

Decision making via End-to-End Lossy Distributed Wireless Cooperative Networks

- A Distributed Hypothesis Testing based Formulation -
Full Tutorial: MMMM DD, YYYY @ University of ZZZZ

Tad Matsumoto*, **, ***

IEEE Life Fellow

***International Chair, Invited Professor, IMT -Atlantic**

Technopôle Brest-Iroise CS 83818 29238 Brest cedex 03, France

Tadashi.matsumoto@imt-atlantique.fr

**** Professor Emeritus, JAIST**

matumoto@jaist.ac.jp

***** Professor Emeritus, CWC, University of Oulu,**

tadeshi.matsumoto@oulu.fi

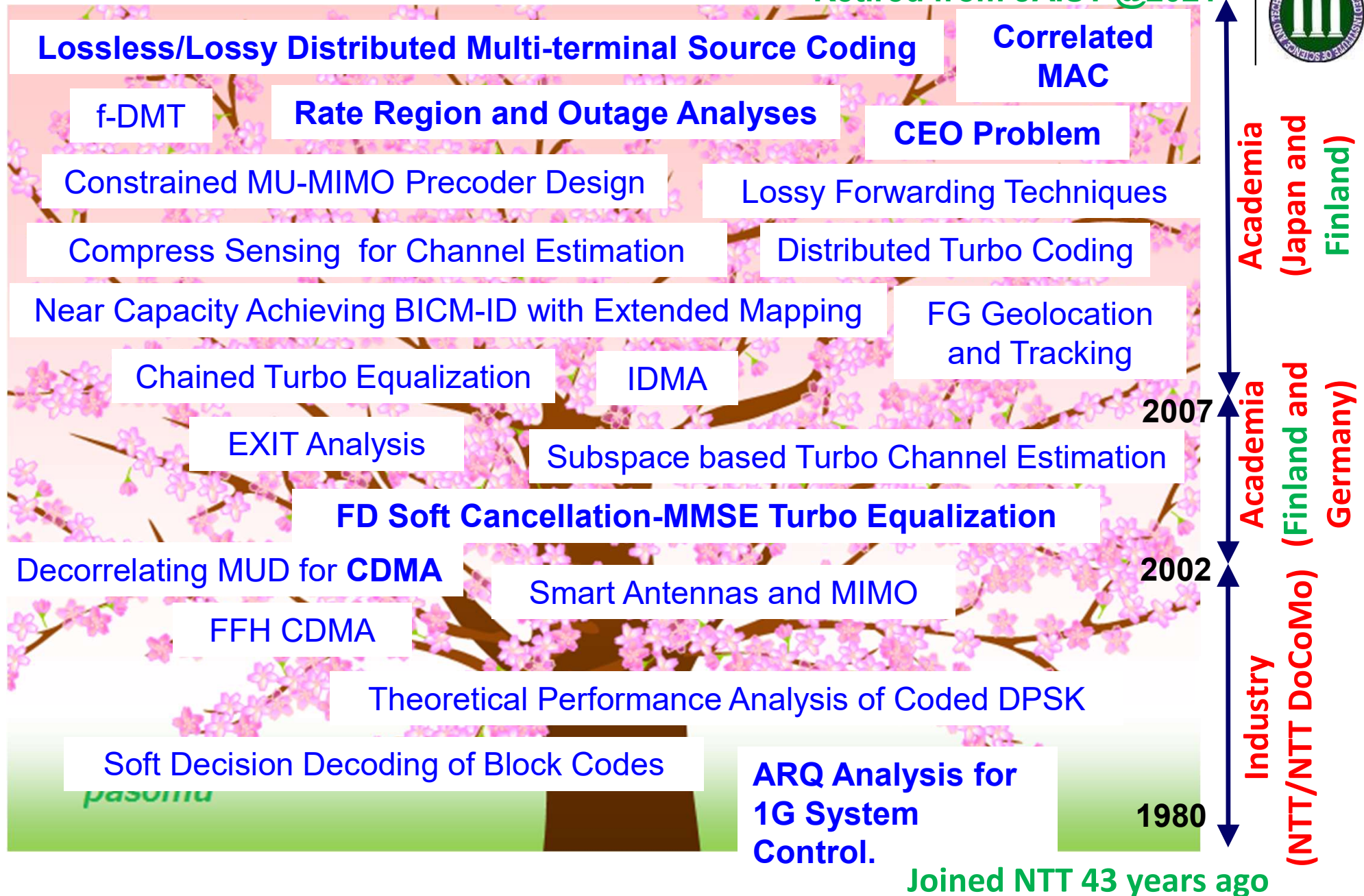


IMT Atlantique
Bretagne-Pays de la Loire
École Mines-Télécom



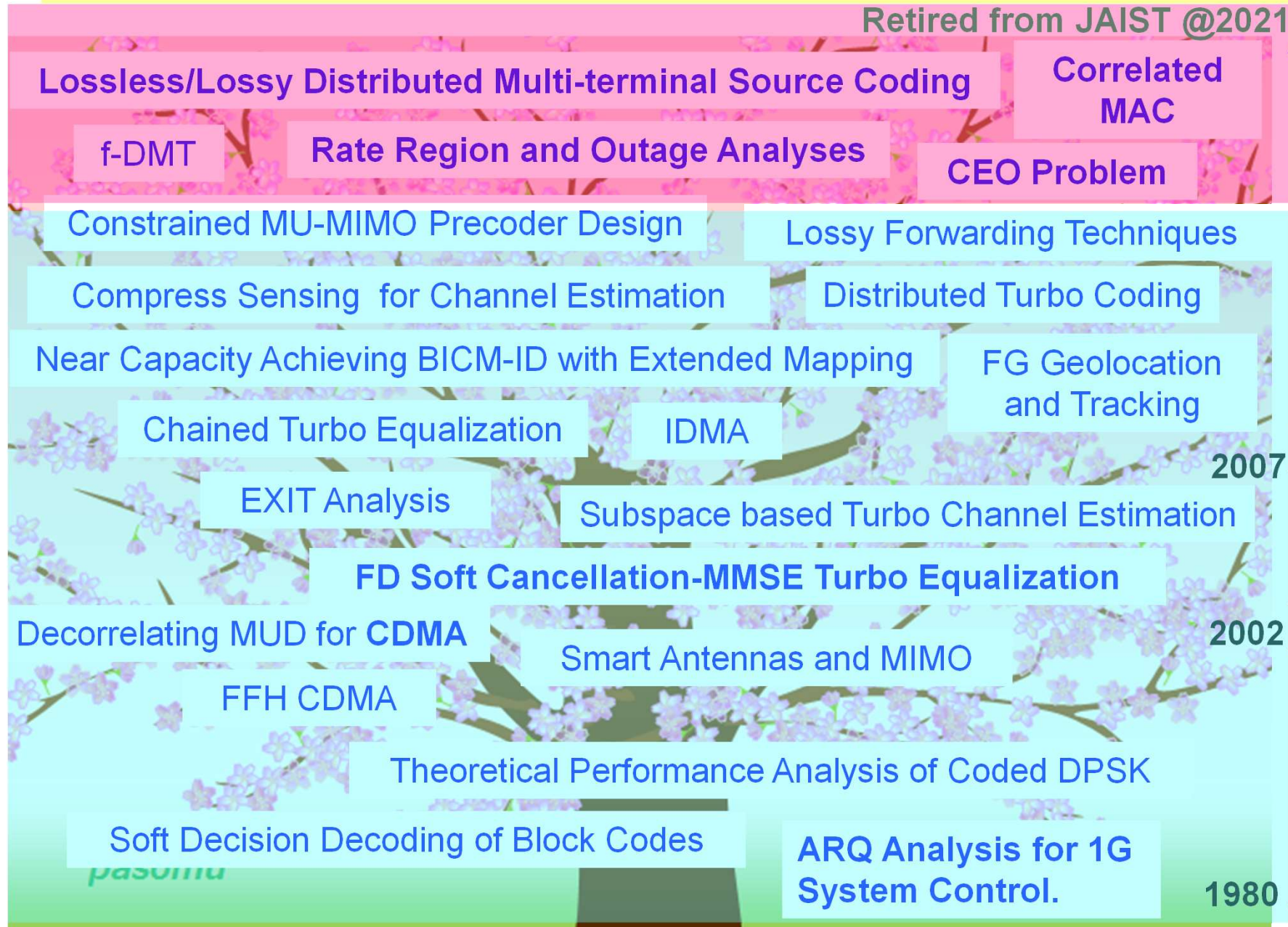
Tree of Tad's SISU: **Wireless Communications** Today

Retired from JAIST @2021



Tree of Tad's SISU: **Wireless Communications** Today

Retired from JAIST @2021



Joined NTT 43 years ago

Contents of Full Tutorial:

- 0. Revisit to Fundamental Theorems in Network Information Theory
- 1. End-to-End **Lossless** Relaying: Slepian Wolf Theorem with Source-Channel Separation
 - 1.1 EXIT Analysis for Source Bit-Flipped MIMO Transmission with Turbo Equalization
 - 1.2 Slepian-Wolf Formulation for Lossless Two-Way Relay Networks
- 2. End-to-End **Lossy** Distributed Multi-terminal Networks: Rate Distortion Analysis
 - 2.1 Wyner-Ziv Formulation for End-to-End Lossy Two-Way Relay Network
 - 2.2 Berger-Tung Formulation for Two Source One Helper Network
 - 2.3 End-to-End Lossless and Lossy Multiple Access Channels
 - 2.4 Two Stage Wyner-Ziv Network: Distortion Transfer Analysis
- 3. Wyner-Ziv Formulation for Decision Making Process
 - 3.1 Revisit of Helper-aided Lossy Networks
 - 3.2 Distributed Hypothesis Testing (DHT)
 - 3.3 Semantic Communications
 - 3.4 Learning Process in Machine Learning

Contents of Full Tutorial:

- 0. Revisit to Fundamental Theorems in Network Information Theory
- 1. End-to-End Lossless Relaying: Slepian Wolf Theorem with Source-Channel Separation
 - 1.1 EXIT Analysis for Source Bit-Flipped MIMO Transmission with Turbo Equalization
 - 1.2 Slepian-Wolf Formulation for End-to-End Lossless Two-Way Relay Networks
- 2. End-to-End Lossy Distributed Multi-terminal Networks: Rate Distortion Analysis
 - 2.1 Wyner-Ziv Formulation for End-to-End Lossy Two-Way Relay Network
 - 2.2 Berger-Tung Formulation for Two Source One Helper Network
 - 2.3 End-to-End Lossless and Lossy Multiple Access Channels
 - 2.4 Two Stage Wyner-Ziv Network: Distortion Transfer Analysis
- 3. Wyner-Ziv Formulation for Decision Making Process
 - 3.1 **Revisit** of Helper-aided Lossy Networks
 - 3.2 Distributed Hypothesis Testing (DHT)
 - 3.3 Semantic Communications
 - 3.4 Learning Process in Machine Learning
 - 3.5 Information Bottleneck (IB)

Lossy Multi-terminal Cooperative Networks, Queueing, and Decision Making:

Erlang, Shannon, and Neyman-Pearson Meet in 6G Networks

March 27, 2023 @ Uoulu CWC Research Seminar by Remote

Tad Matsumoto*, **, ***

In what fields are they famous as land-mark tower builders? IEEE Life Fellow

***International Chair, Invited Professor, IMT -Atlantic**

Technopôle Brest-Iroise CS 83818 29238 Brest cedex 03, France

Tadashi.matsumoto@imt-atlantique.fr

**** Professor Emeritus, JAIST**

matumoto@jaist.ac.jp

***** Professor Emeritus, CWC, University of Oulu,**

tadashi.matsumoto@oulu.fi



IMT Atlantique
Bretagne-Pays de la Loire
École Mines-Télécom

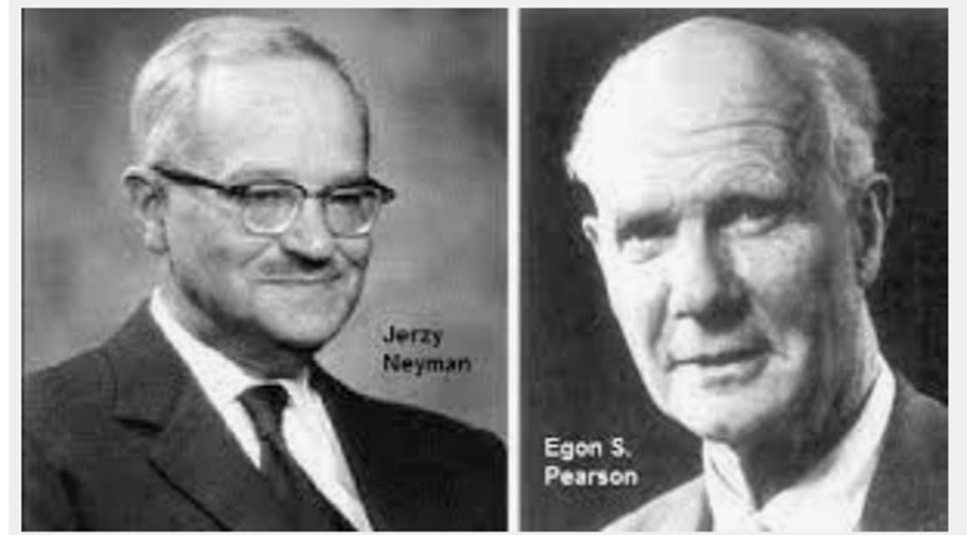




Shannon:
Information Theory



Erlang:
Queueing Theory



Neyman-Pearson:
Hypothesis Testing

Why “Neyman Pearson” Involved?



Unclear but still Accident Avoidable
Make left turn or right turn?

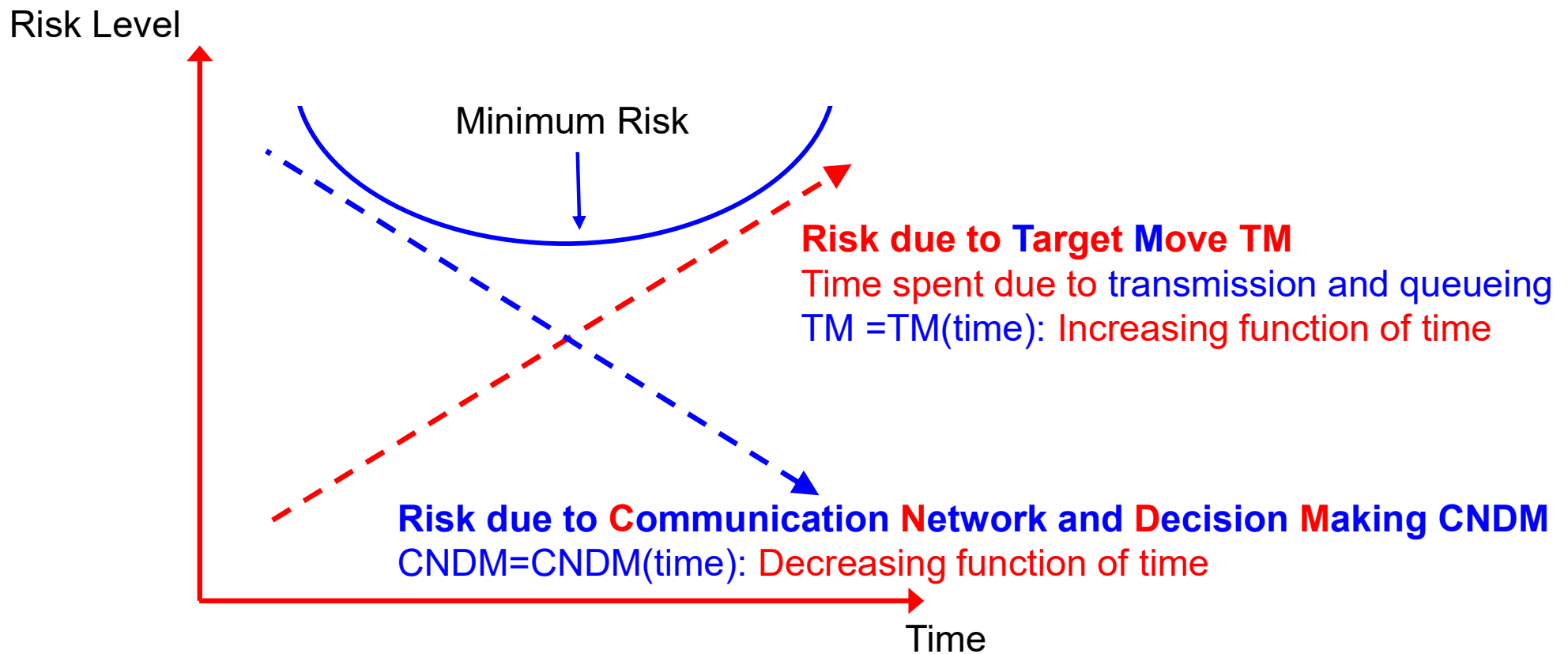


Clearer but maybe Too Late to Avoid Accident
Decision: Make left turn!

Making correct decision is most important than lossless reconstruction
of the observation for risk avoidance!

Is Lossless reconstruction Needed?

$$\text{Risk} = \text{Risk}(\text{TM}(\text{time}), \text{CNDM}(\text{time}))$$



**Motivation behind the 2023 March 27 Seminar:
Formulate Risk under the Three Landmark Builders' Framework!**

ITW 2024 Category

Welcome to ITW 2024 (<https://IEEE-ITW2024.org>)

Register a paper for 2024 IEEE Information Theory Workshop

Topics

- ☐ Deep Learning for Communication Networks
- ☐ Detection and Estimation
- ☐ Distributed Storage and Computing
- ☐ Emerging Applications of Information Theory
- ☐ Information Theory and Statistics
- ☐ Information Theory for Decision and Control
- ☐ Information Theory in Biology
- ☐ Information Theory in Computer Science



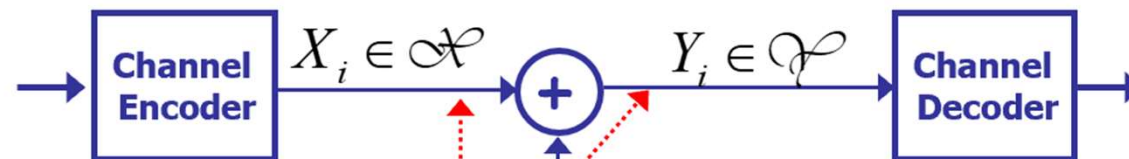
ITW'2024

Chapter 0. Revisit of Fundamental Theorems in Network Information Theory

1. Channel Capacity: Point-to-Point Lossless Channel's Maximum Capability

Theorem 3.1 (Channel Coding Theorem). The capacity of the discrete memoryless channel $p(y|x)$ is given by the information capacity formula

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



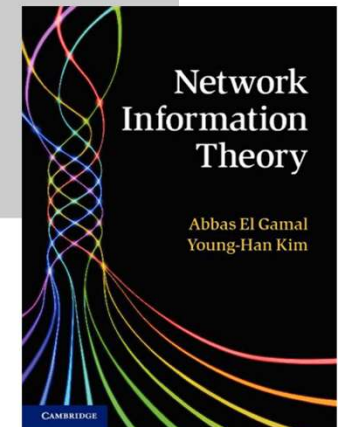
Binary/Non-binary finite alphabet

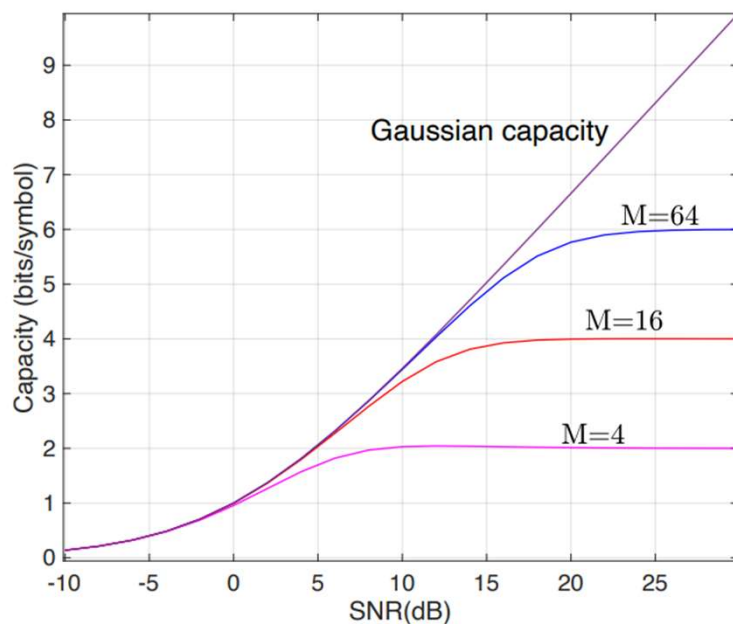
Noise = Error source

$$C = \max I(X; Y) \geq I(X; Y) \geq 0$$

$$C \leq \log |\mathcal{X}| \text{ because } C = \max I(X; Y) \leq \max H(X) = \log |\mathcal{X}|$$

$$C \leq \log |\mathcal{Y}| \text{ because } C = \max I(X; Y) \leq \max H(Y) = \log |\mathcal{Y}|$$





Gaussian Code book



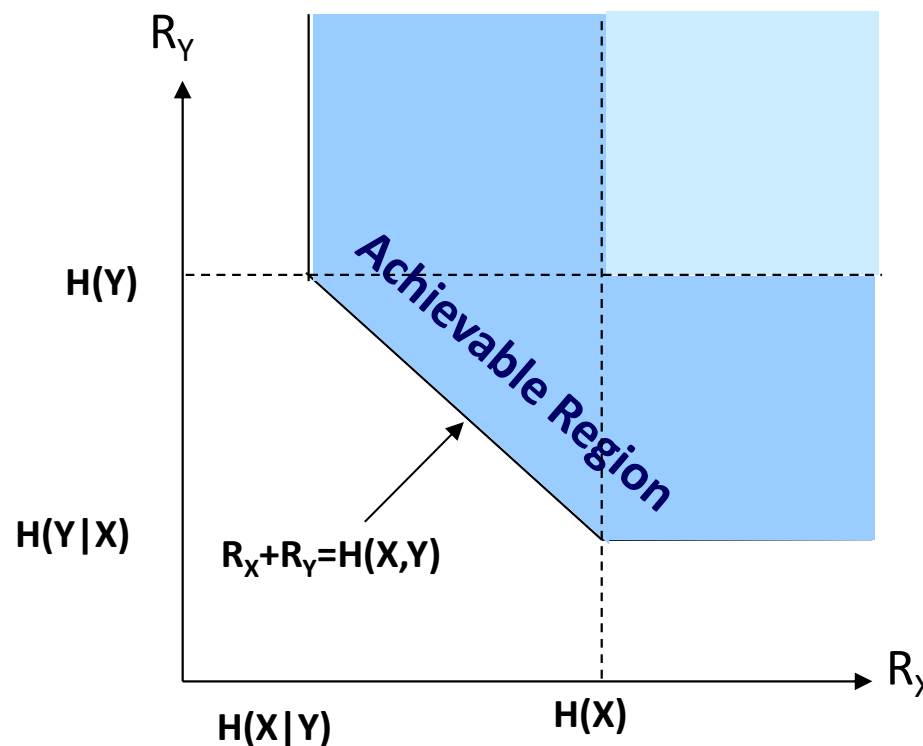
Gaussian Noise

$$C = \max_{p(x): EX^2 \leq P} I(X;Y) = \log(1 + SNR)$$

2. Rate Region: Distributed Multi-Source Lossless Coding

■ Slepian-Wolf Theorem:

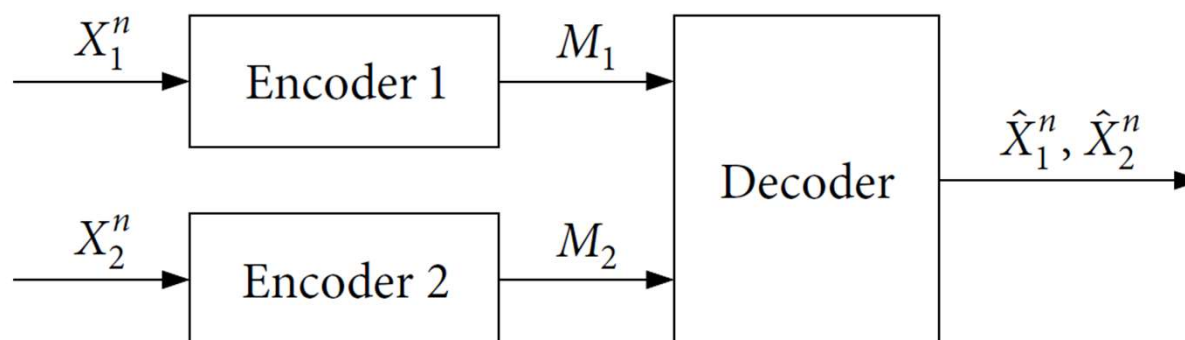
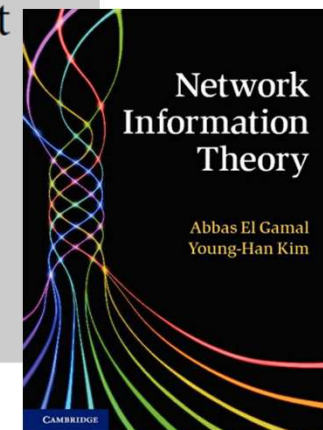
$$\begin{aligned} R_X &\geq H(X|Y) \\ R_Y &\geq H(Y|X) \\ R_X + R_Y &\geq H(X,Y) \end{aligned}$$



Two Sources:

Theorem 10.1 (Slepian–Wolf Theorem). The optimal rate region \mathcal{R}^* for distributed lossless source coding of a 2-DMS (X_1, X_2) is the set of rate pairs (R_1, R_2) such that

$$\begin{aligned} R_1 &\geq H(X_1|X_2), \\ R_2 &\geq H(X_2|X_1), \\ R_1 + R_2 &\geq H(X_1, X_2). \end{aligned}$$



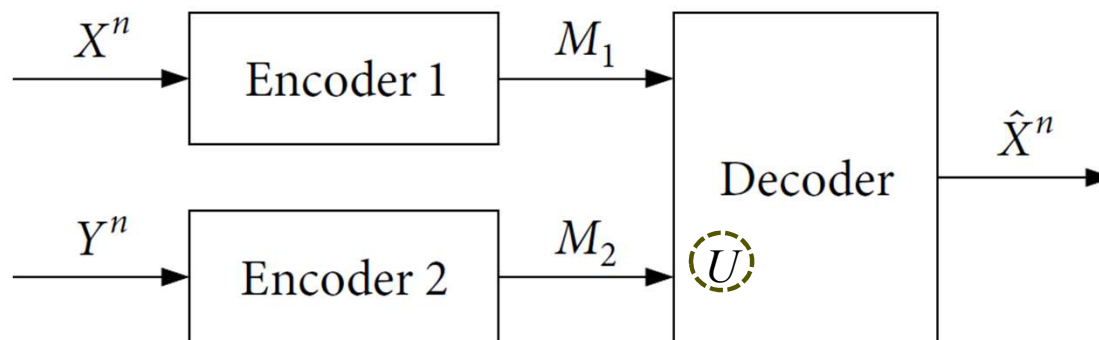
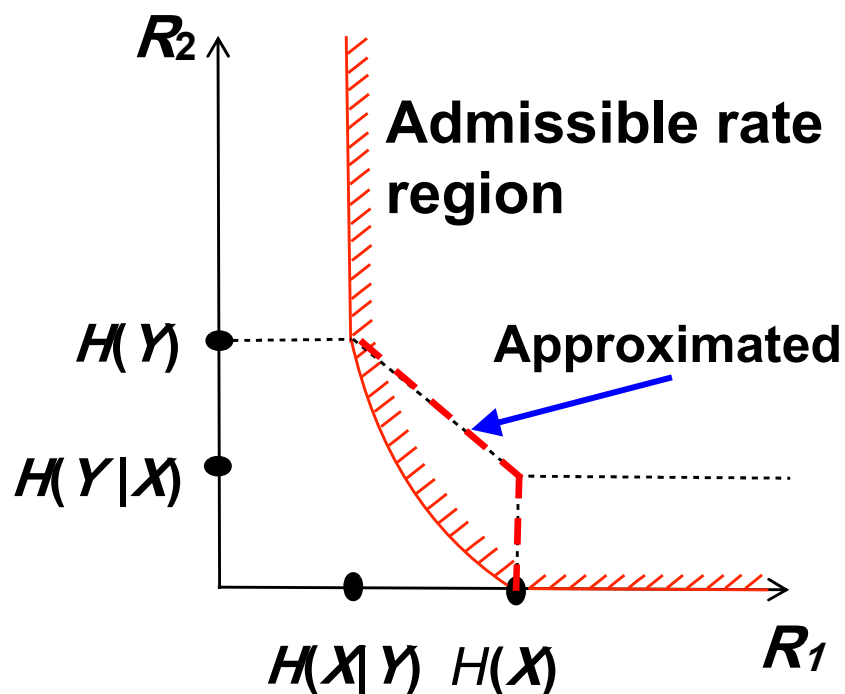
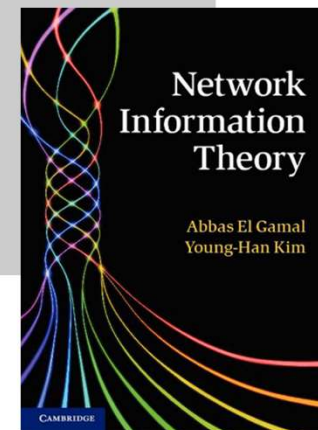
One Source One Helper:

Theorem 10.2. Let (X, Y) be a 2-DMS. The optimal rate region \mathcal{R}^* for lossless source coding of X with a helper observing Y is the set of rate pairs (R_1, R_2) such that

$$R_1 \geq H(X|U),$$

$$R_2 \geq I(Y; U)$$

for some conditional pmf $p(u|y)$, where $|\mathcal{U}| \leq |\mathcal{Y}| + 1$.



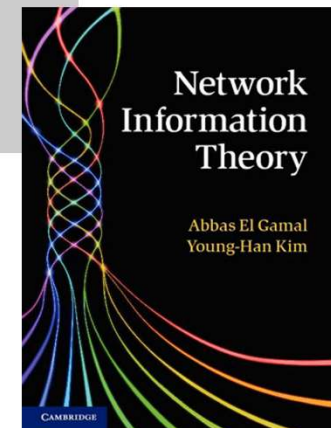
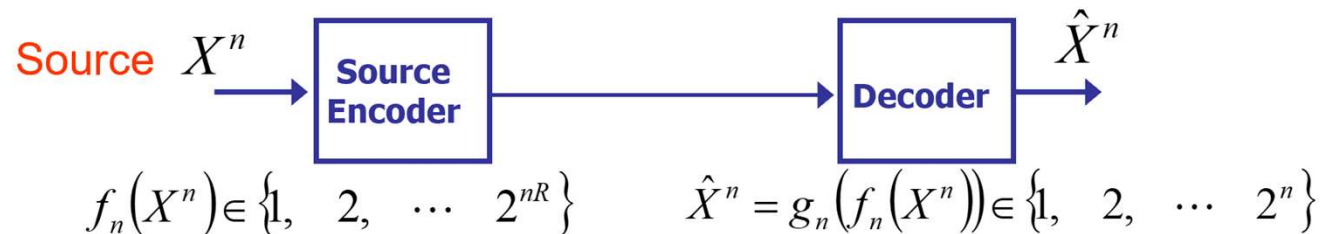
Remember! Coded Side Information=Helper

3. Lossy Source Coding:

Theorem 3.5 (Lossy Source Coding Theorem). The rate–distortion function for a DMS X and a distortion measure $d(x, \hat{x})$ is

$$R(D) = \min_{p(\hat{x}|x): E(d(X, \hat{X})) \leq D} I(X; \hat{X})$$

for $D \geq D_{\min} = \min_{\hat{x}(x)} E[d(X, \hat{x}(X))]$.



Example 3.4 (Bernoulli source with Hamming distortion). The rate–distortion function for a $\text{Bern}(p)$ source X , $p \in [0, 1/2]$, and Hamming distortion measure is

$$R(D) = \begin{cases} H(p) - H(D) & \text{for } 0 \leq D < p, \\ 0 & \text{for } D \geq p. \end{cases}$$

$$\begin{aligned}
 I(X; \hat{X}) &= H(X) - H(X|\hat{X}) \\
 &= H(p) - H(X \oplus \hat{X} | \hat{X}) \\
 &\geq H(p) - H(X \oplus \hat{X}) \\
 &\stackrel{(a)}{\geq} H(p) - H(D),
 \end{aligned}$$

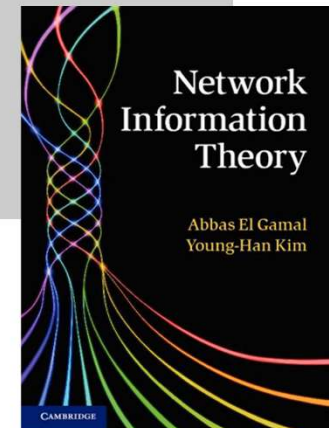
with $P\{X \neq \hat{X}\} \leq D$.

4. Source-Channel Separation:

A Connecting point between Source Coding and Channel Coding

Theorem 3.7 (Source–Channel Separation Theorem). Given a DMS U and a distortion measure $d(u, \hat{u})$ with rate–distortion function $R(D)$ and a DMC $p(y|x)$ with capacity C , the following statements hold:

- If $rR(D) < C$, then (r, D) is achievable.
- If (r, D) is achievable, then $rR(D) \leq C$.

