

## A LAW OF LARGE NUMBERS ON RANDOMLY DELETED SETS

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Consider a system into which units having random magnitude enter at arbitrary times and remain “active” (present in the system) for random periods. Suppose units of high magnitude have stochastically greater lifetimes (tend to stay active for longer periods) than units of low magnitude. Of interest is the process  $\{\mu(t): t \geq 0\}$ , where  $\mu(t)$  denotes the average magnitude of all units active at time  $t$ . We give conditions which guarantee the convergence of  $\mu(t)$  and we determine the form of the limit. Some related processes are also studied.

**1. Introduction.** Consider a system into which units of varying magnitude enter at fixed points in time. Suppose each is endowed with a lifetime, during which the unit is “active” (alive, in service, etc.), and that unit lifetime and magnitude are positively associated. Then, at any specific point in time, the collection of active units comprises only a portion of those that have entered the system. Moreover, since large units tend to remain active for longer durations than small units, one cannot regard the magnitudes of the active units as a random sample from some underlying distribution of magnitudes. For example, it is reasonable to assume that marriages ending ultimately in divorce possess stochastically shorter lifetimes than those that do not. Thus, the expected fraction of active marriages that will end in divorce is smaller than the probability that a new marriage will end so. Similarly, in business, the time required to complete a task (lifetime) is often positively associated with its complexity (magnitude). An inspector observing the system at a specific point in time may be interested in the distribution (or the mean) complexity of tasks currently not completed, rather than the underlying distribution (or expected value) of task complexity.

Let  $(X, L), (X_1, L_1), (X_2, L_2), \dots$  be an independent and identically distributed sequence of random vectors with  $P\{L \geq 0\} = 1$  and  $P\{X \leq x\} = G(x)$ . Suppose  $\{t_n, n \geq 1\}$  is a strictly increasing sequence of nonnegative real numbers with  $t_n \rightarrow \infty$ . For  $k \geq 1$ , let  $t_k$  be the time of arrival of some  $k$ th unit into a system, let  $X_k$  be the magnitude of that unit and let  $L_k$  be the time it remains in the system (its lifetime) prior to deletion.

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We call such a unit active at time  $t$  if  $I_{k,t} = I\{t_k \leq t < t_k + L_k\} = 1$ . We also define for  $t \geq 0$ ,

$$A_t = \sum_{k \geq 1} I_{k,t}, \quad \Gamma_t = \sum_{k \geq 1} P\{t_k \leq t < t_k + L_k\},$$

$$S_t = \sum_{k \geq 1} X_k I_{k,t} \quad \text{and} \quad \mu(t) = \begin{cases} S_t/A_t, & \text{if } A_t \geq 1, \\ 0, & \text{if } A_t = 0. \end{cases}$$

Here,  $A_t$  represents the number of units active at time  $t$ ,  $\Gamma_t$  represents the expected number of such units and  $\mu(t)$  represents their average magnitude. Our goal is to determine conditions under which the continuous time process of averages  $\{\mu(t): t \geq 0\}$  is almost surely convergent, and in these cases to identify the limit.

In Rothmann and Russo (1994) we assumed additionally that  $X$  and  $L$  are independent. When  $X$  possesses a moment generating function in an open interval about the origin, we prove (Theorem 2) that  $\mu(t) \rightarrow EX$  almost surely if  $\Gamma_{t_n}/\log n \rightarrow \infty$ . When  $E|X|^r$  is finite for some  $r$  in  $[1, 2)$ , we require the stronger condition  $\liminf(n^{-1/r}\Gamma_{t_n}) > 0$ . When  $r \geq 2$ , we require also that  $\Gamma_{t_n}$  be nondecreasing (Theorems 3 and 3a). Furthermore, all results are shown to be “sharp.”

Here we consider the more interesting case where unit life is influenced by the corresponding magnitude. For example, “large” units may have stochastically greater lifetimes than “small” units. In this case, the effect of large units on the process tends to be longer lasting than that of small units, and one expects the process limit (when it exists) to exceed  $EX$ . In Section 2 we present our main results, in Section 3 some applications and in Section 4 we comment on the case where the interarrivals are independent random variables.

**2. The main results.** Let  $S$  denote the support of  $X$ . We assume in this section that  $\{R_x(\cdot): x \in S\}$  is a collection of functions for which

$$P\{L > t \mid X\}(\omega) = R_x(t) \quad \text{if } X(\omega) = x,$$

where  $\omega$  is any point in the basic space, and there exists a distribution function  $1 - R^*$  with  $R^*(0) > 0$  and

$$(2.1a) \quad R_x(t) \leq R^*(t) \quad \text{for } x \in S \text{ and } t \geq 0.$$

