## TIGHTNESS OF THE STUDENT T-STATISTIC

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submitted March 19, 2002 Final version accepted September 27, 2002

AMS 2000 Subject classification: 60F05 Tightness, t-statistic, self-normalized sum

Abstract

Let  $X, X_1, X_2, \ldots$  be a sequence of nondegenerate, independent and identically distributed random variables and set  $S_n = X_1 + \cdots + X_n, V_n^2 = X_1^2 + \cdots + X_n^2$ . We answer a question of Götze, Giné and Mason by providing a simple necessary and sufficient condition for tightness of  $S_n/V_n$ .

#### 1 Introduction

Let  $X, X_1, X_2, \ldots$  be a sequence of nondegenerate, independent and identically distributed random variables and set

$$S_n = X_1 + \dots + X_n, \quad V_n^2 = X_1^2 + \dots + X_n^2$$
 (1.1)

and

$$t_n = \frac{S_n}{\sqrt{\frac{n}{n-1} \sum_{1}^{n} (X_i - \overline{X})^2}},$$
(1.2)

where  $\overline{X} = n^{-1}S_n$ . Then  $t_n$  is the classical Student t-statistic which may be expressed equivalently as

$$t_n = \frac{S_n}{V_n} \sqrt{\frac{n-1}{n - (\frac{S_n}{V_n})^2}}. (1.3)$$

In a beautiful paper Götze, Giné and Mason (1997) solved a long standing conjecture of Logan, Mallows, Rice and Shepp (1973), by proving that  $t_n$ , or equivalently the self-normalized sum  $S_n/V_n$  (see Proposition 1), is asymptotically standard normal if and only if X is in the domain of attraction of the normal law and EX = 0. A key step in their proof was to show that if

$$\frac{S_n}{V_n}$$
 is tight (1.4)

then it is uniformly subgaussian in the sense that

$$\sup_{n} E \exp\left(t\frac{S_n}{V_n}\right) \le 2 \exp(ct^2) \tag{1.5}$$

for all  $t \in \mathbb{R}$  and some c > 0. This is clearly an important property of the self-normalized sum  $S_n/V_n$  which is not shared by scalar normalized sums, *i.e.* sums of the form  $(S_n - a_n)b_n^{-1}$  for scalar sequences  $a_n$  and  $b_n$ . Thus Giné, Götze and Mason asked for precise conditions under which (1.4) holds. In a subsequent paper, Giné and Mason (1998) gave such a characterization for distributions which are in the Feller class. Here we will solve the problem in general. To describe the result we need to introduce a little notation. For r > 0 set

$$G(r) = P(|X| > r), \quad K(r) = r^{-2}E(X^2; |X| \le r), \quad M(r) = r^{-1}E(X; |X| \le r),$$
 (1.6)

and

$$Q(r) = G(r) + K(r). (1.7)$$

Each of these functions is right continuous with left limits and tends to 0 as r approaches infinity. We can now give an analytic characterization of the two classes of random variables mentioned above. X is in the domain of attraction of the normal law and EX = 0 if and only if

$$\limsup_{r \to \infty} \frac{G(r) + |M(r)|}{K(r)} = 0, \tag{1.8}$$

while X is in the Feller class if and only if

$$\limsup_{r \to \infty} \frac{G(r)}{K(r)} < \infty. \tag{1.9}$$

The result of Giné and Mason is that if X is in the Feller class, then (1.4) holds if and only if

$$\limsup_{r \to \infty} \frac{|M(r)|}{K(r)} < \infty. \tag{1.10}$$

The main result of this paper is

**Theorem 1** The following are equivalent:

$$t_n$$
 is tight,  $(1.11)$ 

$$\frac{S_n}{V_n}$$
 is tight, (1.12)

$$\limsup_{r \to \infty} \frac{|M(r)|}{Q(r)} < \infty. \tag{1.13}$$

Examples of distributions satisfying (1.13) but not (1.9) and (1.10) are easily found, for example any symmetric distribution for which the tail function G is slowly varying.

