

## MULTIVARIATE MAJORIZATION AND DIRECTIONAL MAJORIZATION; POSITIVE RESULTS

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**SUMMARY.** General relations between directional majorization and multivariate majorization are studied, and sufficient conditions for directional majorization to imply multivariate majorization are obtained.

### 1. INTRODUCTION

For two matrices  $X^{(m \times n)}$  and  $Y^{(m \times n)}$ , Marshall and Olkin (1979) defined  $X$  to be majorized by  $Y$ , written as  $X \prec Y$ , if  $X = YP$ , for some  $n \times n$  doubly stochastic matrix  $P$ . Following Marshall and Olkin (1979, p. 433), we define  $X$  to be directionally majorized by  $Y$ , written as  $X \prec_a Y$ , if  $aX \prec aY$  for all  $a \in R^m$ . Marshall and Olkin (p. 433) posed the open question whether  $X \prec_a Y$  implies  $X \prec Y$ . A more general problem stated in Marshall and Olkin is whether  $AX \prec AY$  for all  $A: k \times m$  (for fixed  $k$ ) implies  $X \prec Y$ . In this paper, sufficient conditions are given under which directional majorization implies multivariate majorization.

It will be reported in a subsequent communication that the above implication is not true under some specified conditions.

### 2. MAIN RESULTS

**Theorem 2.1:** For a fixed  $Y$ ,  $X^{(2 \times n)} \prec_a Y^{(2 \times n)}$  implies  $X \prec Y$  for all  $X^{(2 \times n)}$ , if all the column vectors of  $Y$  (in  $R^2$ ) are boundary points in the convex hull of the column vectors of  $Y$ , and this convex hull has 2-dimensional positive volume.

**Theorem 2.2:** Suppose every column vector of  $Y: m \times n$  is an extreme point in the convex hull generated by the columns of  $Y$ , which has  $r$ -dimensional positive volume, and at least  $(n-r+2)$  of these column vectors are co-planar. Then  $X \prec_a Y$  implies  $X \prec Y$  for all  $X$ . Moreover,  $AX \prec AY$  for all  $A: k \times m$  implies  $X \prec Y$ .

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## 3. PROOF OF THE RESULTS

*Definition 3.1:* A function  $f: R^m \rightarrow R$  is said to be *directional convex function*, if it is of the form  $f(x) = g(\alpha, x)$ , for fixed  $\alpha \in R^m$  and  $g: R \rightarrow R$  convex.

Note that directional convex functions are convex functions.

*Lemma 3.1:* For  $X(m \times n) = (x_1^t, \dots, x_n^t)$ ,  $Y(m \times n) = (y_1^t, \dots, y_n^t)$ ,  $X \prec_d Y$  if and only if,

$$\sum_{t=1}^n F(x_t^t) < \sum_{t=1}^n F(y_t^t),$$

for all functions  $F$  which are sums of finitely many directional convex functions.

*Proof:* First note that for  $x = (x_1, \dots, x_n)$ ,  $y = (y_1, \dots, y_n)$ ,  $x \prec_d y$  if

$$\sum_{t=1}^n g(x_t) < \sum_{t=1}^n g(y_t)$$

for all convex functions  $g: R \rightarrow R$  (see Marshall and Olkin, 1979, p. 108 or Hardy, Littlewood and Polya, 1934).

Now for  $X: m \times n$ ,  $Y: m \times n$ ,

$$X \prec_d Y$$

$$\Leftrightarrow \alpha X \prec_d \alpha Y, \quad \text{for all } \alpha \in R^m$$

$$\Leftrightarrow (\alpha x_1^t, \dots, \alpha x_n^t) \prec_d (\alpha y_1^t, \dots, \alpha y_n^t), \quad \text{for all } \alpha \in R^m$$

$$\Leftrightarrow \sum_{t=1}^n g(\alpha x_t^t) < \sum_{t=1}^n g(\alpha y_t^t), \quad \text{for all } \alpha \in R^m \text{ and all convex functions } g: R \rightarrow R.$$

$$\Leftrightarrow \sum_{t=1}^n F(x_t^t) < \sum_{t=1}^n F(y_t^t), \quad \text{for all directional convex functions } F.$$

$$\Leftrightarrow \sum_{t=1}^n F(x_t^t) < \sum_{t=1}^n F(y_t^t), \quad \text{for all } F \text{ which are sums of finitely many directional convex functions.}$$

*Definition 3.2:* For  $a, b \in R$ , a line  $L$  in  $R^2$  (having equation  $l(x) = 0$  for  $x \in R^2$ ) for a point  $Z \in R^2$  with  $Z \notin L$ , define  $C_{L,a,b,Z}: R^2 \rightarrow R$  by

$$C_{L,a,b,Z}(x) = a.d(L, x), \text{ if } l(x). l(Z) \geq 0$$

$$= b.d(L, x), \text{ if } l(x). l(Z) < 0,$$

where for  $A \subseteq R^2$ ,  $p \in R^2$

$$d(A, p) = \inf \{\|q-p\| : q \in A.\}$$

Clearly  $C_{L,a,b,Z}$  is a directional convex function for  $a \geq 0$ ,  $b \geq 0$ .

