

## GENERALIZED DISTRIBUTION FUNCTIONS: THE $\sigma$ -LOWER FINITE CASE<sup>1,2</sup>

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A mass  $m(x) \geq 0$  is assigned to each point  $x$  of a partially ordered countable set  $X$ . It is further assumed that  $M(x) = \sum_{y \leq x} m(y) < \infty$  for each  $x \in X$ .  $M$  is called a distribution function. For certain sets  $X$ , it is shown that  $M$  determines  $m$ . For others,  $M$  need not determine  $m$  uniquely. A theory is presented for  $\sigma$ -lower finite spaces (sets), which are defined in the paper. Such spaces are locally finite. That is, each interval  $[x, y] = \{z \in X: x \leq z \leq y\}$  has a finite number of points. Möbius functions, which have been defined for locally finite spaces, are used throughout. Distribution functions on a particular  $\sigma$ -lower finite space arise naturally from boundary crossing problems analyzed by Doob and Anderson. The theory is applied to this example and to another.

**1. Introduction.** Let  $X$  be a partially ordered countable set with each point  $x \in X$  possessing a nonnegative mass  $m(x)$ . We assume  $M(x) = \sum_{y \leq x} m(y) < \infty$ ,  $x \in X$ , and refer to the function  $M$  as the (cumulative) *distribution function*. Sometimes, we shall require the total mass  $m(X) = \sum_{x \in X} m(x)$  to be unity.<sup>3</sup> We shall concern ourselves with the following questions:

- (i) When does the distribution function determine the individual masses  $m(x)$ ,  $x \in X$ ?
- (ii) How are they found when they are determined?
- (iii) When is a function  $M(x)$ ,  $x \in X$ , actually a distribution function?

When  $X$  is finite, one has an inversion formula expressed in terms of the *Möbius function*  $\mu(x, y)$  of  $X$ :

$$(1) \quad m(y) = \sum_{x \leq y} M(x) \mu(x, y), \quad y \in X.$$

Section 3 of Rota's (1964) fundamental paper on the theory of Möbius functions provides the relevant background. Thus, *the distribution function always determines the individual masses whenever  $X$  is finite.*

We shall be concerned with the more difficult situation in which  $X$  is infinite.

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<sup>3</sup> Of course, the requirement  $m(X) = 1$  is quite natural in a probabilistic context. However, we shall refrain from making this an assumption *at the outset* since its inclusion would tend to complicate the theory presented below.

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The full range of possibilities is much more than we can cope with at this early stage, and we shall be content with a modest beginning. We shall confine all of our attention to *locally finite* spaces since it is for such spaces that a Möbius function is defined. That is, for each pair of points  $x, y \in X$ , we shall insist that the interval  $[x, y] = \{z : x \leq z \leq y\}$  be finite.

A rather uninteresting extension of the finite theory discussed in the second paragraph can be made when the number of summands in (1) is finite for each  $y \in X$ . Formula (1) still applies. We refer to such an  $X$  as *lower finite*. A lower finite space is necessarily locally finite.

An interesting example for which  $X$  is locally finite but not lower finite arises (apparently unnoticed) in a much cited paper by Doob (1949): Let  $X$  consist of a maximal point  $(0, 1)$  and pairs of points  $(n, 1), (n, 2)$  for  $n \geq 1$ .  $x = (n, j) < x' = (n', j')$  if and only if  $n > n', n' \geq 0$ . See Fig. 1. Let  $\{W(t), t \geq 0\}$  be a standard Wiener process (mean zero and variance  $t$ ) and let  $U$  and  $L$  be two lines with  $U$  (the upper) having positive slope and intercept, and  $L$  (the lower) having negative slope and intercept. Let  $M(0, 1) = 1$  and, for  $n \geq 1$ , let  $M(n, 1)$  and  $M(n, 2)$  denote the probability that there exist  $n$  time  $0 < t_1 < \dots < t_n$  with  $(t_1, W(t_1)), \dots, (t_n, W(t_n))$  alternately in  $U$  and  $L$  beginning with  $U$  and  $L$ , respectively. (Anything may happen before  $t_1$ , between times, and after  $t_n$ .) Then  $\{M(x), x \in X\}$  is a distribution function corresponding to individual masses such as  $m(0, 1) = P(W \text{ never touches } U \text{ or } L)$ ,  $m(1, 1) = P(W \text{ touches } U \text{ but never touches } L)$  and  $m(2, 2) = P(W \text{ touches } L \text{ before } U \text{ then touches } U \text{ then never touches } L \text{ again})$ .

