

## RENEWAL THEORY FOR $M$ -DEPENDENT VARIABLES

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Let  $S_n, n = 1, 2, \dots$ , denote the partial sums of a stationary  $m$ -dependent sequence of random variables with positive expectation. The first passage times  $\min\{n: S_n > t\}$  are investigated. Several results are extended from the case of independent variables.

**0. Introduction.** Let  $\{X_n\}_1^\infty$  be a stationary  $m$ -dependent sequence of random variables. ( $X$  will be used to denote a generic variable in the sequence.) The nonnegative integer  $m$  will be fixed throughout the paper. The purpose of this paper is to study the sequence of partial sums  $S_n = \sum_1^n X_i$ , and the stopping times  $\tau(t) = \min\{n: S_n > t\}$ , when  $X$  has positive expectation. In particular, we are interested in the existence and the asymptotic behaviour of the moments of  $\tau(t)$  and the overshoot  $S_{\tau(t)} - t$  for various integrability conditions on  $X$ .

For independent variables (the special case  $m = 0$ ) such problems have been extensively studied, see e.g. [7] and the references listed therein. Some of these results are generalized in this paper.

Related problems, including a version of Blackwell's renewal theorem, are treated for dependent sequences by Berbee [2].

Section 1 uses martingale theory to establish some basic results for the sequence  $\{S_n\}$  and arbitrary stopping times, most notably a version of Wald's lemma (Theorem 1.1).

Section 2 applies these results to the renewal times  $\tau(t)$ . Using these more complicated martingale results, the proofs for the independent case hold with only minor modifications. One of the main results is  $E\tau(t) = t/EX + o(t^{1/r})$  as  $t \rightarrow \infty$ , provided  $E|X|^r < \infty$ .

Section 3 contains a refinement for the case  $X \geq 0$ . Then  $E\tau(t) = t/EX + O(1)$ , provided  $EX^2 < \infty$ .

Section 4 is devoted to applications.

**1. Martingales and stopping times.** In this section we make the following assumptions.

(i)  $\{X_n\}_1^\infty$  is a stationary sequence of random variables adapted to an increasing sequence of  $\sigma$ -fields  $\{\mathcal{F}_n\}_1^\infty$  on a probability space  $(\Omega, \mathcal{F}_\infty, P)$ .

(ii)  $m$  is an integer such that  $\{X_{n+i}\}_{i=m+1}^\infty$  is independent of  $\mathcal{F}_n$  for every  $n$ .

(iii)  $\mu = EX$  exists (in this section not necessarily positive).

(iv)  $\tau$  is a stopping time relative to  $\{\mathcal{F}_n\}$ .

Let  $\mathcal{F}_n = \{\emptyset, \Omega\}$  for  $n \leq 0$ . We define  $S_n = \sum_1^n X_k$  and  $U_n = E(S_{n+m} - (n+m)\mu | \mathcal{F}_n)$ ,  $n \geq 0$ . (For  $n \leq 0$  let  $U_n = 0$ .)

Let  $V_n = U_n - (S_n - n\mu) = E(\sum_{i=1}^m (X_{n+i} - \mu) | \mathcal{F}_n)$  and  $\Delta U_n = U_n - U_{n-1} = X_n - \mu + V_n - V_{n-1}$ .

If  $EX^2 < \infty$ , let  $\gamma^2 = \text{Cov}(X_n, S_{n+m}) = \text{Var } X_n + 2 \sum_{i=1}^m \text{Cov}(X_n, X_{n+i})$  ( $n > m$ ). Note that  $\gamma^2 = \lim_{n \rightarrow \infty} (1/n) \text{Var } S_n \geq 0$ .

**LEMMA 1.1.**  $\{U_n\}_0^\infty$  is a martingale.

**PROOF.**  $E(U_n | \mathcal{F}_{n-1}) = E(S_{n+m} - (n+m)\mu | \mathcal{F}_{n-1}) = U_{n-1} + E(X_{n+m} - \mu | \mathcal{F}_{n-1}) = U_{n-1}$ .

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**THEOREM 1.1.** *If  $X \geq 0$  a.s. or  $E\tau < \infty$ , then*

$$ES_{\tau+m} = (E\tau + m)\mu.$$

**PROOF.** By Lemma 1.1,  $E(S_{\tau \wedge N+m} - (\tau \wedge N + m)\mu) = EU_{\tau \wedge N} = EU_0 = 0$ . Thus,  $ES_{\tau \wedge N+m} = (E(\tau \wedge N + m))\mu$ . For positive  $X$ , the result follows by monotone convergence as  $N \rightarrow \infty$ . If  $E\tau < \infty$ , we use the decomposition  $X_n = X_n^+ - X_n^-$ .

For independent variables ( $m = 0$ ) this theorem reduces to Wald's lemma  $ES_\tau = E\tau\mu$ . This formula fails for  $m$ -dependent variables, but Theorem 1.1 gives a useful substitute.

We next turn to the variance of  $S_{\tau+m} - (\tau + m)\mu$  (cf. [4] for  $m = 0$ ). We single out a special case as a lemma.

**LEMMA 1.2.** *Assume that  $EX^2 < \infty$  and that  $\tau$  is a bounded stopping time. Then*

$$EU_{\tau+m}^2 = (E\tau + m)\gamma^2 + EV_{\tau+m}^2.$$

**PROOF.** We may assume that  $\mu = 0$ . (Otherwise, we replace  $X_n$  by  $X_n - \mu$ .) Since  $I(\tau \geq i - m)$  is  $\mathcal{F}_{i-m-1}$ -measurable,

$$\begin{aligned} EU_{\tau+m}^2 &= E \sum_{i \leq \tau+m} (\Delta U_i)^2 = E \sum_1^\infty I(\tau \geq i - m) (\Delta U_i)^2 \\ &= \sum_1^\infty E(I(\tau \geq i - m) E((\Delta U_i)^2 | \mathcal{F}_{i-m-1})). \end{aligned}$$

