James K. Pringle 550.621 Probability Dr. Jim Fill Assignment 1 February 19, 2014

## Assignment 1

An application of the strong law of large numbers

Suppose  $X, X_1, X_2, \ldots$  are i.i.d. r.v.'s. Find necessary and sufficient conditions on the distribution of X in order that

$$\frac{S_n}{n/\log n} \to 0 \quad \text{wp1} \tag{1}$$

where  $S_n = \sum_{i=1}^n X_i$ 

### Discussion

Notice  $x/\log x$  is decreasing on the interval  $x \in (0, e]$ . To create an increasing function on  $[0, \infty)$ , define

$$f(x) = \begin{cases} x & \text{for } x \in [0, e) \\ \frac{x}{\log x} & \text{for } x \in [e, \infty) \end{cases}$$

Since f'(x) = 1 on (0, e) and  $f'(x) = (1/\log x)(1 - 1/\log x)$  on  $(e, \infty)$ , it is clear f is strictly increasing, except at x = e where the derivative does not exist. On  $(e, \infty)$ , the function f grows sublinearly (f'(x) < 1 for all  $x \in (e, \infty)$ ). Nonetheless, f is injective. Since f tends to infinity as x tends to infinity, f is also surjective. Therefore, f has an inverse  $f^{-1}$ , which sends f is injective. Since f tends to infinity as f is also surjective. Therefore, f has an inverse  $f^{-1}$ , which sends f is injective. Since f tends to infinity as f is also surjective. Therefore, f has an inverse f is that f(x) = f(x) is also surjective. Therefore, f has an inverse f is that f(x) = f(x) is also surjective. Therefore, f has an inverse f is that f(x) = f(x) is also surjective. Therefore, f has an inverse f in f in f is also surjective. Therefore, f has an inverse f in f in

It is proposed that the necessary and sufficient condition for (1) is that

$$E[f^{-1}(|X|)] < \infty \tag{2}$$

and

$$EX = 0 (3)$$

# Results given without proof

### Chung 3.2.1

$$\sum_{n=1}^{\infty} P(|X| \ge n) \le E(|X|) \le 1 + \sum_{n=1}^{\infty} P(|X| \ge n)$$

#### First Borel-Cantelli Lemma

For arbitrary events  $\{E_n\}$ ,

$$\sum_{n=1}^{\infty} P(E_n) < \infty \quad \Rightarrow \quad P(E_n \text{ i.o.}) = 0$$

#### Second Borel-Cantelli Lemma

If the events  $\{E_n\}$  are independent, then

$$\sum_{n=1}^{\infty} P(E_n) = \infty \quad \Rightarrow \quad P(E_n \text{ i.o.}) = 1$$

#### Course Notes Lemma 3

Let  $\{X_n\}_{n\geq 1}$  be a sequence of independent random variables with zero means (and finite variances). Then

$$\sum_{k=1}^{\infty} \operatorname{var}(X_k) < \infty$$

implies (finite variances and)

$$P\left\{\sum X_k \text{ converges to a finite limit}\right\} = 1$$

#### Kronecker's Lemma

Let  $\{b_n\}_{n\geq 1}$  and  $\{x_n\}_{n\geq 1}$  be two real sequences such that

- (i)  $\sum_{m=1}^{\infty} \frac{x_m}{b_m}$  exists and is finite
- (ii)  $b_n \uparrow \infty$

Then

(iii) 
$$\frac{S_n}{b_n} \to 0$$

where  $S_n = \sum_{m=1}^n x_m$ 

#### Classical Strong Law of Large Numbers

Let  $\{X_n\}$  be a sequence of independent and identically distributed r.v.'s. Then we have

$$E(|X_1|) < \infty \quad \Rightarrow \quad \frac{S_n}{n} \to E(X_1)$$
 a.e.

### **Dominated Convergence Theorem**

If  $\lim_{n\to\infty} X_n = X$  a.e. or merely in measure on  $\Lambda$  and  $\forall n: |X_n| \leq Y$  a.e. on  $\Lambda$ , with  $\int_{\Lambda} Y dP < \infty$ , then

$$\lim_{n \to \infty} \int_{\Lambda} X_n dP = \int_{\Lambda} X dP = \int_{\Lambda} \lim_{n \to \infty} X_n dP$$

#### A Generalization of Cesaro's Theorem

If real numbers  $x, x_1, x_2, \ldots$  satisfy  $x_n \to x$ , and if  $b_n \uparrow \infty$ , then, with  $b_0 := 0$ 

$$\frac{1}{b_n} \sum_{m=1}^{n} (b_m - b_{m-1}) x_m \to x \text{ as } n \to \infty$$

