A LIMIT THEOREM FOR CONDITIONED RECURRENT RANDOM WALK ATTRACTED TO A STABLE LAW¹

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1. Introduction. Consider an ensemble of independent particles whose motion describes a random walk on Z^d , the d-dimensional lattice of integers. If A is an arbitrary subset of Z^d and the random walk is assumed recurrent (consequently $d \le 2$), then as time passes it becomes increasingly unlikely that any given particle has avoided A. Suppose, however, that at each stage attention is restricted to only those particles whose past history is such that A has been avoided. Then it is of interest to investigate the possible distortive effects of this conditioning on the asymptotic behavior of the particle motion. Suppose A is finite and $\tilde{g}_A(0) \neq 0$ (the function $\tilde{g}_A(x)$ of potential-theoretic interest is defined below and the connection between this condition and the motion of the random walk established) and suppose that the underlying distribution F governing the particle transitions is attracted to a stable law $G_{\alpha}(1 \le \alpha \le 2)$ is the index of the stable law). The principal result of the paper (Theorem 2.1) states that the conditional distribution of the particles whose past motion has avoided the set A is also attracted to a limit distribution H_{α} . Except for the case d=1 with G_{α} a Cauchy distribution and the case d=2 with G_{α} a normal distribution, the distributions G_{α} and H_{α} are in general different. For d=1and $\alpha = 2$, under certain further restrictions on A, G_{α} turns out to be a two-sided Rayleigh distribution. It is the case, however, that the same constants normalizing the particle position may be used in the statement of the attraction of the conditioned motion to H_{α} as in the statement of the attraction of the unconditioned motion to the stable law G_{α} . In preparation we first review some basic definitions and record some preliminary facts about recurrent lattice random walk.

We let $p: \mathbb{Z}^d \times \mathbb{Z}^d \to [0,1]$ be the transition function of the random walk. Thus,

(i)
$$p(x_1, x_2) = p(0, x_2 - x_1)$$
 for $x_1, x_2 \in \mathbb{Z}^d$

(ii)
$$\sum_{x \in Z^d} p(0, x) = 1,$$

and we inductively define

$$p_n(x_1, x_2) = \sum_{y \in Z^d} p_{n-1}(x_1, y) p(y, x_2)$$
 for $n = 2, 3 \cdots$.

An underlying probability space (Ω, P, B) is assumed to have been constructed, on which a sequence of independent random variables X_i , $i = 1, 2, \cdots$ (the increments of the random walk) are defined, such that $P[X_i = x] = p(0, x)$, $i = 1, 2, \cdots$.

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We denote by F the common distribution of the increments. The starting point x_0 is fixed but arbitrary, and we use the notation P^x for the underlying probability measure to indicate that $x_0 = x$. Similarly we let $E^x f = \int_{\Omega} f dP^x$ for any $f: \Omega \to R$ (the reals) for which the integral on the right is defined. When x = 0 we simply write P[A].

We will call $S_n = x_0 + \sum_{i=1}^n X_i$ the *n*th partial sum of the random walk. Unless explicitly stated otherwise the following assumptions will be made. All random walks are (i) aperiodic, (ii) recurrent.

Aperiodicity is defined in [8], but for our purposes the following characterization is more convenient. If $\phi(t)$ with $t = (t_1, \dots, t_d)$ is the characteristic function of X_1 , then the associated random walk is *aperiodic* iff $\phi(t) = 1$ implies each coordinate of t is an integral multiple of 2π .

A random walk is said to be *recurrent* if for each x, $\sum_{n=1}^{\infty} p_n(0, x) = \sum_{n=1}^{\infty} P[S_n = x] = \infty$, and *transient* if the alternative is true. Again as a matter of convenience in application we require the following equivalent statement (see [8] once again). A random walk is recurrent iff

(1)
$$\int_{C^d} \operatorname{Re} \frac{dt}{1 - \phi(t)} = \infty, \quad \text{where } C^d = \{t : |t_i| \le \pi, \ i = 1, 2, \dots d\}.$$

We now make a list of useful definitions and related notation. Let A be an arbitrary subset of \mathbb{Z}^d , then

(1.1)
$$T_{\mathbf{A}} = \min[n > 0: S_n \in \mathbf{A}] \quad \text{if such an } n \text{ exists,}$$
$$= \infty, \quad \text{otherwise;}$$

and $r_n(x, \mathbf{A}) = P^x[T_{\mathbf{A}} > n]$, for $x \in \mathbb{Z}^d$, $n \ge 0$, $(T = T_{\{0\}})$ and $r_n = P[T > n]$. We remark that by recurrence $T_{\mathbf{A}}$ is finite with probability one and $\lim_{n \to \infty} r_n(x, \mathbf{A}) = 0$.

(1.2)
$$Q_{A}^{(0)}(x, y) = \delta(x, y) \text{(the Kronecker } \delta)$$

$$Q_{A}^{(n)}(x, y) = P^{x} [S_{n} = y; T_{A} \ge n]$$

$$Q^{(n)}(x, y) = Q_{\{0\}}^{(n)}(x, y); \qquad f_{n} = Q^{(n)}(0, 0).$$

(1.3) $\tilde{g}_{\mathbf{A}}(x, y) = \sum_{n=0}^{\infty} Q_{\mathbf{A}}^{(n)}(x, y) =$ the expected number of visits to y starting at x up to and including the first visit to \mathbf{A} .

(1.4)
$$\widetilde{\Pi}_{\mathbf{A}}(x, y) = P^{x}[S_{T_{\mathbf{A}}} = y] \quad \text{for} \quad y \in \mathbf{A}$$
$$= 0 \quad \text{for} \quad y \in \mathbf{A}.$$

It is shown in [8] by applying the integral criterion (I) that for $d \ge 3$ all random walks are transient, and so from now on d = 1 or 2. We now record some important results about recurrent random walks for later use.

Let |y| denote the ordinary d-dimensional Euclidean distance from y to the origin. If a random walk is recurrent and d=1 with $\sigma^2=\sum_{-\infty}^{\infty}x^2p(0,x)=\infty$ or d=2, then for A finite

(1.5)
$$\tilde{g}_{A}(x) = \lim_{|y| \to \infty} \tilde{g}_{A}(x, y) \quad \text{exists};$$

while for d = 1 with $\sigma^2 < \infty$

(1.6)
$$\tilde{g}_{\mathbf{A}}(x) = \frac{1}{2} \lim_{y \to +\infty} \left[\tilde{g}_{\mathbf{A}}(x, y) + \tilde{g}_{\mathbf{A}}(x, -y) \right] \text{ exists.}$$

For the proof see [8]. In addition it is shown in [4] that for $x \in A$, $\tilde{g}_A(x, y) = \tilde{\Pi}_{-A}(-y, -x)$. Thus for d = 1 with $\sigma^2 = \infty$ or d = 2 and $x \in A$

(1.7)
$$\tilde{g}_{\mathbf{A}}(x) = \lim_{|\mathbf{y}| \to \infty} \tilde{\Pi}_{-\mathbf{A}}(-y, -x);$$

while for d = 1 with $\sigma^2 < \infty$

(1.8)
$$\tilde{g}_{\mathbf{A}}(x) = \frac{1}{2} \lim_{y \to +\infty} \left[\widetilde{\Pi}_{-\mathbf{A}}(-y, -x) + \widetilde{\Pi}_{-\mathbf{A}}(y, -x) \right].$$

Our primary aim in this paper then is to investigate the probability measures $P^{y}[\cdot \mid T_{A} > n]$ and the behavior as $n \to \infty$ of the associated sample paths when A is a finite set under the condition that $\tilde{g}_{A}(x) > 0$ for appropriate $x \in Z^{d}$. By checking the definitions one sees that this is in the nature of a condition that the random walk starting at x can *escape* to infinity along a path which avoids the set A. If we let I_{A} denote the smallest d-dimensional interval containing the finite set A, $E_{A} = Z^{d} - I_{A}$ and for d = 1

$$x_{+}(\mathbf{A}) = \max\{x \in \mathbf{A}\}, \qquad x_{-}(\mathbf{A}) = \min\{x \in \mathbf{A}\},$$

 $\mathbf{A}_{+} = \{x > x_{+}\}, \qquad \mathbf{A}_{-} = \{x < x\},$

the precise statement is the following

PROPOSITION. Let A be a finite subset of Z^d . If d=2 or d=1 with $\sigma^2 < \infty$, then for $x \in Z^d$

(1.9)
$$\tilde{g}_{A}(x) > 0 \quad \text{iff} \quad P^{x} \lceil T_{E_{A}} < T_{A} \rceil > 0;$$

if d = 1 with $\sigma^2 = \infty$, then

(1.10)
$$\tilde{g}_{A}(x) > 0$$
 iff both $P^{x}[T_{A_{+}} < T_{A}] > 0$ and $P^{x}[T_{A_{-}} < T_{A}] > 0$.

