

A CHARACTERIZATION OF A NEW SOURCE ENTROPY

B. FORTE (*) and C.C.A. SASTRI (**)

Abstract. A new source entropy was introduced recently² and was shown, for discrete memoryless channels, to be an improvement over the classical one. It is shown here that this new entropy can be characterized by certain simple and natural properties.

Classically, in communication theory, source entropy (for any channel) is defined as follows: if H_n denotes the uncertainty associated with a message of length n , then the source entropy is

$H_\infty \equiv \lim_{n \rightarrow \infty} \frac{H_n}{n}$. A new source entropy was introduced recently in

[2]: Let p_n ($n=0,1,2,\dots$) be the probability that a message is of length n and h_n the uncertainty associated with a message given

(*) Department of Applied Mathematics, University of Waterloo, Waterloo, Ontario, Canada, M2L 3G1, research supported by NSERC grant # A7677.

(**) Department of Mathematics, Statistics and Computing Science, Dalhousie University, Halifax, Nova Scotia, Canada, B3H 4H8, research supported by NSERC grant # A4825.

that it is of length n . Then the source entropy is

$$I \equiv \frac{\sum_n H_n p_n}{\sum_n n p_n}$$

We characterize this entropy, in effect, by characterizing the numerator, namely $\sum_n H_n p_n$. (Alternatively, one can regard $\sum_n H_n p_n$ as the source entropy and I as the source entropy per unit length of the message).

In practice all messages, however long, are finite. The limit of $\frac{H_n}{n}$ as $n \rightarrow \infty$ has been used because, a priori, the length of a message is unknown but could be large. For practical purposes, H_n is often replaced by $\frac{H}{n}$ for some maximal n . In that case, I gives the same result if $p_n = 1$ for the maximal n and 0 otherwise.

The principal advantage in adopting I for the source entropy instead of H_∞ is the following². Using the notation of [1], consider a message of length n consisting of letters from an alphabet of size M . Define $\langle P_e(n) \rangle$, the average probability of error per unit length in such a message by

$$\langle P_e(n) \rangle = \frac{1}{n} P_e(n) \equiv \frac{1}{n} \sum_{i=1}^n P_e(i, n),$$

where $P_e(i, n)$ denotes the probability of an error in the i^{th} position. Then define the average probability $\langle P \rangle$ of error per unit

length (in an arbitrary message) by $\langle P_e \rangle = \lim_{n \rightarrow \infty} \langle P_e(n) \rangle$. An example was given in [2] to show that this limit does not always exist. If, however, the average probability of error per unit length is defined

by $\frac{E(P_e(n))}{E(n)}$, where E denotes expectation, then it exists whenever

$E(n) < \infty$. (The statistics collected from past experience can be used to estimate the probabilities used in computing these expectations.)

For a discrete memoryless channel, replacement of $\langle P_e \rangle$ by $\frac{E(P_e(n))}{E(n)}$

and of H_∞ by I yields a better lower bound in the classical Fano inequality¹

$$\langle P_e \rangle \log(M-1) + H(P_e) \geq H_\infty - \frac{\tau_s}{\tau_c} C,$$

where C is the capacity of the channel, H the two-event Shannon entropy, τ_s the time interval between source letters, and τ_c the interval between channel letters. For details, the reader is referred to [2].

The aim of this note is to show that the new definition is not ad hoc and in fact that it has certain "natural" properties which, conversely, characterize this new entropy. This is achieved by appealing twice to a theorem, proved in [3], characterizing the entropy associated with a random vector. A statement and explanation of the theorem follows.

Let $X = (X_1, X_2, \dots, X_n)$ be a random vector with real components.

