

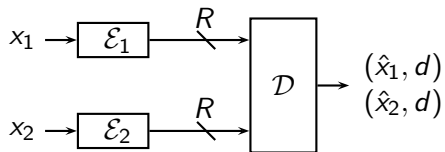
# Integer-Forcing Source Coding

Or Ordentlich  
Joint work with Uri Erez

June 30th, 2014  
ISIT, Honolulu, HI, USA

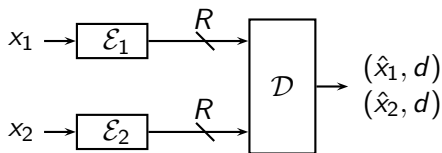
# Motivation 1 - Universal Quantization

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \sim \mathcal{N}(\mathbf{0}, \mathbf{K}_{xx})$$



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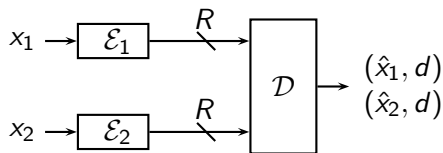


## Goal:

- Simple, identical, universal, non-cooperating quantizers  $\mathcal{E}_1, \mathcal{E}_2$
- Simple decoder  $\mathcal{D}$  that can depend on  $\mathbf{K}_{xx}$
- Good performance for all  $\mathbf{K}_{xx}$  with the same  $\log \det \left( \mathbf{I} + \frac{1}{d} \mathbf{K}_{xx} \right)$

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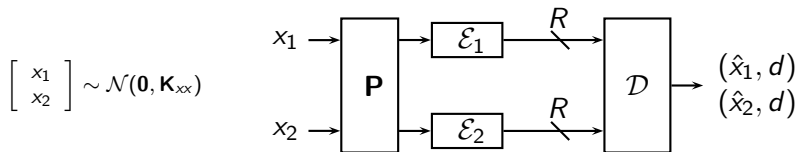
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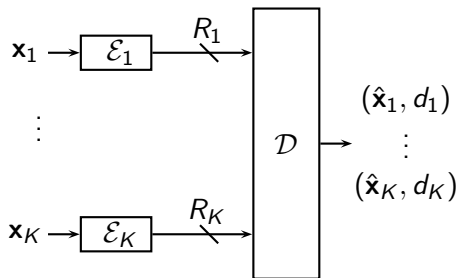
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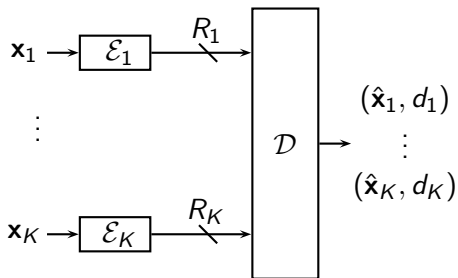
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Willing to apply a **universal** linear transformation before quantization

## Motivation 2 - Distributed Lossy Compression

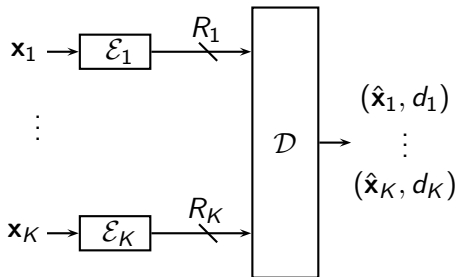


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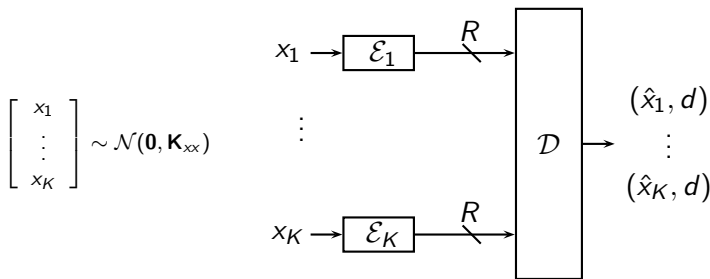
- Fundamental limits understood in some cases
- Inner and outer bounds known

