

Non-existence of some affinely equivariant location functionals in dimension  $d \geq 2$ 

An *affine transformation* from  $\mathbb{R}^d$  to itself is one of the form  $Ax = Bx + v$  for all  $x \in \mathbb{R}^d$  where  $B$  is a linear transformation ( $d \times d$  matrix) and  $v$  is a fixed vector. Then  $A$  will be called *non-singular* if and only if  $B$  is. Here  $x$  and  $v$  are  $d \times 1$  column vectors.

For any probability measure  $P$  and random variable  $X$ , which may be vector-valued, we have another probability measure  $P \circ X^{-1}$ , the distribution of  $X$  or image measure of  $P$  by  $X$ . For example, if  $P$  is defined on  $\mathbb{R}^d$  and  $x_j$  is the  $j$ th coordinate function on  $\mathbb{R}^d$ , then  $P \circ x_j^{-1}$  is the  $j$ th marginal of  $P$ , on  $\mathbb{R}$ .

Let  $\mathcal{P}$  be a collection of probability measures on  $\mathbb{R}^d$  and  $m$  a function from  $\mathcal{P}$  into  $\mathbb{R}^d$ . Then  $m$  will be called an *affinely equivariant location functional* on  $\mathcal{P}$  iff whenever  $P \in \mathcal{P}$  and  $A$  is a non-singular affine transformation, we have  $P \circ A^{-1} \in \mathcal{P}$  and  $m(P \circ A^{-1}) = Am(P)$ . Also,  $m(\cdot)$  will be called *singularly affine(ly) equivariant* if the same holds when  $A$  may be singular.

When  $d = 1$ , the median is a singularly affine equivariant location functional defined on the class of *all* probability measures on  $\mathbb{R}$ . For  $d = 1$ , a singular linear transformation  $B$  is just multiplication by 0, and so for any  $P$ ,  $P \circ A^{-1}$  is concentrated in the point  $v$ . It turns out not to be restrictive to say that for such a distribution  $m$  should equal  $v$ . For  $d \geq 2$ , however, there are more singular matrices, and we will see that singular affine equivariance becomes very restrictive.

Recall that  $\delta_x(A) := 1_A(x) := 1$  if  $x \in A$  and 0 otherwise. For  $n = 1, 2, \dots$ , and  $d = 1, 2, \dots$ , let  $\mathcal{P}_{n,d}$  be the class of all empirical measures  $P_n = \frac{1}{n} \sum_{j=1}^n \delta_{x_j}$  on  $\mathbb{R}^d$  where each  $x_j = (x_{1j}, \dots, x_{dj})' \in \mathbb{R}^d$ . Clearly, for any transformation  $A$  from  $\mathbb{R}^d$  into itself (affine or not) and  $P_n$  as given,  $P_n \circ A^{-1} = \frac{1}{n} \sum_{j=1}^n \delta_{A(x_j)} \in \mathcal{P}_{n,d}$ . Here is the main fact in this handout:

**Theorem** (Obenchain, 1971). Let  $d \geq 2$  and suppose  $m$  is a singularly affine equivariant location functional defined on  $\mathcal{P}_{n,d}$  for a given  $n$ . Then  $m(P_n) = \int x dP_n = \bar{x} = \sum_{j=1}^n x_j/n$  for all  $P_n \in \mathcal{P}_{n,d}$ .

**Remark.** For  $d = 1$  there are some robust singularly affine equivariant location functionals such as the median (and trimmed means, e.g. Randles and Wolfe, problem 7.4.2 pp. 246-247). But the sample mean  $\bar{x}$  has breakdown point 0 for all  $n$ , so a singularly affine equivariant location functional on  $\mathcal{P}_{n,d}$  for  $d \geq 2$  can't have any robustness. Thus, researchers consider affinely (not singularly) equivariant functionals, not defined on all of  $\mathcal{P}_{n,d}$ , e.g. not defined on  $P_n \circ A^{-1}$  for  $A$  singular.

**Proof.** For  $X_j \in \mathbb{R}^d$ ,  $j = 1, \dots, n$ , with  $X_j = (X_{1j}, \dots, X_{dj})'$ , let  $X$  be the  $d \times n$  data matrix  $X_{ij}$  for  $i = 1, \dots, d$  and  $j = 1, \dots, n$ , so that  $X_j$  is the  $j$ th column of  $X$ . Let  $P_n := \frac{1}{n} \sum_{j=1}^n \delta_{X_j} \in \mathcal{P}_{n,d}$ . Then  $m(P_n)$  is a function of  $X$ , say  $m(P_n) \equiv M(X)$ . Let  $B$  be any  $d \times d$  matrix. Then the data matrix for  $BX_1, \dots, BX_n$  is  $BX$ , i.e. the  $j$ th column of  $BX$  is  $BX_j$ , so

$$M(BX) = m(P_n \circ B^{-1}) = Bm(P_n) = BM(X)$$

by singular affine equivariance.