In the course of the proof of Theorem 1 we also answer the question of when does there exist a centering sequence  $\alpha_n$  for which

$$\frac{S_n - \alpha_n}{V_n} \text{ is tight.} \tag{1.14}$$

In the case of scalar normalization this reduces to centering at the median of  $S_n$  since for any scalar sequence  $b_n$ , if  $(S_n - \alpha_n)b_n^{-1}$  is tight for some  $\alpha_n$ , then it is tight with  $\alpha_n = median(S_n)$ . For self-normalization this is not the case. We illustrate this by giving an example for which (1.12) holds but (1.14) fails when  $\alpha_n = median(S_n)$ .

In concluding the introduction we would like to mention that there have been several other interesting lines of investigation into the Student t-statistic. These include large deviation results (Shao (1997)), law of the iterated logarithm results (Griffin and Kuelbs (1991), Giné and Mason (1998)) and Berry-Esseen bounds (Bentkus and Götze (1994)). In addition Chistyakov and Götze (2001) have recently confirmed a second conjecture of Logan, Mallows, Rice and Shepp that the Student t-statistic has a non-trivial limiting distribution if and only if X is in the domain of attraction of a stable law. This last paper contains further references to the literature on self-normalized sums.

# 2 Preliminaries

We begin by showing that for tightness, and indeed for many asymptotic properties, the behavior of  $t_n$  and  $S_n/V_n$  are equivalent. In order that  $S_n/V_n$  always make sense, we define  $S_n/V_n = 0$  if  $V_n = 0$ .

**Proposition 1** If  $EX^2 < \infty$  and  $EX \neq 0$  then

$$\lim_{n \to \infty} \frac{t_n}{S_n/V_n} = \frac{(EX^2)^{1/2}}{(EX^2 - (EX)^2)^{1/2}} \quad a.s.$$
 (2.1)

If  $EX^2 = \infty$  or EX = 0 then

$$\lim_{n \to \infty} \frac{t_n}{S_n/V_n} = 1 \quad a.s. \tag{2.2}$$

*Proof.* If  $EX^2 < \infty$  and  $EX \neq 0$  then (2.1) follows immediately from (1.3) and the strong law. To prove (2.2) it suffices to show

$$\lim_{n \to \infty} \frac{(n^{-1}S_n)^2}{n^{-1}V_n^2} = 0 \quad a.s.$$
 (2.3)

If EX = 0 this follows immediately from the strong law. Thus we are left to deal with the case  $EX^2 = \infty$ . Fix L > 0, then

$$|S_n| \le \sum_{i=1}^n |X_i| I(|X_i| \le L) + \sum_{i=1}^n |X_i| I(|X_i| > L)$$

$$\le nL + V_n (\sum_{i=1}^n I(|X_i| > L))^{1/2}.$$
(2.4)

Hence

$$\frac{n^{-1}|S_n|}{n^{-1/2}V_n} \le \frac{L}{n^{-1/2}V_n} + \left(\frac{\sum_{i=1}^n I(|X_i| > L)}{n}\right)^{1/2}.$$
 (2.5)

Thus again by the strong law

$$\limsup_{n \to \infty} \frac{n^{-1} S_n}{n^{-1/2} V_n} \le (P(|X| > L))^{1/2}. \tag{2.6}$$

The result then follows by letting  $L \to \infty$ .

The functions defined in (1.6) and (1.7) are defined for r > 0. It will be convenient to extend them to r = 0 by continuity. Thus set

$$G(0) = P(|X| > 0), K(0) = M(0) = 0.$$
(2.7)

We will be particularly interested in the function Q of (1.7) which is in fact continuous. This is most easily seen by observing that

$$Q(r) = r^{-2}E(X^2 \wedge r^2) = r^{-2} \int_0^r 2sG(s) \ ds.$$
 (2.8)