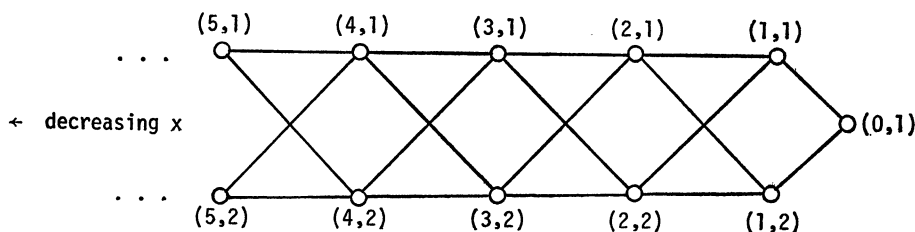


FIG. 1.

Doob describes how to compute  $M(x), x \in X$ . His interest is in expressing, in terms of these, a probability such as  $m(0, 1)$ . In particular, he obtains a formula which, in our notation, becomes

$$(2) \quad m(0, 1) = 1 - \sum_{n=1}^{\infty} (-1)^{n-1} \{M(n, 1) + M(n, 2)\}.$$

Anderson (1960) obtains a formula for  $P(W \text{ touches } U \text{ before } L)$ . ( $W$  does not need to touch  $L$ .) This can be expressed in terms of the individual masses as  $\sum_{n=1}^{\infty} m(n, 1)$ . Anderson evaluates the probability as  $M(1, 1) - M(2, 2) + M(3, 1) - M(4, 2) + \dots$ .

For the  $X$  of Fig. 1, we find that the distribution function always determines

the individual masses. Besides (2), we have the related equations:

$$(3) \quad m(n, j) = M(n, j) - \sum_{k=n+1}^{\infty} (-1)^{k-1} \{M(k, 1) + M(k, 2)\} \quad n \geq 1, j = 1, 2.$$

These equations can be checked by direct substitution.

Before we present some theory, we shall show that a locally finite space can have distribution functions which fail to determine the individual masses. Our example is only slightly more complicated than that of Fig. 1. See Fig. 2.  $X$  consists of a maximal point  $(0, 1)$  and triplets  $(n, 1), (n, 2), (n, 3)$  for  $n \geq 1$ .  $x = (n, j) < x' = (n', j')$  if and only if  $n > n', n' \geq 0$ .

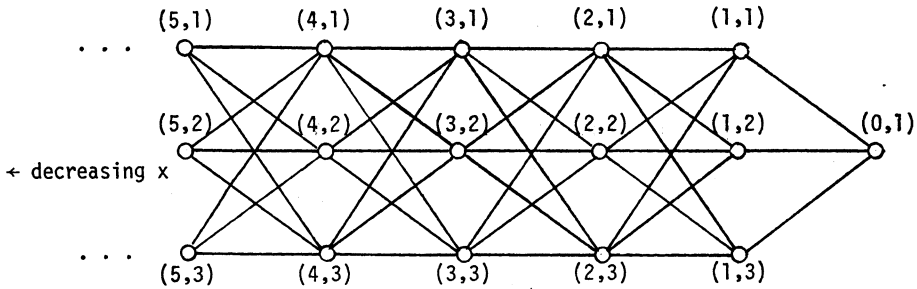


FIG. 2.

EXAMPLE 1.  $M(0, 1) = 1$  and  $M(n, 1) = M(n, 2) = M(n, 3) = 2^{-n}$ ,  $n \geq 1$ . There are many possible values for the individual masses but all of the possibilities can be expressed as convex combinations of two extremal solutions:

SOLUTION 1 a.  $m(0, 1) = \frac{1}{2}$ ;  $m(n, 1) = m(n, 2) = m(n, 3) = 2^{-n-1}$  for  $n = 2, 4, 6, \dots$ ; all other  $m(x) = 0$ .

SOLUTION 1 b.  $m(n, 1) = m(n, 2) = m(n, 3) = 2^{-n-1}$  for  $n = 1, 3, 5, \dots$ ; all other  $m(x) = 0$ .

EXAMPLE 2.  $M(0, 1) = 1$  and  $M(n, 1) = M(n, 2) = M(n, 3) = 3^{-n}$ ,  $n \geq 1$ . There is only one solution:  $m(0, 1) = \frac{2}{5}$  and  $m(n, 1) = m(n, 2) = m(n, 3) = \frac{2}{5} \cdot 3^{-n}$ ,  $n \geq 1$ .

These examples show that *the issue of uniqueness for the individual masses depends on the actual distribution function as well as on the structure of  $X$* . We shall return to these examples later after we have some theory with which to justify our claims.

