

State-Dependent DMC with a Causal Helper

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Joint work with Amos Lapidoth

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State-dependent DMC

- ▶ Input, output, and state alphabets are \mathcal{X} , \mathcal{Y} , and \mathcal{S}
- ▶ State sequence is IID according to P_S
- ▶ Given input $X = x$ and state $S = s$, output equals y with probability

$$W(y|x, s)$$

Capacity depends on whether or not channel-state information (CSI) is available, to whom, and how.

Causal CSI: Shannon's classic result

At time i , encoder knows s^i , so time- i input is produced via

$$x_i = f_i(m, s^i)$$

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Theorem [Shannon '58]

Capacity with causal CSI at Transmitter is the maximum of

$$I(U; Y)$$

over joint distributions of the form

$$P_S(s)P_U(u)P_{X|US}(x|u, s)W(y|x, s).$$

Without loss of optimality, x can be chosen as a deterministic function of (u, s) .

How this capacity is achieved

- ▶ u is a mapping (or “strategy”) that maps s to x
- ▶ Capacity is that of the “super channel” with input u and output y
- ▶ Notice that, at time i , the optimal encoder only uses s_i and ignores s^{i-1} :

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Related to the above: **strictly causal CSI**, where

$$x_i = f_i(m, s^{i-1}),$$

does not increase capacity.

This work: Imperfect causal CSI via Helper

At time i :

- ▶ Helper observes s^i and produces $t_i \in \mathcal{T}$:

$$t_i = h_i(s^i)$$

(No additional constraint on Helper except that \mathcal{T} is fixed, with $|\mathcal{T}| < |\mathcal{S}|$)

- ▶ Transmitter sees t^i and produces input

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Main question: Is it optimal to choose $t_i = h_i(s_i)$ and $x_i = f_i(m, t_i)$?

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We shall also consider some variants of the above setting.

Some related works

- ▶ Rosenzweig, Steinberg, and Shamai '05:
Full CSI at Receiver and quantized CSI at Transmitter
(In the causal case, $t_i = h_i(s_i)$ is assumed as part of the setup)
- ▶ Steinberg '08: Full CSI at Transmitter and quantized CSI at Receiver
- ▶ Bross, Lapidoth, and Marti '20 (two papers):
Additive-noise channels with quantized CSI at Transmitter or at Receiver

Scalar-quantization lower bound

- ▶ Helper: $t_i = g(s_i)$
- ▶ Encoder: Shannon strategies treating t as the effective state: $x_i = u_i(t_i)$.

This achieves rate

$$I(U; Y)$$

with joint distribution

$$P_S(s)P_U(u)P_{T|S}(t|s)P_{X|UT}(x|u, t)W(y|x, s)$$

which satisfies three conditions:

$$\begin{array}{c} (U, T) \text{---} \circ \text{---} (X, S) \text{---} \circ \text{---} Y \\ S \text{---} \circ \text{---} (U, T) \text{---} \circ \text{---} X \\ U \perp\!\!\!\perp (S, T). \end{array}$$

(It's optimal to choose both $P_{T|S}$ and $P_{X|UT}$ to be deterministic.)

An upper bound

Define for every i

$$U_i \triangleq (M, T^{i-1}, Y^{i-1}).$$

Then

$$\begin{aligned} n(R - \epsilon) &\leq I(M; Y^n) \\ &= \sum_{i=1}^n I(M; Y_i | Y^{i-1}) \\ &\leq \sum_{i=1}^n I(M, Y^{i-1}; Y_i) \\ &\leq \sum_{i=1}^n I(U_i; Y_i). \end{aligned}$$

Let's check the conditions

Recall $U_i \triangleq (M, T^{i-1}, Y^{i-1})$.

$$(U_i, T_i) = (M, T^i, Y^{i-1}) \text{---} \circ \text{---} (X_i, S_i) \text{---} \circ \text{---} Y_i \quad \checkmark$$

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$$U_i = (M, T^{i-1}, Y^{i-1}) \not\equiv (S_i, T_i) \quad \times$$

For example, both T and S binary, $T_{i-1} = S_{i-1}$ and $T_i = S_i \oplus S_{i-1}$

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For example, both T and S binary, $T_{i-1} = S_{i-1}$ and $T_i = S_i \oplus S_{i-1}$

We only have

$$U_i \perp\!\!\!\perp S_i$$

i.e., joint distribution looks like

$$P_S(s)P_U(u)P_{T|US}(t|u, s)P_{X|UT}(x|u, t)W(y|x, s)$$

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- ▶ If neither works, then we need to think about a better lower bound, but

Why on earth would Helper want to tell Transmitter anything about S^{i-1} at time i ?