PROOF. We first show the sufficiency of the conditions in (1.9) and (1.10). Inasmuch as for $x \notin A$

$$P^{x}[T_{E_{A\cup\{x\}}} < T_{A\cup\{x\}}] > 0 \quad \text{iff} \quad P^{x}[T_{E_{A}} < T_{A}] > 0$$

with a similar result for \mathbf{A}_{\pm} and $\tilde{g}_{\mathbf{A} \cup \{x\}}(x,y) \leq \tilde{g}_{\mathbf{A}}(x,y)$, there is no loss of generality in assuming $x \in \mathbf{A}$.

The main tool in the proof is the following adaptation of a result in [9]. If A_n is a collection of finite subsets of Z^d increasing to Z^d , then for each fixed y and $\varepsilon > 0$ there is an $n(y,\varepsilon)$ such that $n \ge n(y,\varepsilon)$ and $y \in A_n$ imply $\lim_{|x| \to \infty} \widetilde{\Pi}_{A_n}(x,y) < \varepsilon$. We apply this result to the reversed random walk, i.e. the random walk with transition function p_* such that $p_*(0,x) = p(x,0)$. Let $A_1 = I_A$, but otherwise the A_n may be an arbitrary sequence of finite sets increasing to Z^d . Then

(1.11)
$$\lim_{|y| \to \infty} P_*^{y} [T_{A_n - I_A} < T_{I_A}] > 0$$

for n sufficiently large. Now if $x_1, x_2 \in A_+$ or $x_1, x_2 \in A_-$ in the case d = 1, or $x_1, x_2 \in E_A$ in the case d = 2, we have

$$(1.12) P_*^{x_1} [T_{\{x_2\}} < T_{I_A}] > 0.$$

For d=1 this is a consequence of the fact that by recurrence there is some path from x_1 to x_2 , and thus, by choosing an appropriate permutation of the transitions comprising this path there must in fact be such a path which does not enter A. When $x_1, x_2 \in A_+$, for example, this may be achieved by taking a permutation which puts all of the transitions to the right (positive steps) before all of those to the left (negative steps). The argument for d=2 follows similar lines.

By hypothesis, for d=1 with $\sigma^2<\infty$ and for d=2 there exists an $x_2\in E_A$ such that

$$(1.13) P_*^{x_2} [S_{T_A} = x] > 0;$$

while for d = 1 with $\sigma^2 = \infty$ there exist $x_2 \in A_+$ and $x_2' \in A_-$ such that

(1.14)
$$P_*^{x_2}[S_{T_A} = x] > 0 \text{ and } P_*^{x_2'}[S_{T_A} = x] > 0.$$

Combining (1.11) through (1.14) we obtain for d = 1 with $\sigma^2 = \infty$ and d = 2

(1.15)
$$\lim_{|y| \to \infty} P_*^{y} [S_{T_A} = x] > 0.$$

For d = 1 with $\sigma^2 < \infty$ we require the additional fact that

(1.16)
$$\lim_{y \to -\infty} \widetilde{\Pi}_{Z_+}(y, x) = P[\xi \ge x] / E[\xi],$$

where Z_+ is the positive integers and ξ is the positive ladder random variable. (See [8] for the definition and a proof of (1.16).) A similar result holds for $y \to +\infty$ for Z_- , the negative integers, and the negative ladder random variable. Combining this result with (1.12) and (1.13) we obtain for d = 1, $\sigma^2 < \infty$

(1.17)
$$\frac{1}{2} \lim_{y \to \infty} \left(P_*^{y} [S_{T_A} = x] + P_*^{-y} [S_{T_A} = x] \right) > 0.$$

It is shown in [4] that $P_*^y[S_{T_A} = x] = P^{-y}[S_{T_{-A}} = -x]$. In view of (1.4) and (1.8) therefore, (1.15) and (1.17) imply $\tilde{g}_A(x) > 0$.

The necessity of the conditions in (1.9) and (1.10) is a straightforward consequence of the definitions of the quantities involved. This completes the proof of the proposition.

We will confine our attention until Section 4 to the case d=1 in which the distribution F of the increments of the random walk belongs to the domain of attraction of a stable law of index α (0 < $\alpha \le 2$), i.e., there exist constants $B_n > 0$ and A_n and a distribution G_n on R^d such that

(1.18)
$$\lim_{n\to\infty} P[S_n/B_n - A_n \le x] = G_n(x).$$

Here again we require some preliminary discussion. It was shown by P. Lévy and Y. Khintchine (a discussion appears in [2]) that if G_{α} has characteristic function ϕ_{α} , then the following representation theorem holds:

(1.19)
$$\ln \phi_{\alpha}(t) = i\gamma t - c |t|^{\alpha} (1 + i\beta |t|^{-1} t\omega(t,\alpha)),$$

where α , β , γ and c are constants such that $0 < \alpha \le 2$, $-1 \le \beta \le 1$ and $c \ge 0$ with

$$\omega(t, \alpha) = \tan \frac{1}{2}\pi\alpha$$
 $\alpha \neq 1$
= $2\pi^{-1} \ln |t|$ $\alpha = 1$.

It can be shown by applying the criterion (I) to the Lévy-Khintchine representation that the assumption of recurrence for a stable law implies $1 \le \alpha \le 2$.

The following criterion (again discussed in [2]) is very useful for determining when a distribution F is attracted to a stable law.

THEOREM 1.1. (Gnedenko and Doeblin) In order that the distribution F belong to the domain of attraction of a stable law of index α , $0 < \alpha \le 2$, it is necessary and sufficient that for $0 < \alpha < 2$

(i)
$$F(-x)/[1-F(x)] \to c_1/c_2$$
 as $x \to \infty$, with $c_1, c_2 \ge 0$,

(ii)
$$x^{\alpha}[1-F(x)+F(-x)] = L(x) \quad with \quad L(x) \text{ slowly varying},$$

while for $\alpha = 2$

$$x^2 \int_{|y| \ge x} dF(y) / \int_{|y| \le x} y^2 dF(y) \to 0$$
 as $x \to \infty$.

Several comments concerning the theorem are necessary.

(A) A nonnegative function L(x) on $(0, \infty)$ is said to be slowly varying if for every fixed $y > 0 \lim_{x \to \infty} [L(yx)/L(x)] = 1$. Karamata showed in his classic paper [3] that L is slowly varying if and only if it can be represented in the form

$$(1.20) L(x) = c(x) \exp\left[\int_1^x t^{-1} \zeta(t) dt\right]$$

with $\lim_{x\to\infty} c(x) = c$, $0 < c < \infty$ and $\lim_{x\to\infty} \zeta(x) = 0$. It is easily shown from this characterization that given any $\delta > 0$, there is an x_0 such that $x \ge x_0$ implies $L(x) < x^{\delta}$. We will make use of this fact later on.

(B) Under conditions (i) and (ii) F(x) in fact belongs to the domain of attraction of the stable law of index α with $\beta = (c_1 - c_2)/(c_1 + c_2)$ for $\alpha \neq 1$ and $\beta = (c_2 - c_1)/(c_1 + c_2)$ for $\alpha = 1$. The constants c and γ of the limit stable law are not uniquely determined. Once it is known that there is some choice of constants A_n and B_n for which (1.18) holds, then it is not difficult to see that for any a > 0 and b there is a choice of the A_n and B_n for which (1.18) holds with $G_{\alpha}(x)$ replaced by $G_{\alpha}(ax+b)$. We can however make the following statement. Let $\chi(x) = 1 - F(x) + F(-x)$ and define the inverse function $\chi^{-1}(x) = \inf[y: \chi(y) \leq x]$. Then it is embodied in the Kolmogorov-Gnedenko proof of Theorem (1.1) that for $0 < \alpha < 2$ the choice

(1.21)
$$B_n = \chi^{-1}(n^{-1}(c_1 + c_2))$$

is possible, in which case for $\alpha = 1$, $c = \frac{1}{2}[(c_1 + c_2)\pi]$; while for $0 < \alpha \le 2$, $\alpha \ne 1$, $c = (c_1 + c_2)\Gamma(1 - \alpha)\cos\frac{1}{2}\pi\alpha$.

