1}) of K . Equivalently, one can define

$$h(K, u) = \sup\{\langle x, u \rangle, x \in K\}, \quad u \in \mathbb{R}^d. \quad (25.2.2)$$

Its geometrical meaning is the signed distance of the support hyperplane from the coordinate origin.

An important property of $h(K, u)$ is its additivity:

$$h(K_1 \oplus K_2, u) = h(K_1, u) + h(K_2, u),$$

where $K_1 \oplus K_2 = \{a + b : a \in K_1, b \in K_2\}$ is the Minkowski sum of K_1 and K_2 . For $K \in \mathfrak{C}'$ let $\check{K} = \{-k, k \in K\}$. We say that K is *centrally symmetric* if $K' = \check{K}'$ for some translate K' , i.e., if K has a center of symmetry.

The Minkowski sum of finitely many centered line segments is called a *zonotope*. Consider a zonotope

$$\mathcal{Z} = \bigoplus_{i=1}^k a_i [v_i, -v_i], \quad (25.2.3)$$

where $a_i > 0$, $v_i \in S^{d-1}$. Its support function is given by

$$h(\mathcal{Z}, u) = h_{\mathcal{Z}}(u) = \sum_{i=1}^k a_i |\langle u, v_i \rangle|. \quad (25.2.4)$$

We use the notation \mathcal{K}' for the space of all compact subsets of \mathbb{R}^d with the Hausdorff metric

$$d_H(K_1, K_2) = \max\left\{\sup_{x \in K_1} \text{dist}(x, K_2), \sup_{y \in K_2} \text{dist}(y, K_1)\right\}, \quad (25.2.5)$$

where $\text{dist}(x, K) = \inf_{z \in K} \|x - z\|$.

¹See, for example, Ziegler (1995) and Beneš and Rataj (2004).

A set $\mathcal{Z} \in \mathcal{C}'$ is called a *zonoid* if it is a limit in a d_H distance of a sequence of zonotopes.

It is known that a convex body \mathcal{Z} is a zonoid if and only if its support function has a representation

$$h(\mathcal{Z}, u) = \int_{\mathbb{S}^{d-1}} |\langle u, v \rangle| d\mu_{\mathcal{Z}}(v) \tag{25.2.6}$$

for an even measure $\mu_{\mathcal{Z}}$ on \mathbb{S}^{d-1} . The measure $\mu_{\mathcal{Z}}$ is called the *generating measure* of \mathcal{Z} . It is known that the generating measure is unique for each zonoid \mathcal{Z} .

25.3 \mathfrak{N} -Distances

Suppose that $(\mathfrak{X}, \mathfrak{A})$ is a measurable space and \mathcal{L} is a strongly negative definite kernel on \mathfrak{X} . Denote by $\mathcal{B}_{\mathcal{L}}$ the set of all probabilities μ on $(\mathfrak{X}, \mathfrak{A})$ for which there exists the integral

$$\int_{\mathfrak{X}} \int_{\mathfrak{X}} \mathcal{L}(x, y) d\mu(x) d\mu(y) < \infty. \tag{25.3.1}$$

For $\mu, \nu \in \mathcal{B}_{\mathcal{L}}$ consider

$$\begin{aligned} \mathcal{N}(\mu, \nu) &= 2 \int_{\mathfrak{X}} \int_{\mathfrak{X}} \mathcal{L}(x, y) d\mu(x) d\nu(y) \\ &\quad - \int_{\mathfrak{X}} \int_{\mathfrak{X}} \mathcal{L}(x, y) d\mu(x) d\mu(y) \\ &\quad - \int_{\mathfrak{X}} \int_{\mathfrak{X}} \mathcal{L}(x, y) d\nu(x) d\nu(y). \end{aligned} \tag{25.3.2}$$

It is known (Klebanov 2005) that

$$\mathfrak{N}(\mu, \nu) = \left(\mathcal{N}(\mu, \nu) \right)^{1/2}$$

is a distance on $\mathcal{B}_{\mathcal{L}}$.

Described below are some examples of negative definite kernels.