### Some applications require

- Extremely simple encoders/decoder
- Extremely short delay



## Motivation 2 - Distributed Lossy Compression



We restrict attention to:

- Gaussian sources  $\mathbf{x} \sim \mathcal{N}(\mathbf{0}, \mathbf{K}_{xx})$
- One-shot compression - block length is 1
- Symmetric rates  $R_1 = \dots = R_K = R$
- Symmetric distortions  $d_1 = \dots = d_K = d$
- MSE distortion measure:  $E(x_k - \hat{x}_k)^2 \leq d$

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- Simple encoders: uniform scalar quantizers
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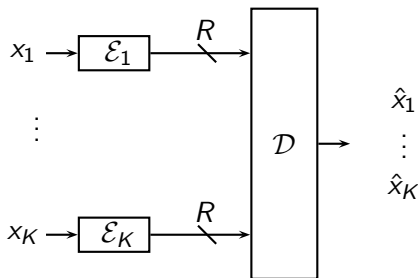
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## Scalar Modulo

- A simple 1-D binning operation
- Allows for efficient decoding using integer-forcing

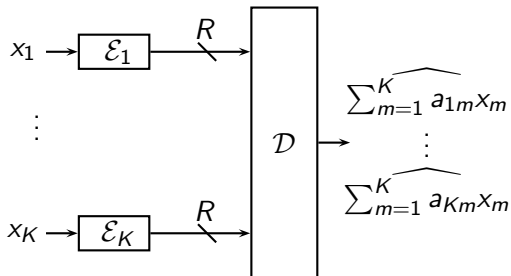
# Integer-Forcing Source Coding: Overview

**Basic Idea:** Rather than solving the problem



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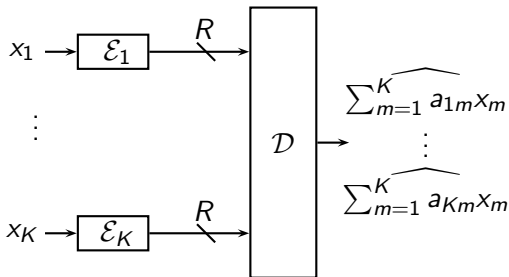
First solve



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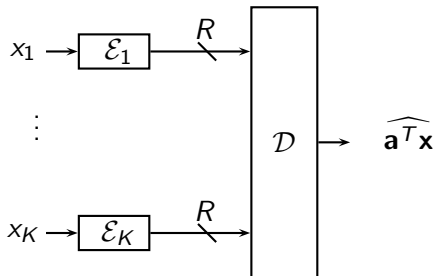
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and then invert equations to get  $\hat{x}_1, \dots, \hat{x}_K$

- Problem reduces to simultaneous distributed compression of  $K$  linear combinations
- Can be efficiently solved with small rates for certain choices of coefficients
- Equation coefficients can be chosen to optimize performance

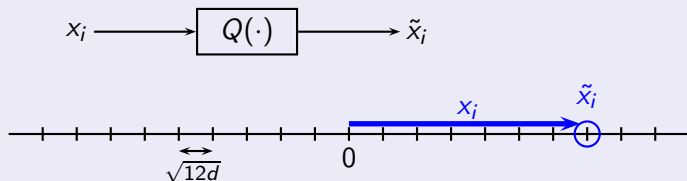
# Distributed Compression of Integer Linear Combination





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## Scalar Quantization



- High resolution/dithered quantization:

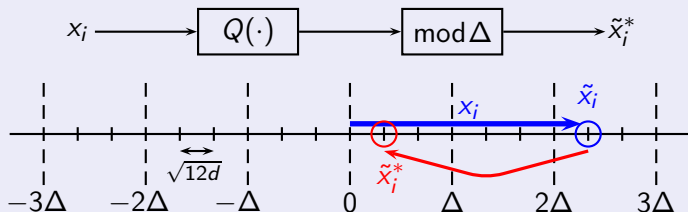
$$\tilde{x}_i = x_i + u_i$$

where  $u_i \sim \text{Uniform}\left(\left[-\frac{\sqrt{12d}}{2}, \frac{\sqrt{12d}}{2}\right]\right)$ ,  $u_i \perp\!\!\!\perp x_i$

