

# Networks with point-to-point codes

Abbas El Gamal

Stanford University

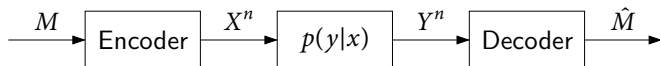
Shannon Memorial Lecture, UCSD 2013

Based on joint work with B. Bandemer, D. Tse, F. Bacelli, and Y.-H. Kim

*“The fundamental problem of communication is that of reproducing **at one point**, either exactly or approximately, a message selected **at another point**.”*

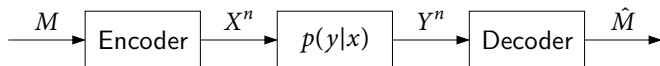
*C.E. Shannon (1948)*

# Shannon's point-to-point communication system



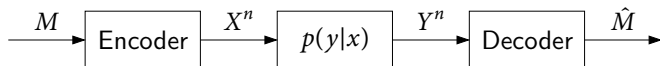
- Discrete memoryless channel (DMC)  $p(y|x)$
- $(2^{nR}, n)$  block code:
  - ▶ Message:  $M \sim \text{Unif}[1 : 2^{nR}]$
  - ▶ Encoder:  $x^n(m), m \in [1 : 2^{nR}]$
  - ▶ Decoder:  $\hat{m}(y^n) \in [1 : 2^{nR}] \cup \{e\}$

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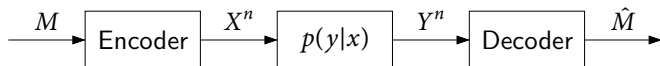
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- Probability of error  $P_e^{(n)} = \mathbb{P}\{\hat{M} \neq M\}$
- $R$  achievable if  $\exists (2^{nR}, n)$  codes with  $\lim_{n \rightarrow \infty} P_e^{(n)} = 0$
- Capacity  $C$  is supremum of all achievable rates

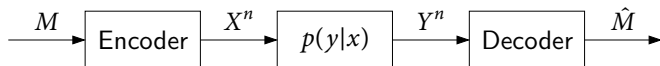
# Shannon's channel coding theorem



## Theorem (Shannon 1948)

$$C = \max_{p(x)} I(X; Y)$$

# Shannon's channel coding theorem



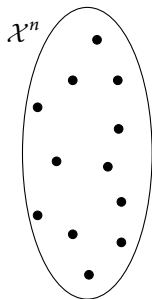
## Theorem (Shannon 1948)

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- Shannon gave an **existential proof** of achievability via **random coding**

# Achievability using random point-to-point (ptp) codes

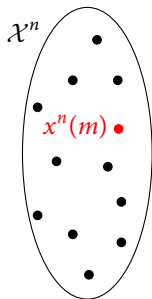
- **Codebook generation:** Fix  $p(x)$ 
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- **Decoding:**
  - ▶ Optimal decoding rule is **maximum likelihood** (MLD):

$$\hat{m}(y^n) = \arg \max_{m \in [1:2^{nR}]} \prod_{i=1}^n p_{Y|X}(y_i | x_i(m))$$

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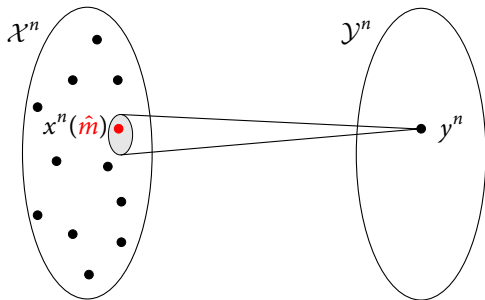
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- **Analysis of the probability of error**, e.g., Gallager (1965):
  - ▶ Show that  $E[P_e^{(n)}(\mathcal{C}_n(p))] \rightarrow 0$  if  $R < I(X; Y)$ ; hence good codes exist
  - ▶ Tight **error exponents**, but difficult to extend analysis to networks

# Shannon's joint typicality proof

- Decoding:

- ▶ Find **unique message**  $\hat{m}$  such that  $(x^n(\hat{m}), y^n) \in \mathcal{T}_\epsilon^{(n)}$
- ▶ Otherwise declare an error



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- Several ways to define typicality, e.g., Orlitsky–Roche (2001):

$$\mathcal{T}_\epsilon^{(n)} = \{(x^n, y^n): |\pi(x, y|x^n, y^n) - p(x, y)| \leq \epsilon \cdot p(x, y) \text{ for all } (x, y)\},$$

where  $\pi(x, y|x^n, y^n)$  is joint type of  $(x^n, y^n)$

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  - ▶ If  $\lim_{n \rightarrow \infty} E[P_\epsilon^{(n)}(\mathcal{C}_n(p))] = 0$ , then  $R \leq I(X; Y)$
  - ⇒ Joint typicality decoding achieves same rate as MLD
  - ▶ Extensions are useful for networks where MLD is difficult to analyze

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- Several such codes have been found:
  - ▶ Algebraic codes (e.g., BCH, Reed–Solomon, polar codes)
  - ▶ Random codes with structure (turbo, LDPC, fountain, spatially coupled)
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- These codes are widely used in communication networks and storage
- Results in network information theory suggest we need [network codes](#)

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- Outline:
  - ▶ Brief introduction to network information theory
  - ▶ Discuss various network models with random ptp codes

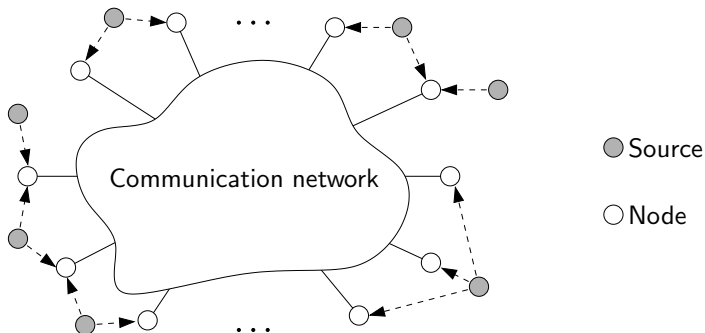
# This lecture

- How well do **random ptp codes** perform over networks?
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- Outline:
  - ▶ Brief introduction to network information theory
  - ▶ Discuss various network models with random ptp codes
- Preview of the results:
  - ▶ Random ptp codes with more **sophisticated decoding** can perform very well
  - ▶ Joint-typicality-based decoding continues to achieve same rates as MLD
  - ▶ There are settings where we may need to develop **network codes**