Furthermore  $\Delta U_i = X_i + V_i - V_{i-1}$ , which by orthogonality yields

$$E((\Delta U_i)^2 | \mathcal{F}_{i-1}) = E((X_i + V_i)^2 | \mathcal{F}_{i-1}) - E(V_{i-1}^2 | \mathcal{F}_{i-1})$$

and

$$E((\Delta U_i)^2 | \mathcal{F}_{i-m-1}) = E(X_i^2 + 2X_i V_i + V_i^2 - V_{i-1}^2 | \mathcal{F}_{i-m-1}).$$

Using  $V_i = E(\sum_{j=1}^m X_{i+j} | \mathcal{F}_i)$  we obtain  $X_i V_i = E(\sum_1^m X_i X_{i+j} | \mathcal{F}_i)$  and (by assumption (ii))

$$E(X_i^2 + 2X_i V_i | \mathcal{F}_{i-m-1}) = E(X_i^2 + 2 \sum_1^m X_i X_{i+j} | \mathcal{F}_{i-m-1}) = E(X_i^2 + 2 \sum_1^m X_i X_{i+j}) = \gamma^2.$$

Consequently,

$$E((\Delta U_i)^2 | \mathcal{F}_{i-m-1}) = \gamma^2 + E(V_i^2 - V_{i-1}^2 | \mathcal{F}_{i-m-1})$$

and

$$\begin{aligned} EU_{\tau+m}^2 &= \sum_1^\infty E(I(\tau \geq i - m)(\gamma^2 + E(V_i^2 - V_{i-1}^2 | \mathcal{F}_{i-m-1}))) \\ &= \sum_1^\infty E(I(\tau \geq i - m)(\gamma^2 + V_i^2 - V_{i-1}^2)) = E \sum_1^{\tau+m} (\gamma^2 + V_i^2 - V_{i-1}^2) \\ &= (E\tau + m)\gamma^2 + EV_{\tau+m}^2. \end{aligned}$$

**THEOREM 1.2.** *Assume that  $EX^2 < \infty$  and  $E\tau < \infty$ . Then*

- (i)  $EU_{\tau+m}^2 = (E\tau + m)\gamma^2 + EV_{\tau+m}^2$
- (ii)  $E(S_{\tau+m} - (\tau + m)\mu)^2 = (E\tau + m)\gamma^2 - 2E(S_{\tau+2m} - S_{\tau+m} - m\mu)(S_{\tau+m} - S_\tau - m\mu)$
- (iii)  $E(S_{\tau+2m} - (\tau + 2m)\mu)^2 = E\tau \cdot \gamma^2 + E(S_{2m} - 2m\mu)^2$ .

**PROOF.** Again, for convenience, we assume that  $\mu = 0$ . By Hölder's and Cauchy-Schwarz' inequalities,

$$V_{\tau \wedge N+m}^2 \leq E((\sum_1^m X_{\tau \wedge N+i})^2 | \mathcal{F}_{\tau \wedge N}) \leq mE(\sum_1^m X_{\tau \wedge N+i}^2 | \mathcal{F}_{\tau \wedge N}) \leq mE(\sum_1^{\tau+m} X_n^2 | \mathcal{F}_{\tau \wedge N}).$$

Theorem 1.1 applied to  $\{X_n^2\}$  shows that  $\sum_1^{\tau+m} X_n^2$  is integrable. Hence, the family  $\{E(\sum_1^{\tau+m} X_n^2 | \mathcal{F}_{\tau \wedge N})\}_{N=1}^\infty$  is uniformly integrable [11, Lemma IV-2-4]. Thus,  $\{V_{\tau \wedge N+m}^2\}$  is uniformly integrable and, since  $V_{\tau \wedge N+m} \rightarrow V_{\tau+m}$  a.s.,  $EV_{\tau \wedge N+m}^2 \rightarrow EV_{\tau+m}^2$  as  $N \rightarrow \infty$ .

Since, by Lemma 2,  $E \sum_1^{\tau \wedge N+m} (\Delta U_i)^2 = (E(\tau \wedge N) + m)\gamma^2 + EV_{\tau \wedge N+m}^2$ , monotone convergence yields  $E \sum_1^{\tau+m} (\Delta U_i)^2 = (E\tau + m)\gamma^2 + EV_{\tau+m}^2 < \infty$  and (i) follows from [4, Theorem 1].

Since  $U_{\tau+m} = S_{\tau+m} + V_{\tau+m}$  and  $U_{\tau+m} = E(S_{\tau+2m} | \mathcal{F}_{\tau+m})$ ,

$$\begin{aligned} (E\tau + m)\gamma^2 &= EU_{\tau+m}^2 - EV_{\tau+m}^2 = E(U_{\tau+m} - V_{\tau+m})(U_{\tau+m} + V_{\tau+m}) \\ &= ES_{\tau+m}(2U_{\tau+m} - S_{\tau+m}) \\ &= 2ES_{\tau+m}S_{\tau+2m} - ES_{\tau+m}^2 = ES_{\tau+m}^2 + 2ES_{\tau+m}(S_{\tau+2m} - S_{\tau+m}) \\ &= ES_{\tau+m}^2 + 2E(S_{\tau+2m} - S_{\tau+m})(S_{\tau+m} - S_{\tau}) + 2E(S_{\tau+2m} - S_{\tau+m})S_{\tau}. \end{aligned}$$

(i) follows from  $E(S_{\tau+2m} - S_{\tau+m})S_{\tau} = E(E(S_{\tau+2m} - S_{\tau+m} | \mathcal{F}_{\tau})S_{\tau}) = 0$ .

To prove (iii), note that by the computation above

$$ES_{\tau+2m}^2 - E\tau\gamma^2 = E(S_{\tau+2m}^2 - 2S_{\tau+m}S_{\tau+2m} + S_{\tau+m}^2) + m\gamma^2 = E(E(S_{\tau+2m} - S_{\tau+m})^2 | \mathcal{F}_{\tau}) + m\gamma^2.$$

However,  $E((S_{\tau+2m} - S_{\tau+m})^2 | \mathcal{F}_{\tau})$  is a constant independent of  $\tau$ . Hence  $ES_{\tau+2m}^2 - E\tau\gamma^2$  does not depend on  $\tau$ , and the trivial case  $\tau = 0$  shows that it equals  $ES_{2m}^2$ , which proves (iii).