Taking the right derivative in (2.8) shows that Q is constant on  $[0, r_0]$  and strictly decreasing on  $[r_0, \infty)$  where

$$r_0 = \inf\{r > 0 : G(r) < G(0)\}. \tag{2.9}$$

Thus for each fixed  $\lambda > 0$ , we can define a sequence  $a_n(\lambda)$  for all  $n > (\lambda Q(0))^{-1}$  by

$$Q(a_n(\lambda)) = \frac{1}{\lambda n}. (2.10)$$

Observe that  $a_n(\lambda)$  is increasing in both n and  $\lambda$ . For  $n > (\lambda Q(0))^{-1}$  set

$$U_n(\lambda) = \sum_{i=1}^n X_i^2 \wedge a_n^2(\lambda). \tag{2.11}$$

**Lemma 1** Fix  $\lambda > 0$ . For any  $\delta \in (0, \lambda^{-\frac{1}{2}})$  and  $n > (\lambda Q(0))^{-1}$ 

$$P(U_n(\lambda) > \delta^2 a_n^2(\lambda)) \ge \frac{(1 - \lambda \delta^2)^2}{1 + \lambda}.$$

*Proof.* First observe that for any  $n > (\lambda Q(0))^{-1}$ 

$$EU_n(\lambda) = na_n^2(\lambda)Q(a_n(\lambda)) = \frac{a_n^2(\lambda)}{\lambda}$$
(2.12)

and

$$EU_n(\lambda)^2 = nE(X^4 \wedge a_n^4(\lambda)) + 2\binom{n}{2} (E(X^2 \wedge a_n^2(\lambda)))^2$$

$$\leq na_n^4(\lambda)Q(a_n(\lambda)) + n^2(a_n^2(\lambda)Q(a_n(\lambda)))^2$$

$$= a_n^4(\lambda)(\frac{1}{\lambda} + \frac{1}{\lambda^2}).$$
(2.13)

Thus by a reverse Chebyshev inequality, see Durrett (1996) Exercise 3.8 on page 16, for any  $\delta \in (0, \lambda^{-\frac{1}{2}})$ 

$$P(U_n(\lambda) > \delta^2 a_n^2(\lambda)) = P(U_n(\lambda) > \lambda \delta^2 E U_n(\lambda))$$

$$\geq (1 - \lambda \delta^2)^2 \frac{(E U_n(\lambda))^2}{E U_n(\lambda)^2}$$

$$\geq \frac{(1 - \lambda \delta^2)^2}{1 + \lambda}$$
(2.14)

by (2.12) and (2.13).

Corollary 1 Fix  $\lambda > 0$ . For any  $\delta \in (0, \lambda^{-\frac{1}{2}})$  and  $n > (\lambda Q(0))^{-1}$ 

$$P(V_n > \delta a_n(\lambda)) \ge \frac{(1 - \lambda \delta^2)^2}{1 + \lambda}.$$
 (2.15)

*Proof.* This follows immediately from Lemma 1 since  $V_n^2 \ge U_n(\lambda)$  for  $n > (\lambda Q(0))^{-1}$ .

$$X_n^* = \max_{1 \le i \le n} |X_i|.$$

**Lemma 2** Fix  $\lambda > 0$ , L > 0 and  $n > (\lambda Q(0))^{-1}$ , then

$$P(V_n > La_n(\lambda)) \le \frac{1}{\lambda L^2} + 1 - (1 - \frac{1}{\lambda n})^n.$$
 (2.16)

*Proof.* Since  $V_n^2 = U_n(\lambda)$  on  $\{X_n^* \le a_n(\lambda)\}$ , we have

$$P(V_{n} > La_{n}(\lambda)) \leq P(V_{n} > La_{n}(\lambda), X_{n}^{*} \leq a_{n}(\lambda)) + P(X_{n}^{*} > a_{n}(\lambda))$$

$$\leq P(U_{n}(\lambda) > L^{2}a_{n}^{2}(\lambda)) + P(X_{n}^{*} > a_{n}(\lambda))$$

$$\leq \frac{EU_{n}(\lambda)}{L^{2}a_{n}^{2}(\lambda)} + 1 - (1 - G(a_{n}(\lambda)))^{n}$$

$$\leq \frac{1}{\lambda L^{2}} + 1 - (1 - \frac{1}{\lambda n})^{n}.$$
(2.17)

