# Hybrid Random-Structured Coding 

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## Outline

(1) Random vs structured codes: Point-to-point systems
(2) Random vs. structured coding: Multiterminal systems

- Slepian-Wolf coding
- Körner \& Marton’s binary two-help-one problem
(3) The Gaussian two-help-one problem
- Berger-Tung (BT) random coding
- Krithivasan-Pradhan (KP) structured coding
- Hybrid random-structured coding
- Partial sum-rate tightness
- Gap to optimal sum-rate
(4) Conclusions


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## What are they?

Codes with randomness

- Invented by Shannon in 1948

Key theoretical tool

- In proving Shannon's classic source and channel coding theorems
Recent invention/rediscovery of codes based on random graphs
- Turbo/LDPC codes
- Fulfilled Shannon's prophecy (after 50 years) What do we learn from Shannon?
- Random codes are optimal for point-to-point systems


## Random graphs


$\qquad$


## What are they?

Codes with structure

- Linear/lattice/trellis codes

Widely used in communication systems

- For their low complexity
- Potentially limit-approaching (as promised by info theory)
- Achievable capacity $\frac{1}{2} \log ($ SNR $) \rightarrow \frac{1}{2} \log (1+$ SNR $)$ for AWGN channels
- Optimal for at least some point-to-point systems as well
- Structure "comes for free"


## Nested lattice codes



Can structured codes exceed the info-theoretic limits?

- No, at least for memoryless point-to-point systems


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## Slepian-Wolf coding'73

- $X, Y$ : two correlated sources with finite alphabet
- Separate encoding and joint decoding
- Near-lossless decoding, i.e., $\lim _{n \rightarrow \infty} P_{e}\left(\left(X^{n}, Y^{n}\right) \neq\left(\hat{X}^{n}, \hat{Y}^{n}\right)\right)=0$



## Slepian-Wolf theorem

- Slepian-Wolf rate region (proved by using random coding/bining)

$$
\begin{aligned}
R_{1} & \geq H(X \mid Y) \\
R_{2} & \geq H(Y \mid X) \\
R_{1}+R_{2} & \geq H(X, Y)
\end{aligned}
$$



- No rate loss compared to joint encoding of $X$ and $Y$


## Slepian-Wolf coding example

Assumptions:

- $X, Y \in\{0,1\}^{3} \rightarrow$ binary triplets
- $H(X)=H(Y)=3$ bits $\rightarrow$ equiprobable triplets
- Correlation between $X$ and $Y$
- x and y differ at most in one position
- Hamming distance $d_{H}(\mathrm{x}, \mathrm{y}) \leq 1$
- $H(X \mid Y)=2$ bits

Question:

- If $y$ is perfectly known at the decoder but not at the encoder, is it possible
- to send 2 bits instead of 3 for x and
- reconstruct x without loss?


## Slepian-Wolf coding example

## Solution:

- Form 4 cosets and send 2-bit index of the coset $x$ belongs to:
- coset $Z_{00}:\{000,111\} \leftarrow$ codewords of rate- $\frac{1}{3}$ repetition code
- coset $Z_{01}:\{001,110\}$
- coset $Z_{10}:\{010,101\}$
- coset $Z_{11}:\{011,100\}$
- In each set: 2 members at $d_{H}=3$
- Joint decoder: in the set indexed by $Z$ :
- Using $y$, pick $\hat{x}$ s.t. $d_{H}(\hat{x}, \mathrm{y}) \leq 1$
- This guarantees correct/lossless decoding

Example: $\mathrm{y}=[000]$, index 00 from encoder, $\hat{x}=[000]$ index 01 from encoder, $\hat{x}=[001]$ index 10 from encoder, $\hat{x}=[010]$ index 11 from encoder, $\hat{x}=[100]$

- Separate encoding as efficient as joint encoding!