In the next section we shall study a family of stopping times, keeping  $\{X_n\}$  fixed. Therefore, we shall use  $o(E\tau)$  to denote quantities  $\delta(\tau) = \delta(\tau, \{X_n\})$  such that, for fixed  $\{X_n\}$ ,

$$\sup\{|\delta(\tau)|/E\tau: \tau \text{ is a stopping time such that } A < E\tau < \infty\}$$

is finite for any  $A > 0$  and converges to 0 as  $A \rightarrow \infty$ .  $o((E\tau)^{1/r})$  etc. are defined similarly.

Next, we collect some important consequences of Theorems 1.1 and 1.2.

**COROLLARY 1.1.** *Assume that  $E|X|^r < \infty$ , where  $1 \leq r < \infty$ . For stopping times  $\tau$  such that  $E\tau < \infty$ ,*

- (i)  $E|X_{\tau}|^r = o(E\tau)$
- (ii)  $E|X_{\tau}| = o((E\tau)^{1/r})$
- (iii)  $E|S_{\tau+m} - S_{\tau}|^r = o(E\tau)$
- (iv)  $E|S_{\tau+m} - S_{\tau}| = o((E\tau)^{1/r})$
- (v)  $ES_{\tau} = E\tau \cdot \mu + o((E\tau)^{1/r})$ .

Furthermore, if  $r \geq 2$ ,

- (vi)  $\|S_{\tau} - \tau\mu\|_2 = \sqrt{E\tau}\gamma + o((E\tau)^{1/r})$
- (vii)  $E(S_{\tau} - \tau\mu)^2 = E\tau\gamma^2 + o((E\tau)^{1/2+1/r})$ .

If  $r = \infty$  ( $X$  is bounded), (ii) (trivially) and (iv) – (vii) hold with  $o$  replaced by  $O$ .

**PROOF.** By Theorem 1.1 applied to  $\{|X_n|^r\}$ ,

$$E|X_{\tau}|^r \leq E \sum_{i=1}^{\tau+m} |X_i|^r = (E\tau + m)E|X|^r.$$

This estimate is improved to “ $o$ ” in the following standard way. Let  $\varepsilon > 0$  and let  $X'_n = X_n \cdot I(|X_n| > A)$  and  $X''_n = X_n - X'_n$  where  $A$  is so large such that  $E|X'_n|^r < \varepsilon$ . Then

$$E|X_{\tau}|^r = E|X'_{\tau}|^r + E|X''_{\tau}|^r \leq (E\tau + m)E|X'|^r + A^r < \varepsilon E\tau + C_{\varepsilon}.$$

This proves (i). (ii) follows by Lyapunov’s inequality. (iii) and (iv) are proved similarly, using Hölder’s inequality  $|S_{\tau+m} - S_{\tau}|^r = |\sum_{i=1}^m X_{\tau+i}|^r \leq m^{r-1} \sum_{i=1}^m |X_{\tau+i}|^r$ . (v) follows immediately from (iv) and Theorem 1.1.

If  $r \geq 2$ , Theorem 1.2 (iii) yields

$$\|S_{\tau+2m} - (\tau + 2m)\mu\|_2 = \sqrt{E\tau}\gamma + O((E\tau)^{-1/2}).$$

Since  $\|S_{\tau+2m} - S_{\tau+m}\|_2$  is constant (cf. the proof of Theorem 1.2), and  $\|S_{\tau+m} - S_{\tau}\|_2 \leq \|S_{\tau+m} - S_{\tau}\|_r = o((E\tau)^{1/r})$  by (iii), (vi) follows from Minkowski’s inequality. (vii) is obtained by squaring. The modifications in the case  $r = \infty$  are easy.

Finally, we give an estimate for arbitrary moments of  $S_{\tau} - \tau\mu$ . For the independent case, see [7] and [8].

LEMMA 1.3. Let  $1 \leq r < \infty$  and  $r_1 = \max(r/2, 1)$ . Suppose that  $E|X|^r < \infty$ ,  $E\tau^{r_1} < \infty$  and  $EX = 0$ . Then, for any non-negative integer  $k$ ,

$$E|\sum_{n=1}^{\tau} E(X_{n+k}|\mathcal{F}_n)|^r \leq C_{m,r,k} E\tau^{r_1} E|X|^r.$$

( $C_{m,r,k}$  is a universal constant.)

PROOF. If  $k > m$ ,  $E(X_{n+k}|\mathcal{F}_n) = EX_{n+k} = 0$  and there is nothing to prove. We perform an induction on  $k$  (backwards) and  $r$ , assuming the estimate to hold for  $r, k + 1$  as well as for  $r/2$  and any  $k$  (if  $r \geq 2$ ).

$$\sum_{n=1}^{\tau} E(X_{n+k}|\mathcal{F}_n) = \sum_1^{\tau} (E(X_{n+k}|\mathcal{F}_n) - E(X_{n+k}|\mathcal{F}_{n-1})) + \sum_1^{\tau} E(X_{n+k+1}|\mathcal{F}_n) - E(X_{\tau+k+1}|\mathcal{F}_{\tau}).$$

By the  $c_r$ -inequalities, it suffices to estimate the three terms on the right-hand side separately. The estimate holds for the second term by the induction hypothesis, and for the third term by

$$E|E(X_{\tau+k+1}|\mathcal{F}_{\tau})|^r \leq E|X_{\tau+k+1}|^r \leq E\sum_1^{\tau+m} |X_i|^r = (E\tau + m)E|X|^r$$

(if  $k < m$ , otherwise the term vanishes).

The first term above is a stopped martingale and we use the Burkholder-Gundy inequality [6]

$$E|\sum_1^{\tau} (E(X_{n+k}|\mathcal{F}_n) - E(X_{n+k}|\mathcal{F}_{n-1}))|^r \leq C_r E Q^r,$$

where the square function  $Q$  is defined by

$$\begin{aligned} Q^2 &= \sum_1^{\tau} (E(X_{n+k}|\mathcal{F}_n) - E(X_{n+k}|\mathcal{F}_{n-1}))^2 \leq \sum_1^{\tau} 2(E(X_{n+k}|\mathcal{F}_n)^2 + E(X_{n+k}|\mathcal{F}_{n-1})^2) \\ &\leq 2\sum_1^{\tau} E(X_{n+k}|\mathcal{F}_n)^2 + 2\sum_1^{\tau} E(X_{n+k+1}|\mathcal{F}_n)^2. \end{aligned}$$

We will estimate the  $r/2$ th moment of the first sum, the second sum is treated the same way. We look at two cases separately.