Some special choices of  $B$  will be made. First, for each  $u = 1, \dots, d$ , let  $B_{ir}^{(u)} = 0$  if  $i \geq 2$  or if  $i = 1$  and  $r \neq u$ , with  $B_{1u}^{(u)} := 1$ . Let  $X^{(u)}$  denote the  $u$ th row of  $X$ , so that  $(X^{(u)})_j \equiv X_{uj}$  for  $j = 1, \dots, n$ . For any  $1 \times n$  vector  $V$ , let  $\tilde{V}$  be the  $d \times n$  matrix whose first row is  $V$  and whose other rows are all 0's. Then  $B^{(u)}X = \tilde{X}^{(u)}$ , so

$$M(\tilde{X}^{(u)}) = M(B^{(u)}X) = B^{(u)}M(X) = (M_u(X), 0, \dots, 0)',$$

where  $M(X) = (M_1(X), \dots, M_d(X))'$ . Thus

$$(1) \quad M_1(\tilde{X}^{(u)}) \equiv M_u(X).$$

Next, for any real numbers  $a$  and  $b$ , define a  $d \times d$  matrix  $B^{a,b}$  by  $B_{11}^{a,b} := a$ ,  $B_{12}^{a,b} := b$ , and  $B_{ij}^{a,b} := 0$  for all other  $i$  and  $j$ , i.e. for  $i \geq 2$  or  $j \geq 3$ . Then  $B^{a,b}X = (aX^{(1)} + bX^{(2)})^\sim$ , so

$$(2) \quad M([aX^{(1)} + bX^{(2)}]^\sim) = M(B^{a,b}X) = B^{a,b}M(X) = (aM_1(X) + bM_2(X), 0, \dots, 0)'.$$

By (1),  $M_1(X) = M_1(\tilde{X}^{(1)})$  and  $M_2(X) = M_1(\tilde{X}^{(2)})$ . Equating first components in (2) gives

$$aM_1(\tilde{X}^{(1)}) + bM_1(\tilde{X}^{(2)}) = M_1(a\tilde{X}^{(1)} + b\tilde{X}^{(2)}).$$

For any (row vector)  $y \in \mathbb{R}^n$ , we have a map  $y \mapsto L(y) := M_1(\tilde{y})$  which is linear since  $X^{(1)}$  and  $X^{(2)}$  can be any two  $1 \times n$  vectors and  $a, b$  any two real numbers. Thus  $M_1(\tilde{y}) \equiv yz$  for some column vector  $z \in \mathbb{R}^n$ .

Now for any data matrix  $X$ , we have by (1)

$$\begin{aligned} M(X) &= (M_1(X), \dots, M_d(X))' = (M_1(\tilde{X}^{(1)}), \dots, M_1(\tilde{X}^{(d)}))' \\ &= (X^{(1)}z, \dots, X^{(d)}z)' = Xz. \end{aligned}$$

Next, any permutation of the columns  $X_j$  of  $X$  gives the same  $P_n$  and thus the same  $M(X) = m(P_n)$ , so the components of  $z$  are all equal,  $z = (z_1, \dots, z_1)'$ . Thus  $M(X) \equiv nz_1\bar{X}$ .

Now suppose all  $X_j$  equal some  $v \neq 0$  and let  $Ax \equiv 2x - v$ . Then  $Av = v$ , so  $M(AX) = M(X) = nz_1v = AM(X) = 2nz_1v - v$ . It follows that  $z_1 = 1/n$  and  $M(X) \equiv \bar{X}$ , proving the theorem.  $\square$

**Remarks.** If an affinely invariant location functional  $m$  is defined on all of  $\mathcal{P}_{n,d}$  and  $M$  is continuous as a function of  $X_1, \dots, X_n$ , then  $m$  must be singularly affine equivariant and so is equal to  $\bar{X}$ .

Recall that a sequence  $Q_n$  of probability measures is said to converge weakly to  $Q_0$  if  $\int f dQ_n \rightarrow \int f dQ_0$  for every bounded continuous function  $f$ . (This form of convergence is used in the central limit theorem, for example.) Let  $Q_n = (n-1)\delta_0/n + \delta_n/n$ . Suppose  $m$  is an affinely equivariant location functional defined on  $\mathcal{P}_{n,d}$  for all  $n$  for a given  $d \geq 2$  and that  $m$  is continuous for weak convergence. Then it is continuous in  $X_1, \dots, X_n$  for fixed  $n$ , so it is singularly affine equivariant, and by Obenchain's theorem,  $m(Q_n) = \int x dQ_n = 1$

for all  $n$ . But  $Q_n$  converge weakly to  $\delta_0$ , for which  $m(\delta_0) = 0$ , contradicting the weak continuity, so no such  $m$  exists.

**Note.** The theorem is essentially contained in the statement and proof of Obenchain (1971, Lemma 1).

#### REFERENCE

Obenchain, R. L. (1971). Multivariate procedures invariant under linear transformations. *Ann. Math. Statist.* **42**, 1569-1578.