

## THE RECURRENCE OF BLOCKS FOR BERNOULLI PROCESSES

DONG HAN KIM

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### 1. Introduction

Convergence of the logarithm of the first return time normalized by the block length  $n$  has been investigated in relation to data compression methods such as Ziv-Lempel algorithms [11]. For each sample sequence  $x = (x_1, x_2, \dots)$  from an ergodic stationary information source, define  $P_n(x)$  to be the probability of the initial  $n$ -block in  $x$ , i.e.,  $P_n(x) = \Pr(x_1 \cdots x_n)$ . The classical Shannon-Breiman-McMillan Theorem states that  $-(\log P_n)/n$  converges to entropy in  $L^1$  and almost surely. Throughout the article,  $\log$  denotes the logarithm with respect to base 2 and  $\ln$  denotes the natural logarithm.

DEFINITION 1.1. Given a block size  $n$ , the first return time  $R_n$  is defined by

$$R_n(x) = \min\{j \geq 1 : x_1 \cdots x_n = x_{j+1} \cdots x_{j+n}\}.$$

Kac's Lemma [3] states that  $E[R_n \mid x_1 \dots x_n = B] = 1/\Pr(B)$ . This suggests that  $R_n(x)$  is close to  $1/P_n(x)$ , hence we expect that  $(\log R_n)/n$  converges to entropy  $h$  in a suitable sense. It was proved that  $(\log R_n)/n$  converges to entropy in probability by Wyner and Ziv [8] and almost surely by Ornstein and Weiss [6]. For a comprehensive introduction to the subject consult Shields [7] and the references therein. For the application to the testing pseudorandom numbers, see [2]. Recently several interesting results have been obtained regarding convergence rates by other investigators for  $R_n$  and related concepts such as the longest match-length, the waiting time and the redundancy rate, etc. See [4], [10]. In this article we investigate the relation between first return time and entropy for a Bernoulli process. Since the formula contains a correction terms, it approximates the entropy very well. See the last section for simulations.

In his Ph.D thesis [9] A.J. Wyner discovered that for a stationary aperiodic Markov chain with entropy  $h$  we have a second order limit law:

$$\lim_{n \rightarrow \infty} \Pr \left( \frac{\log R_n - nh}{\sigma \sqrt{n}} \leq \alpha \right) = \Phi(\alpha)$$

where

$$\Phi(\alpha) = \int_{-\infty}^{\alpha} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) dx$$

and

$$\sigma^2 = \lim_{n \rightarrow \infty} \frac{\text{Var}(-\log P_n(x))}{n}.$$

Kontoyiannis ([4, Corollary 1]) showed that for any  $\beta > 0$

$$\log[R_n(x)P_n(x)] = o(n^\beta)$$

almost surely for mixing Markov chains. Later A.J. Wyner ([10, Corollary B5]) proved that for any  $\epsilon > 0$

$$-(1 + \epsilon) \cdot \log n \leq \log[R_n(x)P_n(x)] \leq \log \log n$$

eventually, almost surely for mixing Markov chains. Hence we have

$$-(1 + \epsilon) \cdot \log n \leq E[\log R_n P_n] \leq \log \log n$$

approximately for large  $n$ . In this paper we investigate the speed of convergence of the average of  $\log R_n$  to entropy. Now we state the main theorem.

**Theorem 1.2.** *For a Bernoulli process with entropy  $h$ , we have*

$$\lim_{n \rightarrow \infty} E[\log(R_n P_n)] = -\frac{\gamma}{\ln 2}$$

and

$$\lim_{n \rightarrow \infty} E[\log R_n] - n \cdot h = -\frac{\gamma}{\ln 2}.$$

Maurer [5] studied the *non-overlapping first return time*

$$R'_n(x) \equiv \min\{j \geq 1 : x_1 \cdots x_n = x_{jn+1} \cdots x_{jn+n}\}.$$

In computing  $R'_n(x)$  we need approximately  $n$  times more digits of  $x$  than  $R_n(x)$ . So the overlapping algorithm is efficient compared to the non-overlapping one.

**DEFINITION 1.3.** For  $0 < r < 1$ , define

$$v(r) \equiv r \sum_{i=1}^{\infty} (1-r)^{i-1} \log i.$$

Put  $r = 2^{-n}$ . Then the expectation of  $\log R'_n$  equals  $v(r)$  in case of the Bernoulli  $(1/2, 1/2)$ -process. Note that

$$\begin{aligned} \lim_{r \rightarrow 0^+} [v(r) + \log r] &= \lim_{s \rightarrow 1^-} [v(1-s) + \log(1-s)] \\ &= \sum_{i=1}^{\infty} \left( \ln \frac{i+1}{i} - \frac{1}{i} \right) / \ln 2 \\ &= -\frac{\gamma}{\ln 2} \\ &= -0.832746 \dots, \end{aligned}$$

where  $\gamma = \lim_{n \rightarrow \infty} (\sum_{i=1}^n (1/i) - \ln n)$  is Euler's constant. Hence the expectation of  $\log R'_n$  is approximately equal to  $n - \gamma / \ln 2$  for large  $n$ . In Markov case a similar result is obtained in [1].

In Section 2 we prove Theorem 1.2 and we propose a practical formula for entropy approximation in Section 3.

**2. Proof of Theorem 1.2**

An *alphabet* is a finite set  $\mathcal{A}$  and we call each element of  $\mathcal{A}$  a *symbol*. A *block* is a finite sequence of symbols, and an *n-block* is a block of length  $n$ . Let  $|B|$  be the length of the block  $B$ . For an  $n$ -block  $B = a_1 a_2 \dots a_n$  we write  $B_{[i,j]} = a_i a_{i+1} \dots a_j, 1 \leq i \leq j \leq n$ .

