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## ON THE STRONG CONVERSE OF THE CODING THEOREM FOR SYMMETRIC CHANNELS WITHOUT MEMORY<sup>1</sup>

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**1. Introduction.** First we describe the channels we will discuss in this paper. The alphabet in which we send words contains just two letters, which we denote by 0, 1. Thus a sent word of length  $n$  is a sequence of  $n$  letters, each letter being a zero or a one. If we send the word  $(x_1, \dots, x_n)$ , then the received word is  $(Y_1, \dots, Y_n)$ , where  $Y_1, \dots, Y_n$  are independent chance variables, the probability distribution of  $Y_i$  depending only on the value of the parameter  $x_i$ . If there are just two possible values for  $Y_i$ , which we can assume are 0, 1, the channel is called a "binary channel." If  $Y_i$  has a probability density function whether  $x_i$  is zero or one, the channel is called a "semi-continuous channel." For a binary channel,  $f_{x_i}(y)$  denotes  $P(Y_i = y, \text{ when the } i\text{th letter sent is } x_i)$ . For a semi-continuous channel,  $f_{x_i}(y)$  denotes the probability density function of  $Y_i$  when the  $i$ th letter sent is  $x_i$ .

A binary channel is called "symmetric" if  $f_0(0) = f_1(1)$  (and therefore  $f_0(1) = f_1(0)$ ). A semi-continuous channel is called "symmetric" if the probability distribution of  $2[f_0(Y) + f_1(Y)]^{-1}f_0(Y)$  when  $Y$  has the probability density function  $f_0(y)$  is the same as the probability distribution of  $2[f_0(Y) + f_1(Y)]^{-1}f_1(Y)$  when  $Y$  has the probability density function  $f_1(y)$ .

A code of length  $L$ , word length  $n$ , and probability of error not greater than  $\lambda$  is a sequence of  $L$  pairs  $(u_1, A_1), \dots, (u_L, A_L)$  with the following properties:

- (a) For each  $i$ ,  $u_i$  is a sequence of zeros and ones,  $n$  symbols altogether;
- (b) For each  $i$ ,  $A_i$  is a collection of words of length  $n$ , each being a possible received word in the particular problem under consideration;
- (c) For each  $i$ , when  $u_i$  is the sent word,  $P((Y_1, \dots, Y_n) \text{ is in } A_i) \geq 1 - \lambda$ ;
- (d) The sets  $A_1, \dots, A_L$  are disjoint.

The use of such a code is well known. If the received word is in  $A_i$ , the receiver assumes that the word  $u_i$  was actually sent. Then, no matter which of the words  $u_1, \dots, u_L$  is sent, the probability that the receiver will be in error is not greater than  $\lambda$ .

A "converse to the coding theorem" is an inequality giving an upper bound for  $L$ , or, alternatively, for  $\log_2 L$ . (In this paper, each log is to the base  $e$ , unless another base is explicitly indicated.) Since several types of converse have appeared in the literature, it seems worthwhile to classify them carefully. The following classification seems useful.

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$C$  denotes the capacity of the channel as defined in Feinstein [2]. A “weak converse” states the following. For any fixed  $\epsilon > 0$ , there is a positive value  $Z$ , such that there cannot exist a code of length  $2^{n(C+\epsilon)}$  and probability of error not greater than  $Z$ , for large  $n$ . A “strong converse” states the following. For any fixed  $\epsilon > 0$ , and any fixed  $\lambda$  in the open interval  $(0, 1)$ , there cannot exist a code of length  $2^{n(C+\epsilon)}$  and probability of error not greater than  $\lambda$ , for  $n$  large. A “stronger converse” states the following. For any fixed  $\lambda$  in the open interval  $(0, 1)$ , there is a constant  $K_\lambda$  such that there cannot exist a code of length  $2^{n(C+K_\lambda n^{1/2})}$  and probability of error not greater than  $\lambda$ , for large  $n$ .

Clearly, each of the converses listed is stronger than its predecessors. An interesting weak converse applicable to many types of channels is given in Theorem 5 of [3]. Wolfowitz [4] has proved the stronger converse for a binary channel, with  $K_\lambda$  a positive constant, and [5] has proved the strong converse for a semi-continuous channel. It is the purpose of the present paper to show that for both binary symmetric channels and semi-continuous symmetric channels, the stronger converse can be proved with  $K_\lambda$  a negative constant if  $\lambda < \frac{1}{2}$ . This makes the converse still stronger.