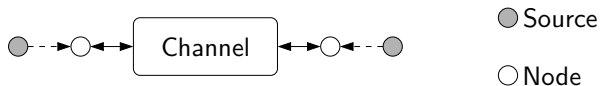
# Network information theory

- Extends Shannon's point-to-point information theory to networks with:
  - ▶ Multiple sources and destinations
  - ▶ Multiple access, broadcast, and interference
  - ▶ Feedback and interactive communication
  - ▶ Cooperation (multihop)



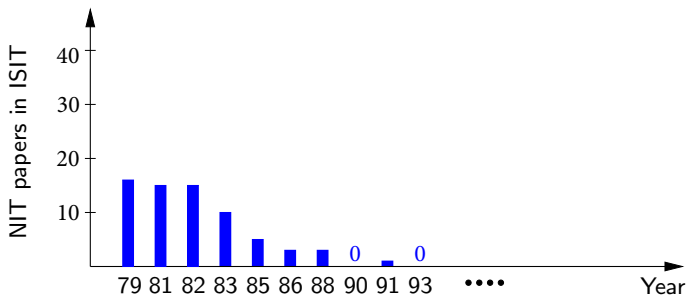
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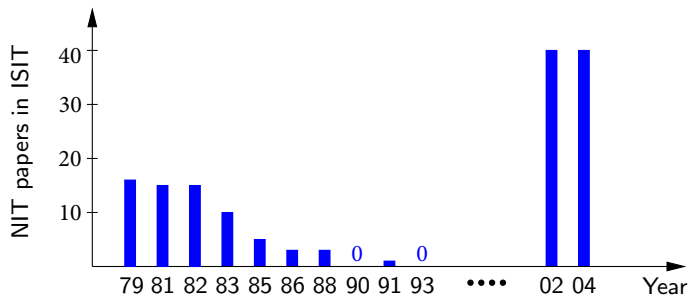
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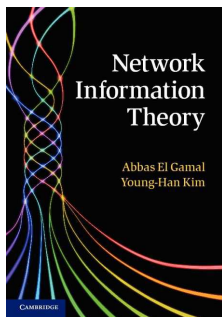
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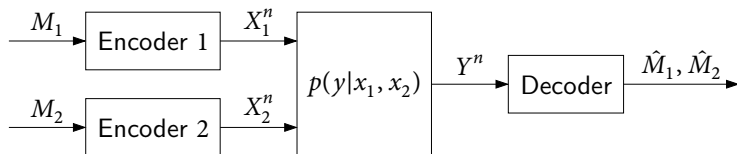
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- State of the theory:



# Network models with ptp codes

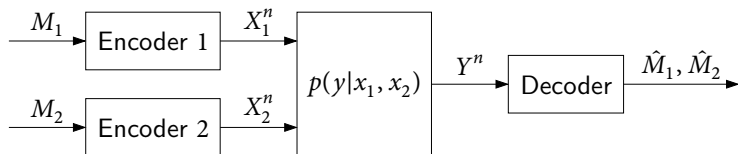
- Multiple access channel
- Interference channel
- Broadcast channel
- Relay channel
- Multicast networks
- Mutimessage networks

# Multiple access channel (MAC)



- $(2^{nR_1}, 2^{nR_2}, n)$  block code:
  - ▶ **Message pair:**  $(M_1, M_2) \sim \text{Unif}([1 : 2^{nR_1}] \times [1 : 2^{nR_2}])$
  - ▶ **Encoder  $j = 1, 2$ :**  $x_j^n(m_j), m_j \in [1 : 2^{nR_j}]$
  - ▶ **Decoder:**  $(\hat{m}_1, \hat{m}_2) \in [1 : 2^{nR_1}] \times [1 : 2^{nR_2}]$
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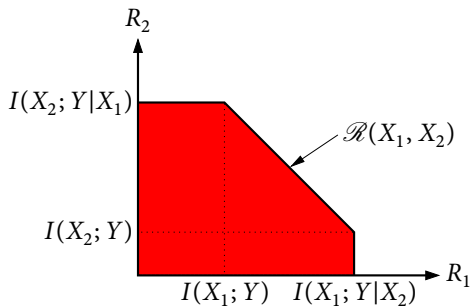
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- $(R_1, R_2)$  achievable if  $\exists (2^{nR_1}, 2^{nR_2}, n)$  codes with  $\lim_{n \rightarrow \infty} P_e^{(n)} = 0$
- **Capacity region  $\mathcal{C}$ :** Closure of the set of achievable  $(R_1, R_2)$



# MAC capacity region

Theorem (Ahlsvede 1971, Liao 1972)

The capacity region is the convex hull of  $\bigcup_{p(x_1)p(x_2)} \mathcal{R}(X_1, X_2)$

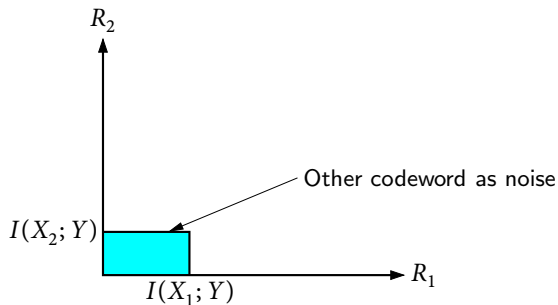


# MAC with random ptp codes

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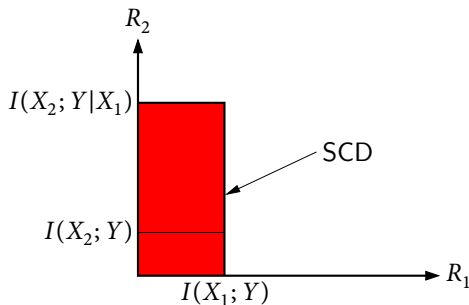
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- **Encoding:** To send  $(m_1, m_2)$ , transmit  $x_1^n(m_1)$  and  $x_2^n(m_2)$
- **Decoding:** Use joint typicality decoding, treating the other codeword as noise:



# MAC with random ptp codes

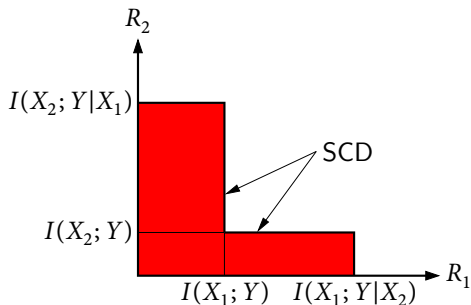
- Successive cancellation decoding (SCD):

- ▶ Find unique  $\hat{m}_1: (x_1^n(\hat{m}_1), y^n) \in \mathcal{T}_\epsilon^{(n)}$
- ▶ If such  $\hat{m}_1$  is found, find unique  $\hat{m}_2: (x_1^n(\hat{m}_1), x_2^n(\hat{m}_2), y^n) \in \mathcal{T}_\epsilon^{(n)}$



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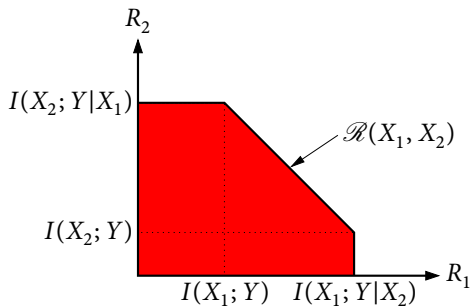
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- Can achieve other corner point by reversing decoding order



# MAC with random ptp codes

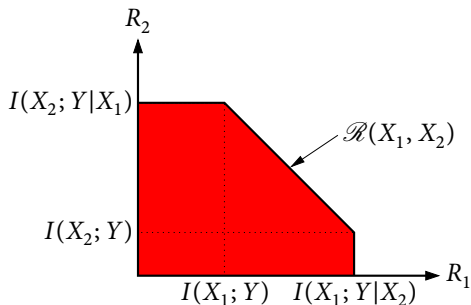
- Simultaneous decoding (SD):

- ▶ Find unique pair  $(\hat{m}_1, \hat{m}_2) : (x_1^n(\hat{m}_1), x_2^n(\hat{m}_2), y^n) \in \mathcal{T}_\epsilon^{(n)}$



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  - Converse for ptp codes: Given  $p = p(x_1)p(x_2)$  and decoding rule
    - ▶ If  $\lim_{n \rightarrow \infty} E[P_e^{(n)}(C_n(p))] = 0$ , then  $(R_1, R_2) \in \mathcal{R}(X_1, X_2)$
- ⇒ SD achieves same rates as MLD



# Random ptp codes perform extremely well over MAC

Theorem (Ahlswede 1971, Liao 1972)

The capacity region is the convex hull of  $\bigcup_{p(x_1)p(x_2)} \mathcal{R}(X_1, X_2)$

- $\mathcal{R}(X_1, X_2)$  achieved using **random ptp codes + simultaneous decoding**
- Rest of the capacity region is achieved using **time-sharing**



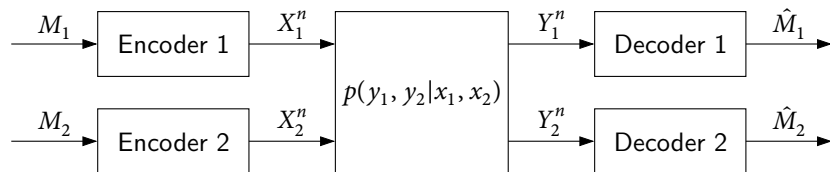
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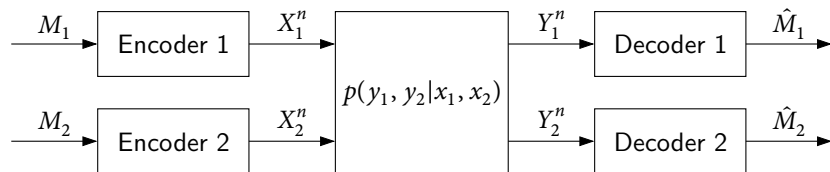
- $\mathcal{R}(X_1, X_2)$  achieved using **random ptp codes + simultaneous decoding**
- Rest of the capacity region is achieved using **time-sharing**
- Results generalize to more than two senders

# Interference channel



- First studied by Ahlswede (1974)

# Interference channel



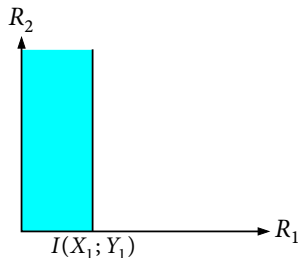
- First studied by Ahlswede (1974)
- $(2^{nR_1}, 2^{nR_2}, n)$  code,  $P_e^{(n)}$ , achievability, capacity region  $\mathcal{C}$ : Same as MAC
- Capacity region is not known in general
- Coding schemes that are optimal in some cases

# Interference channel with random ptp codes

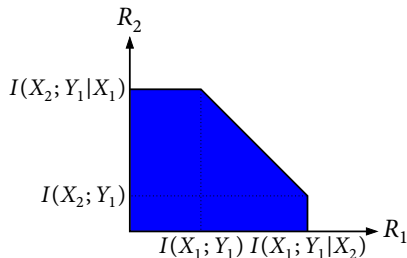
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- **Encoding:**
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- **Decoding schemes we used for the MAC (receiver 1):**



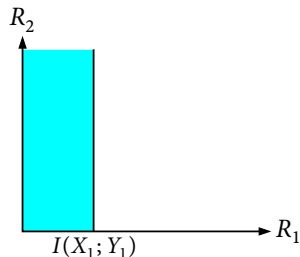
Treating interference as noise (IAN)



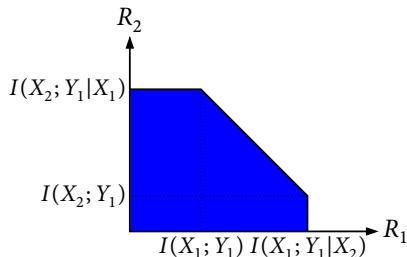
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# Interference channel with random ptp codes