One can think of  $R^*$  as the survival function of a “uniformly dominant” lifetime variable  $L^*$ . For  $k \geq 2$  define the increment  $\alpha_k = t_k - t_{k-1}$ , and for  $t \geq 0$  define

$$\Gamma_t^* = \sum_{k \geq 1} R^*(t - t_k) I(t_k \leq t) \quad \text{and} \quad \Gamma_t(x) = \sum_{k \geq 1} R_x(t - t_k) I(t_k \leq t),$$

where  $\Gamma_t^*$  [resp.  $\Gamma_t(x)$ ] represents the expected number of units active at time  $t$  were all units endowed with lifetime  $L^*$  (resp., with the lifetime of a unit

having magnitude  $x$ ). We assume further that for all  $x$  in  $S$ ,

$$\begin{aligned}
 \Gamma_{t_n}(x)/\Gamma_{t_n}^* &= \sum_{1 \leq k \leq n} R_x(t_n - t_k) \bigg/ \sum_{1 \leq k \leq n} R^*(t_n - t_k) \\
 (2.1b) \quad &= \sum_{1 \leq k \leq n} P\{L > t_n - t_k \mid X = x\} \bigg/ \sum_{1 \leq k \leq n} P\{L^* > t_n - t_k\} \\
 &\rightarrow \phi(x)
 \end{aligned}$$

for some measurable function  $\phi$  having  $E\phi(x) > 0$ , and

$$(2.1c) \quad \Gamma_{t_n}^*/\log n \rightarrow \infty.$$

Conditions (2.1b) and (2.1c) insure that active units accumulate quickly enough for convergence to occur. Since  $R^*(0) > 0$ , (2.1c) holds if  $a_n \log n \rightarrow 0$  [see the proof of Corollary 2.1 in Rothmann and Russo (1994)]. Later in this section, we remark on the “reasonableness” of condition (2.1b).

**THEOREM 2.1.** *Suppose (2.1) holds and  $E \exp\{tX\} < \infty$  for all  $t$  in an open interval containing the origin. Then  $\mu(t_n) \rightarrow EX\phi(X)/E\phi(X)$  almost surely. If, in addition,  $\liminf(\Gamma_{t_{n+1}}^*/\Gamma_{t_n}^*) \geq 1$ , then  $\mu(t) \rightarrow EX\phi(X)/E\phi(X)$  almost surely.*

**REMARKS.** The conclusion of the theorem holds if we simultaneously weaken the condition on  $X$  and strengthen condition (2.1c), so that (1)  $E|X|^r < \infty$  for some  $r$  in  $[1, 2)$  and  $\liminf(n^{-1/r}\Gamma_{t_n}^*) > 0$  or (2)  $E|X|^r < \infty$  for some  $r \geq 2$ ,  $\Gamma_{t_n}^*$  is nondecreasing and  $\liminf n^{-1/r}\Gamma_{t_n}^* > 0$ . This is evident from our proof of Theorem 2.1 [see Theorems 3 and 3a of Rothmann and Russo (1994)]. When  $a_n$  is a nonincreasing sequence,  $\Gamma_{t_n}^*$  is a nondecreasing sequence and  $\liminf(\Gamma_{t_{n+1}}^*/\Gamma_{t_n}^*) \geq 1$ . If  $R_x(t)$  is nondecreasing in  $x$  for each real  $t$ , then  $EX$  is a lower bound to the almost sure limit [by Proposition 7.1.5 of Ross (1983), since  $\phi$  is nondecreasing]. We illustrate this last point with two examples:

**EXAMPLE 1 (Random detection).** Suppose  $X$  is  $U(0, 1)$ ,  $a_n \log n \downarrow 0$  and  $R_x(t) = (1 - t)x$  for  $0 \leq t \leq 1$  and  $0 \leq x \leq 1$ . Let  $R_x = R_0$  for  $x < 0$  and  $R_x = R_1$  for  $x > 1$ . Then, if  $X_k = x$ ,  $L_k$  is zero with probability  $1 - x$  (the  $k$ th unit is “undetected”), but is otherwise uniform on  $(0, 1)$ . We set  $R^* = R_1$ , so that  $\phi(x) = x$  for  $0 \leq x \leq 1$  and  $\Gamma_{t_n}^*/\log n \rightarrow \infty$ . Since  $a_n$  is nonincreasing,  $\mu(t) \rightarrow 2/3$  almost surely.

**EXAMPLE 2 (The limiting proportion of types).** Suppose  $a_n \equiv \delta > 0$ ,  $P\{X = 0\} = p = 1 - P\{X = 1\}$ ,  $R_0(t)/R_1(t) \rightarrow \alpha$ , some  $0 \leq \alpha \leq 1$ , and  $tR_1(t) \rightarrow \infty$  as  $t \rightarrow \infty$ . [For a concrete example, take  $R_0(t) = \alpha(t + 1)^{-1/2}$  and  $R_1(t) = (t + 1)^{-1/2}$  for  $t > 0$ .] If  $X_k = i$  we will say that the  $k$ th entering unit is “type  $i$ ,”  $i = 0, 1$ . In the limit,  $p$  is the proportion of entering units which are type 0. However, if  $0 \leq \alpha < 1$ , such units tend to have shorter lifetimes than type 1 units, and are thus expected to comprise a smaller (than  $p$ ) proportion of the

active population. At time  $t$ , we call this proportion  $\pi_t$  and observe that  $\pi_t = 1 - \mu(t)$ . Set  $R^* = R_1$ . From a routine calculation we have  $\phi(0) = \alpha$  and  $\phi(1) = 1$ . We have also

$$\begin{aligned} \Gamma_{t_n}^*/\log n &= \sum_{1 \leq k \leq n} R^*(t_n - t_k)/\log n \\ &= \sum_{1 \leq k \leq n} (1/n - k)(n - k)R_1((n - k)\delta)/\log n \rightarrow \infty. \end{aligned}$$

Since  $a_n$  is nonincreasing,  $\mu(t) \rightarrow (1 - p)/(\alpha p + (1 - p))$  almost surely. Thus,  $\pi_t \rightarrow 1 - (1 - p)/(\alpha p + (1 - p)) = \alpha p/(\alpha p + 1 - p)$  almost surely.