While the spaces described in Figs. 1 and 2 are not lower finite, they are what we shall refer to as  $\sigma$ -lower finite. That is there exists a sequence of partitions  $X = A_k + B_k$  with  $A_k > B_k$  (i.e., each point of  $A_k$  exceeds each point of  $B_k$ ),  $A_k \nearrow X$  as  $k \rightarrow \infty$ , and each  $A_k$  is lower finite (i.e., for each  $y \in X$  and each  $k \geq 1$ ,  $\{x \in A_k : x \leq y\}$  is finite). A  $\sigma$ -lower finite space is necessarily locally finite. We shall give a definitive answer to questions (i), (ii) and (iii) for  $\sigma$ -lower

finite spaces in Section 3. Although the  $\sigma$ -lower finite assumption is stronger than one might prefer, it permits a wide range of spaces. Departures from this assumption can be analyzed but the assumption permits us to develop a reasonably uncomplicated theory.

**2. Some preliminaries.** Let  $X$  be locally finite. It will be recalled that the Möbius function can be defined recursively by

$$(4) \quad \begin{aligned} \mu(x, y) &= 1 && \text{for } x = y, \\ &= -\sum_{x \leq z < y} \mu(x, z) && \text{for } x < y, \\ &= 0 && \text{for } x \not\leq y. \end{aligned}$$

Another useful formula is

$$(5) \quad \mu(x, y) = -\sum_{x < z \leq y} \mu(z, y) \quad \text{for } x < y.$$

Let  $A'$  denote the complement of  $A$  for each subset  $A$  of  $X$ .

Suppose  $X = A + B + C$  with  $A > C > B$ , where  $A, B$  or  $C$  may be the empty set  $\emptyset$ . Define whenever the number of summands is finite:

$$(6) \quad \begin{aligned} \mu(x, A) &= -\sum_{x \leq z < A} \mu(x, z), && x \in A', \\ \mu(B, y) &= -\sum_{B < z \leq y} \mu(z, y), && y \in B', \\ \mu(B, A) &= -1 + \sum_{B < x, y < A} \mu(x, y). \end{aligned}$$

It is easily checked that

$$(7) \quad \mu(B, A) = -1 - \sum_{B < x < A} \mu(x, A) = -1 - \sum_{B < y < A} \mu(B, y).$$

It is most helpful to have an intuitive understanding of (6).  $\mu(x, A)$ ,  $\mu(B, y)$  and  $\mu(B, A)$  are actual Möbius function values corresponding to various clustered versions of  $X$ . If one views  $A$  as a single point and the points of  $A'$  as individual entities, (4) with  $y = A$  yields the definition of  $\mu(x, A)$ . In a similar manner,  $\mu(B, y)$  arises from (5).  $\mu(B, A)$  arises from viewing  $A$  and  $B$  as points and the points in between as individual entities.

**PROPOSITION 1.** *Suppose  $X = A + B$  where  $A$  and  $B$  are not empty and  $A > B$ . Then  $A$  and  $B$  have at least one minimal and one maximal point, respectively. Moreover,  $\mu(b, a_0) = \mu(b, A)$  and  $\mu(b_0, a) = \mu(B, a)$  for each  $a \in A, b \in B$ , minimal point  $a_0 \in A$  and maximal point  $b_0 \in B$ .*

**PROOF.** Let  $a \in A$  and  $b \in B$ .  $[b, a]$  is a finite interval and must contain a minimal point in  $A$  and maximal point in  $B$ . The equalities above easily follow from definitions.  $\square$

**PROPOSITION 2.** *Suppose  $X = A + B$  where  $A > B$ . Then*

$$(8) \quad \mu(b, a) = -\mu(b, A)\mu(B, a)$$

(with both factors well defined) for each  $a \in A$  and  $b \in B$ .

**PROOF.** Since  $\mu(b_0, A) = \mu(B, a_0) = -1$  for each minimal point  $a_0 \in A$  and

maximal point  $b_0 \in B$ , the desired equality follows from Proposition 1 when  $a$  is a minimal point of  $A$  or  $b$  is a maximal point of  $B$ . The remainder of the proof uses induction based on the total number of elements in  $[b, a]$ . The induction step is:

$$\begin{aligned} \mu(b, a) &= -\sum_{b < z \leq a} \mu(z, a) = -\sum_{b < z < A} \mu(z, a) + \mu(B, a) \\ &= \sum_{b < z < A} \mu(z, A)\mu(B, a) + \mu(B, a) \\ &= (\sum_{b < z \leq a_0} \mu(z, a_0))\mu(B, a) \\ &= -\mu(b, a_0)\mu(B, a) = -\mu(b, A)\mu(B, a). \quad \square \end{aligned}$$