- Neither scheme uniformly outperforms the other



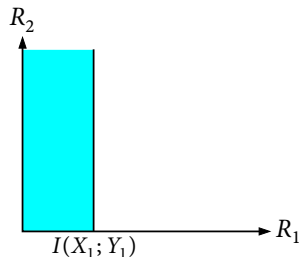
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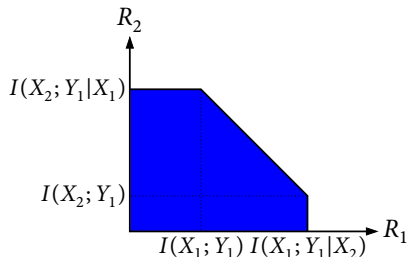
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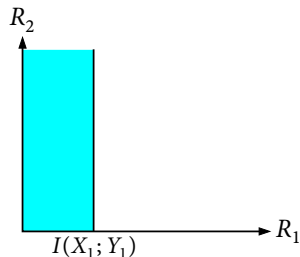
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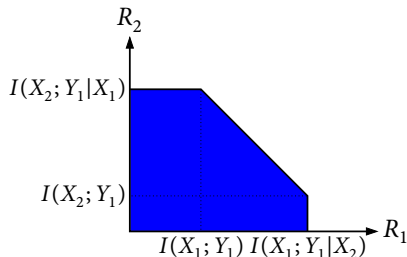
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- SD: Receiver 1 doesn't really want to recover  $M_2$ 
  - ▶ Insisting on recovering  $M_2$  when  $R_2$  is high artificially limits  $R_1$



Treating interference as noise (IAN)



Simultaneous decoding (SD)

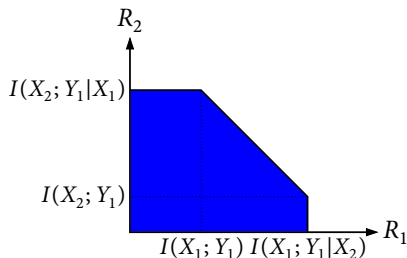


# Interference channel with random ptp codes

- Simultaneous nonunique decoding:
  - ▶ Receiver 1 finds unique  $\hat{m}_1$ :  $(X_1^n(\hat{m}_1), X_2^n(m_2), Y_1^n) \in \mathcal{T}_\epsilon^{(n)}$  for some  $m_2$

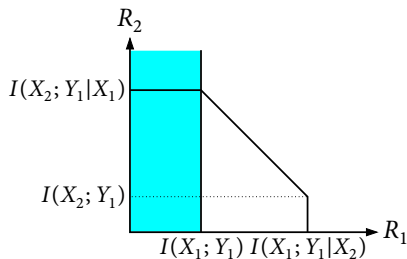
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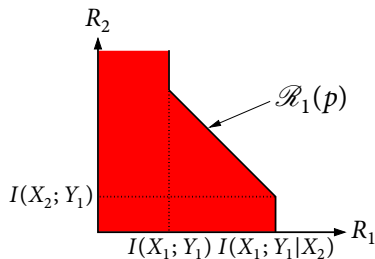
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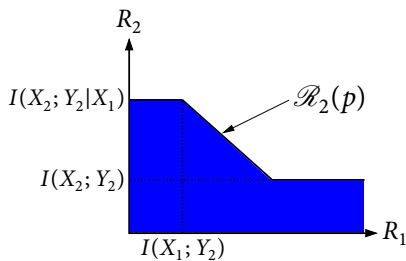
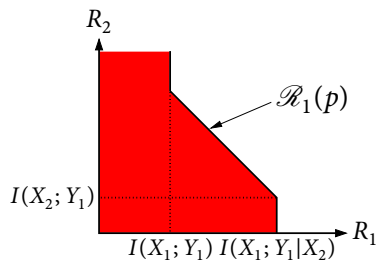
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$\Rightarrow$  SND achieves union of regions for SD and IAN



# Interference channel with random ptp codes

- Similar analysis can be performed for receiver 2, yielding  $\mathcal{R}_2(p)$



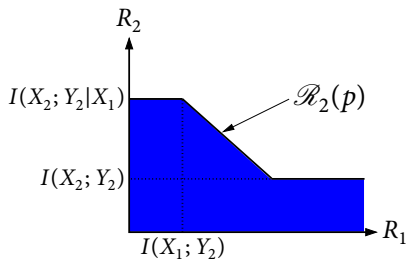
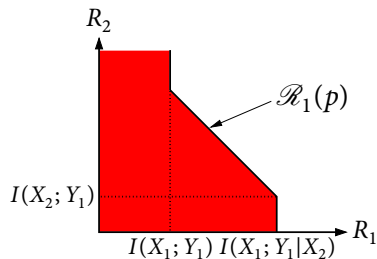
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- SND cannot achieve more than union of SD and IAN regions
- SND achieves same rates as MLD

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- Generalizes result for **deterministic IC** (Bandemer–EG 2011)
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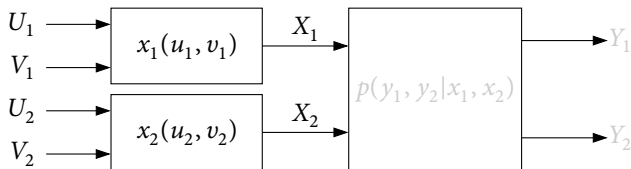
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- But, random ptp codes **can do better**

# Han–Kobayashi (1981) coding scheme

- Idea: Decode part of interference and treat rest as noise:
  - ▶ Split message  $M_j$ ,  $j = 1, 2$ , into public message  $M_{j0}$  and private message  $M_{jj}$