Example 25.3.1. Let $\mathfrak{X} = \mathbb{R}^1$. For $r \in [0, 2]$ define

$$\mathcal{L}_r(x, y) = |x - y|^r.$$

The function \mathcal{L}_r is a negative definite kernel. For $r \in (0, 2)$, \mathcal{L}_r is a strongly negative definite kernel.

For the proof of the statement in this example and the statement in the next example (Example 25.3.2), see Klebanov (2005).

Example 25.3.2. Let $\mathcal{L}(x, y) = f(x - y)$, where $f(t)$ is a continuous function on \mathbb{R}^d , $f(0) = 0$, $f(-t) = f(t)$. \mathcal{L} is a negative definite kernel if and only of

$$f(t) = \int_{\mathbb{R}^d} (1 - \cos\langle t, u \rangle) \frac{1 + \|u\|^2}{\|u\|^2} d\Theta(u), \quad (25.3.3)$$

where Θ is a finite measure on \mathbb{R}^d . Representation (25.3.3) is unique. Kernel \mathcal{L} is strongly negative definite if the support of the measure Θ coincides with the whole space \mathbb{R}^d .

We will give an alternative proof for the fact that $|x - y|$ is a negative definite kernel. For the case $\mathfrak{X} = \mathbb{R}^1$ define

$$\mathcal{L}(x, y) = 2 \max(x, y) - x - y = |x - y|. \quad (25.3.4)$$

Then \mathcal{L} is a negative definite kernel.

Proof. It is sufficient to show that $\max(x, y)$ is a negative definite kernel. For arbitrary $a \in \mathbb{R}^1$ consider

$$u_a(x) = \begin{cases} 1, & x < a, \\ 0, & x \geq a. \end{cases} \quad (25.3.5)$$

It is clear that

$$u_a(\max(x, y)) = u_a(x)u_a(y).$$

Let $F(a)$ be a nondecreasing bounded function on \mathbb{R}^1 . Define

$$\mathcal{K}(x, y) = \int_{-\infty}^{\infty} u_a(\max(x, y)) dF(a).$$

For any integer $n > 1$ and arbitrary c_1, \dots, c_n under condition $\sum_{j=1}^n c_j = 0$ we have

$$\begin{aligned} \sum_{i=1}^n \sum_{j=1}^n \mathcal{K}(x_i, x_j) c_i c_j &= \int_{-\infty}^{\infty} \sum_{i=1}^n \sum_{j=1}^n u_a(x_i) u_a(x_j) c_i c_j dF(a) \\ &= \int_{-\infty}^{\infty} \left(\sum_{i=1}^n u_a(x_i) c_i \right)^2 dF(a) \geq 0. \end{aligned}$$

But

$$\begin{aligned} \mathcal{K}(x, y) &= \int_{-\infty}^{\infty} u_a(\max(x, y))dF(a) \\ &= F(+\infty) - F(\max(x, y)). \end{aligned}$$

Let us fix arbitrary $A > 0$ and apply the previous equality to the function

$$F(a) = F_A(a) = \begin{cases} A & \text{for } a > A, \\ a & \text{for } -A \leq a \leq A, \\ -A & \text{for } a < -A. \end{cases} \quad (25.3.6)$$

In this case, $\mathcal{K}(x, y) = A - \max(x, y)$ for $x, y \in [-A, A]$, and, as $A \rightarrow \infty$, we obtain that $\max(x, y)$ is a negative definite kernel. \square

Directly from the definition of a negative definite kernel and Example 25.3.1 we obtain the next example.

Example 25.3.3. Let $x, y \in \mathbb{R}^d$, and $f : \mathbb{R}^d \rightarrow \mathbb{R}^1$. Define

$$\mathcal{L}(x, y) = |f(x) - f(y)|.$$

Then \mathcal{L} is a negative definite kernel.

Of course, the mixture of negative definite kernels is again a negative definite kernel.

Example 25.3.4. Let us choose and fix a vector $\theta \in \mathbb{S}^{d-1}$ and consider the kernel

$$\mathcal{L}_\theta(x, y) = |\langle x, \theta \rangle - \langle y, \theta \rangle|.$$

From previous considerations it is clear that \mathcal{L}_θ is a negative definite kernel on \mathbb{R}^d , and for the σ -finite measure Ξ

$$\mathcal{L}_\Xi(x, y) = \int_{\mathbb{S}^{d-1}} \mathcal{L}_\theta(x, y)d\Xi(\theta) \quad (25.3.7)$$

is, again, a negative definite kernel.