Suppose that X_1, X_2, \dots, X_n are discrete random variables s.t. the range of X_i is $(a_{i1}, a_{i2}, \dots, a_{im_i})$. Denote the collection of ranges

by $X^{(n)} = ((a_{i1}, a_{i2}, \dots, a_{im_i}), i=1, 2, \dots, n)$. Let the joint

probability distribution be $\Pi_{X^{(n)}} \in \Gamma_{m_1 m_2 \dots m_n}$, where

$$\Gamma_{m_1 m_2 \dots m_n} \equiv \{ \pi_{j_1 j_2 \dots j_n}, j_i = 1, 2, \dots, m_i, i=1, 2, \dots, n \}$$

$$\pi_{j_1 j_2 \dots j_n} \geq 0; \sum_{j_1 j_2 \dots j_n} \pi_{j_1 j_2 \dots j_n} = 1 \}$$

Let $I_{m_1 m_2 \dots m_n}^{(n)}(X^{(n)}; \Pi_{X^{(n)}})$ denote the entropy associated with X ,

i.e., the uncertainty about which values its components take. Observe that this uncertainty can be regarded as the uncertainty associated with a message of length n , the i th character of which can be any one of an alphabet of m_i characters. To establish the correspondence, we need only set $a_{i,j} = j_i$ iff the i th character of the message is the j_i th character of the i th alphabet. Observe also that this entropy is quite general in the sense that it could depend not only on the probability distribution $\Pi_{X^{(n)}}$ but also on the range $X^{(n)}$ (the actual content for messages) and the sizes of the ranges of the components of X (the lengths of the alphabets for messages). Consider now the following properties for the entropy:

1. SUB-ADDITIVITY

$$I_{m_1 m_2 \dots m_n}^{(n)}(X^{(n)}; \Pi_{X^{(n)}}) \leq I_{m_1 m_2 \dots m_k}^{(k)}(X^{(k)}; \Pi_{X^{(k)}}) +$$

$$+ I_{m_{k+1} \dots m_n}^{(n-k)}(X^{(n-k)}; \Pi_{X^{(n-k)}})$$

where $\Pi_{X^{(k)}}$ and $\Pi_{X^{(n-k)}}$ are marginal distributions of $\Pi_{X^{(n)}}$ defined in the usual manner,

$$X^{(k)} = \{(a_{i1}, a_{i2}, \dots, a_{im_i}) \quad , \quad i = 1, 2, \dots, k\}$$

$$X^{(n-k)} = \{(a_{i1}, a_{i2}, \dots, a_{im_i}) \quad , \quad i = k+1, \dots, n\}$$

This property means that if a message of length n is divided into two blocks, one of length k and the other of length $n-k$, then the uncertainty about the full message cannot be bigger than the sum of the uncertainties about the two blocks. If, however, the two blocks are independent, the uncertainties should add up, i.e. the entropy should have the following property.

2. ADDITIVITY

$$I_{m_1 m_2 \dots m_n}^{(n)}(X^{(n)}; \Pi_{X^{(n)}}) = I_{m_1 m_2 \dots m_k}^{(k)}(X^{(k)}; \Pi_{X^{(k)}}) +$$

$$I_{m_{k+1} \dots m_n}^{(n-k)}(X^{(n-k)}; \Pi_{X^{(n-k)}})$$

whenever the distribution $\Pi_{X^{(n)}}$ is the product of its marginals

$$\Pi_X(k) \quad \text{and} \quad \Pi_X(n-k)$$

3. LOCAL SYMMETRY

For any positive integer s , let $X^{(2s)} = \{(a_{i1}, \dots, a_{im_i}), i = 1, 2, \dots, 2s\}$, $X^{(s)} = \{(a_{i1}, \dots, a_{im_i}), i=1, 2, \dots, s\}$; $X'^{(s)} = \{(a_{i1}, a_{i2}, \dots, a_{im_i}), i=s+1, \dots, 2s\}$. Let $a_{i+s,k} = a_{i,k}$ ($i=1, 2, \dots, k = 1, 2, \dots, m_i$) and assume that $X^{(s)}$ and $X'^{(s)}$ are independent.