**PROPOSITION 3.** *Suppose  $X = A + B$  where  $A > B$  and  $B \neq \emptyset$ . Let  $x_0$  be a minimal point of  $A$ . Further, let  $x$  and  $y$  be distinct points satisfying  $x \neq x_0$  and  $y > x_0$ . Then*

$$\sum_{B < z \leq y, z \neq x_0} \mu(x, z) = 0.$$

**PROOF.** Using (4):

$$\begin{aligned} 0 &= \sum_{x \leq z \leq y} \mu(x, z) = \sum_{x \leq z \leq y, z \in B} \mu(x, z) + \sum_{x \leq z \leq y, z \in A} \mu(x, z) \\ &= \sum_{x \leq z < x_0} \mu(x, z) + \sum_{B < z \leq y} \mu(x, z) \\ &= -\mu(x, x_0) + \sum_{B < z \leq y} \mu(x, z) = \sum_{B < z \leq y, z \neq x_0} \mu(x, z). \quad \square \end{aligned}$$

We describe now, in terms of the notation used in the definition, the three possible types of  $\sigma$ -lower finite spaces:

Type I:  $X$  is lower finite.

Type II:  $X$  is not lower finite and  $\mu(B_{k+1}, A_k) = 0$  for infinitely many  $k$ .

Type III:  $X$  is not lower finite and  $\mu(B_{k+1}, A_k) = 0$  for only finitely many  $k$ .

**PROPOSITION 4.** *The distinction between types II and III is independent of the particular sequence of partitions  $X = A_k + B_k, k \geq 1$ .*

**PROOF.** By viewing the points of  $B_{k+2}$  and the points of  $A_k$  as single points, it follows from Proposition 2 that  $\mu(B_{k+2}, A_k) = -\mu(B_{k+2}, A_{k+1})\mu(B_{k+1}, A_k)$ . In turn,

$$(9) \quad \mu(B_{k+l}, A_k) = \pm \prod_{j=0}^{l-1} \mu(B_{k+j+1}, A_{k+j}), \quad l \geq 2.$$

It follows that the type, II or III, is unaltered by adding or deleting partitions from a given sequence.  $\square$

**3. Some theory.** We shall successively examine  $\sigma$ -lower finite spaces of types I, II and III.

We have already commented about type I spaces (lower finite spaces) in the introduction. They are so easily analyzed because each set  $\{x: x \leq y\}, y \in X$ , is finite and the restriction of a distribution function (on  $X$ ) to  $\{x: x \leq y\}$  is a distribution function on that finite space. Therefore, questions (i), (ii) and (iii) (appearing in the introduction) are easily answered with the use of (1).

Suppose  $X$  is a  $\sigma$ -lower finite space of type II.  $X$  has the following important property:

**PROPOSITION 5.** *For a type II  $\sigma$ -lower finite space  $X$ , each set  $\{x: \mu(x, y) \neq 0\}$ ,  $y \in X$ , is finite.*

**PROOF.** In view of (9), we may assume, without sacrificing generality, that  $\mu(B_{k+1}, A_k) = 0$  for  $k \geq 1$ . Suppose  $y \in X$ . Then, necessarily,  $y \in A_k$  for some  $k$ . Since  $X$  is not lower finite,  $A_{k+1}$  must be a proper subset of  $X$ . Consequently, there exists a point  $x_0 \in B_{k+1}$ . Since  $[x_0, y]$  is a finite set, it suffices to show that  $\mu(x, y) = 0$  for each  $x \notin [x_0, y]$ . We only need to consider  $x \in B_{k+1}$ . For such an  $x$ , we have, with successive applications of Proposition 2,  $\mu(x, y) = -\mu(x, A_k)\mu(B_k, y) = \mu(x, A_{k+1})\mu(B_{k+1}, A_k)\mu(B_k, y) = 0$ .  $\square$

The following theorem tells us that (1) holds for type II spaces:

**THEOREM 1.** *For any locally finite space, (1) holds for a given  $y \in X$  whenever the number of nonzero summands in (1) is finite.*

**PROOF.** Under the assumption,

$$\sum_{x \leq y} \sum_{z \leq x} |m(z)\mu(x, y)| \leq M(y) \sum_{\{x: x \leq y, M(x) \neq 0\}} |\mu(x, y)| < \infty.$$