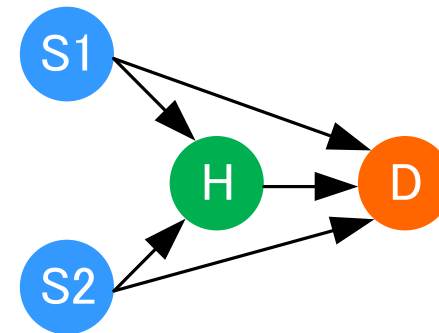
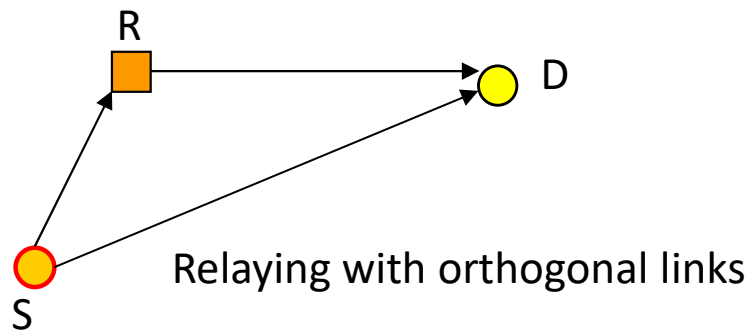


Remark 3.14. As a special case of joint source–channel coding, consider the problem of sending U over a DMC losslessly, i.e., $\lim_{k \rightarrow \infty} P\{\hat{U}^k \neq U^k\} = 0$. The separation theorem holds with the requirement that $rH(U) \leq C$.

Note:

Source-Channel Separation applies to:

- **Orthogonal** transmission with multiple Point-to-Point links,
- Both **Lossless** and **Lossy**, so far as each link is orthogonal,
- **Helper** link,
- (Experts say it holds with majority of the cases....)



Multiple Access Relaying with orthogonal links

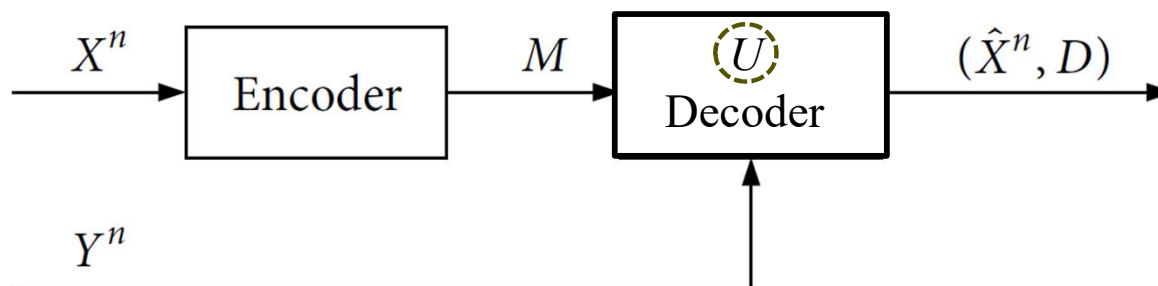
5. Rate Region: Lossy Source Coding with Side information/a Helper

With Side information:

Theorem 11.3 (Wyner–Ziv Theorem). Let (X, Y) be a 2-DMS and $d(x, \hat{x})$ be a distortion measure. The rate–distortion function for X with side information Y available noncausally at the decoder is

$$R_{\text{SI-D}}(D) = \min (I(X; U) - I(Y; U)) = \min I(X; U|Y) \quad \text{for } D \geq D_{\min},$$

where the minimum is over all conditional pmfs $p(u|x)$ with $|\mathcal{U}| \leq |\mathcal{X}| + 1$ and functions $\hat{x}(u, y)$ such that $\mathbb{E}[d(X, \hat{X})] \leq D$, and $D_{\min} = \min_{\hat{x}(y)} \mathbb{E}[d(X, \hat{x}(Y))]$.



Notice: $U \rightarrow X \rightarrow Y$ forms a Markov Chain

\Rightarrow

$$\begin{aligned} I(X; U) - I(Y; U) &= I(XY; U) - I(Y; U|X) - I(Y; U) \\ &= I(XY; U) - I(Y; U) = I(X; U|Y). \end{aligned}$$

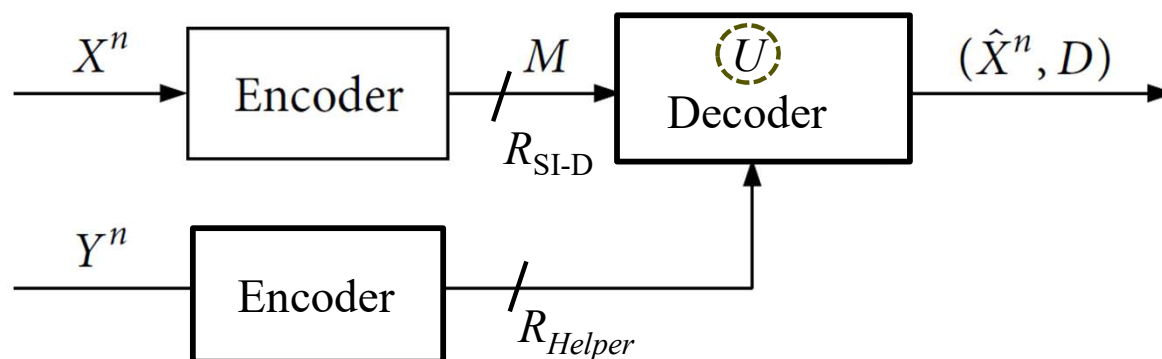
With a Helper:

Theorem 11.3 (Wyner–Ziv Theorem). Let (X, Y) be a 2-DMS and $d(x, \hat{x})$ be a distortion measure. The rate–distortion function for X with side information Y available noncausally at the decoder is

$$R_{\text{SI-D}}(D) = \min (I(X; U) - I(Y; U)) = \min I(X; U|Y) \quad \text{for } D \geq D_{\min},$$

$$R_{\text{Helper}} \geq I(Y; U)$$

where the minimum is over all conditional pmfs $p(u|x)$ with $|\mathcal{U}| \leq |\mathcal{X}| + 1$ and functions $\hat{x}(u, y)$ such that $\mathbb{E}[d(X, \hat{X})] \leq D$, and $D_{\min} = \min_{\hat{x}(y)} \mathbb{E}[d(X, \hat{x}(Y))]$.



Coded Side Information=Helper

Tad's Book?

6. Rate Region: Distributed Multipoint-to-Multipoint Lossy Coding

Without Helper:

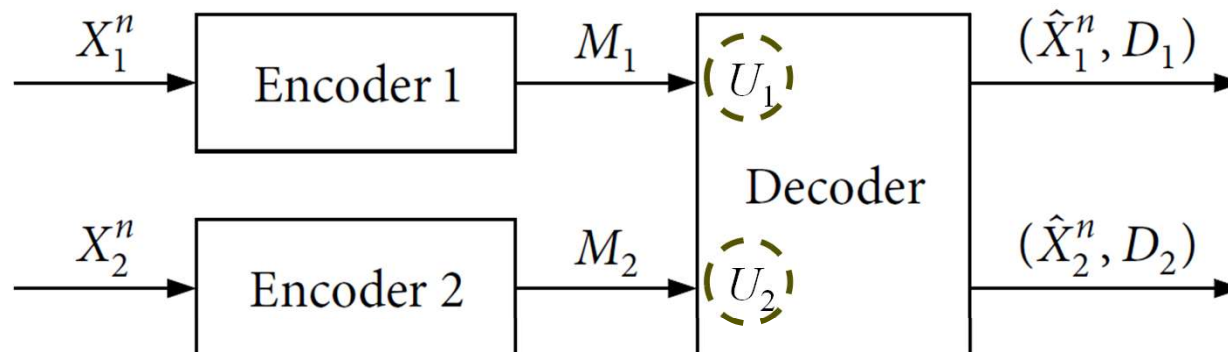
Theorem 12.1 (Berger–Tung Inner Bound). Let (X_1, X_2) be a 2-DMS and $d_1(x_1, \hat{x}_1)$ and $d_2(x_2, \hat{x}_2)$ be two distortion measures. A rate pair (R_1, R_2) is achievable with distortion pair (D_1, D_2) for distributed lossy source coding if

$$R_1 > I(X_1; U_1 | U_2, Q),$$

$$R_2 > I(X_2; U_2 | U_1, Q),$$

$$R_1 + R_2 > I(X_1, X_2; U_1, U_2 | Q)$$

for some conditional pmf $p(q)p(u_1|x_1, q)p(u_2|x_2, q)$ with $|\mathcal{U}_j| \leq |\mathcal{X}_j| + 4$, $j = 1, 2$, and functions $\hat{x}_1(u_1, u_2, q)$ and $\hat{x}_2(u_1, u_2, q)$ such that $E(d_j(X_j, \hat{X}_j)) \leq D_j$, $j = 1, 2$.



Notice: $U_1 \rightarrow X_1 \rightarrow X_2 \rightarrow U_2$

With a Helper:

Theorem 12.1 (Berger–Tung Inner Bound). Let (X_1, X_2) be a 2-DMS and $d_1(x_1, \hat{x}_1)$ and $d_2(x_2, \hat{x}_2)$ be two distortion measures. A rate pair (R_1, R_2) is achievable with distortion pair (D_1, D_2) for distributed lossy source coding if

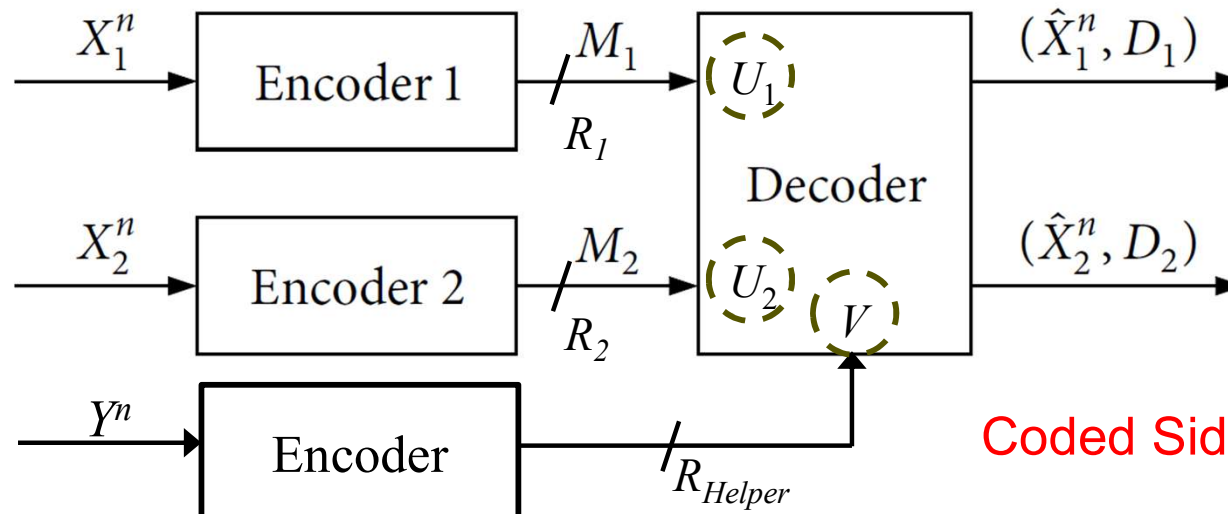
$$R_1 > I(X_1; U_1 | U_2, V, Q),$$

$$R_2 > I(X_2; U_2 | U_1, V, Q),$$

$$R_1 + R_2 > I(X_1, X_2; U_1, U_2 | V, Q),$$

$$R_{\text{Helper}} > I(Y; V)$$

for some conditional pmf $p(q)p(u_1|x_1, q)p(u_2|x_2, q)$ with $|\mathcal{U}_j| \leq |\mathcal{X}_j| + 4$, $j = 1, 2$, and functions $\hat{x}_1(u_1, u_2, q)$ and $\hat{x}_2(u_1, u_2, q)$ such that $E(d_j(X_j, \hat{X}_j)) \leq D_j$, $j = 1, 2$.



Coded Side Information=Helper

7. Multiple Access Channels (MAC)

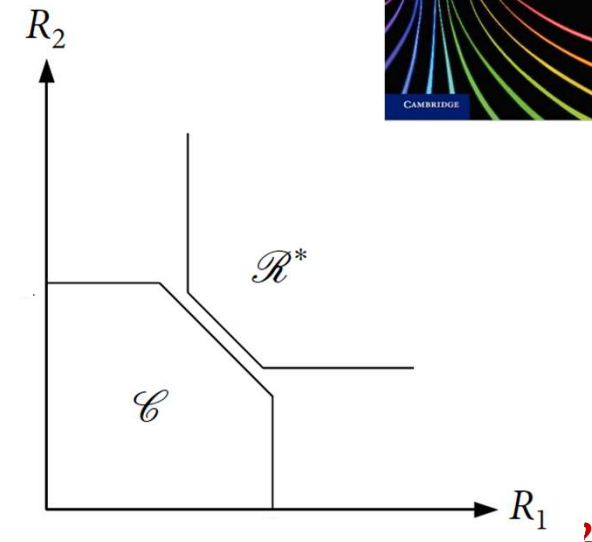
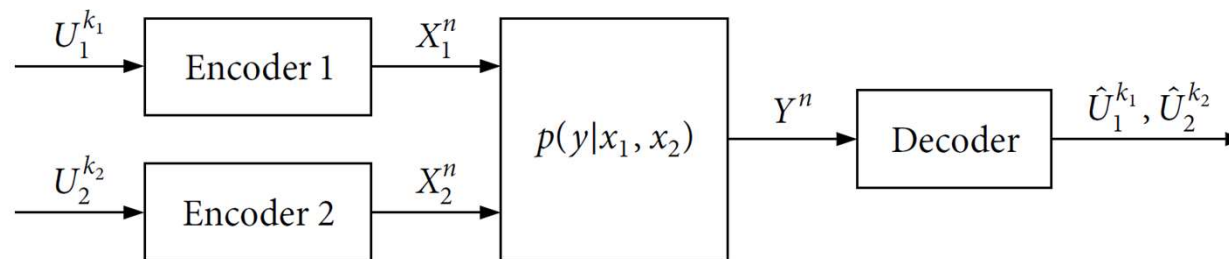
Correlated Sources Transmission over MAC:

First consider the following sufficient condition for separate source and channel coding. We know that the capacity region \mathcal{C} of the DM-MAC is the set of rate pairs (R_1, R_2) such that

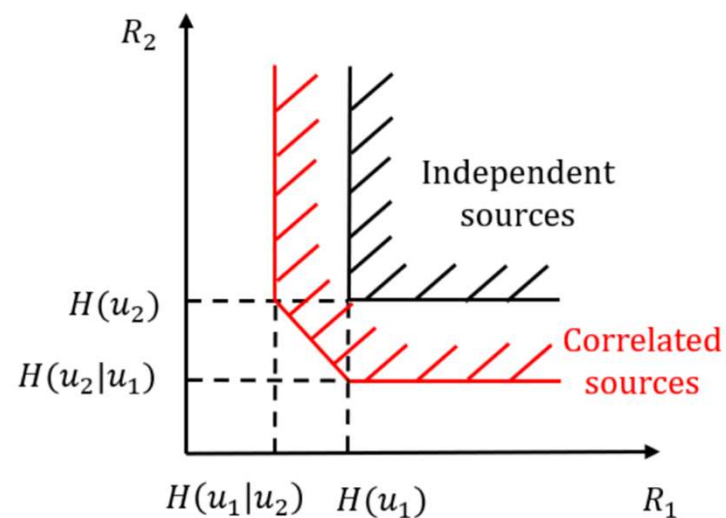
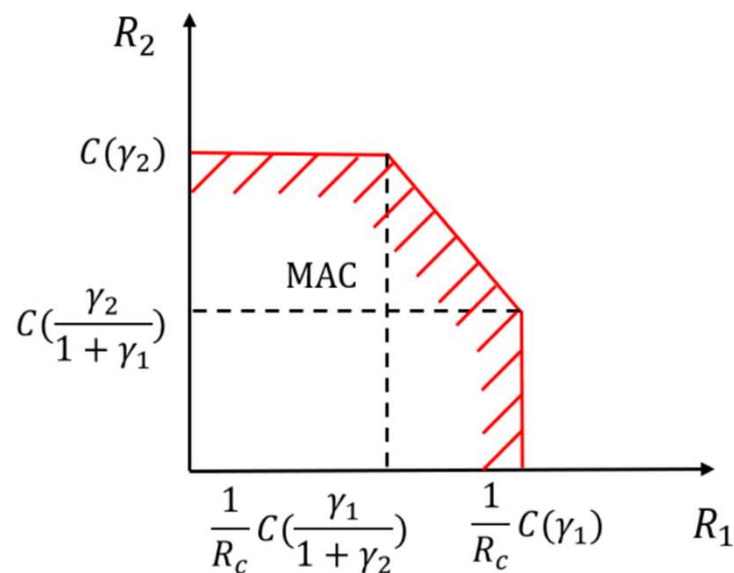
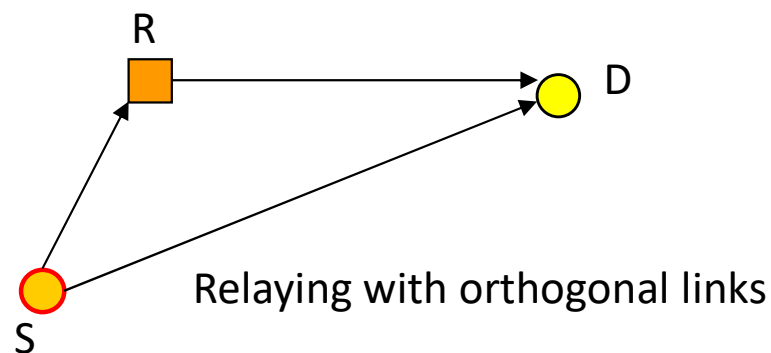
$$\begin{aligned} R_1 &\leq I(X_1; Y | X_2, Q), \\ R_2 &\leq I(X_2; Y | X_1, Q), \\ R_1 + R_2 &\leq I(X_1, X_2; Y | Q) \end{aligned}$$

for some pmf $p(q)p(x_1|q)p(x_2|q)$. We also know from the Slepian–Wolf theorem that the optimal rate region \mathcal{R}^* for distributed lossless source coding is the set of rate pairs (R_1, R_2) such that

$$\begin{aligned} R_1 &\geq H(U_1 | U_2), \\ R_2 &\geq H(U_2 | U_1), \\ R_1 + R_2 &\geq H(U_1, U_2). \end{aligned}$$

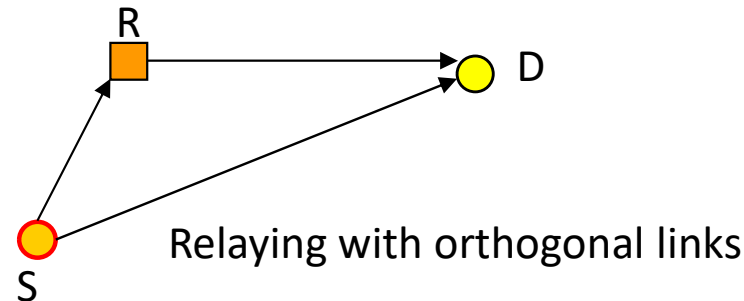


There are two regions in this set up: SW and MAC regions.



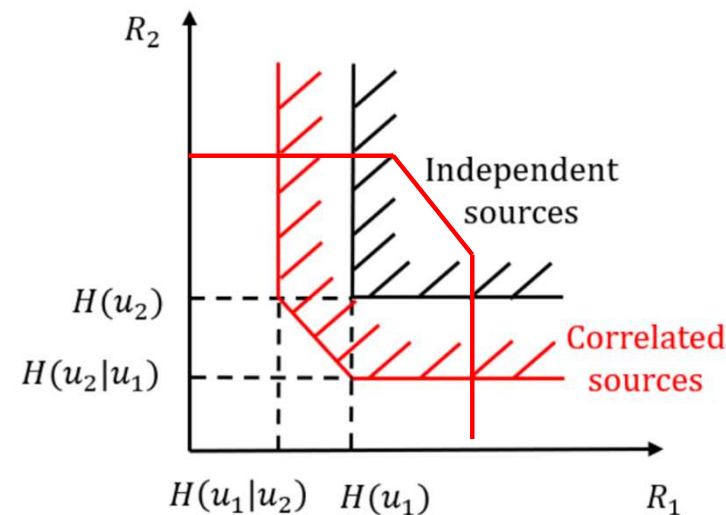
Revisit to Source-Channel Separation:

- **Orthogonal** transmission with multiple Point-to-Point links,
- **Both Lossless and Lossy**, so far as orthogonal,
- **Helper link**,



Region intersection: The rate-pair plot belongs to the both MAC and SW regions.

→ **Source-channel separation holds!**



Separation holds in:

- MAC transmission when the rate-pair-plot is in **intersection** (Sufficient condition, **NOT** optimal. Separation vs. Joint),
- (Experts say it holds in **many** cases....)

A sufficient condition for Lossless Recovery.

- Recovery for two sources

$$H(U_1|U_2) < I(X_1; Y|X_2, Q),$$

$$H(U_2|U_1) < I(X_2; Y|X_1, Q),$$

$$H(U_1, U_2) < I(X_1, X_2; Y|Q) .$$

- Recovery for one source with one helper

$$R_1 \leq I(X_1; Y|X_2, Q),$$

$$R_2 \leq I(X_2; Y|X_1, Q),$$

$$R_1 + R_2 \leq I(X_1, X_2; Y|Q)$$

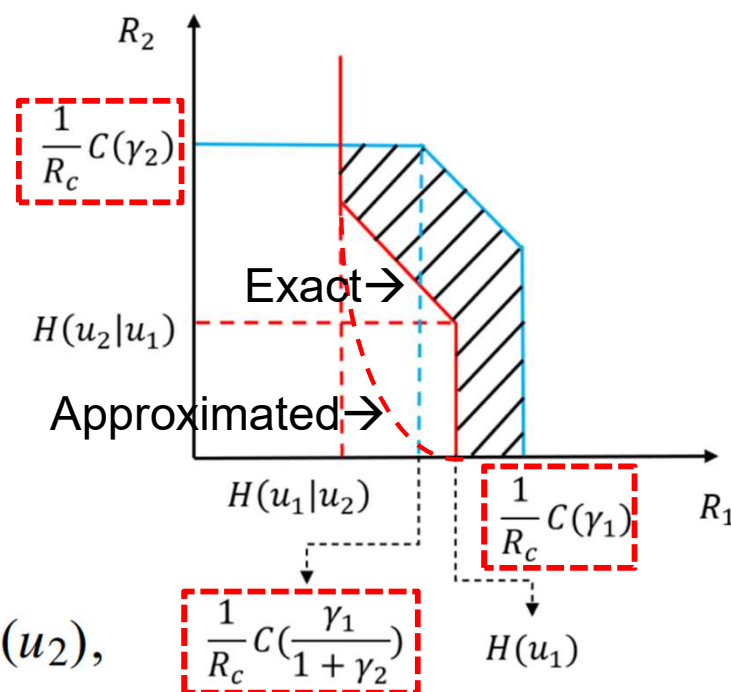
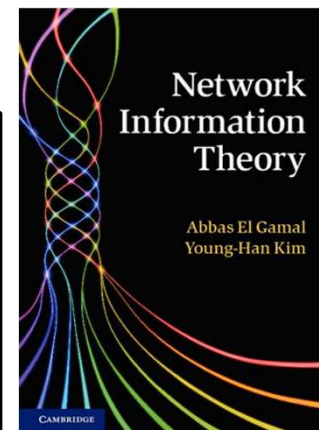
and

$$R_1 \geq H(X_1|U)$$

$$R_2 \geq I(X_2; U)$$

which can be approximated by

$$R_1 \geq \begin{cases} H(u_1|u_2), & \text{for } R_2 \geq H(u_2), \\ H(u_1, u_2) - R_2, & \text{for } H(u_2|u_1) \leq R_2 \leq H(u_2), \\ H(u_1), & \text{for } 0 \leq R_2 \leq H(u_2|u_1), \end{cases}$$



A sufficient condition for Lossy Recovery.

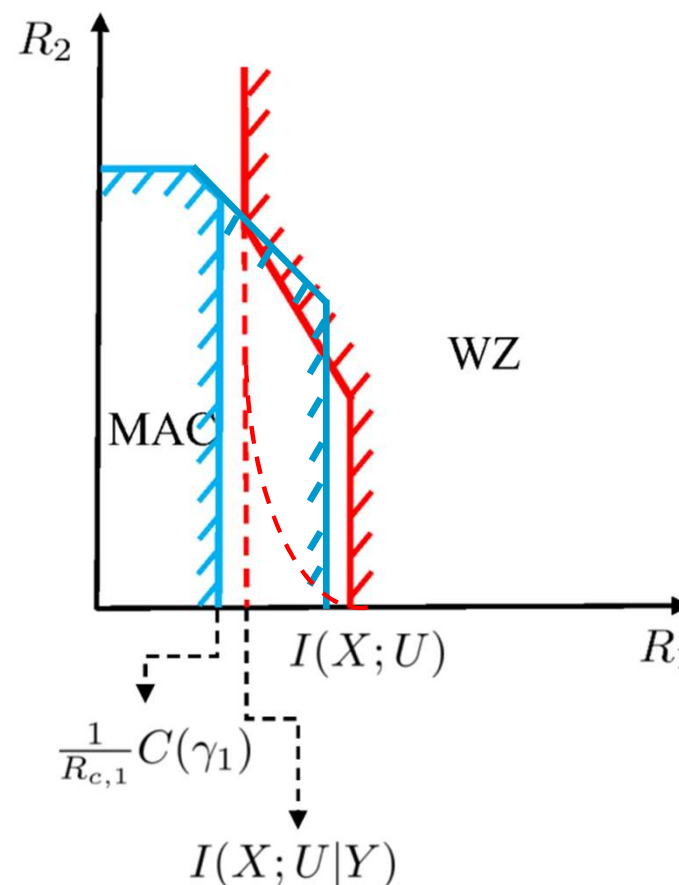
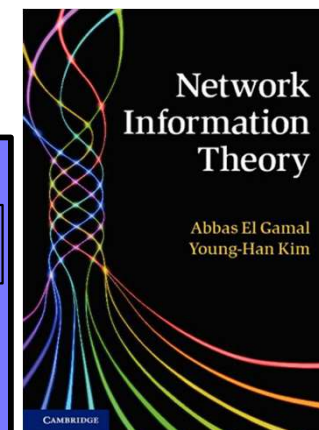
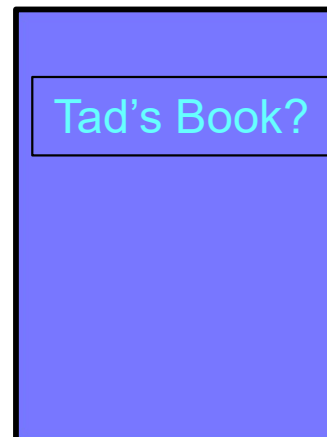
- Recovery for one source with one helper

$$\begin{aligned} R_1 &\leq I(X_1; Y | X_2, Q), \\ R_2 &\leq I(X_2; Y | X_1, Q), \\ R_1 + R_2 &\leq I(X_1, X_2; Y | Q) \end{aligned}$$

and

$$\begin{aligned} R_1 &\geq I(X_1; U | V) \\ R_2 &\geq I(X_2; V) \end{aligned}$$

Region intersection
→ Source-channel separation holds!



Properties of Binary Convolution:

Binary Convolution

$$x * y = x(1 - y) + (1 - x)y = x + y - 2xy$$

- For variables $x, t \in [0, 0.5]$ and $y \in [0, 0.5]$

$$x * y \leq t \Rightarrow x \leq \Lambda(t, y) \triangleq \frac{1}{2} \left(1 - \frac{2t - 1}{2y - 1} \right)$$

- $x * y \leq t$ inherently involves $y \leq t$
- $\Lambda(y, t)$ is a monotonically decreasing function of y , with a maximum $\Lambda(y = 0, t) = t$
- $\Lambda(y, t)$ is a linearly increasing function of t , with a maximum $\Lambda(y, t = 0.5) = 0.5$

- **Recursive structure:**

$$\begin{aligned} y * z \leq s &\Rightarrow y \leq \Lambda(s, z) \\ x * y * z \leq t &\Rightarrow x \leq \Lambda(t, \Lambda(s, z)) \end{aligned}$$

$$v * w \leq c_1 \Rightarrow v \leq \Lambda(c_1, w)$$

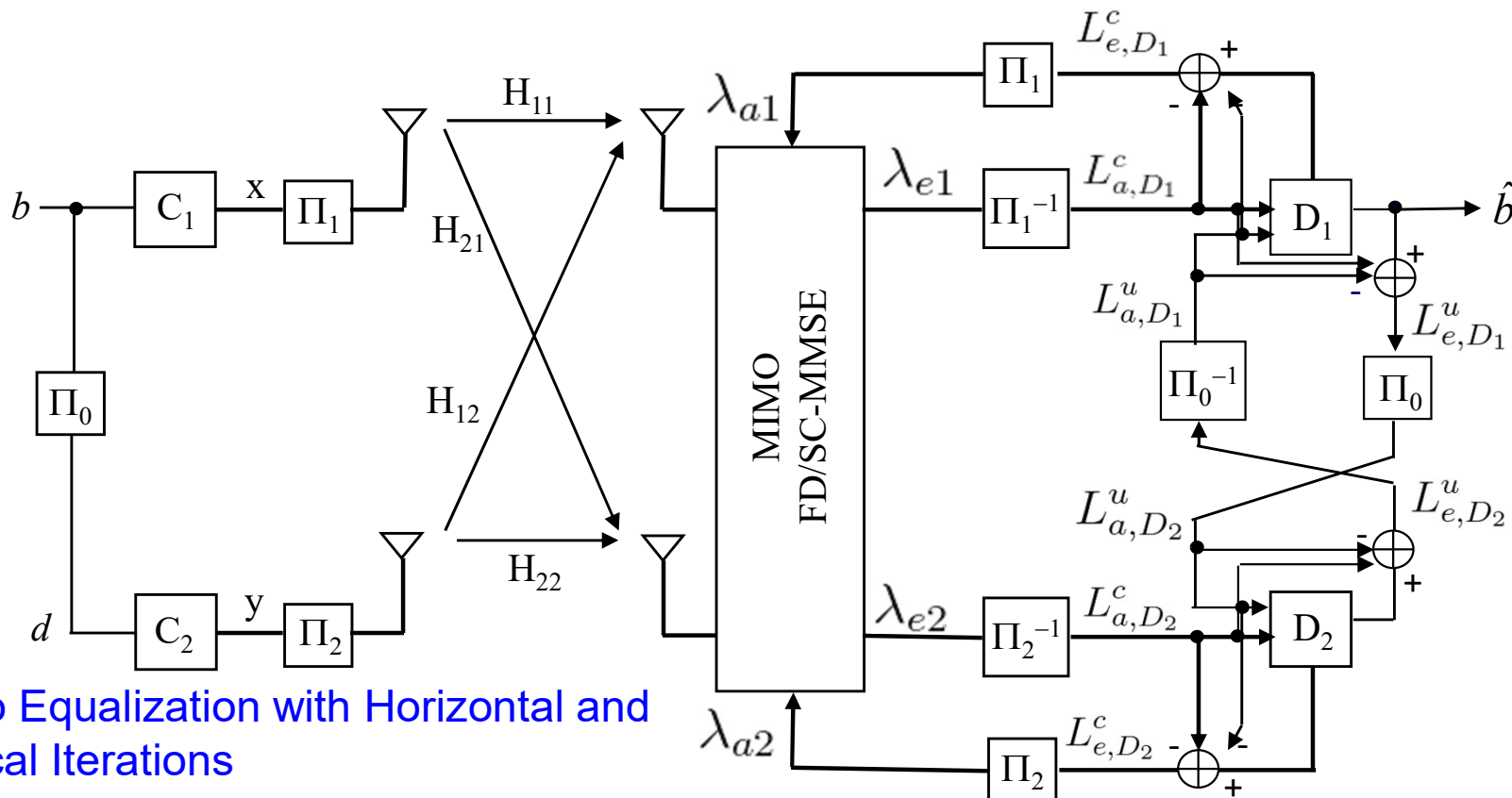
$$\vdots$$

$$x * y * z * \cdots v * w \leq c_n \Rightarrow x \leq \Lambda(c_n, \Lambda(c_{n-1}, \Lambda(\dots, \Lambda(c_1, w))))$$

Tad's Book?