Now let

$$T_n(\lambda) = \sum_{i=1}^n X_i I(|X_i| \le a_n(\lambda)), \quad R_n(\lambda) = \sum_{i=1}^n X_i I(|X_i| > a_n(\lambda))$$
$$J_n(\lambda) = \sum_{i=1}^n I(|X_i| > a_n(\lambda))$$

and set

$$\alpha_n(\lambda) = ET_n(\lambda) = na_n(\lambda)M(a_n(\lambda)). \tag{2.18}$$

**Lemma 3** Fix  $\lambda > 0$ , L > 0 and  $n > (\lambda Q(0))^{-1}$ , then

$$P(|R_n(\lambda)| > LV_n) \le \frac{1}{\lambda L^2}.$$
(2.19)

Proof. Observe that by the Cauchy-Schwartz inequality

$$|R_n(\lambda)| \le V_n \sqrt{J_n(\lambda)}.$$

Thus

$$P(|R_n(\lambda)| > LV_n) \le P(J_n(\lambda) > L^2)$$

$$\le \frac{nG(a_n(\lambda))}{L^2}$$

$$\le \frac{1}{\lambda L^2}.$$
(2.20)

**Lemma 4** Fix L > 0,  $\lambda > 0$  and  $\delta \in (0, \lambda^{-\frac{1}{2}})$ . Then for any  $n > (\lambda Q(0))^{-1}$ 

$$P(|S_n - \alpha_n(\lambda)| > 2LV_n) \le \frac{1}{\lambda} \left( \frac{1}{L^2 \delta^2} + \frac{1}{L} \right) + 1 - \frac{(1 - \lambda \delta^2)^2}{1 + \lambda}.$$

Proof. Since

$$S_n = T_n(\lambda) + R_n(\lambda)$$

we have

$$\{|S_n - \alpha_n(\lambda)| > 2LV_n\} \subset \{|T_n(\lambda) - \alpha_n(\lambda)| > LV_n\} \cup \{|R_n(\lambda)| > LV_n\}$$
$$\subset \{|T_n(\lambda) - \alpha_n(\lambda)| > L\delta a_n(\lambda)\}$$
$$\cup \{V_n \leq \delta a_n(\lambda)\} \cup \{|R_n(\lambda)| > LV_n\}.$$

Hence by Chebyshev's inequality, (2.15) and (2.19)

$$P(|S_n - \alpha_n(\lambda)| > LV_n) \le \frac{na_n^2(\lambda)K(a_n(\lambda))}{L^2\delta^2 a_n^2(\lambda)} + 1 - \frac{(1 - \lambda\delta^2)^2}{1 + \lambda} + \frac{1}{\lambda L^2}$$
$$\le \frac{1}{\lambda} \left(\frac{1}{L^2\delta^2} + \frac{1}{L^2}\right) + 1 - \frac{(1 - \lambda\delta^2)^2}{1 + \lambda}.$$

Corollary 2 For any  $\lambda > 0$ 

$$\limsup_{L \to \infty} \limsup_{n \to \infty} P(|S_n - \alpha_n(\lambda)| > LV_n) \le \frac{\lambda}{1 + \lambda}.$$

*Proof.* In Lemma 4, let  $n \to \infty$ , then  $L \to \infty$  and finally  $\delta \to 0$ .

## 3 Proofs

We first derive a necessary and sufficient condition for tightness of the centered self-normalized sum then specialize this to the case of centering at 0.

**Theorem 2** Fix a centering sequence  $\alpha_n$ . Then the following are equivalent:

$$\frac{S_n - \alpha_n}{V_n} \text{ is tight,} \tag{3.1}$$

$$\limsup_{n \to \infty} \left| \frac{\alpha_n - na_n(\lambda)M(a_n(\lambda))}{a_n(\lambda)} \right| < \infty \text{ for all } \lambda > 0,$$
 (3.2)

$$\limsup_{n \to \infty} \left| \frac{\alpha_n - na_n(\lambda)M(a_n(\lambda))}{a_n(\lambda)} \right| < \infty \text{ for all sufficiently small } \lambda > 0.$$
 (3.3)

