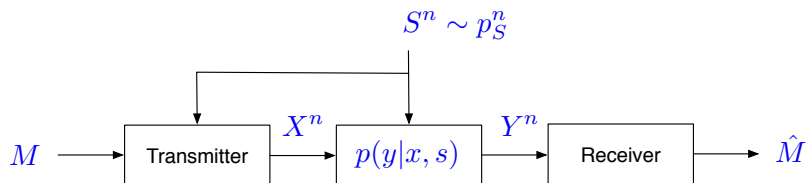


# Approximately Optimal Distributions via the ADT Linear Deterministic Model

Tie Liu

June-19-2014 @CUHK

# Communication with side information



- $S^n$ : **Non-causally** known at the transmitter as side information

What is the capacity of the channel?

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- A simple upper bound:

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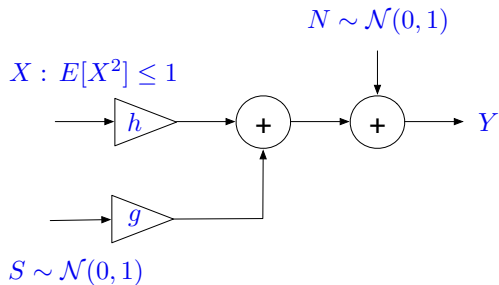
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One can get “lucky” though ...

## Writing on dirty paper



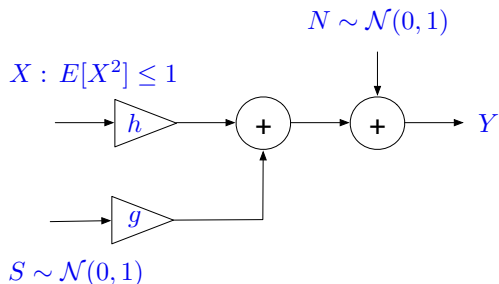
- $X \sim \mathcal{N}(0, 1)$ ,  $X \perp S$ , and  $U = hX + \frac{h^2}{h^2+1}gS$  (Costa 1983):

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However, “luck” may be running out sometimes ...

# Running out of “luck”

- No obvious choice of input/auxiliary random variables in the single-letter capacity/achievable rate expressions to match the simple upper bound:
  - ▶ Writing on **fading** paper
  - ▶ **Secret** writing on dirty paper
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What can we do?

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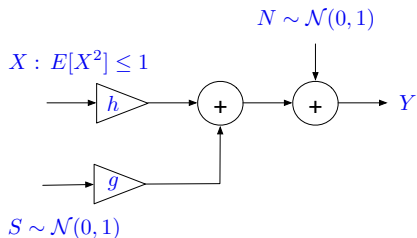
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  - ▶ Apply the insight to the problems of: 1) **secret writing on dirty paper**; and 2) **two-user symmetric Gaussian interference channel**

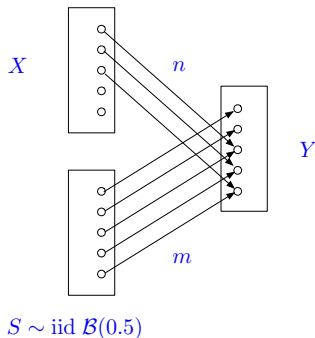
# Writing on dirty paper

Gaussian model



$$Y = hX + gS + N$$

ADT linear deterministic model



$$Y = D_q^{q-n} X + D_q^{q-m} S + N$$



# Capacity of deterministic model

- $Y$  is a **deterministic** function of  $(X, S)$ :
  - ▶ Simplifying the upper bound:

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- ▶ Conclusion:

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- For ADT linear deterministic model:

$$\begin{aligned} H(Y|S) &= H(D_q^{q-n}X + D_q^{q-m}S|S) \\ &\leq H(D_q^{q-n}X) \\ &\leq \text{rank}(D_q^{q-n}) \\ &= n \end{aligned}$$

where equality holds when  $X$  is Bernoulli-1/2 and independent of  $S$

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$$U = Y = D_q^{q-n} X + D_q^{q-m} S$$

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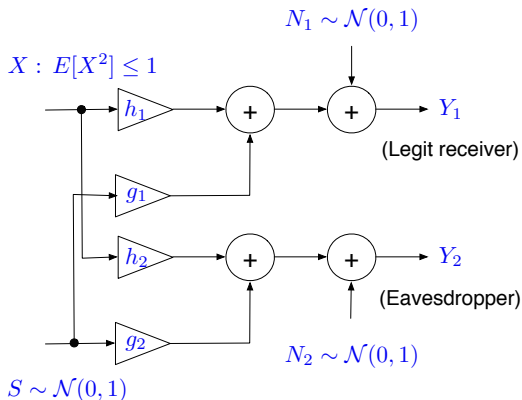
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How robust is this approach?