## Lemmas

**Lemma 1.** Fix  $\omega \in \Omega$ . Let  $\{a_n\}$  be a sequence of positive numbers increasing to infinity. Then

$$\frac{S_n}{a_n} \to 0$$
 implies  $\frac{X_n}{a_n} \to 0$ 

*Proof.* Let  $\epsilon > 0$  and let  $S_n/a_n \to 0$ . Since  $S_n/a_n \to 0$ , for  $\epsilon/2$ , there exists an integer  $M(\epsilon/2)$  such that for all  $m > M(\epsilon/2)$ , it is true that  $|S_m/a_m| < \epsilon/2$ . Calculating with

 $m > M(\epsilon/2),$ 

$$\left| \frac{X_{m+1}}{a_{m+1}} \right| = \left| \frac{S_m}{a_{m+1}} + \frac{X_{m+1}}{a_{m+1}} - \frac{S_m}{a_{m+1}} \right|$$

$$= \left| \frac{S_{m+1}}{a_{m+1}} - \frac{S_m}{a_{m+1}} \right|$$

$$\leq \left| \frac{S_{m+1}}{a_{m+1}} \right| + \left| \frac{S_m}{a_{m+1}} \right| \text{ by triangle inequality}$$

$$= \left| \frac{S_{m+1}}{a_{m+1}} \right| + \left| \frac{S_m}{a_m} \right| \left| \frac{a_m}{a_{m+1}} \right|$$

$$\leq \left| \frac{S_{m+1}}{a_{m+1}} \right| + \left| \frac{S_m}{a_m} \right| \text{ since } \{a_n\} \text{ increases}$$

$$\leq \frac{\epsilon}{2} + \frac{\epsilon}{2} = \epsilon$$

Therefore, for all  $m > M(\epsilon/2) + 1$  it is true that  $|X_m/a_m| < \epsilon$ . Since  $\epsilon$  is arbitrary, it follows  $X_n/a_n \to 0$ , and the proof is concluded.

**Lemma 2.** Fix  $\omega \in \Omega$ . Let  $\{a_n\}$  be a sequence of positive numbers increasing to infinity. Then

$$\frac{S_n}{a_n} \to 0$$
 only if for every positive integer N, both  $\frac{1}{a_n} \sum_{i=1}^N X_i \to 0$  and  $\frac{1}{a_n} \sum_{i=N+1}^n X_i \to 0$  as  $n \to \infty$ 

*Proof.* Let  $\epsilon > 0$  and let  $S_n/a_n \to 0$ . Since the sequence  $\{S_n/a_n\}$  converges, it follows that  $\{X_i\} < \infty$ . Therefore,  $\sum_{i=1}^{N} X_i$  is finite. Hence,

$$\frac{1}{a_n} \sum_{i=1}^{N} X_i \to 0 \text{ as } n \to \infty$$

because  $a_n \to \infty$ . By definition of limit, there exists  $N_1$  and  $N_2$  such that

$$\left| \frac{1}{a_n} \sum_{i=1}^{N} X_i \right| < \frac{\epsilon}{2}$$

for  $n > N_1$ , and

$$\left| \frac{1}{a_n} \sum_{i=1}^n X_i \right| < \frac{\epsilon}{2}$$

for  $n > N_2$ . Let  $N_3 = \max(N_1, N_2)$ . Therefore, for  $n > N_3$ 

$$\left| \frac{1}{a_n} \sum_{i=N+1}^n X_i \right| = \left| \frac{1}{a_n} \sum_{i=1}^n X_i - \frac{1}{a_n} \sum_{i=1}^N X_i \right|$$

$$\leq \left| \frac{1}{a_n} \sum_{i=1}^n X_i \right| + \left| \frac{1}{a_n} \sum_{i=1}^N X_i \right|$$

$$= \frac{\epsilon}{2} + \frac{\epsilon}{2} = \epsilon$$

Since  $\epsilon$  is arbitrary, it follows  $\frac{1}{a_n} \sum_{i=N+1}^n \to 0$  as  $n \to \infty$ , and the proof is concluded.  $\square$ 