- $\mathbb{E}(\tilde{x}_i - x_i)^2 = d$

# Distributed Compression of Integer Linear Combination

## Modulo Scalar Quantization



- $\Delta = 2^R \sqrt{12d} \implies$  Compression rate is  $R$
- High resolution/dithered quantization:

$$\tilde{x}_i^* = [x_i + u_i]^*$$

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## Encoders

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## Simple modulo property

For any set of integers  $a_1, \dots, a_K$  and real numbers  $\tilde{x}_1, \dots, \tilde{x}_K$

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## Decoder

- Gets:  $\tilde{x}_1^*, \dots, \tilde{x}_K^*$
- Outputs:

$$\widehat{\mathbf{a}^T \mathbf{x}} = \left[ \sum_{k=1}^K a_k \tilde{x}_k^* \right]^* = \left[ \sum_{k=1}^K a_k \tilde{x}_k \right]^* = \left[ \mathbf{a}^T (\mathbf{x} + \mathbf{u}) \right]^*$$

# Compression of Integer Linear Combination - $P_e$

$$\widehat{\mathbf{a}^T \mathbf{x}} = \left[ \mathbf{a}^T (\mathbf{x} + \mathbf{u}) \right]^*$$

$$\widehat{\mathbf{a}^T \mathbf{x}} = \begin{cases} \mathbf{a}^T \mathbf{x} + \mathbf{a}^T \mathbf{u} & \text{if } \mathbf{a}^T (\mathbf{x} + \mathbf{u}) \in \left[-\frac{\Delta}{2}, \frac{\Delta}{2}\right) \\ \text{error} & \text{otherwise} \end{cases}$$

- $P_e$  is small if  $\frac{\Delta}{\sqrt{\text{Var}(\mathbf{a}^T(\mathbf{x}+\mathbf{u}))}}$  is large
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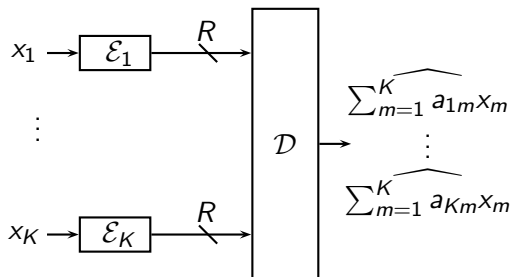
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For  $\mathbf{a}$  with small  $\text{Var}(\mathbf{a}^T(\mathbf{x} + \mathbf{u}))$  we can take small  $R$



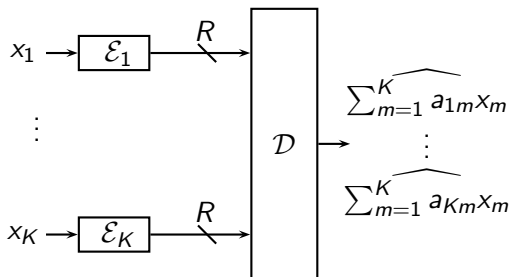
# Integer-Forcing Source Coding



- Need to estimate  $K$  linearly independent integer linear combinations
- If all combinations estimated without error, can compute

$$\hat{\mathbf{x}} = \mathbf{A}^{-1} \widehat{\mathbf{A}} \mathbf{x} = \mathbf{A}^{-1} (\mathbf{A} \mathbf{x} + \mathbf{A} \mathbf{u}) = \mathbf{x} + \mathbf{u}$$