# Secret writing on dirty paper



- $S^n$ : **Non-causally** known at the transmitter as side information
- Secrecy constraint:  $(1/t)I(M; Y_2^t) \rightarrow 0$

# Secrecy capacity bounds

- A single-letter achievable secrecy rate (Chen-Vinck 2008):

$$C_s \geq \max_{p(u,x|s)} \min[I(U; Y_1) - I(U; S), I(U; Y_1) - I(U; Y_2)]$$

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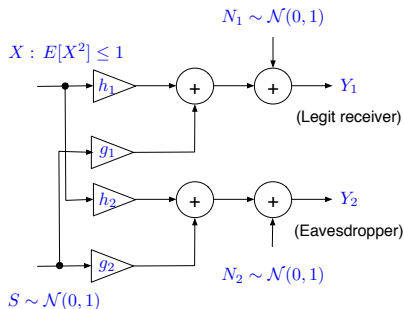
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Let' try the deterministic approach ...

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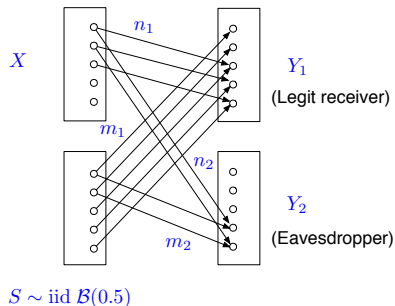
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- For ADT linear deterministic model:
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## A technical lemma

Let  $A$  and  $B$  be two matrices in  $\mathbb{F}_2$  with the same number of columns.  
Then

$$\max H(AZ|BZ) = \text{rank} \left( \begin{bmatrix} A \\ B \end{bmatrix} \right) - \text{rank}(B)$$

where the maximization is over all possible binary random vectors  $Z$ . The maximization is achieved when  $Z$  is i.i.d. Bernoulli-1/2



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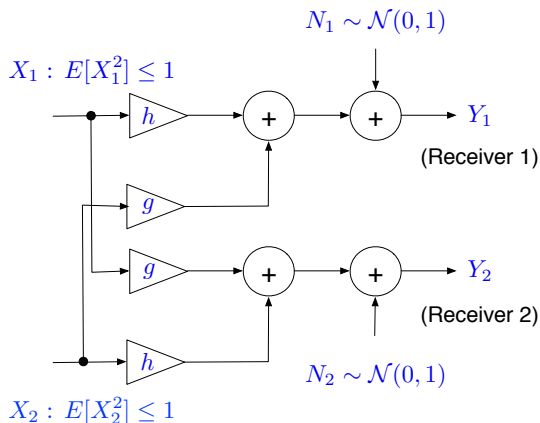
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- Secrecy capacity to within 1/2 bit



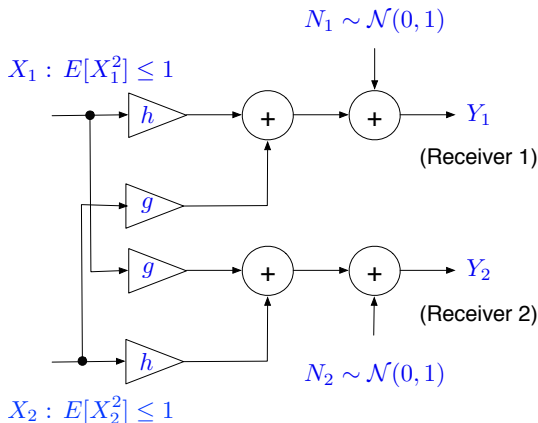
Mustafa El-Halabi, Tie Liu, Costas N. Georghiades, and Shlomo Shamai (Shitz), "Secret writing on dirty paper: A deterministic view," *IEEE Transactions on Information Theory*, vol. 58, no. 6, pp. 3419–3429, June 2012

# Two-user symmetric Gaussian interference channel



- Two **independent** messages, one between each transmitter-receiver pair

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  - ▶ Independent Gaussian signaling for all sub-messages
  - ▶ Approximately optimal rate and power split parameters can be determined via the ADT linear deterministic model (Bresler-Tse 2008)

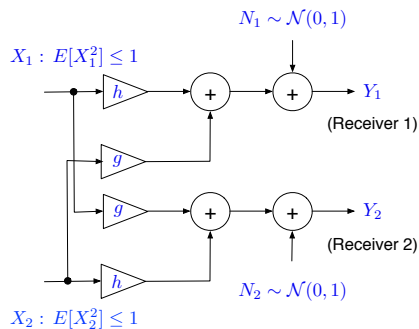


# Sum capacity to within one bit

- No known single-letter expression for the sum capacity
- Best lower bound achieved by the Han-Kobayashi scheme:
  - ▶ Split each message into a private and a common part
  - ▶ Independent Gaussian signaling for all sub-messages
  - ▶ Approximately optimal rate and power split parameters can be determined via the ADT linear deterministic model (Bresler-Tse 2008)
  - ▶ Sum capacity to within one bit (Etkin-Tse-Wang 2008)