Consider expression (25.3.2) constructed on the basis of (25.3.7). Let us rewrite (25.3.2) in a different form. Suppose that X and Y are two random vectors in \mathbb{R}^d with distributions μ and ν , respectively. We write $\mathcal{N}(X, Y)$ instead of $\mathcal{N}(\mu, \nu)$, so that

$$\mathcal{N}(X, Y) = 2E\mathcal{L}_\Xi(X, Y) - E\mathcal{L}_\Xi(X, X') - E\mathcal{L}_\Xi(Y, Y'),$$

where $X' \stackrel{d}{=} X$ and $Y' \stackrel{d}{=} Y$ are independent copies of X and Y , respectively. Note that we use the sign $\stackrel{d}{=}$ for the equality in a distribution. We have

$$\begin{aligned} \mathcal{N}(X, Y) &= E \int_{\mathbb{S}^{d-1}} [4 \max(\langle X, \theta \rangle, \langle Y, \theta \rangle) \\ &\quad - 2 \max(\langle X, \theta \rangle, \langle X', \theta \rangle) - 2 \max(\langle Y, \theta \rangle, \langle Y', \theta \rangle)] d\Xi(\theta). \end{aligned}$$

Denote $X_\theta = \langle X, \theta \rangle$, $Y_\theta = \langle Y, \theta \rangle$. Then

$$\begin{aligned} \mathcal{N}(X, Y) &= 2 \int_{\mathbb{S}^{d-1}} \lim_{A \rightarrow \infty} E \int_{-A}^A (u_a(X_\theta)u_a(X'_\theta) \\ &\quad + u_a(Y_\theta)u_a(Y'_\theta) - 2u_a(X_\theta)u_a(Y_\theta)) dF_A(a) d\Xi(\theta). \end{aligned}$$

But $E u_a(X_\theta) = \Pr\{X_\theta < a\}$, and therefore

$$\begin{aligned} \mathcal{N}(X, Y) &= 2 \lim_{A \rightarrow \infty} \int_{\mathbb{S}^{d-1}} d\Xi(\theta) \int_{-A}^A (\Pr\{X_\theta < a\} \Pr\{X'_\theta < a\} \\ &\quad + \Pr\{Y_\theta < a\} \Pr\{Y'_\theta < a\} - 2\Pr\{X_\theta < a\} \Pr\{Y_\theta < a\}) dF_A(a) \\ &= 2 \int_{\mathbb{S}^{d-1}} d\Xi(\theta) \int_{-\infty}^\infty (F_\theta(a) - G_\theta(a))^2 da, \end{aligned}$$

where $F_\theta(a) = \Pr\{X_\theta < a\}$, $G_\theta(a) = \Pr\{Y_\theta < a\}$. So finally we have

$$\mathcal{N}(X, Y) = 2 \int_{\mathbb{S}^{d-1}} d\Xi(\theta) \int_{-\infty}^\infty (F_\theta(a) - G_\theta(a))^2 da. \tag{25.3.8}$$

If the support of Ξ coincides with \mathbb{S}^{d-1} , then $\mathfrak{N}(X, Y) = (\mathcal{N}(X, Y))^{1/2}$ is a distance between the distributions of X and Y .

Let us return to the kernel

$$\mathcal{L}_\theta(x, y) = 2 \max(\langle x, \theta \rangle, \langle y, \theta \rangle) - \langle x, \theta \rangle - \langle y, \theta \rangle.$$

Choose arbitrary $\theta_o \in \mathbb{S}^{d-1}$, and consider the measure

$$\Xi_o = \frac{1}{2}(\delta_{\theta_o} + \delta_{-\theta_o}),$$

where δ_{θ_o} is the measure concentrated at point θ_o . Then

$$\begin{aligned} \mathcal{L}_{\Xi_{\theta_o}}(x, y) &= \int_{\mathbb{S}^{d-1}} \mathcal{L}_{\theta}(x, y) d\Xi_{\theta_o}(\theta) \\ &= \max(\langle x, \theta_o \rangle, \langle y, \theta_o \rangle) + \max(-\langle x, \theta_o \rangle, -\langle y, \theta_o \rangle) \\ &= |\langle x - y, \theta \rangle|. \end{aligned}$$

