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INFORMATION CAPACITY OF GAUSSIAN CHANNELS.(U)
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INFORMATION CAPACITY OF GAUSSIAN CHANNELS

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Abstract

Consider a communication channel without feedback, with transmitted signal $A(X)$, and with additive Gaussian noise N . The information capacity of this channel is obtained subject to the constraints $E||A(X)||_W^2 \leq P$, where $||\cdot||_W$ can be regarded as the RKHS norm of the stochastic process W . The class of admissible processes W includes all Gaussian processes having induced measure equivalent to the measure induced by N .

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Introduction

This paper considers the information capacity of the Gaussian channel without feedback. The channel input is a sample function from a stochastic process X ; it is encoded into the signal sample function by a coding operation A ; the channel adds a sample function from a Gaussian noise process N (independent of X); the channel output is then a sample function from the process $Y = A(X) + N$. The quantity of interest is the information capacity

$$C = \sup_Q I[X, A(X) + N]$$

where $I[U, V]$ is the mutual information of the processes U and V , and Q is a set of (A, X) defined by appropriate constraints.

Let $\|\cdot\|_N$ denote the reproducing kernel Hilbert space (RKHS) of N ; under the constraint $E\|A(X)\|_N^2 \leq P$, a complete solution to the information capacity problem is given in [1]. However, there is also considerable interest in the capacity problem using constraints of a different type. The following constraint has been examined in special cases in various publications [2], [3], [4], [6]: Q is the set of all (A, X) such that $E\|A(X)\|_W^2 \leq P$, where W is a second Gaussian process. There are various motivations for this definition of Q . For example, if W is the Wiener process on $[0, T]$, as in [2], and $[A(X)]_t = \int_0^t V_s ds$, then $\|A(X)\|_W^2 = \int_0^T V_t^2 dt$. This is the usual power constraint. A more general motivation is that in many applications one may not know the precise covariance of N . It is then of interest to calculate upper and lower bounds for the capacity, over all Gaussian processes N whose induced measures are mutually absolutely continuous to the measure induced by some "most likely" (or reference) Gaussian process W .

A complete solution is obtained here for the capacity problem using the above definition of Q . In a subsequent publication, the results obtained here will be applied in an analysis of the feedback channel of [2].

Mathematical Structure

The channel model is defined as in [1]. The channel noise N is represented by a measure μ_N on the Borel σ -field of a real separable Hilbert space H_2 . The message X is modeled by a measure μ_X on a real separable Hilbert space H_1 . The inner product on H_1 is denoted by $\langle \cdot, \cdot \rangle_1$. $A: H_1 \rightarrow H_2$ is a Borel-measurable coding function. μ_W is a strong second order measure on H_2 ($\int_{H_2} \|x\|_2^2 d\mu_W(x) < \infty$). R_N and R_W denote the covariance operators of μ_N and μ_W . The following assumptions are made.

- (1) $R_N = R_W^{1/2}(I+S)R_W^{1/2}$, where S is a compact operator in H_2 , and S does not have -1 as an eigenvalue. Without loss of generality, it is assumed that $\overline{\text{range}(R_N)} = H_2$.

- (2) The admissible set Q is the set of all (A, μ_X) such that

$$\int_{H_1} \|R_W^{-1/2} A(x)\|_2^2 d\mu_X(x) \leq P.$$

The definition of Q given in (2) implies that $\mu_X \circ A^{-1}$ is strong second order. Since we can (and do) assume that μ_N , μ_W , and $\mu_X \circ A^{-1}$ each have zero mean, the constraint in (2) is equivalent to $\text{trace } R_W^{-1/2} R_{A(X)} R_W^{-1/2} \leq P$, where $R_{A(X)}$ is the covariance operator of $A(X)$. Note that $R_W^{-1/2}$ exists because of assumption (1). If $\overline{\text{range}(R_N)} \neq H_2$ in a given problem, one can replace H_2 WLOG by $\overline{\text{range}(R_N)}$. Alternatively, one could use the original H_2 and apply the constraint

$$\int_{H_2} \sum_n \delta_n^{-1} \langle A(x), Z_n \rangle_2^2 d\mu_X(x) \leq P, \text{ where } R_W = \sum_n \delta_n Z_n \otimes Z_n, \text{ with each } \delta_n > 0 \text{ and } \{Z_n, n \geq 1\} \text{ an o.n. set.}$$

Much of the following analysis will hinge on the properties of the strictly negative eigenvalues of S . These eigenvalues will be designated as $\{\lambda_n, n \geq 1\}$,

$\lambda_n \leq \lambda_{n+1}$, with $\{e_n, n \geq 1\}$ associated o.n. eigenvectors. Of course, depending on the particular R_N and R_W , the set $\{\lambda_n, n \geq 1\}$ can be empty, finite, or countably infinite.