Our analysis will require more detailed information about the sequences A_n and

 B_n . We have already indicated a choice for the B_n in the case $0 < \alpha < 2$. For $\alpha = 2$ we have from [2] (Section 26 Theorem 4 and its proof)

$$(1.22) B_n^2 = n \left[\int_{|x| < C_n} x^2 dF(x) - \left(\int_{|x| < C_n} x dF(x) \right)^2 \right],$$

with C_n a sequence of constants the only properties of which concern us are: (i) $C_n \to \infty$ as $n \to \infty$ and (ii) $C_n = o(B_n)$ as $n \to \infty$. For $0 < \alpha < 2$ it follows from Lemma 2-A of [11] that under the hypotheses of Theorem 1.1

$$\lim_{x \to \infty} [\chi^{-1}(x)/\chi^{-1}(xy)] = y^{1/\alpha}$$
 for fixed $y > 0$.

Hence $B_n = n^{1/\alpha} \hat{L}(n)$ where $\hat{L}(x)$ is slowly varying.

The treatment of the case $\alpha=2$ requires a different approach. The argument we give now holds in fact for any law attracted to a symmetric stable law when the A_n may be taken to be zero (which we will see below to be the case for $1 < \alpha \le 2$ if $\int_{-\infty}^{\infty} x dF(x) = 0$ and for $0 < \alpha < 1$ in general).

Let $F^{(n)} = F * F * \cdots * F$ (*n* times) be the *n*th fold convolution of *F* and let G_{α} be the limit stable law. Since all stable laws have continuous densities (Section 36 of [2])

$$F^{(n)}(B_n x) \to G_{\alpha}(x)$$
 uniformly in x as $n \to \infty$.

Let $k_0 \in N$ be fixed and let $X_1, X_2 \cdots$ be independent, identically distributed with distribution F. Then as $n \to \infty$

$$P\left[\frac{X_1 + X_2 + \dots + X_n}{B_n} + \dots + \frac{X_{(k_0 - 1)n + 1} + \dots + X_{k_0 n}}{B_n} \le \frac{B_{k_0 n}}{B_n} x\right] \to G_{\alpha}(x)$$

on the one hand, and on the other differs for large n from $G_{\alpha}^{(k_0)}(xB_{k_0n}/B_n)$ by very little (inasmuch as for probability distributions $F_{n,1}$ and $F_{n,2}$, $F_{n,1} \to F_1$ and $F_{n,2} \to F_2$ imply $F_{n,1}*F_{n,2} \to F_1*F_2$ (see, e.g., Lemma 1 of Section 17 in [6])). But by the stability and symmetry of G_{α} , this latter expression is the same as $G_{\alpha}(xk_0^{-1/\alpha}B_{k_0n}/B_n)$, and therefore $B_{k_0n}/B_n \to k_0^{-1/\alpha}$ as $n\to\infty$. Thus B_n has the form $B_n = n^{1/\alpha}\hat{L}(n)$ with $\hat{L}(n)$ slowly varying for $\alpha = 2$ as well. We note that if we extend the definition of B_n to R_+ by setting $B(x) = B_{[x]}$, then B(x) remains of the form $x^{1/\alpha}\hat{L}(x)$ with $\hat{L}(x)$ slowly varying.

For the sequence A_n we use another basic result of Kolmogorov and Gnedenko, Theorem 4 of Section 25 in [2], stating that the most general choice of A_n is

$$(1.23) A_n = n \int_{|x| < t} x \, dF(B_n x) - \gamma_n(t),$$

where t > 0 is fixed and $\gamma_n(t)$ is any convergent sequence. From this characterization it is shown in the Appendix of [1] that

(1.24)
$$A_{n} = nB_{n}^{-1} \int_{-\infty}^{\infty} x \, dF(x), \qquad 1 < \alpha < 2,$$

$$= 0, \qquad \alpha < 1,$$

$$= n \operatorname{Im} \left[1 - \phi(B_{n}^{-1}) \right], \qquad \alpha = 1$$

are possible choices. First we remark that if F lies in the domain of attraction of a stable law of index α , then it is known (Theorem (3) of Section 35 in [2]) that it

possesses all δ th order moments for $0 \le \delta < \alpha$. In particular then, for $1 < \alpha \le 2$ the mean μ exists and our assumption of recurrence implies $\mu = 0$. Consequently, we may take $A_n \equiv 0$. However, when $\alpha = 1$ a first moment may or may not exist and it is necessary to introduce the notion of *normal* attraction.

DEFINITION. A distribution F is said to belong to the domain of normal attraction of a stable law G_{α} of index α , $0 < \alpha \le 2$ if it belongs to its domain of (general) attraction with $B_n = n^{1/\alpha}$ a possible choice for the norming constants.

An equivalent way to formulate the criterion for normal attraction is to require for $\alpha < 2$ that the slowly varying function in the relation $x^{\alpha}\chi(x) = L(x)$ have a nonzero finite limit as $x \to \infty$, and to require a finite variance for $\alpha = 2$ (see Theorems 4 and 5 of Section 35 in [2]).

We now state the following result (proved in [1]).

THEOREM 1.2. Let F belong to the domain of normal attraction of a stable law of index 1. Then

(i)
$$\lim_{t\to\infty} \operatorname{Im} \left[t^{-1}(1-\phi(t))\right] = \mu \quad \text{if and only if}$$

(ii)
$$\lim_{x \to \infty} \int_{-x}^{x} \zeta \, dF(\zeta) = \mu.$$

In particular, it follows from (1.24) that the centering constants A_n may be taken to be zero if and only if (ii) holds for μ finite.

Finally we record the following result. The proof is essentially a generalization of the argument relating the asymptotic tail behavior of the distribution of a symmetric stable law to the behavior of its characteristic function near the origin. A detailed proof appears in [1].

THEOREM 1.3. Let F be the probability distribution of a random variable X. Assume F satisfies the hypotheses of Theorem 1.1. Then in the notation of that theorem:

(i) For
$$1 < \alpha < 2$$
 and $E[X] = 0$

$$\lim_{t \to 0^{\pm}} \frac{1 - \phi(t)}{\gamma(1/|t|)} = \frac{c}{c_1 + c_2} (1 \pm i\beta \tan \frac{1}{2}\pi\alpha).$$

(ii) For $0 < \alpha < 1$

$$\lim_{t \to 0^{\pm}} \frac{1 - \phi(t)}{\chi(1/|t|)} = \frac{c}{c_1 + c_2} (1 \pm i\beta \tan \frac{1}{2}\pi\alpha).$$

(iii) For $\alpha = 2$ and E[X] = 0

$$\lim_{t\to 0} \frac{1-\phi(t)}{t^2 \int_{-1/|t|}^{1/|t|} x^2 dF(x)} = \frac{1}{2}.$$

(iv) For $\alpha = 1$.

$$\lim_{t\to 0} \operatorname{Re} \left[\frac{1-\phi(t)}{\chi(1/|t|)} \right] = \frac{1}{2}\pi;$$

and if for $\alpha = 1$ the additional hypothesis is made that F is normally attracted to its limit stable law, then

$$\lim_{t\to 0\pm} \operatorname{Im}\left[\frac{1-\phi(t)}{\ln|t|\chi(1/|t|)}\right] = \pm\beta.$$

2. Basic limit theorem. The discussion in this section will be limited to the special class of one-dimensional recurrent random walks whose increments have their common distribution belonging to the domain of attraction of a stable law of index α , $1 \le \alpha \le 2$.