# Two-user symmetric interference channel

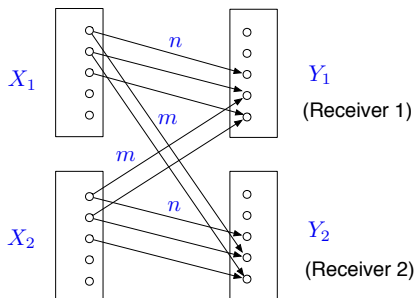
Gaussian model



$$Y_1 = hX_1 + gX_2 + N_1$$

$$Y_2 = gX_1 + hX_2 + N_2$$

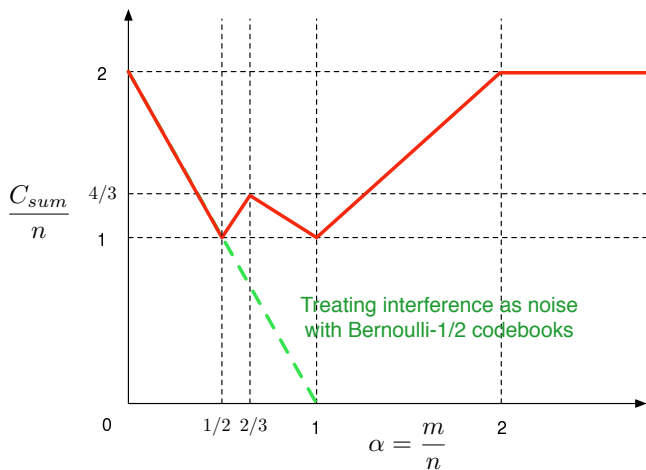
ADT linear deterministic model



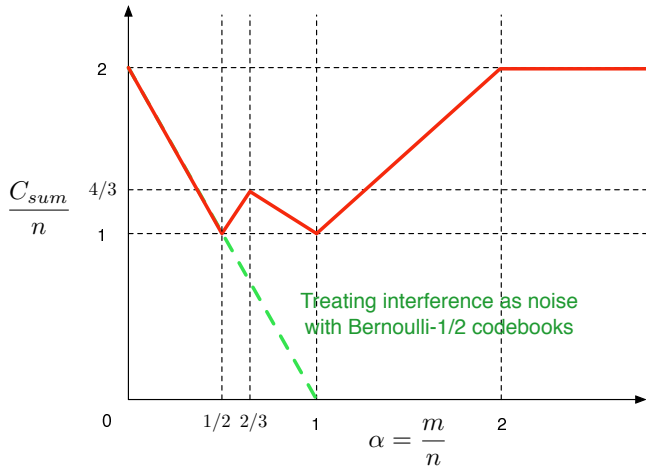
$$Y_1 = D_q^{q-n} X_1 + D_q^{q-m} X_2$$

$$Y_2 = D_q^{q-m} X_1 + D_q^{q-n} X_2$$

# Sum capacity of ADT linear deterministic model



## Sum capacity of ADT linear deterministic model



Can the simple strategy of treating interference as noise be good beyond the “very-weak” interference regime?

# The limit of treating interference as noise

- Treating interference as noise can be **arbitrarily good**:

$$C_{sum} = \lim_{k \rightarrow \infty} \frac{C_{sum}^{(k)}}{k}$$

where

$$C_{sum}^{(k)} := \max_{p(x_1^k)p(x_2^k)} [I(X_1^k; Y_1^k) + I(X_2^k; Y_2^k)]$$

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Again let' try the deterministic approach ...

# ADT linear deterministic channel

- Fix  $k$ :

$$I(X_1^k; Y_1^k) = H(AX_1^k + BX_2^k) - H(BX_2^k)$$

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- ▶  $(1, I_q)$  is sufficient for the “very-weak” interference regime
- ▶ What about the other regimes?

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- Clearly,

$$\text{rank}([AE \ BE]) - \text{rank}(BE) = 2n - n = n = \frac{C_{\text{sum}}}{2}$$



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- May require  $k$  up to **2**

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- The other regimes: **Mixture Gaussian (convolution between Gaussian and discrete)**
- Sum capacity within  $\log \log \max(|h|^2, |g|^2)$  bits (preliminary analysis)

# Summary

- Identifying an **optimal** choice of input/auxiliary random variables in a single/multi-letter capacity/achievable rate expression for Gaussian networks can be extremely challenging
- We look for a more **systematic** search guided by the ADT linear deterministic model:
  - ▶ May settle for **approximate** optimality
- A more refined deterministic model (than the ADT linear deterministic model) might be needed to achieve **universal** approximation