If  $r \leq 2$ ,

$$\begin{aligned} E(\sum_1^{\tau} E(X_{n+k}|\mathcal{F}_n)^2)^{r/2} &\leq E\sum_1^{\tau} |E(X_{n+k}|\mathcal{F}_n)|^r \leq E\sum_1^{\tau} E(|X_{n+k}|^r|\mathcal{F}_n) \\ &\leq \sum_1^{\infty} E(I(\tau \geq n - m)E(|X_{n+k}|^r|\mathcal{F}_n)) \\ &= \sum_1^{\infty} EI(\tau \geq n - m)E|X_{n+k}|^r = (E\tau + m)E|X|^r. \end{aligned}$$

If  $r > 2$ , let  $\sigma^2 = EX^2$ . Then

$$\sum_1^{\tau} E(X_{n+k}|\mathcal{F}_n)^2 \leq \sum_1^{\tau} E(X_{n+k}^2|\mathcal{F}_n) = \tau\sigma^2 + \sum_1^{\tau} E(X_{n+k}^2 - \sigma^2|\mathcal{F}_n).$$

$E(\tau\sigma^2)^{r/2} \leq E\tau^{r/2} E|X|^r$  and by the induction hypothesis applied to  $\{X_n^2 - \sigma^2\}$ ,

$$E|\sum_1^{\tau} E(X_{n+k}^2 - \sigma^2|\mathcal{F}_n)|^{r/2} \leq C_{m,r/2,k} E\tau^{\max(r/4,1)} E|X^2 - \sigma^2|^{r/2}.$$

Thus, for any  $r$ ,  $E Q^r = E(Q^2)^{r/2} \leq C_{m,r,k} E\tau^{r_1} E|X|^r$ . The proof is complete.

THEOREM 1.3. Suppose that  $E|X|^r < \infty$ , where  $1 \leq r < \infty$ .

- (i) If  $E\tau, E\tau^{r/2} < \infty$ , then  $E|S_{\tau} - \tau\mu|^r \leq C_{m,r}(E\tau + E\tau^{r/2})E|X|^r < \infty$ .
- (ii) If  $E\tau^r < \infty$ , then  $E|S_{\tau}|^r \leq C_{m,r}E\tau^r E|X|^r < \infty$ .

PROOF. (i) follows by taking  $k = 0$  in Lemma 3 (applied to  $\{X_n - \mu\}$ ) and (ii) is an immediate consequence.

**2. Renewal theory.** From now on, we assume that  $\mu = EX > 0$ . We shall study the stopping times  $\tau(t)$  defined in the introduction. (We may take  $\mathcal{F}_n = \mathcal{F}(X_1, \dots, X_n)$ .) By the law of large numbers  $\tau(t) < \infty$  a.s. Also,  $\tau(t) \rightarrow \infty$  and thus  $E\tau(t) \rightarrow \infty$  as  $t \rightarrow \infty$ .

For completeness, we include the following theorem which is proved exactly as for independent variables.

**THEOREM 2.1.**

- (i)  $\tau(t)/t \rightarrow 1/\mu$  a.s.
- (ii)  $S_{\tau(t)}/t \rightarrow 1$  a.s.
- (iii) If  $E|X|^r < \infty$ ,  $1 \leq r < 2$ , then  $\tau(t) - t/\mu = o(t^{1/r})$  a.s. and  $S_{\tau(t)} - t = o(t^{1/r})$  a.s.
- (iv) If  $EX^2 < \infty$  and  $\gamma^2 \neq 0$ , then  $\frac{\tau(t) - t/\mu}{\sqrt{\gamma^2 t/\mu^3}} \rightarrow_d N(0, 1)$ .

**PROOF.** By the law of large numbers  $S_n/n \rightarrow \mu$  and  $X_n/n \rightarrow 0$  a.s. as  $n \rightarrow \infty$ . Hence  $S_{\tau(t)}/\tau(t) \rightarrow \mu$  and  $X_{\tau(t)}/\tau(t) \rightarrow 0$  a.s. as  $t \rightarrow \infty$ , which imply  $t/\tau(t) \rightarrow \mu$  a.s., from which (i) and (ii) follow.

(iii) is proved similarly, cf. [7; Theorem 28].

(iv) follows from the central limit theorem, Anscombe's theorem [1] and the estimate  $(S_{\tau(t)} - t)/\sqrt{t} \rightarrow_P 0$  (which follows e.g. from Theorem 2.2 (iii) below).

In the remainder of this section we shall combine the martingale estimates of Section 1 with arguments from [7] to estimate moments.

**LEMMA 2.1.** For any  $t \geq 0$ ,  $E\tau(t) < \infty$ .

**PROOF.** Define  $X'_n = X_n \wedge A$ , where  $A$  is a large constant such that  $\mu' = EX' > 0$ . Let  $S'_n$  and  $\tau'(t)$  have the obvious meanings. Then  $S'_n \leq S_n$  whence  $\tau'(t) \geq \tau(t)$ . Thus, it suffices to show that  $E\tau'(t) < \infty$ . Since  $S'_n \leq t$  for  $n < \tau'(t)$ , and  $X'_i \leq A$ ,  $S'_n \leq t + (m + 1)A$  for  $n \leq \tau'(t) + m$ . Hence, by Theorem 1.1,

$$(E\tau'(t) \wedge N + m)\mu' = ES'_{\tau'(t) \wedge N + m} \leq t + (m + 1)A.$$

By monotone convergence,  $E\tau'(t) \leq (t + (m + 1)A)/\mu' < \infty$ .

**THEOREM 2.2.** Suppose that  $E|X|^r < \infty$ , where  $1 \leq r < \infty$ . Then, as  $t \rightarrow \infty$ ,

- (i)  $E\tau(t) = t/\mu + o(t^{1/r})$
- (ii)  $E(S_{\tau(t)} - t)^r = o(t)$
- (iii)  $ES_{\tau(t)} - t = o(t^{1/r})$ .