DEFINITION 2.1. Let  $B$  be an  $n$ -block. Suppose  $m$  satisfies  $1 \leq m < n$  and

$$(B_{[1,m]} B_{[1,m]} \dots B_{[1,m]})_{[1,n]} = B,$$

for some  $1 \leq j \leq m$ . The smallest such  $m$  is denoted by  $\lambda_1(B)$ , and the next smallest such  $m$  that is not a multiple of  $\lambda_1(B)$  is  $\lambda_2(B)$ , and we can define  $\lambda_k(B)$  by the smallest such  $m$  which is not a multiple of  $\lambda_i(B)$  for every  $i < k$ .

Let  $\Lambda(B) = \{\lambda_1(B), \lambda_2(B), \dots\}$  and if  $B$  has no such  $m$ , we write  $\Lambda(B) = \emptyset$ .

EXAMPLE 2.2. Consider the case of binary blocks, in other words, the symbols are 0 and 1. The number of different binary 4-blocks is 16. By symmetry we only have to examine 8 different blocks having '0' as the first symbol. We have

$$\begin{aligned} \Lambda(0000) &= \{1\}, & \Lambda(0010) &= \Lambda(0100) = \Lambda(0110) = \{3\}, \\ \Lambda(0101) &= \{2\}, & \Lambda(0001) &= \Lambda(0011) = \Lambda(0111) = \emptyset. \end{aligned}$$

If we consider the 5-block  $B = 00100$ , we have  $\Lambda(B) = \{3, 4\}$  and  $B_{[1,\lambda_1(B)]} = 001, B_{[1,\lambda_2(B)]} = 0010$ .

We classify  $n$ -blocks into the following sets

$$\begin{aligned}\mathcal{T}(n) &= \left\{ |B| = n : \lambda_1(B) > \frac{n}{2} \text{ or } \Lambda(B) = \emptyset \right\}, \\ \mathcal{R}(n) &= \left\{ |B| = n : \lambda_1(B) \leq \frac{n}{2} \right\}.\end{aligned}$$

**Lemma 2.3.** *For a Bernoulli process,  $\Pr(x_1 \cdots x_n \in \mathcal{R}(n))$  converges to 0 exponentially as  $n \rightarrow \infty$ .*

*Proof.* Let  $d$  be the maximal probability of the symbols. Then for  $i < n$  we have

$$\Pr(i \in \Lambda(x_1 \cdots x_n)) \leq d^{n-i}$$

and

$$\Pr(x_1 \cdots x_n \in \mathcal{R}(n)) \leq \sum_{i=1}^{\lfloor n/2 \rfloor} d^{n-i} = \frac{d^{n-\lfloor n/2 \rfloor} - d^n}{1-d},$$

where  $\lfloor t \rfloor$  is the greatest integer that does not exceed  $t$ . □

**Lemma 2.4.** *Let  $B$  be an  $n$ -block.*

- (i) *If  $B = (CB)_{[1,m]}$  for some  $m$ -block  $C$ ,  $1 \leq m < n$ , then  $m \in \Lambda(B)$  or  $m$  is a multiple of some  $\lambda \in \Lambda(B)$ .*
- (ii) *If  $B = B_{[m+1,n]}B_{[1,m]}$  for some  $1 \leq m < n$ , then there is  $\lambda \in \Lambda(B)$  such that  $\lambda$  divides  $n$  and  $m$ .*

*Proof.* (i) is directly derived from the definition of  $\Lambda(B)$ .

(ii) Let  $m' = \gcd(m, n)$  and  $n = hm'$ ,  $m = lm'$ . Put  $B_i = B_{[(i-1)m'+1, im']}$ . Then  $B_1 \cdots B_h = B_{l+1} \cdots B_h B_1 \cdots B_l$ . So we have  $B_i = B_j$  if  $i \equiv j + l \pmod{h}$ . Since  $l$  and  $h$  are relatively prime,  $B_i$ 's are identical for every  $i$ . □

**DEFINITION 2.5.** (i) For an  $n$ -block  $B$  and  $k \geq n$  let  $\mathcal{F}(B, k)$  be the set of all  $k$ -blocks  $C$  such that  $BC$  of length  $k+n$  does not contain  $B$  except for the first  $B$ , in other words,

$$\mathcal{F}(B, k) = \{C : (BC)_{[i, i+n-1]} \neq B \text{ for any } i > 1\}.$$

For  $1 \leq k < n$ , let  $\mathcal{F}(B, k)$  be the set of all  $k$ -blocks.

(ii) Let  $\mathcal{S}(B, k)$  be the set of  $k$ -blocks  $C$ ,  $k \geq 1$ , such that  $BCB$  of length  $k+2n$  does not contain  $B$  except for the first and the last  $B$ 's, or equivalently

$$\mathcal{S}(B, k) = \{C : (BCB)_{[i, i+n-1]} \neq B \text{ for any } i, 1 < i \leq k+n\}.$$

Clearly, we have  $S(B, k) \subset \mathcal{F}(B, k)$ .

EXAMPLE 2.6. Take  $B = 010$  and  $k = 3$ . The 3-blocks ‘001’ is not in  $S(010, 3)$  but in  $\mathcal{F}(010, 3)$ , since the 6-block ‘010001010’ has three ‘010’ blocks (e.g. 010001010). Now we have

$$\begin{aligned} \mathcal{F}(010, 3) &= \{000, 001, 011, 110, 111\}, \\ S(010, 3) &= \{000, 011, 110, 111\}. \end{aligned}$$

The following shows the relation between  $\mathcal{F}(B, k)$  and  $S(B, k)$ .