Then

$$I_{m_1 m_2 \dots m_s m_1 m_2 \dots m_s}^{(2s)}(X^{(2s)}; \Pi_X^{(2s)}) = I_{m_1 m_2 \dots m_s m_1 m_2 \dots m_s}^{(2s)}(X^{(2s)}; \Pi_X^{T(\vec{h}, \vec{k})}),$$

where $\vec{h} = (h_1, h_2, \dots, h_s)$, $\vec{k} = (k_1, k_2, \dots, k_s)$ ($1 \leq h_i, k_i \leq m_i$)

and $\Pi_X^{T(\vec{h}, \vec{k})}$ is obtained from $\Pi_X^{(2s)}$ by interchanging the entries

$$\pi_{h_1 h_2 \dots h_s k_1 k_2 \dots k_s} \quad \text{and} \quad \pi_{k_1 k_2 \dots k_s h_1 h_2 \dots h_s}$$

This property is a technical necessity, but it can be motivated in commutation theory as follows. Suppose that the sender of the message is a spy who has infiltrated enemy territory and that the receiver is his employer. Suppose there is an understanding between them that whenever he sends a specific message it is meant to be another specific message (of the same length). Clearly then the interchange of these messages should not affect the uncertainty.

4. BOUNDEDNESS.

For each $q \in [0, 1]$, let

$$\Pi'_X(n) = \{ \pi_{j_1 j_2 \dots j_n} \pi_{h_1 h_2 \dots h_n} = q, \pi_{k_1 k_2 \dots k_n} = 1-q \text{ and } \pi_{j_1 j_2 \dots j_n} = 0 \text{ otherwise} \}.$$

For fixed $X^{(n)}$, let $f_{h_1 h_2 \dots h_n k_1 k_2 \dots k_n}^{(n)}(q)$ denote the function

that takes q to $I_{m_1 m_2 \dots m_n}^{(n)}(X^{(n)}; \Pi'_X(n))$. Intuitively, we expect that

$$f_{h_1 h_2 \dots h_n k_1 k_2 \dots k_n}^{(n)}(0) = f_{h_1 h_2 \dots h_n k_1 k_2 \dots k_n}^{(n)}(1) = 0. \text{ We shall require that there exist}$$

real numbers $M_{h_1 \dots h_n k_1 \dots k_n}^{(n)}$

$$f_{h_1 h_2 \dots h_n k_1 k_2 \dots k_n}^{(n)}(q) \geq M_{h_1 h_2 \dots h_n k_1 k_2 \dots k_n}^{(n)} \quad \forall q \in [0, 1].$$

This regularity property is a technical necessity

THEOREM³. If and only if $I_{m_1 m_2 \dots m_n}^{(n)}(X^{(n)}; \Pi_X(n))$ has Properties

1-4, it has the following form:

$$I_{m_1 m_2 \dots m_n}^{(n)}(X^{(n)}; \Pi_X(n)) = -A \sum_{j_1 j_2 \dots j_n} \pi_{j_1 j_2 \dots j_n} \log \pi_{j_1 j_2 \dots j_n} + \sum_{i=1}^j B_i (a_{i1}, a_{i2}, \dots, a_{ij})$$

$$(X^{(n)}; S)$$

where A is a non-negative constant, the B_i 's are arbitrary real-valued

lued fiinctions of their arguments and

$$\text{Supp } (\mathbb{E}_{X^{(n)}}) = \{(j_1, j_2, \dots, j_n) \mid \pi_{j_1 j_2 \dots j_n} > 0,$$

$$p_{j_1}^{(i)} = \sum_{j_1} \sum_{j_2} \dots \sum_{j_{i-1}} \sum_{j_{i+1}} \dots \sum_{j_n} \tilde{p}_{j_1 j_2 \dots j_n}$$

$\tilde{G}^{(n)}$ being a function of its arguments that satisfies 1-3.

Now consider a source which sends messages of arbitrary but finite length.

