

# Transmission of Correlated Sources over a MAC: A Gaussian Approximation-Based Analysis

**Vincent Y. F. Tan**

Institute for Infocomm Research (I2R)  
National University of Singapore (NUS)

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# Transmission of Correlated Sources over a MAC

- We have a **2-DMS**  $S^n, T^n$  with distribution

$$p_{S^n, T^n}(s^n, t^n) = \prod_{i=1}^n p_{S, T}(s_i, t_i)$$

- They are to be **separately encoded** so  $x_1^n = \phi_n^1(s^n) \in \mathcal{X}_1^n$  and  $x_2^n = \phi_n^2(t^n) \in \mathcal{X}_2^n$

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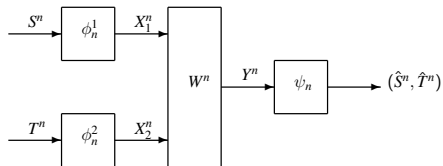
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- What is the condition on  $p_{S, T}$  and  $W$  so that

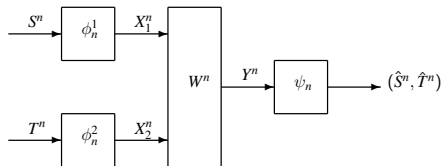
$$\lim_{n \rightarrow \infty} \mathbb{P}[(\hat{S}^n, \hat{T}^n) \neq (S^n, T^n)] = 0$$

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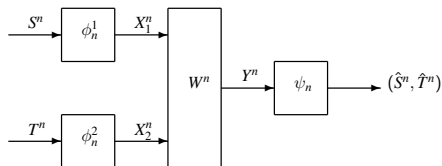
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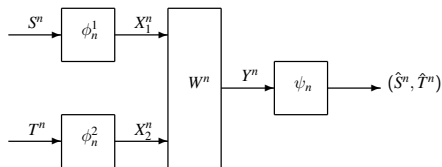
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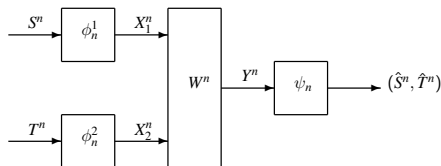


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- Unlike the MAC for channel coding,  $S^n$  and  $T^n$  can be **correlated**
- The **ratio** of channel uses to source symbols is assumed to be 1
- Second-order coding analysis has been done for
  - **Slepian-Wolf** (Tan-Kosut 2012) – [Will review](#)
  - **DM-MAC** (Tan-Kosut 2012, Huang-Moulin 2012 and MolavianJazi-Laneman 2012) – [Will review](#)
  - **JSCC** (Wang-Ingber-Kochman 2011, Kostina-Verdú 2012)

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- Surprisingly, at blocklength  $n$ , two inequalities that can be removed for CES **cannot be eliminated** in our second-order characterization

# A Brief Recap I

- In the asymptotic setting, by combining **Slepian-Wolf coding** and by encoding the compressed bits using a **multiple-access channel code**, if there exists  $p_Q(q), p_{X_1|Q}(x_1|q), p_{X_2|Q}(x_2|q)$  such that

$$H(S|T) < I(X_1; Y|X_2, Q)$$

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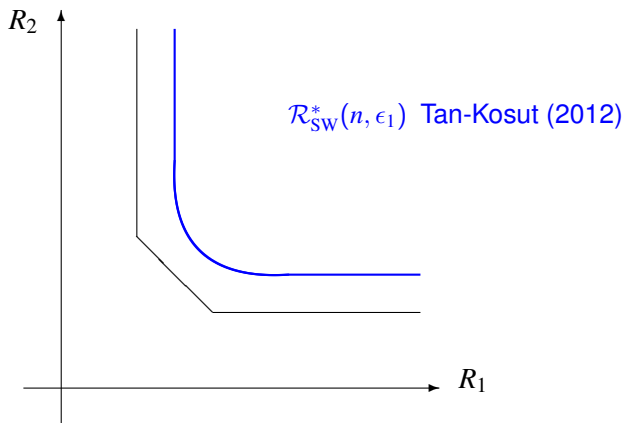
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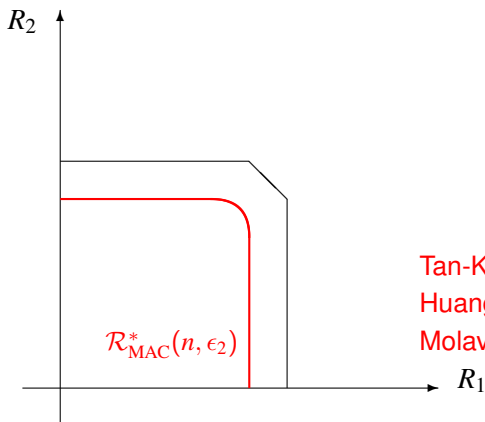
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- Corresponds to a **separation** strategy
- CES showed that this is strictly suboptimal