In Rothmann and Russo (1997) we prove the following results which show that condition (2.1b) is not nearly as restrictive as it looks.

1. If  $na_n \rightarrow 0$ , then  $\phi(x) = R_x(0)/R^*(0)$ , in which case  $EX\phi(X)/E\phi(X) = E(X | L > 0)$ .
2. If  $na_n \rightarrow c \in (0, \infty)$ , then  $\phi(x) = (1 - E(e^{-L/c} | X = x))/(1 - E(e^{-L^*/c}))$ , in which case

$$EX\phi(X)/E\phi(X) = E(X(1 - E(e^{-L/c} | X)))/(1 - E(e^{-L^*/c})).$$

3. If  $na_n \uparrow \infty$ ,  $a_n \downarrow 0$  and  $EL^* < \infty$ , then  $\phi(x) = E(L | X = x)/EL^*$ , in which case  $EX\phi(X)/E\phi(X) = E(XE(L | X))/EL$ .
4. If  $na_n \uparrow \infty$ ,  $a_n \downarrow \gamma \geq 0$  and  $EL = \infty$ , then  $\phi(x) = \lim_{t \rightarrow \infty} R_x(t)/R^*(t)$ , provided this limit exists.

It can be shown that in case 1,  $(\log A_t)/t \rightarrow \infty$  a.s. (faster than exponential growth of the active population); in case 2,  $(\log A_t)/t \rightarrow 1/c$  a.s. (exponential growth); and in cases 3 and 4,  $(\log A_t)/t \rightarrow 0$  a.s. (slower than exponential growth). Case 2 gives applicable results for a population that grows exponentially; for example, a population of biological units or a population of carriers of a contagious disease.

In cases 1–4, if the conditional life distributions are Laplace transform ordered in  $x$  [see Shaked and Shantikumar (1994)], then

$$E(X\phi(X))/E\phi(X) \geq E(X).$$

Note that Laplace transform ordering is a weaker condition than stochastic ordering. For  $0 \leq c \leq \infty$ , let  $m(c)$  denote the almost sure limit of  $\mu(t)$  as given in cases 1–4. If the hazard rate functions of the conditional life distributions are nonincreasing in  $x$ , then  $m(c)$  is nonincreasing in  $c$  [see Rothmann and Russo (1997)]. Larger  $c$ 's correspond to slower rates of entry (slower growth of the active population) and a larger limiting mean.

The following result is applicable to “short” interarrivals and requires neither that  $X$  possess a moment generating function nor that a uniformly dominant life exists.

**THEOREM 2.2.** *Suppose  $E|X| < \infty$ . If  $\Gamma_{t_n}(x)/n \rightarrow \phi(x)$  for some measurable function  $\phi$  with  $E\phi(X) > 0$ , then  $\mu(t) \rightarrow E(X\phi(X))/E\phi(X)$  almost surely.*

Suppose  $R_x(0) > 0$  for  $x$  in  $S$ . If  $\limsup na_n < \infty$ , then  $\delta_x < \Gamma_{t_n}(x)/n \leq 1$  for some  $\delta_x > 0$ . If  $na_n \rightarrow c \in [0, \infty)$ , then  $\Gamma_{t_n}(x)/n \rightarrow \phi(x) = R_x(0)$  or  $1 - E(e^{-L/c} | X = x)$  according as  $c = 0$  or  $c > 0$ . The resulting limits of  $\mu(t)$  are as in cases 1 and 2 above.

EXAMPLE 3. Suppose  $X$  has d.f.  $G(x) = 1 - 1/x^2$  for  $x \geq 1$ ,  $na_n \downarrow 1$  and the conditional life distribution of  $L$ , given  $X = x$ , is exponential with mean  $x$ . Then  $\phi(x) = 1 - E(e^{-L} | X = x) = x/1 + x$  and thus  $\mu(t) \rightarrow E(X^2/1 + X)/E(X/1 + X) = \log 2/(1 - \log 2)$  a.s.

The proof of Theorem 2.1 will require three lemmas. Define  $t_{nk} = t_n - t_k$  and let  $\varepsilon$  denote an arbitrary constant in  $(0, 1)$ . If  $Z$  is a random variable,  $r(Z)$  denotes the ratio  $Z/EZ$ . All statements involving random denominators are asserted to hold on the set where those denominators are nonzero.

LEMMA 1. For  $n \geq 1$ , let  $T_n$  denote the row sum of a rowwise independent, triangular array of indicator variables. If  $ET_n/\log n \rightarrow \infty$ , then  $r(T_n) \rightarrow 1$  almost surely.

PROOF. We have  $\text{var}(T_n) \leq ET_n$  by independence. By Bernstein's inequality [see either Serfling (1980) or Uspensky (1937)], for  $0 < \delta < 1$  and all large  $n$  we have  $P\{|T_n - ET_n| > \delta ET_n\} \leq 2 \exp\{-\delta^2(ET_n)^2/(2ET_n + \delta ET_n)\} \leq n^{-2}$ .  $\square$

LEMMA 2. Suppose  $\mathcal{C}$  is a Borel set for which  $E(\phi(X)I(X \in \mathcal{C})) > 0$ . If (2.1) holds, then

$$r\left(\sum_{1 \leq k \leq n} I(X_k \in \mathcal{C}, L_k > t_{nk})\right) \rightarrow 1 \quad \text{almost surely.}$$