Furthermore, if  $r > 2$ ,

- (iv)  $\text{Var } \tau(t) = t\gamma^2/\mu^3 + o(t^{1/2+1/r})$
- (v)  $E(\tau(t) - t/\mu)^2 = t\gamma^2/\mu^3 + o(t^{1/2+1/r})$ .

If  $r = \infty$  ( $X$  is bounded) these estimates (except (ii)) holds with  $o$  replaced by  $O$ .

**REMARK 2.1.** For positive variables, (i) and (iii) will be sharpened, but we postpone this to the next section.

**PROOF.** Observe that

$$0 < S_{\tau(t)} - t \leq X_{\tau(t)}.$$

Hence, using Corollary 1.1 (ii) and (v),

$$t = ES_{\tau(t)} + o((E\tau(t))^{1/r}) = E\tau(t)\mu + o((E\tau(t))^{1/r}).$$

Thus,  $t \rightarrow \infty$  implies

$$t/E\tau(t) \rightarrow \mu, \text{ i.e. } E\tau(t)/t \rightarrow 1/\mu \text{ as } t \rightarrow \infty.$$

Hence, all terms  $o((E\tau(t))^{1/r})$  may be replaced by  $o(t^{1/r})$  and (i) follows from the computations above. (ii) and (iii) follow from Corollary 1.1 (i) and (ii). If  $r \geq 2$ , (ii) yields  $\|S_{\tau(t)} - t\|_2 \leq \|S_{\tau(t)} - t\|_r = o(t^{1/r})$ . By Corollary 1.1 (vi),

$$\|t - \tau(t)\mu\|_2 = \sqrt{E\tau(t)}\gamma + o(t^{1/r}) = \sqrt{t/\mu}\gamma + o(t^{1/r})$$

and (v) follows by squaring. (v) and (i) yield (iv). The modifications for  $r = \infty$  are omitted.

**THEOREM 2.3.** *Let  $1 \leq r < \infty$ .*

- (i) *If  $E(X^+)^r < \infty$  then  $ES_{\tau(t)}^r < \infty$  and  $ES_{\tau(t)}^r/t^r \rightarrow 1$  as  $t \rightarrow \infty$ .*
- (ii) *If  $E(X^-)^r < \infty$  then  $E\tau(t)^r < \infty$  and  $E\tau(t)^r/t^r \rightarrow \mu^{-r}$  as  $t \rightarrow \infty$ .*

**PROOF.** (i)  $E(X_{\tau(t)}^+)^r = o(E\tau(t)) = o(t)$  by Corollary 1.1 and Theorem 2.2. Thus,  $\|S_{\tau(t)} - t\|_r \leq \|X_{\tau(t)}^+\|_r = o(t^{1/r})$  and  $\|S_{\tau(t)}\|_r = t + o(t^{1/r})$ . (ii) We assume that  $E|X|^r < \infty$ . (Otherwise truncate as in the proof of Lemma 2.1. Cf. [7; Theorem 2.3].) For  $r = 1$  there is nothing new to prove. If  $r > 2$  we assume, by induction on  $r$ , that the theorem holds for  $r/2$ . Thus, with  $r_1 = \max(r/2, 1)$ ,  $E\tau(t)^{r_1} = O(t^{r_1})$ . By Theorem 1.3 (i).

$$E|S_{\tau(t)} - \tau(t)\mu|^r \leq CE\tau(t)^{r_1}E|X|^r = O(t^{r_1}).$$

Thus

$$\|S_{\tau(t)} - \tau(t)\mu\|_r = O(t^{r_1/r}).$$

Minkowski's inequality and (i) finally yield

$$\|\tau(t)\mu\|_{L^r} = t + O(t^{r_1/r}) = t + o(t).$$

**REMARK 2.2** Under the hypothesis of Theorem 2.3,  $\{S_{\tau(t)}/t\}_{t \geq 1}$  and  $\{\tau(t)/t\}_{t \geq 1}$ , respectively, are uniformly integrable. This follows from a combination with Theorem 2.1.

**REMARK 2.3.** (i) may be compared to Theorem 3.1 which shows that (for  $X \geq 0$ )  $E(S_{\tau(t)} - t)^r$  is bounded as  $t \rightarrow \infty$  if and only if  $EX^{r+1} < \infty$ .

**REMARK 2.4.** Since  $X_1^+ \leq S_{\tau(t)}$ , the converse of (i) holds, viz. if  $ES_{\tau(t)}^r < \infty$  for some  $t \geq 0$ , then  $E(X^+)^r < \infty$ . For independent summands, the converse of (ii) also holds [7], but for  $m$ -dependent variables this is not true, as is shown by the following example.

**EXAMPLE 2.1.** Let  $r > 1$ . Let  $\{\xi_n\}_0^\infty$  be positive i.i.d. random variables such that  $P(\xi_n < 1) > 0$  and  $E\xi_n^r = \infty$ . Define

$$X_n = \begin{cases} -\xi_n & \text{if } \xi_{n-1} < 1 < \xi_n \\ 1 + \xi_{n-1} & \text{otherwise.} \end{cases}$$

Then  $\{X_n\}$  is 1-dependent,  $E(X^-)^r = \infty$ , but  $E\tau(t)^r < \infty$ . In fact, since every negative  $X_n$  is more than cancelled by the next one,  $\tau(t) < 2(t + 1)$ .

**REMARK 2.5.** Several of the results may be extended to the case  $\mu = +\infty$ , i.e.  $EX^- < \infty, EX^+ = \infty$ , by truncation. For instance, with  $X' = X \wedge t$ , where  $t$  is large enough,  $(E\tau'(t) + m)EX' = ES'_{\tau(t)+m} \leq (m + 2)t$ . Hence  $E\tau(t) \leq E\tau'(t) \leq (m + 2)t/E(X \wedge t)$ . Thus,  $E\tau(t)/t \rightarrow 0 = 1/\mu$ . Some results can be extended to  $0 < r < 1$ , e.g.  $E(X^+)^r < \infty \Leftrightarrow ES_{\tau(t)}^r < \infty$ .