The joint measure on $H_1 \times H_2$ representing message and channel output is μ_{XY} , with μ_Y the measure representing the channel output process Y . They are defined as in [1]:

$$\mu_Y(B) = \mu_X \otimes \mu_N\{(x,y): A(x) + y \in B\}$$

$$\mu_{XY}(C) = \mu_X \otimes \mu_N\{(x,y): (x, A(x)+y) \in C\}$$

where $\mu_X \otimes \mu_N$ is product measure on $H_1 \times H_2$ (all measures are defined on the usual Borel σ -fields, as in [1]). With these definitions, $I[X, A(X) + N] = I[\mu_{XY}]$, where $I[\mu_{XY}] = \infty$ if μ_{XY} is not absolutely continuous with respect to $\mu_X \otimes \mu_Y$, and otherwise

$$I[\mu_{XY}] = \int_{H_1 \times H_2} \log \left[\frac{d\mu_{XY}}{d\mu_X \otimes \mu_Y}(x,y) \right] d\mu_{XY}(x,y).$$

Two results proved in [1] will be central to the following analysis. The first is that for any fixed covariance operator $R_{A(X)}$ of the signal process, the information $I(\mu_{XY})$ is maximized by choosing $A(X)$ to be Gaussian [1; Lemma 6]. The second is that if $A(X)$ is Gaussian with covariance operator

$$R_{A(X)} = \sum_i \alpha_i [R_N^{1/2} v_i] \otimes [R_N^{1/2} v_i]$$

where $\sum \alpha_i < \infty$ and $\{v_n, n \geq 1\}$ is an o.n. set in H_2 , then $I[\mu_{XY}] = (1/2) \sum_n \log[1 + \alpha_n]$ [1, pp. 83-84].

Finally, it is noted that $\|R_W^{-1/2} x\|_2 \equiv \|x\|_W$ can be viewed as the norm of x in the RKHS defined by the kernel $r_W(t,s): H_2 \times H_2 \rightarrow \mathbb{R}$, $r_W(t,s) = \langle R_W t, s \rangle_2$. r_W actually determines a RKHS of real-valued functions on H_2 ; however, this RKHS is a subset of the bounded linear functionals on H_2 , and thus can be regarded as a subset of H_2 .

Main Result

The solution for the information capacity problem defined in the preceding section is given in the following theorem.

Theorem. Let $C = \sup_Q I[\mu_{XY}]$, where Q is defined by assumptions (1) and (2) of the preceding section.

(a) If H_2 is finite-dimensional, then

$$C = \frac{1}{2} \sum_{n=1}^K \log \left[\frac{\sum_{i=1}^K (1+\gamma_i) + P}{K(1+\gamma_n)} \right]$$

where K is the largest integer such that $\sum_1^K \gamma_n + P > K\gamma_K$, and $\gamma_1 \leq \gamma_2 \leq \dots$ is the set of all eigenvalues of S .

(b) If H_2 is infinite-dimensional, $\{\lambda_n, n \geq 1\}$ is not empty, and $\sum_1^K \lambda_n + P > K\lambda_K$ for all negative eigenvalues λ_K of S , then $\sum_n |\lambda_n| \leq P$ and

$$C = \frac{1}{2} \sum_n \log \left[\frac{1}{1+\lambda_n} \right] + 1/2 \left[P + \sum_m \lambda_m \right].$$

(c) If H_2 is infinite-dimensional, $\{\lambda_n, n \geq 1\}$ is not empty, and there exists a largest integer K such that $\sum_1^K \lambda_i + P > K\lambda_K$ and $\lambda_K < \sup\{\lambda_n, n \geq 1\}$ then

$$C = \frac{1}{2} \sum_{n=1}^K \log \left[\frac{P + \sum_{i=1}^K (1+\lambda_i)}{K(1+\lambda_n)} \right]$$

(d) If H_2 is infinite-dimensional, and $\{\lambda_n, n \geq 1\}$ is empty, then $C = P/2$.

In (a) and (c), the capacity can be attained. In (a), it is attained using a Gaussian signal with covariance

$$R_{A(X)} = \sum_{n=1}^K \tau_n [R_N^{1/2} v_i] \otimes [R_N^{1/2} v_i].$$

where $\{v_1, \dots, v_K\}$ is an o.n. set, $Sv_i = \gamma_i v_i$, and $\tau_n = (1 + \gamma_n)^{-1} \left[\frac{\sum_{i=1}^K \gamma_i + P}{K} - \gamma_n \right]$.

The capacity in (c) is attained with a Gaussian signal having covariance of the same form as that for (a), but with γ_i replaced by λ_i and v_i replaced by e_i , $i=1, \dots, K$.

In (b) and (d), the capacity cannot be attained, except in (b) for the special case where $P = -\sum_n \lambda_n$.