Let P_i denote the probability that the length of a message will be i and let H_i denote the uncertainty associated with a message given that it is of length i . Let

$$H^{(1)} = \{H_1, H_2, \dots\}$$

$$P^{(1)} = \{P_1, P_2, \dots\}$$

It is natural to assume that the source entropy $I^{(1)}$ for such a source depends on $H^{(1)}$ and $P^{(1)}$ — indeed, it can be regarded as the uncertainty associated with the random variable which takes the values H_1, H_2, \dots with probabilities P_1, P_2, \dots . Thus the source entropy $I^{(1)}(P^{(1)}; H^{(1)})$ is an example of the kind of entropy characterized by the above theorem. Moreover, properties 1-4 become meaningful for such an entropy when suitably interpreted. For example, sub-additivity means that if there are two sources sending messages — say, two spies — and one regards them together as a single source, then the source entropy of the composite source should not exceed the sum of the source entropies of the constituent sources, with equality holding when the two sources are independent (and

ditivity). Similarly, local symmetry means invariance under the interchange of sources in specific instances. Finally, boundedness on one side is a weak regularity property — in fact it would be reasonable to assume that the source entropy is non-negative. All these properties could be written down explicitly, but we shall not do so for the sake of brevity.

It follows then from the characterization theorem — with obvious changes in notation — that

$$I^{(1)}(P^{(1)}; H^{(1)}) = -A \sum_i P_i \log P_i + \sum_i B_i(B_1, H_2, \dots) P_i + G(H_1, H_2, \dots; \text{Supp } (P^{(1)}))$$

Suppose that in addition to properties 1-4, $I^{(1)}(P^{(1)}; H^{(1)})$ has the following two properties:

5. If $P_j = 0 \forall j \neq i$ and $P_i = 1$, $I^{(1)}(P^{(1)}, H^{(1)}) = H_i$

6. If $P_1 = \frac{1}{2}$, $P_2 = \frac{1}{2}$, $H_1 = H_2$, $P_i = 0 \forall i \neq 1, 2$ then

$$I^{(1)}(P^{(1)}, H^{(1)}) = H_1$$

Property 5 implies that $H_i = B_i(H_1, H_2, \dots) + G$.

Hence

$$\sum_i B_i P_i + G = \sum_i (B_i + G) P_i = \sum_i H_i P_i$$

so

$$I^{(1)}(P^{(1)}; H^{(1)}) = -A \sum_i P_i \log P_i + \sum_i H_i P_i$$

Property 6 gives

$$H_1 = -A \log 2 + H_1$$

which implies that $A=0$. Thus we have

$$I^{(1)}(P^{(1)}; H^{(1)}) = \sum_n H_n P_n$$

The conditional entropies H_n can themselves be characterized by properties 1-4 plus a few additional ones. For instance, in order to recover the Shannon entropy, we shall assume the following in addition to properties 1-4:

7. H_n depends only on the distribution $\Pi_X^{(n)}$ and not on the content $X^{(n)}$.

8. For $1 \leq h, k_i \leq m_i, 1 \leq i \leq n$,

$$\lim_{q \rightarrow 0^+} f_{h_1 h_2 \dots h_n k_1 k_2 \dots k_n}^{(n)}(q) = 0 = f_{h_1 h_2 \dots h_n k_1 k_2 \dots k_n}^{(n)}(0)$$

Observe that property 8 is a continuity property traditionally used to eliminate the Hartley entropy.

Now properties 1-4 and 7 imply that

$$H = -A \sum_{j_1 j_2 \dots j_n} \pi_{j_1 j_2 \dots j_n} \log \pi_{j_1 j_2 \dots j_n} + \sum_{i=1}^n \sum_{j_i=1}^{m_i} B_{j_i} P_{j_i}^{(i)} + G^{(n)}(\text{Supp}(\Pi_X^{(n)}))$$

where the B_{j_i} are arbitrary constants and $G^{(n)}$ is a function of the specified argument that satisfies 1-3. In particular we have

$$f_{h_1 h_2 \dots h_n k_1 k_2 \dots k_n}^{(q)} = -A(q \log q + (1-q) \log(1-q))$$

$$+ \sum_{r=1}^n (B_{h_r} - B_{k_r}) q + \sum_{s=1}^n B_{k_s} + G^{(n)}((h_1, h_2, \dots, h_n), (k_1, k_2, \dots, k_n))$$