**3. Further results.** Theorem 2.2 is not completely satisfactory since the error terms are coarser than what presumably is required. For independent variables it is e.g. known that (in the non-lattice case)  $E\tau(t) - t/\mu$  converges to a finite limit, provided only that  $EX^2 < \infty$ . We have not been able to prove this for  $m$ -dependent variables, but with the extra assumption  $X \geq 0$  we now will prove a somewhat weaker result (Theorem 3.1). Cf. [2, Chapter 3] and [10] for related material.

**LEMMA 3.1.** *Assume that  $X \geq 0$  a.s. and that  $EX^r < \infty$ , where  $1 < r < \infty$ . Then  $E(S_{\tau(t)+m} - t)^{r-1} = O(1)$ .*

**PROOF.** Extend  $\{X_n\}_1^\infty$  to a doubly infinite stationary sequence  $\{X_n\}_{-\infty}^\infty$ . We may

assume that  $\Omega = R^\infty$  and that  $\{X_n\}_{-\infty}^\infty$  are the coordinate functions. Let  $T$  denote the measure preserving shift mapping  $\Omega \rightarrow \Omega$  defined by  $X_n(T\omega) = X_{n+1}(\omega)$ .

We extend the definition  $\tau(t, \omega) = \inf\{n \geq 0 : S_n(\omega) > t\}$  to all real  $t$ . Thus  $\tau(t, \omega) = 0$  for  $t < 0$ . Let  $\varphi(t, \omega) = (S_{\tau(t, \omega)+m}(\omega) - t)^{r-1}$ . Thus, for  $t < 0$ ,  $\varphi(t) = (S_m - t)^{r-1}$ . Since  $S_n(\omega) = X_1(\omega) + S_{n-1}(T\omega)$ ,  $n > 0$ , it follows that

$$\tau(t, \omega) = \tau(t - X_1(\omega), T\omega) + 1, \quad t \geq 0,$$

and

$$\varphi(t, \omega) = \varphi(t - X_1(\omega), T\omega) = \varphi(t - X_0(T\omega), T\omega), \quad t \geq 0.$$

Thus,

$$\int \varphi(t, \omega) dP = \int \varphi(t - X_0(T\omega), T\omega) dP = \int \varphi(t - X_0(\omega), \omega) dP, \quad t \geq 0.$$

Let  $\nu$  be the measure  $I(0 \leq s < X_0) ds dP$  on  $R \times \Omega$ . The total mass of  $\nu$  equals  $\int X_0 dP = \mu$ . If  $t \geq 0$ ,

$$\int \varphi(t - s, \omega) d\nu = \iint_{0 \leq s < X_0} \varphi(t - s, \omega) ds dP = \iint_{t \geq u > t - X_0} \varphi(u, \omega) du dP$$

and

$$\begin{aligned} \int \varphi(t - s, \omega) d\nu - \int \varphi(-s, \omega) d\nu &= \iint (I(t \geq u > t - X_0) - I(0 \geq u > -X_0))\varphi(u, \omega) du dP \\ &= \iint (I(t \geq u > 0) - I(t - X_0 \geq u > -X_0))\varphi(u, \omega) du dP \\ &= \iint I(t \geq u > 0)(\varphi(u, \omega) - \varphi(u - X_0, \omega)) du dP \\ &= \int_0^t \left( \int \varphi(u, \omega) dP - \int \varphi(u - X_0, \omega) dP \right) du = 0. \end{aligned}$$

Thus,

$$\begin{aligned} \int \varphi(t - s, \omega) d\nu &= \int \varphi(-s, \omega) d\nu = \iint_{0 \leq s < X_0} (S_m + s)^{r-1} ds dP \\ &\leq \int \frac{1}{r} (X_0 + S_m)^r dP = \frac{1}{r} ES_{m+1}^r < \infty, \quad t \geq 0. \end{aligned}$$

Let  $A$  denote this common value of  $\int \varphi(t - s, \omega) d\nu$ ,  $t \geq 0$ .  $\tau(t)$  and  $S_{\tau(t)+m}$  are non-decreasing functions of  $t$ . Thus

$$S_{\tau(t)+m} - t \leq S_{\tau(t+h)+m} - (t + h) + h, \quad h > 0.$$

For simplicity, we assume that  $r \leq 2$ , in which case  $\varphi(t, \omega) \leq \varphi(t + h, \omega) + h^{r-1}$ . (The proof for  $r > 2$  is similar, using  $(a + b)^r \leq (1 + \epsilon)a^r + C_{r,\epsilon}b^r$ ,  $\epsilon > 0$ .)

Choose  $\delta > 0$  such that  $P(X > \delta) > 0$ . Then, if  $t \geq 0$ ,

$$\begin{aligned} \delta \int \varphi(t, \omega) I(X_0 \geq \delta) dP &\leq \int_0^\delta \int \varphi(t+h, \omega) I(X_0 \geq \delta) dP dh + \delta^r \\ &= \int_0^\delta \int \varphi(t+\delta-s, \omega) I(X_0 \geq \delta) dP ds + \delta^r \\ &\leq \int \int I(X_0 > s > 0) \varphi(t+\delta-s, \omega) dP ds + \delta^r = A + \delta^r. \end{aligned}$$

Furthermore, if  $t \geq 0$ ,

$$\varphi(t, \omega) = \varphi(t - X_1(\omega), T\omega) \leq \varphi(t, T\omega) + X_1(\omega)^{r-1}.$$

By iteration,

$$\varphi(t, \omega) \leq \varphi(t, T^m\omega) + X_1(\omega)^{r-1} + \dots + X_m(\omega)^{r-1}.$$

Thus, since  $X_0$  is independent of  $\varphi(t, T^m\omega)$ ,

$$\begin{aligned} \int \varphi(t, \omega) I(X_0 < \delta) dP &\leq \int \varphi(t, T^m\omega) I(X_0 < \delta) dP + mEX^{r-1} \\ &= P(X_0 < \delta) \int \varphi(t, T^m\omega) dP + mEX^{r-1} = P(X < \delta) \int \varphi(t, \omega) dP + mEX_1^{r-1}. \end{aligned}$$

Combining these two estimates we obtain

$$\int \varphi(t, \omega) dP \leq A/\delta + \delta^{r-1} + P(X < \delta) \int \varphi(t, \omega) dP + mEX^{r-1}.$$

Since  $\int \varphi(t, \omega) dP = E(S_{\tau(t)+m} - t)^{r-1}$  is finite by Corollary 1.1,

$$E(S_{\tau(t)+m} - t)^{r-1} \leq (A/\delta + \delta^{r-1} + mEX^{r-1})/P(X \geq \delta).$$

**THEOREM 3.1.** Assume that  $X \geq 0$  a.s.

- (i)  $EX^2 < \infty \Leftrightarrow E\tau(t) = t/\mu + O(1)$
- (ii)  $EX^r < \infty \Rightarrow E\tau(t) = t/\mu + o(t^{2-r})$  as  $t \rightarrow \infty$ ,  $1 < r < 2$
- (iii)  $EX^r < \infty \Leftrightarrow E(S_{\tau(t)} - t)^{r-1} = O(1)$ ,  $1 < r < \infty$ .