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$$P_e \leq 2K \exp \left\{ -\frac{3}{2} 2^{2 \left( R - \frac{1}{2} \log \left( \frac{\max_{m=1, \dots, K} a_m^T (\mathbf{K}_{\mathbf{x}\mathbf{x}} + d\mathbf{I}) \mathbf{a}_m}{d} \right) \right)} \right\}$$

# Integer-Forcing Source Coding - Performance

Let

$$R_{\text{IF}}(\mathbf{A}, d) \triangleq \frac{1}{2} \log \left( \max_{m=1, \dots, K} \mathbf{a}_m^T \left( \mathbf{I} + \frac{1}{d} \mathbf{K}_{\text{xx}} \right) \mathbf{a}_m \right)$$

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## Theorem

Let  $R = R_{\text{IF}}(\mathbf{A}, d) + \delta$ . IF source coding produces estimates with average MSE distortion  $d$  for all  $x_1, \dots, x_K$  with probability  $> 1 - 2K \exp \left\{ -\frac{3}{2} 2^{2\delta} \right\}$

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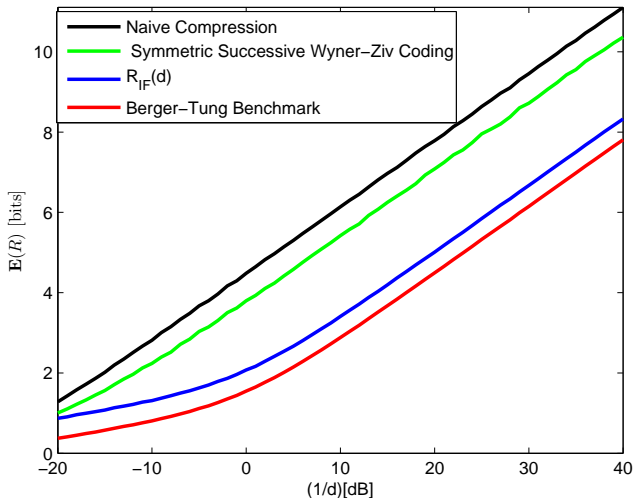
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Can minimize compression rate by minimizing  $R_{\text{IF}}(\mathbf{A}, d)$  w.r.t.  $\mathbf{A}$

# Integer-Forcing Source Coding: Example

$\mathbf{x} \sim \mathcal{N}(\mathbf{0}, \mathbf{K}_{\mathbf{xx}})$ ,  $\mathbf{K}_{\mathbf{xx}} = \mathbf{I} + \text{SNR}\mathbf{H}\mathbf{H}^T$ ,  $\text{SNR} = 20\text{dB}$  and  $\mathbf{H} \in \mathbb{R}^{8 \times 2}$



# Back to Motivation 1

How close is  $R_{\text{IF}}(d)$  to the optimal performance?

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- But... the gap can be arbitrarily large.

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**However, if we change the setting...**

