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## A refined upper bound for entropy of stochastic process

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**Abstract.** Estimation of Shannon's entropies of stochastic process from numerical simulation of long orbits is difficult. Our aim within this paper is to present a strong upper bound for the Shannon's entropy of information sources.

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**Keywords and Phrases:** Entropy, Shannon's entropy, Information source, Stochastic process, Random variable.

### 1 Introduction

Entropy and mutual information for discrete-valued random variables play important roles in information theory. The entropy actually measures the degree of irregularities of a dynamic system, and researchers have done so much to calculate this concept, which is often successful [1, 4], but numerical calculations of entropy are still difficult. Tapus and Popescu presented a strong upper bound for the classical Shannon entropy [3]. In [3, 6, 8], the authors presented a strong upper bound for the classical Shannon entropy. In [5], the authors presented the algebraic and Shannon entropies for hypergroupoids and commutative

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hypergroups, respectively, and studies their fundamental properties. In [8], the author applying Jensens inequality in information theory and we obtain some results for the Shannons entropy of random variables and Shannons entropy of stochastic process. Our purpose within this work is to present a strong upper bound for the Shannon entropy of information sources, refining recent results from the literature.

Let  $X \neq \emptyset$  be a set. Then  $(X, \mathcal{F}, \mu)$  is called measure probability space if  $\mathcal{F}$  is an  $\sigma$ -algebra of subsets of  $X$ ,  $\mu$  is a measure on  $X$ , and  $\mu(X) = 1$ . A finite set of measurable sets  $\alpha = \{A_1, \dots, A_n\}$  is called a finite partition if the following properties are fulfilled [7]:

$$\bigcup_{i=1}^n A_i = X, \quad \text{and} \quad A_i \cap A_j = \emptyset \quad \text{for every } i, j (1 \leq i \neq j \leq n).$$

For a partition  $\alpha = \{A_1, \dots, A_n\}$ , the entropy of  $\alpha$  is defined by

$$H_\mu(\alpha) := - \sum_{i=1}^n \mu(A_i) \log(\mu(A_i)).$$

**Definition 1.1.** [2] Let  $S$  be a random variable on  $X$  with discrete finite state space  $A = \{a_1, \dots, a_N\}$ . We define  $p : A \rightarrow [0, 1]$  by  $p(s) = \mu\{\omega \in X : S(\omega) = s\}$ . The Shannon's entropy of  $S$  is defined by

$$H_\mu(S) := - \sum_{s \in A, p(s) \neq 0} p(s) \log p(s).$$

A stochastic process  $\mathbf{S}$  is a sequence  $(S_n)_{n=1}^\infty$  of the random variables  $S_n : X \rightarrow A$ , where  $n \in \mathbb{N}$ . For given  $L \geq 1$  we define a mapping  $p : A^L \rightarrow [0, 1]$  by  $p(s_1^L) = \mu\{\omega \in X : S_1(\omega) = s_1, \dots, S_L(\omega) = s_L\}$ . The Shannon entropy of order  $L$  and the Shannon entropy of source  $\mathbf{S}$  are respectively defined by

$$H_\mu(S_1^L) = - \frac{1}{L} \sum_{s_1^L \in A^L} p(s_1, \dots, s_L) \log p(s_1, \dots, s_L), \quad \text{and} \quad h_\mu(\mathbf{S}) = \lim_{L \rightarrow \infty} H_\mu(S_1^L).$$

where the summation is taken over the collection  $\{s_1^L \in A^L : p(s_1^L) \neq 0\}$ . In this paper we use the symbol  $s_1^L$  instead of notation  $(s_1, \dots, s_L)$  and Let  $p(s_1^L) \neq 0$  for every  $L \in \mathbb{N}$ .

## 2 main results

In this section, we continue with a refinement of Theorem 2.1 from [8], as follows:

**Theorem 2.1.** *Let  $I = [a, b]$  be an interval,  $H : A^L \rightarrow I$  be a function, and  $f : I \rightarrow \mathbb{R}$  be a convex function, then*

$$\begin{aligned} & \sum_{s_1^L \in A^L} p(s_1^L) f(H(s_1^L)) - f\left(\sum_{s_1^L \in A^L} p(s_1^L) H(s_1^L)\right) \\ & \geq \max\{p(r_1^L) f(H(r_1^L)) + p(t_1^L) f(H(t_1^L)) + p(u_1^L) f(H(u_1^L)) \\ & \quad - (p(r_1^L) + p(t_1^L) + p(u_1^L)) f\left(\frac{p(r_1^L)H(r_1^L) + p(t_1^L)H(t_1^L) + p(u_1^L)H(u_1^L)}{p(r_1^L) + p(t_1^L) + p(u_1^L)}\right)\}, \\ & \geq \max\{p(r_1^L) f(H(r_1^L)) + p(t_1^L) f(H(t_1^L)) + p(u_1^L) f(H(u_1^L))\} \\ & \quad - (p(r_1^L) + p(t_1^L) + p(u_1^L)) f\left(\frac{p(r_1^L)H(r_1^L) + p(t_1^L)H(t_1^L) + p(u_1^L)H(u_1^L)}{p(r_1^L) + p(t_1^L) + p(u_1^L)}\right), \end{aligned}$$

where the maximum is taken over all distinct  $r_1^L, t_1^L, u_1^L \in A^L$ .