Chapter 1. End-to-End Lossless Relaying: Slepian Wolf Theorem with Source-Channel Separation

1.1 EXIT Analysis for Source Bit-Flipped MIMO Transmission with Turbo Equalization

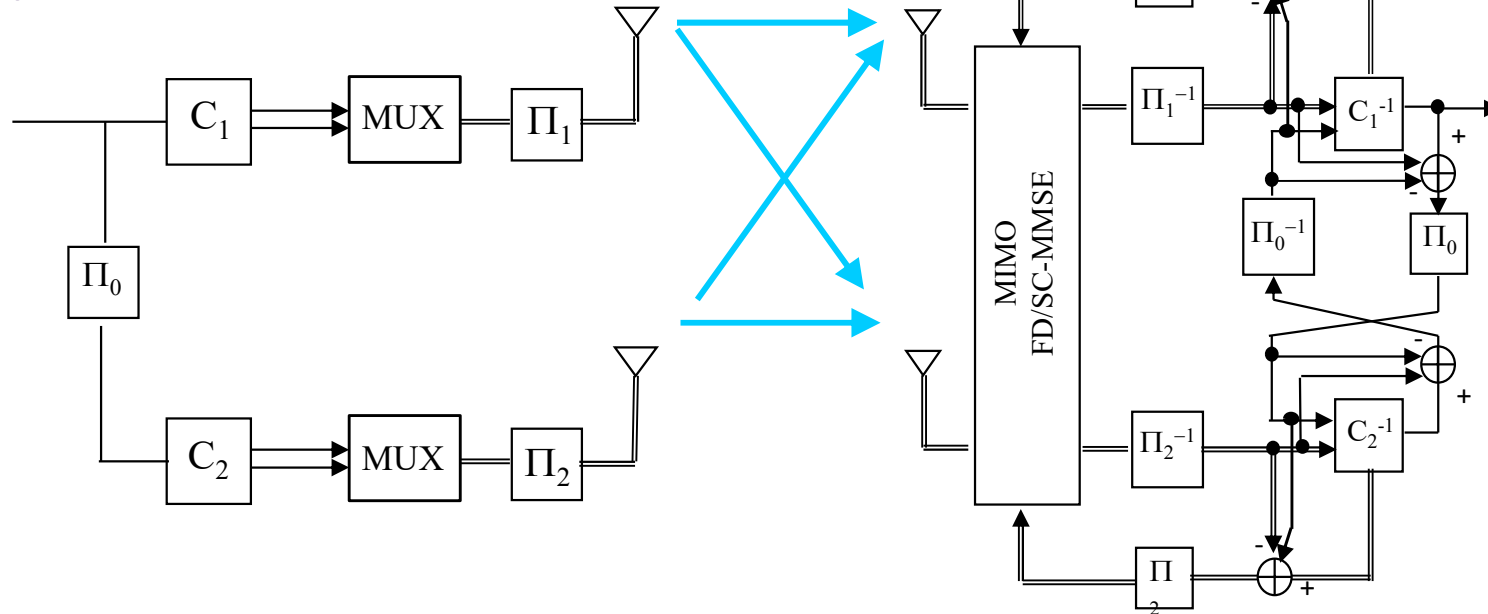


Turbo Equalization with Horizontal and Vertical Iterations

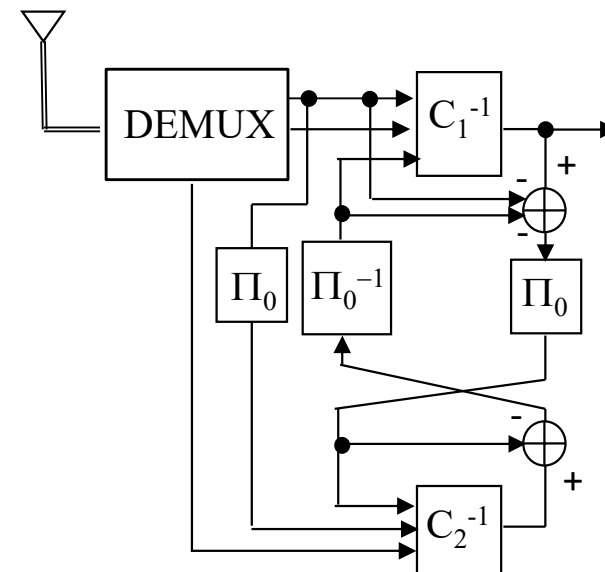
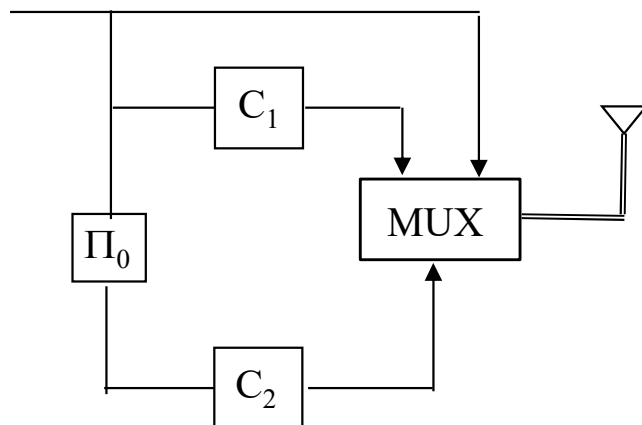
- Vertical iteration is expected to improve performance because of space diversity gain from using antenna 1 and 2, and coding gain. Mariella Sarestoniemi, Tad Matsumoto, Kimmo Kansanen, and Jari Iinatti, "Turbo Diversity Based on SC/MMSE Equalization", *IEEE Transactions on Vehicular Technology*, Vol. 54, No. 2, pp. 749-752, March, 2005
- This design is called as **Spatial Turbo Code (STC)** because coded sequences are multiplexed in the spatial domain, not in the time domain as in the Turbo codes.

STC vs. Turbo Code

■ Spatial Turbo Code

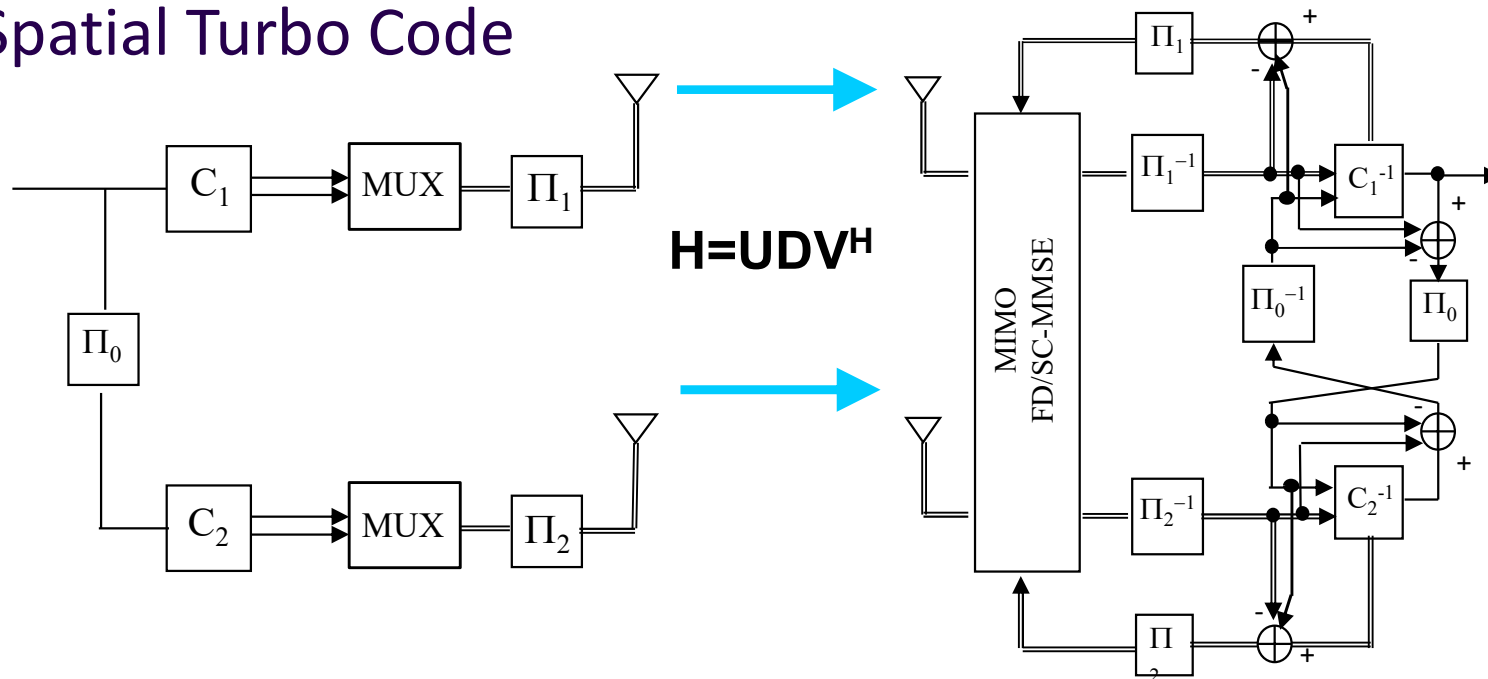


■ Turbo Code

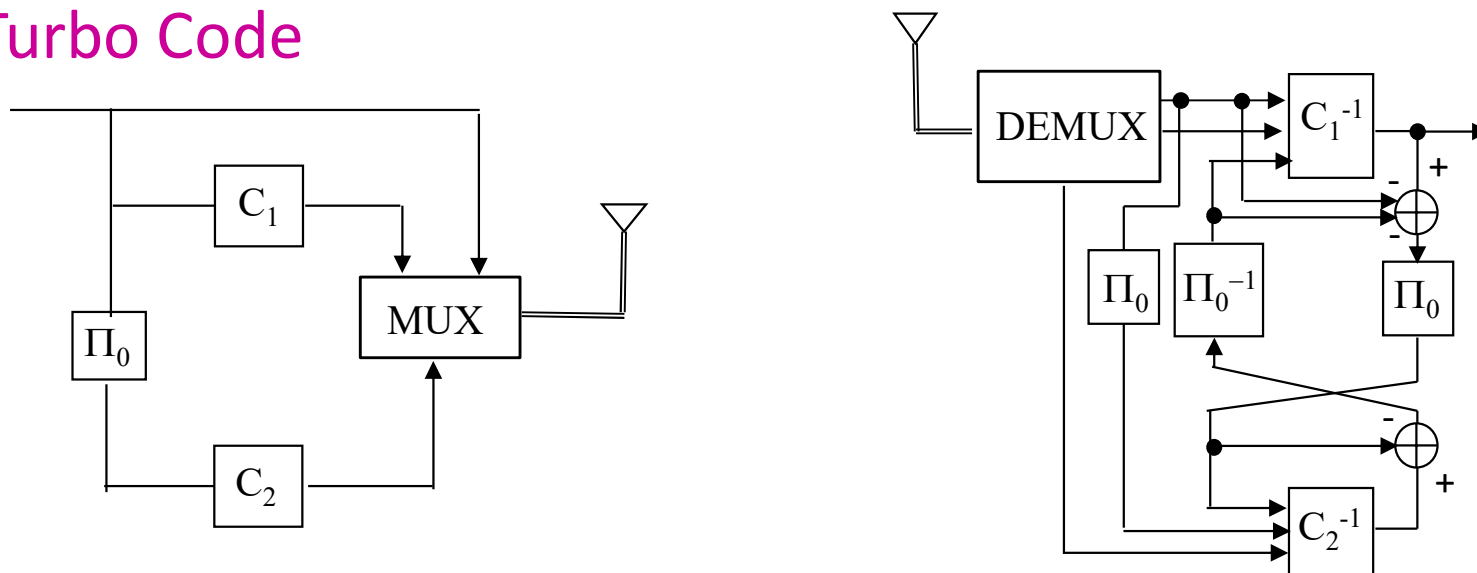


STC vs. Turbo Code

■ Spatial Turbo Code



■ Turbo Code



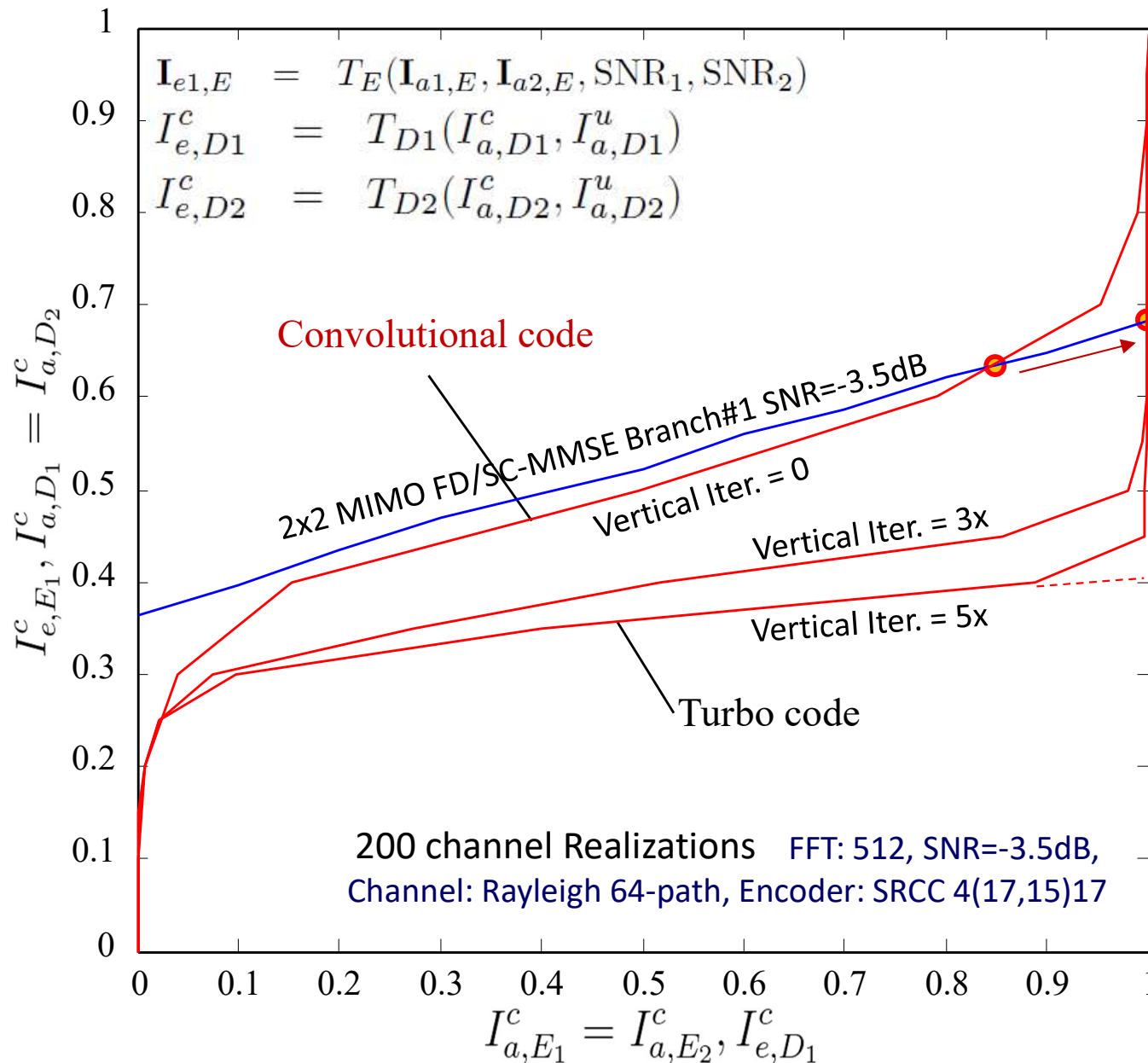
- **We* developed Frequency Domain Turbo Equalization Algorithms**
for single carrier signalling: It requires computational complexity of only
"high school levelmath"!
- Convergence property analysis made significantly easy!

"Do you still spread?" ← Famous words said many times, said by a CWC person.

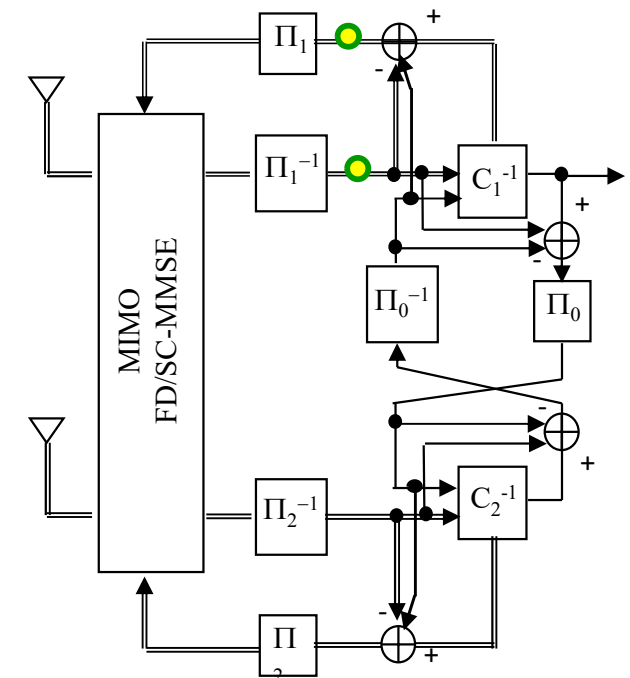
- Kimmo Kansanen, and Tad Matsumoto, "An Analytical Method for MMSE MIMO Turbo Equalizer EXIT Chart Computation", *IEEE Transactions on Wireless Communications*, Vol. 6, No.1, pp.59-63, January, 2007



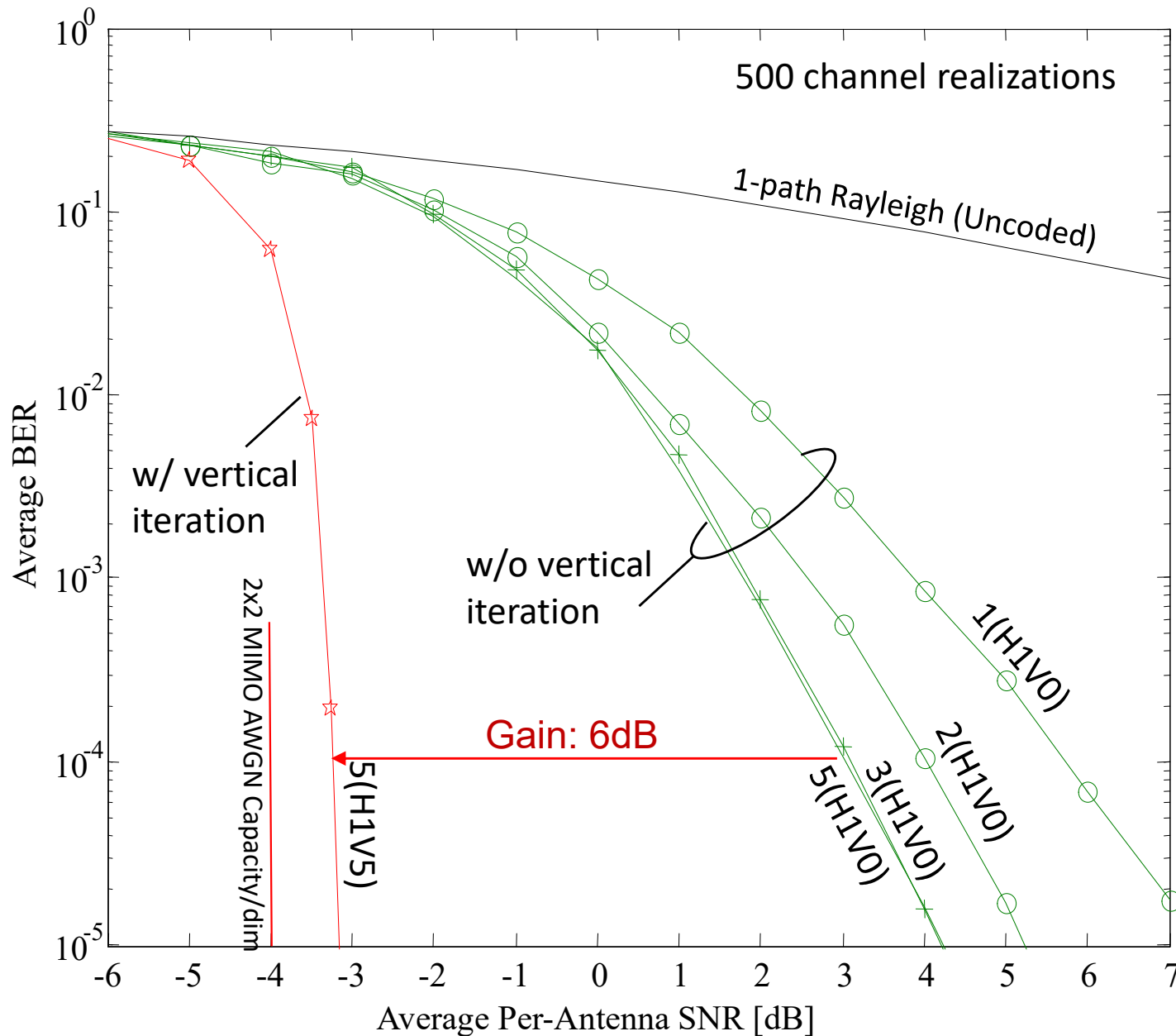
Contribution of Vertical Iterations



- Vertical Iteration converts CC \rightarrow Turbo
- Stuck point is shifted to the right side.



BER Performance of STC



Parameters:



Transmitter:

Encoder: SRCC
4(17,15),17
Interleaver=1024
(random)

Channel:

MIMO 2x2
Equal Power 64-
path

Receiver:

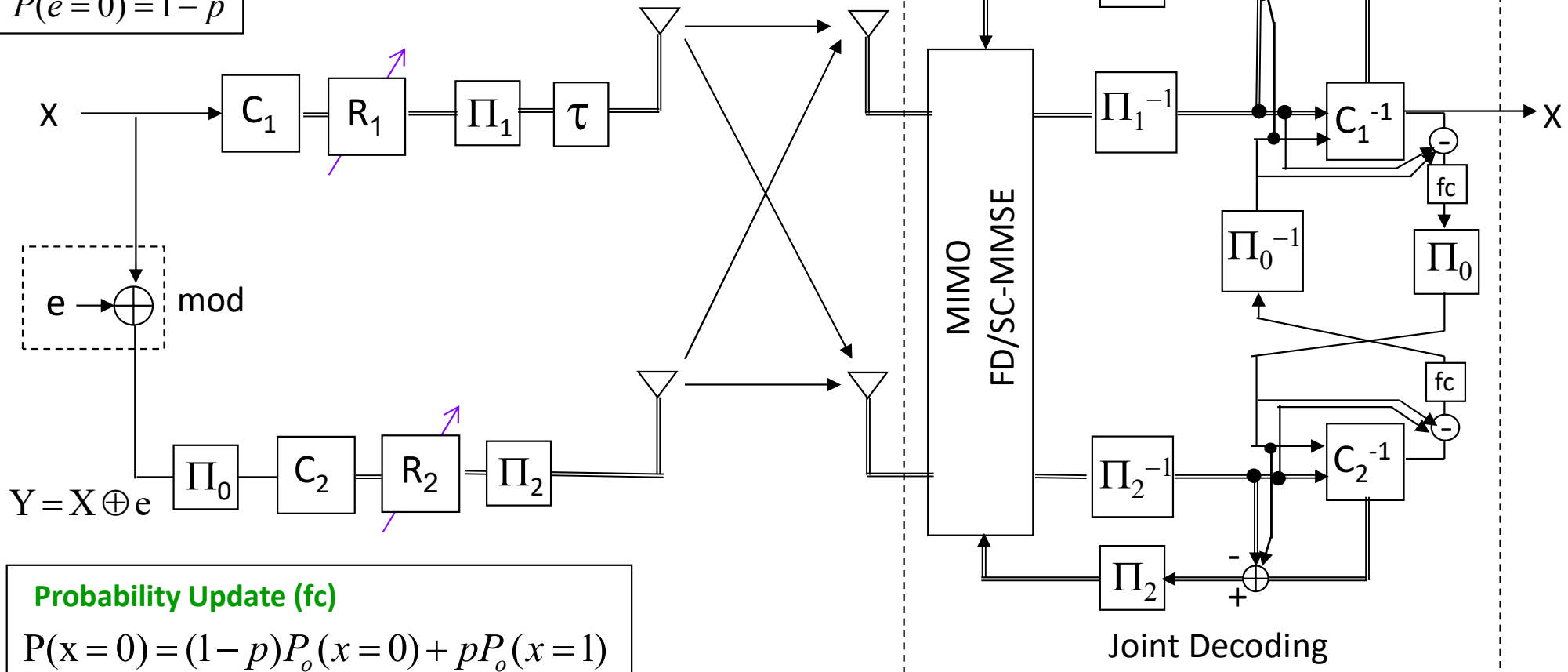
Decoder: BCJR
Log-MAP
FFT=512

How to Model Correlated Sources?

Bit flipping \mathbf{e}

$$P(e=1) = p$$

$$P(e=0) = 1 - p$$



Probability Update (fc)

$$P(x=0) = (1-p)P_o(x=0) + pP_o(x=1)$$

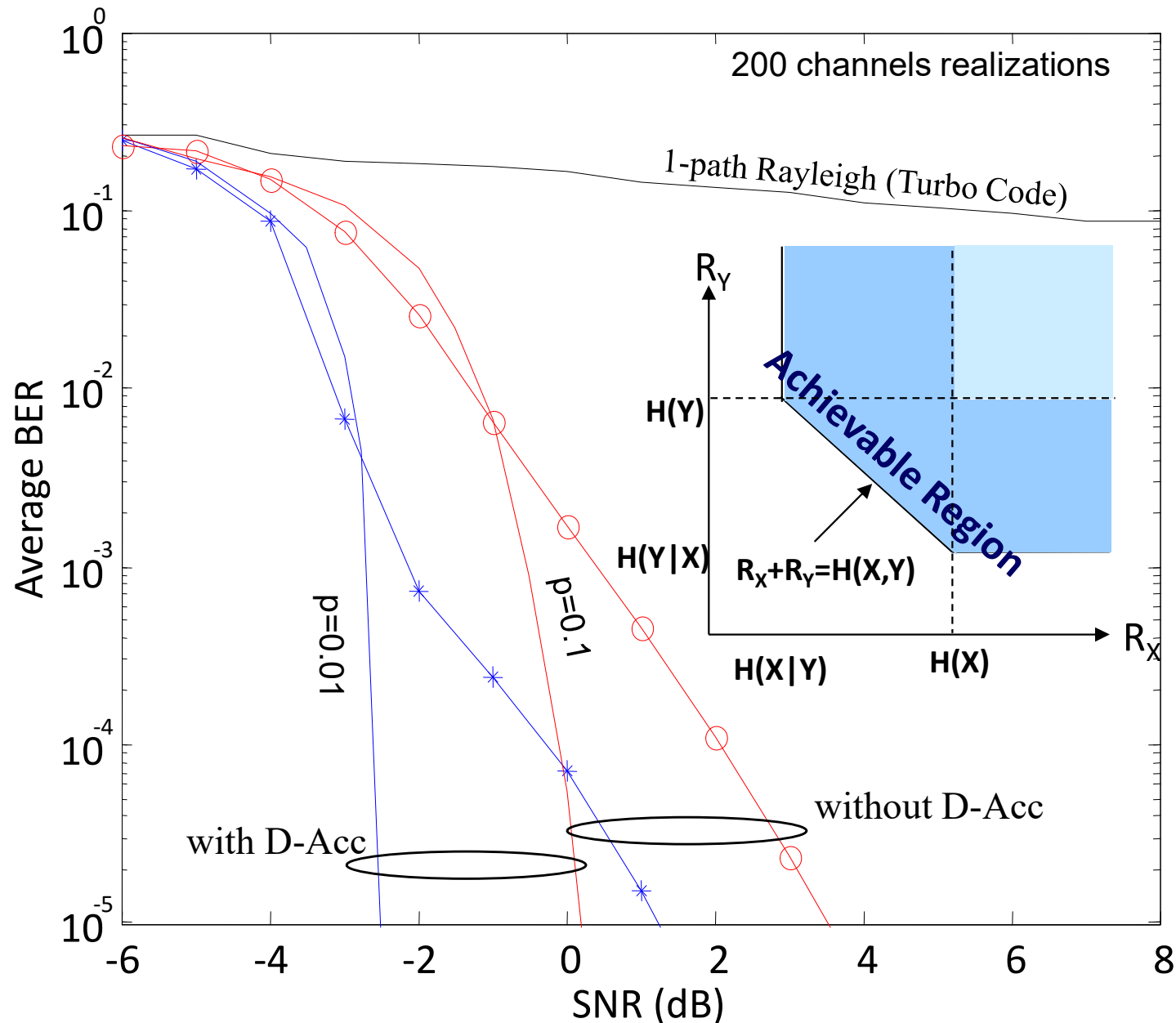
$$P(x=1) = (1-p)P_o(x=1) + pP_o(x=0)$$

$$LLR_{update} = \ln \frac{(1-p)e^L + p}{(1-p) + pe^L}$$

How to estimate p at the receiver?

$$\hat{p} = \frac{1}{K} \sum_{k=1}^K \{P_o(x_k=1)P_o(y_k=0) + P_o(x_k=0)P_o(y_k=1)\}$$

Average BER in Block Frequency-Selective Block Rayleigh Fading Channels: Source Bit-Flipped MIMO Transmission with Turbo Equalization - Bit-flipped sequences are correlated sources!



Parameters:

Transmitter:

Encoder: CC

4(17,15),17

Interleaver=1024

(random)

Correlation Model:

Bit-flipping

Channel:

MIMO 2x2

Equal Power 64-path

Receiver:

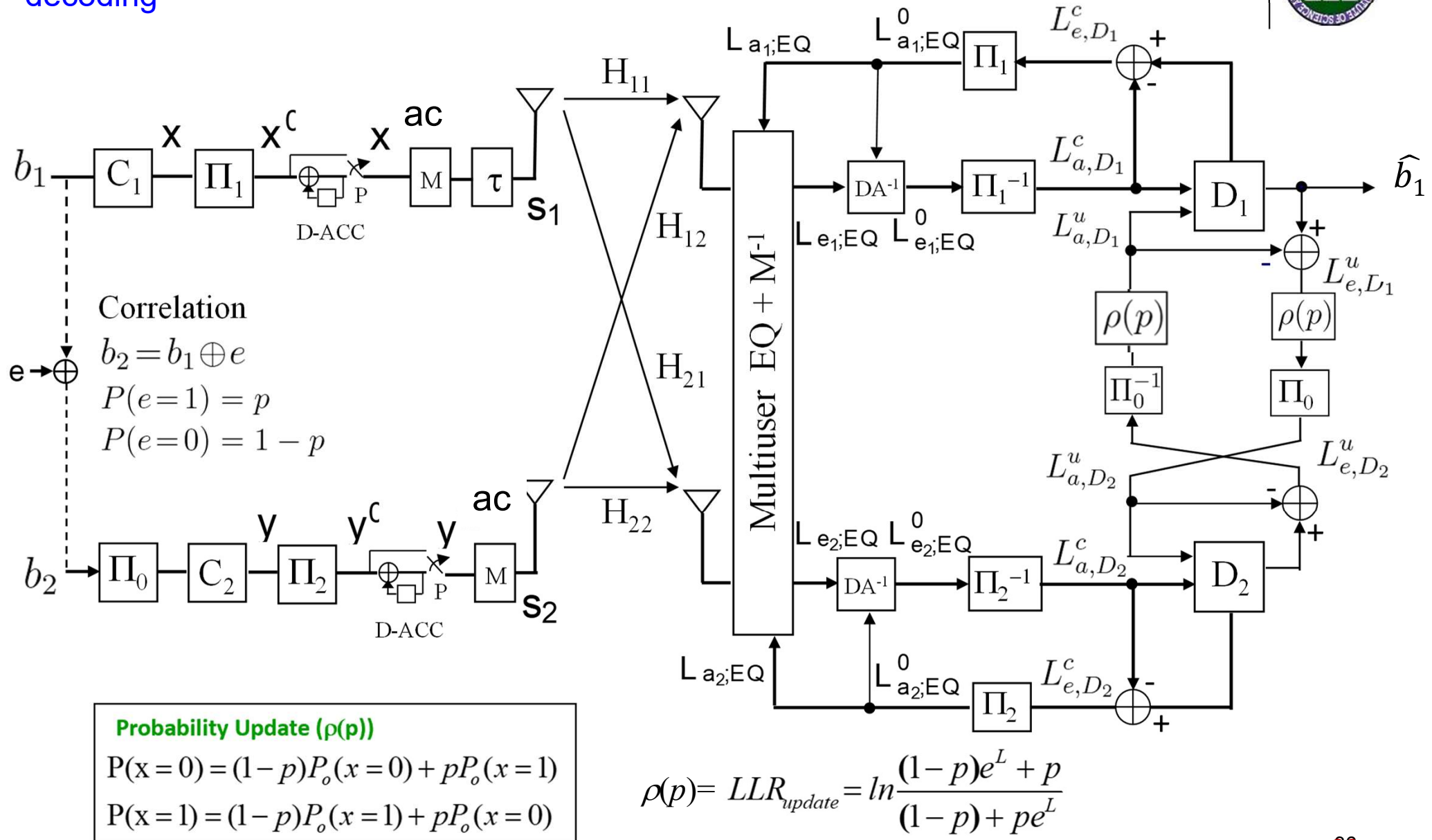
Decoder: BCJR

Log-MAP

FFT=512

Source Bit-Flipped MIMO Transmission with Turbo Equalization:

With the bit flipping e between b_1 and b_2 , b_1 can be recovered losslessly by joint decoding



EXIT Chart for Source Bit-Flipped MIMO Transmission with Turbo Equalization

Parameters:

Transmitter:

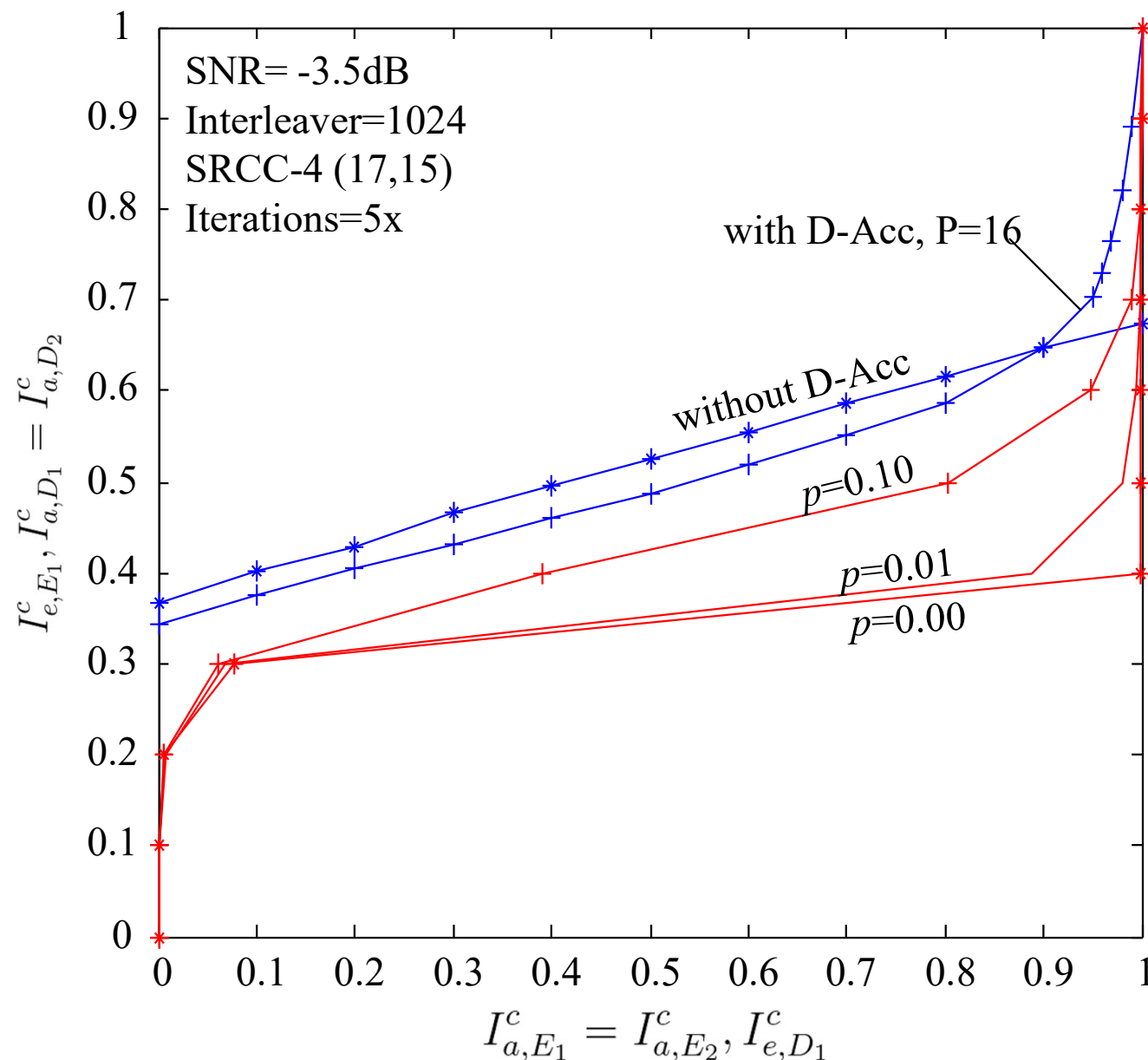
Encoder: CC
4(17,15),17
Interleaver=5000
(random)
Correlation Model:
Bit-flipping