**Lemma 3.** Suppose r.v.'s  $\{X_n\}$  converge to r.v. X almost everywhere and r.v.'s  $\{Y_n\}$  conerge to r.v. Y almost everywhere, then r.v.'s

$$\{X_n + Y_n\}$$
 converge to  $X + Y$  almost everwhere

*Proof.* By definition of convergence almost everywhere, there exists a null set  $N_1$  such that for all  $\omega \in \Omega \setminus N_1$ 

$$\lim_{n \to \infty} X_n(\omega) = X(\omega)$$

Similarly, there exists a null set  $N_2$  such that for all  $\omega \in \Omega \setminus N_2$ 

$$\lim_{n \to \infty} Y_n(\omega) = Y(\omega)$$

Let  $\epsilon > 0$ . Let  $\omega \in \Omega \setminus (N_1 \cup N_2)$ . Then there exists  $M_1$  such that for all  $m > M_1$ 

$$|X_m(\omega) - X(\omega)| < \frac{\epsilon}{2}$$

and there exists  $M_2$  such that for all  $m > M_2$ 

$$|Y_m(\omega) - Y(\omega)| < \frac{\epsilon}{2}$$

Therefore for all  $m > M_3 = \max(M_1, M_2)$ 

$$|X_m(\omega) + Y_m(\omega) - X(\omega) - Y(\omega)| = |X_m(\omega) - X(\omega) + Y_m(\omega) - Y(\omega)|$$

$$\leq |X_m(\omega) - X(\omega)| + |Y_m(\omega) - Y(\omega)|$$

$$< \frac{\epsilon}{2} + \frac{\epsilon}{2} = \epsilon$$

Since  $\epsilon$  is arbitrary and  $N_1 \cup N_2$  is a null set, it follows that

$$\lim_{n \to \infty} X_n + Y_n = X + Y$$

almost everywhere.

### Proof of the main result

*Proof.* ( $\Rightarrow$ ) Let (1) hold. Then for  $n \geq 3$ 

$$\frac{S_n}{n \log n} = \frac{S_n}{f(n)}$$
 so  $\frac{S_n}{f(n)} \to 0$  wp1

By Lemma 1,

$$\frac{X_n}{f(n)} \to 0 \tag{4}$$

almost surely. Define

$$E_k := \left\{ \left| \frac{X_k}{f(k)} \right| \ge 1 \right\}$$

By definition of convergence of the limit in (4), for all  $\omega$  off a null set, there exists an integer  $N(\omega)$  such that for  $n > N(\omega)$  it is the case that

$$\left| \frac{X_n(\omega)}{f(n)} \right| < 1$$

Therefore,  $P(E_k \text{ i.o.}) = 0$ . Since  $X_k$  are independent by assumption, it follows that  $E_k$  are independent. Applying the contrapositive of the **Second Borel-Cantelli Lemma**,

$$\sum_{i=1}^{\infty} P(E_k) < \infty$$

Therefore, by Chung 3.2.1

$$\infty > 1 + \sum_{k=1}^{\infty} P(E_k)$$

$$= 1 + \sum_{k=1}^{\infty} P\{|X_k| \ge f(k)\}$$

$$= 1 + \sum_{k=1}^{\infty} P\{|X| \ge f(k)\} \text{ since } \{X_i\} \text{ are identically distributed}$$

$$= 1 + \sum_{k=1}^{\infty} P\{f^{-1}|X| \ge k\} \text{ because } f^{-1} \text{ is increasing}$$

$$\ge E[f^{-1}(|X|)]$$

Thus condition (2) is met.

Note  $f^{-1}(x) = x$  for  $x \in (0, e]$ . For  $x \in (e, \infty)$ , the first derivative of f(x) is strictly between 0 and 1. That means that  $f(x) \leq x$ , or equivalently  $x \leq f^{-1}(x)$ , for  $x \in (0, \infty)$ . Thus E[|X|] is finite, i.e.

$$E|X| \le E[f^{-1}(|X|)] < \infty \tag{5}$$

Therefore, by the Classical Strong Law of Large Numbers,

$$S_n/n \to EX \text{ a.s.}$$
 (6)

Fix  $\epsilon > 0$ . Fix  $\omega$  such that (1) and (6) hold. Then there exists  $N_1$  such that for all  $n > N_1$ ,

$$\left| \frac{S_n}{n} - EX \right| < \frac{\epsilon}{2}$$
 or equivalently  $\left| EX \log n - \frac{S_n}{n/\log n} \right| < \frac{\epsilon \log n}{2}$ 

By (1) there exists  $N_2$  such that for all  $n > N_2$ ,

$$\left| \frac{S_n}{n/\log n} \right| < \frac{\epsilon}{2}$$

Therefore, for all  $n > N_3 = \max(N_1, N_2, e)$ ,

$$|EX \log n| = \left| EX \log n - \frac{S_n}{n/\log n} + \frac{S_n}{n/\log n} \right|$$

$$\leq \left| EX \log n - \frac{S_n}{n/\log n} \right| + \left| \frac{S_n}{n/\log n} \right| \text{ by triangle inequality}$$

$$\leq \frac{\epsilon \log n}{2} + \frac{\epsilon}{2}$$

Dividing by  $\log n$ ,

$$|EX| \le \frac{\epsilon}{2} + \frac{\epsilon}{2 \log n}$$
 and by definition of  $N_3$   
  $\le \frac{\epsilon}{2} + \frac{\epsilon}{2} = \epsilon$ 

Since  $\epsilon$  is arbitrary, |EX| = EX = 0, i.e. (3).