**PROOF.** If  $EX^2 < \infty$ , then  $E\tau(t)\mu = ES_{\tau(t)+m} - m\mu = t + O(1)$  by Theorem 1.1 and Lemma 3.1.

If  $EX^r < \infty$ ,  $1 < r < 2$ , we combine Lemma 3.1, Theorem 2.2 and Corollary 1.1 by Hölder's inequality to obtain

$$E(S_{\tau(t)+m} - t) \leq (E(S_{\tau(t)+m} - t)^{r-1})^{r-1} (E(S_{\tau(t)+m} - t)^r)^{2-r} = o(t^{2-r}),$$

and (ii) follows by Theorem 1.1.

The direct implication of (iii) follows immediately from the lemma and  $0 < S_{\tau(t)} - t \leq S_{\tau(t)+m} - t$ .

To prove the converse implication of (iii), assume that  $E(S_{\tau(t)} - t)^{r-1} \leq M$ ,  $0 < t < \infty$ . Then

$$\begin{aligned} r \int_0^T (S_{\tau(t)} - t)^{r-1} dt &\geq \int_0^{S_n(T)-1} r(S_{\tau(t)} - t)^{r-1} dt \\ &= \sum_{i=1}^{r(T)-1} \int_{S_{n-1}}^{S_n} r(S_n - t)^{r-1} dt = \sum_{i=1}^{r(T)-1} X_n^r \geq \sum_{i=1}^{r(T)-1} (X_n \wedge A)^r. \end{aligned}$$



Theorem 1.1, this estimate and Fubini's theorem yield

$$\begin{aligned} (E\tau(T) + m)E(X \wedge A)^r &= E \sum_1^{\tau(T)+m} (X_n \wedge A)^r \\ &\leq E \left( r \int_0^T (S_{\tau(t)} - t)^{r-1} dt + (m + 1)A^r \right) \leq rTM + (m + 1)A^r. \end{aligned}$$

We divide this by  $T$  and take the limits as first  $T \rightarrow \infty$  and then  $A \rightarrow \infty$  to obtain  $\mu^{-1}EX^r \leq rM$  and  $EX^r \leq rM\mu$ . To show that  $\mu < \infty$ , we assume temporarily that  $EX^p < \infty$  where  $p \leq 1$ . By Theorem 1.1  $(E\tau(T) + m)EX^p = E \sum_1^{\tau(T)+m} X_n^p \geq E(\sum_1^{\tau(T)+m} X_n)^p \geq T^p, T > 0$ .

Since  $E(X \wedge A)^r \geq A^r P(X > A)$  we obtain, choosing  $T = A^r$  in the inequalities above,

$$EX^p(rM + m + 1)A^r \geq EX^p(E\tau(A^r) + m)E(X \wedge A)^r \geq A^{rp}A^r P(X > A).$$

Thus  $P(X > A) \leq CA^{-rp}$ , which implies that  $EX^q < \infty$  for  $q < rp$ . Since  $EX^{r-1} < \infty$  by Remarks 2.4 and 2.5, we may iteratively improve the exponent by this argument until we reach  $\mu = EX < \infty$ . This completes the proof of  $EX^r \rightarrow \infty$ .

The converse implication of (i) follows from this and Theorem 1.1.

REMARK 3.1. If  $EX^2 < \infty$ , then

$$\int_0^T (S_{\tau(t)+m} - t) dt = \sum_1^{\tau(T)-1} (X_n^2/2 + X_n \sum_{i=1}^m X_{n+i}) + \theta(X_{\tau(T)}^2/2 + X_{\tau(T)} \sum_1^m X_{\tau(T)+i})$$

for some  $\theta, 0 \leq \theta \leq 1$ . Using  $E(X_n^2/2 + \sum_{i=1}^m X_n X_{n+i} | \mathcal{F}_{n-m-1}) = \gamma^2/2 + (m + 1/2)\mu^2$ , one obtains

$$\begin{aligned} E \int_0^T (S_{\tau(t)+m} - t) dt &= E \sum_1^{\tau(T)+m} (X_n^2/2 + \sum_{i=1}^m X_n X_{n+i}) + o(T) \\ &= (E\tau(T) + m)(\gamma^2/2 + (\frac{1}{2} + m)\mu^2) + o(T) = (\gamma^2/2\mu + (m + \frac{1}{2})\mu)T + o(T). \end{aligned}$$

Hence

$$\frac{1}{T} \int_0^T \frac{E\tau(t) - t}{\mu} dt = \frac{1}{\mu T} \int_0^T (ES_{\tau(t)+m} - t) dt - m \rightarrow \frac{\gamma^2}{2\mu^2} + \frac{1}{2}.$$

We conjecture that  $E\tau(t) - t/\mu \rightarrow \gamma^2/2\mu^2 + 1/2$  as  $t \rightarrow \infty$  (with minor modifications when  $X$  has a lattice distribution) (this is true for independent variables), but we have not been able to prove this.

REMARK 3.2. Similarly  $(1/T) \int_0^T E(S_{\tau(t)} - t)^{r-1} dt \rightarrow EX^r/r\mu$  as  $T \rightarrow \infty$ . We conjecture that  $E(S_{\tau(t)} - t)^{r-1} \rightarrow EX^r/r\mu$  (in the non-lattice case).