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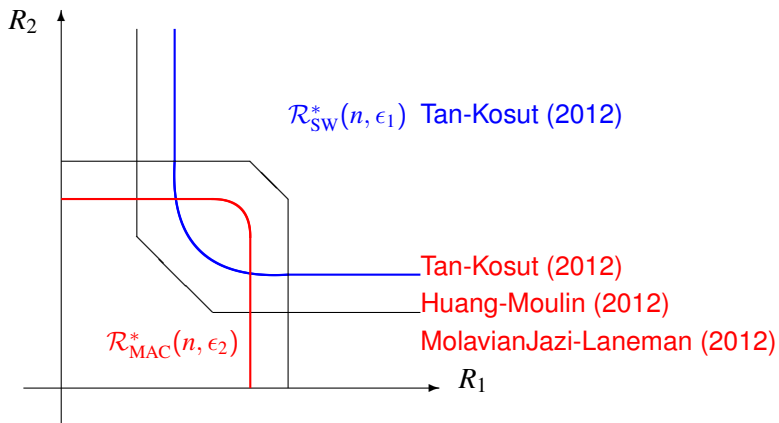


Tan-Kosut (2012)

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# Stephan-Wolf and MAC finite blocklength regions



If  $\mathcal{R}_{SW}^*(n, \epsilon_1) \cap \mathcal{R}_{MAC}^*(n, \epsilon_2) \neq \emptyset$  for some  $p(q), p(x_1|q), p(x_2|q)$ , then source is  $(n, \tilde{\epsilon})$ -transmissible using a separation strategy where

$$\tilde{\epsilon} = \epsilon_1 + \epsilon_2 - \epsilon_1 \epsilon_2$$

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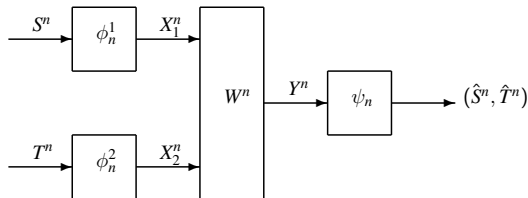
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- Generalization of the CES region when we only **allow a blocklength  $n$** ?

# Formal Definition of a Code



## Definition

An  $(|S|^n, |T|^n, n, \epsilon)$  **joint source-channel code** for transmitting the correlated source  $(S, T)$  over the MAC  $W$  consists of two encoders  $\phi_n^1 : S^n \rightarrow \mathcal{X}_1^n$ ,  $\phi_n^2 : T^n \rightarrow \mathcal{X}_2^n$  and a decoder  $\psi_n : \mathcal{Y}^n \rightarrow S^n \times T^n$  s.t.

$$\mathbb{P}[(\hat{S}^n, \hat{T}^n) \neq (S^n, T^n)] \leq \epsilon$$

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Define the set

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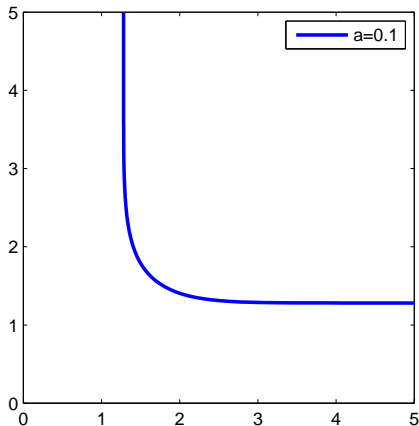
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- This set was also used to characterize the  $(n, \epsilon)$ -rate region for Slepian-Wolf coding