## Equivalent way of viewing last example from a syndrome concept

- Form parity-check matrix of rate- $\frac{1}{3}$ repetition code

$$
\boldsymbol{H}=\left[\begin{array}{lll}
1 & 1 & 0 \\
1 & 0 & 1
\end{array}\right]
$$

- Syndrome=coset/bin index
- Coset/bin 0: $\{000,111\}$ has syndrome $Z=00$
- Coset/bin 1: $\{001,110\}$ has syndrome $Z=01$
- Coset/bin 2: $\{010,101\}$ has syndrome $Z=10$
- Coset/bin 3: $\{011,100\}$ has syndrome $Z=11$
- All 4 cosets preserve the distance properties of the repetition code
- Encoding corresponds to matrix multiplication $\boldsymbol{H x}$
- Compression 3:2
- Separate encoding as efficient as joint encoding!

1. Random coding optimal for this symmetric Slepian-Wolf coding example

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## Structured codes for multiterminal systems

## The binary two-help-one problem

How to encode the mod-2 sum of binary sources? Introduced by Körner \& Marton in 1979


- $Y_{1}$ and $Y_{2}$ are doubly symmetric binary sources
- Only the first two encoders are allowed to transmit, the decoder reconstructs $Z=Y_{1} \oplus Y_{2}$ losslessly
- This is combined compression and inference (for big data)
- Goes beyond Slepian-Wolf coding


## Structured codes for multiterminal systems

## The rate region of Körner-Marton coding

- Slepian-Wolf coding before forming $Z=Y_{1} \oplus Y_{2}$ certainly works
- Structured coding strictly improves random (Slepian-Wolf) coding!

Structured coding


Random coding


- Using the same linear code, encoder $i$ transmits $\boldsymbol{H} y_{i}$
- So both encoders use the same rate $\boldsymbol{H}(Z)$
- The decoder forms $\boldsymbol{H} y_{1} \oplus \boldsymbol{H y}_{2}=\boldsymbol{H}\left(\mathrm{y}_{1} \oplus \mathrm{y}_{2}\right)=\boldsymbol{H z}$ before recovering z
- by picking the element with $d_{H} \leq 1$ in the coset indexed by z


## Körner-Marton coding example

Recall 4 cosets at each encoder (from the Slepian-Wolf coding example)

- $\operatorname{coset} Z_{00}:\{000,111\}$; coset $Z_{01}:\{001,110\}$
- $\operatorname{coset} Z_{10}:\{010,101\} ; \operatorname{coset} Z_{11}:\{011,100\}$

Suppose $y_{1}=[101]$, encoder 1 transmits index 10

- $\mathrm{y}_{2}=[101]$, encoder 2 transmits 10 , decoder forms 00 before reconstructing z as [000]
- $\mathrm{y}_{2}=[001]$, encoder 2 transmits 01 , decoder forms 11 before reconstructing z as [100]
- $\mathrm{y}_{2}=[111]$, encoder 2 transmits 00 , decoder forms 10 before reconstructing z as [010]
- $\mathrm{y}_{2}=$ [100], encoder 2 transmits 11 , decoder forms 01 before reconstructing z as [001]
- First instance of linear coding beating the best-known random coding

2. Linear coding optimal for this symmetric Körner-Marton coding example

## Multiterminal systems

## Structured vs. random codes

It was long held that random codes are optimal for many comm. systems

- Körner and Marton's work showed advantage of structured code for some multiterminal systems
- Partially responsible for their recent back-to-back Shannon awards
- Structured coding for multiterminal systems currently a very active area of research Reprise
- Linear coding optimal for symmetric Körner-Marton coding
- Symmetry means $H\left(Y_{1} \mid Y_{2}\right)=H\left(Y_{2} \mid Y_{1}\right)$ or $P\left(Y_{1}=0 \mid Y_{2}=1\right)=P\left(Y_{1}=1 \mid Y_{2}=0\right)$

What about the general asymmetric case?