THEOREM 2.1. Let $S_n = x_0 + \sum_{k=1}^n X_k$ be the nth partial sum of an integer-valued, recurrent, aperiodic walk. If F is the distribution of X_1 , we assume

(i) F belongs to the domain of attraction of a stable law of index α , $1 < \alpha \le 2$. Thus there is a sequence $B_n > 0$ such that

$$\lim_{n \to \infty} P[S_n/B_n \le x] = G_n(x) \qquad x \in R,$$

where G_{α} is a probability distribution with a characteristic function ϕ_{α} of the form

$$\ln \phi_{\alpha}(t) = -c \left| t \right|^{\alpha} (1 + it \left| t \right|^{-1} \beta \tan \frac{1}{2} \pi \alpha) \equiv -b \left| t \right|^{\alpha}$$

with c > 0 and $-1 \le \beta \le 1$.

Alternatively, we assume

(ii) F belongs to the domain of normal attraction of a stable law of index $\alpha = 1$ and, in addition, $\lim_{x\to\infty} \int_{-x}^{x} \zeta \, dF(\zeta) = \mu < \infty$.

Thus there is a sequence $B_n > 0$ such that $\lim_{n \to \infty} P[S_n | B_n \le x] = G_1(x), x \in R$, where G_1 has characteristic function ϕ_1 such that $\ln \phi_1(t) = -c|t|$ with c > 0.

Then in both cases (i) and (ii) if $T = T_{\{0\}}$, we have that

$$\lim_{n\to\infty} P[S_n/B_n \le x \mid T > n] = H_{\alpha}(x),$$

where H_{α} is a probability distribution with a bounded continuous density h_{α} with characteristic function Ψ_{α} given by

(2.2)
$$\Psi_{\alpha}(t) = 1 - b \left| t \right|^{\alpha} \int_{0}^{1} x^{(1/\alpha) - 1} \phi_{\alpha} \left[t(1 - x)^{1/\alpha} \right] dx.$$

The two special cases $\alpha = 2$ (normal) and $\alpha = 1$ (Cauchy) permit an explicit evaluation of the limit law:

$$h_2(x) = \frac{1}{2}\sigma^{-2}x^2 \exp\left[-\frac{1}{2}\sigma^{-2}x^2\right]$$
 (a two-sided Rayleigh density),

where $\sigma^2 = 2c$ is the variance of the limit normal law with characteristic function ϕ_2 :

$$h_1(x) = \frac{1}{\pi} \frac{c}{c^2 + x^2} \,.$$

Before proceeding to the proof we make several remarks and prove a lemma.

First, in the statement of the theorem we have made use of our earlier remark that for $\alpha > 1$ the sequence A_n of centering constants may be taken to be identically

zero. For $\alpha=1$ we note that by Theorem 1.2 Condition 2.1 guarantees that $\lim_{t\to 0} \operatorname{Im}\left[t^{-1}(1-\phi(t))\right] = \mu$. It then follows from Condition (I) for recurrence and statement (iv) of Theorem 1.3 that the underlying random walk must be recurrent and that $\beta=0$ in the limit stable law (and therefore $\gamma=-\mu$). Consequently, $\lim_{n\to\infty} P[S_n/B_n-\mu\leq x]=G_1(x+\mu)$. Therefore taking G_1 as the limit law we may assume $A_n=0$ for $\alpha=1$ as well.

The second fact we need is that without any loss of generality we may assume B_n to be of the form $B_n = n^{1/\alpha} \tilde{L}(n)$, $0 < \alpha \le 2$, where \tilde{L} is a slowly varying function. In the particular case $\alpha = 1$, we further require $\lim_{n \to \infty} \tilde{L}(n)$ is finite and non-zero (i.e., the attraction must be normal). Finally, we remark that in the Cauchy case the theorem states the interesting result that conditioning on the event [T > n] plays no role in the limit.

We now prove the following lemma.

Lemma 2.1. Under the hypotheses of Theorem 2.1 for $1 < \alpha \le 2$

(2.3)
$$\lim_{n\to\infty} \frac{nr_n}{B_n} = \frac{\sin \pi/\alpha}{\pi g_\alpha(0)},$$

where g_{α} is the density of G_{α} ; for $\alpha = 1 \lim_{n \to \infty} r_n \ln n = \frac{1}{2}\pi^2 l$ where $l = \lim_{n \to \infty} \tilde{L}(n)$ is finite and non-zero.

PROOF. Let $R(x) = \sum_{n=0}^{\infty} r_n x^n$ and $U(x) = \sum_{n=0}^{\infty} u_n x^n$. Then $R(x) = [(1-x)U(x)]^{-1}$. By the local limit theorem for lattice variables attracted to a stable law² (recalling our assumption of aperiodicity) we have that

$$\lim_{n\to\infty} B_n p_n(0,0) = \lim_{n\to\infty} B_n u_n = g_\alpha(0).$$

By a standard Abelian theorem it easily follows that

$$U(x) \sim \frac{g_{\alpha}(0)\Gamma(1-1/\alpha)(1-x)^{(1/\alpha)-1}}{\tilde{L}(1/1-x)}$$
 as $x \to 1-$.

Hence

(2.4)
$$R(x) \sim \frac{\hat{L}(1/1-x)}{g_{\alpha}(0)\Gamma(1-1/\alpha)} (1-x)^{-(1/\alpha)} \quad \text{as} \quad x \to 1-x$$

Finally, since r_n is a nonincreasing sequence, we may apply Karamata's Tauberian theorem for $\alpha \neq 1$ to (2.4) to obtain

$$\begin{split} r_n &\sim \frac{\widetilde{L}(n)}{n^{1-1/\alpha}} \frac{1}{g_{\alpha}(0)\Gamma(1-1/\alpha)\Gamma(1/\alpha)} \\ &= \frac{\widetilde{L}(n)}{n^{1-1/\alpha}} \frac{\sin \pi/\alpha}{\pi a.(0)} \qquad \text{as} \quad n \to \infty. \end{split}$$

Since $B_n = n^{1/\alpha} \tilde{L}(n)$ we have demonstrated (2.3) for $1 < \alpha \le 2$.

² As stated in Section 49 and Section 50 of [2] the theorem is valid except when $\alpha = 2$, $\sigma^2 = \infty$. However, the latter case is proved by C. Stone in [10].

The case $\alpha = 1$ is contained in the proof of Theorem 18 in [5]. This completes the proof.

PROOF OF THEOREM 2.1. For $x \neq 0$, a simple decomposition of the event $[T \leq n]$ gives

$$(2.5) \quad P[S_n/B_n \in dx \mid T > n] = r_n^{-1} P[S_n/B_n \in dx] - r_n^{-1} \sum_{k=1}^{n-1} f_k P[S_{n-k}/B_n \in dx].$$

After a summation by parts this expression reduces to

(2.6)
$$\sum_{k=0}^{n-1} r_n^{-1} r_k (P \lceil S_{n-k} / B_n \in dx \rceil - P \lceil S_{n-k-1} / B_n \in dx \rceil).$$

If we let $\Psi_{\alpha,n}$ be the characteristic function of this probability measure, we obtain

$$\Psi_{\alpha,n}(t) = \sum_{k=0}^{n-1} r_n^{-1} r_k [\phi^{n-k}(t/B_n) - \phi^{n-k-1}(t/B_n)]$$

$$-\sum_{k=0}^{n-1} r_n^{-1} r_k (P \lceil \hat{S}_{n-k} = 0 \rceil - P \lceil S_{n-k-1} = 0 \rceil);$$

and since $\sum_{k=0}^{n} r_k u_{n-k} = 1$,

(2.7)
$$\Psi_{\alpha,n}(t) = 1 - \sum_{k=0}^{n-1} r_n^{-1} r_k [1 - \phi(t/B_n)] \phi^{n-k-1}(t/B_n).$$

Now we recall that $B_n = B(n) = n^{1/\alpha} \tilde{L}(n)$ with \tilde{L} a slowly varying function. Therefore

$$\frac{B(n-(k+1))}{B(n)} = \frac{B(n(1-(k+1)/n))}{B(n)} \sim \left(1 - \frac{k+1}{n}\right)^{1/\alpha} \text{ for large } n \text{ and } 0 \le k \le n(1-\varepsilon).$$

By our hypotheses $\lim_{n\to\infty} \phi^n(t/B_n) = \phi_{\alpha}(t)$, with the convergence uniform for t on finite intervals. Thus

(2.8)
$$\lim_{n\to\infty} (\phi^{n-(k+1)}(t/B_n) - \phi_{\alpha}[t(1-n^{-1}(k+1))^{1/\alpha}]) = 0,$$

with the convergence uniform in $0 \le k \le (1 - \varepsilon)n$.