In (b) and (c), the capacity is strictly greater than the capacity obtained using the constraint $E_{\mu_X} \|A(X)\|_N^2 \equiv \int_{H_1} \|R_N^{-1/2} A(x)\|_2^2 d\mu_X(x) \leq P$; in (d), the capacity is the same. In (a), the capacity is strictly less than that for the constraint $E_{\mu_X} \|A(X)\|_N^2 \leq P$ if all $\gamma_n \geq 0$ with $\gamma_K > 0$; strictly greater if all $\gamma_n \leq 0$ and $\gamma_1 < 0$; and no general statement holds if $\gamma_K > 0$ and $\gamma_1 < 0$.

Proof of the Main Result

The proof of the Theorem will be given after having obtained several lemmas.

Lemma 1 Let $N \geq 1$ be fixed, and suppose $\{\rho_n, n=1, \dots, N\}$ is a set of strictly positive scalars, $\rho_1 \geq \rho_2 \geq \dots \geq \rho_N$. Let $A \subset \mathbb{R}^N$ be the set of all x such that $x_n \geq 0$ for $n=1, \dots, N$, and $\prod_{n=1}^k x_n \leq \prod_{n=1}^k \rho_n$ for $k=1, \dots, N$. Then $\sup_A \prod_{n=1}^N [1+x_n] = \prod_{n=1}^N [1+\rho_n]$.

Proof Define $G_N: \mathbb{R}^N \rightarrow \mathbb{R}$ by $G_N(x) = \sum_{n=1}^N \log[1+x_n]$. It is sufficient to show that $G_N(x) \leq G_N(\rho)$, subject to the constraints

$$-x_n \leq 0 \quad n=1, \dots, N \quad (C_1)$$

$$\sum_{n=1}^k \log x_n - \sum_{n=1}^k \log \rho_n \leq 0 \quad k=1, \dots, N \quad (C_2).$$

The constraints C_1, C_2 define a convex set in $\mathbb{R}^N$, and G_N is concave on $\mathbb{R}^N$.

Thus, one has the problem of maximizing a concave function over a convex set in $\mathbb{R}^N$,

with concave and differentiable constraints; by Kuhn-Tucker theory [7] any solution to this problem will define a global maximum over the set A. A solution is any $\bar{x}^*$ in $\mathbb{R}^N$ satisfying the following set of equations for some γ, β in $\mathbb{R}^N$ such that $\gamma_i \leq 0$ and $\beta_i \leq 0$ for $i=1, \dots, N$ [7]:

$$\frac{1}{1+x_n^*} - \gamma_n + \frac{1}{x_n^*} \sum_{k \geq n} \beta_k = 0, \quad n=1, \dots, N \quad (S_1)$$

$$\gamma_n x_n^* = 0 \quad \text{and} \quad -x_n^* \leq 0, \quad n=1, \dots, N \quad (S_2)$$

$$\left. \begin{aligned} \beta_k \left[\sum_{n=1}^k \log x_n^* - \sum_{n=1}^k \log \rho_n \right] &= 0 \\ \sum_{n=1}^k \log x_n^* - \sum_{n=1}^k \log \rho_n &\leq 0 \end{aligned} \right\} \quad k=1, \dots, N \quad (S_3).$$

The system of equations (S_1) , (S_2) , (S_3) is easily seen to be solved by taking

$x_n^* = \rho_n$, $\gamma_n = 0$, and $\sum_{k=n}^N \beta_k = -\rho_n/(1+\rho_n)$ for $n=1, \dots, N$. The fact that this solution gives $\beta_k \leq 0$ for all $k=1, \dots, N$ follows by induction on $N - k+1$, using $\rho_n \leq \rho_{n-1}$ for $2 \leq n \leq N$. $\square$

Lemma 2 Let $\{x_n^2, n \geq 1\}$ be a summable sequence, with $x_n^2 \geq x_{n+1}^2$. Suppose that S is a compact operator in H_2 which is symmetric, has $M \leq \infty$ strictly negative eigenvalues, and $I + S$ is strictly positive. Then for any finite $N \leq M$ and any o.n. set $\{u_1, \dots, u_N\}$,

$$\prod_{n=1}^N [1+x_n^2] \|(I+S)^{1/2} u_n\|^{-2} \leq \prod_{n=1}^N [1+x_n^2 (1+\lambda_n)^{-1}]$$

where $\lambda_1 \leq \lambda_2 \leq \dots$ are the negative eigenvalues of S .

Proof Using the inequality $\|(I+S)^{1/2} u_n\|_2^{-2} \leq \|(I+S)^{-1/2} u_n\|_2^2$, it suffices to show that $\prod_{n=1}^N [1+x_n^2] \|(I+S)^{-1/2} u_n\|_2^2 \leq \prod_{n=1}^N [1+x_n^2 (1+\lambda_n)^{-1}]$.