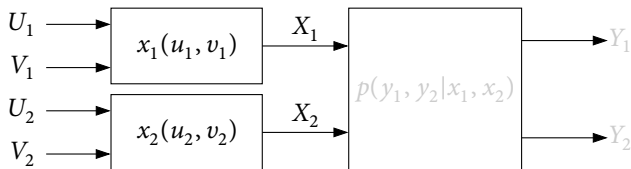
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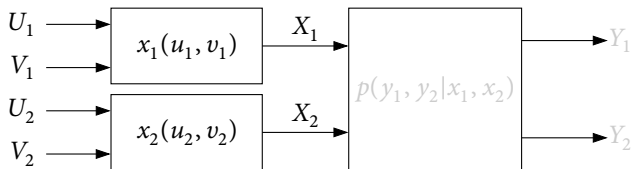
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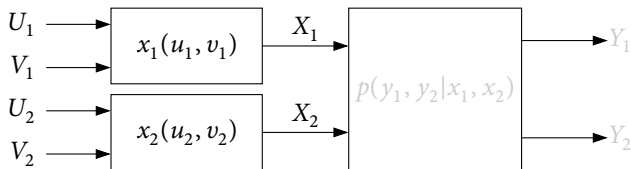
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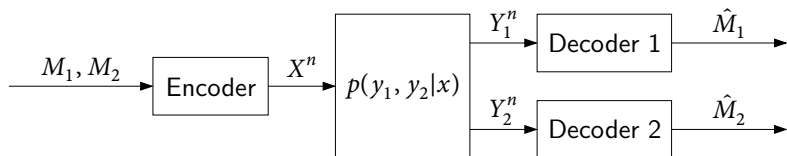


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- Decoding: **SND is rate optimal** (Bandemer–EG–Kim 2012)

# Summary

- Multiple access channel:
- Interference channel:
  - ▶ Random ptp codes + superposition + SND achieve H-K bound
  - ▶ SND achieves the same rates as MLD
  - ▶ We don't know how to do better than H-K
- Broadcast channel
- Multihop networks
- Multimessage networks

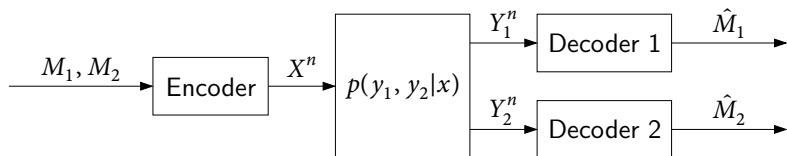
# Broadcast channel



- First studied by Cover (1972)



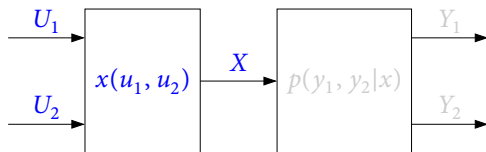
# Broadcast channel



- First studied by Cover (1972)
- $(2^{nR_1}, 2^{nR_2}, n)$  code,  $P_e^{(n)}$ , achievability, capacity region  $\mathcal{C}$ : Same as MAC
- Capacity region is not known in general
- Coding schemes that are optimal in some cases

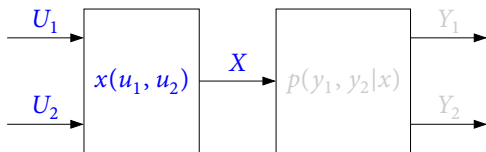
# Broadcast channel with random ptp codes

- Use superposition coding: Fix  $p(u_1)p(u_2)$ , function  $x(u_1, u_2)$



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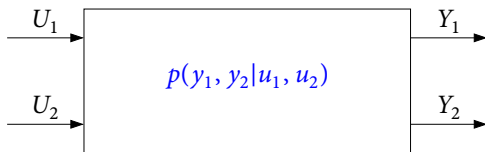
- ▶ Randomly generate  $2^{nR_1}$  sequences  $u_1^n(m_1) \sim \prod_{i=1}^n p_{U_1}(u_{1i})$ ,  $m_1 \in [1:2^{nR_1}]$
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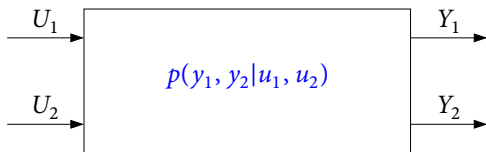
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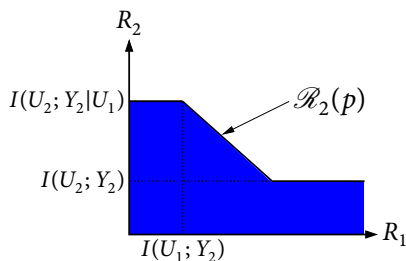
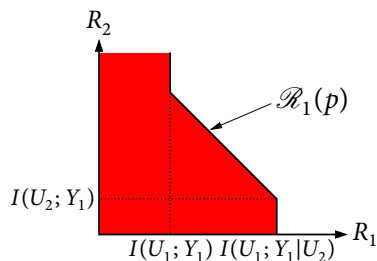
⇒ SND is rate optimal

# Broadcast channel with random ptp codes

## Theorem (Bandemer–EG–Kim 2012)

The optimal rate region with random ptp codes  $p(u_1)p(u_2)$ ,  $x(u_1, u_2)$  is:

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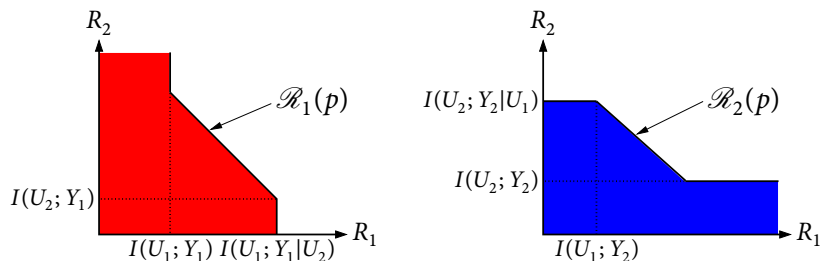


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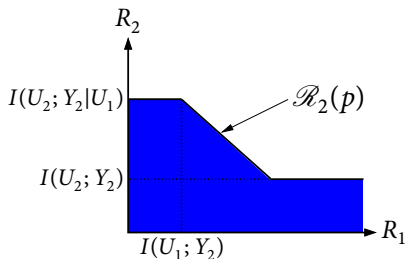
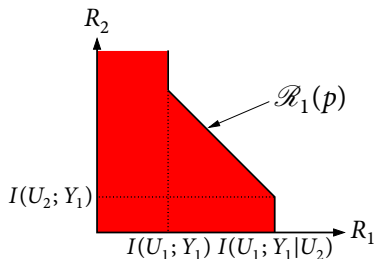
- Includes superposition coding region (Cover 1972, Bergmans 1973):
  - ▶ Optimal for degraded, less noisy, more capable BCs
- Also includes Cover–van der Meulen (1975) region