It is an easy consequence of Theorem 1.3 that

$$(2.9) \quad \lim_{n\to\infty} n\left[1-\phi(t/B_n)\right] = c(1+i\operatorname{sgn}(t)\beta(\tan\tfrac{1}{2}\pi\alpha)|t|^{\alpha}) \quad \text{for} \quad 1<\alpha\leq 2;$$

and $\lim_{n\to\infty} n[1-\phi(t/B_n)] = c|t|$ for $\alpha = 1$.

By Lemma (2.1) we have that uniformly for $\varepsilon n \le k \le n$, $r_k/r_n \sim (n/k)^{1-(1/\alpha)}$ as $n \to \infty$ for $1 < \alpha \le 2$, and $r_k/r_n \to 1$ as $n \to \infty$ for $\alpha = 1$. Therefore, we see that $1 - \sum_{k=\epsilon n}^{(1-\epsilon)n} r_n^{-1} r_k [1 - \phi(t/B_n)] \phi^{n-(k+1)}(t/B_n)$ is approxi-

mated by (their difference tends to zero as $n \to \infty$)

$$1 - \sum_{k=en}^{(1-\epsilon)n} (n/k)^{1-(1/\alpha)} b \left| t \right|^{\alpha} n^{-1} \phi_{\alpha} \left[t (1-n^{-1}(k+1))^{1/\alpha} \right],$$

where $b = c(1 + i \operatorname{sgn}(t)\beta \tan \frac{1}{2}\pi\alpha)$ for $1 < \alpha \le 2$ and b = c for $\alpha = 1$. This last expression in turn is an approximating sum to the Riemann integral

$$1 - b |t|^{\alpha} \int_{\varepsilon}^{1-\varepsilon} x^{(1/\alpha)-1} \phi_{\alpha} [t(1-x)^{1/\alpha}] dx \quad \text{for} \quad 1 \le \alpha \le 2.$$

Now $\int_0^1 x^{(1/\alpha)-1} \phi_{\alpha} [t(1-x)^{1/\alpha}] dx$ is an absolutely convergent integral. Hence, in order to show that for every $t \in R$

(2.10)
$$\lim_{n\to\infty} \Psi_{\alpha,n}(t) = 1 - b |t|^{\alpha} \int_0^1 x^{(1/\alpha)-1} \phi_{\alpha}[t(1-x)^{1/\alpha}] dx,$$

it is enough to show

(2.11)
$$\limsup_{\varepsilon \to 0} \limsup_{n \to \infty} \left| \sum_{k=0}^{\varepsilon n} + \sum_{k=(1-\varepsilon)n}^{n} r_n^{-1} r_k [1 - \phi(t/B_n)] \phi^{n-k-1}(t/B_n) \right| = 0.$$

We estimate the expression in (2.11) using Theorem 1.3 and Lemma 2.1: Fsrst

$$(2.12) 1 - \phi(t/B_n) \le K_1 n^{-1} |t|^{\alpha}$$

for some constant K_1 . For $1 < \alpha \le 2$, $\lim_{n \to \infty} [r_n n^{1-(1/\alpha)}/\tilde{L}(n)]$ is finite and non-zero. For $\alpha = 1$, $\lim_{n \to \infty} r_n \ln n$ is finite and non-zero.

Thus we obtain

(2.13)
$$\sum_{k=0}^{M} \frac{r_k}{r_n} \frac{|t|^{\alpha}}{n} \leq |t|^{\alpha} \sum_{k=0}^{M} \frac{1}{n^{1/\alpha} \widetilde{L}(n)} = \frac{|t|^{\alpha} (M+1)}{n^{1/\alpha} \widetilde{L}(n)} \to 0, \text{ as } n \to \infty$$

for each fixed positive integer M. Also

(2.14)
$$|t|^{\alpha} \sum_{k=M}^{\varepsilon n} \frac{r_k}{r_n} \frac{1}{n} = |t|^{\alpha} \sum_{k=M}^{\varepsilon n} \left(\frac{n}{k}\right)^{1-(1/\alpha)} \frac{1}{n} \frac{\widetilde{L}(k)}{\widetilde{L}(n)}.$$

The expression on the right in (2.14) is asymptotically of the same order as

$$\frac{1}{n^{1/\alpha}\tilde{L}(n)}\int_{M}^{\varepsilon n}\frac{\tilde{L}(x)}{x^{1-(1/\alpha)}}dx.$$

We now appeal to an argument given in the Appendix of [1] which shows that we make take \tilde{L} to be differentiable. We may therefore apply L'Hospital's rule in estimating this ratio. It follows that

(2.15)
$$\lim_{M\to\infty} \limsup_{n\to\infty} \frac{1}{n^{1/\alpha} \widetilde{L}(n)} \int_{M}^{\epsilon_n} \frac{\widetilde{L}(x)}{x^{1-(1/\alpha)}} dx = \epsilon \alpha.$$

Finally.

(2.16)
$$\sum_{k=(1-\varepsilon)n}^{n} \frac{r_k}{r_n} \frac{1}{n} \le \varepsilon K_2,$$

where

$$K_2 = \sup_n \sup_{(1-\varepsilon)n \le k \le n} \frac{r_k}{r_n} \le \frac{1}{(1-\varepsilon)^{1-(1/\alpha)}} \sup_n \sup_{(1-\varepsilon)n \le k \le n} \frac{\widetilde{L}(k)}{\widetilde{L}(n)} < \infty,$$

since \tilde{L} varies slowly. Combining the estimates (2.12)–(2.16), we get (2.11). Thus for $1 < \alpha \le 2$ we have proved $\lim_{n \to \infty} \Psi_{\alpha,n}(t) = \Psi_{\alpha}(t)$.

That Ψ_{α} is in fact the characteristic function of a probability distribution is a result of $|1-\Psi_{\alpha}(t)| \leq |b||t|^{\alpha} \int_{0}^{1} x^{(1/\alpha)-1} dx$, which implies Ψ_{α} is continuous at the origin. Actually a stronger result holds. By an easy dominated convergence argument

(2.17)
$$\lim_{t\to 0} \frac{1-\Psi_{\alpha}(t)}{|t|^{\alpha}} = b \int_{0}^{1} x^{(1/\alpha)-1} dx.$$

The estimates for $\alpha = 1$ are very much the same and we omit the details.

The only two cases in which we attempt an explicit evaluation of H_{α} are for $\alpha=1, 2$. A routine computation shows $\Psi_1(t)=\exp(-ct)$. The case $\alpha=2$ can be handled as follows. The characteristic function $\overline{\Psi}_2$ corresponding to the density h_2 with $h_2(x)=\frac{1}{2}\sigma^{-2}|x|\exp(-\frac{1}{2}\sigma^{-2}x^2)$ is $\overline{\Psi}_2(t)=1-t\int_0^\infty \exp\left[-\frac{1}{2}\sigma^{-2}x^2\right]\sin xt\,dx$. Now

$$\Psi_2(t) = 1 - \frac{1}{2}t^2\sigma^2 \int_0^1 x^{-\frac{1}{2}} \exp\left[-\frac{1}{2}t^2\sigma^2(1-x)\right] dx.$$

To see that $\overline{\Psi}_2 = \Psi_2$ we define

$$\varphi_2(t) = t^{-1} [1 - \Psi_2(t)]$$
 and $\overline{\varphi}_2(t) = t^{-1} [1 - \overline{\Psi}_2(t)].$

It is then a simple matter to check that

(i)
$$\bar{\varphi}_2(0) = \varphi_2(0) = 0$$

(ii)
$$d\overline{\varphi}_2/dt = [1 - t\overline{\varphi}_2]\sigma^2; \quad d\varphi_2/dt = [1 - t\varphi_2]\sigma^2.$$

To complete the proof of the theorem it remains only to demonstrate that for $1 < \alpha < 2$, Ψ_{α} corresponds to a probability law with a bounded continuous density. For this we will show