We define  $\beta_\lambda$  by the equation

$$\int_{-\infty}^{\beta_\lambda} (2\pi)^{-1/2} \exp(-\frac{1}{2}t^2) dt = 1 - \lambda.$$

Then if  $\lambda < \frac{1}{2}$ ,  $\beta_\lambda > 0$ .

**2. The binary symmetric channel.** We denote the common value of  $f_0(0)$  and  $f_1(1)$  by  $q$ , and  $1 - q$  by  $p$ . We assume that  $q$  is in the open interval  $(\frac{1}{2}, 1)$ . The capacity  $C$  for this channel is  $1 + p \log_2 p + q \log_2 q$ .

We have the following theorem. *For any  $\delta > 0$ , there is a number  $n_\delta$  such that if  $n > n_\delta$ , then the length  $L$  of any code of word length  $n$  and probability of error not greater than  $\lambda$  must satisfy the inequality  $\log_2 L < nC - n^{1/2} [\beta_\lambda(pq)^{1/2} \log_2(q/p) - \delta]$ .*

*Proof.* If the word  $u_i$  is sent, the most probable received word is  $u_i$  itself, with probability  $q^n$ ; the  $\binom{n}{1}$  words differing from  $u_i$  in exactly one letter are tied for next most probable received word, each having probability  $pq^{n-1}$ ; the  $\binom{n}{2}$  words differing from  $u_i$  in exactly two letters are tied for next most probable received word, each having probability  $p^2q^{n-2}$ ; etc.

We define  $K$  as the largest integer such that

$$\sum_{j=0}^K \binom{n}{j} p^j q^{n-j} \leq 1 - \lambda. \tag{1}$$

Denote by  $M_i$  the number of words in  $A_i$ . Then we must have

$$M_i \geq \sum_{j=0}^K \binom{n}{j},$$

since even the  $\sum_{j=0}^K \binom{n}{j}$  which are the most probably received words have a total probability no greater than  $1 - \lambda$ .

Since there are  $2^n$  different words of length  $n$ , and since  $A_1, \dots, A_L$  are disjoint, we have

$$2^n \geq \sum_{i=1}^L M_i \geq L \sum_{j=0}^K \binom{n}{j}, \quad \text{or} \quad L \leq 2^n / \sum_{j=0}^K \binom{n}{j} < 2^n / \binom{n}{K}.$$

Since on the left-hand side of (1) we are summing binomial probabilities, and since the binomial distribution approaches the normal distribution as  $n$  increases, we have by the central-limit theorem that  $K = np + \beta(n, \lambda) (npq)^{1/2}$ , where for any given positive value  $\Delta$ , a number  $n_\Delta$  can be found such that if  $n > n_\Delta$ , then  $\beta_\lambda - \Delta \leq \beta(n, \lambda) \leq \beta_\lambda + \Delta$ . We denote  $\beta(n, \lambda) (pq)^{1/2}$  by  $B$ . Then  $K = np + Bn^{1/2}$ , where for  $n > n_\Delta$ ,  $(\beta_\lambda - \Delta) (pq)^{1/2} \leq B \leq (\beta_\lambda + \Delta) (pq)^{1/2}$ .

Now

$$1 / \binom{n}{K} = K!(n - K)!/n!,$$

and using Stirling's inequalities  $r^r (2\pi r)^{1/2} \exp(-r) < r! < r^r (2\pi r)^{1/2} \exp(-r + 1/12r)$ , we find

$$1 / \binom{n}{K} < \frac{K^K (2\pi K)^{1/2} \exp(-K + 1/12K) (n - K)^{n - K} [2\pi(n - K)]^{1/2} \exp\{-n + K + 1/12(n - K)\}}{n^n (2\pi n)^{1/2} \exp(-n)}. \tag{2}$$

