

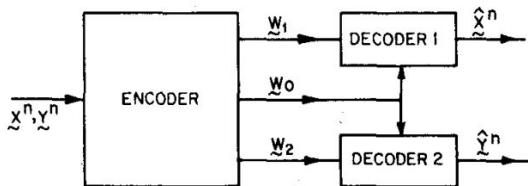
# Variations on Common Information

Robert Graczyk



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## Wyner's Common Information

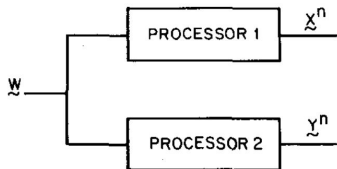


### Definition 1 (Wyner 1975)

The common information  $C_1(X; Y)$  between  $X$  and  $Y$  is the least common rate  $R_0$  under which almost-lossless compression of  $(X^n, Y^n)$  is possible subject to the no-excess-rate constraint

$$R_0 + R_1 + R_2 = H(X, Y)$$

## Wyner's Common Information



### Definition 2 (Wyner 1975)

The common information  $C_2(X; Y)$  between  $X$  and  $Y$  is the least common rate  $R_W$  under which simulation of  $(X^n, Y^n)$  is possible in the sense that

$$\frac{1}{n} \mathcal{D}(P_{X^n Y^n} \| P_{X^n} P_{Y^n}) \rightarrow 0$$

## Wyner's Common Information

### Theorem (Wyner 1975)

$$C_1(X; Y) = C_2(X; Y) = C_W(X; Y)$$

where

$$C_W(X; Y) \triangleq \min_{\substack{P_{W|XY}: \\ X \rightarrow W \rightarrow Y}} I(W; X, Y)$$

## Variation 1

Recall the Rényi entropy of  $X \sim P_X$

$$H_\alpha(X) = \frac{1}{1-\alpha} \log \left( \sum_x P_X(x)^\alpha \right), \quad \alpha \in \mathbb{R} \setminus \{1\}$$

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The Rényi entropy generalizes Shannon's

$$H(X) = \lim_{\alpha \rightarrow 1} H_\alpha(X)$$

Task: Find a Rényi-type common information measure  $C_\alpha(X; Y)$

$$C_W(X; Y) = \lim_{\alpha \rightarrow 1} C_\alpha(X; Y)$$

## Variation 2

When  $X = (U, V)$  and  $Y = (V, W)$  with  $U \perp V \perp W$

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Assume now that  $Z$  is independent of  $U$  and  $W$  but not of  $V$   
The common information between  $X$  and  $Y$  relevant to  $Z$  is

$$C(X; Y \rightarrow Z) = I(V; Z)$$

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Task: Generalize this notion of relevant common information

## An Operational Approach Towards $C_\alpha(X; Y)$

Yu and Tan suggested to replace the criterion

$$\frac{1}{n} \mathcal{D}(P_{X^n Y^n} \| P_{XY}^n) \rightarrow 0$$

in Wyner's definition of  $C_2(X; Y)$  with

$$\frac{1}{n} \mathcal{D}_\alpha(P_{X^n Y^n} \| P_{XY}^n) \rightarrow 0, \quad \alpha \in \mathbb{R}$$

where

$$\mathcal{D}_\alpha(P \| Q) = \frac{1}{\alpha - 1} \log \left( \sum_x \frac{P(x)^\alpha}{Q(x)^{\alpha-1}} \right), \quad \alpha \in \mathbb{R} \setminus \{1\}$$

## An Operational Approach Towards $C_\alpha(X; Y)$

### Theorem (Yu and Tan, 2018)

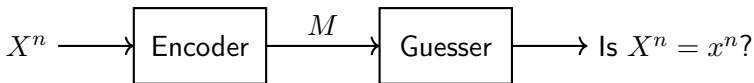
$$C_\alpha^{\text{YT}}(X; Y) = \begin{cases} 0 & \text{when } \alpha = 0 \\ C_W(X; Y) & \text{when } \alpha \in (0, 1] \end{cases}$$