Thus, Fubini's theorem applies. Then,

$$\begin{aligned} \sum_{x \leq y} M(x)\mu(x, y) &= \sum_{x \leq y} \sum_{z \leq x} m(z)\mu(x, y) \\ &= \sum_{z \leq y} m(z) \sum_{z \leq x \leq y} \mu(x, y) = m(y). \end{aligned} \quad \square$$

While (1) can be used directly to answer question (iii) for type II spaces, it is easier to use the following theorem:

**THEOREM 2.** *A function  $M$  on a type II  $\sigma$ -lower finite space  $X$  is a distribution function if and only if*

- (a) *the sum in (1) is nonnegative for each  $y \in X$ , and*
- (b) *the set  $\{x: x \leq y, |M(x)| \geq \epsilon\}$  is finite for each  $\epsilon > 0$  and  $y \in X$ .*

**PROOF.** Assume (a) and (b), and fix  $y$ . Find an  $A_k$  containing  $y$  and an  $x_k \leq y$  which is a minimal point of  $A_k$ . Define  $m$  in terms of  $M$  by (1). Except for a finite number of  $x \in X$ ,  $\mu(x, z) = 0$  for all  $z$  in any given finite subset of  $X$ . Thus, we may interchange the order of summation below, and we have with the aid of Proposition 3:

$$\begin{aligned} \sum_{B_k < z \leq y, z \neq x_k} m(z) &= \sum_{x \leq y} M(x) \sum_{B_k < z \leq y, z \neq x_k} \mu(x, z) \\ &= M(y)\mu(y, y) - M(x_k)\mu(x_k, x_k) = M(y) - M(x_k). \end{aligned}$$

Letting  $k \rightarrow \infty$  leads to  $\sum_{x \leq y} m(z) = M(y)$ . Thus,  $M$  is a distribution function. Conversely, if  $M$  is a distribution function for the individual masses  $m(x)$ ,  $x \in X$ , then (a) follows from Theorem 1 and (b) follows from the local finiteness of  $X$ .  $\square$

Suppose  $X$  is a  $\sigma$ -lower finite space of type III. Depending on the structure of  $X$ , there may be two distinct sets of individual masses with the same distribution function. This contrasts with type I and type II spaces where the answer to question (i) is "Always."

Proposition 4 permits us to assume that  $A_1 \neq \emptyset$  and  $\mu(B_k, A_1) \neq 0$  for each  $k \geq 1$ . For each  $x \in X$ , choose an arbitrary  $A_k$  containing  $x$  and define  $\beta(x) = -\mu(B_k, x)/\mu(B_k, A_1)$ .

PROPOSITION 6.  $\beta$  is well defined in the sense that the value of  $\beta(x)$  does not depend on how one chooses  $k$ .  $\beta(x) = \mu(B_1, x)$  for  $x \in A_1$ .  $\beta$  is not identically zero.

PROOF. For  $x \in A_k$ ,  $\mu(B_{k+1}, x) = -\mu(B_{k+1}, A_k)\mu(B_k, x)$  (cf., (8)), and  $\mu(B_{k+1}, A_1) = -\mu(B_{k+1}, A_k)\mu(B_k, A_1)$  (cf., (8)). Thus  $\beta(x)$  is well defined. If  $x \in A_1$ ,  $\mu(B_1, A_1) = -1$  and  $\beta(x) = \mu(B_1, x)$ . Finally, if  $x_k$  is a minimal point of  $A_k$ , then  $\mu(B_k, x_k) = -1$  and  $\beta(x_k) = \mu(B_k, A_1)^{-1} \neq 0$ .  $\square$

Let  $\beta^+$  and  $\beta^-$  denote the positive and negative parts of  $\beta$ , respectively.

THEOREM 3. For each  $y \in X$ ,

$$(10) \quad \sum_{x \leq y} \beta^+(x) = \sum_{x \leq y} \beta^-(x).$$

Thus, if  $\sum_{x \leq y} |\beta(x)| < \infty$  for each  $y \in X$ ,  $\{\beta^+(x)\}$  and  $\{\beta^-(x)\}$  represent two distinct sets of individual masses with the same distribution function.

PROOF. Fix  $y$  and choose a minimal point  $x_k$  of  $A_k$  satisfying  $x_k \leq y$ , for each  $A_k$  containing  $y$ . Then  $\sum_{B_k < z \leq y, z \neq x_k} \mu(B_k, z) = 0$  (cf., Proposition 3), and hence,

$$(11) \quad \sum_{B_k < z \leq y, z \neq x_k} \beta(z) = 0.$$

Then (10) follows by letting  $k \rightarrow \infty$ .  $\square$

A space  $X$  will be called a *determining space* if every distribution function on  $X$  corresponds to a unique set of individual masses.