**Proof.** Choose arbitrary  $t_1^L, r_1^L, u_1^L \in A^L$ . So,

$$\begin{aligned} & f\left(\sum_{s_1^L \in A^L} p(s_1^L) H(s_1^L)\right) = f\left(\sum_{\substack{s_1^L \neq r_1^L, t_1^L, u_1^L \in A^L}} p(s_1^L) H(s_1^L)\right) \\ & \quad + (p(r_1^L) + p(t_1^L) + p(u_1^L))\left(\frac{p(r_1^L)H(r_1^L) + p(t_1^L)H(t_1^L) + p(u_1^L)H(u_1^L)}{p(r_1^L) + p(t_1^L) + p(u_1^L)}\right) \\ & \leq \sum_{\substack{s_1^L \neq r_1^L, t_1^L, u_1^L \in A^L}} p(s_1^L) f(H(s_1^L)) \\ & \quad + (p(r_1^L) + p(t_1^L) + p(u_1^L)) f\left(\frac{p(r_1^L)H(r_1^L) + p(t_1^L)H(t_1^L) + p(u_1^L)H(u_1^L)}{p(r_1^L) + p(t_1^L) + p(u_1^L)}\right). \end{aligned}$$

Therefore,

$$\begin{aligned} & \sum_{s_1^L \in A^L} p(s_1^L) f(H(s_1^L)) - f\left(\sum_{s_1^L \in A^L} p(s_1^L) H(s_1^L)\right) \\ & \geq p(r_1^L) f(H(r_1^L)) + p(t_1^L) f(H(t_1^L)) + p(u_1^L) f(H(u_1^L)) \\ & \quad - (p(r_1^L) + p(t_1^L) + p(u_1^L)) f\left(\frac{p(r_1^L)H(r_1^L) + p(t_1^L)H(t_1^L) + p(u_1^L)H(u_1^L)}{p(r_1^L) + p(t_1^L) + p(u_1^L)}\right). \end{aligned}$$

Since  $s_1^L, t_1^L \in A^L, u_1^L$  are arbitrary,

$$\begin{aligned} & \sum_{s_1^L \in A^L} p(s_1^L) f(H(s_1^L)) - f\left(\sum_{s_1^L \in A^L} p(s_1^L) H(s_1^L)\right) \\ & \geq \max\{p(r_1^L) f(H(r_1^L)) + p(t_1^L) f(H(t_1^L)) + p(u_1^L) f(H(u_1^L))\} \\ & \quad - (p(r_1^L) + p(t_1^L) + p(u_1^L)) f\left(\frac{p(r_1^L) H(r_1^L) + p(t_1^L) H(t_1^L) + p(u_1^L) H(u_1^L)}{p(r_1^L) + p(t_1^L) + p(u_1^L)}\right). \end{aligned}$$

where the maximum is taken over all distinct  $r_1^L, t_1^L, u_1^L \in A^L$ . On the other hand,

$$\begin{aligned} & f\left(\frac{p(r_1^L) H(r_1^L) + p(t_1^L) H(t_1^L) + p(u_1^L) H(u_1^L)}{p(r_1^L) + p(t_1^L) + p(u_1^L)}\right) \\ & = f\left(\frac{p(r_1^L) + p(t_1^L)}{p(r_1^L) + p(t_1^L) + p(u_1^L)} \frac{p(r_1^L) H(r_1^L) + p(t_1^L) H(t_1^L)}{p(r_1^L) + p(t_1^L)} + \frac{p(u_1^L) H(u_1^L)}{p(r_1^L) + p(t_1^L) + p(u_1^L)}\right) \\ & \leq \frac{p(r_1^L) + p(t_1^L)}{p(r_1^L) + p(t_1^L) + p(u_1^L)} f\left(\frac{p(r_1^L) H(r_1^L) + p(t_1^L) H(t_1^L)}{p(r_1^L) + p(t_1^L)}\right) \\ & \quad + \frac{p(u_1^L)}{p(r_1^L) + p(t_1^L) + p(u_1^L)} f(H(u_1^L)). \end{aligned}$$

So,

$$\begin{aligned} & (p(r_1^L) + p(t_1^L) + p(u_1^L)) f\left(\frac{p(r_1^L) H(r_1^L) + p(t_1^L) H(t_1^L) + p(u_1^L) H(u_1^L)}{p(r_1^L) + p(t_1^L) + p(u_1^L)}\right) \\ & \leq (p(r_1^L) + p(t_1^L)) f\left(\frac{p(r_1^L) H(r_1^L) + p(t_1^L) H(t_1^L)}{p(r_1^L) + p(t_1^L)}\right) + (p(u_1^L)) f(H(u_1^L)). \end{aligned}$$