Yu and Tan also obtained bounds on  $C_\alpha^{\text{YT}}(X; Y)$  for  $\alpha \in (1, 2]$

## A Different Operational Approach Towards $C_\alpha(X; Y)$

We propose a different approach based on

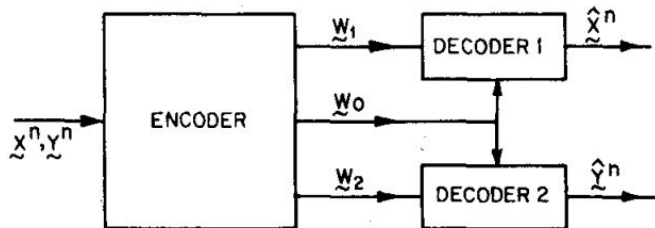
### A Simple Observation



The least description rate  $R$  of  $M$  that is required to drive  $\frac{1}{n} \log E[G(X^n | M)^\rho]$  to zero is  $H_{\tilde{\rho}}(X)$  where  $\tilde{\rho} = 1/(1 + \rho)$

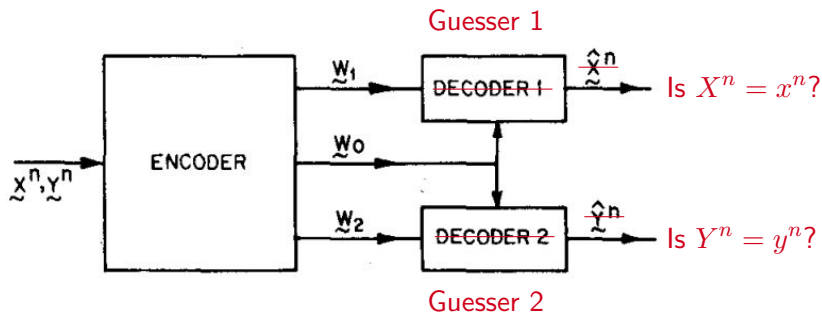
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Instead of ...



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... consider the setup



## Guessing on the Gray-Wyner Network

The rate triple  $(R_0, R_1, R_2)$  is  $(E_X, E_Y)$ -achievable if there exists a joint encoder and guessing strategies for  $X^n$  and  $Y^n$  that satisfy

$$\lim_{n \rightarrow \infty} \frac{1}{n} \log \mathbb{E}[G(X^n | M_0, M_1)^\rho] \leq E_X$$
$$\lim_{n \rightarrow \infty} \frac{1}{n} \log \mathbb{E}[G(Y^n | M_0, M_2)^\rho] \leq E_Y$$



## Guessing on the Gray-Wyner Network

### Theorem (Graczyk and Lapidoth, 2021)

The set of all  $(E_X, E_Y)$ -achievable rate triples  $(R_0, R_1, R_2)$  is given by

$$\bigcap_{Q_{XY}} \bigcup_{Q_{W|XY}} \left\{ (R_0, R_1, R_2) : \right.$$
$$R_0 \geq I_Q(W; X, Y)$$
$$R_1 \geq H_Q(X | W) - \frac{1}{\rho} (E_X + \mathcal{D}(Q_{XY} \| P_{XY}))$$
$$R_2 \geq H_Q(Y | W) - \frac{1}{\rho} (E_Y + \mathcal{D}(Q_{XY} \| P_{XY})) \left. \right\}$$

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Red: Gray-Wyner Source Coding Region

## Proof Outline

1. Assume  $(X^n, Y^n)$  are equiprobable over a type class  $\mathcal{T}^{(n)}(Q_{XY})$  (rather than IID according to  $P_{XY}$ )
2. Find the  $(E_X, E_Y)$ -achievable rate triples under that assumption (direct part via type covering, converse mostly standard)
3. Account for the assumption via the factor  $2^{-n\mathcal{D}(Q_{XY} \| P_{XY})}$