PROOF. We have

$$P\{X_k \in \mathcal{C}, L_k > t_{nk}\} = \int_{\mathcal{C}} P\{L > t_{nk} | X = x\} dG(x)$$

so that for large  $n$ , by the dominated convergence theorem,

$$\begin{aligned} & \sum_{1 \leq k \leq n} P\{X_k \in \mathcal{C}, L_k > t_{nk}\} / \log n \\ &= \int_{\mathcal{C}} \sum_{1 \leq k \leq n} P\{L > t_{nk} | X = x\} dG(x) / \log n \\ &= (\Gamma_{t_n}^* / \log n) \int_{\mathcal{C}} (\Gamma_{t_n}(x) / \Gamma_{t_n}^*) dG(x) \\ &\geq (\Gamma_{t_n}^* / \log n) E(\phi(X)I(X \in \mathcal{C})) / 2. \end{aligned}$$

The result now follows by (2.1c) and Lemma 1.  $\square$

The following lemma is a consequence of Theorem 1 of Rothmann and Russo (1997):

LEMMA 3. Suppose  $P\{X = 1\} = p = 1 - P\{X = 0\}$ . If  $\Gamma_{t_n}(1)/\Gamma_{t_n} \rightarrow \gamma$ ,  $\Gamma_{t_n}/\log n \rightarrow \infty$  and  $\liminf(\Gamma_{t_{n+1}}/\Gamma_{t_n}) \geq 1$ , then  $\mu(t) \rightarrow p\gamma$  almost surely.

PROOF OF THEOREM 2.1. We prove Theorem 2.1 in the continuous time case only. The proof in discrete time is essentially the same. We first consider the case where  $X$  is bounded. The result is trivial if  $X$  is degenerate, so we assume that  $-\infty < \text{ess inf } X < \text{ess sup } X < \infty$ . By Lemma 2,

$$(2.2) \quad r(A_{t_n}) \rightarrow 1 \quad \text{a.s.}$$

By the dominated convergence theorem (DCT), upon integration of (2.1b) we have

$$(2.3) \quad \Gamma_{t_n}/\Gamma_{t_n}^* \rightarrow E\phi(X).$$

We observe that the following inequalities hold for  $t_n \leq t \leq t_{n+1}$ :

$$(2.4a) \quad \begin{aligned} A_{t_{n+1}} - 1 \leq A_t \leq A_{t_n}, \quad \Gamma_{t_{n+1}} - 1 \leq \Gamma_t \leq \Gamma_{t_n}, \\ \Gamma_{t_{n+1}}(x) - 1 \leq \Gamma_t(x) \leq \Gamma_{t_n}(x) \quad \text{and} \quad \Gamma_{t_{n+1}}^* - 1 \leq \Gamma_t^* \leq \Gamma_{t_n}^*. \end{aligned}$$

For  $t_n \leq t \leq t_{n+1}$  we have also

$$(2.4b) \quad \begin{aligned} 1 \geq \Gamma_t/\Gamma_{t_n} &= (\Gamma_t/\Gamma_{t_{n+1}})(\Gamma_{t_{n+1}}/\Gamma_{t_{n+1}}^*)(\Gamma_{t_{n+1}}^*/\Gamma_{t_n}^*)(\Gamma_{t_n}^*/\Gamma_{t_n}), \\ 1 \geq A_t/A_{t_n} &= r(A_{t_{n+1}})(\Gamma_{t_{n+1}}/\Gamma_{t_{n+1}}^*)(\Gamma_{t_n}^*/\Gamma_{t_n}) \\ &\quad \times (\Gamma_{t_{n+1}}^*/\Gamma_{t_n}^*)(A_t/A_{t_{n+1}})/r(A_{t_n}), \end{aligned}$$

so that by (2.2), (2.3), (2.4) and our  $\liminf$  condition,

$$(2.5) \quad A_t/A_{t_n} \rightarrow 1 \quad \text{a.s.} \quad \text{and} \quad \Gamma_t/\Gamma_{t_n} \rightarrow 1 \quad \text{uniformly in } t_n \leq t \leq t_{n+1}.$$

Now, by (2.2) and (2.5),

$$(2.6) \quad r(A_t) \rightarrow 1 \quad \text{a.s.}$$

The following inequalities hold for  $t_n \leq t \leq t_{n+1}$  and follow from (2.4a):

$$\begin{aligned} ((\Gamma_{t_{n+1}}(x) - 1)/\Gamma_{t_{n+1}}^*)(\Gamma_{t_{n+1}}^*/\Gamma_{t_n}^*) &\leq \Gamma_t(x)/\Gamma_t^* \leq (\Gamma_{t_n}(x)/\Gamma_{t_n}^*)(\Gamma_{t_n}^*/(\Gamma_{t_{n+1}}^* - 1)), \\ ((\Gamma_{t_{n+1}} - 1)/\Gamma_{t_{n+1}}^*)(\Gamma_{t_{n+1}}^*/\Gamma_{t_n}^*) &\leq \Gamma_t/\Gamma_t^* \leq (\Gamma_{t_n}/\Gamma_{t_n}^*)(\Gamma_{t_n}^*/(\Gamma_{t_{n+1}}^* - 1)). \end{aligned}$$

These inequalities, when combined with (2.1b), (2.1c), (2.3) and our  $\liminf$  condition, yield

$$(2.7) \quad \Gamma_t(x)/\Gamma_t^* \rightarrow \phi(x) \quad \text{and} \quad \Gamma_t/\Gamma_t^* \rightarrow E\phi(X).$$