A variant (special case): S is part of the output

i.e. CSI is available to Receiver (causality plays no role).

(For clarity, Y denotes the part of output without S .)

Lower bound on capacity becomes

$$I(U; Y, S) = I(U; Y|S) = I(X; Y|S)$$

for joint distribution

$$P_S(s)P_{T|S}(t|s)P_{X|T}(x|t)W(y|x, s)$$

where it's again optimal to choose $P_{T|S}$ to be deterministic.

S known to Receiver: Upper bound

Define

$$U_i \triangleq (M, Y^{i-1}), \quad V_i \triangleq S^{i-1}$$

Then

$$\begin{aligned} n(R - \epsilon) &\leq I(M; Y^n, S^n) \\ &= \sum_{i=1}^n I(M; Y_i, S_i | Y^{i-1}, S^{i-1}) \\ &\leq \sum_{i=1}^n I(M, Y^{i-1}; Y_i, S_i | S^{i-1}) \\ &= \sum_{i=1}^n I(M, Y^{i-1}; Y_i | S^{i-1}, S_i) \\ &= \sum_{i=1}^n I(U_i; Y_i | V_i, S_i) \end{aligned}$$

S known to Receiver: Upper bound (contd.)

So capacity is upper-bounded by the maximum of

$$I(U; Y|V, S)$$

over distributions of the form

$$P_V(v)P_S(s)P_{U|V}(u|v)P_{T|SV}(t|s, v)P_{X|TUV}(x|t, u, v)W(y|x, s)$$

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Observation: V can be removed via **maximization over $V = v$** , yielding

$$I(U; Y|S) = I(X; Y|S)$$

over

$$P_S(s)P_{T|S}(t|s)P_{X|T}(x|t)W(y|x, s)$$

which coincides with lower bound.

S known to Receiver: Result

Theorem

When states are known to the Receiver, capacity is given by

$$\max I(X; Y|S)$$

where max is over joint distributions of the form

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Note: in this variant it is optimal to choose

$$t_i = h(s_i), \quad x_i = f_i(m, t_i).$$

Another variant: Helper knows message M

That is, at time i , Helper produces

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Our upper bound in the original setting continues to hold in this case:

$$\text{capacity} \leq \max I(U; Y)$$

over

$$P_S(s)P_U(u)P_{T|US}(t|u, s)P_{X|UT}(x|u, t)W(y|x, s).$$

Helper knows M : Achievability

- ▶ Codebook: $\{u^n(m), m \in \mathcal{M}\}$ all generated IID according to P_U .
- ▶ Helper knows m and hence also $u^n(m)$; it generates

$$t_i = h(u_i, s_i)$$

Now t_i does depend on u_i !

- ▶ Encoder generates

$$x_i = f(u_i, t_i)$$

Helper knows M : Result

Theorem

When the message is known to the helper, capacity is given by

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Again, it is optimal to let t_i not depend on s^{i-1} !

Helper knows M : An example

- ▶ State contains two independent uniform bits:

$$S = (S^{(0)}, S^{(1)})$$

- ▶ Helper has one bit to use:

$$\mathcal{T} = \{0, 1\}$$

- ▶ Input contains two bits

$$X = (A, B), \quad A, B \in \{0, 1\}$$

- ▶ Output is also two bits

$$Y = (A, B \oplus S^{(A)})$$

Helper knows M example: Solution

We can send two information bits (k, ℓ) as follows:

- ▶ Help is $T = S^{(k)}$
- ▶ Transmitter sends $(k, \ell \oplus T)$
- ▶ Output is then (k, ℓ) (no decoding needed)

It is easy to prove that the above is optimal, so

$$\text{capacity} = 2 \text{ bits.}$$

(We can also use the capacity formula to get this.)