Thus (1) implies (2) and (3).

*Proof.* ( $\Leftarrow$ ) Let (2) and (3) hold. Define

$$Y_n = X_n I_{\{|X_n| < f(n)\}}$$

Calculating,

$$\begin{split} \sum_{n=1}^{\infty} \text{var}(Y_n/f(n)) &\leq \sum_{n=1}^{\infty} E\left[\frac{Y_n^2}{f(n)^2}\right] \\ &= \sum_{n=1}^{\infty} E\left[\frac{(X_n I_{\{|X_n| < f(n)\}})^2}{f(n)^2}\right] \text{ since } X_n \text{ are i.i.d.} \\ &= \sum_{n=1}^{\infty} E\left[\frac{(X^2 I_{\{|X| < f(n)\}})^2}{f(n)^2}\right] \text{ by Monotone Convergence Theorem} \\ &\leq E\left[\sum_{n=1}^{\infty} \frac{X^2 I_{\{|X| < f(n)\}}}{f(n)^2}\right] \text{ by Monotone Convergence Theorem} \\ &\leq E\left[\sum_{n=1}^{2} \frac{f(n)^2}{f(n)^2} + \sum_{n=3}^{\infty} \frac{X^2 I_{\{|X| < f(n)\}}}{f(n)^2} \frac{f(n+1)^2}{f(n+1)^2}\right] \\ &= E\left[2 + X^2 \sum_{n=3}^{\infty} \frac{I_{\{f^{-1}(|X|) < n\}}}{f(n+1)^2} \frac{f(n+1)^2}{f(n)^2}\right] \\ &\leq E\left[2 + 4X^2 \sum_{n=3}^{\infty} \frac{I_{\{f^{-1}(|X|) < n\}}}{f(n+1)^2}\right] \text{ by the fact above} \\ &\leq E\left[2 + 4X^2 \left(I_{\{f^{-1}(|X|) \ge 3\}} \int_{f^{-1}(|X|)}^{\infty} \frac{d\xi}{f(\xi)^2} + I_{\{f^{-1}(|X|) < 3\}} \int_{3}^{\infty} \frac{d\xi}{f(\xi)^2}\right)\right] \\ &= 2 + E\left[4X^2 I_{\{f^{-1}(|X|) \ge 3\}} \int_{f^{-1}(|X|)}^{\infty} \frac{d\xi}{f(\xi)^2}\right] + E\left[4X^2 I_{\{f^{-1}(|X|) < 3\}} \int_{3}^{\infty} \frac{d\xi}{f(\xi)^2}\right] \end{aligned}$$

For the first expectation in (7), let  $Y = f^{-1}(|X|)$ . Then  $X^2 = f(Y)^2$ . On the set  $\{f^{-1}(|X|) \ge 3\} = \{Y \ge 3\}$ , it is the case that  $f(Y)^2 = Y^2/\log^2 Y$ . Calculating,

$$\begin{split} E\left[4X^{2}I_{\{f^{-1}(|X|)\geq3\}}\int_{f^{-1}(|X|)}^{\infty}\frac{d\xi}{f(\xi)^{2}}\right] &= E\left[I_{\{Y\geq3\}}4f(Y)^{2}\int_{Y}^{\infty}\frac{\log^{2}\xi}{\xi^{2}}d\xi\right] \\ &= E\left[I_{\{Y\geq3\}}4\left(\frac{Y^{2}}{\log^{2}Y}\right)\left(-\frac{\log^{2}\xi+2\log\xi+2}{\xi}\Big|_{\xi=Y}^{\infty}\right] \\ &= E\left[I_{\{Y\geq3\}}4\left(\frac{Y^{2}}{\log^{2}Y}\right)\frac{\log^{2}Y+2\log Y+2}{Y}\right] \\ &= E\left[I_{\{Y\geq3\}}\left(4Y+\frac{8Y}{\log Y}+\frac{8Y}{\log^{2}Y}\right)\right] \\ &\leq E[I_{\{Y\geq3\}}20Y] \\ &= 20E[I_{\{f^{-1}(|X|)\geq3\}}f^{-1}(|X|)] \\ &\leq 20E[f^{-1}(|X|)] \quad \text{ since } f^{-1}(|X|)\geq0 \\ &<\infty \end{split}$$