- $Y_{1}$ and $Y_{2}$ are binary sources with joint PMF ( $p_{01} \neq p_{10}$ in general)

| $Y_{1} \backslash Y_{2}$ | 0 | 1 |
| :--- | :---: | :---: |
| 0 | $p_{00}$ | $p_{01}$ |
| 1 | $p_{10}$ | $p_{11}$ |

- Q: Which coding scheme is better? A: Neither


## How to encode the mod-2 sum of binary sources?

## Ahlswede-Han coding

- Introduced by Ahlswede \& Han in 1983
- Random coding: First quantize $Y_{1}^{n}$ and $Y_{2}^{n}$ as $U_{1}^{n}$ and $U_{2}^{n}$
- Structured coding: Then apply Körner-Marton coding on $Y_{1}^{n}$ and $Y_{2}^{n}$ with $U_{1}^{n}$ and $U_{2}^{n}$ as decoder side info
- Achievable rate pairs

$$
\begin{aligned}
R_{1} & \geq I\left(Y_{1} ; U_{1} \mid U_{2}\right) \quad+H\left(Z \mid U_{1}, U_{2}\right) \\
R_{2} & \geq I\left(Y_{2} ; U_{2} \mid U_{1}\right) \quad+H\left(Z \mid U_{1}, U_{2}\right) \\
R_{1}+R_{2} & \geq I\left(Y_{1}, Y_{2} ; U_{1}, U_{2}\right)+2 H\left(Z \mid U_{1}, U_{2}\right)
\end{aligned}
$$

- Performs no worse than Slepian-Wolf and Körner-Marton coding for general correlation


## How to encode the mod-2 sum of binary sources?

## Ahlswede-Han coding example

- Expanded rate region when

| $Y_{1} \backslash Y_{2}$ | 0 | 1 |
| :--- | :---: | :---: |
| 0 | 0.00392 | 0.97608 |
| 1 | 0.01992 | 0.00008 |



- Due to asymmetry, time sharing between Slepian-Wolf and Körner-Marton always exists
- Ahlswede-Han coding achieves points (e.g., P) outside the time-sharing region
- Optimal coding scheme not known


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## The Gaussian two-help-one problem

## Definition

- Separate compression and joint decompression of a linear combination $\mathrm{Z}=Y_{1}-c Y_{2}$ of jointly Gaussian sources $Y_{1}$ and $Y_{2}$ subject to an MSE distortion constraint on $Z$
- Problem characterized by the linear coefficient $c$, the source correlation coefficient $\rho$, and the MSE distortion constraint $D$ on $Z$



## Motivation

- Arises in many practical video surveillance applications, e.g., reconstructing the motion difference between two video sequences


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## The Gaussian two-help-one problem

## Berger-Tung's generic random coding scheme 1977

- Independent quantization of
- $Y_{1}$ to $U_{1}$ s.t. $U_{1}=Y_{1}+Q_{1}$ with $Q_{1} \sim \mathcal{N}\left(0, q_{1}\right)$
- $Y_{2}$ to $U_{2}$ s.t. $U_{2}=Y_{2}+Q_{2}$ with $Q_{2} \sim \mathcal{N}\left(0, q_{2}\right)$
- Followed by Slepian-Wolf compression (or binning) of $U_{1}$ and $U_{2}$ leads to rate region

$$
\mathcal{R}^{B T}\left(q_{1}, q_{2}\right)=\left\{\begin{array}{rr}
R_{1} & \geq H\left(U_{1} \mid U_{2}\right) \\
\left(R_{1}, R_{2}\right): & R_{2}
\end{array} \geq H\left(U_{2} \mid U_{2}\right),\right.
$$

- Berger-Tung (BT) achievable rate region

$$
\begin{array}{r}
\mathcal{R}_{B T}(D)=\operatorname{conv}\left(\bigcup _ { ( U _ { 1 } , U _ { 2 } ) \in \mathcal { U } ( Y _ { 1 } , Y _ { 2 } ) } \left\{\left(R_{1}, R_{2}\right): R_{1} \geq I\left(Y_{1} ; U_{1} \mid U_{2}\right), R_{2} \geq I\left(Y_{2} ; U_{2} \mid U_{1}\right),\right.\right. \\
\left.\left.R_{1}+R_{2} \geq I\left(Y_{1}, Y_{2} ; U_{1}, U_{2}\right)\right\}\right)
\end{array}
$$

## The Gaussian two-help-one problem

## When $c \cdot \rho \leq 0$, e.g., $\rho>0, c=-1$

- Referred to as the $\mu$-sum problem (e.g., with $Z=Y_{1}+Y_{2}$ )
- Considered by Wagner et al. in 2005
- Berger-Tung (or random QB) coding is optimal