THEOREM 4. A type III  $\sigma$ -lower finite space  $X$  is a determining space if and only if  $\sum_{x \leq y_0} |\beta(x)| = \infty$  for some  $y_0 \in X$ .

We shall defer the proof of the "if" part until later. The "only if" part is immediate from Theorem 3.

Define

$$\begin{aligned} \nu(x, y) &= \mu(x, y) && \text{for } x \in A_1, \\ &= \mu(x, y) + \mu(x, A_1)\beta(y) && \text{for } x \in B_1. \end{aligned}$$

$\nu(x, y) = 0$  whenever  $x \in B_k$  and  $y \in A_k$  for some  $k \geq 1$  (cf., (8)). Likewise,  $\nu(x, y) = 0$  whenever  $x \in A_1$  and  $x \not\leq y$  (cf., (4)). Thus, the sum  $\sum_{x \in X} M(x)\nu(x, y)$  has at most a finite number of nonzero summands for each  $y \in X$ .

PROPOSITION 7. Let  $M$  be a distribution function corresponding to the individual masses  $\{m(x)\}$  and let  $\alpha = m(B_1)$ .  $M$  and  $\alpha$  together determine  $m$ . In particular,

$$(12) \quad m(y) = \sum_{x \in X} M(x)\nu(x, y) + \alpha\beta(y), \quad y \in X.$$

PROOF.  $\alpha < \infty$  since there exists a point  $y_0 \in A_1$  and  $\alpha = m(B_1) \leq M(y_0) < \infty$ . Fix  $k \geq 1$  and view  $B_k$  as a point. Then (cf., (1)),

$$(13) \quad m(y) = \sum_{x \in A_k} M(x)\mu(x, y) + m(B_k)\mu(B_k, y), \quad y \in A_k.$$

Next, view both  $D = \{z \in A_1 : z \leq y_0\}$  and  $B_k$  as points. Then (cf., (1)),

$$M(y_0) - \alpha = m(D) = M(y_0) \cdot 1 + \sum_{x \in B_1 - B_k} M(x)\mu(x, A_1) + m(B_k)\mu(B_k, A_1).$$

Consequently,

$$(14) \quad \alpha + \sum_{x \in B_1 - B_k} M(x)\mu(x, A_1) + m(B_k)\mu(B_k, A_1) = 0.$$

Combining (13) and (14), we obtain for  $y \in A_k$ ,

$$\begin{aligned} m(y) &= \sum_{x \in A_k} M(x)\mu(x, y) + (\sum_{x \in B_1 - B_k} M(x)\mu(x, A_1) + \alpha)\beta(y) \\ &= \sum_{x \in X} M(x)\nu(x, y) + \alpha\beta(y). \end{aligned} \quad \square$$

PROOF OF THEOREM 4 ("if" part). Let  $\{m_1(x)\}$  and  $\{m_2(x)\}$  be distinct sets of individual masses which give rise to the distribution function  $M$ . From (12), we have  $\Delta m(x) = \Delta\alpha\beta(x)$ , where  $\Delta m = m_2 - m_1$  and  $\Delta\alpha = \Delta m(B_1)$ . Since  $\Delta m(x) \neq 0$  for some  $x$ ,  $\Delta\alpha \neq 0$ . Thus for any  $y \in X$ ,

$$\sum_{x \leq y} |\beta(x)| = |\Delta\alpha^{-1}| \sum_{x \leq y} |\Delta m(x)| \leq |2\Delta\alpha^{-1}|M(y) < \infty. \quad \square$$

THEOREM 5. A function  $M$  on a type III  $\sigma$ -lower finite space is a distribution function if and only if

(a) there exists an  $\alpha$  which makes the right-hand side of (12) nonnegative for each  $y \in X$ , and

(b) the set  $\{x : x \leq y, |M(x)| \geq \epsilon\}$  is finite for each  $\epsilon > 0$  and  $y \in X$ .

Each such  $\alpha$  corresponds to a unique set of individual masses  $\{m(x)\}$  defined by (12), and for this set,  $\alpha = m(B_1)$ .

PROOF. The proof of the "if" part parallels that for Theorem 2. But here one defines  $m$  by (12), using the  $\alpha$  predicated in assumption (a), instead of (1). The complications brought in by  $\beta$  (both directly and indirectly through  $\nu(x, y)$ ) are taken care of by using (11). One obtains  $M(y) = \sum_{x \leq y} m(x)$ ,  $y \in X$ . If  $\alpha$  were not equal to  $m(B_1)$ , Proposition 7 would be contradicted. For the converse, (a) is a consequence of Proposition 7 and (b) is due to the local finiteness of  $X$ .  $\square$

Let  $M$  be a distribution function. It is easy to see that the possible value for  $\alpha = m(B_1)$  is an interval  $[\alpha_{\min}, \alpha_{\max}]$ , perhaps a point.