For the second expectation in (7), over the set  $\{f^{-1}(|X|) < 3\}$ , it is the case that  $0 \le X^2 \le f(3)^2 = 9/\log^2 3$ . Thus

$$E\left[4X^{2}I_{\{f^{-1}(|X|)<3\}}\int_{3}^{\infty}\frac{d\xi}{f(\xi)^{2}}\right] \leq E\left[I_{\{f^{-1}(|X|)<3\}}4\left(\frac{9}{\log^{2}3}\right)\int_{3}^{\infty}\frac{\log^{2}\xi}{\xi^{2}}d\xi\right]$$

$$=E\left[I_{\{f^{-1}(|X|)<3\}}4\left(\frac{9}{\log^{2}3}\right)\left(-\frac{\log^{2}\xi+2\log\xi+2}{\xi}\Big|_{\xi=3}^{\infty}\right]$$

$$=E\left[I_{\{f^{-1}(|X|)<3\}}4\left(\frac{9}{\log^{2}3}\right)\frac{(\log^{2}(3/\log3))+2\log(3/\log3)+2}{3/\log3}\right]$$

$$<\infty$$

Since all three terms in (7) are finite, their sum is finite, and it follows that

$$\sum_{n=1}^{\infty} \operatorname{var}(Y_n/f(n)) < \infty$$

As shown above, the series of the variances of the truncated  $\{X_n/f(n)\}$  converges. By definition of  $Y_n$ , it is true that  $|Y_n| < f(n)$ , thus

$$|EY_n| \le E|Y_n| < f(n) < \infty \tag{8}$$

Hence the series of variances of the centered, truncated  $\{X_n/f(n)\}$  also converges, i.e.

$$\sum_{n=1}^{\infty} \operatorname{var}\left(\frac{Y_n - EY_n}{f(n)}\right) = \sum_{n=1}^{\infty} \operatorname{var}(Y_n / f(n)) < \infty$$

By Course Notes Lemma 3,

$$P\left(\sum_{n=1}^{\infty} \frac{Y_n - EY_n}{f(n)} \text{ converges to a finite limit}\right) = 1$$

Then by Kronecker's Lemma,

$$\lim_{n \to \infty} \frac{1}{f(n)} \sum_{i=1}^{n} (Y_i - EY_i) = 0$$

almost surely. Calculating,

$$\sum_{n=1}^{\infty} P\{Y_n \neq X_n\} = \sum_{n=1}^{\infty} P\{|X_n| \geq f(n)\}$$

$$= \sum_{n=1}^{\infty} P\{|X| \geq f(n)\}$$

$$= \sum_{n=1}^{\infty} P\{f^{-1}(|X|) \geq n\}$$

$$\leq E[f^{-1}(|X|)]$$

$$< \infty$$

By the **First Borel-Cantelli Lemma**,  $P(Y_n \neq X_n \text{ i.o.}) = 0$ . It follows that for  $\omega$  off a null set there exists  $N(\omega)$  with the property that for all  $n > N(\omega)$ , one has  $Y_n(\omega) = X_n(\omega)$ . By **Lemma 2**, as n increases to infinity,

$$\frac{1}{f(n)} \sum_{i=N(\omega)+1}^{n} (X_i(\omega) - EY_i) = \frac{1}{f(n)} \sum_{i=N(\omega)+1}^{n} (Y_i(\omega) - EY_i) \to 0$$

Since  $E[f^{-1}(|X|)] < \infty$  by hypothesis,  $E|X| < \infty$  by the reasoning in (5). Therefore  $\{X_i\}$  is finite off a null set. For  $\omega$  off the union of the previously two mentioned null sets, it follows that

$$\sum_{i=1}^{N(\omega)} X_i(\omega)$$

is finite. Since  $|EY_i|$  is finite by (8), it follows that

$$\sum_{i=1}^{N(\omega)} (X_i(\omega) - EY_i)$$

is finite. Since f(n) diverges to infinity,

$$\lim_{n \to \infty} \frac{1}{f(n)} \sum_{i=1}^{N(\omega)} (X_i(\omega) - EY_i) = 0$$

Combining the previous four statements, it is possible to conclude

$$\lim_{n \to \infty} \frac{1}{f(n)} \sum_{i=1}^{n} (X_i - EY_i) = \lim_{n \to \infty} \frac{1}{n/\log n} \sum_{i=1}^{n} (X_i - EY_i) = 0$$
 (9)

almost surely.