Fix  $x_0 < x_1 < \dots < x_m$  so that

$$x_0 < \text{ess inf } X < \text{ess sup } X < x_m$$

and

$$x_{j+1} - x_j < \varepsilon \quad \text{for } 0 \leq j \leq m - 1.$$

Define

$$h_j = [x_{j-1}, x_j), \quad p_j = P\{X \in h_j\}$$

and

$$A_t(j) = \sum_{\{k: t_k \leq t\}} I(X_k \in h_j, L_k > t_n - t_k).$$

Note that  $P\{L > t \mid X \in h_j\} = (1/p_j) \int_{h_j} R_x(t) dG(x)$  if  $p_j > 0$ . Thus, by (2.7) and the DCT,

$$\begin{aligned} & \sum_{\{k: t_k \leq t\}} P\{L > t - t_k \mid X \in h_j\} / \Gamma_t \\ &= (1/p_j)(1/\Gamma_t) \int_{h_j} \sum_{\{k: t_k \leq t\}} R_x(t - t_k) dG(x) \\ (2.8) \quad &= (1/p_j)(\Gamma_t^* / \Gamma_t) \int_{h_j} \Gamma_t(x) / \Gamma_t^* dG(x) \\ &\rightarrow (1/p_j E\phi(X)) \int_{h_j} \phi(x) dG(x). \end{aligned}$$

By Lemma 3, (2.1c), (2.3) and (2.8) we have

$$(2.9) \quad A_t(j)/A_t \rightarrow (1/E\phi(X)) \int_{h_j} \phi(x) dG(x) \quad \text{a.s.}$$

Now

$$(1/A_t) \sum_{1 \leq j \leq m} x_{j-1} A_t(j) \leq \mu(t) \leq (1/A_t) \sum_{1 \leq j \leq m} x_j A_t(j) \leq u(t) + \varepsilon,$$

so that almost surely, by (2.9),

$$\begin{aligned} (1/E\phi(X)) \int x \phi(x) dG(x) - \varepsilon &\leq (1/E\phi(X)) \sum_{1 \leq j \leq m} \int_{h_j} x_{j-1} A_t(j) \\ &\leq \liminf_{n \rightarrow \infty} \mu(t) \leq \limsup_{n \rightarrow \infty} \mu(t) \\ &\leq (1/E\phi(X)) \sum_{1 \leq j \leq m} \int_{h_j} x_j A_t(j) \\ &\leq (1/E\phi(X)) \int x \phi(x) dG(x) + \varepsilon. \end{aligned}$$

Thus, since  $\varepsilon$  is arbitrary, we conclude that  $\mu(t) \rightarrow E(X\phi(X))/E\phi(X)$  almost surely.

We now remove the boundedness assumption. Fix  $m_0 > 0$  so that  $E(\phi(X)I(-m_0 < X < m_0)) > 0$ . Fix  $m > m_0$  and define

$$\mathcal{A}_{t,m} = \sum_{k \geq 1} I(-m \leq X_k \leq m) I_{k,t},$$

$$W_{n,m} = X_n I(X_n > m) \quad \text{and} \quad V_{n,m} = X_n I(X_n < -m).$$

We have

$$\begin{aligned} S_t/A_t &= \sum_{k \geq 1} X_k I(-m \leq X_k \leq m) I_{k,t}/A_t + \sum_{k \geq 1} W_{k,m} I_{k,t}/A_t \\ (2.10) \quad &+ \sum_{k \geq 1} V_{k,m} I_{k,t}/A_t \\ &= B_{t,m,1} + B_{t,m,2} + B_{t,m,3}. \end{aligned}$$

We define a new process where the  $k$ th entering unit has respective magnitude and lifetime

$$Y_{k,m} = \begin{cases} X_k, & \text{if } X_k \in [-m, m], \\ -2m, & \text{otherwise} \end{cases}$$

and

$$\lambda_{k,m} = \begin{cases} L_k, & \text{if } X_k \in [-m, m], \\ 0, & \text{otherwise.} \end{cases}$$

We also define  $\chi_{k,t} = I(t_k \leq t < t_k + \lambda_{k,m})$ , so that

$$(2.11) \quad B_{t,m,1} = \frac{\sum_{k \geq 1} Y_{k,m} \chi_{k,t} / \sum_{k \geq 1} \chi_{k,t}}{\mathcal{A}_{t,m} r(A_t) \Gamma_t / r(\mathcal{A}_{t,m}) E \mathcal{A}_{t,m} \sum_{k \geq 1} \chi_{k,t}}.$$

By (2.6) and Lemma 2 (using similar arguments for  $\mathcal{A}_{t,m}$  as for  $A_t$ ),  $r(A_t)/r(\mathcal{A}_{t,m}) \rightarrow 1$  a.s. Now, by (2.7),

$$\begin{aligned} \lim_{t \rightarrow \infty} (\Gamma_t / E \mathcal{A}_{t,m}) &= \lim_{t \rightarrow \infty} (\Gamma_t / \Gamma_t^*) \Big/ \lim_{t \rightarrow \infty} \int_{[-m, m]} (\Gamma_t(x) / \Gamma_t^*) dG(x) \\ &= E\phi(X) \Big/ \int_{[-m, m]} \phi(x) dG(x). \end{aligned}$$

By Theorem 1 applied to the bounded  $Y_{k,m}$ 's,

$$\begin{aligned} \lim_{t \rightarrow \infty} \sum_{k \geq 1} Y_{k,m} \chi_{k,t} \Big/ \sum_{k \geq 1} \chi_{k,t} \\ = \int_{[-m, m]} x \phi(x) dG(x) \Big/ \int_{[-m, m]} \phi(x) dG(x) \quad \text{a.s.} \end{aligned}$$