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## The Gaussian two-help-one problem

## When $c \cdot \rho>0$, e.g., $\rho>0, c=1$

- Referred to as the $\mu$-difference problem (e.g., with $Z=Y_{1}-Y_{2}$ )
- Considered by Krithivasan-Pradhan in 2009 using structured/lattice codes
- Two lattices $\left(\Lambda_{1}, \Lambda_{2}\right)$ for SC ; one lattice $\Lambda_{C}$ with $\Lambda_{C} \subseteq \Lambda_{i}$ for CC
- Independent lattice quantizers $\left(\Lambda_{1}, \Lambda_{2}\right)$ on $Y_{1}$ and $c Y_{2}$
- Encoders send quantized versions modulo the same lattice $\Lambda_{C}$
- Transmission rates

$$
R_{i}=\log _{2} \frac{\sigma^{2}\left(\Lambda_{C}\right)}{\sigma^{2}\left(\Lambda_{i}\right)}
$$

- Krithivasan-Pradhan (KP) achievable rate region

$$
\mathcal{R}_{K P}(D)=\left\{\left(R_{1}, R_{2}\right): 2^{-2 R_{1}}+2^{-2 R_{2}} \leq \frac{D}{1+c^{2}-2 c \rho}\right\}
$$

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- Considered by Krithivasan-Pradhan in 2009 using structured/lattice codes
- Smaller sum-rate than the random Berger-Tung scheme for certain $(\rho, c)$ pairs
- Structured codes beat random codes!



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## The Gaussian two-help-one problem

## When $c \cdot \rho>0$, e.g., $\rho>0, c=1$

- For the $\mu$-difference problem, can we do better?
- New hybrid random-structured coding scheme
- Inspired by Ahlswede \& Han's for encoding the mod-2 sum of binary sources
- Hybrid random BT coding (layer I) and structured KP coding (layer II)

Encoder 1


## The Gaussian two-help-one problem

## When $c \cdot \rho>0$, e.g.,

- Theorem 1: Achievable rate region of hybrid random-structured coding

$$
\left.\begin{array}{rl}
\mathcal{R}_{\text {new }}(D)=\operatorname{conv}\left(\begin{array} { l } 
{ \bigcup _ { ( U _ { 1 } , U _ { 2 } ) \in \mathcal { U } ( c , D ) } }
\end{array} \quad \left\{\left(R_{1}, R_{2}\right):\right.\right. \\
R_{1} & \geq I\left(Y_{1} ; U_{1} \mid U_{2}\right)+I\left(V_{1}-V_{2} ; Y_{1}, V_{2} \mid U_{1}, U_{2}\right), \\
R_{2} & \geq I\left(Y_{2} ; U_{2} \mid U_{1}\right)+I\left(V_{1}-V_{2} ; V_{1}, Y_{2} \mid U_{1}, U_{2}\right), \\
R_{1}+R_{2} \geq I\left(Y_{1}, Y_{2} ; U_{1}, U_{2}\right)+I\left(V_{1}-V_{2} ; Y_{1}, V_{2} \mid U_{1}, U_{2}\right) \\
\left.\left.\quad+I\left(V_{1}-V_{2} ; V_{1}, Y_{2} \mid U_{1}, U_{2}\right)\right\}\right)
\end{array}\right\} \begin{array}{r}
\mathcal{U}(c, D) \triangleq\left\{\left(U_{1}, U_{2}, V_{1}, V_{2}\right): U_{i}=Y_{i}+P_{i}, V_{1}=Y_{1}+Q_{1}, V_{2}=c Y_{2}+Q_{2},\right. \\
P_{i} \sim \mathcal{N}\left(0, p_{i}\right), Q_{i} \sim \mathcal{N}\left(0, q_{i}\right), i=1,2, \text { indep. of each other and } \\
\left.\left(Y_{1}, Y_{2}\right), \text { such that } E\left[\left(Z-E\left(Z \mid U_{1}, U_{2}, V_{1}-V_{2}\right)\right)^{2}\right] \leq D\right\}
\end{array}
$$