Property 8 then gives

$$0 = \sum_{s=1}^n B_{k_s} + G^{(n)}((h_1, h_2, \dots, h_n), (k_1, k_2, \dots, k_n)).$$

Since this must be true for every choice of (h_1, h_2, \dots, h_n) and (k_1, k_2, \dots, k_n) , $G^{(n)}$ must be a constant for each n , and

$$B_{k_s} = \text{const.} =: B, \quad s = 1, 2, \dots, n, \quad k_s = 1, 2, \dots, m_s$$

Hence $G^{(n)}(\text{Supp}(\Pi_{X^{(n)}})) = -nB$, whenever the cardinality of

$\text{Supp}(\Pi_{X^{(n)}})$ is 1 or 2.

Let $\Pi'_{X^{(n)}}$ and $\Pi''_{X^{(n)}}$ be any two probability distributions on the same $X^{(n)}$

Let

$$C := \text{Sup}(\Pi'_{X^{(n)}}) \cap \text{Supp}(\Pi''_{X^{(n)}})$$

$$D' := \text{supp}(\Pi'_{X^{(n)}}) / C$$

$$D'' := \text{supp}(\Pi''_{X^{(n)}}) / C.$$

By imposing properties 2, 3 and 1 in that order on $G^{(n)}(\text{Supp}(\Pi_{X^{(n)}}))$

with a standard technique³ we obtain

$$G^{(n)}(D') - G^{(n)}(D' \cup D'') \leq G^{(n)}(D \cup D') - G^{(n)}(C \cup D'') \leq G^{(n)}(D' \cup D'') - G^{(n)}(D'')$$

By choosing $\Pi'_{X^{(n)}}$ and $\Pi''_{X^{(n)}}$ so that D' and D'' have cardinality 1,

$$G^{(n)}(C \cup D') - G^{(n)}(C \cup D'') = 0.$$

Hence $G^{(n)}(\text{Supp}(\Pi_{X^{(n)}}))$ depends only on the cardinality of $\text{Supp}(\Pi_{X^{(n)}})$. By choosing $\Pi''_{X^{(n)}}$ so that $D'' = \emptyset$ one can recognize that $G^{(n)}(\text{Supp}(\Pi_{X^{(n)}}))$ is a non-decreasing function of the cardinality of $\text{Supp}(\Pi_{X^{(n)}})$. A last recourse to additivity yields

$$G^{(n)}(\text{Supp}(\Pi_{X^n})) = -nB$$

for all possible values of the cardinality of $\text{Supp}(\Pi_{X^n})$.

Hence

$$\begin{aligned} H &= -A \prod_{j_1 j_2 \dots j_n}^{\Sigma} \pi_{j_1 j_2 \dots j_n} \log \pi_{j_1 j_2 \dots j_n} + nB + G^{(n)}(\text{Supp}(\Pi_{X^{(n)}})) \\ &= -A \prod_{j_1 j_2 \dots j_n}^{\Sigma} \pi_{j_1 j_2 \dots j_n} \log \pi_{j_1 j_2 \dots j_n} \end{aligned}$$

Acknowledgement. We wish to thank an anonymous referee for making certain remarks which led to a clarification of the original paper

REFERENCES

- [1] R.G.GALLAGER: "*Information Theory and Reliable Communication*", John Wiley and Sons, New York (1968).
- [2] B.FORTE and A.CIAMPI: "*Source Entropy for Messages of Random Length*", to appear in *Rendiconti di Matematica* in 1982.
- [3] B.FORTE and M.LO SCHIAVO: "*Non-Expansible, Additive and Subadditive Entropies for a Random Vector*", submitted to *Utilitas Mathematica*.

*Lavoro pervenuto alla Redazione il 30 Luglio 1982
ed accettato per la pubblicazione il 18 Maggio 1983
su parere favorevole di G. Andreassi e P. Benvenuti*