Setting  $K = np + Bn^{1/2}$ , simplifying the right-hand side of (2), and taking logs, we get

$$-\log \binom{n}{K} < \frac{1}{2} \log(2\pi n) + \frac{1}{12[npq + Bn^{1/2}(q - p) - B^2]} + (np + Bn^{1/2} + \frac{1}{2}) \log(p + Bn^{-1/2}) + (nq - Bn^{1/2} + \frac{1}{2}) \log(q - Bn^{-1/2}). \tag{3}$$

Expanding  $\log(p + Bn^{-1/2})$  and  $\log(q - Bn^{-1/2})$  around  $p$  and  $q$  respectively, and substituting into (3), we get

$$-\log \binom{n}{K} < n(p \log p + q \log q) - n^{1/2} B \log(q/p) + \Omega \log n, \tag{4}$$

where  $\Omega$  is a positive constant which does not depend on  $n$ . Converting the logarithms in (4) to the base 2, we find

$$-\log_2 \binom{n}{K} < n(p \log_2 p + q \log_2 q) - n^{1/2} [B \log_2(q/p) - \Omega n^{-1/2} \log_2 n].$$

Then

$$\log_2 L < n(1 + p \log_2 p + q \log_2 q) - n^{1/2} [B \log_2(q/p) - \Omega n^{-1/2} \log_2 n].$$

If

$$n > n_\Delta, \log_2 L < nC - n^{1/2} [\beta_\lambda (pq)^{1/2} \log_2(q/p) - \Delta (pq)^{1/2} \log_2(q/p) - \Omega n^{-1/2} \log_2 n].$$

This proves the theorem, since  $\Delta$  can be taken as close to zero as desired, and  $n^{-1/2} \log_2 n$  approaches zero as  $n$  increases.

**3. A theorem of Cramér.** Before discussing the semi-continuous channel, we quote a theorem of Cramér, [1], which will be used later.

$Z_1, Z_2, \dots$  are independent, identically distributed chance variables, each with

probability density function  $v(z)$ , expectation zero, and finite positive variance  $\sigma^2$ . There is a value  $A > 0$  such that

$$R(h) = \int_{-\infty}^{\infty} \exp(hz)v(z) dz \quad \text{converges for } |h| < A.$$

$m(h)$  denotes the first derivative of  $\log R(h)$  with respect to  $h$ , and  $\sigma_1^2(h)$  denotes the second derivative of  $\log R(h)$  with respect to  $h$ . We define  $A_1$  as  $\sup \{h \mid R(h) \text{ converges}\}$ . From our assumption,  $A_1$  is positive and may be infinite.  $M$  is defined as  $\sigma^{-1} \lim_{h \rightarrow A_1, 0} m(h)$ .  $M$  is positive and may be infinite.

*Theorem.* For any value  $g$  in the open interval  $(0, M)$ , the equation  $m(h) = \sigma g$  has a unique root  $h(g)$ , which is positive.  $P(Z_1 + \dots + Z_n \geq \sigma gn) =$

$$n^{-1/2} [\{h(g)\sigma_1(h(g))(2\pi)^{1/2}\}^{-1} + Q(n, g)] \exp \{-n[h(g)m(h(g)) - \log R(h(g))]\},$$

where for any values  $\gamma_1, \gamma_2$  with  $0 < \gamma_1 < \gamma_2 < M$ , there is a positive finite value  $B(\gamma_1, \gamma_2)$  with  $n \mid Q(n, g) \mid < B(\gamma_1, \gamma_2)$  for all  $g$  in the closed interval  $[\gamma_1, \gamma_2]$ .

**4. The semi-continuous symmetric channel.** We assume that

$$\int_{-\infty}^{\infty} \frac{1}{2}(f_0(y) + f_1(y)) [\log \{2[f_0(y) + f_1(y)]^{-1} f_0(y)\}]^2 dy$$

exists. Also, for any value  $y$  for which  $f_0(y) = f_1(y) = 0$ , we consider  $2[f_0(y) + f_1(y)]^{-1} f_i(y)$  as zero for  $i = 0, 1$ , and  $0 \log^k 0$  is always to be considered as equal to zero, for any positive  $k$ . The capacity  $C$  for the semi-continuous symmetric channel is

$$\int_{-\infty}^{\infty} f_0(y) \log_2 \{2[f_0(y) + f_1(y)]^{-1} f_0(y)\} dy.$$

For any given sequence  $(x_1, \dots, x_n)$  of zeros and ones,  $W(x_1, \dots, x_n)$  denotes a subset of  $(Y_1, \dots, Y_n)$  space such that