Channel:

MIMO 2x2
Equal Power 64-
path

Receiver:

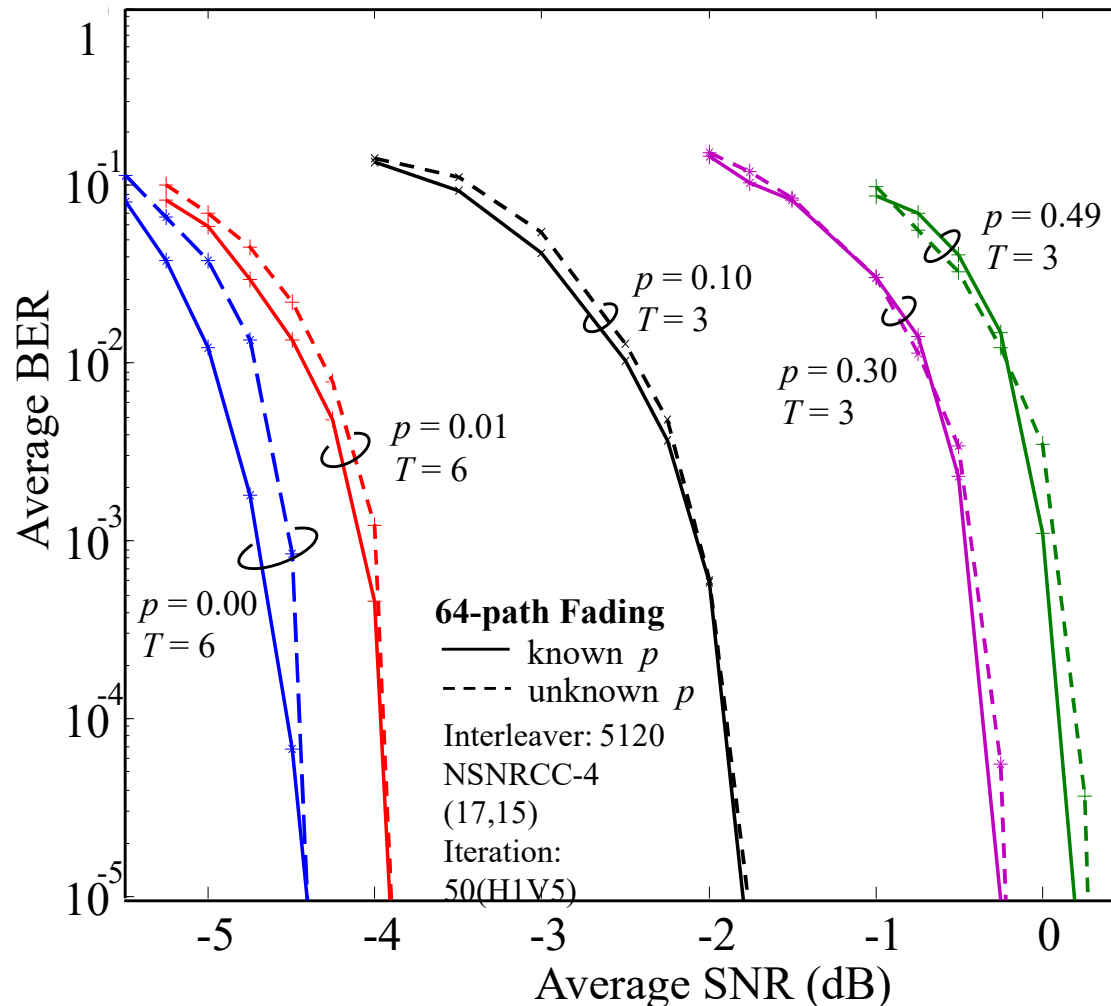
Decoder: BCJR
Log-MAP
FFT=512



Comparison in SNR to Slepian-Wolf Bound @ BER=10⁻⁵

| p | $\mathcal{H}(b_1, b_2)$ | \mathcal{R}_{SW} | Bit-Flipped MIMO TEQ | | |
|------|-------------------------|--------------------|----------------------|----------------------------|------|
| | | | SNR_{lim} | $\text{SNR}_{BER=10^{-5}}$ | Gap |
| 0.00 | 1.000 | 0.250 | -5.40 | -4.38 | 1.02 |
| 0.01 | 1.081 | 0.270 | -5.05 | -3.88 | 1.17 |
| 0.10 | 1.469 | 0.367 | -3.15 | -1.88 | 1.27 |
| 0.30 | 1.881 | 0.470 | -1.50 | -0.25 | 1.25 |
| 0.49 | 1.999 | 0.499 | -1.15 | 0.13 | 1.28 |

One Source One Helper
Slepian Wolf Theorem



Transmitter:

Encoder: CC 4(17,15)
Interleaver=10000
(random)
Correlation Model:
Bit-flipping

Channel:

MIMO 2x2
Equal Power 64-path

Receiver:

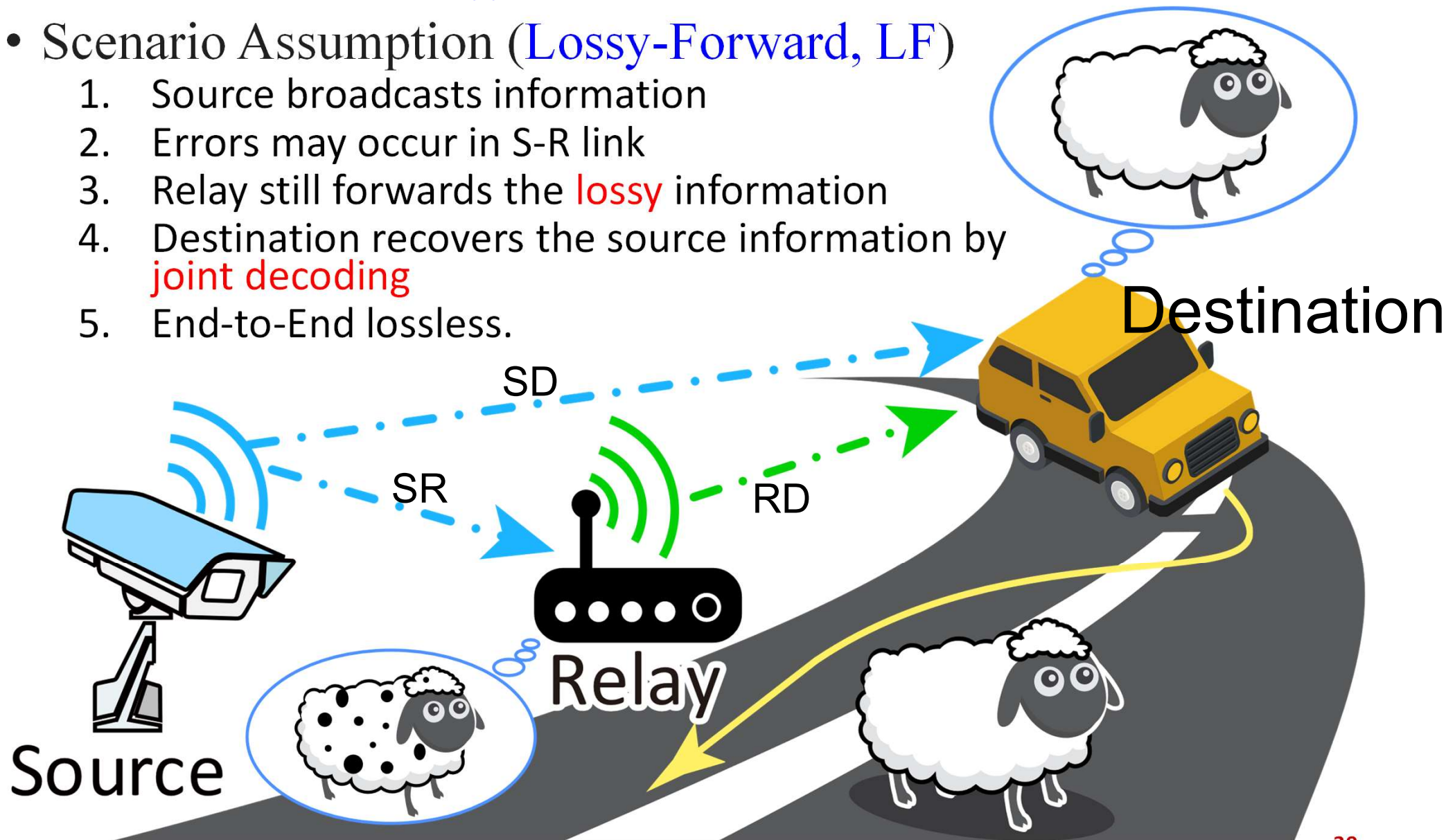
Decoder: BCJR
Log-MAP
FFT=512

1.2 Slepian-Wolf Formulation for Lossless Two-Way Relay Networks

Observation on Bit-flipped MIMO TEQ: BF Model Works as Correlated Sources!

- Scenario Assumption (**Lossy-Forward, LF**)

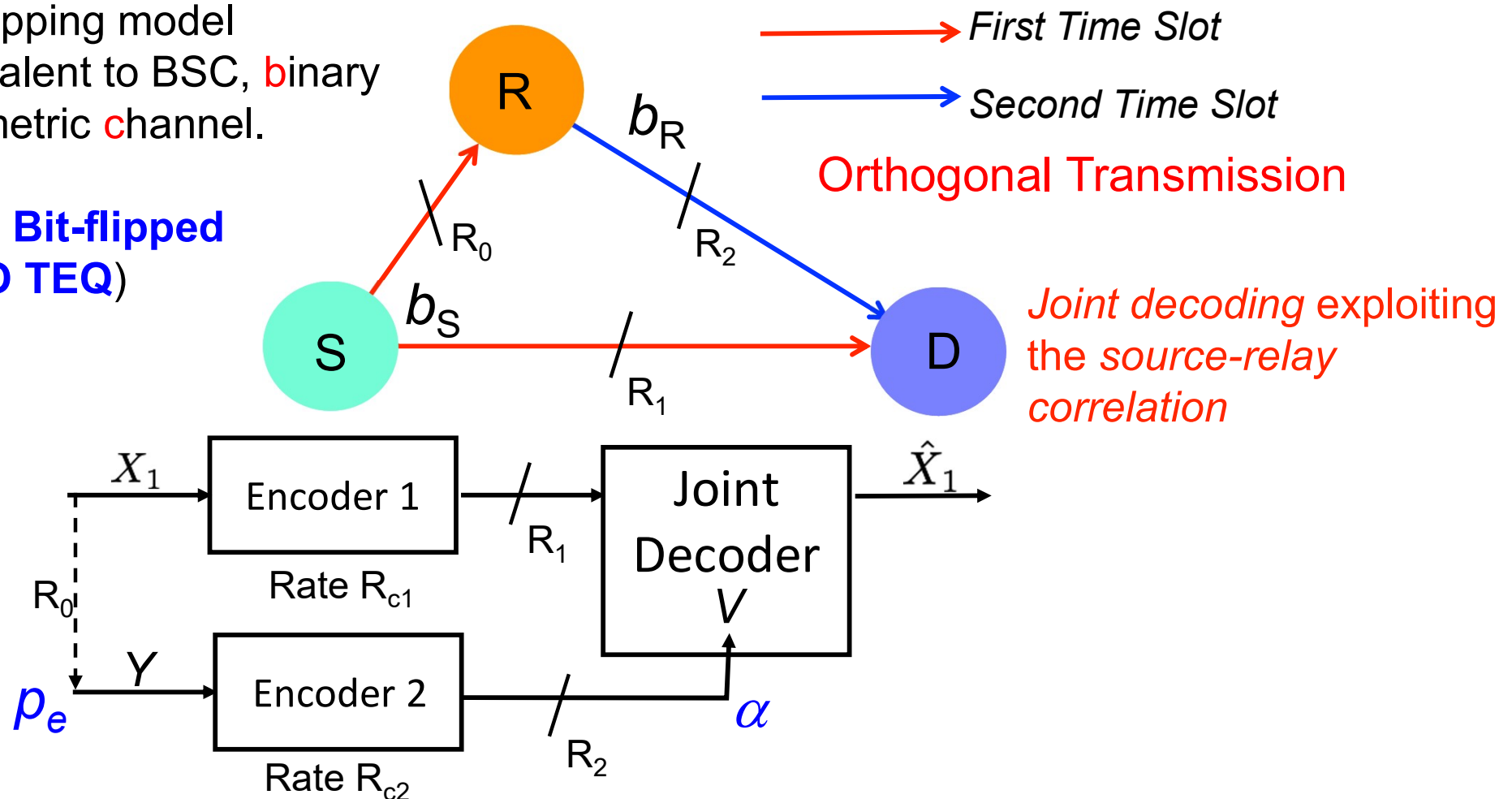
1. Source broadcasts information
2. Errors may occur in S-R link
3. Relay still forwards the **lossy** information
4. Destination recovers the source information by **joint decoding**
5. End-to-End lossless.



Do we need to recover the relay information b_R ?

Source-Relay Correlation
(bit-flipping model
equivalent to BSC, **b**inary
symmetric **c**hannel.

As in Bit-flipped
MIMO TEQ)



We do not care about the decoding result ($=V$) of b_R , but we can **use b_R as a helper!**
→ One Source One Helper Slepian Wolf Theorem for Lossless Multi-terminal Source Coding

LF Rate Region Analysis: *Slepian –Wolf Theorem for Lossless Multi-terminal Source Coding with a helper.*

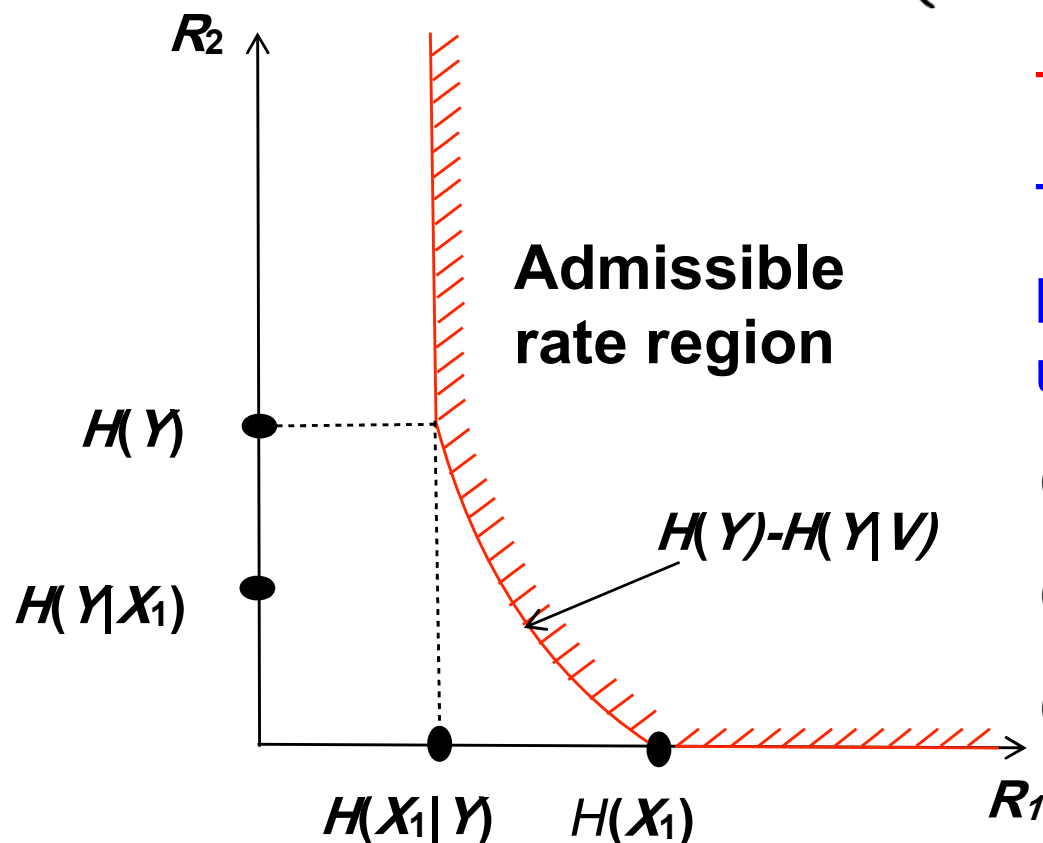
With LF, the S-R link is **lossy**, the admissible rate region is given by:

$$\begin{cases} R_1 & \geq H(X_1 | V) \\ R_2 & \geq I(Y; V) = H(Y) - H(Y | V) \end{cases}$$

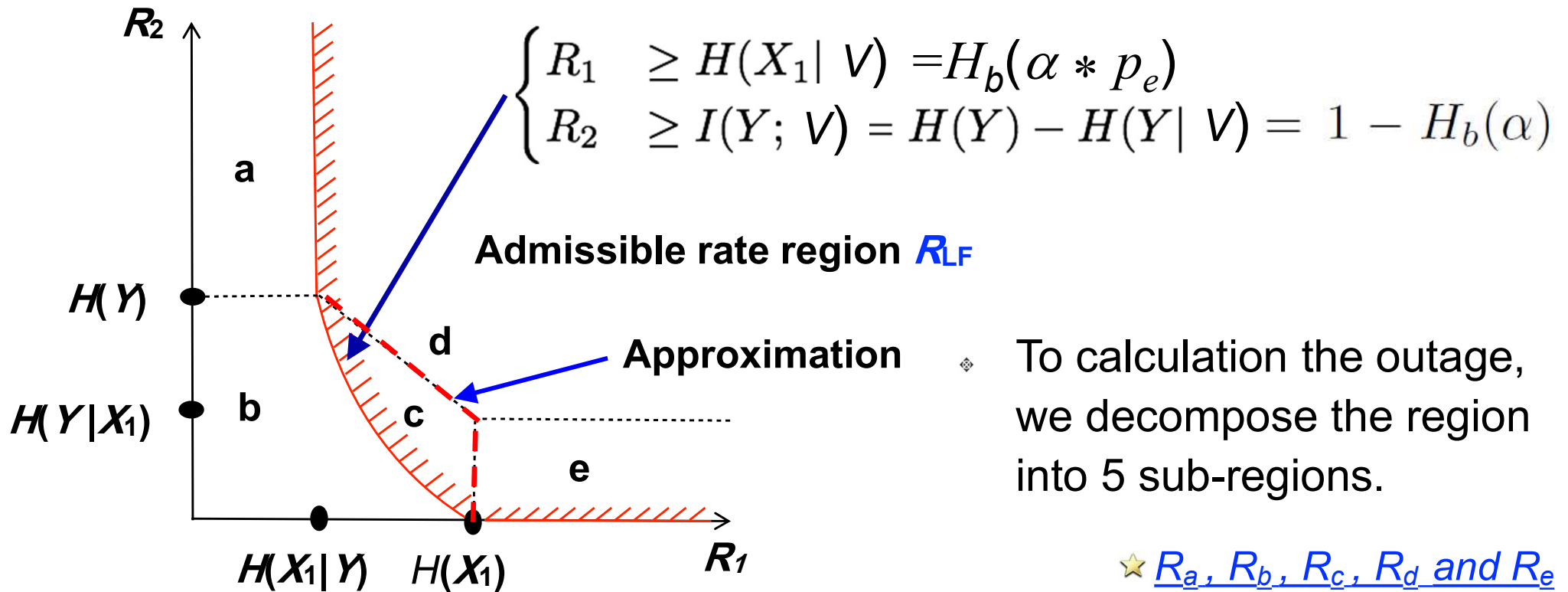
This is a general expression.

To calculate the rate region using parameters related to the links, we use :

- (1) Shannon's Source-Channel Separation Theorem,
- (2) Test Channel Model of Binary $R(D)$ function to represent each link's threshold, and
- (3) Utilization of Markov Chain $V \rightarrow Y \rightarrow X_1$.
→ Binary Convolution



Rate Region Analysis: we need **threefold** Integral!



✦ This region is a function of γ_0 , γ_1 , and γ_2 .
(SNR of S-R, S-D and R-D links)

→ Threefold integral needed
with respect to pdf's of γ_0 , γ_1 , and γ_2 .

★ $R_{LF} = R_c \cup R_d \cup R_e$

LF Rate Region Analysis: **SR Link**

- How can we combine **Shannon's Separation Theorem** and the **Rate Region**?

By using the lossy Separation theorem $R_{c,1} \cdot R(\mathcal{D}) \leq C(\gamma_0)$.

and with Inverse $C^{-1}(\gamma_0)$ of the Capacity Function $C(\gamma_0)$, we calculate the binary distortion ($D=BER$) of the S-R link after decoding, as

$$p_e = \begin{cases} H_b^{-1}[1 - \Phi_1(\gamma_0)], & \text{for } \Phi^{-1}(0) \leq \gamma_0 \leq \Phi_1^{-1}(1) \\ 0, & \text{for } \gamma_0 \geq \Phi_1^{-1}(1), \end{cases}$$

and $\Phi_1(\gamma_0) = \frac{C(\gamma_0)}{R_{c,1}}$ **Separation Theorem**

with $H_b^{-1}(\cdot)$ denotes the inverse function of the binary entropy function $H_b(x) = -x \log_2 x - (1 - x) \log_2(1 - x)$, and $\Phi_1^{-1}(\cdot)$ is the inverse function of $\Phi_1(\cdot)$.

$$C(\gamma_0) = \log(1 + \gamma_0)$$

This means that given the *instantaneous SNR* γ_0 and $R_{c,1}$, we can calculate the binary distortion ($D=BER=p_e$) of S-R link after decoding!

LF Rate Region Analysis: *Test Channel*

Binary Source

Consider a Binary source $x \in X$, $Prob(x=1)=p$, $Prob(x=0)=1-p$

Assume that $p < 1/2$. The rate distortion function is given by:

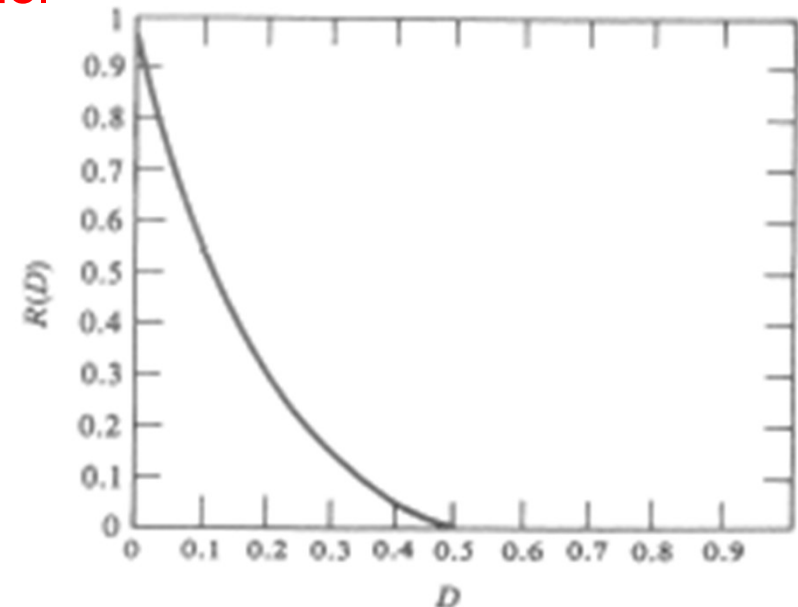
$$R(D) = \begin{cases} H(p) - H(D) & , \quad 0 \leq D \leq \min(p, 1-p) \\ 0 & , \quad D > \min(p, 1-p) \end{cases}$$

where Hamming distortion measure is assumed.

With $p=1/2$, $R(D)=1-H(D)$, hence **SR** test channel
is BSC with $D=p_e$

$$\begin{aligned} &\downarrow \\ H_b(p_e) &= 1 - R(p_e) \\ &\downarrow \\ p_e &= H_b^{-1}\left(1 - \frac{C(\gamma_0)}{R_{c,1}}\right) \end{aligned}$$

Separation Theorem



LF Rate Region Analysis: *RD Link*

- ◆ We also **do not** need **lossless** R-D link. R-D link's error probability α after decoding can be calculated in the same way, as

$$\alpha = \begin{cases} H_b^{-1}[1 - \Phi_1(\gamma_2)], & \text{for } \Phi_1^{-1}(0) \leq \gamma_2 \leq \Phi_1^{-1}(1) \\ 0, & \text{for } \gamma_2 \geq \Phi_1^{-1}(1), \end{cases}$$

with $\Phi_1(\gamma_2) = \frac{C(\gamma_2)}{R_{c,1}}$ Separation Theorem

By combining all, we have

$$\begin{cases} R_1 & \geq H(X_1 | V) = H_b(\alpha * p_e), \text{ because } V \rightarrow Y \rightarrow X_1 \text{ forms Markov Chain.} \\ R_2 & \geq I(Y; V) = H(Y) - H(Y | V) = 1 - H_b(\alpha) \end{cases}$$

with $\alpha * p_e = (1 - \alpha)p_e + \alpha(1 - p_e)$

We do not know $\gamma_0, \gamma_1, \gamma_2$ but we know their distributions.

To Calculate the Outage, we need **threefold** Integrals

$$\begin{aligned}
 P_{1,a} &= \Pr\{p = 0, R_2 \geq 1, 0 \leq R_1 \leq H_b(p)\} \\
 &= \Pr\{\gamma_0 \geq \Phi_1^{-1}(1), \gamma_2 \geq \Phi_2^{-1}(1), \\
 &\quad \Phi_1^{-1}(0) \leq \gamma_1 \leq \Phi_1^{-1}(0)\} \\
 &= \int_{\Phi_1^{-1}(0)}^{\Phi_1^{-1}(1)} d\gamma_0 \int_{\Phi_2^{-1}(0)}^{\Phi_2^{-1}(1)} d\gamma_2 \\
 &\quad \cdot \int_{\Phi_1^{-1}(0)}^{\Phi_1^{-1}(0)} p(\gamma_0) \cdot p(\gamma_1) \cdot p(\gamma_2) d\gamma_1 \\
 &= 0,
 \end{aligned}$$

$$\begin{aligned}
 P_{2,a} &= \Pr\{0 < p \leq 0.5, R_2 \geq 1, 0 \leq R_1 \leq H_b(p)\} \\
 &= \Pr\{\Phi_1^{-1}(0) \leq \gamma_0 \leq \Phi_1^{-1}(1), \gamma_2 \geq \Phi_2^{-1}(1), \\
 &\quad \Phi_1^{-1}(0) \leq \gamma_1 \leq \Phi_1^{-1}[1 - \Phi_1(\gamma_0)]\} \\
 &= \int_{\Phi_1^{-1}(0)}^{\Phi_1^{-1}(1)} d\gamma_0 \int_{\Phi_2^{-1}(1)}^{\Phi_2^{-1}(\infty)} d\gamma_2 \\
 &\quad \cdot \int_{\Phi_1^{-1}(0)}^{\Phi_1^{-1}[1 - \Phi_1(\gamma_0)]} p(\gamma_0) \cdot p(\gamma_1) \cdot p(\gamma_2) d\gamma_1 \\
 &= \frac{1}{\Gamma_0} \exp\left[-\frac{\Phi_2^{-1}(1)}{\Gamma_2}\right] \int_{\Phi_1^{-1}(0)}^{\Phi_1^{-1}(1)} \exp\left(-\frac{\gamma_0}{\Gamma_0}\right) \\
 &\quad \cdot \left[1 - \exp\left(-\frac{\Phi_1^{-1}[1 - \Phi_1(\gamma_0)]}{\Gamma_1}\right)\right] d\gamma_0,
 \end{aligned}$$

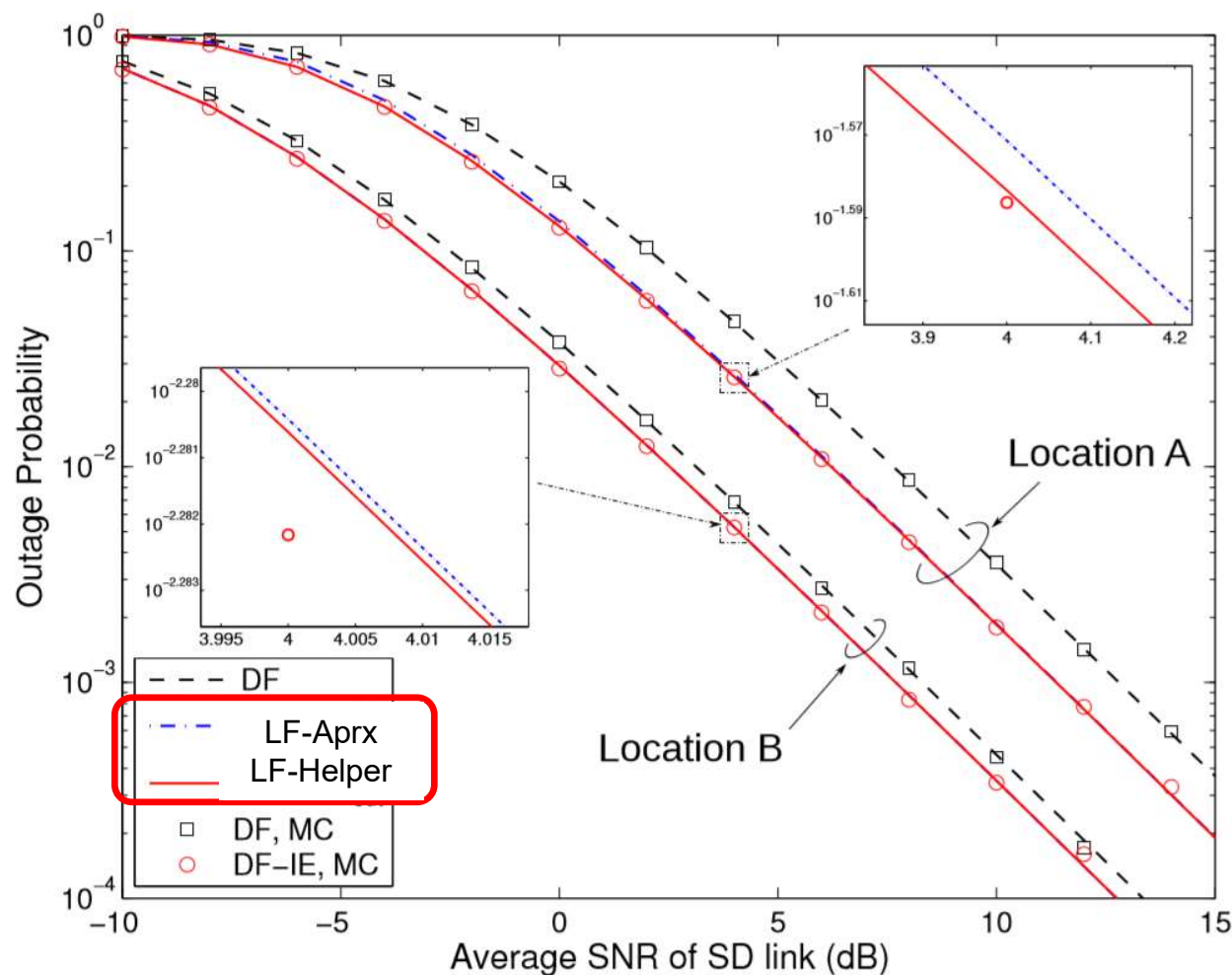
Let's skip the boring threefold integral calculations!