Thus,

$$\begin{aligned} & p(r_1^L) f(H(r_1^L)) + p(t_1^L) f(H(t_1^L)) + p(u_1^L) f(H(u_1^L)) \\ & \quad - (p(r_1^L) + p(t_1^L) + p(u_1^L)) f\left(\frac{p(r_1^L) H(r_1^L) + p(t_1^L) H(t_1^L) + p(u_1^L) H(u_1^L)}{p(r_1^L) + p(t_1^L) + p(u_1^L)}\right) \\ & \geq p(r_1^L) f(H(r_1^L)) + p(t_1^L) f(H(t_1^L)) \\ & \quad - (p(r_1^L) + p(t_1^L)) f\left(\frac{p(r_1^L) H(r_1^L) + p(t_1^L) H(t_1^L)}{p(r_1^L) + p(t_1^L)}\right), \end{aligned}$$

which completes the proof.  $\square$

In order to present the generalization we define some notation, as follows:

$$T_k := \max\left\{\sum_{i=1}^k p(r_{i1}^L) f(H(r_{i1}^L)) - \left(\sum_{i=1}^k p(r_{i1}^L)\right) f\left(\frac{\sum_{i=1}^k p(r_{i1}^L) H(r_{i1}^L)}{\sum_{i=1}^k p(r_{i1}^L)}\right)\right\}$$

where  $2 \leq k \leq N^L - 1$ , the maximum is taken over all distinct  $r_{i1}^L \in A^L$ .

**Theorem 2.2.** *Let  $I = [a, b]$  be an interval,  $H : A^L \rightarrow I$  be a function,  $|A| = N$  and  $f : I \rightarrow \mathbb{R}$  be a convex function, then*

$$0 \leq T_2 \leq T_3 \leq \dots \leq T_{N^L-1} \leq \sum_{s_1^L \in A^L} p(s_1^L) f(H(s_1^L)) - f\left(\sum_{s_1^L \in A^L} p(s_1^L) H(s_1^L)\right).$$

**Proof.** The proof is similar to the proof of Theorem 2.1.  $\square$

### 3 The sources entropy upper bound

In this section we present a strong upper bound for the Shannon's entropy of information sources.

**Theorem 3.1.**  $h_\mu(\mathbf{S}) \leq \log N - \max_k \left\{ \lim_{L \rightarrow \infty} \frac{1}{L} \log \left[ \left\{ \frac{k}{\sum_{i=1}^k p(r_{i1}^L)} \right\}^{\sum_{i=1}^k p(r_{i1}^L)} \right] \times \left[ \prod_{i=1}^k \{p(r_{i1}^L)\}^{p(r_{i1}^L)} \right] \right\}$

**Proof.** Since

$$\begin{aligned} -LH_\mu(S_1^L) + \log(N^L) &\geq \max_k \left\{ -\sum_{i=1}^k p(r_{i1}^L) \log\left(\frac{1}{p(r_{i1}^L)}\right) + \left(\sum_{i=1}^k p(r_{i1}^L)\right) \right. \\ &\quad \times \log\left(\frac{k}{\sum_{i=1}^k p(r_{i1}^L)}\right) \left. \right\} = \max_k \left\{ \log\left(\prod_{i=1}^k \{p(r_{i1}^L)\}^{p(r_{i1}^L)}\right) \right. \\ &\quad \left. + \log\left[\left\{ \frac{k}{\sum_{i=1}^k p(r_{i1}^L)} \right\}^{\sum_{i=1}^k p(r_{i1}^L)}\right] \right\}, \end{aligned}$$

$$\log N - H_\mu(S_1^L) \geq \max\left\{\frac{1}{L} \log \left[ \left\{ \frac{k}{\sum_{i=1}^k p(r_{i1}^L)} \right\}^{\sum_{i=1}^k p(r_{i1}^L)} \right] \left[ \prod_{i=1}^k \{p(r_{i1}^L)\}^{p(r_{i1}^L)} \right] \right\},$$

and

$$H_\mu(S_1^L) \leq \log N - \max_k \left\{ \frac{1}{L} \log \left[ \left\{ \frac{k}{\sum_{i=1}^k p(r_{i1}^L)} \right\}^{\sum_{i=1}^k p(r_{i1}^L)} \right] \left[ \prod_{i=1}^k \{p(r_{i1}^L)\}^{p(r_{i1}^L)} \right] \right\}.$$

Therefore,

$$\begin{aligned} h_\mu(\mathbf{S}) &\leq \log N - \lim_{L \rightarrow \infty} \max_k \left\{ \frac{1}{L} \log \left[ \left\{ \frac{k}{\sum_{i=1}^k p(r_{i1}^L)} \right\}^{\sum_{i=1}^k p(r_{i1}^L)} \right] \left[ \prod_{i=1}^k \{p(r_{i1}^L)\}^{p(r_{i1}^L)} \right] \right\} \\ &\leq \log N - \max_{2 \leq k \leq N^L-1} \left\{ \lim_{L \rightarrow \infty} \frac{1}{L} \log \left[ \left\{ \frac{k}{\sum_{i=1}^k p(r_{i1}^L)} \right\}^{\sum_{i=1}^k p(r_{i1}^L)} \right] \left[ \prod_{i=1}^k \{p(r_{i1}^L)\}^{p(r_{i1}^L)} \right] \right\}. \end{aligned}$$

□

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