**Lemma 2.7.** For  $B \in \mathcal{T}(n)$  and  $k > n$  we have a pairwise disjoint union

$$\begin{aligned} S(B, k) &= \mathcal{F}(B, k) \setminus \bigcup_{\lambda \in \Lambda(B)} \{C \in \mathcal{F}(B, k) : (BC)_{[k+n-\lambda+1, k+n]} = B_{[1, \lambda]}\} \\ &= \mathcal{F}(B, k) \setminus \bigcup_{\lambda \in \Lambda(B)} \{CB_{[1, \lambda]} : C \in S(B, k - \lambda)\}. \end{aligned}$$

Proof. Take a  $k$ -block  $C \in \mathcal{F}(B, k)$ . If  $(BCB)_{[s, s+n-1]} = B$  for some  $s$ , then  $s > k + 1$  and

$$B = (BCB)_{[s, s+n-1]} = (BC)_{[s, k+n]}B_{[1, s-k-1]}.$$

Put  $\lambda = k + n - s + 1$ . Then by Lemma 2.4(i)  $\lambda \in \Lambda(B)$  and  $(BC)_{[s, k+n]} = B_{[1, \lambda]}$ . Hence we have

$$\begin{aligned} S(B, k) &= \{C : (BCB)_{[i, i+n-1]} \neq B \text{ for any } i, i < i \leq k+n\} \\ &= \{C \in \mathcal{F}(B, k) : (BC)_{[k+n-\lambda+1, k+n]} \neq B_{[1, \lambda]} \text{ for any } \lambda \in \Lambda(B)\} \\ &= \mathcal{F}(B, k) \setminus \bigcup_{\lambda \in \Lambda(B)} \{C \in \mathcal{F}(B, k) : (BC)_{[k+n-\lambda+1, k+n]} = B_{[1, \lambda]}\}. \end{aligned}$$

Suppose that there exists  $C \in \mathcal{F}(B, k)$  such that  $C_{[k+n-\lambda+1, k+n]} = B_{[1, \lambda]}$  and  $C_{[k+n-\lambda'+1, k+n]} = B_{[1, \lambda']}$  for some  $\lambda, \lambda' \in \Lambda(B)$  with  $\lambda < \lambda'$ . Then  $B_{[1, \lambda]} = B_{[\lambda'-\lambda+1, \lambda']}$  and

$$B_{[1, \lambda']} = (B_{[1, \lambda]}B_{[1, \lambda]})_{[1, \lambda']} = B_{[1, \lambda]}B_{[1, \lambda'-\lambda]} = B_{[\lambda'-\lambda+1, \lambda']}B_{[1, \lambda'-\lambda]}.$$

By Lemma 2.4(ii)  $B_{[1, \lambda']} = B_{[1, \lambda'-\lambda]} \cdots B_{[1, \lambda'-\lambda]}$  and this contradicts  $\lambda' \in \Lambda(B)$ . Hence the sets  $\{C \in \mathcal{F}(B, k) : C_{[k+n-\lambda+1, k+n]} = B_{[1, \lambda]}\}$  are disjoint.

For every  $C \in S(B, k - \lambda)$  we have  $CB_{[1, \lambda]} \in \mathcal{F}(B, k)$  obviously. Put  $C \in \mathcal{F}(B, k)$  with  $C_{[k-\lambda+1, k]} = B_{[1, \lambda]}$ . If  $C_{[1, k-\lambda]} \notin S(B, k - \lambda)$ , then there is  $\lambda'$  with  $\lambda' < n - \lambda$  such that  $C_{[1, k-\lambda-\lambda']}B = (C_{[1, k-\lambda]}B)_{[1, k+n-\lambda-\lambda']}$  or  $B = (C_{[k-\lambda-\lambda'+1, k-\lambda]}B)_{[1, n]}$ . So by Lemma 2.4(i)  $\lambda' \in \Lambda(B)$  or  $\lambda'$  is a multiple of  $\lambda_1(B)$ . Since  $\lambda' < n - \lambda < n/2$ , this

contradicts  $B \in \mathcal{T}(n)$ . Hence we have

$$\{C \in \mathcal{F}(B, k) : (BC)_{[k+n-\lambda+1, k+n]} = B_{[1, \lambda]}\} = \{CB_{[1, \lambda]} : C \in \mathcal{S}(B, k - \lambda)\}. \quad \square$$

DEFINITION 2.8. For a given  $n$ -block  $B$ , define

$$\begin{aligned} p_i(B) &= \Pr(R_n(x) = i \mid x_1 \cdots x_n = B, R_n(x) \geq i), \\ r_i(B) &= \Pr(x_{n+1} \cdots x_{n+i} \in \mathcal{F}(B, i) \mid x_1 \cdots x_n = B), \\ s_i(B) &= \Pr(x_{n+1} \cdots x_{n+i} \in \mathcal{S}(B, i) \mid x_1 \cdots x_n = B). \end{aligned}$$

We have  $r_i(B) \geq s_i(B)$ . Put  $r_0(B) = 1$ ,  $s_0(B) = 1$ .

**Proposition 2.9.** For Bernoulli processes we have

$$\begin{aligned} \Pr(R_n(x) > i \mid x_1 \cdots x_n = B) &= r_i(B), \\ \Pr(R_n(x) = i + n \mid x_1 \cdots x_n = B) &= s_i(B) \Pr(B). \end{aligned}$$

Proof. Let  $x_1 \cdots x_n = B$ . Since  $R_n(x) > i$  if and only if  $x_1 \cdots x_{i+n} = BC$  for some  $C \in \mathcal{F}(B, i)$ , we have

$$\Pr(R_n(x) > i \mid x_1 \cdots x_n = B) = \Pr(x_{n+1} \cdots x_{i+n} \in \mathcal{F}(B, i)) = r_i(B).$$

And since  $R_n(x) = i + n$  if and only if  $x_1 \cdots x_{i+2n} = BCB$  for some  $C \in \mathcal{S}(B, i)$ , we have

$$\begin{aligned} \Pr(R_n(x) = i + n \mid x_1 \cdots x_n = B) &= \Pr(x_{n+1} \cdots x_{i+n} \in \mathcal{S}(B, i)) \cdot \Pr(x_{i+n+1} \cdots x_{i+2n} = B) \\ &= s_i(B) \cdot \Pr(B). \end{aligned}$$

Since  $r_0(B) = s_0(B) = 1$ , the equations hold for  $i = 0$ . □

Now we find the recurrence relations between  $r_k(B)$  and  $s_k(B)$ .