Let $\{u_n, n \geq 1\}$ be any fixed CON set in H_2 . Define $X = \sum_n |x_n| u_n \otimes u_n$. The previous inequality will be proved if one shows that

$$\prod_1^N [1 + \|(I+S)^{-1/2} X u_n\|_2^2] \leq \prod_1^N [1 + x_n^2 (1 + \lambda_n)^{-1}].$$

By a result of Horn [5],

$$\prod_1^k \|(I+S)^{-1/2} X u_n\|_2^2 \leq \prod_1^k \tau_n(p) |x_n|^{2-1/4p}$$

for all $k \leq N$ and any fixed $p \geq 1$, where $\{\tau_n(p), p \geq 1\}$ are the eigenvalues of $X^{1/2p} (I+S)^{-1} X^{1/2p}$ and $\tau_n(p) \geq \tau_{n+1}(p)$. This follows from the fact that $(I+S)^{-1/2} X^{1/2p}$ is compact, as is $X^{1-1/2p} = \sum |x_n|^{1-1/2p} u_n \otimes u_n$.

Let $\alpha > 0$ be given. For sufficiently large p , $(1+\alpha)(I+S)^{-1} > X^{1/2p} (I+S)^{-1} X^{1/2p}$ and then $\prod_1^k \tau_n(p) < (1+\alpha)^k \prod_1^k (1+\lambda_n)^{-1}$, so that

$$\prod_1^k \|(I+S)^{-1/2} X u_n\|_2^2 < (1+\alpha)^k \prod_1^k (1+\lambda_n)^{-1} |x_n|^{2-1/4p}, \quad k = 1, 2, \dots, N.$$

Thus, for all $\alpha > 0$, $\prod_1^k \|(I+S)^{-1/2} X u_n\|_2^2 < (1+\alpha)^k \prod_1^k (1+\lambda_n)^{-1} x_n^2$, giving

$$\prod_1^k \|(I+S)^{-1/2} X u_n\|_2^2 \leq \prod_1^k (1+\lambda_n)^{-1} x_n^2, \quad \text{for } k = 1, 2, \dots, N.$$

Applying Lemma 1, this yields

$$\prod_1^N [1 + \|(I+S)^{-1/2} X u_n\|_2^2] \leq \prod_1^N [1 + x_n^2 (1 + \lambda_n)^{-1}]. \quad \square$$

Lemma 3 Suppose that all the eigenvalues $\{\lambda_n, n \geq 1\}$ of S are strictly negative, $\lambda_1 \leq \lambda_2 \leq \dots$, with $S e_i = \lambda_i e_i$, $i \geq 1$, and $\{e_i, i \geq 1\}$ an o.n. set.

(a) If there exists a largest integer $K \geq 1$ such that $\sum_1^K \lambda_n + P > K \lambda_K$, then

$$C = \frac{1}{K} \sum_{n=1}^K \log \left[\frac{\sum_{i=1}^K (1 + \lambda_i) + P}{K(1 + \lambda_n)} \right].$$

The capacity can be achieved; it is attained with a Gaussian signal having covariance operator

$$R_A(X) = \sum_1^K \tau_i [R_N^{1/2} e_i] \otimes [R_N^{1/2} e_i]$$

where $\tau_i = \frac{(1+\lambda_i)^{-1}}{K} \left(\sum_{n=1}^K \lambda_n + P - K\lambda_i \right)$, $i=1, \dots, K$.

This result includes the case when H_2 is finite dimensional (so that $K \leq \dim(H_2)$).

Moreover, this result is also obtained when one adds the additional restriction that support $(\mu_X \circ A^{-1}) \leq M < \infty$. With this restriction, $K = M$ if $\sum_1^M \lambda_n + P > M\lambda_M$; otherwise there exists $K < M$ such that the above expression is the capacity.

(b) If there does not exist a largest integer K such that $\sum_1^K \lambda_n + P > K\lambda_K$, then $\sum_n |\lambda_n| \leq P$, and

$$C = \frac{1}{2} \sum_{n=1}^{\infty} \log \left[\frac{1}{1+\lambda_n} \right] + \frac{1}{2} (P + \sum_n \lambda_n).$$

Capacity can be attained only if $P = -\sum \lambda_n$; it is then attained by a Gaussian signal with covariance $R_{AX} = \sum_1^{\infty} \tau_i [R_N^{\frac{1}{2}} U^* e_i] \otimes [R_N^{\frac{1}{2}} U^* e_i]$ where $\tau_i = \frac{-\lambda_i}{1+\lambda_i}$. If $P > -\sum \lambda_n$, then the capacity is the limit of the mutual information for a sequence of Gaussian signals (μ_{AX}^M) , with covariance $R_{AX}^M = \sum_1^M \tau_i^M [R_N^{\frac{1}{2}} U^* e_i] \otimes [R_N^{\frac{1}{2}} U^* e_i]$ and

$$\tau_i^M = \frac{(1+\lambda_i)^{-1}}{M} \left(\sum_1^M \lambda_n + P - M\lambda_i \right) \quad i=1, \dots, M.$$