## The Gaussian two-help-one problem

## When $c \cdot \rho>0$, e.g., $\rho>0, c=1$

- Comparison between $\mathcal{R}_{\text {new }}(D), \mathcal{R}_{K P}(D)$ and $\mathcal{R}_{B T}(D)$
- Hybrid coding always subsumes structured KP coding

$$
\mathcal{R}_{\text {new }}(D) \supseteq \mathcal{R}_{K P}(D)
$$

- It becomes a QB random coding with additional rate of $\frac{1}{2} \log _{2} \frac{1}{\alpha}$ and $\frac{1}{2} \log _{2} \frac{1}{\beta}$ (with $\alpha+\beta=1$ ) at the two encoders
- Lemma 1:

$$
\mathcal{R}_{\text {new }}(D) \supseteq \mathcal{R}_{K P}(D) \cup\left[\mathcal{R}_{B T}(D) \uplus\left\{\left(\frac{1}{2} \log _{2} \frac{1}{\alpha}, \frac{1}{2} \log _{2} \frac{1}{\beta}\right): \alpha+\beta=1\right\}\right]
$$

New rate region $\mathcal{R}_{\text {new }}(D)$ strictly improves the time-sharing region between $\mathcal{R}_{K P}(D)$ and $\mathcal{R}_{B T}(D)$

## The Gaussian two-help-one problem

## When $c \cdot \rho>0$, e.g., $\rho>0, c=1$

- Comparison between $\mathcal{R}_{\text {new }}(D), \mathcal{R}_{K P}(D)$ and $\mathcal{R}_{B T}(D)$



## The Gaussian two-help-one problem

## When $c \cdot \rho>0$, e.g., $\rho>0, c=1$

- We look deeper at the minimum achievable sum-rate

$$
R_{\text {new }}(D) \triangleq \min \left\{R_{1}+R_{2}:\left(R_{1}, R_{2}\right) \in \mathcal{R}_{\text {new }}(D)\right\}
$$

- Theorem 2: Achievable sum-rate of hybrid random-structured coding

$$
R_{\text {new }}(D)=\left\{\begin{array}{l}
\frac{1}{2} \log _{2} \frac{16 c^{2}\left(1-\rho^{2}\right)(1-c \rho)^{2}}{D^{2}}, \\
\text { if } c \leq \frac{1}{\rho+\sqrt{1-\rho^{2}}} \& D \leq 2 c^{2}\left(1-\rho^{2}\right) \\
\min \left(\log _{2} \frac{2 \sigma_{Z}^{2}}{D}, \frac{1}{2} \log _{2} \frac{16 c\left(\left(1-\rho^{2}\right) c-\rho D\right)}{D^{2}}\right), \\
\text { if } c>\frac{1}{\rho+\sqrt{1-\rho^{2}}} \& D \leq \frac{2 c^{2}\left(1-\rho^{2}\right)}{1+c \rho} \\
\min \left(\log _{2}^{+} \frac{2 \sigma_{Z}^{2}}{D}, \frac{1}{2} \log _{2}^{+} \frac{4(1-c \rho)^{2}}{D-c^{2}\left(1-\rho^{2}\right)}\right),
\end{array}\right.
$$

otherwise

## The Gaussian two-help-one problem

## When $c \cdot \rho>0$, e.g., $\rho>0, c=1$

- Comparison between $R_{\text {new }}(D), R_{K P}(D)$ and $R_{B T}(D)$
- Corollary to Lemma 1 :

$$
R_{\text {new }}(D) \leq \min \left(R_{K P}(D), R_{B T}(D)+1\right)
$$

- When can $R_{\text {new }}(D)$ strictly improve both $R_{K P}(D)$ and $R_{B T}(D)$ ?
- Lemma 2:

$$
R_{\text {new }}(D)<\min \left(R_{K P}(D), R_{B T}(D)\right)
$$

if either $\frac{1}{2 \rho}<c<\min \left(\frac{\sqrt{3}}{2 \rho}, \frac{1}{\rho+\sqrt{1-\rho^{2}}}\right) \& D<\frac{c\left(1-\rho^{2}\right)(3-2 c \rho)(2 c \rho-1)}{\rho}$

$$
\text { or } \frac{\sqrt{3}}{2 \rho}<c<\frac{1}{\rho+\sqrt{1-\rho^{2}}} \& D<4(2-\sqrt{3}) c^{2}\left(1-\rho^{2}\right)
$$