REMARK 3.3. In the case of independent variables, it is often possible to reduce theorems to the case of positive variables by the introduction of the ladder variables  $\{Y_n\}$  defined by  $N_0 = 0, N_{i+1} = \tau(S_{N_i})$  and  $Y_i = S_{N_i} - S_{N_{i-1}}$ . This fails for  $m$ -dependent variables, at least in its simplest version. The following example shows that, in general,  $\{Y_n\}$  is neither stationary nor  $m$ -dependent.

EXAMPLE 3.1. Let  $\{\xi_n\}_0^\infty$  be i.i.d. r.v. with  $P(\xi_n = 0) = P(\xi_n = 1) = 1/2$ . Define  $\{X_n\}$  by

$$X_n = \begin{cases} 2 & \text{if } \xi_{n-1} = 0, \xi_n = 0 \\ 4 & \text{if } \xi_{n-1} = 0, \xi_n = 1 \\ -1 & \text{if } \xi_{n-1} = 1, \xi_n = 0 \\ 5 & \text{if } \xi_{n-1} = 1, \xi_n = 1. \end{cases}$$

$\{X_n\}$  is 1-dependent.

The ladder variables take the values 1, 2, 3, 4, 5. They constitute a Markov chain with transition matrix

$$P = \begin{cases} 0 & \frac{1}{2} & 0 & \frac{1}{2} & 0 \\ 0 & \frac{1}{2} & 0 & \frac{1}{2} & 0 \\ \frac{1}{4} & 0 & \frac{1}{4} & 0 & \frac{1}{2} \\ \frac{1}{4} & 0 & \frac{1}{4} & 0 & \frac{1}{2} \\ \frac{1}{4} & 0 & \frac{1}{4} & 0 & \frac{1}{2} \end{cases}$$

The initial distribution  $\pi_1 = (\frac{1}{6}, \frac{1}{4}, \frac{1}{6}, \frac{1}{4}, \frac{1}{4})$  differs from the stationary one  $\pi_\infty = (\frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6})$ . Thus, the ladder variables are not identically distributed. Furthermore, if  $Y_n$  and  $Y_{n+m+1}$  were independent for some  $m, n \geq 1$ , the rows of  $P^{m+1}$  would have to coincide. This would imply that  $P^{m+1} = P^\infty$ , which is impossible since the entries in  $P^{m+1}$  are dyadic rationals, while  $P^\infty$  contains  $\frac{1}{6}$  and  $\frac{1}{3}$ . Hence  $\{Y_n\}$  is not  $m$ -dependent for any  $m$ .

**4. Applications.** Our first application is due to Carl-Gustav Esseen. For further results, see [5].

**EXAMPLE 4.1.** Let  $\{\xi_n\}_1^\infty$  be independent random variables, uniformly distributed on  $(0, 1)$ , and set  $X_n = I(\xi_{n+1} < \xi_n)$ . Then  $\{X_n\}$  is 1-dependent.  $\tau(k-1) = \inf\{n : S_n = k\}$  equals the position of the  $k$ th decrease in the sequence  $\{\xi_n\}$ . Thus  $L_k = \tau(k-1) - \tau(k-2)$  is the length of the  $k$ th increasing run.  $L_k$  may be interpreted as the length of the  $k$ th run of a "very long" random permutation. In this example,  $\mu = \frac{1}{2}$  and  $\gamma^2 = \frac{1}{12}$  (from  $EX^2 = \frac{1}{2}$  and  $EX_1X_2 = \frac{1}{6}$ ). Thus, by Theorems 2.2 and 3.1

$$E \sum_1^n L_k = E\tau(n-1) = 2n + O(1)$$

$$\text{Var}(\sum_1^n L_k) = \text{Var} \tau(n-1) = 2n/3 + O(n^{1/2}).$$

The following example yields new proofs of some results on how many random letters are required until a given sequence occurs. (See [3], [9] and further references given there.) We only consider the simplest case.

**EXAMPLE 4.2.** Let  $\{\xi_n\}_1^\infty$  be independent, uniformly distributed random letters from an alphabet with  $N$  letters. Let  $\alpha_1 \dots \alpha_{m+1}$  be a fixed sequence of  $m+1$  letters and define  $X_n = I(\xi_n \dots \xi_{n+m} = \alpha_1 \dots \alpha_{m+1})$ .

Let  $L_k = \tau(k-1) - \tau(k-2)$ .  $L_k$  is the distance from the  $(k-1)$ th to the  $k$ th occurrence of  $\alpha_1 \dots \alpha_{m+1}$ . In this case  $L_2, L_3, \dots$  are independent and identically distributed. Thus, Theorem 2.2 implies, with  $\varepsilon_k = I(\alpha_1 \dots \alpha_k = \alpha_{m+2-k} \dots \alpha_{m+1})$ , that  $EL_n = 1/\mu = N^{m+1}, n \geq 2$

$$\text{Var}(L_n) = \gamma^2/\mu^3 = N^{m+1}(N^{m+1} + s \sum_1^m \varepsilon_k N^k - 2m - 1), \quad n \geq 2.$$

It is easily seen that  $EX_{\tau(k)+i} = E(X_{n+i} | X_n = 1) = \varepsilon_{m+1-i} N^{-i}, i = 0 \dots m$ . Thus

$$ES_{\tau(0)+m} = ES_{\tau(0)} + \sum_{i=1}^m EX_{\tau(0)+i} = 1 + \sum_1^m \varepsilon_{m+1-i} N^{-i} = \sum_1^{m+1} \varepsilon_i N^{i-m-1}.$$

By Lemma 1.1  $ES_{\tau(0)+m} = (E\tau(0) + m)N^{-m-1}$  whence  $EL_1 = E\tau(0) = \sum_1^{m+1} \varepsilon_i N^i - m$ . With some effort one obtains, using Theorem 1.2,

$$\text{Var} L_1 = (\sum_1^{m+1} \varepsilon_i N^i)^2 - \sum_1^{m+1} (2i-1)\varepsilon_i N^i.$$

**REMARK 4.1.** These examples are of the form  $X_n = \varphi(\xi_n, \dots, \xi_{n+m})$ , with  $\xi_n$  i.i.d.; it is an interesting and apparently open problem whether every stationary  $m$ -dependent sequence can be written in this way.

**Note added in proof.** The lattice variable version of the conjecture in Remark 3.1 is false, see Janson, Runs in  $m$ -dependent sequences (to appear).

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