Now, if we have an arbitrary even measure Ξ_s on sphere \mathbb{S}^{d-1} , then

$$\begin{aligned} \mathcal{L}_{\Xi_s}(x, y) &= \int_{\mathbb{S}^{d-1}} \mathcal{L}_{\theta}(x, y) d\Xi_s(\theta) \\ &= \int_{\mathbb{S}^{d-1}} |\langle x - y, \theta \rangle| d\Xi_s(\theta) \end{aligned}$$

is a negative definite kernel. Let us note that the function

$$h(z) = \int_{\mathbb{S}^{d-1}} |\langle z, \theta \rangle| d\Xi_s(\theta), \quad z \in \mathbb{R}^d \tag{25.3.9}$$

is the support function of a zonoid with generating measure Ξ_s .

Summarizing all the preceding relations we may formulate the following result.

Theorem 25.3.1. Each zonoid \mathcal{Z} generates a negative definite kernel on \mathbb{R}^d

$$\mathcal{L}_{\mathcal{Z}}(x, y) = h_{\mathcal{Z}}(x - y) = \int_{\mathbb{S}^{d-1}} |\langle x - y, \theta \rangle| d\mu_{\mathcal{Z}}(\theta). \tag{25.3.10}$$

This kernel is strongly negative definite if the support of $\mu_{\mathcal{Z}}$ coincides with the whole sphere \mathbb{S}^{d-1} , and

$$\begin{aligned} \mathcal{N}(\mu, \nu) &= 2 \int_{\mathbb{R}^d} \int_{\mathbb{R}^d} \mathcal{L}_{\mathcal{Z}}(x, y) d\mu(x) d\nu(y) - \int_{\mathbb{R}^d} \int_{\mathbb{R}^d} \mathcal{L}_{\mathcal{Z}}(x, y) d\mu(x) d\mu(y) \\ &\quad - \int_{\mathbb{R}^d} \int_{\mathbb{R}^d} \mathcal{L}_{\mathcal{Z}}(x, y) d\nu(x) d\nu(y) \end{aligned}$$

is the square of a distance between measures $\mu, \nu \in \mathcal{B}_{\mathcal{L}}$. This distance has the following representation:

$$\mathfrak{N}(\mu, \nu) = \left(\int_{\mathbb{S}^{d-1}} d\mu_{\mathcal{Z}}(\theta) \int_{-\infty}^{\infty} (F_{\theta}(a) - G_{\theta}(a))^2 da \right)^{1/2}, \tag{25.3.11}$$

where

$$\begin{aligned} \mu(\mathcal{A}) &= \Pr\{X \in \mathcal{A}\}, \quad \nu(\mathcal{A}) = \Pr\{Y \in \mathcal{A}\}, \\ F_{\theta}(a) &= \Pr\{\langle X, \theta \rangle < a\}, \quad G_{\theta}(a) = \Pr\{\langle Y, \theta \rangle < a\}. \end{aligned} \tag{25.3.12}$$

According to Example 25.3.2, the function $h_{\mathcal{Z}}(u)$ from (25.3.10) may be represented in the form (25.3.3). Let us investigate the connection between $\mu_{\mathcal{Z}}$ in (25.3.10) and Θ in (25.3.3). To do so, we will use the following identity:

$$|z| = \frac{2}{\pi} \int_0^\infty (1 - \cos(zt)) \frac{dt}{t^2}. \tag{25.3.13}$$

We have

$$\begin{aligned} h_{\mathcal{Z}}(u) &= \frac{2}{\pi} \int_{\mathbb{S}^{d-1}} \int_0^\infty (1 - \cos\langle u, \theta \rangle) \frac{dt}{t^2} d\mu_{\mathcal{Z}}(\theta) \\ &= \frac{2}{\pi} \int_{\mathbb{R}^d} (1 - \cos\langle u, v \rangle) \frac{1 + \|v\|^2}{\|v\|^2} d\Theta(v). \end{aligned}$$