*Lemma 3.2:* For  $m = 2$ ,  $X \prec_d Y$  implies that the column vectors of  $X$  are in the convex hull of the column vectors of  $Y$ .

*Proof:* Let  $C$  denote the convex hull of the column vectors of  $Y$ . Suppose that for some  $i$ , the  $i$ th column vector  $x_i^T$  of  $X$  is not in  $C$ . As  $C$  is closed, there exists a line  $L$  which separates  $x_i^T$  from  $C$  and does not contain  $x_i^T$ . Now consider the directional convex function  $\varphi = C_{L, 1.0, x_i^T}$ . Note that

$$\sum_{j=1}^n \varphi(y_j) = 0 < \sum_{j=1}^n \varphi(x_j^T),$$

since  $\varphi(x_i^T) > 0$ . This contradicts Lemma 3.1. Hence  $x_i^T$  is in  $C$ .

*Proof of Theorem 2.1:* First note that  $X : (m \times n) \rightarrow Y : (m \times n)$  iff

$$\sum_{i=1}^n \varphi(x_i^T) < \sum_{i=1}^n \varphi(y_i), \quad \dots \quad (3.1)$$

for all convex functions  $\varphi : R^m \rightarrow R$  (See Fischer and Holbrook, 1977, p. 564 or Blackwell, 1953). Hence it is sufficient to show the above inequality for our case  $m = 2$ .

Let the polygon  $O \subseteq R^2$  denote the convex hull of the column vectors of  $Y$  which are assumed to be distinct. Suppose  $y_i^T$ 's are the  $n$  vertices of  $C$ , i.e.  $y_i^T$ 's are the extreme points. We name these vertices by  $A_1, A_2, \dots, A_n$  in consecutive order. By Lemma 3.2, all  $x_i^T$ 's are in  $C$ . Consider a convex function  $\varphi$  on  $C$ . Define  $\alpha_i = \varphi(A_i)$ ,  $\alpha = (\alpha_1, \dots, \alpha_n)$ , and

$$F_\alpha = \sup \{ f : f \text{ convex on } C, f(A_i) = \alpha_i \text{ for all } i \}. \quad \dots \quad (3.2)$$

In view of Lemmas 3.1 and 3.2 it is sufficient to show that  $F$  is the sum of finitely many directional convex functions, since

$$\varphi(x_i^T) \leq F_\alpha(x_i^T), \varphi(y_i) = F_\alpha(y_i) \text{ for all } i. \quad \dots \quad (3.3)$$

We can assume  $\alpha_1 = \alpha_2 = 0$ , since otherwise we can make  $\alpha_1 = \alpha_2 = 0$  by adding a suitable affine function to  $\varphi$ . We can furthermore assume that  $\alpha_i \geq 0$  for all  $i > 2$ , since this can be achieved by adding the affine function  $C_{L, i-1, A_1}$  for suitable large  $s > 0$ , where  $L$  is the line joining the distinct points  $A_1$  and  $A_2$  and  $i > 2$ . Note that  $C_{L, s, x}$  is affine if  $a = -b$ .

Consider  $C_{L, t, 0, A_3}$  for  $t \geq 0$  and note that this function is affine on  $C$ . For  $t = 0$

$$C_{L, t, 0, A_3}(A_i) \leq \alpha_i, \text{ for all } i > 2. \quad \dots \quad (3.4)$$

Now as we increase  $t$ , at some point (say at  $t = t_0$ ) at least one equality in (3.4) will be attained preserving the other inequalities. Let  $A_{i_1}, A_{i_2}, \dots, A_{i_r}$

( $r \leq n-2$ ) be the vertices at which the equality in (3.4) is attained. If  $r = n-2$ , define  $F_a = C_{L, t_0, 0, A_3}$  and we are done.

If  $r < n-2$ , consider the following possible configuration :

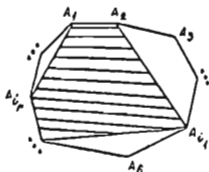


Fig. 1

Let  $\beta_i = \alpha_i - C_{L, t_0, 0, A_3}(A_i)$ . Then

$$\beta_i \geq 0, \beta_1 = \beta_2 = \beta_{i_1} = \dots = \beta_{i_r} = 0. \quad \dots (3.5)$$

Consider now the polygon  $A_1 A_2 A_{i_1} A_{i_2} \dots A_{i_r}$ . Note that  $C - A_1 A_2 A_{i_1} \dots A_{i_r}$  is the union of disjoint polygons. Because of (3.5) we can apply the above operation on each of these polygons, taking the two initial vertices to that  $\beta_i$ 's are zero on them.