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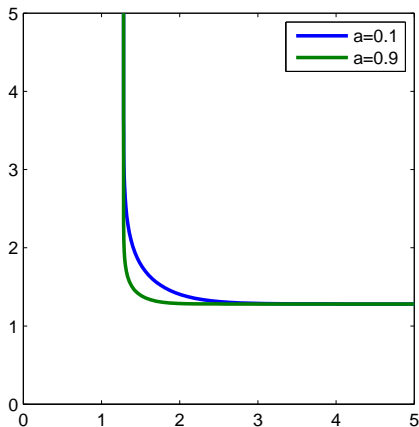
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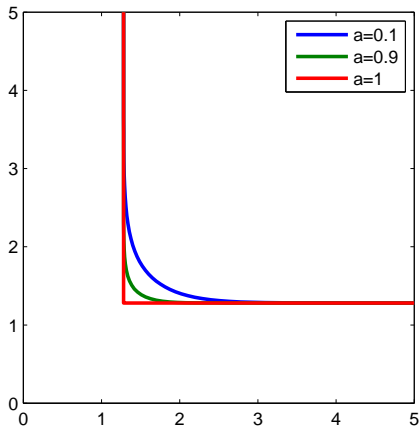
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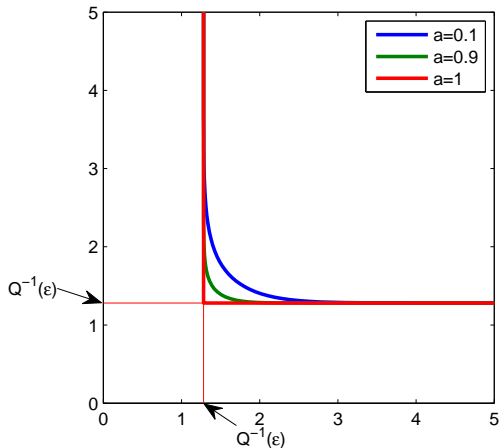
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where the **information dispersion matrix**  $\mathbf{V}(C, X_1, X_2)$  is the covariance of the random vector of differences between **information** and **entropy densities** (see paper).

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Can be improved using a **time-sharing rv  $Q$**  [Huang and Moulin, 2012]

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- All constraints are **coupled**
- Gaussian approximations and Chernoff bounds in the proof
- But two extra inequalities that cannot be removed when  $n$  is finite

$$I(X_1, C; Y|X_2, T) < H(S|T) + \sqrt{\frac{V_3}{n}}$$

$$I(X_2, C; Y|X_3, S) < H(T|S) + \sqrt{\frac{V_4}{n}}$$

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because of the chain rule and  $I(C; Y|X_2, T) \geq 0$ .

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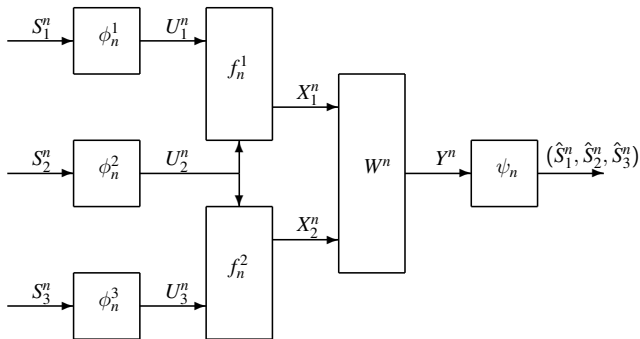
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- But region reduces to CES when  $n \rightarrow \infty$



# Proof Idea I: An Auxiliary System (Ahlsvede-Han)

- Consider transmitting a 3-DMS  $(S_1, S_2, S_3)$  over a MAC  
 $W : \mathcal{X}_1 \times \mathcal{X}_2 \rightarrow \mathcal{Y}$