So

$$\begin{aligned} d\Theta(v) &= \frac{2}{\pi} \frac{1}{1 + t^2} dt d\mu(\theta), \\ v &= t \cdot \theta, \quad \theta \in \mathbb{S}^{d-1}, \quad t \geq 0. \end{aligned} \tag{25.3.14}$$

If $h_{\mathcal{Z}}(u)$ is a support function of a zonoid \mathcal{Z} , then clearly

$$h_{\mathcal{Z}}(\tau \cdot u) = \tau h_{\mathcal{Z}}(u)$$

for all $\tau > 0$ and $u \in \mathbb{R}^d$, and, as was shown previously, $h_{\mathcal{Z}}(x - y)$ is a negative definite kernel. The inverse is also true.

Theorem 25.3.2. Suppose that f is a continuous function on \mathbb{R}^d such that $f(0) = 0$, $f(-u) = f(u)$. Then the following facts are equivalent:

- Fact 1. $f(\tau \cdot u) = \tau f(u)$ and $f(x - y)$ is a negative definite kernel.
- Fact 2. f is a support function of a zonoid.

Proof. Previously we saw that Fact 2 implies Fact 1, and we must prove only that Fact 1 implies Fact 2. According to Example 25.3.2,

$$f(u) = \int_{\mathbb{R}^d} (1 - \cos\langle u, v \rangle) d\Theta_1(v), \tag{25.3.15}$$

where

$$d\Theta_1(v) = \frac{1 + \|v\|^2}{\|v\|^2} d\Theta(v),$$

and Θ is the measure from (25.3.3).

We have

$$f(\tau \cdot u) = \tau f(u) \tag{25.3.16}$$

for any $\tau > 0$, $u \in \mathbb{R}^d$. Substituting (25.3.15) into (25.3.16) and using the uniqueness of the measure Θ in (25.3.3) we obtain

$$\int_{\mathbb{R}^d} (1 - \cos\langle \tau \cdot u, v \rangle) d\Theta_1(v) = \tau \int_{\mathbb{R}^d} (1 - \cos\langle u, v \rangle) d\Theta_1(v),$$

$$(1 - \cos\langle u, v \rangle) d\Theta_1(v/\tau) = \tau \int_{\mathbb{R}^d} (1 - \cos\langle u, v \rangle) d\Theta_1(v)$$

and

$$\Theta_1(v/\tau) = \tau \Theta_1(v).$$

We write here $v = r \cdot w$ for $r > 0$ and $w \in \mathbb{S}^{d-1}$. We have

$$\Theta_1(r\tau \cdot w) = \tau \Theta_1(r \cdot w)$$

and, finally, for $\tau = r$,

$$\Theta_1(r \cdot w) = \frac{1}{r} \Theta_1(w). \quad (25.3.17)$$

It is clear that representation (25.3.15) for Θ_1 of the form (25.3.17) coincides with (25.3.14).² □

Note that the \mathfrak{N} -distance can be bounded by the Hausdorff distance. Let \mathcal{Z}_μ and \mathcal{Z}_ν be two zonoids with generating measures μ and ν , respectively. The following inequality holds for their supporting functions $h(\mathcal{Z}_\mu, u)$ and $h(\mathcal{Z}_\nu, u)$:

$$|h(\mathcal{Z}_\mu, u) - h(\mathcal{Z}_\nu, u)| \leq d_H(\mathcal{Z}_\mu, \mathcal{Z}_\nu).$$

Obviously, from this inequality it follows that

$$\mathcal{N}(\mu, \nu) \leq 2d_H(\mathcal{Z}_\mu, \mathcal{Z}_\nu),$$

and therefore

$$\mathfrak{N}(\mu, \nu) \leq (2d_H(\mathcal{Z}_\mu, \mathcal{Z}_\nu))^{1/2}. \quad (25.3.18)$$

Note that each \mathfrak{N} -distance generated by a zonoid is an ideal distance of degree 1/2.

References

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²An alternative proof of Theorem 25.3.2 is provided in Burger (2000).