## The Gaussian two-help-one problem

## When $c \cdot \rho>0$, e.g., $\rho>0, c=1$

- Comparison between $R_{\text {new }}(D), R_{K P}(D)$ and $R_{B T}(D)$



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## The Gaussian two-help-one problem

## Partial sum-rate tightness

- Sum-rate lower bound needed -- to compared with achievable sum-rate upper bound from hybrid coding
- Consider a new and more general problem of Gaussian two-terminal SC problem with covariance matrix $\Sigma_{Y}=\left[\begin{array}{ll}1 & \rho \\ \rho & 1\end{array}\right]$ and covariance matrix distortion constraint $\mathcal{D}=\left[\begin{array}{cc}k_{1}^{2} & \theta k_{1} k_{2} \\ \theta k_{1} k_{2} & k_{2}^{2}\end{array}\right]$
- Fact: If the minimum sum-rate for the above problem is $R(\mathcal{D})$, then

$$
R(D)=\min _{\mathcal{D} \in \mathbf{\Upsilon}(\rho, c, D)} R(\mathcal{D}),
$$

where $\Upsilon(\rho, c, D)$ contains all real $2 \times 2$ symmetric matrices $\mathcal{D}$ such that $\mathbf{0} \leq \mathcal{D} \leq \Sigma_{Y}$ and $[1-c] \mathcal{D}[1-c]^{T} \leq D$

## The Gaussian two-help-one problem

## Partial sum-rate tightness

- Lemma 3: A new sum-rate lower bound $R(\mathcal{D}) \geq \max \left(\underline{R}^{\dagger}(\mathcal{D}), \underline{R}^{\ddagger}(\mathcal{D})\right)$, where

$$
\begin{aligned}
& \underline{R}^{\dagger}(\mathcal{D}) \triangleq \begin{cases}\frac{1}{2} \log _{2}\left[\frac{1-\rho^{2}+2 \rho k_{1} k_{2}(1+\theta)}{(1+\theta)^{2} k_{1}^{2} k_{2}^{2}}\right], & \theta \leq \theta^{\star} \\
\frac{1}{2} \log _{2}\left[\frac{\left(1-\rho^{2}\right)^{2}}{(1-\theta)^{2} k_{1}^{2} k_{2}^{2}\left(1-\rho^{2}+2 \rho k_{1} k_{2}(1+\theta)\right)}\right], & \theta>\theta^{\star}\end{cases} \\
& \underline{R}^{\ddagger}(\mathcal{D}) \triangleq \begin{cases}\frac{1}{2} \log _{2}\left[\frac{1-\rho^{2}+2 \rho k_{1} k_{2}(1+\theta)}{(1+\theta)^{2} k_{1}^{2} k_{2}^{2}}\right], & \theta \leq \theta^{\star} \\
\frac{1}{2} \log _{2}\left[\frac{\theta^{2}}{(1-\theta)^{2} k_{i}^{2}\left(4 k_{i}^{2} \rho^{2} \rho^{2}-4 \rho \theta k_{1} k_{2}+k_{j}^{2}\right)}\right], & \theta^{\star}<\theta \leq \theta^{\ddagger} \\
\frac{1}{2} \log _{2}\left[\frac{\left(1-\rho^{2}\right)^{2}\left(1-\rho^{2}-k_{j}^{2}\left(1-\theta^{2}\right)\right)}{\left(1-\theta^{2}\right)^{2} k_{1}^{2} k_{2}^{2}\left(\left(1-\rho^{2}\right)^{2}-k_{j}\left(k_{j}-2 k_{i} \rho \theta\right)\left(1-\rho^{2}\right)-k_{1}^{2} k_{2}^{2} \rho^{2}\left(1-\theta^{2}\right)\right)}\right], & \theta^{\ddagger}<\theta\end{cases}
\end{aligned}
$$