**Proposition 2.10.** For a Bernoulli process with  $B \in \mathcal{T}(n)$ , if  $i \geq n$ ,

$$\begin{aligned} r_i(B) &= r_{i-1}(B) - s_{i-n}(B) \Pr(B), \\ s_i(B) &= r_i(B) - \sum_{\lambda \in \Lambda(B)} \Pr(B_{[1, \lambda]}) s_{i-\lambda}(B). \end{aligned}$$

Proof. From Proposition 2.9 we have

$$\begin{aligned} r_i(B) &= \Pr(R_n(x) > i \mid x_1 \cdots x_n = B) \\ &= \Pr(R_n(x) > i - 1 \mid x_1 \cdots x_n = B) - \Pr(R_n(x) = i \mid x_1 \cdots x_n = B) \\ &= r_{i-1}(B) - s_{i-n}(B) \Pr(B). \end{aligned}$$

By Lemma 2.7 we have

$$\begin{aligned} s_i(B) &= \Pr(x_{n+1} \cdots x_{n+i} \in \mathcal{F}(B, i)) \\ &\quad - \sum_{\lambda \in \Lambda(B)} \Pr(x_{n+1} \cdots x_{n+i-\lambda} \in \mathcal{S}(B, i - \lambda), x_{n+i-\lambda+1} \cdots x_{n+i} = B_{[1, \lambda]}) \\ &= r_i(B) - \sum_{\lambda \in \Lambda(B)} s_{i-\lambda}(B) \Pr(B_{[1, \lambda]}). \end{aligned} \quad \square$$

**Lemma 2.11.** For a Bernoulli process with  $B \in \mathcal{T}(n)$ , if  $i \geq n$ ,

$$p_i(B) = \frac{\Pr(B)}{(1 - p_{i-1}(B)) \cdots (1 - p_{i-n+1}(B))} - \sum_{\lambda \in \Lambda(B)} \frac{\Pr(B_{[1, \lambda]}) p_{i-\lambda}(B)}{(1 - p_{i-1}(B)) \cdots (1 - p_{i-\lambda}(B))}.$$

Proof. From Proposition 2.10 we have for  $i \geq n$

$$s_i(B) = r_i(B) - \sum_{\lambda \in \Lambda(B)} \frac{r_{i+n-\lambda-1}(B) - r_{i+n-\lambda}(B)}{\Pr(B_{[\lambda+1, n]})}$$

and

$$r_{i-1}(B) - r_i(B) = \Pr(B) r_{i-n}(B) - \sum_{\lambda \in \Lambda(B)} \Pr(B_{[1, \lambda]}) (r_{i-\lambda-1}(B) - r_{i-\lambda}(B)).$$

Since  $r_i(B) = (1 - p_1(B))(1 - p_2(B)) \cdots (1 - p_i(B))$ , we conclude the lemma.  $\square$

REMARK 2.12. (i) From the definition of  $\Lambda(B)$  we have for  $1 \leq i < n = |B|$

$$p_i(B) = \begin{cases} 0 & \text{if } i \notin \Lambda(B), \\ \frac{\Pr(B_{[1, i]})}{\prod_{j < i} (1 - p_j(B))} & \text{if } i \in \Lambda(B) \end{cases}$$

and

$$(1 - p_1(B)) \cdots (1 - p_{n-1}(B)) = \begin{cases} 1 & \text{if } \Lambda(B) = \emptyset, \\ 1 - \sum_{\lambda \in \Lambda(B)} \Pr(B_{[1, \lambda]}) & \text{if } \Lambda(B) \neq \emptyset. \end{cases}$$

(ii) For  $B \in \mathcal{T}(n)$  and  $\lambda \in \Lambda(B)$  we have

$$\Pr(B) = \Pr(B_{[1,\lambda]}) \Pr(B_{[1,n-\lambda]}) = \Pr(B_{[1,n-\lambda]})^2 \Pr(B_{[n-\lambda+1,\lambda]}),$$

and

$$\Pr(B) < \Pr(B_{[1,\lambda]}) < \sqrt{\Pr(B)}.$$

**Lemma 2.13.** *For each Bernoulli process there is  $N$  such that for every block  $B \in \mathcal{T}(n)$  with  $n > N$  we have  $p_i(B) < \sqrt{\Pr(B)}$  for each  $i \geq 1$ .*

*Proof.* Let  $d$  be the maximal probability of the symbols. Choose  $N$  so that  $\sqrt{d^n} < 1/n$  and  $n^{1-2/n}/(n-1) < 1$  for all  $n > N$  and  $N \geq 2$ . Put  $\lambda_i = \lambda_i(B)$ . If  $p_{\lambda_j}(B) < \sqrt{\Pr(B)}$  for all  $j < i$ , then

$$\begin{aligned} p_{\lambda_i}(B) &= \frac{\Pr(B_{[1,\lambda_i]})}{(1 - p_{\lambda_1}(B)) \cdots (1 - p_{\lambda_{i-1}}(B))} \\ &= \Pr(B_{[1,\lambda_1]}) \frac{\Pr(B_{[\lambda_1+1,\lambda_2]})}{1 - p_{\lambda_1}(B)} \cdots \frac{\Pr(B_{[\lambda_{i-1}+1,\lambda_i]})}{1 - p_{\lambda_{i-1}}(B)} \\ &< \sqrt{\Pr(B)} \left( \frac{d}{1 - \sqrt{\Pr(B)}} \right)^{i-1} < \sqrt{\Pr(B)} \left( \frac{n^{-2/n}}{1 - \sqrt{d^n}} \right)^{i-1} \\ &< \sqrt{\Pr(B)} \left( \frac{n^{1-2/n}}{n-1} \right)^{i-1} < \sqrt{\Pr(B)}. \end{aligned}$$

Since

$$p_{\lambda_1}(B) = \Pr(B_{[1,\lambda_1]}) < \sqrt{\Pr(B)},$$

by induction rule we have  $p_\lambda(B) < \sqrt{\Pr(B)}$  for all  $\lambda \in \Lambda(B)$ . and  $p_i(B) < \sqrt{\Pr(B)}$  for all  $i < n$ .