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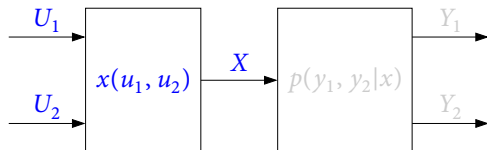


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- Also includes Cover–van der Meulen (1975) region
- We can do better using [schemes beyond ptp codes](#)



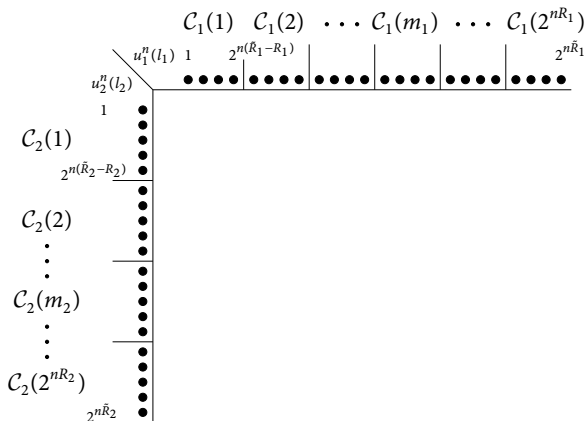
# Marton (1979) coding scheme

- Motivation: Since  $(M_1, M_2)$  is available at sender, jointly code them
- Fix  $p(u_1, u_2)$  (instead of  $p(u_1)p(u_2)$ ) and function  $x(u_1, u_2)$



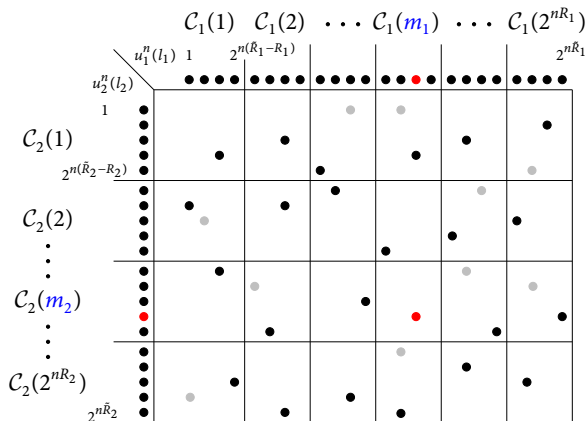
# Marton (1979) coding scheme

- **Codebook generation:** Fix  $p(u_1, u_2)$  and function  $x(u_1, u_2)$ 
  - ▶ Randomly generate ptp codebooks  $u_j^n(l_j)$ ,  $l_j \in [1:2^{n\tilde{R}_j}]$ ,  $\tilde{R}_j > R_j$ ,  $j = 1, 2$
  - ▶ Partition each into **subcodebooks**  $C_j(m_j)$ ,  $m_j \in [1:2^{nR_j}]$ ,  $j = 1, 2$



# Marton (1979) coding scheme

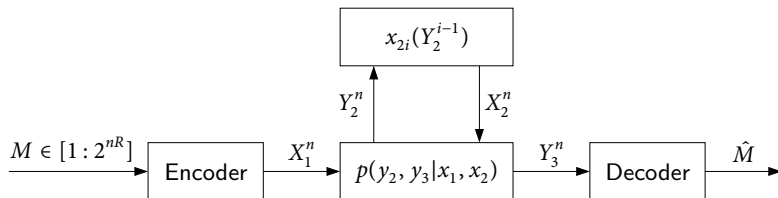
- **Encoding:** To send  $(m_1, m_2)$ :
  - ▶ Find pair  $(u_1^n(l_1), u_2^n(l_2)) \in \mathcal{T}_\epsilon^n$ ,  $l_j \in \mathcal{C}_j(m_j)$ ,  $j = 1, 2$
  - ▶ Transmit  $x(u_{1i}(l_1), u_{2i}(l_2))$ ,  $i \in [1:n]$



# Summary

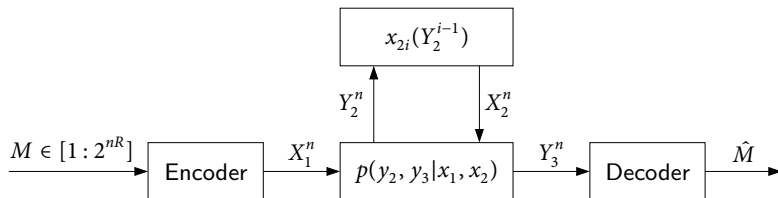
- Multiple access channel:
  - ▶ Random ptp codes achieve capacity region
- Interference channel
  - ▶ Random ptp codes achieve best known inner bound
- Broadcast channel:
  - ▶ Can do better than ptp codes using [Marton coding](#)
- Relay channel
- Multicast networks
- Multimessage networks

# Relay channel



- First studied by van der Meulen (1971)

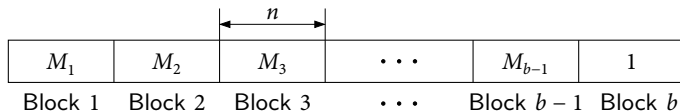
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# RC with random ptp codes: Multihop

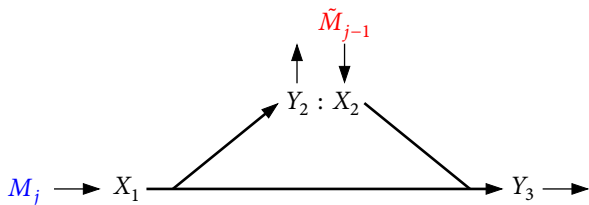
- Send  $b - 1$  messages over  $b$   $n$ -transmission blocks