with $k_{i}=\min \left(k_{1}, k_{2}\right), k_{j}=\max \left(k_{1}, k_{2}\right)$, and

$$
\begin{aligned}
& \theta^{\star} \triangleq \frac{1}{2 \rho k_{1} k_{2}}\left(\sqrt{\left(1-\rho^{2}\right)^{2}+4 \rho^{2} k_{1}^{2} k_{2}^{2}}-\left(1-\rho^{2}\right)\right) \\
& \theta^{\ddagger} \triangleq \frac{1}{2 \rho k_{1} k_{2}}\left(\sqrt{\left(1-\rho^{2}\right)^{2}+4 \rho^{2} k_{1}^{2} k_{2}^{2}-8 k_{i}^{2} \rho^{2}\left(1-\rho^{2}\right)}+\left(1-\rho^{2}\right)\right)
\end{aligned}
$$

## The Gaussian two-help-one problem

## Partial sum-rate tightness

- Lemma 3: A new sum-rate lower bound $R(\mathcal{D}) \geq \max \left(\underline{R}^{\dagger}(\mathcal{D}), \underline{R}^{\ddagger}(\mathcal{D})\right)$, where

$$
\begin{aligned}
& \underline{R}^{\dagger}(\mathcal{D}) \triangleq \begin{cases}\frac{1}{2} \log _{2}\left[\frac{1-\rho^{2}+2 \rho k_{1} k_{2}(1+\theta)}{(1+\theta)^{2} k_{1}^{2} k_{2}^{2}}\right], & \theta \leq \theta^{\star} \\
\frac{1}{2} \log _{2}\left[\frac{\left(1-\rho^{2}\right)^{2}}{(1-\theta)^{2} k_{1}^{2} k_{2}^{2}\left(1-\rho^{2}+2 \rho k_{1} k_{2}(1+\theta)\right)}\right], & \theta>\theta^{\star}\end{cases} \\
& \underline{R}^{\ddagger}(\mathcal{D}) \triangleq \begin{cases}\frac{1}{2} \log _{2}\left[\frac{1-\rho^{2}+2 \rho k_{1} k_{2}(1+\theta)}{(1+\theta)^{2} k_{1}^{2} k_{2}^{2}}\right], & \theta \leq \theta^{\star} \\
\frac{1}{2} \log _{2}\left[\frac{\left(1-\rho^{2}\right)^{2}}{(1-\theta)^{2} k_{i}^{2}\left(4 k_{i}^{2} \rho^{2}-4 \rho \theta k_{1} k_{2}+k_{j}^{2}\right)}\right], & \theta^{\star}<\theta \leq \theta^{\ddagger} \\
\frac{1}{2} \log _{2}\left[\frac{\left(1-\rho^{2}\right)^{2}\left(1-\rho^{2}-k_{j}^{2}\left(1-\theta^{2}\right)\right)}{\left(1-\theta^{2}\right)^{2} k_{1}^{2} k_{2}^{2}\left(\left(1-\rho^{2}\right)^{2}-k_{j}\left(k_{j}-2 k_{i} \rho \theta\right)\left(1-\rho^{2}\right)-k_{1}^{2} k_{2}^{2} \rho^{2}\left(1-\theta^{2}\right)\right)}\right], & \theta^{\ddagger}<\theta\end{cases}
\end{aligned}
$$

- The 1 st lower bound $\underline{R}^{\dagger}(\mathcal{D})$ proved in Xiong' 13 using the estimation-theoretic approach of Wang' 10
- The 2nd lower bound $\underline{R}^{\ddagger}(\mathcal{D})$ newly obtained by combining the approach of Wang' 10 and the technique in Wagner'11, which exploits stochastic degradedness of the channel $Y_{1} \rightarrow Y_{2}$ with respect to $Y_{1} \rightarrow Z$


## The Gaussian two-help-one problem

## Partial sum-rate tightness

- Theorem 3: A new sum-rate lower bound

$$
R(D) \geq \underline{R}(D) \triangleq \min _{\mathcal{D} \in \Upsilon(\rho, c, D)} \max \left(\underline{R}^{\dagger}(\mathcal{D}), \underline{R}^{\ddagger}(\mathcal{D})\right)
$$