If  $p_i(B) < \sqrt{\Pr(B)}$  for all  $i < j$ , Then from Lemma 2.11 we have

$$\begin{aligned} p_j(B) &< \frac{\Pr(B)}{(1 - \sqrt{\Pr(B)})^{n-1}} \\ &\leq \sqrt{\Pr(B)} \frac{\sqrt{d^n}}{(1 - \sqrt{d^n})^{n-1}} < \sqrt{\Pr(B)} \frac{\sqrt{d^n}}{1 - (n-1)\sqrt{d^n}} \\ &= \sqrt{\Pr(B)} \frac{\sqrt{d^n}}{1 - n\sqrt{d^n} + \sqrt{d^n}} \leq \sqrt{\Pr(B)}. \end{aligned} \quad \square$$

**Lemma 2.14.** *If we put*

$$\alpha_n \equiv \frac{n\sqrt{d^n}}{1 - n\sqrt{d^n}},$$



where  $d$  is the maximal probability of the symbols, then for  $i \geq n$  we have

$$p_i(B) < \Pr(B) + \Pr(B)\alpha_n.$$

Proof. By Lemma 2.11 and 2.13 we have

$$\begin{aligned} p_i(B) &\leq \frac{\Pr(B)}{(1 - p_{i-1}(B)) \cdots (1 - p_{i-n+1}(B))} \\ &< \frac{\Pr(B)}{(1 - \sqrt{\Pr(B)})^{n-1}} \leq \frac{\Pr(B)}{(1 - \sqrt{d^n})^{n-1}} \end{aligned}$$

and

$$\begin{aligned} p_i(B) - \Pr(B) &< \Pr(B) \left( \frac{1 - (1 - \sqrt{d^n})^{n-1}}{(1 - \sqrt{d^n})^{n-1}} \right) \\ &< \Pr(B) \left( \frac{(n-1)\sqrt{d^n}}{1 - (n-1)\sqrt{d^n}} \right) < \Pr(B)\alpha_n. \quad \square \end{aligned}$$

**Lemma 2.15.** For sufficiently large  $n$  if  $B \in \mathcal{T}(n)$  and  $i \geq n$ , then we have

$$p_i(B) > \Pr(B) - \Pr(B)\alpha_n.$$

Proof. By Lemma 2.11, 2.13 and 2.14 we have

$$\begin{aligned} p_i(B) &\geq \Pr(B) - \sum_{\lambda} \frac{\Pr(B_{[1,\lambda]})p_{i-\lambda}(B)}{(1 - p_{i-1}(B)) \cdots (1 - p_{i-\lambda}(B))} \\ &> \Pr(B) - \frac{n}{2} \cdot \frac{\Pr(B)(1 + \alpha_n)\sqrt{\Pr(B)}}{(1 - \sqrt{\Pr(B)})^{n-1}} \\ &\geq \Pr(B) - \frac{\Pr(B)(1 + \alpha_n)n\sqrt{d^n}}{2(1 - \sqrt{d^n})^{n-1}} \end{aligned}$$

and

$$\begin{aligned} p_i(B) - \Pr(B) &> -\Pr(B) \frac{(1 + \alpha_n)n\sqrt{d^n}}{2(1 - \sqrt{d^n})^{n-1}} \\ &> -\Pr(B) \frac{\alpha_n(1 + \alpha_n)}{2} > -\Pr(B)\alpha_n \end{aligned}$$

for sufficiently large  $n$ . □

**Lemma 2.16.** For any sequence  $0 \leq c_1 < c_2 < \cdots$ , let

$$F(x_1, x_2, \dots) = \sum_{i=1}^{\infty} (1 - x_1) \cdots (1 - x_{i-1}) x_i c_i$$

be a function of  $x_1, x_2, \dots$  under the conditions of

- (1)  $0 \leq x_i \leq 1, i = 1, 2, \dots,$
- (2)  $\sum_{i=1}^{\infty} x_i$  diverges.

Then  $F$  is monotonously decreasing in  $x_1, x_2, \dots$

Proof. For a fixed  $k$  and  $\delta > 0$ , we have

$$\begin{aligned} & F(x_1, \dots, x_k, \dots) - F(x_1, \dots, x_k + \delta, \dots) \\ &= (1 - x_1) \cdots (1 - x_{k-1}) \delta \left( -c_k + \sum_{i=k+1}^{\infty} (1 - x_{k+1}) \cdots (1 - x_{i-1}) x_i c_i \right) \\ &\geq (1 - x_1) \cdots (1 - x_{k-1}) \delta \left( -c_k + c_{k+1} \sum_{i=k+1}^{\infty} (1 - x_{k+1}) \cdots (1 - x_{i-1}) x_i \right). \end{aligned}$$

Since for  $m \geq k + 1$ ,

$$\prod_{i=k+1}^m (1 - x_i) = 1 - \sum_{i=k+1}^m (1 - x_{k+1}) \cdots (1 - x_{i-1}) x_i,$$

we have

$$\sum_{i=k+1}^{\infty} (1 - x_{k+1}) \cdots (1 - x_{i-1}) x_i = 1 - \prod_{i=k+1}^{\infty} (1 - x_i).$$