(a)  $P((Y_1, \dots, Y_n) \text{ is in } W(x_1, \dots, x_n)) \geq 1 - \lambda$ , when the joint probability density function of  $Y_1, \dots, Y_n$  is  $f_{x_1}(y_1) f_{x_2}(y_2) \dots f_{x_n}(y_n)$ ;

(b)  $P((Y_1, \dots, Y_n) \text{ is in } W(x_1, \dots, x_n))$  is minimized when the joint probability density function of  $Y_1, \dots, Y_n$  is

$$\prod_{i=1}^n [\frac{1}{2}(f_0(y_i) + f_1(y_i))],$$

subject to (a). Then it is clear that the probability in (a) will be exactly  $1 - \lambda$ . We want to find the value of the probability in (b), which we denote by  $P^*$ .

By the familiar Neyman-Pearson lemma, the region  $W(x_1, \dots, x_n)$  is given by the set of points  $(Y_1, \dots, Y_n)$  with

$$\prod_{i=1}^n \{2[f_0(Y_i) + f_1(Y_i)]^{-1} f_{x_i}(Y_i)\} \geq k,$$

where  $k$  is a properly chosen constant. Alternatively,  $W(x_1, \dots, x_n)$  is the set of points  $(Y_1, \dots, Y_n)$  with

$$\sum_{i=1}^n \log \{2[f_0(Y_i) + f_1(Y_i)]^{-1} f_{x_i}(Y_i)\} \geq \log k.$$

By the definition of the symmetry of the channel, the distribution of

$$\sum_{i=1}^n \log \{2[f_0(Y_i) + f_1(Y_i)]^{-1} f_{x_i}(Y_i)\}$$

when the joint probability density function of  $Y_1, \dots, Y_n$  is  $\prod_{i=1}^n f_{x_i}(y_i)$  does not depend on the sequence  $(x_1, \dots, x_n)$ . Therefore the value of  $\log k$  does not depend on the sequence  $(x_1, \dots, x_n)$ .

Also, the probability  $P^*$  does not depend on the sequence  $(x_1, \dots, x_n)$ . To show this, it suffices to show that the distribution of  $2[f_0(Y) + f_1(Y)]^{-1} f_0(Y)$  when  $Y$  has the probability density function  $\frac{1}{2}(f_0(y) + f_1(y))$  is the same as the distribution of  $2[f_0(Y) + f_1(Y)]^{-1} f_1(Y)$  when  $Y$  has the probability density function  $\frac{1}{2}(f_0(y) + f_1(y))$ . The  $t$ th moments of these expressions are respectively

$$\int_{-\infty}^{\infty} 2^{t-1} [f_0(y) + f_1(y)]^{-t+1} f_0'(y) dy, \quad \int_{-\infty}^{\infty} 2^{t-1} [f_0(y) + f_1(y)]^{-t+1} f_1'(y) dy.$$

But these integrals are respectively the  $(t - 1)$ st moment of the chance variable  $2[f_0(Y) + f_1(Y)]^{-1} f_0(Y)$  when  $Y$  has the probability density function  $f_0(y)$ , and the  $(t - 1)$ st moment of the chance variable  $2[f_0(Y) + f_1(Y)]^{-1} f_1(Y)$  when  $Y$  has the probability density function  $f_1(y)$ , and therefore are equal. Since the moments determine the distribution of a bounded chance variable, the demonstration is completed.

Therefore neither  $\log k$  nor  $P^*$  depends on the sequence  $(x_1, \dots, x_n)$ , and it is no loss of generality to assume that  $x_1 = \dots = x_n = 0$ . We denote

$$\int_{-\infty}^{\infty} f_0(y) \log \{2[f_0(y) + f_1(y)]^{-1} f_0(y)\} dy \text{ by } H,$$

and

$$\int_{-\infty}^{\infty} f_0(y) (\log \{2[f_0(y) + f_1(y)]^{-1} f_0(y)\})^2 dy - H^2 \text{ by } J^2,$$

$J$  being taken as positive. Then, by the central-limit theorem,  $\log k$  is equal to  $nH - \beta(n, \lambda)n^{1/2} J$ , where  $\beta(n, \lambda)$  has the properties described in Sec. 2.