- Comparison among sum-rate lower and upper bounds



## The Gaussian two-help-one problem

## Partial sum-rate tightness

- Theorem 4: First partial sum-rate tightness result

$$
\begin{gathered}
R_{Q B}(D)=R(D)=\underline{R}(D) \\
\text { if } \rho \in(0,1), 0 \leq c \leq \frac{1}{1+2 \rho}, D \geq \frac{2 c^{2}\left(1-\rho^{2}\right)(1-2 c \rho)}{1-3 c \rho} \text { or } 0 \leq c \leq \frac{2 \rho}{1+2 \rho^{2}}, D \geq \frac{c\left(1-\rho^{2}\right)\left(1-2 c^{2} \rho^{2}\right)}{\rho(2-3 c \rho)}
\end{gathered}
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## Outline

## (1) Random vs structured codes: Point-to-point systems

(2) Random vs. structured coding: Multiterminal systems

- Slepian-Wolf coding
- Körner \& Marton's binary two-help-one problem


## (3) The Gaussian two-help-one problem

- Berger-Tung (BT) random coding
- Krithivasan-Pradhan (KP) structured coding
- Hybrid random-structured coding
- Partial sum-rate tightness
- Gap to optimal sum-rate
(4) Conclusions


## The Gaussian two-help-one problem

## Gap to optimal sum-rate

- Theorem 5: For any ( $\rho, c, D$ ) triple, it holds that

$$
R_{\text {new }}(D)-R(D) \leq R_{\text {new }}(D)-\underline{R}(D) \leq 2
$$



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R_{\text {new }}(D)-R(D) \leq R_{\text {new }}(D)-\underline{R}(D) \leq 2
$$



## The Gaussian two-help-one problem

## Gap to optimal sum-rate

- Lemma 4: If $c=1$ or $c=\rho$, it holds that

$$
R_{\text {new }}(D)-R(D) \leq R_{\text {new }}(D)-\underline{R}(D) \leq 1
$$



## Conclusions

## Intellectual merits:

- Hybrid scheme conceptually brings together two different worlds
- Philosophically the right approach (with better performance)


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- Hybrid scheme conceptually brings together two different worlds
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Problem addressed:

- Very timely and interesting
- Thanks to Körner \& Marton, Ahlswede \& Han, and other IT gurus
- Combined SC and inference for big data
- The more general many-help-one problem
- Results significant and intriguing
- First partial sum-rate tightness results
- Many open issues (e.g., optimality of hybrid coding)


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- First partial sum-rate tightness results
- Many open issues (e.g., optimality of hybrid coding)

Broader impact:

- Hybrid approach applicable to many other network comm. scenarios
- Cooperative networks: The two-way relay channel
- The interference channels


## References

(1) Slepian and Wolf, "Noiseless coding of correlated information sources," IEEE Trans. Inform. Theory, Jul. 1973.
(2 Körner and Marton, "How to encode the modulo-two sum of binary sources," IEEE Trans. Inform. Theory, Mar. 1979.
(3) Ahlswede and Han, "On source coding with side information via a multiple-access channel and related problems in multi-user information theory," IEEE Trans. Inform. Theory, May 1983.
(9) Krithivasan and Pradhan, "Lattices for distributed source coding: jointly Gaussian sources and reconstruction of a linear function," IEEE Trans. Inform. Theory, Dec. 2009.
(3) Wagner, "On distributed compression of linear functions," IEEE Trans. Inform. Theory, Jan. 2011.
(0) Maddah-Ali and Tse, "Interference neutralization in distributed lossy source coding," Proc. ISIT' 10, Jun. 2010
(1) Yang, Zhang, and Xiong, "A new sufficient condition for sum-rate tightness in quadratic Gaussian multiterminal source coding," IEEE Trans. Inform. Theory, January 2013.
(8) Yang and Xiong, "Distributed compression of linear functions: Partial sum-rate tightness and gap to optimal sum-rate," IEEE Trans. Inform. Theory, to appear.