Since  $\sum_{k \geq 1} \chi_{k,t} = \mathcal{A}_{t,m}$ , we conclude from (2.11) that

$$(2.12) \quad \lim_{m \rightarrow \infty} \lim_{t \rightarrow \infty} B_{t,m,1} = EX\phi(X)/E\phi(X) \quad \text{a.s.}$$

Next, we form an image of our process on a new probability space: Attach to the original space a sequence  $U_k$  of i.i.d.  $U(0, 1)$  random variables which are jointly independent of the  $X_k$ 's. We may redefine the  $L_k$  sequence and also



define sequences  $L_k^*$  and  $L_k(x)$  as follows:

$$L_k(x) = \sup\{y: R_x(y) \geq U_k\}, \quad L_k = L_k(X_k)$$

and

$$L_k^* = \sup\{y: R^*(y) \geq U_k\}.$$

On the new space the joint distributions of the  $X_k$ 's and  $L_k$ 's remain the same. However, in addition we have  $L_k \leq L_k^*$ . Define  $I_{k,t}^* = I(t_k \leq t < t_k + L_k^*)$ . Now,

$$(2.13) \quad 0 \leq B_{t,m,2} \leq \left( \sum_{k \geq 1} W_{k,m} I_{k,t}^* / \sum_{k \geq 1} I_{k,t}^* \right) / \left( A_t / \sum_{k \geq 1} I_{k,t}^* \right).$$

Let  $E_{t,m}$  and  $H_t$  denote, respectively, the numerator and denominator in (2.13). Since for  $|t|$  small,  $E \exp\{tW_{k,m}\} < \infty$ , we have by (2.1c) and Theorem 2.1 of Rothmann and Russo (1994),

$$(2.14) \quad \lim_{m \rightarrow \infty} \lim_{t \rightarrow \infty} E_{t,m} = \lim_{m \rightarrow \infty} \int_{(m,\infty)} x dG(x) = 0 \quad \text{a.s.}$$

Furthermore,

$$H_t = (\Gamma_t / \Gamma_t^*) r(A_t) / r\left(\sum_{k \geq 1} I_{k,t}^*\right).$$

Thus, since  $r(\sum_{k \geq 1} I_{k,t}^*) \rightarrow 1$  a.s. (by Lemma 2), we have by (2.6) and (2.7),

$$(2.15) \quad \lim_{t \rightarrow \infty} H_t = E\phi(X) > 0.$$

Putting (2.14) and (2.15) together we get

$$(2.16) \quad \lim_{m \rightarrow \infty} \limsup_{t \rightarrow \infty} B_{t,m,2} = 0 \quad \text{a.s.}$$

Now

$$\left( \sum_{k \geq 1} V_{k,m} I_{k,t}^* / \sum_{k \geq 1} I_{k,t}^* \right) / \left( A_t / \sum_{k \geq 1} I_{k,t}^* \right) \leq B_{t,m,3} \leq 0,$$

so that, by the same argument that yielded (2.16),

$$(2.17) \quad \lim_{m \rightarrow \infty} \liminf_{t \rightarrow \infty} B_{t,m,3} = 0 \quad \text{a.s.}$$

Statements (2.10), (2.12), (2.16) and (2.17) together yield the final result.  $\square$

**PROOF OF THEOREM 2.2.** The proof is the same as that of Theorem 2.1, with the following changes: Replace  $\Gamma_t^*$  by  $\sum_{k \geq 1} I(t_k \leq t)$  and  $I_{k,t}^*$  by  $I(t_k \leq t)$ . Note that (2.14) follows from the ordinary SLLN.  $\square$

**3. Applications.** The  $p$ th quantile ( $0 < p < 1$ ) associated with the units active at time  $t$  is given by

$$\xi_{t,p} = \begin{cases} \pi X_t(pA_t) + (1 - \pi) X_t(pA_t + 1), & \text{if } pA_t = [pA_t], \\ X_t([pA_t] + 1), & \text{if } pA_t \neq [pA_t], \end{cases}$$

where  $0 \leq \pi \leq 1$  is fixed,  $[y]$  denotes the greatest integer in  $y$  and  $X_t(i)$  is the  $i$ th order statistic among the members of  $\{X_k: I_{k,t} = 1\}$ .

**THEOREM 3.1.** Suppose  $\Gamma_{t_n}(x)/\Gamma_{t_n} \rightarrow \phi(x)$  for some function  $\phi$  satisfying  $\int_{-\infty}^{\infty} \phi(x) dG(x) = 1$  and  $\Gamma_{t_n}/\log n \rightarrow \infty$ . If  $\psi(p)$  is the unique solution to the equation  $p = \int I(x < \psi(p)) \phi(x) dG(x)$ , then  $\xi_{t_n,p} \rightarrow \psi(p)$  almost surely. If, in addition,  $\liminf(\Gamma_{t_{n+1}}/\Gamma_{t_n}) \geq 1$ , then  $\xi_{t,p} \rightarrow \psi(p)$  almost surely.

In Example 1,  $\psi(p) = p^{1/2}$ . In cases 1–4, if the conditional life distributions are Laplace transform ordered in  $x$ , then  $G(\psi(p)) \geq p$ . If the hazard rate functions of the conditional life distributions are nonincreasing in  $x$ , then  $\psi(p)$  is nondecreasing in  $c$  [see Rothmann and Russo (1997)].