**this obstacle can be overcome.**

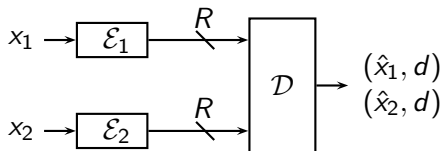


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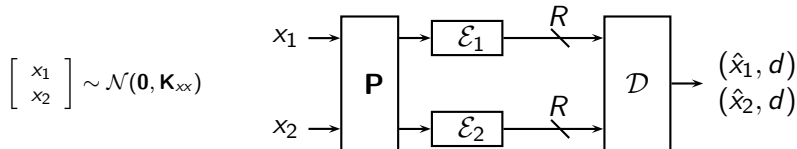
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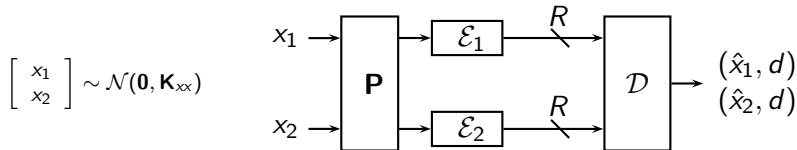
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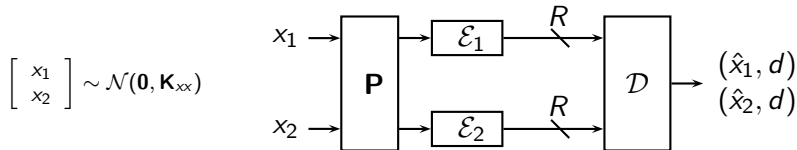
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- Universal precoding matrix  $\mathbf{P}$  (does not depend on  $\mathbf{K}_{xx}$ )
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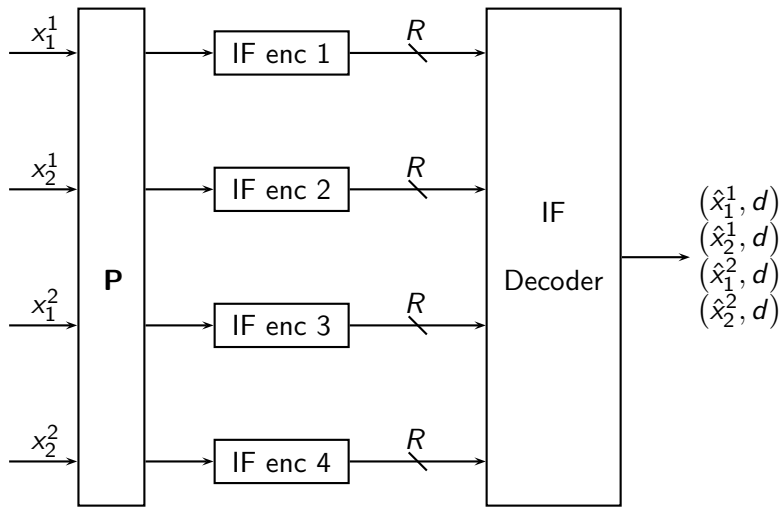


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Price of universality - need to jointly encode  $K$  realizations

# Space-Time Source Coding



# Space-Time Source Coding - Performance Guarantees

Let  $\mathbf{P}$  be a generating matrix of a “perfect” linear dispersion space-time code, with minimum  $\det \delta_{\min}(\mathcal{C}_{\infty}^{\text{ST}})$

## Theorem

For any source with covariance matrix  $\mathbf{K}_{\text{xx}}$ , the rate-distortion function of space-time integer-forcing source coding with precoding matrix  $\mathbf{P}$  is bounded by

$$R_{\text{IF}}(d) < \frac{1}{2K} \log \det \left( \mathbf{I} + \frac{1}{d} \mathbf{K}_{\text{xx}} \right) + \Gamma \left( K, \delta_{\min}(\mathcal{C}_{\infty}^{\text{ST}}) \right)$$

where  $\Gamma \left( K, \delta_{\min}(\mathcal{C}_{\infty}^{\text{ST}}) \right) \triangleq 2K^2 \log(2K^2) + K \log \frac{1}{\delta_{\min}(\mathcal{C}_{\infty}^{\text{ST}})}$

Remark: For  $K = 2$  the golden-code precoding matrix has  $\delta_{\min}(\mathcal{C}_{\infty}^{\text{ST}}) = 1/5$

# Example

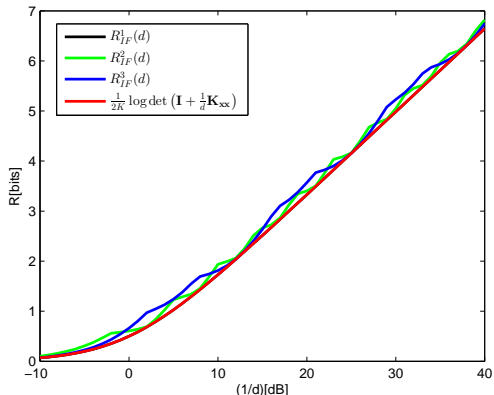
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**Thanks for your attention!**