Proof

From the results of [1, pp. 83-84], $I[\mu_{XY}] = \frac{1}{2} \sum_{n=1}^{\infty} \log[1+\tau_n]$ when $\mu_X \circ A^{-1}$ is Gaussian with covariance operator

$$R_{A(X)} = \sum_{n=1}^{\infty} \tau_n [R_N^{1/2} u_n] \otimes [R_N^{1/2} u_n]$$

with $\{u_n, n \geq 1\}$ any o.n. set in H_2 . By Assumption (1), $R_N^{1/2} = R_W^{1/2} (I+S)^{1/2} U^*$ with U unitary. Thus

$$\begin{aligned} E \|R_W^{-1/2} A(X)\|_2^2 &= \text{Trace } R_W^{-1/2} R_{A(X)} R_W^{-1/2} \\ &= \text{Trace } (I+S)^{\frac{1}{2}} U^* R_N^{-\frac{1}{2}} R_{A(X)} R_N^{-\frac{1}{2}} U (I+S)^{\frac{1}{2}} \\ &= \sum_n \tau_n \| (I+S)^{\frac{1}{2}} U^* u_n \|_2^2. \end{aligned}$$

Moreover, for any choice of covariance operator $R_{A(X)}$, the information is maximized if $\mu_X \circ A^{-1}$ is Gaussian [1, Lemma 6]. Thus, one can assume that $\mu_X \circ A^{-1}$ is Gaussian. The capacity problem now reduces to finding $C = \sup_{Q'} \frac{1}{2} \sum_n \log[1 + \tau_n]$, where Q' is the set of all $\{(\tau_n), (U_n)\}$ such that $\tau_n \geq 0$ for $n \geq 1$, $\sum_n \tau_n < \infty$, $\{u_n, n \geq 1\}$ is an o.n. set, and $\sum_n \tau_n \|(I+S)^{\frac{1}{2}} U^* u_n\|_2^2 \leq P$.

We rewrite the preceding expression as

$$C = \sup_{Q'} \sum_n \log[1 + x_n^2 \|(I+S)^{\frac{1}{2}} U^* u_n\|_2^{-2}],$$

where $x_n^2 \equiv \tau_n \|(I+S)^{\frac{1}{2}} U^* u_n\|_2^2$. Since $\{x_n^2, n \geq 1\}$ and $\{\tau_n, n \geq 1\}$ are summable, and $\{u_n, n \geq 1\}$ is to be selected, one can assume WLOG that $x_n^2 \geq x_{n+1}^2, n \geq 1$. From Lemma 2, for any such choice of $\{x_n^2, 1 \leq n \leq M\}$,

$$\sum_1^M \log[1 + x_n^2 \|(I+S)^{\frac{1}{2}} U^* u_n\|_2^{-2}] \leq \sum_1^M \log[1 + x_n^2 (1 + \lambda_n)^{-1}].$$

We will maximize the right side of this inequality for fixed M , and show that the maximum can be attained by $\{x_n^2, 1 \leq n \leq M\}$ such that $\sum_1^M x_n^2 = P$ and $x_n^2 \geq x_{n+1}^2$ for $n=1, \dots, M$.

For fixed $M \geq 1$, define $f_M: \mathbb{R}^M \rightarrow \mathbb{R}$ by $f_M(\chi) = \sum_{n=1}^M \log[1 + y_n (1 + \lambda_n)^{-1}]$. We seek to maximize $f_M(\chi)$ subject to the constraints

$$g(\chi) \equiv \sum_1^M y_n - P \leq 0,$$

$$h_i(\chi) \equiv -y_i \leq 0, \quad i=1, \dots, M.$$

This is a constrained maximization problem. Since $\log(1 + \alpha y)$ is concave over $\{y: y \geq 0\}$ for any $\alpha > 0$, the function f_M is concave over the convex set $\{\chi \in \mathbb{R}^M: \chi_i \geq 0, i=1, \dots, M\}$. Moreover, each constraint function is concave. Thus, any solution to this problem will define a global maximum for f_M [7]. In order for χ^* to be a solution, it is necessary and sufficient that the following set of equations be satisfied [7]:

$$\frac{1}{1+y_i^*+\lambda_i} + \beta - \gamma_i = 0 \quad i=1,\dots,M \quad (1)$$

$$\sum_1^M y_n^* - P \leq 0, \quad \beta [\sum_1^M y_n - P] = 0 \quad (2)$$

$$-y_i^* \leq 0, \quad \gamma_i y_i^* = 0, \quad i=1,\dots,M \quad (3),$$

for some set of non-positive real numbers $\{\beta, \gamma_1, \dots, \gamma_M\}$.

We first attempt to obtain a solution y^* by setting $\gamma_1 = \gamma_2 = \dots = \gamma_M = 0$.