PROPOSITION 8.

$$(15) \quad \alpha_{\min} = \sup \{ -\sum_{x \in X} M(x)\nu(x, y)/\beta(y) : \beta(y) > 0 \}.$$

$$(16) \quad \alpha_{\max} = \inf \{ -\sum_{x \in X} M(x)\nu(x, y)/\beta(y) : \beta(y) < 0 \}.$$

If  $\sum_{x \leq z} |\beta(x)| = \infty$  for some  $z$  (and necessarily for all  $z$ ), then

$$(17) \quad \alpha_{\min} = \alpha_{\max} = \lim_{k \rightarrow \infty} \{ \sum_{B_k < y < A_1} | \sum_{x \in X} M(x)\nu(x, y) / \sum_{B_k < y < A_1} |\beta(y)| \}.$$

If  $m(B_k)|\mu(B_k, A_1)| \rightarrow 0$  as  $k \rightarrow \infty$ , then

$$(18) \quad \alpha_{\min} = \alpha_{\max} = -\lim_{k \rightarrow \infty} \sum_{B_k < z < A_1} M(x)\mu(x, A_1).$$



PROOF. Formulas (15) and (16) follow easily from Theorem 5. Suppose  $\sum_{z \leq z} |\beta(z)| = \infty$ . We may suppose  $z \in A_1$ . Then from (12), we have for each  $k$ :

$$|\alpha \sum_{B_k < y < A_1} |\beta(y)| - \sum_{B_k < y < A_1} |\sum_{x \in X} M(x)\nu(x, y)|| \leq \sum_{B_k < y < A_1} m(y) \leq M(z) < \infty .$$

The first sum  $\rightarrow \infty$  as  $k \rightarrow \infty$ , and (17) follows. Formula (18) follows directly from (14).  $\square$

The condition for (18) is difficult to validate directly since one is not likely to know the value of  $m(B_k)$  without knowing  $\alpha$ . However,  $m(B_k) \leq M(x)$ ,  $x \in A_k$ ,  $k \geq 1$ . So, an indirect validation is possible.

We now turn our attention toward the evaluation of the total mass  $m(X)$ . A requirement such as  $m(X) = 1$  sometimes determines a unique choice for the individual masses when a distribution function, by itself, does not. The most direct formula, of course, is  $m(X) = \sum_{x \in X} m(x)$ . However, there are some advantages in securing formulas which primarily involve the values of the distribution function.

Let  $X^* = X + \{x^*\}$  be an augmented space satisfying  $x^* > X$ . If  $m(x^*) = 0$ , then  $M(x^*) = m(X)$ . If  $X^*$  is locally finite, then  $\mu^*(x, x^*) = \mu(x, \phi)$ ,  $x \in X$ , where  $\mu^*$  denotes the extension of  $\mu$  to  $X^*$ .<sup>4</sup>

PROPOSITION 9. *Suppose  $X^*$  is a  $\sigma$ -lower finite space. Then  $X$  is a  $\sigma$ -lower finite space of the same type as  $X^*$ . If  $X^*$  is of type I or type II,*

$$(19) \quad m(X) = - \sum_{x \in X} M(x)\mu(x, \phi) ,$$

*a sum with only a finite number of nonzero summands.*

*If  $X^*$  is of type III, then  $A_1$  is a finite set and*

$$(20) \quad m(X) = - \sum_{x \in A_1} M(x)\mu(x, \phi) - \alpha\mu(B_1, \phi) ,$$

*where  $\alpha = m(B_1)$ .*

PROOF. Briefly, (20) follows from (cf., (1)):

$$0 = m(x^*) = m(X)\mu^*(x^*, x^*) + \sum_{x \in A_1} M(x)\mu(x, \phi) + m(B_1)\mu(B_1, \phi) .$$

Formula (19) is shown similarly. The details are left to the reader.  $\square$

Proposition 9 is still usable when  $X^*$  is not  $\sigma$ -lower finite: Express  $X$  as  $\{x_n, n \geq 1\}$ . Then define  $X_n = \{z \in X : z \leq x_j \text{ for some } j = 1, \dots, n\}$  and  $X_n^* = X_n + \{x^*\}$ ,  $n \geq 1$ . If  $X$  is  $\sigma$ -lower finite, then so is each  $X_n^*$  (and of the same type as  $X$ ). Furthermore,  $m(X_n) \nearrow m(X)$  as  $n \rightarrow \infty$ .