From the condition (2)

$$\log \left( \prod_{i=k+1}^{\infty} (1 - x_i) \right) = \sum_{i=k+1}^{\infty} \log(1 - x_i) \leq - \sum_{i=k+1}^{\infty} x_i = -\infty,$$

and

$$\sum_{i=k+1}^{\infty} (1 - x_{k+1}) \cdots (1 - x_{i-1}) x_i = 1.$$

Hence we have

$$\begin{aligned} & F(x_1, \dots, x_k, \dots) - F(x_1, \dots, x_k + \delta, \dots) \\ &\geq (1 - x_1) \cdots (1 - x_{k-1}) \delta (-c_k + c_{k+1}) \geq 0. \end{aligned}$$

□

Proof of Theorem 1.2. Since

$$\Pr(R_n(x) = i \mid x_1 \dots x_n = B) = (1 - p_1(B)) \cdots (1 - p_{i-1}(B)) p_i(B),$$

we have from Lemma 2.14, 2.15 and 2.16

$$\begin{aligned}
E[\log R_n \mid x_1 \cdots x_n = B] &= \sum_{i=1}^{\infty} (1 - p_1(B)) \cdots (1 - p_{i-1}(B)) p_i(B) \log i \\
&\geq \sum_{i=1}^{n-1} (1 - p_1(B)) \cdots (1 - p_{i-1}(B)) p_i(B) \log i \\
&\quad + (1 - p_1(B)) \cdots (1 - p_{n-1}(B)) \sum_{i=n}^{\infty} (1 - \Pr(B)(1 + \alpha_n))^{i-n} \Pr(B)(1 + \alpha_n) \log i \\
&= \sum_{i=1}^{n-1} (1 - p_1) \cdots (1 - p_{i-1}) p_i \log i + \frac{(1 - p_1) \cdots (1 - p_{n-1})}{(1 - \Pr(B)(1 + \alpha_n))^{n-1}} v(\Pr(B)(1 + \alpha_n)) \\
&\quad - (1 - p_1) \cdots (1 - p_{n-1}) \sum_{i=1}^{n-1} (1 - \Pr(B)(1 + \alpha_n))^{i-n} \Pr(B)(1 + \alpha_n) \log i
\end{aligned}$$

and

$$\begin{aligned}
E[\log R_n \mid x_1 \cdots x_n = B] \\
\leq \sum_{i=1}^{n-1} (1 - p_1) \cdots (1 - p_{i-1}) p_i \log i + \frac{(1 - p_1) \cdots (1 - p_{n-1})}{(1 - \Pr(B)(1 - \alpha_n))^{n-1}} v(\Pr(B)(1 - \alpha_n)) \\
\quad - (1 - p_1) \cdots (1 - p_{n-1}) \sum_{i=1}^{n-1} (1 - \Pr(B)(1 - \alpha_n))^{i-n} \Pr(B)(1 - \alpha_n) \log i,
\end{aligned}$$

where  $v$  is the function in Definition 1.3. Put

$$\begin{aligned}
\Sigma_n^{\pm}(B) &\equiv \sum_{i=1}^{n-1} (1 - p_1(B)) \cdots (1 - p_{i-1}(B)) p_i(B) \log i \\
&\quad - (1 - p_1(B)) \cdots (1 - p_{n-1}(B)) \\
&\quad \sum_{i=1}^{n-1} (1 - \Pr(B)(1 \pm \alpha_n))^{i-n} \Pr(B)(1 \pm \alpha_n) \log i.
\end{aligned}$$

Then for all  $B \in \mathcal{T}(n)$  we have

$$\begin{aligned}
&\frac{(1 - p_1(B)) \cdots (1 - p_{n-1}(B))}{(1 - \Pr(B)(1 + \alpha_n))^{n-1}} v(\Pr(B)(1 + \alpha_n)) + \Sigma_n^+(B) \\
&< E[\log R_n \mid x_1 \cdots x_n = B] \\
&< \frac{(1 - p_1(B)) \cdots (1 - p_{n-1}(B))}{(1 - \Pr(B)(1 - \alpha_n))^{n-1}} v(\Pr(B)(1 - \alpha_n)) + \Sigma_n^-(B).
\end{aligned}$$

From Remark 2.12 we have for  $B \in \mathcal{T}(n)$

$$\begin{aligned} & \frac{1 - \sum_{\lambda \in \Lambda(B)} \Pr(B_{[1,\lambda]})}{(1 - \Pr(B))^{n-1}} v(\Pr(B)(1 + \alpha_n)) + \Sigma_n^+(B) \\ & < E[\log R_n \mid x_1 \cdots x_n = B] \\ & < \frac{1 - \sum_{\lambda \in \Lambda(B)} \Pr(B_{[1,\lambda]})}{(1 - \Pr(B))^{n-1}} v(\Pr(B)(1 - \alpha_n)) + \Sigma_n^-(B) \end{aligned}$$

and

$$\begin{aligned} & \frac{1 - \sum_{\lambda \in \Lambda(B)} \Pr(B_{[1,\lambda]})}{(1 - \Pr(B))^{n-1}} v(\Pr(B)(1 + \alpha_n)) - v(\Pr(B)) + \Sigma_n^+(B) \\ & < E[\log R_n - v(\Pr(x_1 \cdots x_n)) \mid x_1 \cdots x_n = B] \\ & < \frac{1 - \sum_{\lambda \in \Lambda(B)} \Pr(B_{[1,\lambda]})}{(1 - \Pr(B))^{n-1}} v(\Pr(B)(1 - \alpha_n)) - v(\Pr(B)) + \Sigma_n^-(B). \end{aligned}$$

By Lemma 2.17 given below we have

$$\lim_{n \rightarrow \infty} E [\log R_n(x) - v(\Pr(x_1 \cdots x_n)) \mid x_1 \cdots x_n \in \mathcal{T}(n)] = 0.$$

and

$$\lim_{n \rightarrow \infty} E [\log R_n(x) + \log P_n(x) \mid x_1 \cdots x_n \in \mathcal{T}(n)] = -\frac{\gamma}{\ln 2}.$$