This requires

$$\frac{1}{1+y_i^*+\lambda_i} = -\beta, \quad i=1,\dots,M; \quad \text{thus}$$

$$\sum_1^M y_i^* + \sum_1^M (1+\lambda_i) = -M\beta^{-1}, \quad \text{and}$$

$$y_n^* = \frac{\sum_1^M y_i + \sum_1^M (1+\lambda_i)}{M} - (1+\lambda_n)$$

for $n=1,2,\dots,M$. This definition of y^* and constraints (3) require that

$$\sum_1^M y_i + \sum_1^M (1+\lambda_i) \geq M(1+\lambda_n), \quad n=1,\dots,M;$$

this inequality is satisfied for all $n \leq M$ if and only if it holds for $n = M$. Also

$\beta = -(1+y_i^*+\lambda_i)$ implies $\beta < 0$, so that $\sum_1^M y_i^* = P$ by constraints (2). Thus, if

$\sum_1^M P + \sum_1^M \lambda_i \geq M\lambda_M$, then an optimum solution is given by

$$y_i^* = \frac{P + \sum_1^M \lambda_j - M\lambda_i}{M}, \quad i=1,\dots,M.$$

If there exists $K < M$ such that

$$P + \sum_1^K \lambda_i \geq K\lambda_K$$

$$P + \sum_1^{K+1} \lambda_i < (K+1)\lambda_{K+1},$$

then constraints (1)-(3) are satisfied by choosing

$$\beta = -K[P + K + \sum_1^K \lambda_i]^{-1}$$

$$\gamma_1 = \gamma_2 = \dots = \gamma_K = 0$$

$$\sum_1^K y_i = P$$

$$y_i = 0, i > K$$

$$y_i = K^{-1}[P + \sum_{n=1}^K \lambda_n - K\lambda_i], \quad i \leq K$$

$$\gamma_i = -K[P + K + \sum_1^K \lambda_n]^{-1} + (1+\lambda_i)^{-1} \quad i > K.$$

Thus, under the assumptions of (a),

$$\sup_{Q''} \sum_1^\infty \log[1 + x_n^2(1+\lambda_n)^{-1}] = \sum_{n=1}^K \log \left[\frac{\sum_{i=1}^K \lambda_i + P+K}{K(1+\lambda_n)} \right]$$

where $Q'' = \{(x_n^2): \sum_1^\infty x_n^2 \leq P\}$. As already noted, when $\mu_X \circ A^{-1}$ is Gaussian with covariance operator $R_{A(X)} = \sum_1^\infty \tau_n [R_N^{1/2} u_n] \otimes [R_N^{1/2} u_n]$, $\{u_n, n \geq 1\}$ an o.n. set, then

$$I[\mu_{XY}] = \frac{1}{2} \sum_{n=1}^\infty \log[1 + \tau_n] \leq \frac{1}{2} \sum_{n=1}^\infty \log[1 + x_n^2(1+\lambda_n)^{-1}]$$

if $x_n^2 \equiv \tau_n || (I+S)^{1/2} U^* u_n ||_2^2$, $x_n^2 \geq x_{n+1}^2$.

Choosing $u_n = U e_n, n \geq 1$,

$$x_n^2 = K^{-1}[P + \sum_{i=1}^K \lambda_i - K\lambda_n], \quad n=1, \dots, K$$

$$x_n^2 = 0, \quad n > K$$

one obtains (a) immediately if H_2 is finite-dimensional. If H_2 is infinite-dimensional, then (a) is obtained as above by taking M sufficiently large, and noting that $\sum_1^M \log[1 + \tau_n]$ is a non-decreasing function of M if $\tau_n \geq 0$ for $n \geq 1$. The proof of (a) under the additional constraint that support $(\mu_X \circ A^{-1}) \leq M < \infty$ can be obtained from the preceding proof and the results of [1, pp. 83-84].

Suppose now that $\sum_1^K \lambda_n + P > K\lambda_K$ for all $K \geq 1$. If $P < \sum_1^\infty |\lambda_n|$, then there exists $K \geq 1$ and $\Delta > 0$ such that $P + \sum_1^K \lambda_n = -\Delta$. Thus,

$$|\lambda_{K+1}| > (1/K) [-\sum_1^K \lambda_n - P] = \Delta/K.$$

Assume $|\lambda_{K+p}| > (1/K)\Delta$ for $1 \leq p \leq N$.