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First consider **scalar quantizer** (independent of M).

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For an upper bound, reveal T to Receiver.

Given $T = t$, we have a “sum channel”:

- ▶ Channel 1: $X = (0, B)$, $Y = (0, B \oplus S^{(0)})$; capacity is $1 - H(S^{(0)}|T = t)$
- ▶ Channel 2: $X = (1, B)$, $Y = (1, B \oplus S^{(1)})$; capacity is $1 - H(S^{(1)}|T = t)$

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Capacity of the sum channel is given by

$$\log \left(2^{1-H(S^{(0)}|T=t)} + 2^{1-H(S^{(1)}|T=t)} \right)$$

Same example when Helper does *not* know M (contd.)

$$\begin{aligned} & \log \left(2^{1-H(S^{(0)}|T=t)} + 2^{1-H(S^{(1)}|T=t)} \right) \\ & \leq \log \left(2 - H(S^{(0)}|T=t) + 2 - H(S^{(1)}|T=t) \right) \\ & \leq \log \left(4 - H(S^{(0)}, S^{(1)}|T=t) \right) \end{aligned}$$

Averaging over T and noting that \log is concave, we have that capacity—with a scalar-quantization Helper who doesn't know M —is at most

$$\log \left(4 - H(S^{(0)}, S^{(1)}|T) \right) \leq \log 3$$

(This bound is tight: It can be achieved when Helper always sends $T = S^{(0)}$).

Example when Helper is non-scalar (does not know M)

Allow Helper to be noncausal, and provide T to both transmitter and receiver.

First consider $t = h(s_1, s_2)$. Given $T = t$, capacity of the “sum channel” is

$$\begin{aligned} & \log \left(2^{2-H(S_1^{(0)}, S_2^{(0)}|T=t)} + 2^{2-H(S_1^{(0)}, S_2^{(1)}|T=t)} + 2^{2-H(S_1^{(1)}, S_2^{(0)}|T=t)} + 2^{2-H(S_1^{(1)}, S_2^{(1)}|T=t)} \right) \\ &= \log \left(2^{1-H(S_1^{(0)}|T=t)} \cdot 2^{1-H(S_2^{(0)}|S_1^{(0)}, T=t)} + 2^{1-H(S_1^{(0)}|T=t)} \cdot 2^{1-H(S_2^{(1)}|S_1^{(0)}, T=t)} \right. \\ & \quad \left. + 2^{1-H(S_1^{(1)}|T=t)} \cdot 2^{1-H(S_2^{(0)}|S_1^{(1)}, T=t)} + 2^{1-H(S_1^{(1)}|T=t)} \cdot 2^{1-H(S_2^{(1)}|S_1^{(1)}, T=t)} \right) \\ &\leq \log \left(2^{1-H(S_1^{(0)}|T=t)} \cdot 2^{1-H(S_2^{(0)}|S_1^{(0)}, S_1^{(1)}, T=t)} + 2^{1-H(S_1^{(0)}|T=t)} \cdot 2^{1-H(S_2^{(1)}|S_1^{(0)}, S_1^{(1)}, T=t)} \right. \\ & \quad \left. + 2^{1-H(S_1^{(1)}|T=t)} \cdot 2^{1-H(S_2^{(0)}|S_1^{(0)}, S_1^{(1)}, T=t)} + 2^{1-H(S_1^{(1)}|T=t)} \cdot 2^{1-H(S_2^{(1)}|S_1^{(0)}, S_1^{(1)}, T=t)} \right) \\ &= \log \left(2^{1-H(S_1^{(0)}|T=t)} + 2^{1-H(S_1^{(1)}|T=t)} \right) + \log \left(2^{1-H(S_2^{(0)}|S_1, T=t)} + 2^{1-H(S_2^{(1)}|S_1, T=t)} \right) \\ &\leq \log(4 - H(S_1|T=t)) + \log(4 - H(S_2|S_1, T=t)) \leq 2 \log \left(4 - \frac{1}{2} H(S_1, S_2|T=t) \right) \end{aligned}$$

Averaging over T we again get $\log 3$ per channel use.