- Fix  $p(x_1)p(x_2)$ , generate (for each block) ptp codes for sender and relay

# RC with random ptp codes: Multihop

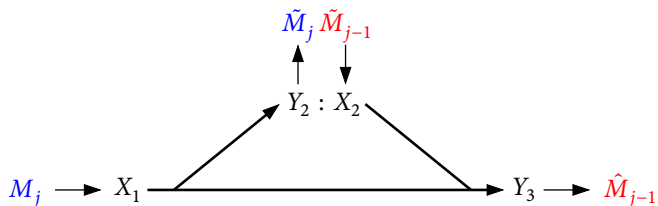
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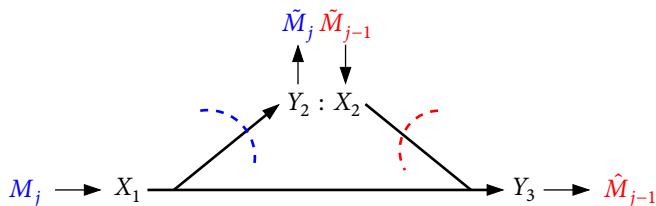
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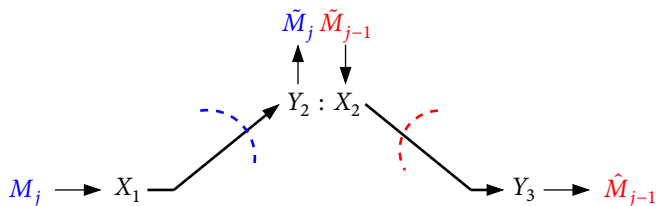


- This achieves:

$$R = \min\{I(X_1; Y_2 | X_2), I(X_2; Y_3)\}$$

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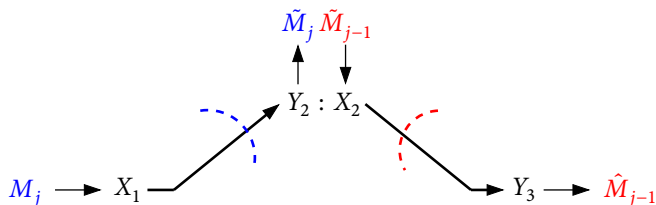
$$R = \min\{I(X_1; Y_2 | X_2), I(X_2; Y_3)\}$$

- Optimal for a **cascade of two DMCs**:  $p(y_2, y_3 | x_1, x_2) = p(y_2 | x_1)p(y_3 | x_2)$

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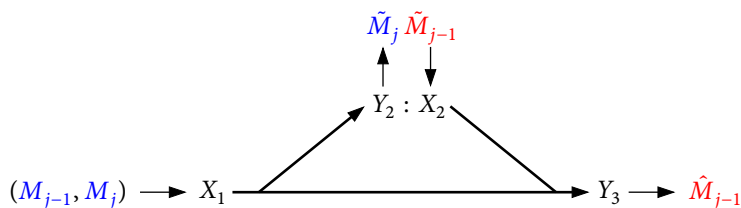
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- But we can do better via superposition and **more sophisticated decoding**

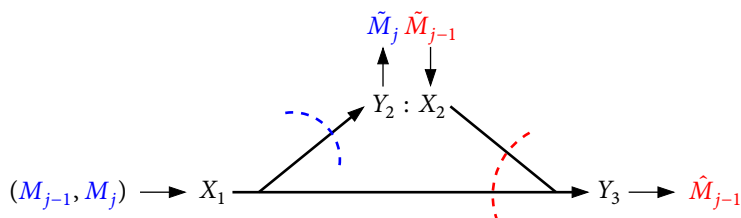
# RC with random ptp codes: Decode–forward (DF)

- The sender knows what the relay knows:
  - ▶ They can **coherently cooperate** via superposition coding at the sender
  - ▶ Fix  $p(x_2)p(u)$  and  $x_1(u, x_2)$ , generate ptp codes for relay and sender
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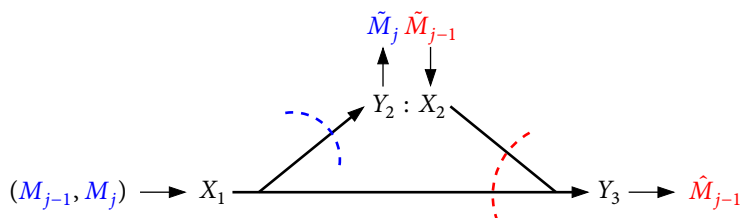


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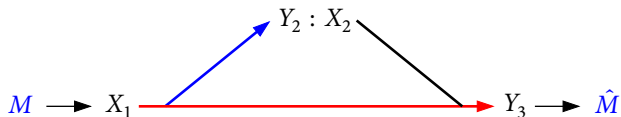
- Achieves (Cover–EG 1979):

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- Optimal for **physically degraded** RC:  $(X_1, X_2) \rightarrow (Y_2, X_2) \rightarrow Y_3$

# Compress-forward (Cover-EG 1979)

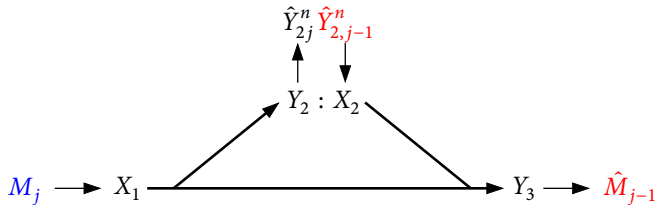
- DF does not do well when  $X_1 \rightarrow Y_2$  is not better than  $X_1 \rightarrow Y_3$





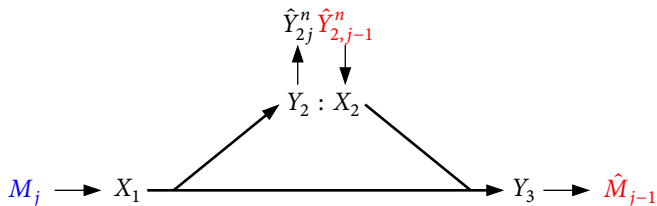
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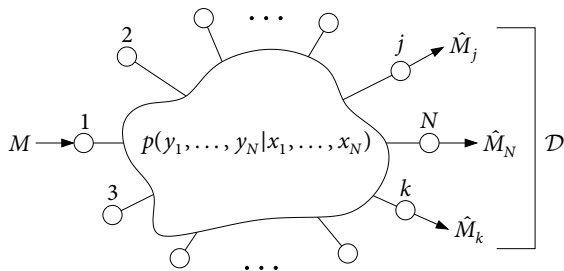