We denote

$$\int_{-\infty}^{\infty} \frac{1}{2} [f_0(y) + f_1(y)] \log \{2[f_0(y) + f_1(y)]^{-1} f_0(y)\} dy \text{ by } S,$$

and

$$\int_{-\infty}^{\infty} \frac{1}{2} [f_0(y) + f_1(y)] (\log \{2[f_0(y) + f_1(y)]^{-1} f_0(y)\})^2 dy - S^2 \text{ by } \sigma^2, \sigma$$

being taken as positive. To find  $P^*$ , we use Cramér's theorem of Sec. 3, with  $Z_i = \log \{2[f_0(Y_i) + f_1(Y_i)]^{-1} f_0(Y_i)\} - S$ , and  $\sigma gn = nH - nS - \beta(n, \lambda)n^{1/2} J$ , so that  $g = (H - S)/\sigma - \beta(n, \lambda) J/\sigma n^{1/2}$ . First we must verify that  $g$  is in the open interval  $(0, M)$ . It is easily shown that  $m(h)$  is equal to

$$-S + \frac{\int_{-\infty}^{\infty} [\frac{1}{2}(f_0(y) + f_1(y))]^{-h+1} f_0^h(y) \log \{2[f_0(y) + f_1(y)]^{-1} f_0(y)\} dy}{\int_{-\infty}^{\infty} [\frac{1}{2}(f_0(y) + f_1(y))]^{-h+1} f_0^h(y) dy},$$

from which it follows that  $m(1) = H - S$ , and that  $m(h)$  is a strictly increasing function of  $h$  for positive  $h$ , except in the trivial case (which we exclude) where  $f_0(y) = f_1(y)$  almost everywhere. It is easily verified that  $H - S$  is positive. This proves that  $g$  is in the open interval  $(0, M)$ , at least for large values of  $n$ .

Our next task is to find  $h(g)$ . We note that  $dm(h)/dh$  is continuous in a neighborhood of  $h = 1$ , and is equal to  $J^2$  at  $h = 1$ . Therefore we have  $m(h) = m(1) + (h - 1)J^2 + \epsilon(h - 1)$ , where  $(1/r) \epsilon(r)$  approaches zero as  $r$  approaches zero. The equation  $m(h(g)) = \sigma g$  becomes

$$H - S + (h(g) - 1)J^2 + \epsilon(h(g) - 1) = H - S - \beta(n, \lambda)Jn^{-1/2},$$

or

$$h(g) = 1 - \beta(n, \lambda)/(n^{1/2}J) + \delta_n,$$

where  $n^{1/2} \delta_n$  approaches zero as  $n$  increases.

Substituting this value of  $h(g)$  in Cramér's theorem, we find that  $\log P^* = -n[H - \beta(n, \lambda)Jn^{-1/2} + \Omega_n]$ , where  $n^{1/2} \Omega_n$  approaches zero as  $n$  increases. Denote by  $J'$  the quantity that  $J$  becomes when logarithms to the base 2 are used in the definition instead of logarithms to the base  $e$ . Then  $\log {}_2P^* = -n[C - \beta(n, \lambda)J'n^{-1/2} + D_n]$ , where  $n^{1/2}D_n$  approaches zero as  $n$  increases.

If we have a code  $(u_1, A_1), \dots, (u_L, A_L)$  of length  $L$  and probability of error not greater than  $\lambda$ , it follows from our discussion that  $P((Y_1, \dots, Y_n) \text{ is in } A_i) \geq P^*$ , when the joint probability density function of  $Y_1, \dots, Y_n$  is  $\prod_{i=1}^n [\frac{1}{2}(f_0(y_i) + f_1(y_i))]$ . Since  $A_1, \dots, A_L$  are disjoint, it follows that  $LP^* \leq 1$ , or that  $\log {}_2L \leq n[C - \beta(n, \lambda)J'n^{-1/2} + D_n]$ , where  $n^{1/2}D_n$  approaches zero as  $n$  increases. Thus the stronger converse is proved for the semi-continuous symmetric channel.

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