Next, the task is to show that

$$\lim_{n \to \infty} \frac{1}{f(n)} \sum_{i=1}^{n} EY_i = \lim_{n \to \infty} \frac{1}{n/\log n} \sum_{i=1}^{n} EY_i = 0$$
 (10)

First, it is claimed that

$$f^{-1}(x) = x \log f^{-1}(x)$$

for x > e. Calculating,

$$f^{-1}(f(x)) = f(x) \log f^{-1}(f(x)) = \frac{x}{\log x} \log x = x$$

ends the short proof. Notice that

$$(\log n)XI_{\{|X|\geq f(n)\}} = (\log n)XI_{\{f^{-1}(|X|)\geq n\}} \to X$$

pointwise as n tends to  $\infty$ . Furthermore, for  $\omega \in \{f^{-1}(|X|) \ge \max(e,n)\}$  it is the case that

$$f^{-1}(|X|) \ge n$$
 
$$\log f^{-1}(|X|) \ge \log n$$
 
$$|X| \log f^{-1}(|X|) \ge (\log n)|X|$$
 
$$f^{-1}(|X|) \ge (\log n)|X|I_{\{f^{-1}(|X|) \ge n\}} \text{ by what was claimed above}$$

For  $\omega \in \{e \le f^{-1}(|X|) < n\},\$ 

$$f^{-1}(|X|) \ge 0$$
  

$$f^{-1}(|X|) \ge I_{\{f^{-1}(|X|) \ge n\}}$$
  

$$f^{-1}(|X|) \ge (\log n)|X|I_{\{f^{-1}(|X|) > n\}}$$

For  $\omega \in \{f^{-1}(|X|) \le e\}$ ,

$$|X| = f^{-1}(|X|) \ge (\log n)|X|I_{\{f^{-1}(|X|) > n\}}$$

since  $0 \le (\log n)I_{\{f^{-1}(|X|) \ge n\}} \le 1$  on this set. Therefore,  $f^{-1}(|X|)$  dominates  $(\log n)|X|I_{\{f^{-1}(|X|) \ge n\}}$  for all n. Since  $f^{-1}(|X|)$  is integrable by (2), by the **Dominated Convergence Theorem** 

$$E[(\log n)XI_{\{f^{-1}(|X|)\geq n\}}] \to EX = 0$$
 as  $n \to \infty$ 

Note EX = 0 by (3). Calculating,

$$0 = EX = E[XI_{\{f^{-1}(|X|) \ge n\}} + XI_{\{f^{-1}(|X|) < n\}}]$$

so that by flip-flop

$$E[XI_{\{f^{-1}(|X|)>n\}}] = -E[XI_{\{f^{-1}(|X|)$$

By the previous calculations

$$-(\log n)EY_n = (\log n)E[XI_{\{f^{-1}(|X|) \ge n\}}]$$
  
=  $E[(\log n)XI_{\{f^{-1}(|X|) \ge n\}}] \to 0 \text{ as } n \to \infty$ 

Define  $a_n = -(\log n)EY_n$ . Since  $\{a_n\} \to 0$ , it follows that the sequence of absolute values  $\{|a_n|\} = \{\log(n)|EY_n|\}$  also converges to 0. Let  $b_0 = 0, b_1 = 1, b_2 = 2$  and  $b_n = n/\log n$  for  $n \ge 3$ . Applying **A Generalization of Cesaro's Theorem**,

$$\frac{1}{b_n} \sum_{m=1}^n (b_m - b_{m-1})|a_m| \to 0 \quad \text{as } n \to \infty$$

or equivalently (for  $n \geq 3$ ),

$$\frac{1}{n/\log n} \left( \log 2|EY_2| + (3 - 2\log 3)|EY_3| + \sum_{m=4}^n \left( \frac{m}{\log m} - \frac{m-1}{\log(m-1)} \right) (\log m)|EY_m| \right) \to 0$$
(11)

as  $n \to \infty$ . Let  $c_1 = 0, c_2 = \log 2, c_3 = 3 - 2 \log 3$  and

$$c_n = \left(\frac{n}{\log n} - \frac{n-1}{\log(n-1)}\right)(\log n)$$

for  $n \geq 4$ . It can be shown that

$$\lim_{n \to \infty} c_n = 1 \tag{12}$$

by tedious algebra and successive applications of L'Hospital's rule. Also see WolframAlpha: http://bit.ly/limX621. Display (11) can be rewritten as