Then

$$|\lambda_{K+N+1}| > \frac{1}{K+N} \left[-\sum_1^{K+N} \lambda_n - P \right] = \frac{1}{K+N} \left[\Delta - \sum_{K+1}^{K+N} \lambda_n \right]$$

so that

$$|\lambda_{K+N+1}| > \frac{1}{K+N} [\Delta + (N/K)\Delta] = \Delta/K.$$

Hence, $|\lambda_{K+p}| > \Delta/K$ for all $p \geq 1$, which contradicts $\lambda_n \rightarrow 0$, proving

$$\sum_1^\infty |\lambda_n| \leq P.$$

A lower bound on C under the assumptions of (b) is now obtained from the proof of (a), by taking C_K to be the value of C under the additional constraint that support $(\mu_X \circ A^{-1})$ has dimension $\leq K$, so that

$$C_K = \frac{1}{2} \sum_{n=1}^K \log \left[\frac{\sum_1^K \lambda_i + P}{K(1+\lambda_n)} \right]$$

and so

$$C \geq \lim_K C_K = \frac{1}{2} \sum_1^\infty \log[(1+\lambda_n)^{-1}] + \frac{1}{2}(P + \sum_1^\infty \lambda_n).$$

To see that $\lim_K C_K$ is an upper bound for C , suppose that $\lim_K C_K < C$. Then there exists a Gaussian $\mu_X \circ A^{-1}$ with covariance operator

$$R_{A(X)} = \sum_1^\infty \tau'_n [R_N^{1/2} u'_n] \otimes [R_N^{1/2} u'_n] \quad \text{with}$$

$$\sum_1^\infty \tau'_n \|(I+S)^{1/2} U^* u'_n\|_2^2 \leq P, \text{ and for some finite } M$$

$$\frac{1}{2} \sum_1^M \log[1 + \tau'_n] > \lim_K C_K.$$

However, as already seen, no selection of $\{(\tau'_n), (u'_n)\}$ satisfying the above conditions can be such that

$$\frac{1}{2} \sum_1^M \log[1 + \tau'_n] > C_M.$$

This contradiction establishes (b). The fact that the capacity in (b) cannot be attained follows in the same way. $\square$

Lemma 4 Let $C_{(N)} \equiv \sup_{\{(A, \mu_X): E_{\mu_X} \|R_N^{-1/2} A(X)\|_2^2 \leq P\}} I[\mu_{XY}]$.

(a) If S has only non-negative eigenvalues, then $C \leq C_{(N)}$.

(b) If S has only non-positive eigenvalues, then $C \geq C_{(N)}$.

(c) If H_2 is infinite-dimensional and all eigenvalues of S are non-negative, then $C = C_{(N)} = P/2$.

Proof (a) Here $\|(I+S)^{-1}\| \leq 1$, and so $\|R_N^{-1/2} A(X)\|_2^2$

$$\leq \|(I+S)^{-1}\| \|R_W^{-1/2} A(X)\|_2^2 \leq \|R_W^{-1/2} A(X)\|_2^2$$

for all $A(X)$ in range $(R_N^{1/2})$. Hence $E_{\mu_X} \|R_W^{-1/2} A(X)\|_2^2 \leq P$ implies

$E_{\mu_X} \|R_N^{-1/2} A(X)\|_2^2 \leq P$, so that C is obtained by a supremum over a smaller set, yielding (a).

(b) In this case $\|I+S\| \leq 1$, and so

$$E_{\mu_X} \|R_N^{-1/2} A(X)\|_2^2 \leq P \text{ implies } E_{\mu_X} \|R_W^{-1/2} A(X)\|_2^2 \leq P.$$

(c) From (a) and [1, Theorem 2], $C \leq P/2$. For fixed $n \geq 1$, let $\mu_{A_n(X_n)}$ be

Gaussian with covariance $R_{A_n(X_n)} = \frac{C}{n} \sum_1^n [R_N^{1/2} u_i] \bullet R_N^{1/2} u_i$ with $\{u_i, i \geq 1\}$

a CON set in H_2 . From [1, Theorem 1], $I[\mu_{X_n Y_n}] = (n/2) \log[1 + \frac{C_n}{n}]$. Define (C_n) by

$$C_n = nP \left[\sum_{i=1}^n \left\| (I+S)^{\frac{1}{2}} u_i \right\|_2^2 \right]^{-1}. \text{ Then } E_{\mu_{X_n}} \left\| R_W^{-1/2} A(X_n) \right\| = P, \text{ so } (A, \mu_{X_n}) \in Q.$$

The fact that $(1/n) \sum_{i=1}^n \left\| (I+S)^{\frac{1}{2}} u_i \right\|_2^2 \rightarrow 1$ follows easily from the fact that

$$\left\| S^{1/2} u_i \right\|_2^2 \rightarrow 0. \text{ Thus, } C_n \rightarrow P, \text{ and so } I[\mu_{X_n Y_n}] \rightarrow P/2, \text{ showing } C \geq P/2. \quad \square$$

Proof of Theorem

(a) is proved exactly as (a) of Lemma 3. (d) is contained in Lemma 4.

To prove (b) and (c) we identify two possibilities for each: (1) S has a finite set of M strictly negative eigenvalues; (2) S has an infinite set of strictly negative eigenvalues. We prove only (b) and (c) for case (1); the proof for (2) is similar but simpler.