Now

$$\begin{aligned} |\Psi_{\alpha}(t)| &= |1 - b|t|^{\alpha} \int_{0}^{1} x^{(1/\alpha) - 1} \exp\left[-b|t|^{\alpha}(1 - x)\right] dx | \\ &\leq |b|t|^{\alpha} \int_{0}^{1 - \delta} x^{(1/\alpha) - 1} \exp\left[-b|t|^{\alpha}(1 - x)\right] dx | \\ &+ |1 - b|t|^{\alpha} \int_{1 - \delta}^{1} x^{(1/\alpha) - 1} \exp\left[-b|t|^{\alpha}(1 - x)\right] dx | \\ &\leq |bt^{\alpha}| \int_{0}^{1 - \delta} x^{(1/\alpha) - 1} \exp\left[-c|t|^{\alpha}(1 - x)\right] dx \\ &+ |1 - b|t|^{\alpha} \int_{1 - \delta}^{1} \exp\left[-b|t|^{\alpha}(1 - x)\right] dx | \\ &+ |bt|^{\alpha} \left[\int_{1 - \delta}^{1} x^{(1/\alpha) - 1} - 1\right] \exp\left[-b|t|^{\alpha}(1 - x)\right] dx |. \end{aligned}$$

The first two of these terms are dominated by $A|bt^{\alpha}|\exp[-c|t|^{\alpha}\delta]$ and $\exp[-c|t|^{\alpha}\delta]$ respectively, for some constant A. Both of these functions are integrable. The third term is dominated by

$$|bt^{\alpha}| \int_{1-\delta}^{1} (x^{(1/\alpha)-1}-1) \exp[-c|t|^{\alpha}(1-x)] dx.$$

However,

$$\int_{0}^{\infty} t^{\alpha} \int_{1-\delta}^{1} (x^{(1/\alpha)-1} - 1) \exp\left[-ct^{\alpha}(1-x)\right] dx dt$$

$$= \int_{1-\delta}^{1} \frac{x^{(1/\alpha)-1} - 1}{(1-x)^{1+(1/\alpha)}} dx \int_{0}^{\infty} t^{\alpha} \exp\left[-ct^{\alpha}\right] dt$$

$$\leq K \int_{1-\delta}^{1} \frac{dx}{(1-x)^{1/\alpha}} < \infty, \quad \text{for some constant } K.$$

This completes the proof of Theorem 2.1.

3. Generalization to finite sets. In this section we prove an analogue of Theorem 2.1 when the event [T > n] is replaced by $[T_A > n]$, where $A = \{x_1, x_2, \dots x_M\}$ is a finite set of integers with $\tilde{g}_A(0) \neq 0$. A rather interesting phenomenon occurs in that the limit distribution $H_{\alpha,A}$ depends on A only when F has a finite variance. The full statement of the theorem is as follows.

THEOREM 3.1. Under the same hypotheses as Theorem 2.1, if $A = \{x_1, x_2, \dots, x_M\}$ is a finite set of integers such that $\tilde{g}_A(0) \neq 0$, then

(3.1)
$$\lim_{n\to\infty} P[S_n/B_n \le x \mid T_A > n] = H_{\sigma,A}(x) \quad \text{for every} \quad x \in R.$$

 $H_{\alpha,A}$ is a probability distribution with characteristic function $\Psi_{\alpha,A}$ with the following properties:

- (i) If $1 \le \alpha < 2$ or $\alpha = 2$ and F has infinite variance then $\Psi_{\alpha,A} = \Psi_{\alpha}$, i.e. the limit distribution is independent of the set A.
 - (ii) If $\alpha = 2$ and the variance of F is finite

$$\Psi_{2,A}(t) = \Psi_{2}(t) - i(\frac{1}{2}\pi)^{\frac{1}{2}} E[S_{T_{A}}] [\tilde{g}_{A}(0)]^{-1} \sigma^{-1} t \exp(-\frac{1}{2}t^{2}\sigma^{2})$$

and

$$h_{2,A}(x) = \frac{1}{2}\sigma^{-2} \exp(\frac{1}{2}\sigma^{-2}x^2) [|x| - (\sigma^2 \tilde{g}_A(0))^{-1} x E[S_{T_A}]].$$

PROOF.

$$\begin{split} P\big[S_{n}/B_{n} \in d\,x \,\big|\, T_{\mathsf{A}} > n\big] \\ &= \big\{P\big[T_{\mathsf{A}} > n\big]\big\}^{-1} \\ &\quad \cdot (P\big[S_{n}/B_{n} \in dx\big] - \sum_{k=1}^{n} \sum_{i=1}^{M} P\big[T_{\mathsf{A}} = k\,; S_{T_{\mathsf{A}}} = x_{i}\big] P^{x_{i}} \big[S_{n-k}/B_{n} \in dx\big] \big) \\ &= \big\{P\big[T_{\mathsf{A}} > n\big]\big\}^{-1} (P\big[S_{n}/B_{n} \in dx\big] - \sum_{k=1}^{n} P\big[T_{\mathsf{A}} = k\big] P\big[S_{n-k}/B_{n} \in dx\big] \big) \\ &\quad + \big\{P\big[T_{\mathsf{A}} > n\big]\big\}^{-1} \\ &\quad \cdot \big\{\sum_{k=1}^{n} \sum_{i=1}^{M} P\big[T_{\mathsf{A}} = k\,; S_{T_{\mathsf{A}}} = x_{i}\big] (P\big[S_{n-k}/B_{n} \in dx\big] - P^{x_{i}} \big[S_{n-k}/B_{n} \in dx\big] \big) \big\} \\ &= \mu_{n}^{(1)} (dx) + \mu_{n}^{(2)} (dx). \end{split}$$

A summation by parts gives

$$\mu_n^{(1)}(dx) = P[S_0 \in dx] - \sum_{k=0}^{n-1} \{P[T_A > k] / P[T_A > n]\}$$

$$(P[S_{n-(k+1)} / B_n \in dx] - P[S_{n-k} / B_n \in dx]).$$

Consequently, if we let $\Psi_n^{(1)} = \Psi_{\alpha,A,n}^{(1)}$ and $\Psi_n^{(2)} = \Psi_{\alpha,A,n}^{(2)}$ be the contributions to the characteristic function of the probability measure $P[S_n/B_n \in dx \mid T_A > n]$ corresponding to $\mu_n^{(1)}$ and $\mu_n^{(2)}$ respectively, then

$$\Psi_n^{(1)}(t) = 1 - \sum_{k=0}^{n-1} \left\{ P[T_A > k] / P[T_A > n] \right\} [1 - \phi(t/B_n)] \phi^{n-(k+1)}(t/B_n).$$

By Theorem 4a in [4], when $\tilde{g}_A(0) \neq 0$, $\{P[T_A > k]/P[T_A > n]\}$ has the same asymptotic behavior for large k and n as r_k/r_n ; hence

(3.2)
$$\lim_{n\to\infty} \Psi_n^{(1)}(t) = \lim_{n\to\infty} \Psi_n(t) = \Psi_n(t),$$

by Theorem 1.1.

Also we may rewrite $\mu_n^{(2)}(dx)$ as

$$\begin{aligned} & \big\{ P \big[T_{\mathsf{A}} > n \big] \big\}^{-1} \sum_{k=1}^{n} \sum_{i=1}^{M} P \big[T_{\mathsf{A}} = k \, ; S_{T_{\mathsf{A}}} = x_{i} \big] \\ & \qquad \qquad \cdot (P \big[S_{n-k} / B_{n} \in dx \big] - P \big[(S_{n-k} + x_{i}) / B_{n} \in dx \big] \big). \end{aligned}$$

Thus we conclude that

$$\Psi_{n}^{(2)}(t) = \{ P[T_{A} > n] \}^{-1} \sum_{k=1}^{n} \sum_{i=1}^{M} P[T_{A} = k; S_{T_{A}} = x_{i}] \cdot [\phi^{n-k}(t/B_{n}) - \phi^{n-k}(t/B_{n}) \exp(itx_{i}/B_{n})].$$

Once again performing a summation by parts we find that

$$\Psi_{n}^{(2)}(t) = \sum_{i=1}^{M} \sum_{k=1}^{n-1} \{ P[T_{A} > k; S_{T_{A}} = x_{i}] / P[T_{A} > n] \} \phi^{n-(k+1)}(t/B_{n})$$

$$\cdot [1 - \phi(t/B_{n})] [1 - \exp(itx_{i}/B_{n})]$$

$$(3.3) \qquad + \sum_{i=1}^{M} \{ P[T_{A} > n] \}^{-1} P[S_{T_{A}} = x_{i}] [1 - \exp(itx_{i}/B_{n})] \phi^{n-1}(t/B_{n})$$

$$- \sum_{i=1}^{M} \{ P[T_{A} > n; S_{T_{A}} = x_{i}] / P[T_{A} > n] \} [1 - \exp(itx_{i}/B_{n})].$$

Since $B_n \to \infty$ as $n \to \infty$, the third term on the right in (3.3), which is bounded by $\sum_{i=1}^{M} |1 - \exp(itx_i/B_n)|$, tends to zero as $n \to \infty$. The first term is dominated in absolute value by

$$\left| \sum_{i=1}^{M} \left[1 - \exp\left(itx_i/B_n\right) \right] \sum_{k=1}^{n-1} \left\{ P[T_A > k] / P[T_A > n] \right\} \left[1 - \phi(t/B_n) \right] \phi^{n-(k+1)}(t/B_n) \right|.$$

Since the expression in the inner summation was already shown to have a finite limit as $n \to \infty$, the first term on the right in (3.3) tends to zero as well.