$$\frac{1}{n/\log n} \sum_{m=1}^{n} c_m |EY_m| \to 0 \quad \text{as } n \to \infty$$
 (13)

for  $n \geq 3$ . Notice that all the terms in (13) are positive. Fix  $1 > \epsilon > 0$ . Then since (13) converges to 0, there exists  $N_1 = \max(3, N_0)$  such that for all  $n > N_1$ ,

$$\left| \frac{1}{n/\log n} \sum_{m=1}^{n} c_m |EY_m| \right| = \frac{1}{n/\log n} \sum_{m=1}^{n} c_m |EY_m| < \frac{(1-\epsilon)\epsilon}{2}$$

Since (12) converges to 1, there exists  $N_2$  such that for all  $n > N_2$ ,

$$|c_n - 1| < \epsilon$$
 or equivalently  $1 - \epsilon < c_n < 1 + \epsilon$ 

Thus for all  $n > N_3 = \max(N_1, N_2)$ ,

$$\frac{(1-\epsilon)\epsilon}{2} > \frac{1}{n/\log n} \sum_{m=N_3+1}^n c_m |EY_m|$$
$$> \frac{1}{n/\log n} \sum_{m=N_3+1}^n (1-\epsilon)|EY_m|$$
$$= \frac{(1-\epsilon)}{n/\log n} \sum_{m=N_3+1}^n |EY_m|$$

Thus for  $n > N_3$ 

$$\frac{1}{n/\log n} \sum_{m=N_3+1}^n |EY_m| < \frac{\epsilon}{2}$$

By (8) it is clear that  $|EY_n| < f(n)$ . Thus define M to be the sum of f(m) for  $1 \le m \le N_3$  so that

$$M = \sum_{m=1}^{N_3} f(m) > \sum_{m=1}^{N_3} |EY_m|$$

Clearly, M is finite. Since  $n/\log n$  diverges to infinity, there exists  $N_4$  such that for all  $n > N_4$ ,

$$\frac{M}{n/\log n} = \left| \frac{M}{n/\log n} \right| < \frac{\epsilon}{2}$$

Therefore, for  $n > N_5 = \max(N_4, N_3)$ 

$$\left| \frac{1}{n/\log n} \sum_{m=1}^{n} EY_m \right| \leq \frac{1}{n/\log n} \sum_{m=1}^{n} |EY_m| \quad \text{by triangle inequality}$$

$$= \frac{1}{n\log n} \left( \sum_{m=1}^{N_3} |EY_m| + \sum_{m=N_3+1}^{n} |EY_m| \right)$$

$$= \frac{1}{n\log n} \sum_{m=1}^{N_3} |EY_m| + \frac{1}{n\log n} \sum_{m=N_3+1}^{n} |EY_m|$$

$$< \frac{1}{n\log n} M + \frac{1}{n\log n} \sum_{m=N_3+1}^{n} |EY_m|$$

$$< \frac{\epsilon}{2} + \frac{\epsilon}{2} = \epsilon$$

Since  $\epsilon$  is arbitrary, (10) holds. Combining (9) with (10) and using **Lemma 3**, it is clear that

$$\lim_{n \to \infty} \frac{1}{f(n)} \sum_{i=1}^{n} X_i = \lim_{n \to \infty} \frac{1}{n/\log n} \sum_{i=1}^{n} X_i = 0$$

almost surely. Or in other words,

$$\frac{S_n}{n/\log n} \to 0 \quad \text{wp1}$$

Thus (2) and (3) imply (1), quod erat demonstrandum.

## Conclusion

It is possible to find equivalent conditions to (2). First a lemma.

**Lemma 4.** Suppose for  $k \in \{1, 2\}$ , the functions  $\{f_k\}$  are asymptotically equivalent and real-valued on  $[0, \infty)$ . Suppose there exists  $x_0$  such that each  $|f_k|$  is bounded on  $[0, x_0]$  and that each  $f_k$  is positive, unbounded, and monotone increasing on  $(x_0, \infty)$ . Then for all random variables X

$$E[f_1(|X|)] < \infty$$
 if and only if  $E[f_2(|X|)] < \infty$ 

*Proof.* By hypothesis, there exists finite, positive  $M_k$  such that  $|f_k| < M_k$  on  $[0, x_0]$  for  $k \in \{1, 2\}$ . Thus

$$-M_k < E[f_k(|X|)I_{\{|X| \le x_0\}}] < M_k$$

Since,

$$E[f_k(|X|)] = E[f_k(|X|)I_{\{|X| < x_0\}}] + E[f_k(|X|)I_{\{|X| > x_0\}}],$$

it follows that

$$E[f_k(|X|)]$$
 is finite if and only if  $E[f_k(|X|)I_{\{|X|>x_0\}}]$  is finite (14)