Ultimately adding these  $C_{L, a, b, z}$  functions obtained at each stage from each of those polygons we get a function which is  $F_a$ ; this follows from the fact that for each point in the polygon  $A_1 A_2 \dots A_n$ , there exists a sub-polygon with vertices in  $\{A_1, A_2, \dots, A_n\}$  on which the derived function is affine.

This construction shows that  $F_a$ , as derived above, is the sum of finitely many directional convex functions. This proves Theorem 2.1 when all the column vectors of  $Y$  are extreme points.

Now suppose the vertices of  $C$  are  $V_1, V_2, \dots, V_k$ , arranged in consecutive order, and  $B$  is a column vector of  $Y$  which lies on the segment  $V_1 V_2$  closest to  $V_1$ . Then we shall follow the above initial operation with  $A_1 = V_1$  and  $A_2 = B$ . By making  $\alpha_1 = \alpha_2 = 0$ , we can ensure that  $\alpha$  at all column vectors lying on  $V_1 V_2$  is  $\geq 0$ . The above proof can now be followed stage by stage.

When the column vectors of  $Y$  are not distinct, the above operation is used only on distinct column vectors of  $Y$ ; the desired result then follows from (3.3).

Lemma 3.3: Let the convex hull of the column vectors of  $Y: m \times n$  have  $r$ -dimensional positive volume,  $r < m$ . Then the problem of equivalence of  $X \prec_d Y$  and  $X \prec Y$  reduced to the corresponding problem in  $r$ -dimension.

Proof: For some nonsingular  $A: m \times m$  and suitable  $b: m \times 1$  and  $Y_1: r \times n$ , we have

$$A[Y + (b, \dots, b)] = \begin{pmatrix} Y_1 \\ 0 \end{pmatrix}.$$

Following the line of proof of Lemma 3.2, we can show that  $X \prec_d Y$  implies that every column vector of  $X$  is in the convex hull of the column vectors of  $Y$ . Thus

$$A[X + (b, \dots, b)] = \begin{pmatrix} X_1 \\ 0 \end{pmatrix},$$

for some  $X_1$ . It can be shown now that  $X \prec_d Y \Leftrightarrow X_1 \prec_d Y_1$  and  $X \prec Y \Leftrightarrow X_1 \prec Y_1$ .

Proof of Theorem 2.2: In view of Lemma 3.3 we may assume, without any loss of generality, that  $r = m$ .

Hence our assumption entails that at least  $(n-m+2)$  of the  $Y_i$ 's are co-planar, i.e. they belong to a 2-dimensional affine space of  $R^m$ . Let those vectors be represented by the points  $A_1, A_2, \dots, A_{n-m+2}$  and their convex hull be a polygon denoted by  $A_1 A_2 \dots A_{n-m+2}$ , written in consecutive order.

The convex hull of  $A_1, A_2$  and the  $(m-2)$  column vectors of  $Y$  outside the above plane has  $(m-1)$ -dimensional positive volume; let this convex hull be contained in a hyperplane  $H$ .

Note that  $H$  does not contain the polygon  $A_1 A_2 \dots A_{n-m+2}$ . Since  $A_1$  and  $A_2$  are in  $H$ , the other  $A_i$ 's ( $i = 3, 4, \dots, n-m+2$ ) are on one side of  $H$ .

Following Definition 3.2, define

$$C_{H, A_1, A_2}(x) = \begin{cases} td(H, x), & \text{if } l(x) l(A_3) \geq 0 \\ 0 & \text{if } l(x) l(A_3) < 0 \end{cases}$$

where  $t \geq 0$  and  $l(x) = 0$  is the equation of  $H$ .

To complete the proof we follow the operations employed in the proof of Theorem 2.1 with a hyperplane  $H$  taking the role of the line defining the  $C$ -function. Note that initially we can make  $a_i$  to be zero at  $A_1, A_2$  and  $(m-2)$  points lying outside the plane by adding a suitable affine function to  $\varphi$ .

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## REFERENCES

- BHANDARI, S. K. (1984): Multivariate majorization and directional majorization. *Tech. Report No. 20/84*, Stat-Math. Division, Indian Statistical Institute.
- BLACKWELL, D. (1953): Equivalent comparisons of experiments. *Ann. Math. Statist.*, 24, 265-272.
- FISCHER, P. and HOLBROOK, J. A. R. (1977): Matrices doubly stochastic by blocks. *Can. J. Math.* 29, 569-577.
- HARDY, G. H., LITTLEWOOD, J. E. and POLYA, G. (1934): *Inequalities*, Cambridge University Press.
- MARSHALL, A. W. and OLKIN, I. (1979): *Inequalities: Theory of Majorization and its Applications*, Academic Press, New York.
- ROCKAFELLAR, R. T. (1970): *Convex Analysis*, Princeton Univ. Press, Princeton.
- SHERMAN, S. (1951): On a theorem of Hardy, Littlewood, Polya and Blackwell. *Proc. Mat. Acad. Sci.* 37, 826-831.

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