- Does not use ptp codes as defined
- Optimal for some RCs (Aleksic-Razaghi-Yu 2009)

# Summary

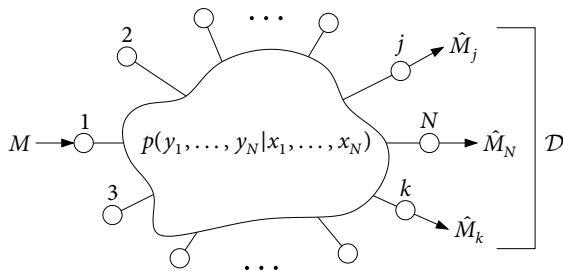
- Multiple access channel:
- Interference channel:
- Broadcast channel
- Relay channel
  - ▶ Random ptp codes + superposition + **backward decoding** achieve DF bound
  - ▶ Can sometimes do better using **schemes beyond ptp codes**, e.g., CF
- Multicast networks
- Multimessage networks:

# Multicast network



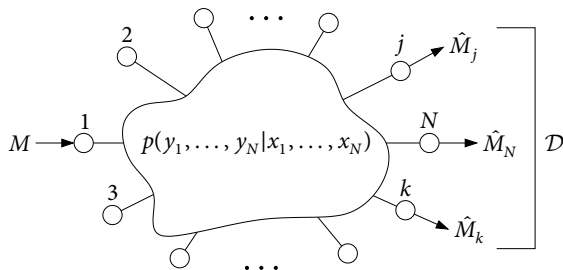
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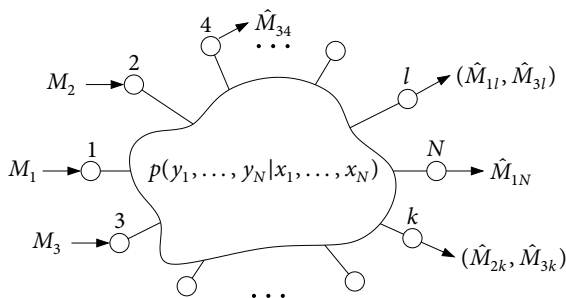
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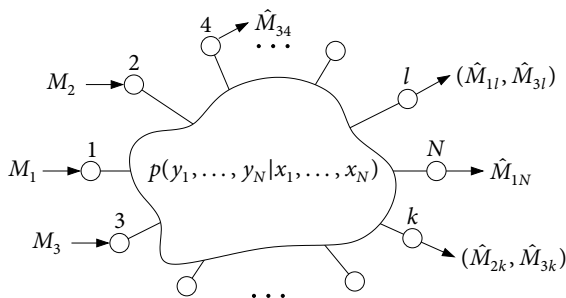
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- DF can be extended (Xie–Kumar 2005, Kramer–Gastpar–Gupta 2005)
- CF can be extended (noisy network coding (EG–Kim 2011))
- **Gaussian multicast network:**
  - ▶ CF achieves within **0.63N bit of capacity** (Lim–Kim–EG–Chung 2011)
  - ▶ DF can have **unbounded gap to capacity**

# Multimessage network



- Node  $j$  wishes to send message  $M_j$  to set of destination nodes  $\mathcal{D}_j$

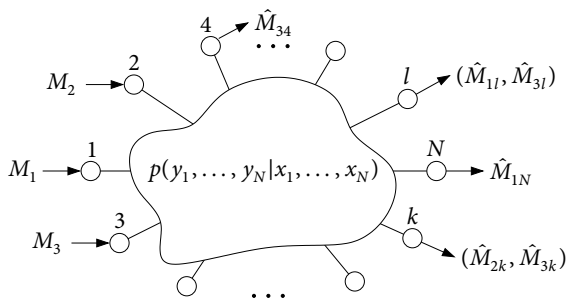
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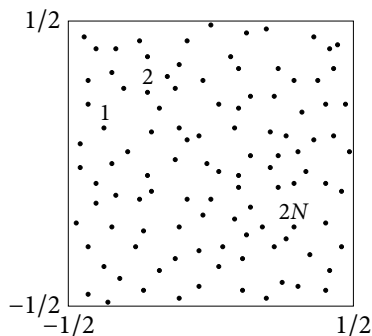


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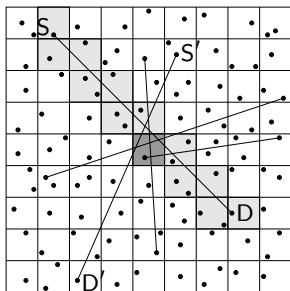
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- How well do ptp codes perform?

# Capacity scaling laws



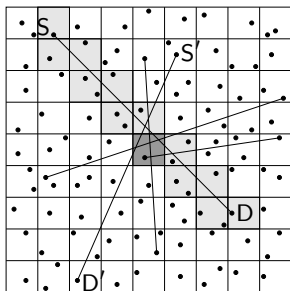
- Random wireless network (Gupta–Kumar 2000):
  - ▶ **Multi-unicast**: Send message  $M_j$  at rate  $R$  from node  $j \in [1 : N]$  to  $k = j + N$
  - ▶ **Gaussian network model**: Path loss exponent  $\nu \geq 2$ , average power constraint
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- Upper bound (Lévêque–Telatar 2005):  $C = O(N^{-1/2+1/\nu} \log N)$

# Conclusion and final remarks

- Random ptp codes with **sophisticated decoding** can perform well:
  - ▶ Achieve capacity region of MAC
  - ▶ Achieve the Han–Kobayashi bound for IC (best known)
  - ▶ Achieve the superposition coding and Cover–van der Meulen bounds for BC
  - ▶ Achieve decode–forward bound for multicast networks
  - ▶ Achieve close to optimal scaling law for random multi-unicast networks

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  - ▶ Work on constructing better decoders
  - ▶ Find better practical codes for broadcasting and relaying
- The best answer, to quote Tom Cover, is:

*“Theory is the first term in the Taylor series expansion of practice.”*

Thank You!

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