Fix  $\epsilon > 0$ . By hypothesis of asymptotic equivalence, there exists positive  $x_1$  such that for all  $x > x_1$ ,

$$\left| \frac{f_1(x)}{f_2(x)} - 1 \right| \le \epsilon$$

or equivalently

$$(1 - \epsilon)f_2(x) \le f_1(x) \le (1 + \epsilon)f_2(x) \tag{15}$$

Let  $x_2 = \max(x_1, x_0)$ . Then

$$\begin{split} E[f_k(|X|)I_{\{|X|>x_0\}}] &= E[f_k(|X|)I_{\{x_2\geq |X|>x_0\}}] + E[f_k(|X|)I_{\{|X|>x_2\}}] \\ &\leq E[f_k(x_2)] + E[f_k(|X|)I_{\{|X|>x_2\}}] \text{ by monotonicity} \\ &= f_k(x_2) + E[f_k(|X|)I_{\{|X|>x_2\}}] \end{split}$$

Suppose  $E[f_1(|X|)] < \infty$ . Then  $E[f_1(|X|)I_{\{|X|>x_0\}}] < \infty$  by (14) and

$$E[f_{2}(|X|)I_{\{|X|>x_{0}\}}] \leq f_{2}(x_{2}) + E[f_{2}(|X|)I_{\{|X|>x_{2}\}}]$$

$$\leq f_{2}(x_{2}) + E\left[\frac{f_{1}(|X|)}{1-\epsilon}I_{\{|X|>x_{2}\}}\right] \text{ by (15)}$$

$$\leq f_{2}(x_{2}) + \frac{1}{1-\epsilon}E\left[f_{1}(|X|)I_{\{|X|>x_{0}\}}\right] \text{ since } f_{1} \text{ is positive for } x > x_{0}$$

$$< \infty$$

Therefore  $E[f_2(|X|)] < \infty$  by (14).

Similarly, suppose  $E[f_2(|X|)] < \infty$ . Then  $E[f_2(|X|)I_{\{|X|>x_0\}}] < \infty$  by (14) and

$$\begin{split} E[f_1(|X|)I_{\{|X|>x_0\}}] &\leq f_1(x_2) + E[f_1(|X|)I_{\{|X|>x_2\}}] \\ &\leq f_1(x_2) + E\left[f_2(|X|)(1+\epsilon)I_{\{|X|>x_2\}}\right] \text{ by (15)} \\ &\leq f_1(x_2) + (1+\epsilon)E\left[f_2(|X|)I_{\{|X|>x_0\}}\right] \text{ since } f_2 \text{ is positive for } x > x_0 \\ &< \infty \end{split}$$

Therefore,  $E[f_1(|X|)] < \infty$  by (14). This concludes the proof of the lemma.

The result of **Lemma 4** leads to the conclusion if g is asymptotically equivalent to  $f^{-1}$ —with g and  $f^{-1}$  positive, unbounded, and monotone increasing on  $(x_0, \infty)$  and bounded on  $[0, x_0]$  for some postive  $x_0$ —then (2) is equivalent to  $E[g(|X|)] < \infty$ .

Let

$$y = f(x) = \frac{x}{\log x}$$

Then

$$\log y = \log x - \log(\log x)$$

It is a fact (that can be shown with L'Hospital's rule) that

$$\lim_{x \to \infty} \frac{\log(\log x)}{\log x} = 0$$

Therefore

$$\lim_{x \to \infty} \frac{\log y}{\log x} = \lim_{x \to \infty} \frac{\log x - \log(\log x)}{\log x} = 1$$

Hence

$$\begin{split} \log y &\sim \log x \\ y \log y &\sim y \log x \\ y \log y &\sim x \quad \text{by definition of } y \\ y \log y &\sim f^{-1}(y) \quad \text{by definition of } f \end{split}$$

Let  $g(x) = x \log x$ . It follows from the above that  $f^{-1}(x) \sim g(x)$ , therefore by **Lemma 4** (let  $x_0 = e$  and all the conditions are met), (2) can be replaced by  $E[g(|X|)] = E[|X| \log |X|] < \infty$ .

Thus necessary and sufficient conditions on the distribution of X in order that

$$\frac{S_n}{n/\log n} \to 0 \quad \text{wp1}$$

are

$$E[|X|\log|X|] < \infty$$

and

$$EX = 0$$