# Proof Idea II: An Auxiliary System (Ahlsvede-Han)

- Input 1  $X_1^n = f_n^1(U_1^n, U_2^n)$  and  $U_j^n$  is a stoc. function of  $S_j^n$
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- Results in seven inequalities of which one can be eliminated
- Because we don't have to explicitly recover the common part  $S_2 = K$

# Proof Idea III: $(n, \epsilon)$ -Transmissibility for Ahlswede-Han

## Theorem $((n, \epsilon)$ -Transmissibility for the joint source $(S_1, S_2, S_3)$ )

If for sufficiently large  $n$ , there exists distributions  $p_{U_1|S_1}, p_{U_2|S_2}, p_{U_3|S_3}$  and functions  $f_1$  and  $f_2$  such that

$$[I(U_{\mathcal{A}}; Y|U_{\mathcal{A}^c}, S_{\mathcal{A}^c}) - H(S_{\mathcal{A}}|S_{\mathcal{A}^c}) : \emptyset \neq \mathcal{A} \subset [3]] \in \frac{\mathcal{S}_{\mathbf{V}(U_1, U_2, U_3)}(\epsilon)}{\sqrt{n}} + \frac{\log n}{n} \mathbf{1}_7,$$

where the information dispersion matrix  $\mathbf{V}(U_1, U_2, U_3)$  is the covariance of the difference between the *information* and *entropy densities*

$$\left[ \log \frac{p_{Y|U_{\mathcal{A}}, U_{\mathcal{A}^c}, S_{\mathcal{A}^c}}(Y|U_{\mathcal{A}}, U_{\mathcal{A}^c}, S_{\mathcal{A}^c})}{p_{Y|U_{\mathcal{A}^c}, S_{\mathcal{A}^c}}(Y|U_{\mathcal{A}^c}, S_{\mathcal{A}^c})} - \log \frac{1}{p_{S_{\mathcal{A}}|S_{\mathcal{A}^c}}(S_{\mathcal{A}}|S_{\mathcal{A}^c})} : \emptyset \neq \mathcal{A} \subset [3] \right],$$

then the source  $(S_1, S_2, S_3)$  is  $(n, \epsilon)$ -transmissible over  $W$ .

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where  $\mathcal{T}_{\delta_n}^{(n)}$  is the intersection of all **typical sets**

$$\mathcal{T}_{\delta_n}^{(n)}(\mathcal{A}) := \left\{ (s_1^n, s_2^n, s_3^n, u_1^n, u_2^n, u_3^n, y^n) : \right. \\ \left. \frac{1}{n} \log \frac{p_{Y^n|U_{\mathcal{A}}^n, U_{\mathcal{A}^c}^n, S_{\mathcal{A}^c}^n}(y^n|u_{\mathcal{A}}^n(s_{\mathcal{A}}^n), u_{\mathcal{A}^c}^n(s_{\mathcal{A}^c}^n), s_{\mathcal{A}^c}^n)}{p_{Y^n|U_{\mathcal{A}}^n, U_{\mathcal{A}^c}^n}(y^n|u_{\mathcal{A}}^n(s_{\mathcal{A}}^n), u_{\mathcal{A}^c}^n(s_{\mathcal{A}^c}^n))} \right. \\ \left. - \frac{1}{n} \log \frac{1}{p_{S_{\mathcal{A}}^n|S_{\mathcal{A}^c}^n}(s_{\mathcal{A}}^n|s_{\mathcal{A}^c}^n)} \geq \delta_n \right\}$$

# Proof Idea V: $(n, \epsilon)$ -Transmissibility for Ahlswede-Han

- The error events are

$$\mathcal{E}_0 := \{(S_1^n, S_2^n, S_3^n, U_1^n(S_1^n), U_2^n(S_2^n), U_3^n(S_3^n), Y^n) \notin \mathcal{T}_{\delta_n}^{(n)}\}$$

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- By **Chernoff bounds**, for every  $\emptyset \neq \mathcal{A} \subset [3]$ ,

$$\mathbb{P}(\mathcal{E}_{\mathcal{A}}) \approx 0$$

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- By using alternative techniques, we could potentially relax our condition on  $(n, \epsilon)$ -transmissibility