Those who Want to Know the Details of the Calculation, please Come to my Place after the Tutorial (TWKDCpCmPaT).

$$\begin{aligned}
 P_{1,b} &= \Pr\{p = 0, 0 \leq R_2 \leq 1, 0 \leq R_1 \leq H_b(\alpha * p)\} \\
 &= \Pr\{\gamma_0 \geq \Phi_1^{-1}(1), \Phi_2^{-1}(0) \leq \gamma_2 \leq \Phi_2^{-1}(1), \\
 &\quad \Phi_1^{-1}(0) \leq \gamma_1 \leq \Phi_1^{-1}[1 - \Phi_1(\gamma_0)]\} \\
 &= \int_{\Phi_1^{-1}(1)}^{\Phi_1^{-1}(\infty)} d\gamma_0 \int_{\Phi_2^{-1}(0)}^{\Phi_2^{-1}(1)} d\gamma_2 \\
 &\quad \cdot \int_{\Phi_1^{-1}(0)}^{\Phi_1^{-1}[1 - \Phi_1(\gamma_0)]} p(\gamma_0) \cdot p(\gamma_1) \cdot p(\gamma_2) d\gamma_1 \\
 &= \frac{1}{\Gamma_2} \exp\left[-\frac{\Phi_1^{-1}(1)}{\Gamma_0}\right] \int_{\Phi_2^{-1}(0)}^{\Phi_2^{-1}(1)} \exp\left(-\frac{\gamma_2}{\Gamma_2}\right) \\
 &\quad \cdot \left[1 - \exp\left(-\frac{\Phi_1^{-1}[1 - \Phi_1(\gamma_2)]}{\Gamma_1}\right)\right] d\gamma_2,
 \end{aligned}$$

$$\begin{aligned}
 P_{2,b} &= \Pr\{0 < p \leq 0.5, 0 \leq R_2 \leq 1, 0 \leq R_1 \leq H_b(\alpha * p)\} \\
 &= \Pr\{\Phi_1^{-1}(0) \leq \gamma_0 \leq \Phi_1^{-1}(1), \Phi_2^{-1}(0) \leq \gamma_2 \leq \Phi_2^{-1}(1), \\
 &\quad \Phi_1^{-1}(0) \leq \gamma_1 \leq \Phi_1^{-1}[\Psi(\gamma_0, \gamma_2)]\} \\
 &= \int_{\Phi_1^{-1}(0)}^{\Phi_1^{-1}(1)} d\gamma_0 \int_{\Phi_2^{-1}(0)}^{\Phi_2^{-1}(1)} d\gamma_2 \\
 &\quad \cdot \int_{\Phi_1^{-1}(0)}^{\Phi_1^{-1}[\Psi(\gamma_0, \gamma_2)]} p(\gamma_0) \cdot p(\gamma_1) \cdot p(\gamma_2) d\gamma_1 \\
 &= \frac{1}{\Gamma_0 \Gamma_2} \int_{\Phi_1^{-1}(0)}^{\Phi_1^{-1}(1)} \int_{\Phi_2^{-1}(0)}^{\Phi_2^{-1}(1)} \exp\left(-\frac{\gamma_0}{\Gamma_0} - \frac{\gamma_2}{\Gamma_2}\right) \\
 &\quad \cdot \left\{1 - \exp\left[-\frac{\Phi_1^{-1}[\Psi(\gamma_0, \gamma_2)]}{\Gamma_1}\right]\right\} d\gamma_0 d\gamma_2
 \end{aligned}$$

Comparison of exact and approximated SW region with a helper (Orthogonal Case)



Location A, $d_0=d_1=d_2$

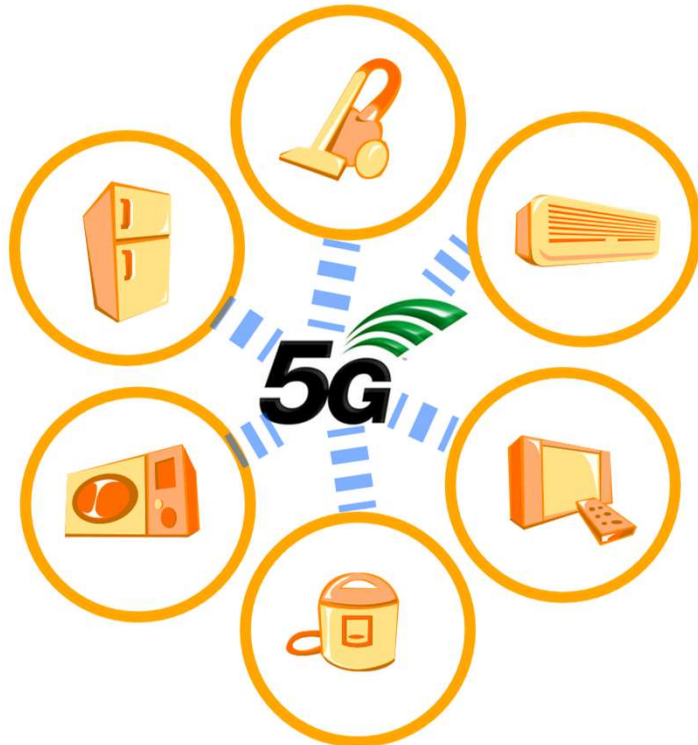
Location B, $d_0=(1/4)d_1$, $d_2=(3/4)d_1$

[1] X. Zhou, M. Cheng, X. He and T. Matsumoto, "Exact and Approximated Outage Probability Analyses for Decode-and- Forward Relaying System Allowing Intra-Link Errors," in IEEE Transactions on Wireless Communications, vol. 13, no. 12, pp. 7062-7071, Dec. 2014.

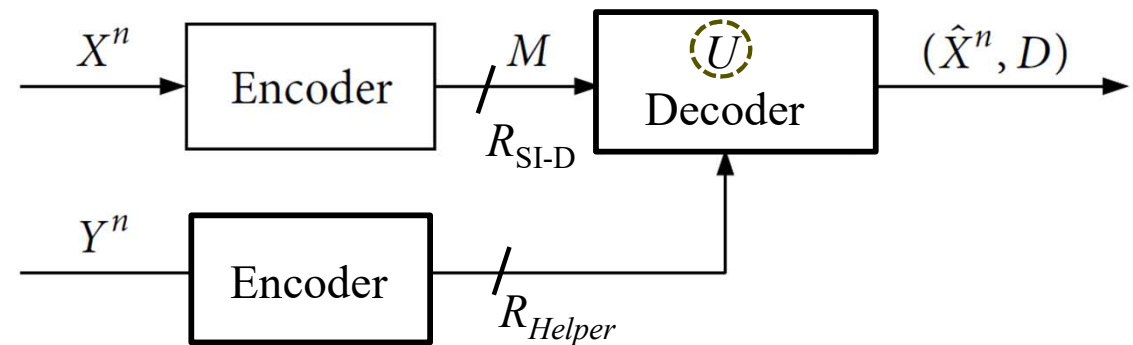
Chapter 2. End-to-End Lossy Distributed Multi-terminal Networks: Rate Distortion Analysis

2.1 Wyner-Ziv Formulation for End-to-End Lossy Two-Way Relay Network

- Internet of Things (IoT)
Connect **objects** to make **Right**
Decisions → E2E Lossy

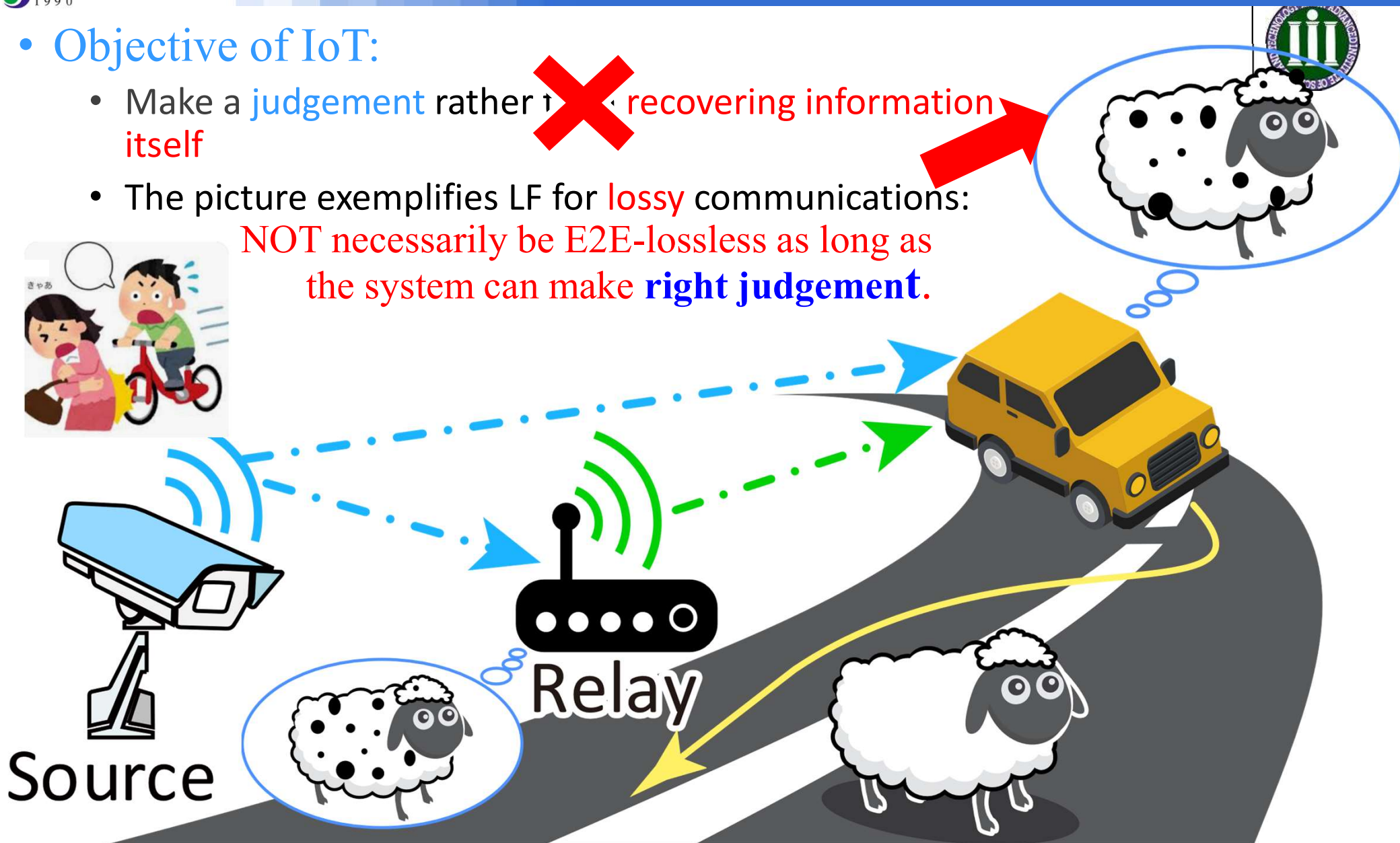


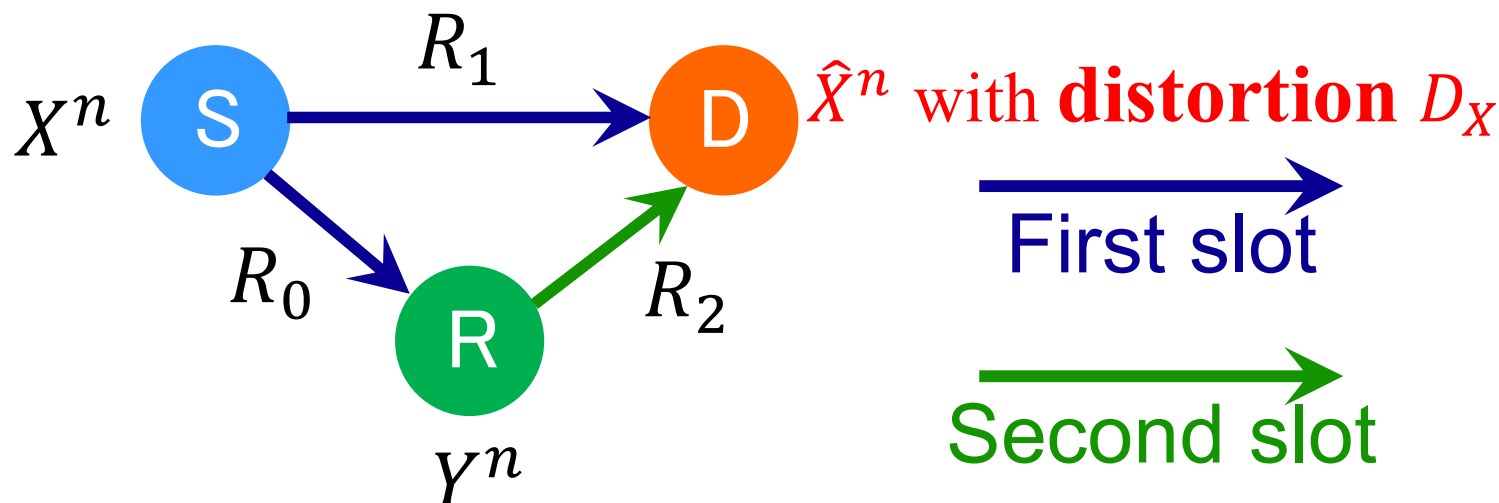
WZ with a Helper:



• Objective of IoT:

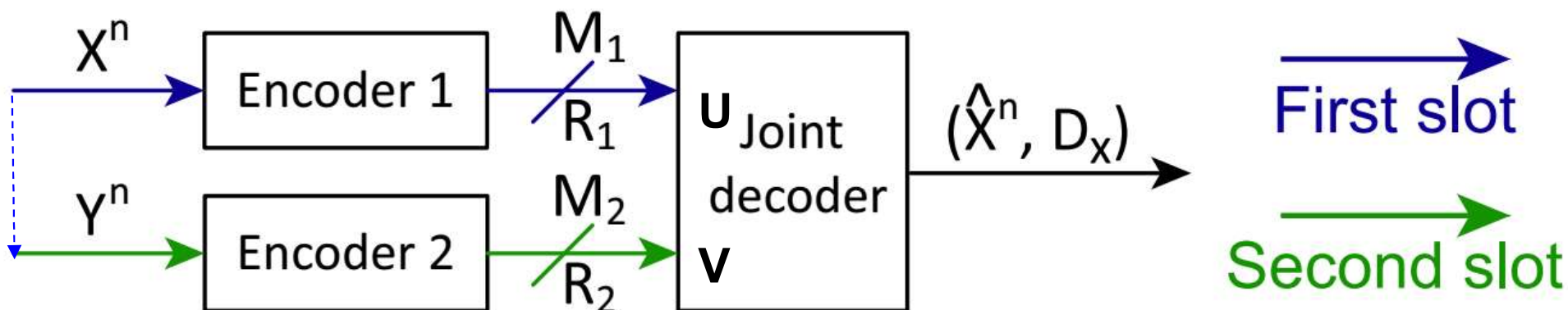
- Make a **judgement** rather than **recovering information itself**
- The picture exemplifies LF for **lossy** communications:
NOT necessarily be E2E-lossless as long as the system can make **right judgement.**





- S-R link: **point-to-point** communication.
- S-D and R-D links: **distributed lossy multi-terminal source coding problem**.

→ As a whole, **Wyner-Ziv Problem**



■ WZ $R(D)$ function for general sources

$$R_1 > I(X; U|V),$$

$$R_2 > I(Y; V).$$

- For binary sources

- S-R link

$$R_0 > 1 - H_b(\rho).$$

- R-D link

$$R_2 > 1 - H_b(\rho').$$

- S-D link

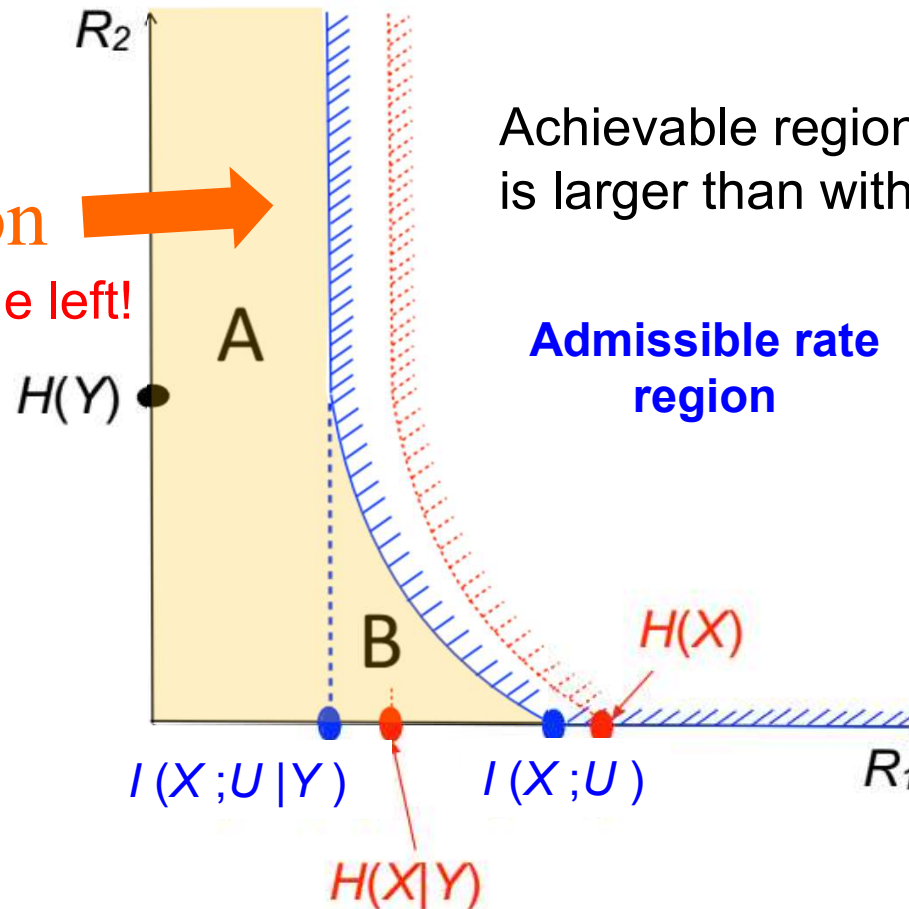
$$R_1 > H_b(\rho' * \rho * D_X) - H_b(D_X).$$

because $V \rightarrow Y \rightarrow X \rightarrow U$ forms a Markov Chain.

ρ : crossover probability between X and Y

ρ' : crossover probability between Y and V

Outage region →
The curve is shifted to the left!



- The link rates (R_0, R_1, R_2) supported by channel capacities **cannot satisfy** the distortion requirement D_X , when they fall **outside** the achievable rate-distortion **region**. → Outage

Again, we need **multifold** Integrals

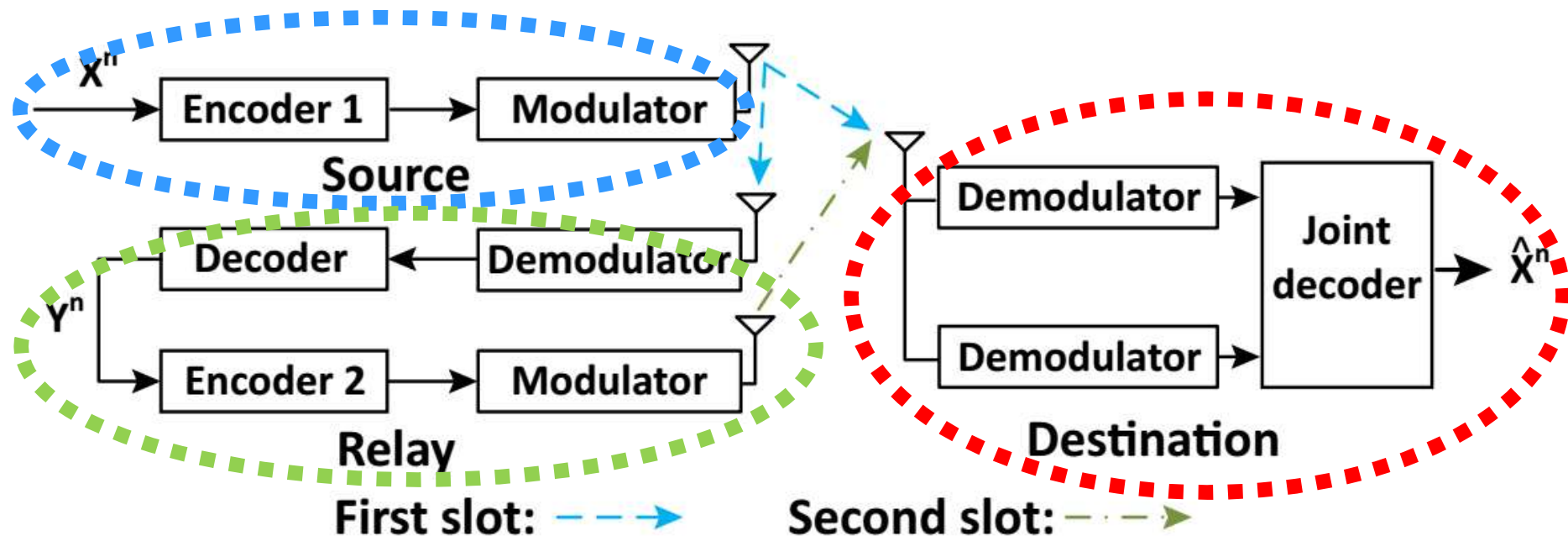
$$\begin{aligned}
 P_{\text{out}} &= \Pr \{ (R_1, R_2) \in \alpha \cup \beta \} \\
 &= \Pr \{ p = 0, (R_1, R_2) \in \alpha \cup \beta \} \\
 &\quad + \Pr \{ p \in (0, 0.5], (R_1, R_2) \in \alpha \cup \beta \} \\
 &= \Pr \{ p = 0, (R_1, R_2) \in \alpha \} \\
 &\quad + \Pr \{ p = 0, (R_1, R_2) \in \beta \} \\
 &\quad + \Pr \{ p \in (0, 0.5], (R_1, R_2) \in \alpha \} \\
 &\quad + \Pr \{ p \in (0, 0.5], (R_1, R_2) \in \beta \} \\
 &= \Pr \{ 0 \leq R_1 \leq H_b(p * D_X) - H_b(D_X), 0 \leq R_2, \\
 &\quad p = 0 \} \\
 &\quad + \Pr \{ H_b(p * D_X) - H_b(D_X) \\
 &\quad \leq R_1 \leq H_b(p' * p * D_X) - H_b(D_X), \\
 &\quad 0 \leq R_2 \leq 1, p = 0 \} \\
 &\quad + \Pr \{ 0 \leq R_1 \leq H_b(p * D_X) - H_b(D_X), 0 \leq R_2, \\
 &\quad 0 < p \leq 0.5 \} \\
 &\quad + \Pr \{ H_b(p * D_X) - H_b(D_X) \\
 &\quad \leq R_1 \leq H_b(p' * p * D_X) - H_b(D_X), \\
 &\quad 0 \leq R_2 \leq 1, 0 < p \leq 0.5 \} \\
 &= P_{1,\alpha} + P_{1,\beta} + P_{2,\alpha} + P_{2,\beta},
 \end{aligned}$$

$$\begin{aligned}
 P_{1,\alpha} &= \Pr \{ 0 \leq R_1 \leq H_b(0 * D_X) - H_b(D_X), 0 \leq R_2, \\
 &\quad p = 0 \} \\
 &= \Pr \{ 0 \leq R_1 \leq 0, 0 \leq R_2, p = 0 \} \\
 &= \Pr \{ \Theta_1^{-1}(0) \leq \gamma_1 \leq \Theta_1^{-1}(0), \Theta_2^{-1}(0) \leq \gamma_2, \\
 &\quad \Theta_0^{-1}(1) \leq \gamma_0 \} \\
 &= \int_{\Theta_2^{-1}(0)}^{\infty} d\gamma_2 \int_{\Theta_1^{-1}(0)}^{\Theta_1^{-1}(0)} d\gamma_1 \\
 &\quad \cdot \int_{\Theta_0^{-1}(1)}^{\infty} f(\gamma_0) f(\gamma_1) f(\gamma_2) d\gamma_0, \\
 P_{1,\beta} &= \Pr \{ H_b(0 * D_X) - H_b(D_X) \\
 &\quad \leq R_1 \leq H_b(p' * 0 * D_X) - H_b(D_X), \\
 &\quad 0 \leq R_2 \leq 1, p = 0 \} \\
 &= \Pr \{ 0 \leq R_1 \leq H_b(p' * D_X) - H_b(D_X), \\
 &\quad 0 \leq R_2 \leq 1, p = 0 \} \\
 &= \Pr \{ \Theta_1^{-1}(0) \leq \gamma_1 \\
 &\quad \leq \Theta_1^{-1}[H_b(\xi(\gamma_2, D_X)) - H_b(D_X)], \\
 &\quad \Theta_2^{-1}(0) \leq \gamma_2 \leq \Theta_2^{-1}(1), \Theta_0^{-1}(1) \leq \gamma_0 \} \\
 &= \int_{\Theta_2^{-1}(0)}^{\Theta_2^{-1}(1)} d\gamma_2 \int_{\Theta_1^{-1}(0)}^{\Theta_1^{-1}[H_b(\xi(\gamma_2, D_X)) - H_b(D_X)]} d\gamma_1 \\
 &\quad \cdot \int_{\Theta_0^{-1}(1)}^{\infty} f(\gamma_0) f(\gamma_1) f(\gamma_2) d\gamma_0 \\
 &= \frac{1}{\bar{\gamma}_2} \exp \left(-\frac{\Theta_0^{-1}(1)}{\bar{\gamma}_0} \right) \int_{\Theta_2^{-1}(0)}^{\Theta_2^{-1}(1)} \exp \left(-\frac{\gamma_2}{\bar{\gamma}_2} \right) \cdot \left[1 \right. \\
 &\quad \left. - \exp \left(-\frac{\Theta_1^{-1}[H_b(\xi(\gamma_2, D_X)) - H_b(D_X)]}{\bar{\gamma}_1} \right) \right] d\gamma_2,
 \end{aligned}$$

Again, we need **threefold** Integrals!

We calculated, but too boring. Let's skip it!

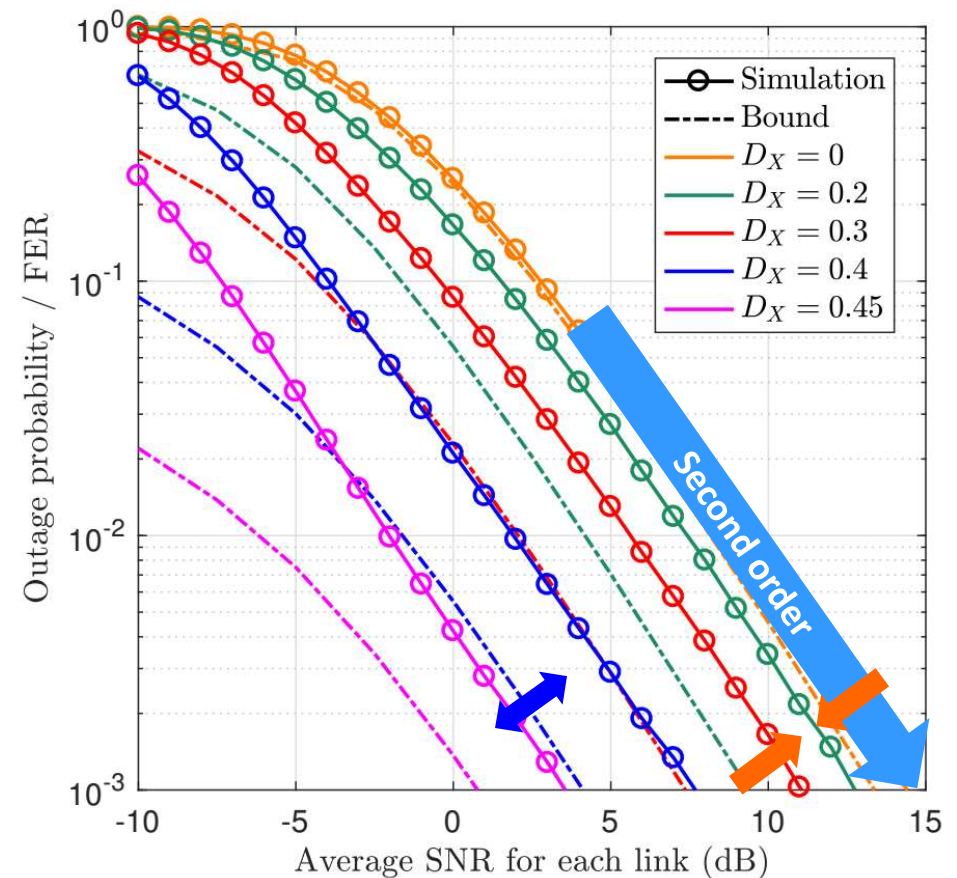
We evaluate the outage probability also by chain simulations using very simple signaling and joint decoding techniques.



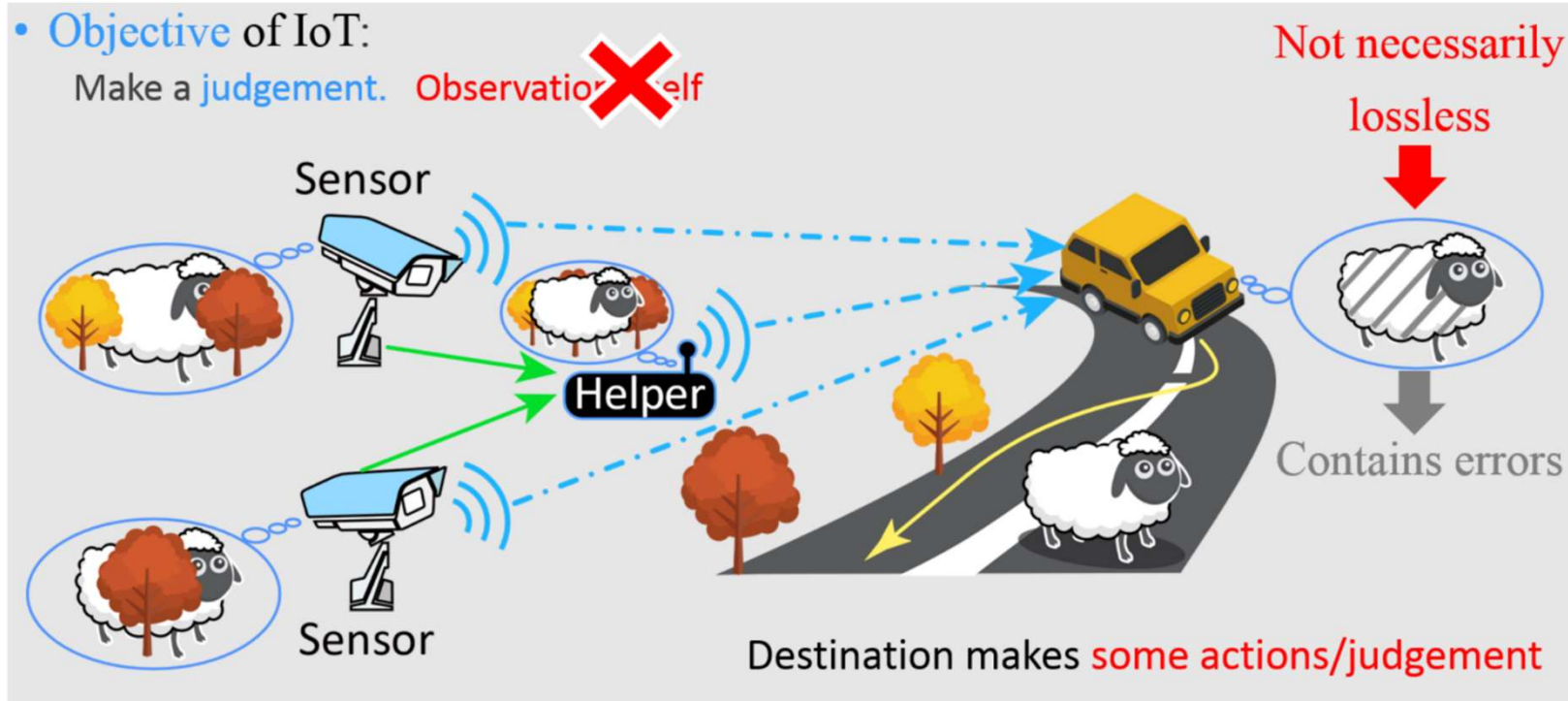
1. Simulation results have the same tendency and the slope decay (=Diversity Order) as the theoretical bound.
2. The gap between the simulation and theoretical results becomes larger as D_X increases. → We need more efficient rate-distortion code.

SIMULATION PARAMETERS

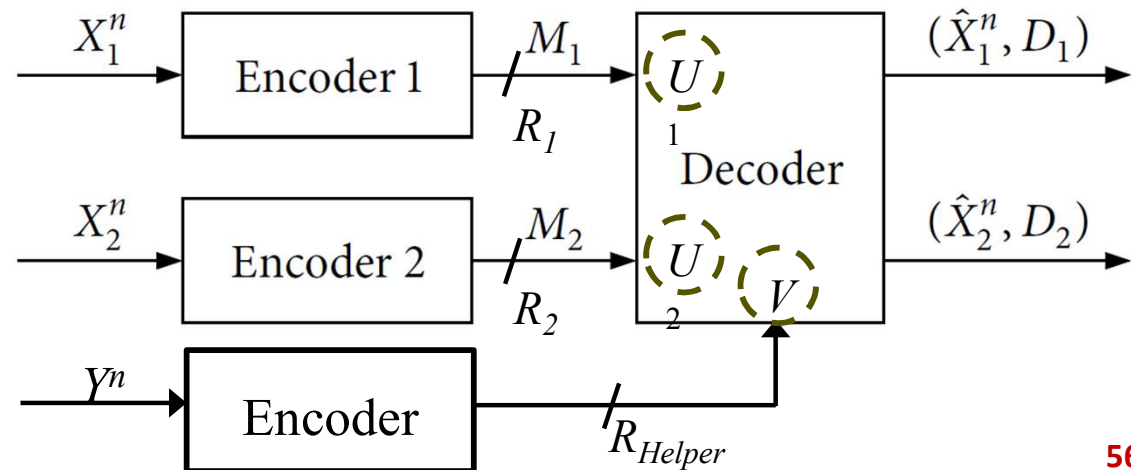
| Parameter | Value |
|----------------------------|--------------------|
| Frame length | 10^4 bits |
| Number of frames | 5×10^5 |
| Source coding rate | 1 |
| Channel coding rate | 1/2 |
| Generator polynomial of CC | $G = ([3, 2]3)_8$ |
| Type of interleaver | random interleaver |
| Modulation method | BPSK |
| Maximum iteration time | 20 |

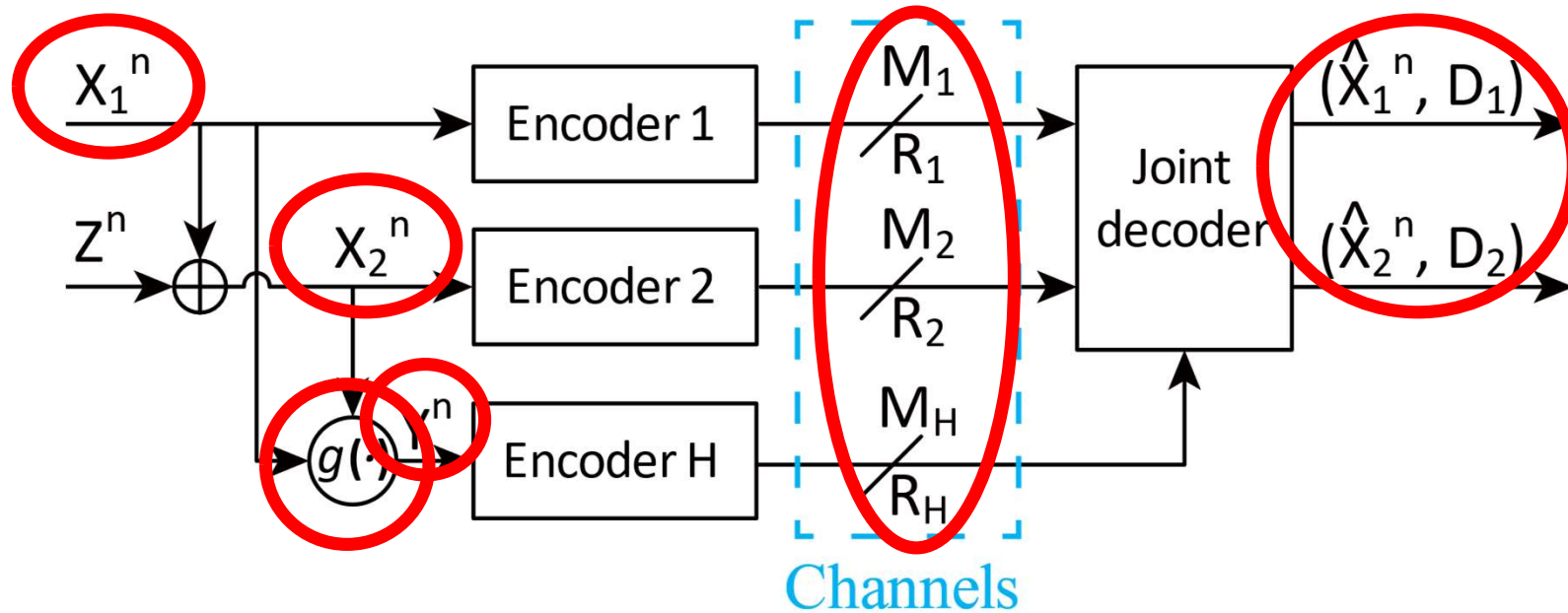


2.2 Berger-Tung (BT) Formulation for Two Source One Helper Network



Multiple Access Relay Channel formulated by BT with a Helper:





X_1, X_2 : two sources M_1, M_2, M_H : codewords \hat{X}_1^n, \hat{X}_2^n : recovered sequences

Y : helper information R_1, R_2, R_H : link rates D_1, D_2 : distortion requirements

$g(\cdot)$: **optimal** helper (it utilizes the **useful** information at the maximum level, since

$(U_1, U_2) \rightarrow (X_1, X_2) \rightarrow Y \rightarrow V$ and by data processing theorem, $I(U_1, U_2; V) \leq I(Y; V) \leq [R_H]^-$)

- What is the **achievable rate-distortion region**?
 - **Condition for reliable communications**: link **rates** can **support** the transmissions to **satisfy** the **distortion** requirements.
- **Inner bound** on the achievable rate-distortion region, given by Berger Tung Bound

$$R_1 > I(X_1; U_1 | U_2, V, Q),$$

$$R_2 > I(X_2; U_2 | U_1, V, Q),$$

$$R_1 + R_2 > I(X_1, X_2; U_1, U_2 | V, Q),$$

$$R_H > I(Y; V),$$

U_i : compressed information of X_i

V : compressed information of Y

Q : an auxiliary variable resulting from time-sharing scheme

Use Inner bound \rightarrow Upper bound of the outage probability

- The inner bound for **binary sources**.