By Jensen's inequality and Kac's lemma, for any  $B$  we have

$$E [\log R_n + \log P_n \mid x_1 \cdots x_n = B] \leq \log E [R_n P_n \mid x_1 \cdots x_n = B] \leq 0$$

and if we let  $\bar{d}$  be the minimal probability of a symbol,

$$E [\log R_n + \log P_n \mid x_1 \cdots x_n = B] \geq E [\log P_n \mid x_1 \cdots x_n = B] \geq n \log \bar{d}.$$

Hence by Lemma 2.3 we have

$$\lim_{n \rightarrow \infty} E [\log R_n + \log P_n] = -\frac{\gamma}{\ln 2}. \quad \square$$

**Lemma 2.17.** For sufficiently large  $n$ , if  $B \in \mathcal{T}(B)$ , then

$$|\Sigma_n^\pm(B)| < (n-1)\sqrt{d^n} \log(n-1) + (n-1)d^n(1 + \alpha_n) \log(n-1)$$

and

$$\begin{aligned} & \left| \frac{1 - \sum_{\lambda \in \Lambda(B)} \Pr(B_{[1,\lambda]})}{(1 - \Pr(B))^{n-1}} v(\Pr(B)(1 \pm \alpha_n)) - v(\Pr(B)) \right| \\ & < \frac{\eta(d^n(1 + \alpha_n))}{(1 - d^n)^{n-1}} - \frac{\log(1 - \alpha_n)}{(1 - d^n)^{n-1}} - \frac{\log d}{2} n^2 d^{n/2}, \end{aligned}$$

where  $\eta(x) = v(x) + \log(x) + \gamma/\ln 2$ .

Proof. By Remark 2.12 for  $1 \leq i < n$  we have

$$(1 - p_1(B)) \cdots (1 - p_{i-1}(B)) p_i(B) = \begin{cases} 0 & \text{if } i \notin \Lambda(B), \\ \Pr(B_{[1,i]}) & \text{if } i \in \Lambda(B). \end{cases}$$

Since if  $B \in \mathcal{T}(n)$ ,  $\Pr(B_{[1,\lambda]}) < \sqrt{\Pr(B)}$  for  $\lambda \in \Lambda(B)$ , we have

$$\begin{aligned} |\Sigma_n^\pm(B)| &\leq \sum_{i=1}^{n-1} (1 - p_1) \cdots (1 - p_{i-1}) p_i \log i \\ &\quad + (1 - p_1) \cdots (1 - p_{n-1}) \sum_{i=1}^{n-1} (1 - \Pr(B)(1 \pm \alpha_n))^{i-n} \Pr(B)(1 \pm \alpha_n) \log i \\ &< (n-1) \sqrt{\Pr(B)} \log(n-1) + (n-1) \Pr(B)(1 + \alpha_n) \log(n-1) \\ &\leq (n-1) \sqrt{d^n} \log(n-1) + (n-1) d^n (1 + \alpha_n) \log(n-1). \end{aligned}$$

Now consider the blocks of  $\mathcal{T}(n)$ . Since  $\Pr(B_{[1,\lambda]}) < \sqrt{\Pr(B)}$ , we have

$$1 - n \sqrt{\Pr(B)} < \frac{1 - \sum_{\lambda \in \Lambda(B)} \Pr(B_{[1,\lambda]})}{(1 - \Pr(B))^{n-1}} < \frac{1}{(1 - \Pr(B))^{n-1}}.$$

The function  $\eta(x) = v(x) + \log(x) + \gamma/\ln 2$  of  $x$  is monotonically increasing with  $\lim_{x \rightarrow 0} \eta(x) = 0$ . Hence

$$\begin{aligned} &\frac{1 - \sum_{\lambda \in \Lambda(B)} \Pr(B_{[1,\lambda]})}{(1 - \Pr(B))^{n-1}} v(\Pr(B)(1 \pm \alpha_n)) - v(\Pr(B)) \\ &< \frac{v(\Pr(B)(1 - \alpha_n))}{(1 - \Pr(B))^{n-1}} - v(\Pr(B)) \\ &= \frac{\eta(\Pr(B)(1 - \alpha_n))}{(1 - \Pr(B))^{n-1}} - \eta(\Pr(B)) - \frac{\log(1 - \alpha_n)}{(1 - \Pr(B))^{n-1}} \\ &\quad - \left( \frac{1}{(1 - \Pr(B))^{n-1}} - 1 \right) \left( \log \Pr(B) + \frac{\gamma}{\ln 2} \right) \\ &< \frac{\eta(\Pr(B)(1 - \alpha_n))}{(1 - \Pr(B))^{n-1}} - \frac{\log(1 - \alpha_n)}{(1 - \Pr(B))^{n-1}} - \frac{(n-1) \Pr(B)}{1 - (n-1) \Pr(B)} \log \Pr(B) \\ &< \frac{\eta(d^n(1 - \alpha_n))}{(1 - d^n)^{n-1}} - \frac{\log(1 - \alpha_n)}{(1 - d^n)^{n-1}} - \frac{n(n-1)d^n}{1 - (n-1)d^n} \log d \\ &< \frac{\eta(d^n(1 - \alpha_n))}{(1 - d^n)^{n-1}} - \frac{\log(1 - \alpha_n)}{(1 - d^n)^{n-1}} - n^2 d^n \log d \end{aligned}$$