First, we note that the capacity is at least C , as given in (b) and (c).

This follows immediately in (c) using a Gaussian μ_{AX} with covariance as specified for (c) in the theorem. For (b), this is shown by using a sequence of Gaussian signals (μ_{AX}^k) having covariance

$$R_{AX}^k = - \sum_{i=1}^M \frac{\lambda_i}{1+\lambda_i} R_N^{1/2} e_i \otimes R_N^{1/2} e_i + \frac{P + \sum_{i=1}^M \lambda_i}{k-M-1} \sum_{i=M+1}^k R_N^{1/2} u_i \otimes R_N^{1/2} u_i, \text{ where}$$

$S e_i = \lambda_i e_i$, $\lambda_i < 0$, $S u_j = \gamma_j u_j$, $\gamma_j \geq 0$, for $i=1, \dots, M$; $j=M+1, \dots, k$; and $\{e_1, \dots, e_M, u_{M+1}, \dots, u_k\}$ is an ON set. As $k \rightarrow \infty$, $I[\mu_{AX}^k] \rightarrow \frac{1}{2} \sum_{i=1}^M \log \left[\frac{1}{1+\lambda_i} \right] + \frac{1}{2} (P + \sum_{i=1}^M \lambda_i) = C$.

Thus, to prove (b) and (c) when S has only a finite set of strictly negative eigenvalues, it suffices to show that the capacity is $\leq C$ as given in the theorem.

Suppose then that the assumptions of either (b) or (c) are satisfied, and that S has strictly negative eigenvalues $\lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_M$. Suppose that the true capacity is greater than C , as given by (b) or (c). Since the capacity is the limit of

$(I[\mu_{XY}^k])$ for a sequence $(\mu_{X^k} \circ A_k^{-1})$ of Gaussian measures, there exists [1] a covariance operator R such that $R = \sum_1^J \tau_j R_N^{1/2} u_j \otimes R_N^{1/2} u_j$, $\frac{1}{2} \sum_1^J \log[1 + \tau_j] > C$, $\{u_j, j \geq 1\}$ an o.n. set, and $\sum_1^J \tau_j \|(I+S)^{\frac{1}{2}} U^* u_j\|_2^2 = P_1 \leq P$. We can assume that $J > M$. Let $T: H_2 \rightarrow H_2$ be the unitary map defined by $T v_j = U^* u_j$, where $\{v_j, j \geq 1\}$ are the eigenvectors of S . Defining $x_j^2 = \tau_j \|(I+S)^{\frac{1}{2}} U^* u_j\|_2^2$, one has that

$$\begin{aligned} \sum_1^J \log[1 + \tau_j] &\leq \sum_1^J \log[1 + x_j^2 \|(I+S)^{-\frac{1}{2}} U^* u_j\|_2^2] \\ &= \sum_1^J \log[1 + x_j^2 \|(I+S)^{-\frac{1}{2}} U^* T v_j\|_2^2]. \end{aligned}$$

We can assume that $x_j^2 \geq x_{j+1}^2$, $j=1, \dots, J-1$; from Lemma 2,

$$\begin{aligned} \sum_1^J \log[1 + \tau_j] &\leq \sum_1^M \log[1 + x_j^2 (1 + \lambda_j)^{-1}] \\ &\quad + \sum_{M+1}^J \log[1 + x_j^2 \|(I+S)^{-1/2} T v_j\|_2^2]. \end{aligned}$$

Define $P_1' = \sum_1^M x_j^2$. Then $\sum_{M+1}^J x_j^2 = P_1 - P_1'$; the eigenvalues of $(I+S)^{-1}$ are the same as those of $T^*(I+S)^{-1}T$, and thus Lemma 3 and Lemma 4(a) yield

$$\sum_1^J \log[1 + \tau_j] \leq C_0(P_1') \equiv \sum_{n=1}^K \log \left[\frac{\sum_1^K (1 + \lambda_i) + P_1'}{K(1 + \lambda_n)} \right] + P_1 - P_1'.$$

We maximize $C_0(P_1')$ with respect to P_1' . The derivative is non-decreasing for increasing P_1' if $\sum_1^K \lambda_i + P_1' \leq 0$. This is satisfied if $K < M$; taking P_1 arbitrarily close to P ($J \rightarrow \infty$), one obtains part (c) of the theorem. If $K = M$, then

$\frac{d}{dP_1'} C_0(P_1') > 0$ if $P_1' < -\sum_1^M \lambda_i$, $\frac{d}{dP_1'} C_0(P_1') < 0$ if $P_1' > -\sum_1^M \lambda_i$, and by continuity of C_0 , $C_0(P_1') \leq C_0(-\sum_1^M \lambda_i)$, proving (b) of the theorem.

The remaining parts of the theorem can be obtained from the proof of Lemma 3, and from Lemma 4. □

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