**PROOF OF THEOREM 3.1.** We prove the continuous time result only. Fix  $\psi_0 < \psi(p)$  so that  $p > \int I(-\infty < x \leq \psi_0) \phi(x) dG(x)$ . Define  $T_n = I(X_n \geq \psi_0)$ ,

$$S_t^* = \sum_{k \geq 1} T_k I_{k,t} \quad \text{and} \quad \gamma = \lim_{n \rightarrow \infty} \sum_{1 \leq k \leq n} P\{L_k \geq t_n - t_k \mid T_k = 1\} / \Gamma_{t_n}.$$

For  $1 \leq k \leq n$ ,

$$\begin{aligned} & P\{L_k \geq t_{nk} \mid T_k = 1\} \\ &= \int_{[\psi_0, \infty)} P\{L_k \geq t_{nk}, T_k = 1 \mid X_k = x\} dG(x) / P\{T_k = 1\}. \end{aligned}$$

Thus, using Fatou's lemma,

$$\begin{aligned} \gamma &= \lim_{n \rightarrow \infty} \int_{[\psi_0, \infty)} \sum_{1 \leq k \leq n} P\{L_k \geq t_{nk} \mid X_k = x\} dG(x) / \Gamma_{t_n} P\{T_k = 1\} \\ &= \int_{[\psi_0, \infty)} \phi(x) dG(x) / P\{T_k = 1\}. \end{aligned}$$

By Lemma 3,

$$S_t^*/A_t \rightarrow \int_{[\psi_0, \infty)} \phi(x) dG(x) > 1 - p$$

so that  $\liminf \xi_{t,p} \geq \psi(p)$  a.s. Additionally, by a similar argument,  $\limsup \xi_{t,p} \leq \psi(p)$  a.s.  $\square$

An application of Theorem 2.2 and 3.1 to the case where  $X = L$  yields a result on the “mean total life” of units active at time  $t$ ,  $\lambda_t = \sum_{k \geq 1} L_k I_{k,t} / A_t$ ,

and the associated  $p$ th quantile  $\beta_{t,p}$  obtained by replacing  $X_k$  by  $L_k$  in the definition of  $\xi_{t,p}$ . One expects units with long life to exert a greater influence on  $\lambda_t$  and  $\beta_{t,p}$  than units with short life. An observer inspecting the system at time  $t$  sees this as a forward shift in the distribution of  $L$ . The result is a variation of the “inspection paradox” [see Feller (1971) or Ross (1983)]:

**THEOREM 3.2.** (a) Suppose  $na_n \rightarrow c \in [0, \infty)$ . If  $0 < EL < \infty$ , then  $\lambda_t \rightarrow E(L | L > 0)$  a.s. when  $c = 0$  and  $\lambda_t \rightarrow E(L(1 - e^{-L/c}))/E(1 - e^{-L/c})$  a.s. when  $0 < c < \infty$ . If  $c = 0$  and  $\tau(p)$  is the unique solution to

$$P\{L > 0\}p = \int I(x < \tau(p)) R_x(0) dP\{L \leq x\},$$

then  $\beta_{t,p} \rightarrow \tau(p)$  almost surely. If  $0 < c < \infty$  and  $\tau(p)$  is the unique solution to

$$pE(1 - e^{-L/c}) = \int I(x < \tau(p))(1 - e^{-x/c}) dP\{L \leq x\},$$

then  $\beta_{t,p} \rightarrow \tau(p)$  almost surely.

(b) Suppose  $a_n$  and  $1/na_n$  are nonincreasing,  $a_n \log n \rightarrow 0$  and  $na_n \rightarrow \infty$ . If  $P\{L = 0\} < P\{0 \leq L \leq m\} = 1$  for some  $m$ , then  $\lambda_t \rightarrow EL^2/EL$  almost surely. If, in addition,  $\tau(p)$  is the unique solution to  $pEL = \int I(x < \tau(p))x dP\{L \leq x\}$ , then  $\beta_{t,p} \rightarrow \tau(p)$  almost surely.

In Theorem 3.2, we observe that the almost sure limit of  $\lambda(t)$  is bounded below by  $EL$ , and that of  $\beta_{t,p}$  is bounded below by the  $p$ th quantile of  $L$ . Thus, the mean eventual life of active units exceeds the expected life of entering units.

**PROOF OF THEOREM 3.2.** (a) This result is an immediate consequence of Theorem 3.1.

(b) For  $x > 0$  let  $h(n, x) = \sum_{1 \leq k \leq n-1} I(t_{nk} \leq x)$ . Fix  $x > 0$  and  $0 < \delta < 1$ . Since  $a_n \downarrow 0$ , we have for large  $n$ ,

$$x(1 - \delta) \leq t_n - t_{n-h(n,x)} \leq x$$

and

$$a_n h(n, x) \leq t_n - t_{n-h(n,x)} \leq h(n, x) a_{n-h(n,x)}.$$

Thus,

$$(3.1) \quad (1 - \delta)x/a_{n-h(n,x)} \leq h(n, x) \leq x/a_n.$$

Define  $n(\delta) = n - [\delta n]$ . Since  $t_n - t_{n(\delta)} \geq a_n[\delta n] \rightarrow \infty$ , we have that  $h(n, x) \leq \delta n$  for large  $n$ . Furthermore,  $n(\delta)a_{n(\delta)} \leq na_n$ , so that by (3.24),  $(1 - \delta)xn(\delta)/na_n \leq h(n, x) \leq x/a_n$ . Since  $\delta$  is arbitrary,  $a_n h(n, x)/x \rightarrow 1$ . Thus,  $h(n, x)/h(n, m) \rightarrow x/m = \phi(x)$  for  $0 \leq x \leq m$ . The result now follows via an application of Theorems 1 and 2. The condition  $a_n \log n \rightarrow 0$  guarantees that  $\Gamma_{t_n}^*/\log n \rightarrow \infty$ .  $\square$