## An Operational Approach Towards $C_{\tilde{\rho}}(X; Y)$

Define the Rényi common information  $C_{\tilde{\rho}}(X; Y)$  of order  $\tilde{\rho} = 1/(1 + \rho)$  between  $X$  and  $Y$  as the least common rate  $R_0$  under which

$$\lim_{n \rightarrow \infty} \frac{1}{n} \log \mathbb{E}[G(X^n | M_0, M_1)^\rho] = 0$$

and

$$\lim_{n \rightarrow \infty} \frac{1}{n} \log \mathbb{E}[G(Y^n | M_0, M_2)^\rho] = 0$$

with  $(R_0, R_1, R_2)$  obeying the no-excess-rate constraint

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We shall focus on the **(0, 0)-achievable** rate triples  $(R_0, R_1, R_2)$

## Least Sum Rate in the Gray-Wyner Guessing Problem

To incorporate the no-excess-rate constraint we need the least  $(0, 0)$ -achievable sum rate

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the least sum rate equals the least  $R_0$  in

$$\bigcap_{Q_{XY}} \bigcup_{Q_{W|XY}} \left\{ \begin{array}{l} R_0 \geq I_Q(W; X, Y) \\ R_0: \quad 0 \geq H_Q(X | W) - \frac{1}{\rho} (0 + \mathcal{D}(Q_{XY} \| P_{XY})) \\ \quad \quad 0 \geq H_Q(Y | W) - \frac{1}{\rho} (0 + \mathcal{D}(Q_{XY} \| P_{XY})) \end{array} \right\}$$



## Least Sum Rate in the Gray-Wyner Guessing Problem

### Lemma (Graczyk and Lapidoth, 2021)

The least  $(0, 0)$ -achievable sum rate  $R_{\Sigma}^*$  equals

$$\sup_{Q_{XY}} \inf_{Q_{W|XY}: \begin{array}{l} H_Q(X|W) \leq \mathcal{D}(Q_{XY} \| P_{XY})/\rho \\ H_Q(Y|W) \leq \mathcal{D}(Q_{XY} \| P_{XY})/\rho \end{array}} I_Q(W; X, Y)$$

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Two observations:

1. In general  $R_{\Sigma}^* < H_{\tilde{\rho}}(X, Y)$
2. Because  $\operatorname{argmax} Q_{XY} \rightarrow P_{XY}$  as  $\rho \rightarrow 0$

$$\lim_{\rho \rightarrow 0} R_{\Sigma}^* = H_P(X, Y)$$

## An Operational Approach Towards $C_{\tilde{\rho}}(X; Y)$

### Theorem (Graczyk and Lapidath, 2021)

The Rényi common information  $C_{\tilde{\rho}}(X; Y)$  of order  $\tilde{\rho}$  between  $X$  and  $Y$  equals

$$\sup_{Q_{XY}} \inf_{\substack{Q_{W|XY}: \\ + \mathbb{H}_Q(X|W) - \mathcal{D}(Q_{XY} \| P_{XY})/\rho)^+ \\ + \mathbb{H}_Q(Y|W) - \mathcal{D}(Q_{XY} \| P_{XY})/\rho)^+ \\ + I_Q(W; X, Y) \leq R_{\Sigma}^*}} I_Q(W; X, Y)$$

where  $(\cdot)^+ = \max(\cdot, 0)$

## Does $C_{\bar{\rho}}(X; Y)$ Generalize $C_W(X; Y)$ ?

A final observation about  $C_{\bar{\rho}}(X; Y)$ :

Because  $\operatorname{argmax} Q_{XY} \rightarrow P_{XY}$  and  $R_{\Sigma}^* \rightarrow H_P(X, Y)$  as  $\rho \rightarrow 0$

$$\begin{aligned} & (H_Q(X | W) - \mathcal{D}(Q_{XY} \| P_{XY})/\rho)^+ \\ & + (H_Q(Y | W) - \mathcal{D}(Q_{XY} \| P_{XY})/\rho)^+ \\ & + I_Q(W; X, Y) \leq R_{\Sigma}^* \end{aligned}$$

is about equivalent to

$$H_P(X | W) + H_P(Y | W) + I_P(W; X, Y) \leq H_P(X, Y)$$

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## Does $C_{\tilde{\rho}}(X; Y)$ Generalize $C_W(X; Y)$ ?