To estimate the second term we consider two separate cases:

Case (i).
$$1 \le \alpha < 2$$
.

First we have

$$\left|1 - \exp\left(itx_i/B_n\right)\right| = O(tx_i/B_n)$$
 as $n \to \infty$.

Also, for $1 < \alpha < 2$,

$$P[T_A > n] \sim \tilde{g}_A(0)r_n \sim \tilde{g}_A(0)\tilde{L}(n)/n^{1-(1/\alpha)}$$
 as $n \to \infty$;

while for $\alpha = 1$.

$$P[T_A > n] \sim \frac{1}{2}\pi^2 l\tilde{g}_A(0)/\ln n$$
 as $n \to \infty$.

Consequently,

(3.4)
$$|1 - \exp(itx_i/B_n)|/P[T_A > n] \le Kn^{1-(2/\alpha)}/[\tilde{L}(n)]^2 \to 0$$

for some constant K when $1 < \alpha < 2$;

$$(3.5) \left|1 - \exp\left(itx_i/B_n\right)\right|/P[T_A > n] \le Kn^{-1}\ln n \to 0$$

when $\alpha = 1$.

For $\alpha=2$, when the variance of F is infinite by our choice of the sequence B_n (see (1.22)) $B_n^2 = n \int_{-C_n}^{C_n} x^2 dF(x)$, and since $C_n \to \infty$ we obtain $n/B_n^2 \to 0$. Thus once again we have that $\lim_{n\to\infty} |1 - \exp(itx_i/B_n)|/P[T_A > n] = 0$.

Combining this with (3.4) and (3.5) it follows that the second term in (3.3) tends to zero.

Case (ii). $\alpha = 2$ and F has finite variance.

Then we have

$$\lim_{n\to\infty} \phi^{n-1}(t/B_n) = \exp\left[-\frac{1}{2}t^2\sigma^2\right], \qquad 1 - \exp\left(itx_i/B_n\right) \sim -itx_i/B_n = -n^{-\frac{1}{2}}itx_i,$$

and

$$\{P[T_A > n]\}^{-1} \sim [\tilde{g}_A(0)r_n]^{-1} \sim [\tilde{g}_A(0)\sigma]^{-1}(\frac{1}{2}\pi)^{\frac{1}{2}}n^{\frac{1}{2}}.$$

Combining these facts with (3.2) gives $\lim_{n\to\infty} \left[\Psi_{2,A,n}^{(1)}(t) + \Psi_{2,A,n}^{(2)}(t) \right] = \Psi_{2,A}(t)$. This completes the proof of Theorem 3.1.

4. The 2-dimensional finite variance case. To this point we have restricted our attention to random walks with state space Z. We now consider the 2-dimensional case.

Lévy's formula [7] for the characteristic function of a *d*-dimensional stable law G_{α} , $0 < \alpha \le 2$ is

$$(4.1) \qquad \qquad \left\{ e^{it \cdot x} dG_{\alpha}(x) = \exp\left\{iA \cdot t - \lambda \left| t \right|^{\alpha} \left[c_{1}(t) + ic_{2}(t)\right]\right\},$$

where A is a constant vector, λ a positive constant and

$$c_1(t) = \int |t|^{-1} |\theta \cdot t|^{\alpha} dH(\theta),$$

$$c_2(t) = -\int \operatorname{sgn}(\theta \cdot t) \tan(\frac{1}{2}\pi\alpha) |t^{-1}\theta \cdot t|^{\alpha} dH(\theta) \quad \text{for } \alpha \neq 1,$$

$$= 2\pi^{-1} \int (|t|^{-1}\theta \cdot t) \ln(\theta \cdot t) dH(\theta) \quad \text{for } \alpha = 1,$$

with H a probability measure on the unit sphere in \mathbb{R}^d .

For a genuinely d-dimensional (as defined in [8]) recurrent random walk with increments $X_k = (Y_k^{(1)}, \cdots Y_k^{(d)})$ having their common distribution in the domain of attraction of a stable law, it can be shown by applying the criterion in (I) of the Introduction that either d=1 or d=2, $\alpha=2$. The case d=1 has already been considered so there remains only the case where the distribution F of X_1 belongs to the domain of attraction of a bivariate normal distribution. We require in addition that $E|X_1|^2 < \infty$. By (7.7) of [8], if ϕ is the characteristic function of F, we then have

$$\lim_{t\to 0} \left[Q(t) \right]^{-1} \left[1 - \phi(t) \right] = \frac{1}{2},$$

where $Q(t) = Q(t_1, t_2) = E[(X \cdot t)^2]$. We define $\sigma_1^2 = \text{Var } Y_1^{(1)}, \sigma_2^2 = \text{Var } Y_1^{(2)}$ and $\rho = [\sigma_1 \sigma_2]^{-1} E[Y_1^{(1)} Y_1^{(2)}]$ and state the following analogue of Lemma 2.1.

LEMMA 4.1. For an aperiodic, recurrent, genuinely 2-dimensional random walk with $E|X_1|^2 < \infty$ we have

(4.3)
$$\lim_{n \to \infty} r_n \ln n = 2\pi \sigma_1 \sigma_2 (1 - \rho^2)^{\frac{1}{2}}.$$

PROOF. As stated in the proof of Lemma 1.1 we have

$$U(x) = (2\pi)^{-2} \int_{C_2} ([1 - x\phi(t)]^{-1} dt.$$

By aperiodicity we have for any fixed $\delta > 0$

$$\lim_{x \to 1^{-}} \frac{U(x)}{\ln(1/1 - x)}$$

$$= \lim_{x \to 1^{-}} \frac{1}{(2\pi)^{2} \ln(1/1 - x)} \int_{C^{2}} \frac{dt}{\frac{1}{2}Q(t) + (1 - x)}$$

$$= \lim_{x \to 1^{-}} \frac{1}{(2\pi)^{2} \ln(1/1 - x)} \int_{0}^{2\pi} \int_{0}^{\delta(1 - x)^{-1/2}} \frac{r}{(\frac{1}{2}r^{2})Q(\cos\theta, \sin\theta) + 1} dr d\theta$$

$$(4.4)$$

$$= \lim_{x \to 1^{-}} \frac{1}{(2\pi)^{2} \ln(1/1 - x)} \int_{0}^{2\pi} \frac{\ln([Q(\cos\theta, \sin\theta)/2(1 - x)] \delta^{2} + 1)}{Q(\cos\theta, \sin\theta)} d\theta$$

$$= \frac{1}{(2\pi)^{2}} \int_{0}^{2\pi} \frac{d\theta}{Q(\cos\theta, \sin\theta)} = \frac{1}{2\pi\sigma_{1}\sigma_{2}(1 - \rho^{2})^{\frac{1}{2}}}.$$

Since U(x) = (1-x)R(x), applying Karamata's Tauberian theorem we obtain (4.3).

Theorem 4.1. Under the hypotheses of Lemma 4.1 if A is a finite set in Z^2 such that $\tilde{g}_A(0) > 0$, then

$$(4.5) \qquad \lim_{n\to\infty} P[S_n/n^{\frac{1}{2}} \le x \mid T_A > n] = G(x),$$

where G is the bivariate normal distribution with parameters σ_1 , σ_2 and ρ .³

Thus we find that conditioning on the event $[T_A > n]$ plays no role in the limit (c.f. (ii) of Theorem 2.1).