**4. Random interarrivals.** In this section we show how the results of Section 2 can be extended to cover the case where the interarrivals are independent random variables. We assume that  $\alpha_n$  and  $\beta_n$  are fixed positive sequences for which

$$P\{\alpha_n \leq a_n \leq \beta_n\} = 1 \quad \text{for } n \geq 1,$$

as would be the case when (for example)  $a_n \sim U(\alpha_n, \beta_n)$ . The following statements correspond to cases 1–3 of Section 2: If  $E|X| < \infty$ ,  $\sum_{n \geq 1} \alpha_n = \infty$  and  $n\beta_n \rightarrow 0$ , then

$$(4.1) \quad \mu(t_n) \rightarrow E(X | L > 0) \quad \text{a.s.}$$

If  $E|X| < \infty$  and  $\lim_{n \rightarrow \infty} n\alpha_n = \lim_{n \rightarrow \infty} n\beta_n = c \in (0, \infty)$ , then

$$(4.2) \quad \mu(t_n) \rightarrow E(X(1 - E(e^{-L/c} | X)))/(1 - Ee^{-L/c}) \quad \text{a.s.}$$

If  $Ee^{tX} < \infty$  for all  $t$  in an open interval containing the origin, condition (2.1a) holds with  $EL^* < \infty$ ,  $n\alpha_n \uparrow \infty$ ,  $\beta_n \downarrow 0$ ,  $\alpha_n/\beta_n \rightarrow 1$  and  $\beta_n \log n \rightarrow 0$ , then

$$(4.3) \quad \mu(t_n) \rightarrow E(XE(L | X))/EL \quad \text{a.s.}$$

PROOF OF (4.1). Define for  $n \geq 1$ ,

$$A_\alpha(n) = \sum_{1 \leq k \leq n} I(L_k > r_{n,k}) \quad \text{and} \quad A_\beta(n) = \sum_{1 \leq k \leq n} I(L_k > s_{n,k}),$$

where  $r_{n,k} = \sum_{n-k+1 \leq j \leq n} \alpha_j$  and  $s_{n,k} = \sum_{n-k+1 \leq j \leq n} \beta_j$ . Define also the process

$$\mu_\beta(s_n) = \sum_{1 \leq k \leq n} X_k I(L_k > s_{n,k}) / A_\beta(n).$$

We have

$$\begin{aligned} |\mu(t_n) - \mu_\beta(s_n)| &\leq \left| \mu(t_n) - \sum_{1 \leq k \leq n} X_k I(L_k > t_{nk}) / A_\beta(n) \right| \\ &\quad + \left| \sum_{1 \leq k \leq n} X_k (I(L_k > t_{nk}) - I(L_k > s_{n,k})) / A_\beta(n) \right| \\ &\leq (A_\alpha(r_n) / A_\beta(s_n) - 1) \sum_{1 \leq k \leq n} |X_k| I(L_k > r_{n,k}) / A_\alpha(r_n) \\ &\quad + (A_\alpha(r_n) / A_\beta(s_n)) \sum_{1 \leq k \leq n} |X_k| I(L_k > r_{n,k}) / A_\alpha(r_n) \\ &\quad - \sum_{1 \leq k \leq n} |X_k| I(L_k > s_{n,k}) / A_\beta(s_n). \end{aligned}$$

Since  $\sum_{1 \leq k \leq n} |X_k| I(L_k > r_{n,k}) / A_\alpha(r_n)$  and  $\sum_{1 \leq k \leq n} |X_k| I(L_k > s_{n,k}) / A_\beta(s_n)$  converge almost surely to the same finite limit and

$$(4.4) \quad \begin{aligned} A_\alpha(r_n) / A_\beta(s_n) &= (A_\alpha(r_n) / EA_\alpha(r_n)) (EA_\alpha(r_n) / EA_\beta(s_n)) \\ &\quad \times (EA_\beta(s_n) / A_\beta(s_n)) \rightarrow 1 \quad \text{a.s.} \end{aligned}$$

we have that  $|\mu(t_n) - \mu_\beta(s_n)| \rightarrow 0$  almost surely. In (4.4) we observe that  $A_\alpha(r_n)/EA_\alpha(r_n)$  and  $EA_\beta(s_n)/A_\beta(s_n)$  are almost surely convergent to 1, by Lemma 2. Also, we have

$$(4.5) \quad EA_\alpha(r_n)/EA_\beta(s_n) = (EA_\alpha(r_n)/n)/(EA_\beta(s_n)/n) \rightarrow 1.$$

(see the remarks following Theorem 2.2). Since  $\mu_\beta(s_n) \rightarrow E(X | L > 0)$  almost surely by Theorem 2.2 and case 1, statement (4.1) follows.  $\square$

The proof of (4.2) is similar to that of (4.1). The proof of (4.3) uses Theorem 2.1 and is also similar to that of (4.1). To obtain (4.5) in this case, one uses an argument like that found in the proof of Theorem 3 of Rothmann and Russo (1995).

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