*Proof.* First assume (3.1) holds. For any  $n > (\lambda Q(0))^{-1}$ 

$$P(|T_n(\lambda) - \alpha_n| > 2L^2 a_n(\lambda))$$

$$\leq P(|T_n(\lambda) - \alpha_n| > 2L^2 a_n(\lambda), La_n(\lambda) \geq V_n) + P(V_n > La_n(\lambda))$$

$$\leq P(|T_n(\lambda) - \alpha_n| > 2LV_n) + P(V_n > La_n(\lambda))$$

$$\leq P(|S_n - \alpha_n| > LV_n) + P(|R_n(\lambda)| > LV_n) + P(V_n > La_n(\lambda)).$$
(3.4)

Thus by (3.1), (2.16) and (2.19), for any  $\lambda > 0$ 

$$\limsup_{L \to \infty} \limsup_{n \to \infty} P(|T_n(\lambda) - \alpha_n| > 2L^2 a_n(\lambda)) \le 1 - e^{-\frac{1}{\lambda}}.$$
(3.5)

On the other hand by Chebyshev's inequality

$$P(|T_n(\lambda) - \alpha_n(\lambda)| > L^2 a_n(\lambda)) \le \frac{n a_n^2(\lambda) K(a_n(\lambda))}{L^4 a_n^2(\lambda)} \le \frac{1}{\lambda L^4}.$$
 (3.6)

Thus for a fixed  $\lambda > 0$ , if  $L^4 > \lambda^{-1} \exp(\lambda^{-1})$ , then by (3.5) and (3.6), for all n sufficiently large

$$|\alpha_n - \alpha_n(\lambda)| \le 3L^2 a_n(\lambda).$$

Hence (3.2) holds.

That (3.2) implies (3.3) is trivial. Finally assume (3.3) holds. Fix  $\lambda > 0$  sufficiently small that

$$c(\lambda) =: \sup_{n > (\lambda Q(0))^{-1}} \frac{|\alpha_n - na_n(\lambda)M(a_n(\lambda))|}{a_n(\lambda)} < \infty.$$

Observe that for any L > 0 and any  $n > (\lambda Q(0))^{-1}$ 

$$\{|S_n - \alpha_n| > 2LV_n\} \subset \{|S_n - \alpha_n(\lambda)| > 2LV_n - c(\lambda)a_n(\lambda)\}$$

$$\subset \{|S_n - \alpha_n(\lambda)| > LV_n\} \cup \{LV_n \le c(\lambda)a_n(\lambda)\}.$$

$$(3.7)$$

Now if L is large enough that  $c(\lambda)L^{-1} < \lambda^{-\frac{1}{2}}$ , then by Corollary 1

$$\limsup_{n \to \infty} P(V_n \le c(\lambda)L^{-1}a_n(\lambda)) \le 1 - \frac{(1 - \lambda(c(\lambda)L^{-1})^2)^2}{1 + \lambda}.$$
 (3.8)

Hence by Corollary 2, (3.7) and (3.8), for all  $\lambda$  sufficiently small

$$\limsup_{L \to \infty} \limsup_{n \to \infty} P(|S_n - \alpha_n| > 2LV_n) \le \frac{\lambda}{1 + \lambda} + 1 - \frac{1}{1 + \lambda}.$$

Thus (3.1) follows by letting  $\lambda \downarrow 0$ .

**Theorem 3** The following are equivalent:

$$\frac{S_n}{V_n}$$
 is tight, (3.9)

$$\limsup_{r \to \infty} \frac{|M(r)|}{Q(r)} < \infty. \tag{3.10}$$

*Proof.* Assume (3.10). Then with  $\alpha_n = 0$  we have for  $n > (\lambda Q(0))^{-1}$ 

$$\left|\frac{\alpha_n - na_n(\lambda)M(a_n(\lambda))}{a_n(\lambda)}\right| = \frac{1}{\lambda} \frac{|M(a_n(\lambda))|}{Q(a_n(\lambda))},$$

so (3.9) holds by Theorem 2. Conversely assume (3.10) fails, so

$$\frac{|M(r_k)|}{Q(r_k)} \to \infty \tag{3.11}$$

for some  $r_k \to \infty$ . Set

$$n_k = \max\{n : nQ(r_k) \le 1\}.$$
 (3.12)