PROOF. Proceeding as in the proof of Theorem 2.1 we let ψ_n be the characteristic function of the probability measure P_n , where $P_n(dx) = P[S_n/n^{\frac{1}{2}} \in dx \mid T > n]$. Then by (4.2), the Central Limit Theorem, (2.6), and Lemma 4.1 we have

$$\begin{split} \psi(t) &= \lim_{n \to \infty} \psi_n(t) \\ &= \lim_{n \to \infty} \left\{ 1 - \sum_{k=0}^{n-1} r_n^{-1} r_k \left[1 - \phi(n^{-\frac{1}{2}}t) \right] \phi^{n-(k+1)}(n^{-\frac{1}{2}}t) \right] \\ &= 1 - \frac{1}{2} Q(t) \int_0^1 \exp\left(-\frac{1}{2} Q(t)(1-x) \right) dx \\ &= \exp\left(-\frac{1}{2} Q(t) \right), \end{split}$$

and (4.5) follows immediately for $A = \{0\}$. The generalization to finite A with $\tilde{g}_A(0) \neq 0$ proceeds as in the proof of Theorem 3.1.

 $[\]sqrt[3]{}$ We say $(x_1, y_1) \le (x_2, y_2)$ if $x_1 \le x_2$ and $y_1 \le y_2$.

5. Counterexample. We saw in the proposition in the introduction that the condition $\tilde{g}_A(x) > 0$ is equivalent to the requirement that the random walk is able to escape to infinity along some path which starts at x and avoids the set A. In the case $d = 1, \sigma^2 < \infty$ this was to be interpreted to mean that the random walk could reach both arbitrarily large positive and arbitrarily large negative values without entering A. It is clear that Theorem 1.1 would fail to hold if an A were so chosen that the condition $T_A > n$ on S_n would force the partial sums of the random walk to be bounded both above and below. However, it is not a priori clear what the appropriate restatement of the theorem should be if the condition $T_A > n$ confines the random walk to a half line. We now give an example showing that Theorem 1.1 as stated may indeed fail in this situation. However, for this particular example an analogous result will hold.

Let F be a distribution function corresponding to a left-continuous (i.e., p(0, x) = 0 for $x \le -2$), recurrent random walk in the domain of normal attraction of a stable law of index α with $1 < \alpha < 2$. In particular, then

(5.1)
$$x^{\alpha}[1 - F(x)] \to c \quad \text{as} \quad x \to \infty.$$

(For simplicity we take c = 1.) Take the set A to be the point $\{-1\}$. Then by Theorem 1.3

(5.2)
$$\lim_{t\to 0\pm} (1-\phi(t))/|t|^{\alpha} = \Gamma(1-\alpha)\cos(\frac{1}{2}\pi\alpha)(h\pm i\tan(\frac{1}{2}\pi\alpha)),$$

Defining $R_1(x) = \sum_{n=0}^{\infty} r_n(1, \{0\}) x^n$ and $U_1(x) = \sum_{n=0}^{\infty} p_n(1, 0) x^n$, it is easily seen that

$$R_1(x) = [(1-x)U(x)]^{-1}[U(x) - U_1(x)].$$

Now the potential kernel a(x) defined by $a(x) = \sum_{n=0}^{\infty} [p_n(0,0) - p_n(x,0)]$ has the Fourier analytic representation $a(x) = (2\pi)^{-1} \int_{-\pi}^{\pi} [1 - x\phi(t)]^{-1} (1 - e^{it}) dt$.

Consequently,

$$\lim_{x \to 1} (U(x) - U_1(x)) = a(1) = (2\pi)^{-1} \int_{-\pi}^{\pi} [1 - \phi(t)]^{-1} (1 - e^{it}) dt.$$

However, for left continuous random walk with $\sigma^2 = \infty$ it is known that a(x) vanishes on the right half line x > 0 (see Section 30 of [8]).

Therefore we may write

$$U(x) - U_1(x) = \frac{1}{2\pi} \int_{-\pi}^{\pi} \frac{(1-x)\phi(t)(1-e^{it})}{(1-\phi(t))(1-x\phi(t))} dt.$$

It follows that for $\delta > 0$ as $x \to 1$

$$\frac{U(x) - U_1(x)}{1 - x} \sim \frac{1}{2\pi} \int_{\pi \ge |t| \ge \delta} \frac{\phi(t)(1 - e^{it})}{(1 - \phi(t))^2} dt + \frac{1}{2\pi} \int_{-\delta}^{\delta} \frac{\phi(t)(1 - e^{it})}{(1 - \phi(t))(1 - x\phi(t))} dt.$$

Now it is a straightforward argument using (5.2) to show that for arbitrary $\varepsilon > 0$ and fixed δ small enough,

$$(1-\varepsilon)K \leq \frac{(1-x)^{2-(2/\alpha)}}{2\pi} \int_{-\delta}^{\delta} \frac{\phi(t)(1-e^{it})}{(1-\phi(t))(1-x\phi(t))} dt \leq (1+\varepsilon)K$$

for x sufficiently close to 1, where

$$K = \frac{1}{\pi \lceil \Gamma(1-\alpha) \rceil^{2/\alpha}} \int_0^\infty \frac{du}{u^{\alpha-1} u^{\alpha+1}} = \frac{\csc(2\pi/\alpha)}{\alpha \lceil \Gamma(1-\alpha) \rceil^{2/\alpha}}.$$

Consequently, as $x \rightarrow 1$

$$R_1(x) \sim -\frac{csc(2\pi/\alpha)(1-x)^{(1/\alpha)-1}}{\alpha g_{\alpha}(0)\Gamma(1-1/\alpha)[\Gamma(1-\alpha)]^{2/\alpha}},$$

and by Karamata's Theorem

$$r_n(0,\{-1\}) \sim \frac{n^{-1/\alpha}}{2\pi\alpha g_\alpha(0)\cos\pi/\alpha[\Gamma(1-\alpha)]^{2/\alpha}}$$
 as $n \to \infty$.

One now observes that in contrast to the situation in Lemma 2.1, where r_n tended to zero asymptotically like $n^{(1/\alpha)-1}$, we now find that $r_n(0,\{-1\})$ tends to zero like $n^{-(1/\alpha)}$.⁴ It is clear from its proof that Theorem 3.1 may now be restated for our example with

$$\Psi_{\alpha}(t) = 1 - b|t|^{\alpha} \int_{0}^{1} x^{-(1/\alpha)} \phi_{\alpha} [t(1-x)^{1/\alpha}] dx.$$

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REFERENCES

- [1] BELKIN, B. (1968). Some results in the theory of recurrent random walk. Doctoral thesis submitted to Cornell University.
- [2] GNEDENKO, B. V. and KOLMOGOROV, A. N. (1954). Limit Distributions for Sums of Independent Random Variables. Addison-Wesley, Reading, Mass.
- [3] KARAMATA, H. J. (1933). Sur un mode de croissance reguliére. Bull. Soc. Math. France, 61 55-62.
- [4] KESTEN, H. and SPITZER, F. (1963). Ratio theorems for random walk I. J. Analysé Math. 9 285-322.
- [5] Kesten, H. (1963). Ratio theorems for random walk II. J. Analysé Math. 9 323-379.
- [6] LAMPERTI, J. (1966). Probability. W. A. Benjamin, Inc., New York.
- [7] LÉVY, P. (1948). Théorie de l'addition des variables aléatories. Gauthier-Villars, Paris.
- [8] Spitzer, F. (1964). Principles of Random Walk. Van Nostrand, Princeton.
- [9] SPITZER, F. and KESTEN, H. (1965). Random walk on countably infinite groups. *Acta Math*. 114 237–265.
- [10] Stone, C. (1965). On local and ratio limit theorems. Proc. Fifth Berkeley Symp. Math. Statist. Prob. 2 217.
- [11] WILLIAMSON, J. A. Random walks and Riesz kernels. To be published in Pacific J. Math.

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⁴ We remark that $1-1/\alpha=1/\alpha$ for $\alpha=2$, as one might suspect, since for any left continuous, recurrent random walk with $\sigma^2 < \infty$, it is necessarily true that $g_A(x) > 0$ for $A = \{-1\}$.