and

$$\begin{aligned}
& \frac{1 - \sum_{\lambda \in \Lambda(B)} \Pr(B_{[1,\lambda]})}{(1 - \Pr(B))^{n-1}} v(\Pr(B)(1 \pm \alpha_n)) - v(\Pr(B)) \\
& > \left(1 - \sum_{\lambda} \Pr(B_{[1,\lambda]})\right) v(\Pr(B)(1 + \alpha_n)) - v(\Pr(B)) \\
& = \left(1 - \sum_{\lambda} \Pr(B_{[1,\lambda]})\right) \eta(\Pr(B)(1 + \alpha_n)) - \eta(\Pr(B)) \\
& \quad - \left(1 - \sum_{\lambda} \Pr(B_{[1,\lambda]})\right) \log(1 + \alpha_n) + \sum_{\lambda} \Pr(B_{[1,\lambda]}) \left(\log \Pr(B) + \frac{\gamma}{\ln 2}\right) \\
& > -\eta(\Pr(B)) - \log(1 + \alpha_n) + \frac{n}{2} \sqrt{\Pr(B)} \log \Pr(B) \\
& > -\eta(d^n) - \alpha_n + \frac{\log d}{2} n^2 d^{n/2}.
\end{aligned}$$

Hence we have

$$\left| \frac{1 - \sum_{\lambda \in \Lambda(B)} \Pr(B_{[1,\lambda]})}{(1 - \Pr(B))^{n-1}} v(\Pr(B)(1 \pm \alpha_n)) - v(\Pr(B)) \right| < A_n$$

where

$$A_n = \frac{\eta(d^n(1 + \alpha_n))}{(1 - d^n)^{n-1}} - \frac{\log(1 - \alpha_n)}{(1 - d^n)^{n-1}} - \frac{\log d}{2} n^2 d^{n/2}.$$

□

### 3. Estimation of entropy

From Theorem 1.2 ( $E[\log R_n] + \gamma/\ln 2)/n$  is close to the entropy for sufficiently large  $n$ . If  $T$  is the left-shift defined by  $(Tx)_k = x_{k+1}$ , then by the ergodicity we have  $(1/M) \sum_{0 \leq i \leq M-1} \log R_n(T^i x)$  converges to  $E[\log R_n]$  almost surely as  $M \rightarrow \infty$ . Hence we approximate the entropy by

$$H(n, M) \equiv \frac{1}{n} \left( \frac{1}{M} \sum_{0 \leq i \leq M-1} \log R_n(T^i x) + \frac{\gamma}{\ln 2} \right).$$

The conventional formula with no correction term is given by

$$H'(n, M) \equiv \frac{1}{n} \frac{1}{M} \sum_{0 \leq i \leq M-1} \log R_n(T^i x).$$

In the following we compare the effectiveness of  $H(n, M)$  and  $H'(n, M)$ .

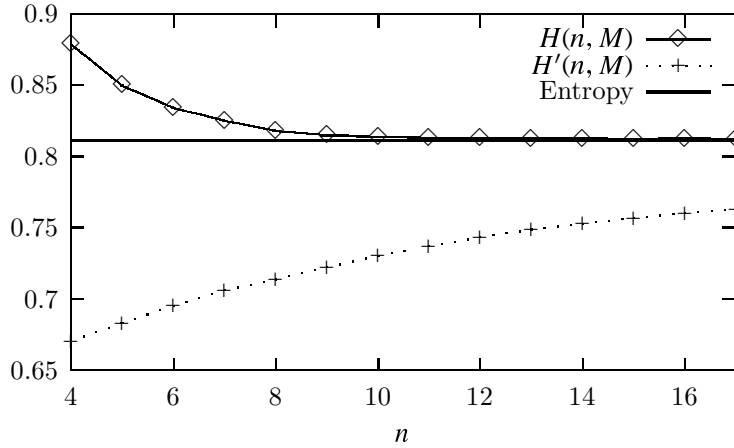


Fig. 1. Test result for Example 3.1 for  $M = 10000$ .

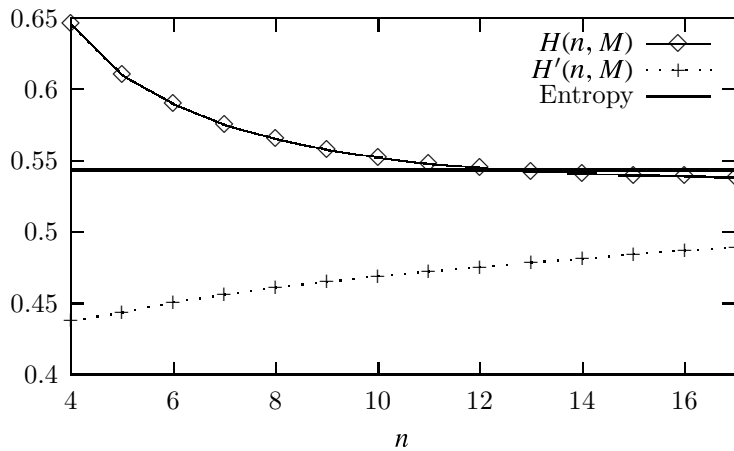


Fig. 2. Test result for Example 3.2 for  $M = 10000$ .

EXAMPLE 3.1. Consider the Bernoulli process associated with the  $(1/4, 3/4)$  product measure. Note that  $h = -1/4 \log_2(1/4) - 3/4 \log_2(3/4) = 0.811278\dots$ . For generating the typical point of Bernoulli process  $x$ , we use the random number generator employed in Fortran 90. Here  $M = 10000$  is rather large to demonstrate the accuracy of the theoretical prediction and in practical applications a sample of small size will do. The test result is given in Fig. 1.

EXAMPLE 3.2. Consider the Bernoulli process associated with the  $(1/8, 7/8)$  product measure. Note that  $h = -1/8 \log_2(1/8) - 7/8 \log_2(7/8) = 0.543564\dots$ . We test this example by the same method as before. The test result is given in Fig. 2.

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School of Mathematics  
Korea Institute for Advanced Study  
Seoul 130-722 Korea  
e-mail: kimdh@kias.re.kr