The proof can be generalized to $t = h(s^n)$ for any finite n .

Example: Summary

Theorem

In the above example, when Helper knows the message,

$$\text{capacity} = 2 \text{ bits.}$$

When Helper does not know the message,

$$\text{capacity} = \log 3.$$

Both equations hold irrespectively of whether Helper is causal or noncausal. Furthermore, they hold irrespectively of whether or not the help is also given to the Receiver.

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We have learned from this example:

1. Helper knowing the message M can indeed make a difference.
2. There is indeed a gap between our lower and upper bounds in the original setting (where Helper does not know M).

Let's go back to the original problem

Recall our upper bound was

$$\frac{1}{n} \sum_{i=1}^n I(U_i; Y_i)$$

with $U_i \triangleq (M, T^{i-1}, Y^{i-1})$. The “problem” was (unlike in the lower bound)

$$U_i \not\ll (S_i, T_i)$$

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We want to find a situation where it is useful to convey T^{i-1} to the Receiver.

WARNING

The following example may cause headache to some audiences.

Example where scalar-quantization Helper is suboptimal

- ▶ State is two uniform bits as in previous example: $S = (S^{(0)}, S^{(1)})$
- ▶ Input has three parts: $X = (A, B, C)$
where A and B are binary, while $|C| = 2^\eta$
- ▶ Output also has three parts: $Y = (A', D^{(0)}, D^{(1)})$
where A' is binary, while $D^{(0)}$ and $D^{(1)}$ each contains η bits
- ▶ Helper has one bit: $\mathcal{T} = \{0, 1\}$

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Channel law is:

- ▶ If $B \neq S^{(A)}$, then $Y \perp\!\!\!\perp (X, S)$ and uniform over its alphabet
- ▶ If $B = S^{(A)}$, then

$$A' = A, \quad D^{(B)} = C, \quad D^{(B \oplus 1)} \perp\!\!\!\perp X.$$

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You really want B to equal $S^{(A)}$...

Coding scheme for this example with non-scalar quantizer

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Let $T_0 \triangleq 0$. At time i ,

$$T_i = S_i^{(T_{i-1})}$$

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How this scheme works:

- ▶ Always guaranteed that $B = S^{(A)}$
- ▶ At time i , Receiver learns B_{i-1} , so it can recover C_{i-1} from $D_i^{(B_{i-1})}$
 \implies we achieve η bits per channel use

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First consider $T_i = S_i^{(0)}$.

- ▶ We must avoid $B \neq S^{(A)}$, so we must always choose $A = 0$ and $B = T$.
- ▶ $D^{(0)}$ or $D^{(1)}$ equals C , but Receiver does not know which one.

For large η , the achieved rate $\approx \eta - 1$ bits.

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Other scalar quantizers are even worse. We can list all possible scalar quantizers and upper-bound the rate that is achievable with each quantizer. Proof omitted.

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- ▶ In the example, T_i wants to depend on S^{i-1} because Transmitter wants to tell Receiver something about S^{i-1} ,
which is why scalar quantization is optimal when Receiver knows S^n !

Some reflections

- ▶ Why on earth would Helper want to tell Transmitter anything about S^{i-1} at time i ?

Perhaps it doesn't want to tell Transmitter anything "about" S^{i-1} .

But **WHICH PART** of S_i to convey can depend on S^{i-1} .

- ▶ In fact, giving S^{i-1} to Transmitter doesn't change anything!
- ▶ In the example, T_i wants to depend on S^{i-1} because Transmitter wants to tell Receiver something about S^{i-1} ,
which is why scalar quantization is optimal when Receiver knows S^n !
- ▶ This can be generalized to a block-Markov scheme; details omitted.

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- ▶ They become optimal if states are revealed to Receiver
- ▶ If Helper knows the message, then (message-dependent) scalar quantizer is optimal
- ▶ Helper knowing the message increases capacity

Thank you!