- (a) for some $0 \leq \tilde{d} \leq D_2$,

$$\begin{cases} R_1 > H_b(D_1 * \rho * \tilde{d}) - H_b(D_1) - [R_H]^-, \\ R_2 > 1 - H_b(\tilde{d}), \end{cases}$$
- (b) for some $0 \leq \tilde{d} \leq D_1$,

$$\begin{cases} R_1 > 1 - H_b(\tilde{d}), \\ R_2 > H_b(\tilde{d} * \rho * D_2) - H_b(D_2) - [R_H]^-, \end{cases}$$
- (c) common case,

$$R_1 + R_2 > 1 + H_b(D_1 * \rho * D_2) - H_b(D_1) - H_b(D_2) - [R_H]^-,$$

ρ : crossover probability
between X_1 and X_2
(representing correlation)

\tilde{d} : dummy variable

H_b : binary entropy function

$a * b = a(1 - b) + b(1 - a)$

$[R_H]^- = \min\{1, R_H\}$

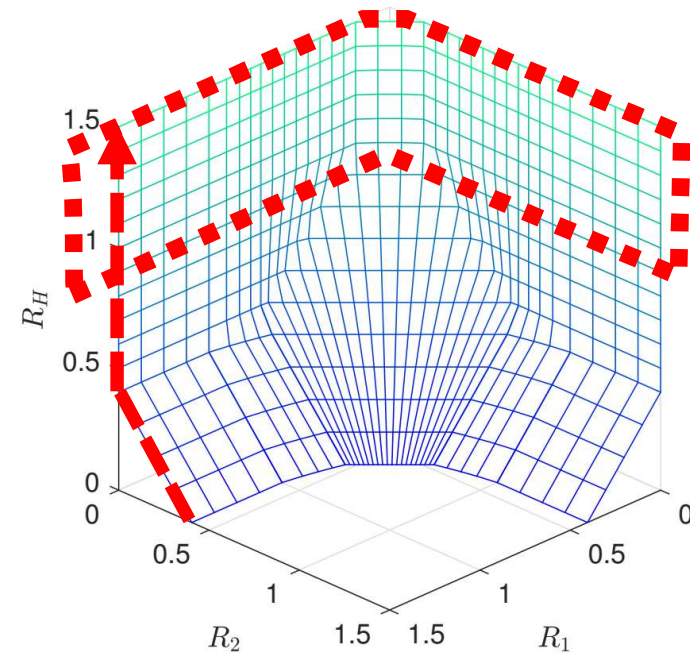
- This is **not** an inner bound **in general**. It is only for the case that the following inequality holds with equality.

$$I(U_{\mathcal{S}}; V | U_{\mathcal{S}^c}) \leq [R_H]^-,$$

where $\mathcal{S} \subseteq \{1, 2\}$, and \mathcal{S}^c represents the complementary set of \mathcal{S} .

- The shape of achievable rate-distortion region.

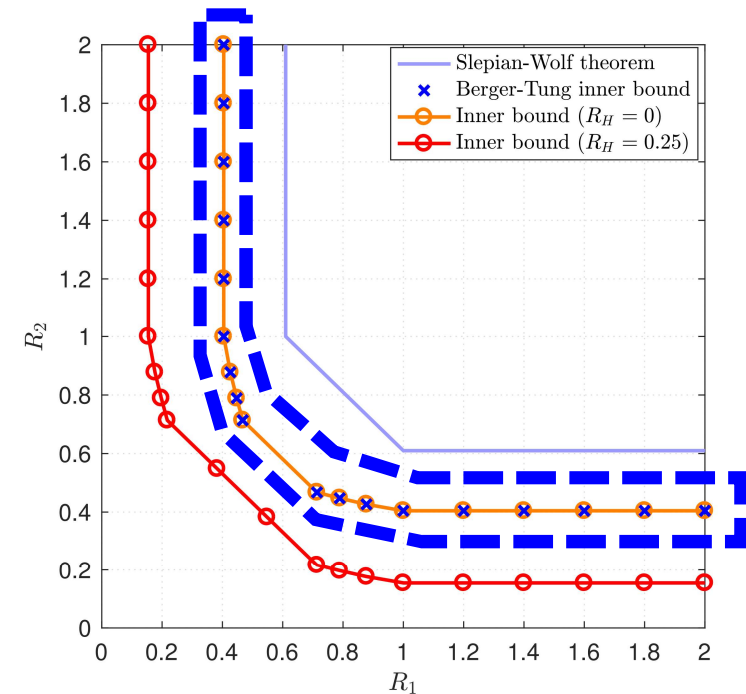
1. The achievable rate-distortion region is expanded as R_H increases.
2. However, the above part of the region for $R_H \geq 1$, does not change even if the helper rate continues increasing.



$$\rho = 0.15, D_1 = D_2 = 0.05$$

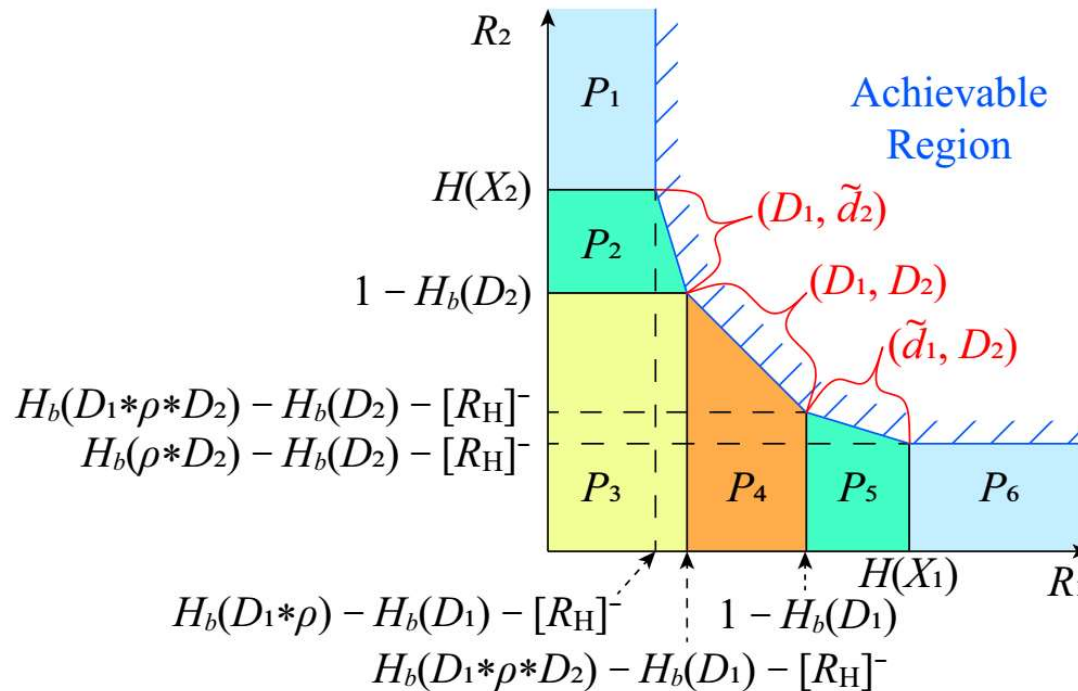
- The achievable rate-distortion region projected on the R_1 - R_2 plane by given R_H .

The derived inner bound perfectly coincides with the Berger-Tung inner bound when $R_H = 0$ (equivalent to no helper).



$$\rho = 0.15$$

$$D_1 = D_2 = 0.05$$



Outage event defined as:

- The link rates fall **outside** the achievable rate-distortion **region**, i.e., the link rates (R_1, R_2, R_H) supported by channel capacities **cannot satisfy** the distortion requirements (D_1, D_2) .

- The outage probability is the **multiple integral** with respect to (R_1, R_2, R_H) .

$$P_{\text{out}} = \iiint \cdots dR_1 dR_2 dR_H$$



- The instantaneous rates (R_1, R_2, R_H) are **supported by** the instantaneous signal-to-noise ratios (SNRs) $(\gamma_1, \gamma_2, \gamma_H)$.



- The outage probability can be calculated by the **threefold integral** with respect to SNRs $(\gamma_1, \gamma_2, \gamma_H)$.

$$P_{\text{out}} = \iiint \cdots d\gamma_1 d\gamma_2 d\gamma_H$$

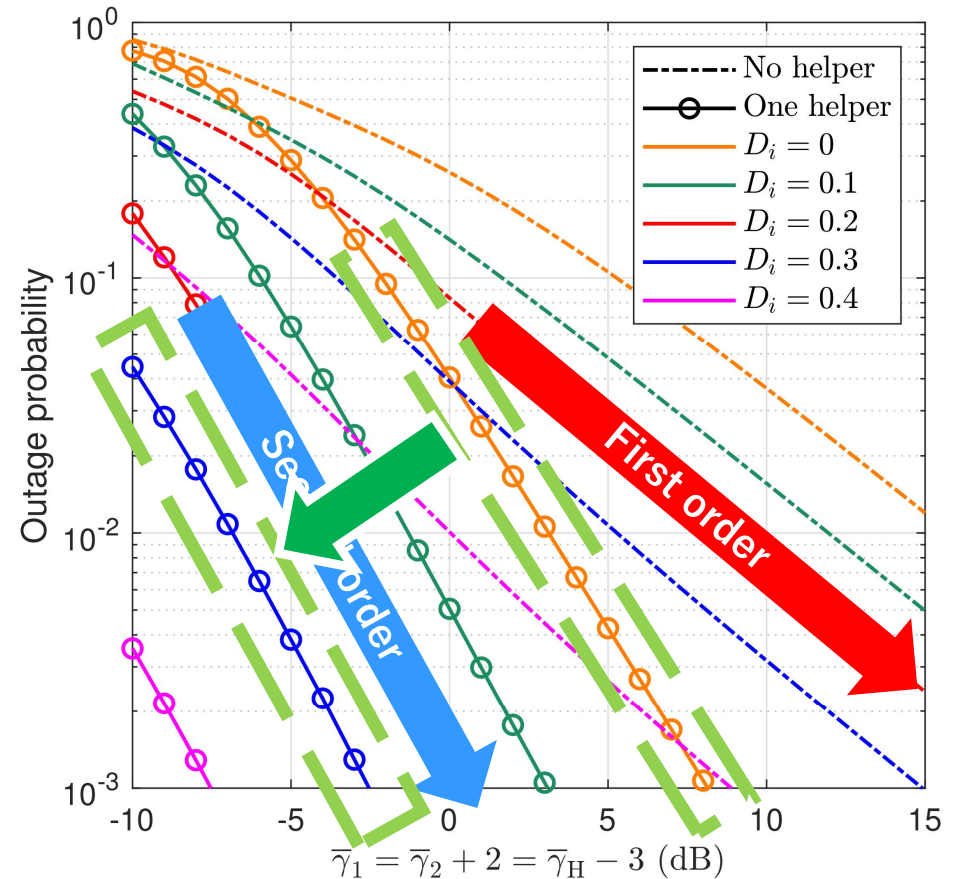
Again, we need **multifold** Integrals

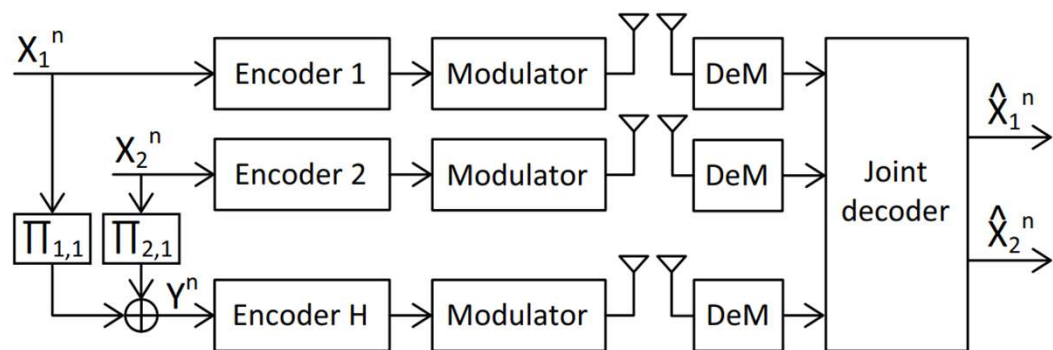
$$\begin{aligned}
 P_1 &= \Pr\{0 \leq R_1 \leq H_2(D_1 * \rho) - H_2(D_1) - [R_H]^- , \\
 &\quad H(X_2) \leq R_2, 0 \leq R_H\} \\
 &= \Pr\{0 \leq \Theta_1(\gamma_1) \leq \lambda_1(0), H(X_2) \leq \Theta_2(\gamma_2), \\
 &\quad 0 \leq \Theta_H(\gamma_H)\} \\
 &= \Pr\{\Theta_1^{-1}(0) \leq \gamma_1 \leq \Theta_1^{-1}[\lambda_1(0)], \\
 &\quad \Theta_2^{-1}[H(X_2)] \leq \gamma_2, \Theta_H^{-1}(0) \leq \gamma_H\} \\
 &= \int_{\Theta_H^{-1}(0)}^{\infty} d\gamma_H \int_{\Theta_1^{-1}(0)}^{\Theta_1^{-1}[\lambda_1(0)]} d\gamma_1 \\
 &\quad \cdot \int_{\Theta_2^{-1}[H(X_2)]}^{\infty} p(\gamma_2)p(\gamma_1)p(\gamma_H) d\gamma_2, \\
 &= \frac{1}{\bar{\gamma}_H} \cdot \exp\left(-\frac{\Theta_2^{-1}[H(X_2)]}{\bar{\gamma}_2}\right) \cdot \int_{\Theta_H^{-1}(0)}^{\Theta_H^{-1}(1)} \exp\left(-\frac{\gamma_H}{\bar{\gamma}_H}\right) \\
 &\quad \cdot \left[1 - \exp\left(-\frac{\Theta_1^{-1}[\lambda_1(0)]}{\bar{\gamma}_1}\right)\right] d\gamma_H. \quad (41)
 \end{aligned}$$

$$\begin{aligned}
 P_2 &= \Pr\{0 \leq R_1 \leq H_2(D_1 * \rho * \tilde{d}_2) - H_2(D_1) - [R_H]^- , \\
 &\quad 1 - H_2(D_2) \leq R_2 < H(X_2), 0 \leq R_H\} \\
 &= \Pr\{\Theta_1^{-1}(0) \leq \gamma_1 \leq \Theta_1^{-1}[\lambda_1(\tilde{d}_2)], \\
 &\quad \Theta_2^{-1}[1 - H_2(D_2)] \leq \gamma_2 < \Theta_2^{-1}[H(X_2)], \\
 &\quad \Theta_H^{-1}(0) \leq \gamma_H\} \\
 &= \int_{\Theta_H^{-1}(0)}^{\infty} d\gamma_H \int_{\Theta_2^{-1}[1 - H_2(D_2)]}^{\Theta_2^{-1}[H(X_2)]} d\gamma_2 \\
 &\quad \cdot \int_{\Theta_1^{-1}(0)}^{\Theta_1^{-1}[\lambda_1(\tilde{d}_2)]} p(\gamma_1)p(\gamma_2)p(\gamma_H) d\gamma_1 \\
 &= \int_{\Theta_H^{-1}(0)}^{\Theta_H^{-1}(1)} d\gamma_H \int_{\Theta_2^{-1}[1 - H_2(D_2)]}^{\Theta_2^{-1}[H(X_2)]} d\gamma_2 \\
 &\quad \cdot \int_{\Theta_1^{-1}(0)}^{\Theta_1^{-1}[\lambda_1(\tilde{d}_2)]} p(\gamma_1)p(\gamma_2)p(\gamma_H) d\gamma_1 \\
 &\quad + \int_{\Theta_H^{-1}(1)}^{\infty} d\gamma_H \int_{\Theta_2^{-1}[1 - H_2(D_2)]}^{\Theta_2^{-1}[H(X_2)]} d\gamma_2 \\
 &\quad \cdot \int_{\Theta_1^{-1}(0)}^{\Theta_1^{-1}[0]} p(\gamma_1)p(\gamma_2)p(\gamma_H) d\gamma_1 \\
 &= \int_{\Theta_H^{-1}(0)}^{\Theta_H^{-1}(1)} d\gamma_H \int_{\Theta_2^{-1}[1 - H_2(D_2)]}^{\Theta_2^{-1}[H(X_2)]} d\gamma_2 \\
 &\quad \cdot \int_{\Theta_1^{-1}(0)}^{\Theta_1^{-1}[\lambda_1(\tilde{d}_2)]} p(\gamma_1)p(\gamma_2)p(\gamma_H) d\gamma_1 + 0 \\
 &= \frac{1}{\bar{\gamma}_2 \bar{\gamma}_H} \cdot \int_{\Theta_H^{-1}(0)}^{\Theta_H^{-1}(1)} d\gamma_H \\
 &\quad \cdot \int_{\Theta_2^{-1}[1 - H_2(D_2)]}^{\Theta_2^{-1}[H(X_2)]} \exp\left(-\frac{\gamma_2}{\bar{\gamma}_2} - \frac{\gamma_H}{\bar{\gamma}_H}\right)
 \end{aligned}$$

• Numerical Results ($\rho = 0.1$)

1. The larger the acceptable distortion, the smaller the outage probability.
($D_j \nearrow \Rightarrow P_{\text{out}} \searrow$).
2. Without a helper, the curves always exhibit **order** diversity.
3. With a helper, it can achieve **second order** diversity (P_{out} decreases faster).





SIMULATION PARAMETERS

| Parameter | Value |
|----------------------------|--------------------|
| Frame length | 10^4 bits |
| Number of frames | 5×10^5 |
| Source coding rate | 1 |
| Channel coding rate | $1/2$ |
| Generator polynomial of CC | $G = ([3, 2]3)_8$ |
| Type of interleaver | random interleaver |
| Modulation method | BPSK |
| Maximum iteration time | 20 |

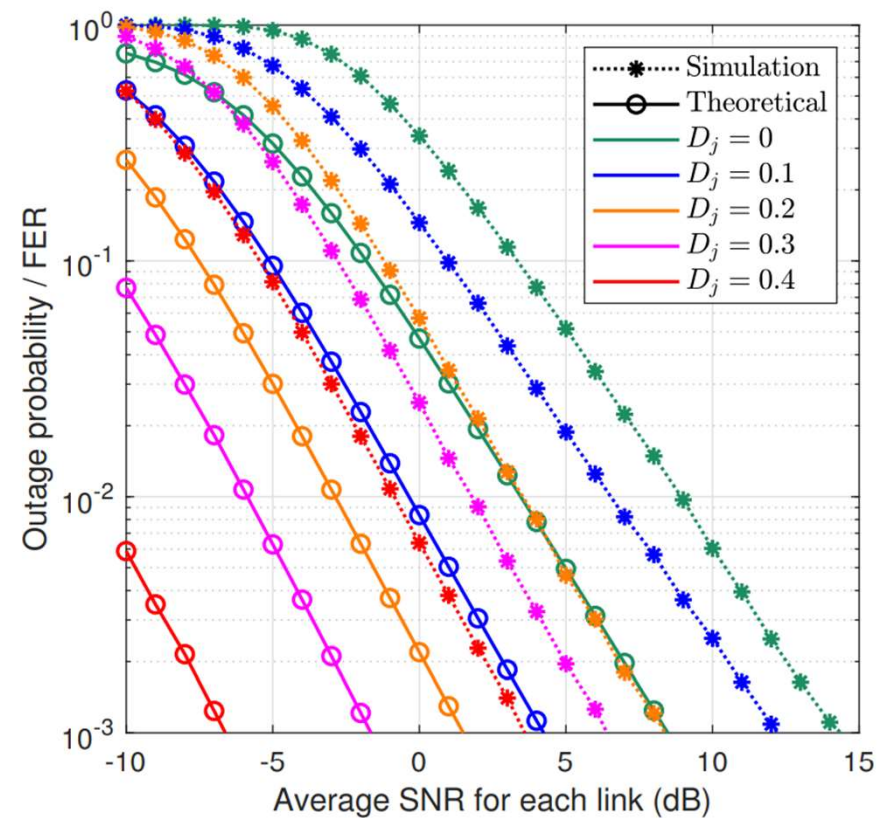


Fig. 13. Simulation results with $\rho = 0.1$.

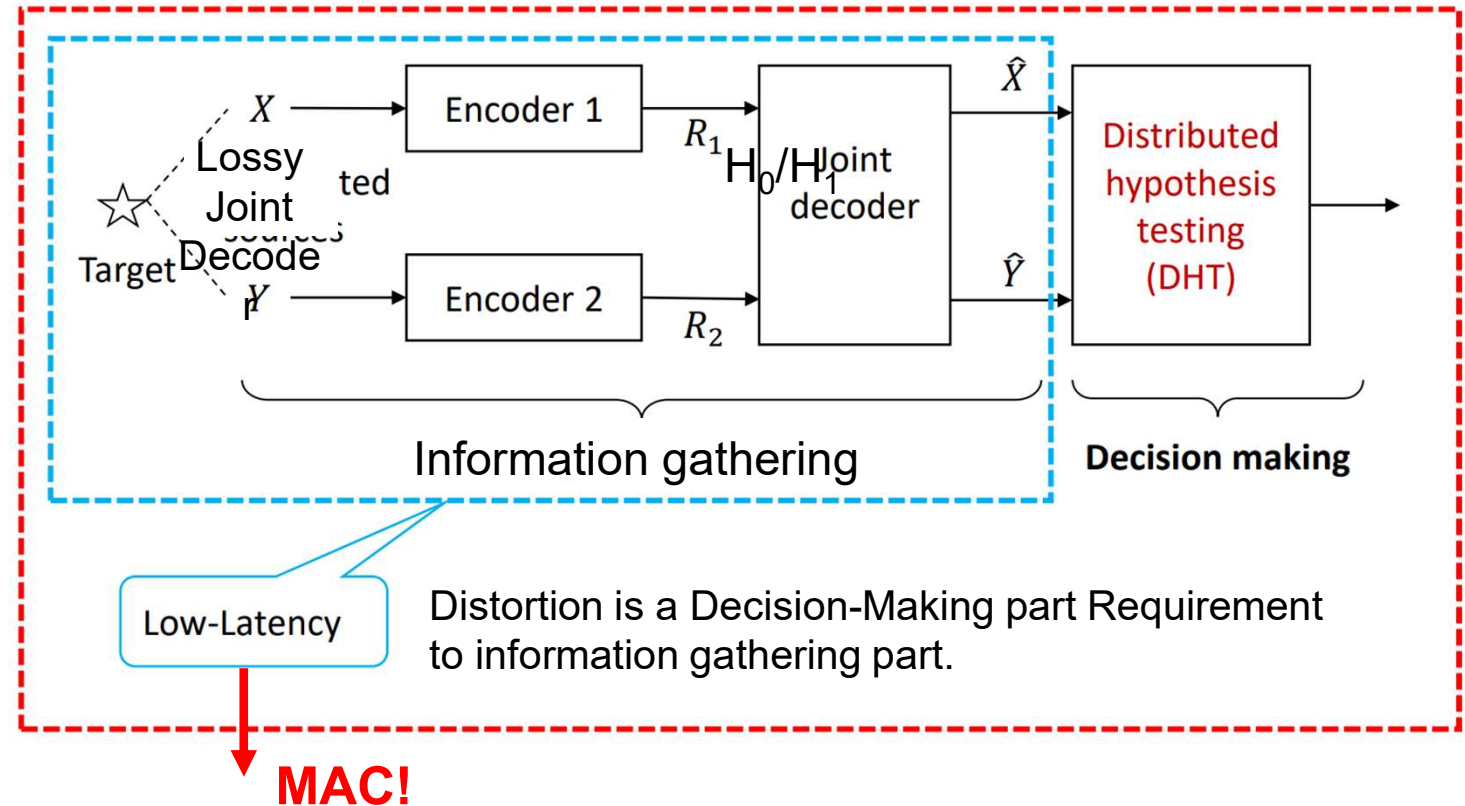
2.3 End-to-End Lossless and Lossy Multiple Access Channels

Internet of things (IoT) system



An example of wireless sensor network.

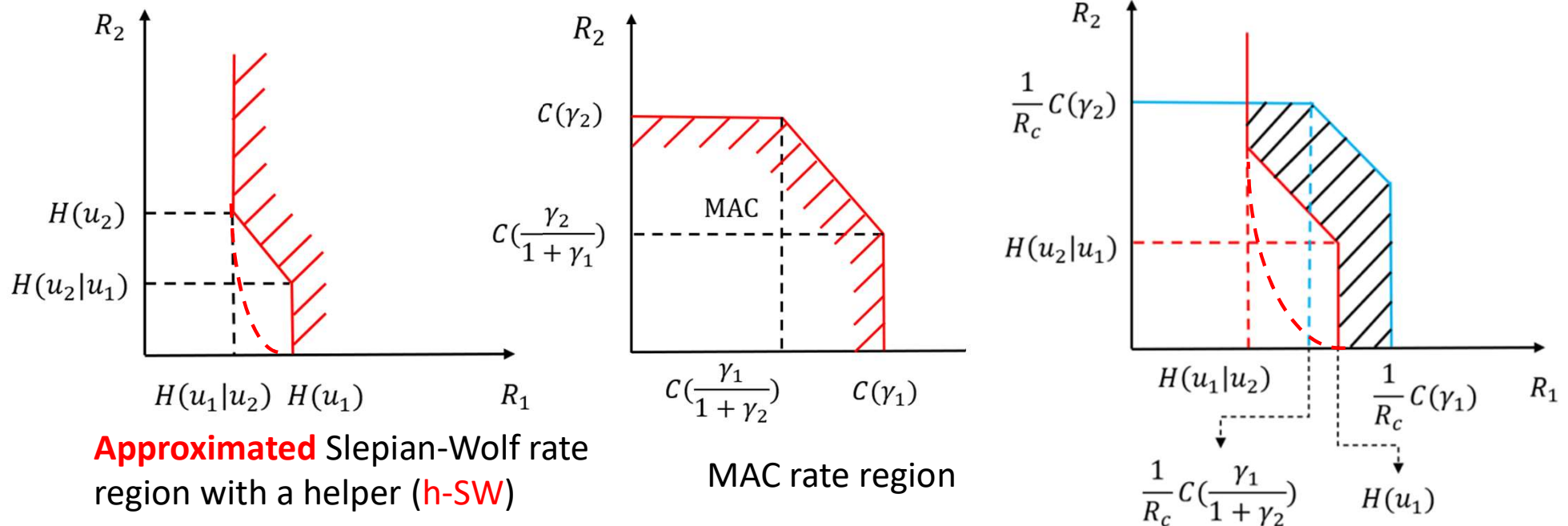
67



Data gathering should not necessarily be lossless.

End-to-End Lossless MAC:

A sufficient condition of successful transmissions is defined as the case **Slepian-Wolf** region with a helper and MAC rate region intersect, where **Source-Channel Separation** holds.



Let the transmission rate of the source and the helper to be R_1 and R_2 , respectively.