THEOREM 6. *Suppose  $X$  is a  $\sigma$ -lower finite space. If  $X$  is of type I or II, then*

$$(21) \quad m(X) = \lim_{n \rightarrow \infty} \sum_{x \in X} \{M(x) \sum_{y \in X_n} \mu(x, y)\} .$$

<sup>4</sup> We shall superscript an extended function with an asterisk only when it aids clarity. Here,  $\mu(x, \phi)$  has a different meaning from  $\mu^*(x, \phi)$ . The latter is zero for all  $x \in X$ .

If  $X$  is of type III,

$$(22) \quad m(X) = \alpha + \lim_{n \rightarrow \infty} \sum_{x \in A_1} \{ (M(x) - \alpha) \sum_{y \in X_n} \mu(x, y) \},$$

where  $\alpha = m(B_1)$ . Each sum has a finite number of nonzero summands.

PROOF. The details easily follow from (6), (19), (20) and the foregoing discussion.

**4. Applications.** We shall confine our applications to the two spaces illustrated in Figs. 1 and 2. Both are  $\sigma$ -lower finite spaces of type III. The basic facts about these spaces are summarized in Table 1. For Fig. 1,  $\alpha_{\min} = \alpha_{\max} = \sum_{n=1}^{\infty} (-1)^{n-1} \{M(n, 1) + M(n, 2)\}$  (cf., (18)). This is consistent with (2). For Fig. 2, define  $S_0 = M(0, 1)$  and, for  $n \geq 1$ ,  $S_n = \sum_{k=1}^n (-2)^{k-1} \{M(k, 1) + M(k, 2) + M(k, 3)\} + (-2)^n \min \{M(n, 1), M(n, 2), M(n, 3)\}$ . Then,  $\alpha_{\min} = \sup \{S_1, S_3, S_5, \dots\}$  and  $\alpha_{\max} = \inf \{S_0, S_2, S_4, \dots\}$  (cf., (15) and (16)).

Finally, we turn our attention to Examples 1 and 2. We see in Example 1 that the first and second solutions correspond to  $m(x) = \frac{1}{2}\beta^-(x)$  and  $m(x) = \frac{1}{2}\beta^+(x)$  ( $x \in X$ ), respectively. For the first solution  $\alpha = \alpha_{\min} = \frac{1}{2}$ , and for the second  $\alpha = \alpha_{\max} = 1$ . For Example 2, (18) applies, and we obtain  $\alpha = \frac{3}{8}$ . With this, the values of  $m(x)$  follow immediately from (12).

TABLE 1

$X$	Fig. 1	Fig. 2
$A_n$	$\{x: x > (n, 1)\}$	$\{x: x > (n, 1)\}$
$\mu((n, j), (n', j'))$	$(-1)^{n-n'}$ for $n' < n$ 1 for $n = n', j = j'$ 0 otherwise	$-(-2)^{n-n'-1}$ for $n' < n$ 1 for $n = n', j = j'$ otherwise
$\mu(B_n, (n', j'))$	$(-1)^{n-n'}$ for $n' < n$	$-(-2)^{n-n'-1}$ for $n' < n$
$\mu((n, j), A_{n'})$	$(-1)^{n-n'+1}$ for $n' \leq n$	$-(-2)^{n-n'}$ for $n' \leq n$
$\mu(B_n, A_{n'})$	$(-1)^{n-n'+1}$ for $n' \leq n$	$-(-2)^{n-n'}$ for $n' \leq n$
$\beta(n, j)$	$(-1)^{n+1}$	$-(-2)^{-n}$
$\sum_{x \leq (0, 1)}  \beta(x) $	$\infty$	4
$\sum_{x \leq (n, j)} \beta^+(x)$	$\infty$	$2^{1-n}$
$\sum_{x \leq (n, j)} \beta^-(x)$	$\infty$	$2^{1-n}$
$\nu((n, j), (n', j'))$	1 for $n = n' = 0, j = j' = 1$ $(-1)^{n-n'-1}$ for $n' > n \geq 1$ -1 for $n = n' \geq 1, j \neq j'$ 0 otherwise	1 for $n = n' = 0, j = j' = 1$ $(-2)^{n-n'-1}$ for $n' > n \geq 1$ $+\frac{1}{2}$ for $n = n' \geq 1, j = j'$ $-\frac{1}{2}$ for $n = n' \geq 1, j \neq j'$ 0 otherwise

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