Then for  $n_k > (Q(0))^{-1}$  we have that

$$r_k = a_{n_k}(\lambda_k) \tag{3.13}$$

where  $1 \leq \lambda_k \leq 1 + n_k^{-1}$ . Now for such k

$$|n_k a_{n_k}(\lambda_k) M(a_{n_k}(\lambda_k)) - n_k a_{n_k}(1) M(a_{n_k}(1))| \le a_{n_k}(\lambda_k) n_k G(a_{n_k}(1))$$

$$\le a_{n_k}(\lambda_k),$$

while by (3.11)

$$n_k|M(a_{n_k}(\lambda_k))| = \frac{|M(a_{n_k}(\lambda_k))|}{\lambda_k Q(a_{n_k}(\lambda_k))} = \frac{|M(r_k)|}{\lambda_k Q(r_k)} \to \infty.$$

Consequently

$$\frac{n_k a_{n_k}(1)|M(a_{n_k}(1))|}{a_{n_k}(\lambda_k)} \to \infty.$$

Since  $a_{n_k}(1) \leq a_{n_k}(\lambda_k)$  it then follows that  $n_k |M(a_{n_k}(1))| \to \infty$ . Thus we conclude that (3.2) fails with  $\alpha_n = 0$  and  $\lambda = 1$ . Hence by Theorem 2, (3.9) fails.

Theorem 1 follows immediately from Proposition 1 and Theorem 3. We conclude by giving an example showing that it is possible for (1.12) to hold, but for (1.14) to fail with  $\alpha_n = median(S_n)$ .

**Example 1** Let X > 0 have distribution given by

$$G(r) = \frac{1}{\ln r}, \quad r \ge e. \tag{3.14}$$

Since G is slowly varying, it follows from Darling (1952) that

$$S_n/X_n^* \xrightarrow{p} 1 \text{ and } V_n/X_n^* \xrightarrow{p} 1.$$
 (3.15)

Consequently  $S_n/V_n^* \stackrel{p}{\to} 1$  and in particular (1.12) holds. Set

$$b_n(\lambda) = e^{\lambda n}. (3.16)$$

Observe that for any  $\lambda_1 > \lambda_2 > 0$ 

$$\frac{b_n(\lambda_1)}{b_n(\lambda_2)} \to \infty. \tag{3.17}$$

Now fix  $\lambda_1 < (\ln 2)^{-1}$ . Then

$$P(S_n > b_n(\lambda_1)) \ge P(X_n^* > b_n(\lambda_1)) = 1 - \left(1 - \frac{1}{\lambda_1 n}\right)^n \to 1 - e^{-\lambda_1^{-1}} > \frac{1}{2}.$$
 (3.18)

Hence the median  $m_n$  of  $S_n$  satisfies

$$\limsup_{n \to \infty} \frac{m_n}{b_n(\lambda_1)} \ge 1. \tag{3.19}$$

Now fix  $\lambda_2 \in (0, \lambda_1)$ . Then for any  $\lambda_3 \in (0, \lambda_2)$ .

$$P(V_n \le b_n(\lambda_2)) \ge P(V_n \le b_n(\lambda_2), \frac{V_n}{X_n^*} \le \frac{b_n(\lambda_2)}{b_n(\lambda_3)})$$

$$\ge P(X_n^* \le b_n(\lambda_3)) - P(\frac{V_n}{X_n^*} > \frac{b_n(\lambda_2)}{b_n(\lambda_3)})$$

$$\to e^{-\lambda_3^{-1}}.$$
(3.20)

by (3.15) and (3.17). Thus by (3.17), (3.19) and (3.20),  $m_n/V_n$  is not tight. Since, as we have already observed, (1.12) holds, it then follows that (1.14) must fail when  $\alpha_n = m_n$ .

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