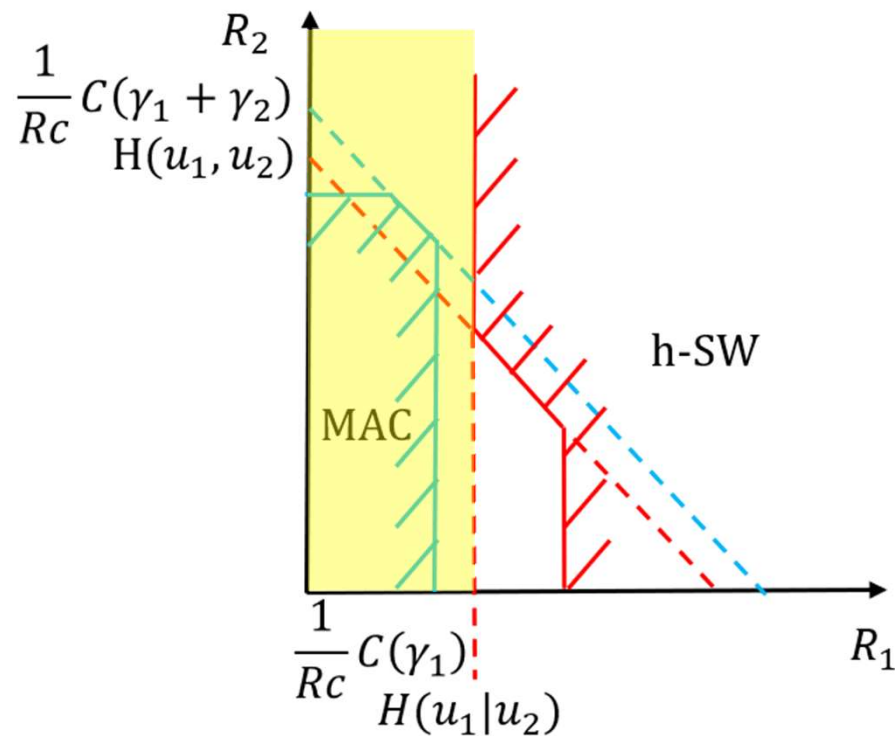
$$R_1 \geq \begin{cases} H(pe), & \text{for } R_2 \geq 1, \\ 1 + H(pe) - R_2, & \text{for } H(pe) \leq R_2 \leq 1, \\ 1, & \text{for } 0 \leq R_2 \leq H(pe). \end{cases}$$

$$\begin{cases} R_1 R_c \leq C(\gamma_1), \\ R_2 R_c \leq C(\gamma_2), \\ R_1 R_c + R_2 R_c \leq C(\gamma_1 + \gamma_2), \end{cases}$$

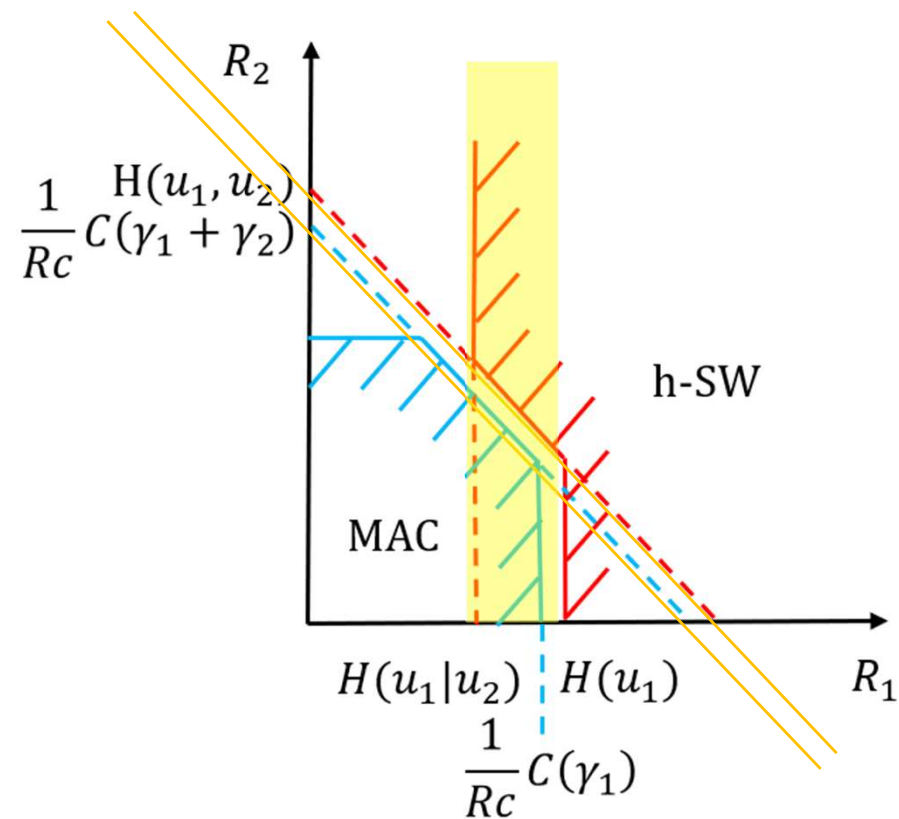
Source-Channel Separation

Source – Channel separation modeled by Bit-Fipping Model (as in BF MIMO TEQ) with flipping probability p_e

Cases where Outage Happens



$$\begin{cases} 0 < \frac{1}{R_c} C(\gamma_1) < H(u_1 | u_2) \\ 0 < \frac{1}{R_c} C(\gamma_2) \end{cases}$$



$$\begin{cases} H(u_1 | u_2) \leq \frac{1}{R_c} C(\gamma_1) < H(u_1) \\ \frac{1}{R_c} C(\gamma_1 + \gamma_2) < H(u_1, u_2) \end{cases}$$

Outage Probability Expressions

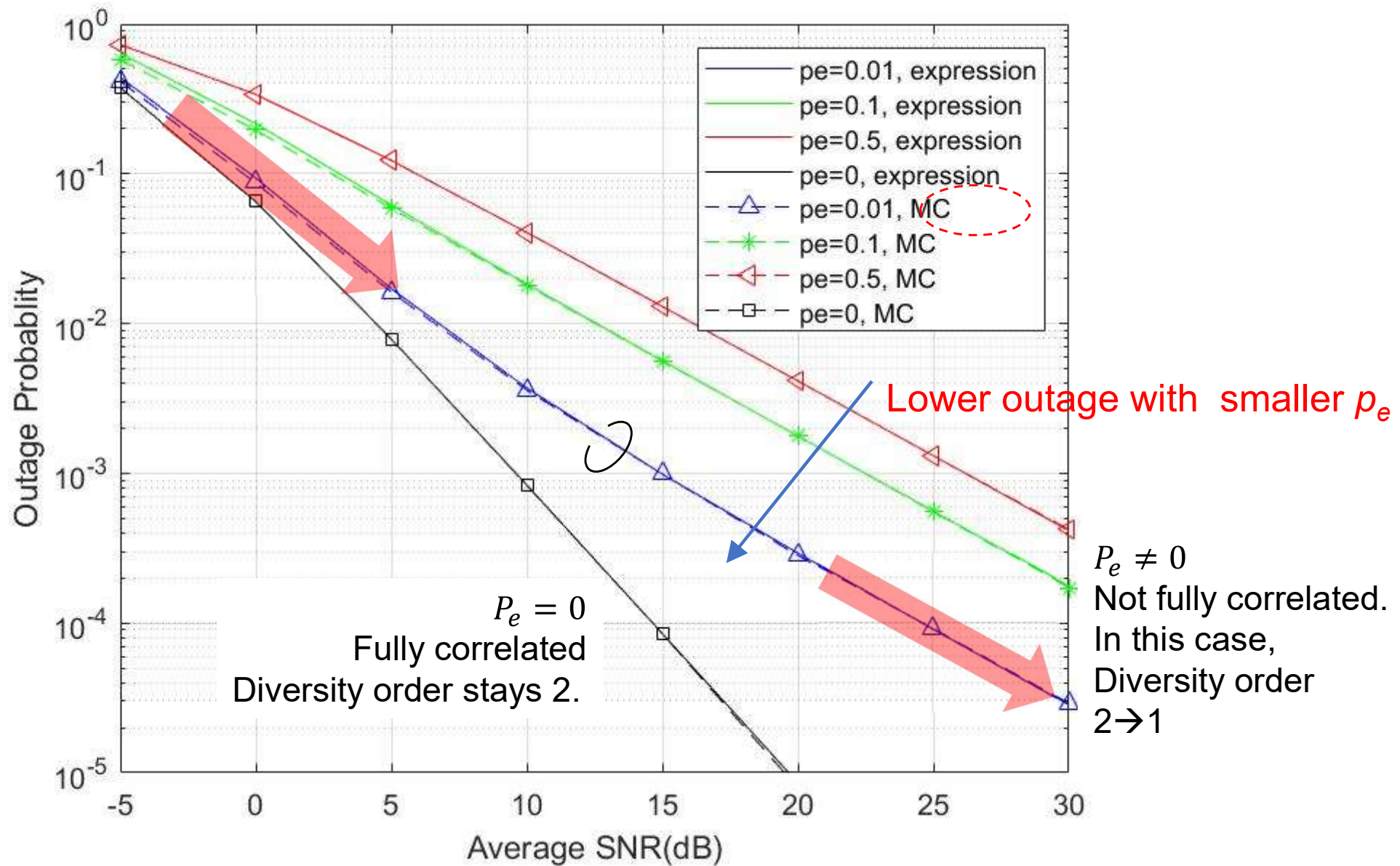
Outage probability can be calculated by multifold integrals with respect to the instantaneous SNR of each link.

$$\begin{aligned}
 P_{out,1} &= \Pr \left\{ \frac{1}{R_c} C(\gamma_1) < H(u_1 | u_2) \right\} \\
 &= \int_{\Phi(0)}^{\Phi[H(u_1|u_2)]} \int_{\Phi(0)}^{\Phi(+\infty)} p(\gamma_1) p(\gamma_2) d\gamma_2 d\gamma_1 \\
 &= \int_0^{2^{R_c H(P_e)} - 1} \int_0^{+\infty} p(\gamma_1) p(\gamma_2) d\gamma_2 d\gamma_1 \\
 &= 1 - \exp \left\{ -\frac{1}{\Gamma_1} [2^{R_c H(P_e)} - 1] \right\},
 \end{aligned}$$

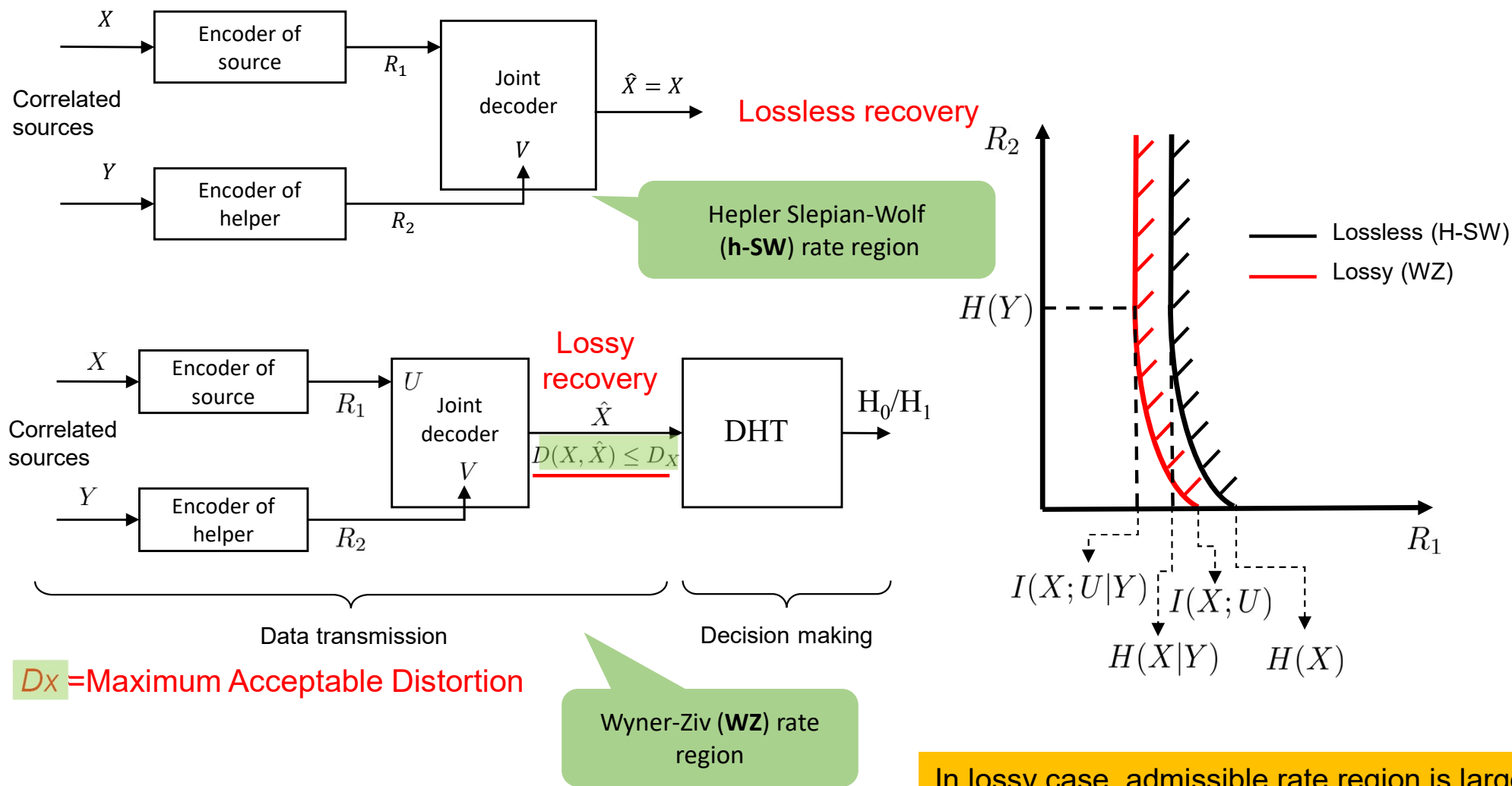
$$P_{out} = P_{out,1} + P_{out,2}$$

$$\begin{aligned}
 P_{out,2} &= \Pr \left\{ \begin{aligned} &H(u_1|u_2) \leq \frac{1}{R_c} C(\gamma_1) < H(u_1); \\ &\frac{1}{R_c} C(\gamma_1 + \gamma_2) < H(u_1, u_2) \end{aligned} \right\} \\
 &= \int_{\Phi[H(u_1|u_2)]}^{\Phi[H(u_1)]} \int_{\Phi(0)}^{\Phi[H(u_1, u_2)] - \gamma_1} p(\gamma_1) p(\gamma_2) d\gamma_2 d\gamma_1 \\
 &= \int_{2^{R_c H(P_e)} - 1}^{2^{R_c} - 1} \int_0^{2^{R_c [1 + H(P_e)]} - 1 - \gamma_1} p(\gamma_1) p(\gamma_2) d\gamma_2 d\gamma_1 \\
 &= \exp \left\{ -\frac{1}{\Gamma_1} [2^{R_c H(P_e)} - 1] \right\} - \exp \left[-\frac{1}{\Gamma_1} (2^{R_c} - 1) \right] \\
 &\quad - \frac{\Gamma_2}{\Gamma_1 - \Gamma_2} \exp \left[-\frac{1}{\Gamma_1} (2^{R_c} - 1) \right] \\
 &\quad \cdot \exp \left\{ -\frac{1}{\Gamma_2} [2^{R_c H(P_e) + R_c} - 2^{R_c}] \right\} \\
 &\quad + \frac{\Gamma_2}{\Gamma_1 - \Gamma_2} \exp \left\{ -\frac{1}{\Gamma_1} [2^{R_c H(P_e)} - 1] \right\} \\
 &\quad \cdot \exp \left\{ -\frac{1}{\Gamma_2} [2^{R_c H(P_e) + R_c} - 2^{R_c H(P_e)}] \right\},
 \end{aligned}$$

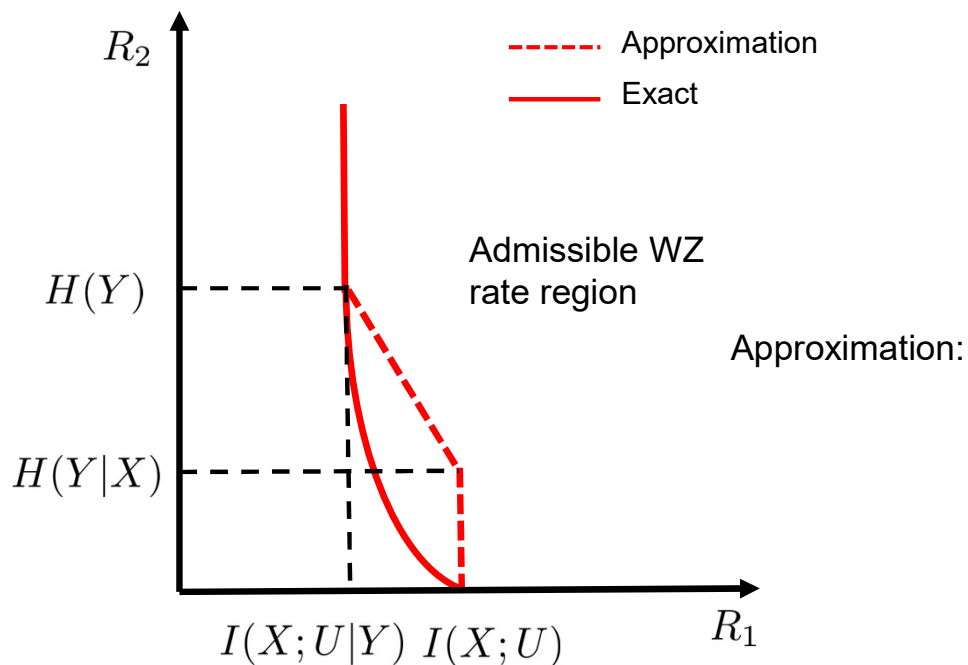
Numerical Result



End-to-End Lossy MAC:



Intersection Analysis

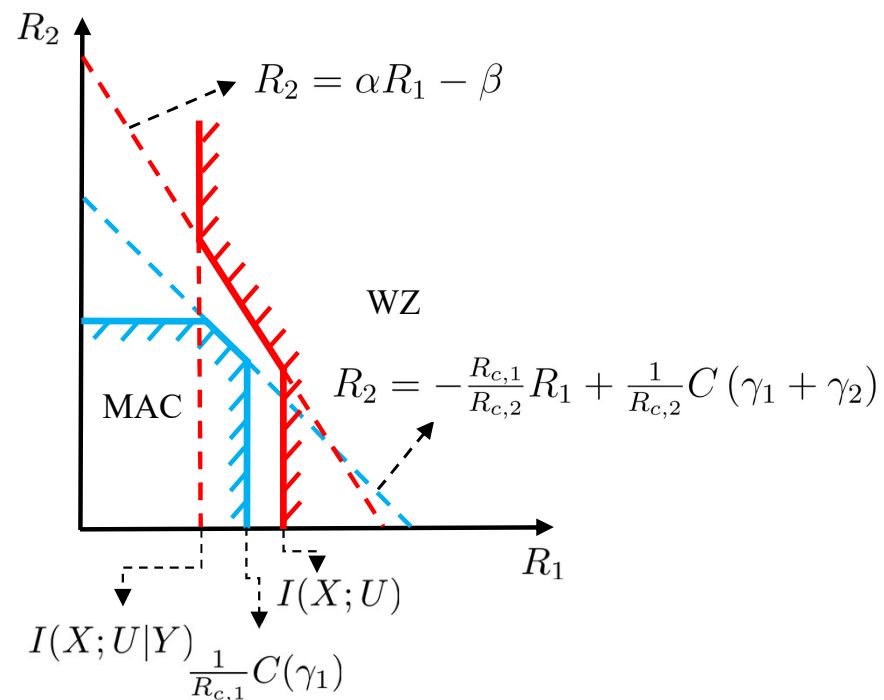
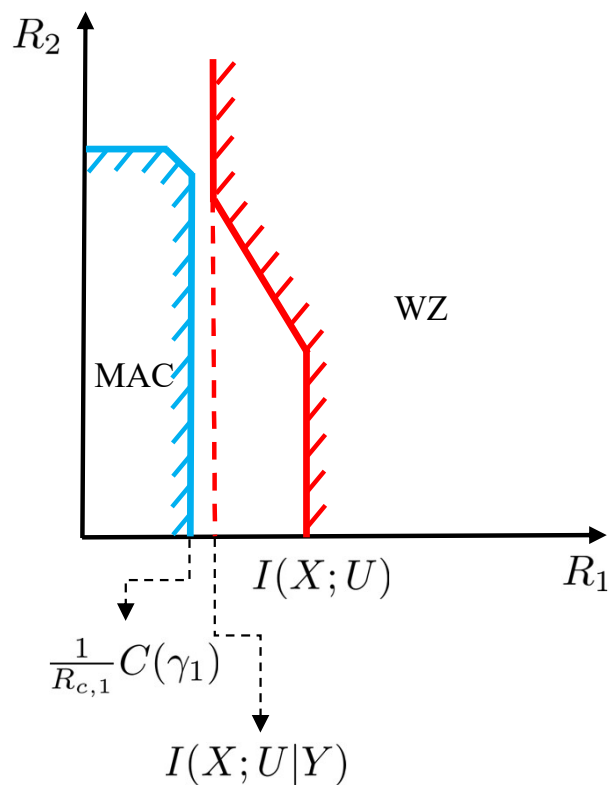


Exact:
$$\begin{cases} R_1 \geq I(X;U|Y), \\ R_2 \geq I(Y|V), \end{cases}$$

Approximation:
$$R_1 \geq \begin{cases} I(X;U|Y), & \text{for } R_2 \geq H(Y), \\ \frac{1}{\alpha}R_2 + \frac{\beta}{\alpha}, & \text{for } H(Y|X) \leq R_2 \leq H(Y), \\ I(X;U), & \text{for } 0 \leq R_2 \leq H(Y|X), \end{cases}$$

Admissible WZ rate region

with:
$$\alpha = \frac{I(X;Y)}{I(X;U|Y) - I(X;U)} \quad \beta = \frac{I(X;U) - I(X;U|Y) \cdot H(Y|X)}{I(X;U|Y) - I(X;U)}$$

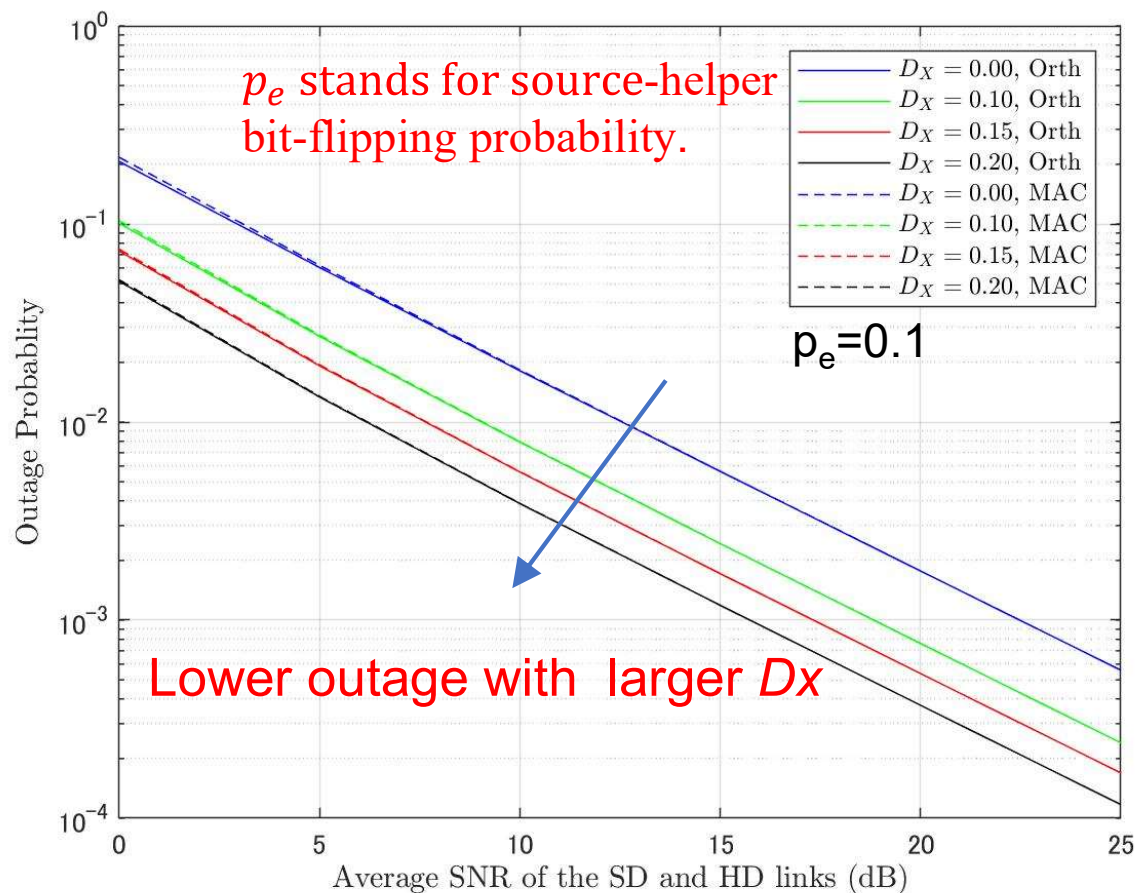


Two scenarios that outage happens. $P_{out,total} = P_{out,1} + P_{out,2}$

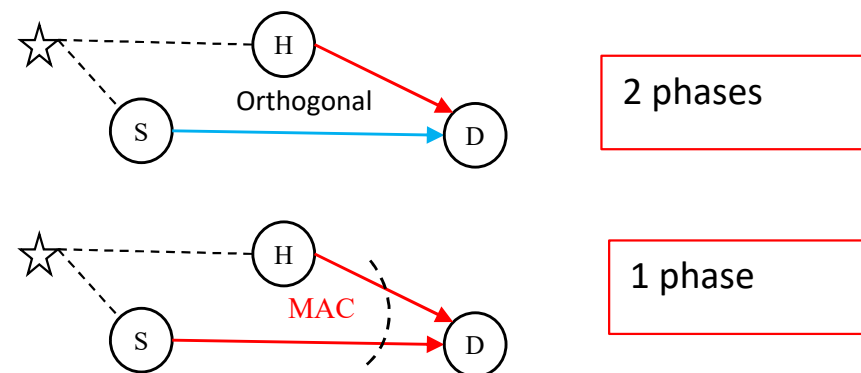
Twofold Integral Similar to Lossless Case

$$\begin{aligned}
 & P_{out,MAC,1} \\
 &= \Pr \left\{ 0 \leq \frac{1}{R_{c,1}} C(\gamma_1) \leq I(X;U|Y); \frac{1}{R_{c,2}} C(\gamma_2) \geq 0 \right\} \\
 &= \Pr \{ \Phi(0) \leq \gamma_1 \leq \Phi[I(X;U|Y)]; \gamma_2 \geq \Phi(0) \} \\
 &= \int_{\Phi(0)}^{\Phi[I(X;U|Y)]} \int_{\Phi(0)}^{+\infty} p(\gamma_1) p(\gamma_2) d\gamma_2 d\gamma_1 \\
 &= \int_0^{2^{R_{c,1}[H_b(D_X * P_e) - H_b(D_X)] - 1}} \int_0^{+\infty} p(\gamma_1) p(\gamma_2) d\gamma_2 d\gamma_1 \\
 & P_{out,MAC,2} \\
 &= \Pr \left\{ \begin{array}{l} I(X;U|Y) \leq \frac{1}{R_{c,1}} C(\gamma_1) \leq I(X;U); \\ 0 \leq -\frac{R_{c,1}}{R_{c,2}} R_1 + \frac{1}{R_{c,2}} C(\gamma_1 + \gamma_2) \leq \alpha R_1 - \beta \end{array} \right\} \\
 &= \Pr \left\{ \begin{array}{l} \Phi[I(X;U|Y)] \leq \gamma_1 \leq \Phi[I(X;U)]; \\ \Phi(0) \leq \gamma_2 \leq M \end{array} \right\} \\
 &= \int_{\Phi[I(X;U|Y)]}^{\Phi[I(X;U)]} \int_{\Phi(0)}^M p(\gamma_1) p(\gamma_2) d\gamma_2 d\gamma_1 \\
 &= \int_{2^{R_{c,1}[H_b(D_X * P_e) - H_b(D_X)] - 1}}^{2^{R_{c,1}[1 - H_b(D_X)] - 1}} \int_0^M p(\gamma_1) p(\gamma_2) d\gamma_2 d\gamma_1,
 \end{aligned}$$

with $M = 2^{-\beta R_{c,2}} (1 + \gamma_1)^{\left(\frac{\alpha R_{c,2}}{R_{c,1}} + 1\right)} - 1 - \gamma_1$.

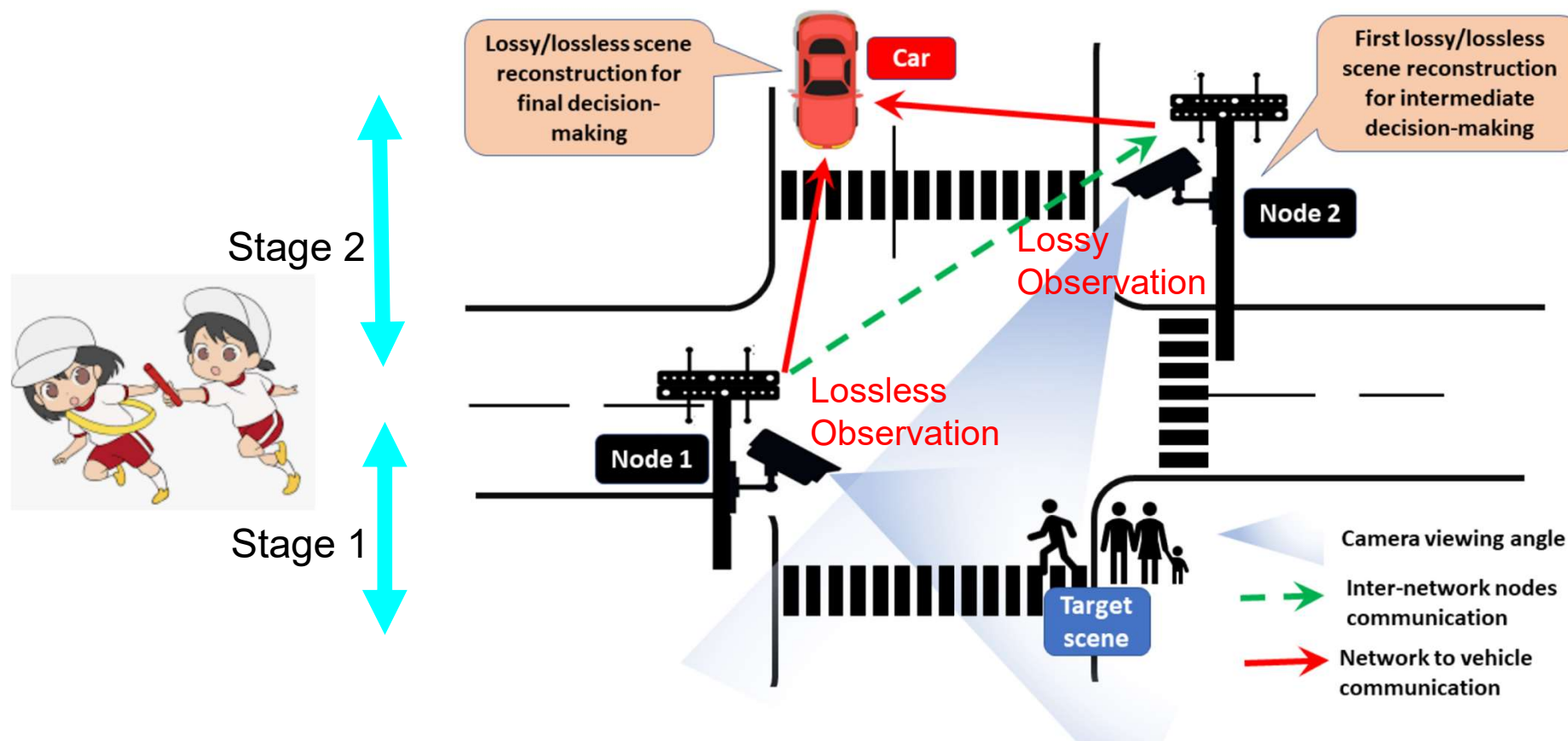


- The results show that the difference between Orthogonal and MAC is **negligibly small**.
- Transmission efficiency** with MAC transmission is **twice as large as** that in orthogonal transmission.



2.4 Two Stage Wyner-Ziv Network: Distortion Transfer Analysis

Analyze: How Distortion causing at the previous stage is **forwarded** to the current stage?
Distortion Transfer Function (DTF)

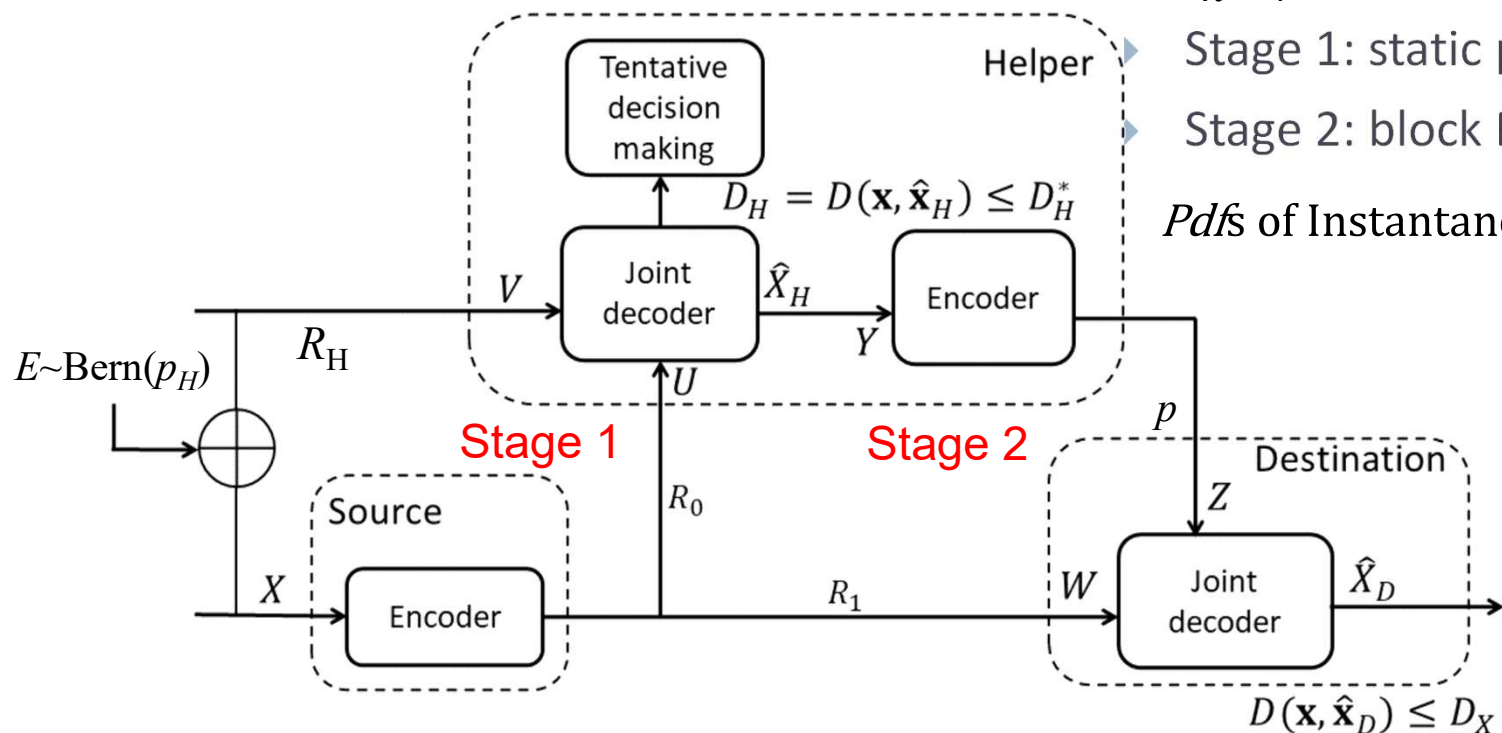


Block Diagram

► Mathematical assumptions

- i.i.d Bit-Flipping model for the correlation between the observations
- Hamming distortion measure
- Definition of Admissible rate-distortion (RD) region:

$$\mathcal{R}(D_X) = \{(R_0, R_1, R_2): (R_0, R_1, R_2) \text{ is admissible if } \lim_{n \rightarrow +\infty} \mathbf{E}(D(\mathbf{x}, \hat{\mathbf{x}}_D) \leq D_X + \epsilon, \forall \epsilon > 0)\}$$



► Stage 1: static parameters

► Stage 2: block Rayleigh fading

Pdfs of Instantaneous SNRs with the links are:

$$p(\gamma_i) = \frac{1}{\Gamma_i} \exp\left(-\frac{\gamma_i}{\Gamma_i}\right), \quad i \in \{SD, HD\}.$$

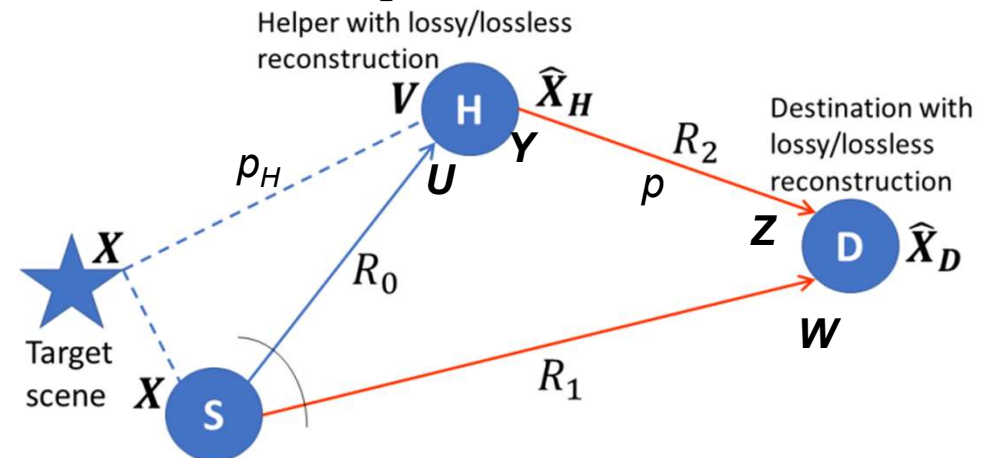
Stage-Independent RD Analysis

Stage 1

$R_0 \geq I(X; U|V)$, by Wyner Ziv Formulation where V is a Helper.