Because

$$\begin{aligned} H_P(X | W) + H_P(Y | W) + I_P(W; X, Y) &\leq H_P(W; X, Y) \\ \iff H_P(X | W) + H_P(Y | W) &\leq H_P(X, Y | W) \\ \iff X \rightarrow W \rightarrow Y &\text{ under } P \end{aligned}$$

we indeed have

$$\lim_{\rho \rightarrow 0} C_{\tilde{\rho}}(X; Y) = \min_{\substack{P_{W|XY}: \\ X \rightarrow W \rightarrow Y}} I_P(W; X, Y) = C_W(X; Y)$$

## Three Follow-Up Questions

1. Can  $C_{\tilde{\rho}}(X; Y)$  be expressed in terms of  $H_{\tilde{\rho}}(\cdot)$ ,  $\mathcal{D}_{\tilde{\rho}}(\cdot \| \cdot)$ , and  $I_{\tilde{\rho}}(\cdot | \cdot)$ ?
2. Can we find a suitable operational definition for  $C_{\alpha}(X; Y)$  when  $\alpha \notin [0, 1]$ ?
3. How to systematically agree on a Rényi extension of  $C_W(X; Y)$ ?  
Proposition: via axiomization of  $C_W(X; Y)$

## Onto Relevant Common Information

Recall the example:  $X = (U, V)$ ,  $Y = (V, W)$  with  $U \perp\!\!\!\perp V \perp\!\!\!\perp W$

$$C_W(X; Y) = H(V) \text{ and } C(X; Y \rightarrow Z) = I(V; Z)$$

## Onto Relevant Common Information

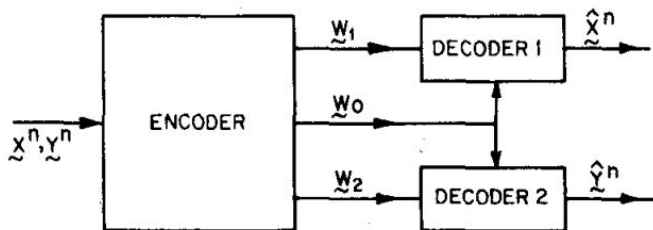
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$$C_W(X; Y) = H(V) \text{ and } \mathbf{C}(X; Y \rightarrow Z) = I(V; Z)$$

Task: Generalize this notion of **relevant common information** following a suitable operational approach

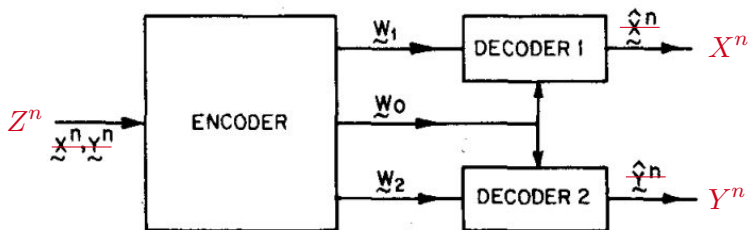
## An Operational Approach Towards $C(X; Y \rightarrow Z)$

Instead of ...



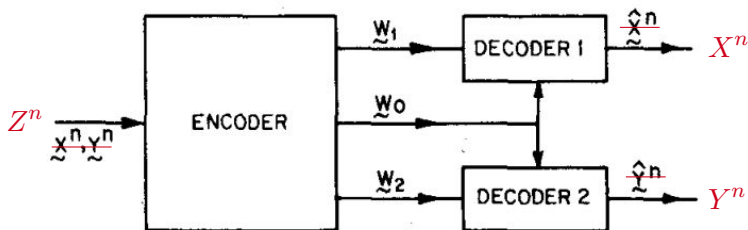
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For a given PMF  $P_{XYZ}$  we require that Decoder 1 and 2 produce  $X^n$  and  $Y^n$  that, together with  $Z^n \sim \text{IID } P_Z$ , coordinate  $P_{XYZ}$  in the **weak sense** that

$$\mathcal{D}(\Pi_{X^n Y^n Z^n} \| P_{XYZ}) \rightarrow 0$$

where  $\Pi_{X^n Y^n Z^n}$  denotes the empirical distribution of  $(X^n, Y^n, Z^n)$

## An Operational Approach Towards $C(X; Y \rightarrow Z)$

Define the common information  $C(X; Y \rightarrow Z)$  between  $X$  and  $Y$  relevant to  $Z$  as the least common rate  $R_0$  that allows for weak coordination of  $P_{XYZ}$  subject to the no-excess-rate constraint

$$R_0 + R_1 + R_2 = I(X, Y; Z)$$



## Weak Coordination on the Gray-Wyner Network

### Theorem (Graczyk, Lapidoth, and Wigger, 2022)

The set of all rate triples  $(R_0, R_1, R_2)$  that allow for weak coordination of  $P_{XYZ}$  subject to the no-excess-rate constraint  $R_0 + R_1 + R_2 = I(X, Y; Z)$  is given by

$$\bigcup_{\substack{P_{W|XYZ}: \\ X \rightarrow W \rightarrow Y \\ W \rightarrow (X, Y) \rightarrow Z}} \left\{ (R_0, R_1, R_2) : \begin{array}{l} R_0 \geq I(Z; W) \\ R_0 + R_1 \geq I(Z; X, W) \\ R_0 + R_2 \geq I(Z; Y, W) \end{array} \right\}$$

## An Operational Approach Towards $C(X; Y \rightarrow Z)$

**Corollary (Graczyk, Lapidath, and Wigger, 2022)**

$$C(X; Y \rightarrow Z) = \min_{\substack{P_{W|XYZ}: \\ X \rightarrow W \rightarrow Y \\ W \rightarrow (X,Y) \rightarrow Z}} I(Z; W)$$

## Proof

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3. Show that we can set

$$R_2 = I(Z; Y, W) - I(Z; W) + \Delta$$

for some  $\Delta \geq 0$  so that  $R_0 + R_1 + R_2 = I(X, Y; Z)$

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This is equivalent to showing that

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Indeed, because  $X \rightarrow W \rightarrow Y$  and  $W \rightarrow (X, Y) \rightarrow Z$ ,

$$\begin{aligned} I(Z; X, W) + I(Z; Y, W) - I(Z; W) &= I(Z; X | W) + I(Z; Y, W) \\ &= H(X | W) - H(X | W, Z) + I(Z; Y, W) \end{aligned}$$

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$$I(Z; X, W) + I(Z; Y, W) - I(Z; W) \leq I(X, Y; Z)$$

Indeed, because  $X \rightarrow W \rightarrow Y$  and  $W \rightarrow (X, Y) \rightarrow Z$ ,

$$\begin{aligned} & I(Z; X, W) + I(Z; Y, W) - I(Z; W) \\ &= I(Z; X | W) + I(Z; Y, W) \\ &= H(X | W) - H(X | W, Z) + I(Z; Y, W) \\ &\leq H(X | W) - H(X | W, Y, Z) + I(Z; Y, W) \\ &= H(X | W, Y) - H(X | W, Y, Z) + I(Z; Y, W) \\ &= I(Z; X | W, Y) + I(Z; Y, W) \\ &= I(Z; X, Y, W) \\ &= I(Z; X, Y) \end{aligned}$$

## Two Follow-Up Questions

1. What result do we obtain in the strong coordination problem?  
(instead of  $\Pi_{X^n Y^n Z^n} \rightarrow P_{XYZ}$  require that  $P_{X^n Y^n Z^n} \rightarrow P_{XYZ}^n$ )
2. How to systematically agree on a definition for relevant common information?

**Thank you for your attention!**