Since $U \rightarrow X \rightarrow V$

$$\begin{aligned} R_0 &\geq H(U|V) - H(U|V, X) \\ &= H(U|V) - H(U|X) \\ &= H_b(D_H * p_H) - H_b(D_H) \end{aligned}$$



Stage 2

$R_1 \geq I(X; W|Z)$, by Wyner Ziv Formulation where Z is a Helper.

$R_2 \geq I(Y; Z)$

Since $Z \rightarrow Y \rightarrow X \rightarrow W$

$$\begin{aligned} R_1 &\geq H(W|Z) - H(W|Z, X) \\ &= H(W|Z) - H(W|X) \\ &= H_b(p * D_H * D_X) - H_b(D_X) \end{aligned}$$

$$R_2 \geq H(Y) - H(Y|Z) = 1 - H_b(p)$$

Note: $H(1*x)=H(0*x)=H(x)$,
 $H(1/2*x)=H(1/2)=1$

Stage-Independent RD Analysis

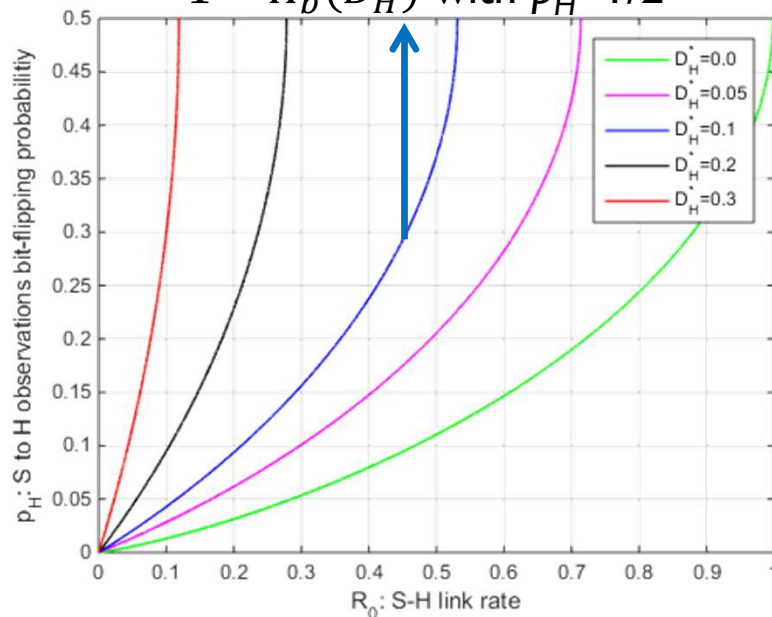
► Stage-by-stage admissible RD region

Stage 1

$$R_0 \geq I(X; U|V)$$

$$= H_b(D_H * p_H) - H_b(D_H)$$

$1 - H_b(D_H)$ with $p_H = 1/2$



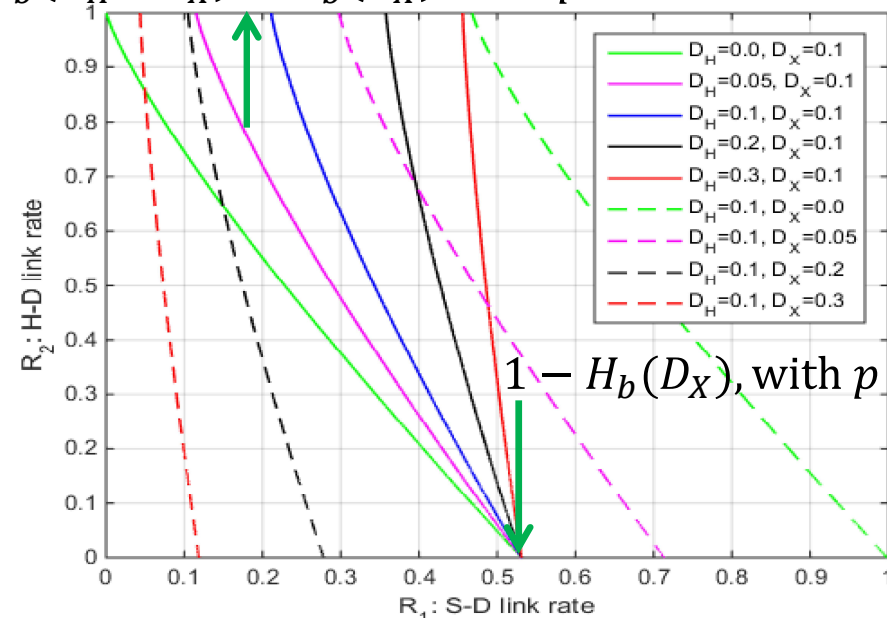
Smaller rate R_0 is required when D_H is larger or p_h is lower

Stage 2

$$R_1 \geq I(X; W|Z) = H_b(p * D_H * D_X) - H_b(D_X)$$

$$R_2 \geq I(Y; Z) = 1 - H_b(p)$$

$H_b(D_H * D_X) - H_b(D_X)$, with $p = 0$



Smaller rates R_1 and R_2 are required when D_X is larger or D_H is smaller

Stage-Dependent RD Analysis

- ▶ The Recursive Structure of the Binary Convolution is Referred to as: Distortion Transfer Function (DTF)

DTF Connects the two stages, as

- ▶ Stage 1:

- ▶ Assume the required distortion D_H at Helper is given by D_H^*
- ▶ It is found that Bit-Flipping probability between the observations should satisfy

$$R(D) = H_b(p) - H_b(D)$$

$$\downarrow$$

$$p = H_b^{-1}(R + H_b(D))$$

$$p_h \leq \Lambda \left[D_H^*, H_b^{-1}(R_0 + H_b(D_H^*)) \right]$$

to distortion requirement
on Side information

DTF

From distortion requirement
at Helper

- ▶ When $R_0 \geq 1 - H_b(D_H^*)$, using $\Lambda(y, t = 0.5) = 0.5$, we have $p_H \leq 0.5$
 - which corresponds to the case no side information is required.
- ▶ When R_0 decreases, $H_b^{-1}(R_0 + H_b(D_H^*))$ also decreases, and hence also p_H decreases,
 - which corresponds to the case higher correlation is needed to satisfy D_H^*

Stage-Dependent RD Analysis: Connecting Stages

► Stage 2

- Assume the required distortion at Destination is given by D_X
- It is found that the distortion at Helper should satisfy

$$D_H^* \leq \Lambda \left[p, \Lambda \left[D_X, H_b^{-1} \left(R_1 + H_b(D_X) \right) \right] \right]$$

to distortion
requirement at Helper

DTF

From distortion requirement
at Destination

- When R_2 is large enough, $p = H_b^{-1}(1 - R_2) = 0$, then using $\Lambda(0, t) = t$:

$$D_H^* \leq \Lambda \left[D_X, H_b^{-1} \left(R_1 + H_b(D_X) \right) \right] = D_{SI}$$

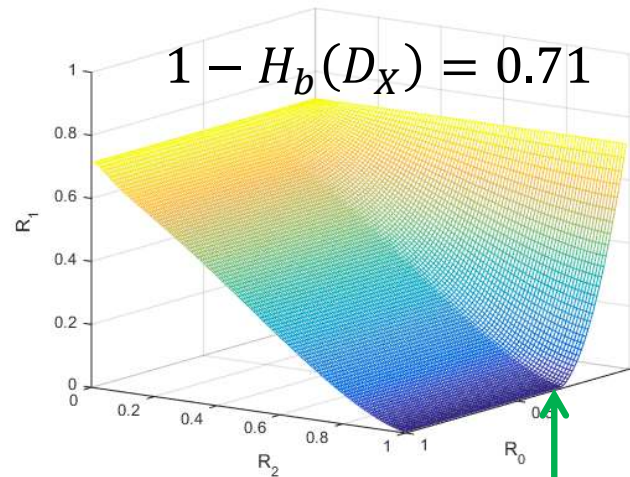
- In this case, **Stage 2** is equivalent to **Stage 1** with distortion requirement D_{SI} on Side Information.
- Condition $p \leq D_{SI}$ is required to achieve D_X at Destination

Rate Surface Calculation

▶ Connecting Stage 1 and Stage 2

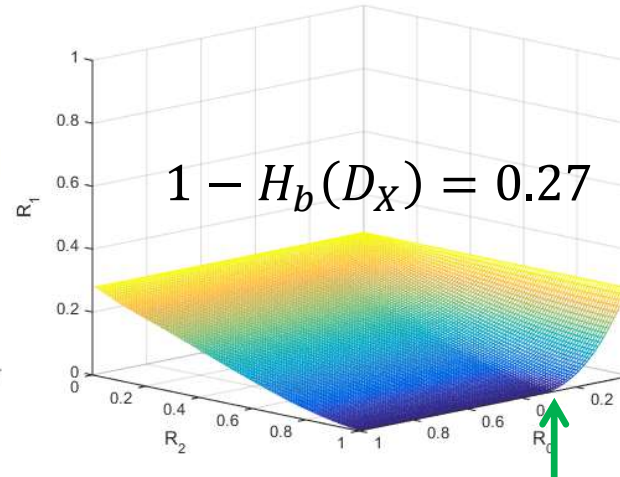
▶ 3D admissible RD region

$$D_X = 0.05, p_H = 0.05$$



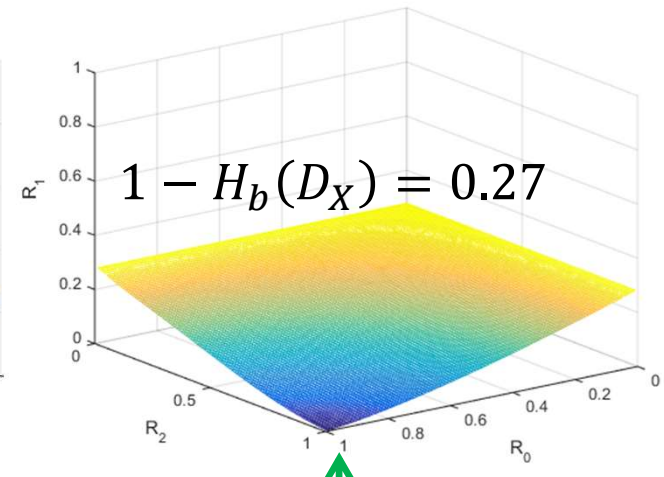
$$H_b(p_H) = 0.28$$

$$D_X = 0.2, p_H = 0.05$$



$$H_b(p_H) = 0.28$$

$$D_X = 0.2, p_H = 0.4$$



$$H_b(p_H) = 0.97$$

Relaxing the requirement with larger D_X expands the admissible RD region

Higher observation correlation reduces distortion requirement at Helper as well as Source-Helper link rate R_0 , resulting in expands the admissible RD region

Outage Probability

► Assumptions:

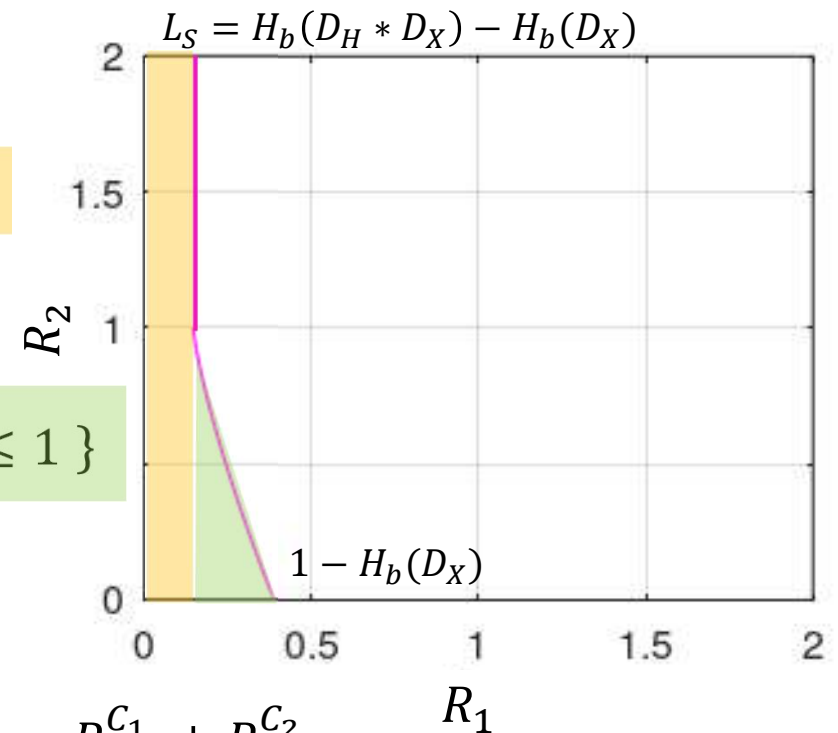
- Static **stage 1**: D_H is a fixed parameter
- Destination is moving: fading variation on S-D and H-D links
- When rates R_1 and R_2 are in the **in**admissible RD region: outage happens

→ Case 1:

$$C_1 \triangleq \{0 \leq R_1 \leq \underbrace{H_b(D_H * D_X) - H_b(D_X)}_{L_S}, R_2 \geq 0\}$$

→ Case 2:

$$C_2 \triangleq \{L_S \leq R_1 \leq \underbrace{H_b(p * D_H * D_X) - H_b(D_X)}_{f(R_2)}, 0 \leq R_2 \leq 1\}$$



$$P_{out} = \Pr\{(R_1, R_2) \in C_1\} + \Pr\{(R_1, R_2) \in C_2\} = P_{out}^{C_1} + P_{out}^{C_2}$$

Twofold Integrals for Outage Probability Calculation

- Utilizing Lossy Source-Channel Separation theorem,

$$R_1 \leq \Phi_S(\gamma_S) \triangleq \frac{C(\gamma_S)}{R_c^{SD}} \quad R_2 \leq \Phi_S(\gamma_H) \triangleq \frac{C(\gamma_H)}{R_c^{HD}}$$

- $C(\gamma) = \log_2(1 + \gamma)$: the channel capacity function with two dimensional signaling

- Case 1 outage probability:

$$\begin{aligned} P_{out}^{C_1} &= \Pr\{0 \leq R_1 \leq L_S, 0 \leq R_2\} \\ &= \Pr\{0 \leq \Phi_S(\gamma_S) \leq L_S, 0 \leq \Phi_H(\gamma_H)\} \\ &= \Pr\{\Phi_S^{-1}(0) \leq \gamma_S \leq \Phi_S^{-1}(L_S), \Phi_H^{-1}(0) \leq \gamma_H\} \\ &= \int_{\Phi_H^{-1}(0)}^{+\infty} \int_{\Phi_S^{-1}(0)}^{\Phi_S^{-1}(L_S)} p(\gamma_S, \gamma_H) d\gamma_S d\gamma_H \end{aligned}$$

- Case 2 outage probability:

$$\begin{aligned} P_{out}^{C_2} &= \Pr\{L_S \leq R_1 \leq H_S(\gamma_H), 0 \leq R_2 \leq 1\} \\ &= \Pr\{L_S \leq \Phi_S(\gamma_S) \leq H_S(\gamma_H), 0 \leq \Phi_H(\gamma_H) \leq 1\} \\ &= \Pr\{\Phi_S^{-1}(L_S) \leq \gamma_S \leq \Phi_S^{-1}(H_S(\gamma_H)), \Phi_H^{-1}(0) \leq \gamma_H \leq \Phi_H^{-1}(1)\} \\ &= \int_{\Phi_H^{-1}(0)}^{\Phi_H^{-1}(1)} \int_{\Phi_S^{-1}(L_S)}^{\Phi_S^{-1}(H_S(\gamma_H))} p(\gamma_S, \gamma_H) d\gamma_S d\gamma_H \end{aligned}$$

$$p = H_b^{-1}(1 - \Phi_H(\gamma_H))$$

$$H_S(\gamma_H) = H_b(H_b^{-1}(1 - \Phi_H(\gamma_H)) * D_H * D_X) - H_b(D_X)$$

Twofold Integrals for Outage Probability Calculation

- For independent fading on S-D and H-D links

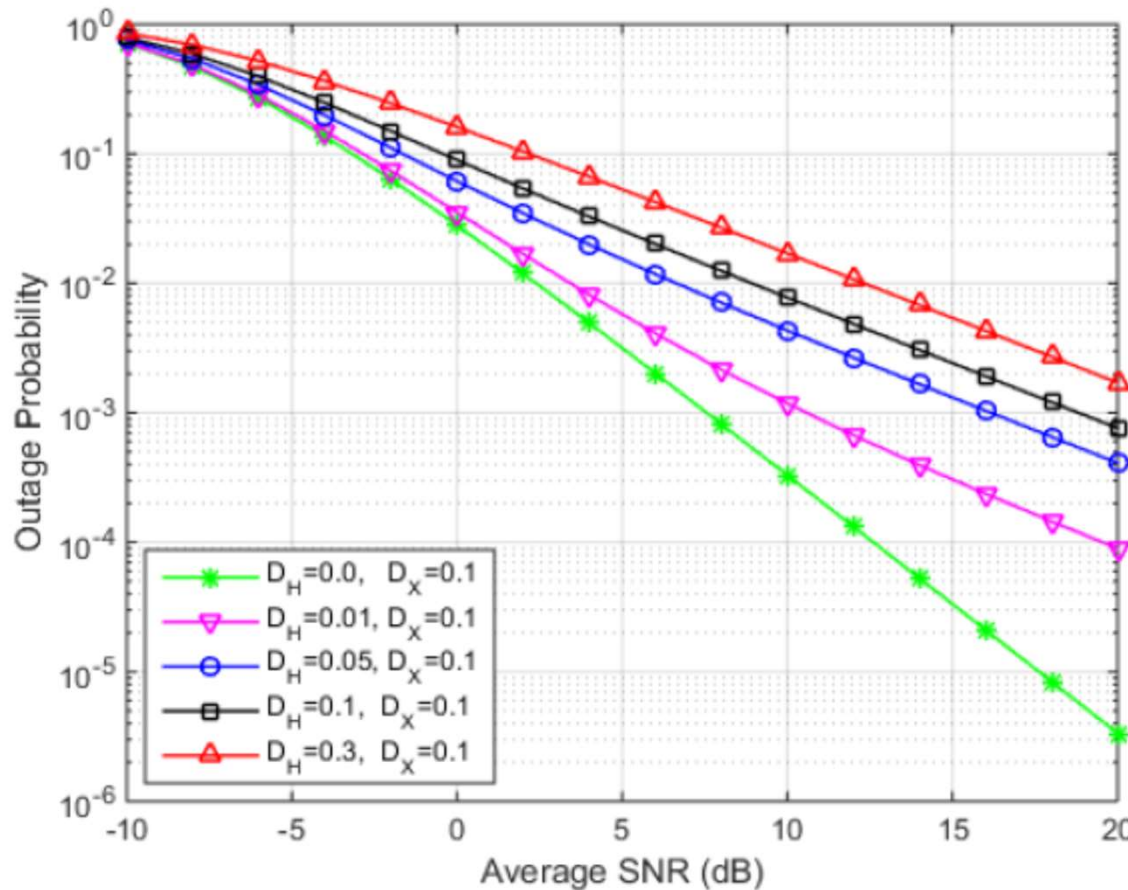
$$\begin{aligned}
 P_{out}^{C_1} &= \frac{1}{\Gamma_S \Gamma_H} \int_{\Phi_H^{-1}(0)}^{+\infty} \int_{\Phi_S^{-1}(0)}^{\Phi_S^{-1}(L_S)} \exp\left(-\frac{\gamma_S}{\Gamma_S}\right) \exp\left(-\frac{\gamma_H}{\Gamma_H}\right) d\gamma_S d\gamma_H \\
 &= 1 - \exp\left(\frac{-\Phi_S^{-1}(L_S)}{\Gamma_S}\right),
 \end{aligned}$$

TwWKDCpCmPaT!

$$\begin{aligned}
 P_{out}^{C_2} &= \frac{1}{\Gamma_S \Gamma_H} \int_{\Phi_H^{-1}(0)}^{\Phi_H^{-1}(1)} \int_{\Phi_S^{-1}(L_S)}^{\Phi_S^{-1}(H_S(\gamma_H))} \exp\left(-\frac{\gamma_S}{\Gamma_S}\right) \exp\left(-\frac{\gamma_H}{\Gamma_H}\right) d\gamma_S d\gamma_H \\
 &= \frac{1}{\Gamma_H} \int_{\Phi_H^{-1}(0)}^{\Phi_H^{-1}(1)} \exp\left(-\frac{\gamma_H}{\Gamma_H}\right) \left[\exp\left(-\frac{\Phi_S^{-1}(L_S)}{\Gamma_S}\right) - \exp\left(-\frac{\Phi_S^{-1}(H_S(\gamma_H))}{\Gamma_S}\right) \right] d\gamma_H
 \end{aligned}$$

Outage Probability

- For independent fading on the S-D and H-D links



First order diversity when **first stage is lossy** and high D_H at Helper

$$P_{out} \approx P_{out}^{C1} = 1 - \exp\left(\frac{-\Phi_S^{-1}(L_S)}{\Gamma_S}\right) \approx \frac{-\Phi_S^{-1}(L_S)}{\Gamma_S} \propto \frac{1}{\Gamma_S}$$

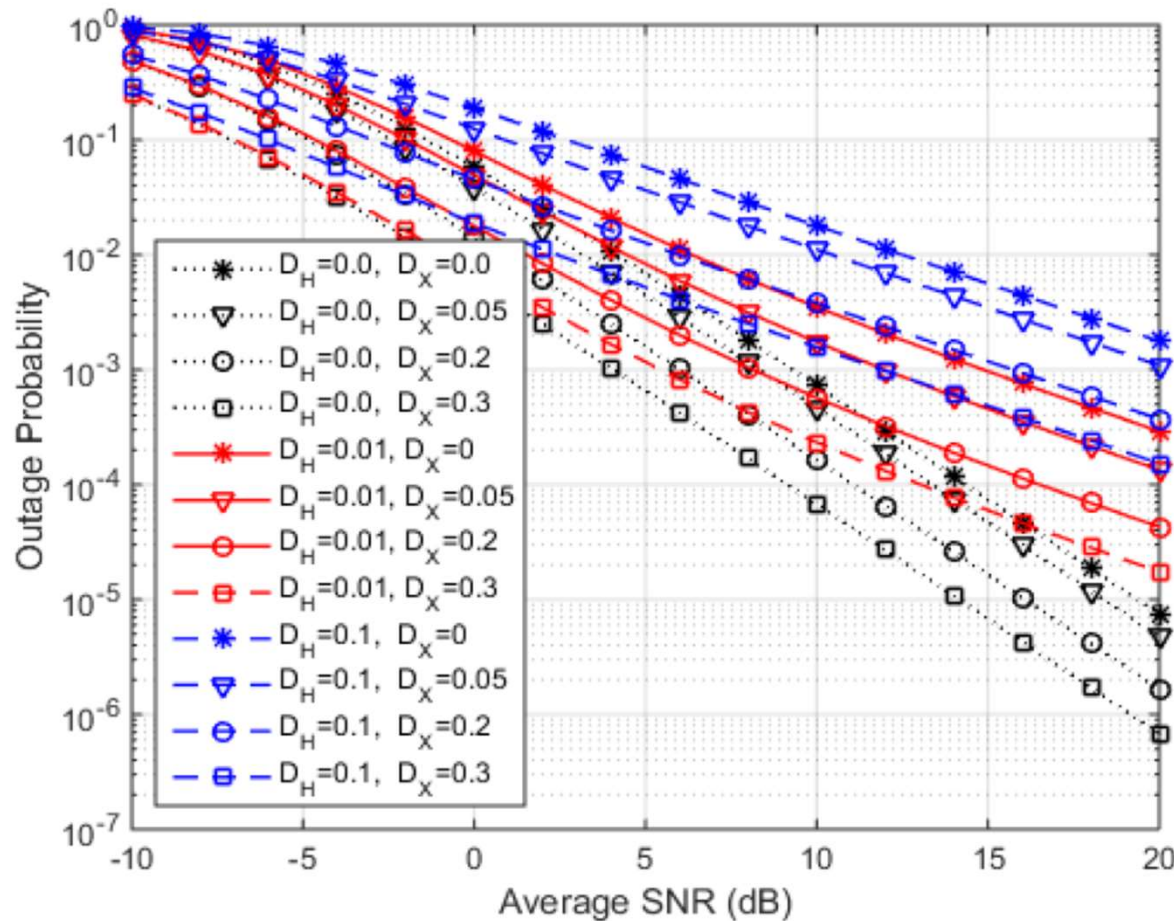
Second-to-first order diversity change when first stage is lossy and D_H is low

Second order diversity achieved when Stage 1 is lossless ($D_H = 0, L_S = 0$)

$$P_{out} = P_{out}^{C2} \approx \frac{1}{\Gamma_H \Gamma_S} \int_{\Phi_H^{-1}(0)}^{\Phi_H^{-1}(1)} \Phi_S^{-1}(H_S(\gamma_H)) d\gamma_H \propto \frac{1}{\Gamma_H \Gamma_S}$$

Outage Probability

- For independent fading on the S-D and H-D links



Increasing the allowed distortion at Destination D_X provides **lower outage probabilities**

However, D_X has no impact on the slope of the outage probability (parallel curves)

Impact of Spatial Correlation on Outage Probability

► For correlated fading on the S-D and H-D links

- $\rho = \langle h_1, h_2^* \rangle$ the correlation of the complex channel gains h_1 and h_2
- The joint PDF of the instantaneous SNRs

$$p(\gamma_S, \gamma_H) = \frac{1}{\Gamma_S \Gamma_H (1 - |\rho|^2)} \exp \left(-\frac{1}{1 - |\rho|^2} \left(\frac{\gamma_S}{\Gamma_S} + \frac{\gamma_H}{\Gamma_H} \right) \right) \times I_0 \left(\frac{2|\rho|}{1 - |\rho|^2} \sqrt{\frac{\gamma_S \gamma_H}{\Gamma_S \Gamma_H}} \right)$$

- $I_0(x)$ is the zero-order modified Bessel's function of the first kind

$$I_0(x) = \sum_{m=0}^{\infty} \frac{1}{(m!)^2} \left(\frac{x}{2} \right)^{2m}$$

- The outage probability of cases 1 and 2 can be written as

$$P_{out}^{C_1} \approx \sum_{m=0}^M A_m \int_{\Phi_H^{-1}(0)}^{+\infty} \int_{\Phi_S^{-1}(0)}^{\Phi_S^{-1}(L_S)} \left(\frac{\gamma_S \gamma_H}{\Gamma_S \Gamma_H} \right)^m \exp \left(-a \frac{\gamma_S}{\Gamma_S} \right) \exp \left(-a \frac{\gamma_H}{\Gamma_H} \right) d\gamma_S d\gamma_H,$$

$$P_{out}^{C_2} \approx \sum_{m=0}^M A_m \int_{\Phi_H^{-1}(0)}^{\Phi_H^{-1}(H_S(\gamma_H))} \int_{\Phi_S^{-1}(L_S)}^{\Phi_S^{-1}(0)} \left(\frac{\gamma_S \gamma_H}{\Gamma_S \Gamma_H} \right)^m \exp \left(-a \frac{\gamma_S}{\Gamma_S} \right) \exp \left(-a \frac{\gamma_H}{\Gamma_H} \right) d\gamma_S d\gamma_H,$$

Impact of Spatial Correlation on Outage Probability

- For **correlated fading** on the S-D and H-D links

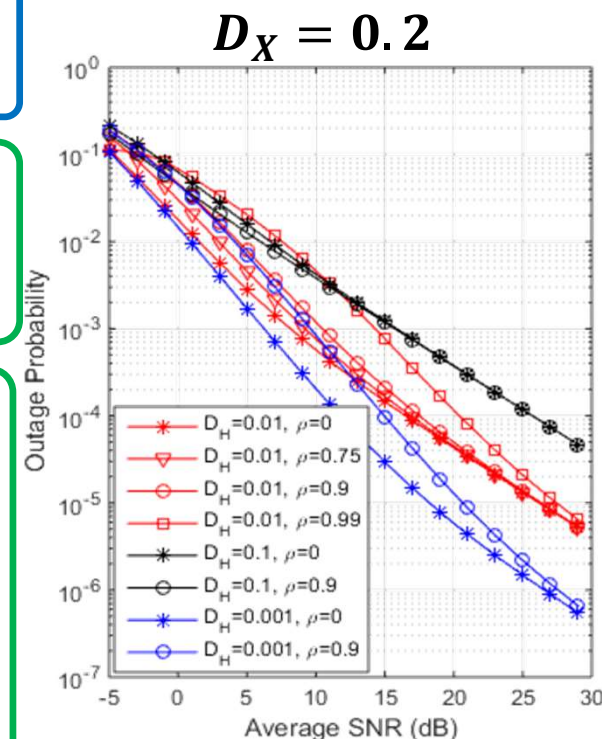
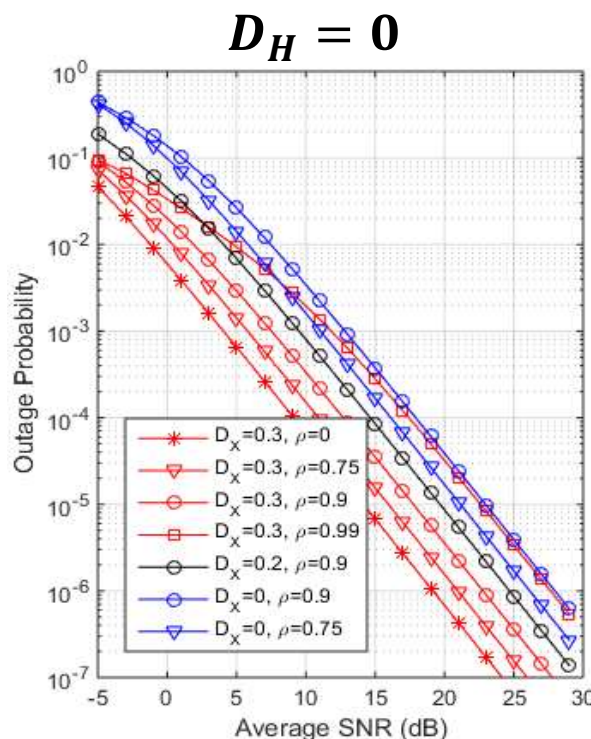
Higher fading **correlation** induces **higher** outage probabilities

Increasing D_X **reduces** the outage probability

1st order diversity is obtained asymptotically

Second order diversity is achieved with $D_H = 0$ (even when $\rho \simeq 1$), independently of D_X

For small D_H and ρ values, **2nd order diversity** can be achieved at low average SNRs



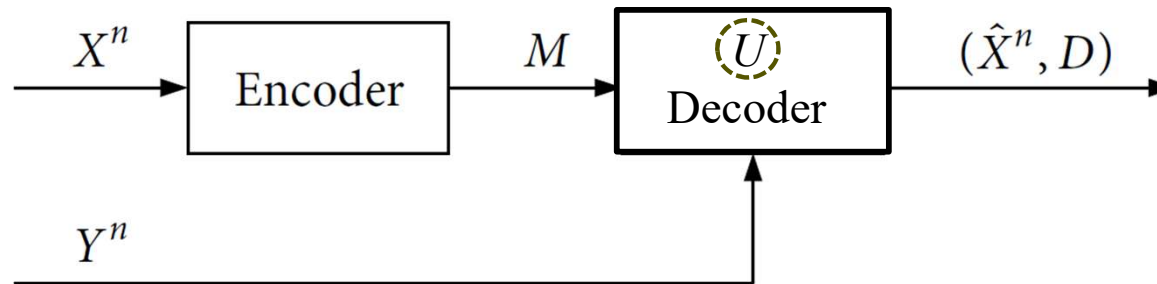
90

Fading correlation has no impact on the asymptotic diversity order

Chapter 3 Wyner-Ziv Formulation for Decision Making Process

3.1 Revisit of Helper-aided Lossy Networks

Wyner Ziv Networks:



Notice: $U \rightarrow X \rightarrow Y$ forms a Markov Chain

$$\begin{aligned} I(X; U) - I(Y; U) &= I(XY; U) - I(Y; U|X) - I(Y; U) \\ &= I(XY; U) - I(Y; U) = I(X; U|Y). \end{aligned}$$

We have used $U \rightarrow X \rightarrow Y$ in the networks of:

- Outage analysis for wireless End-to-End Lossy Communications networks
- A two-stage wireless communications network based on Distortion Transfer Function
- Extension to two-sources one-helper End-to-End Lossy wireless communications network
- ...

Fact: $I(X; U) - I(Y; U) = I(X; U|Y)$ can be understood as:

- Y is training sequence for **Machine Learning**,
- Y is training sequence, maybe followed by online observation, used for the knowledge updating of 1st and 2nd order statistics, *pdf* and *Markov dynamics*, in **Semantic Communications**.
- Y is Side Information for DHT

Hypothesis Testing HT

3.2 Distributed Hypothesis Testing (DHT)

Landmark Builders for Hypothesis Testing (HT): Neyman-Pearson

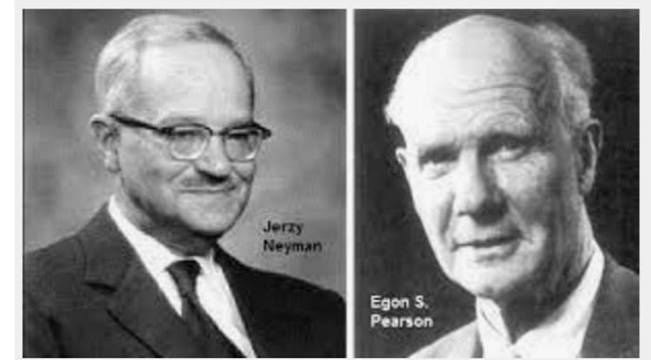
Information Theoretic formulation of HT:

Basically, HT is a Code Design problem:

Design $f^{(n)}$ and $g^{(n)}$ such that

Minimize Type II Error Probability β_n subject to

Type I Error Probability $\alpha_n \leq \varepsilon$

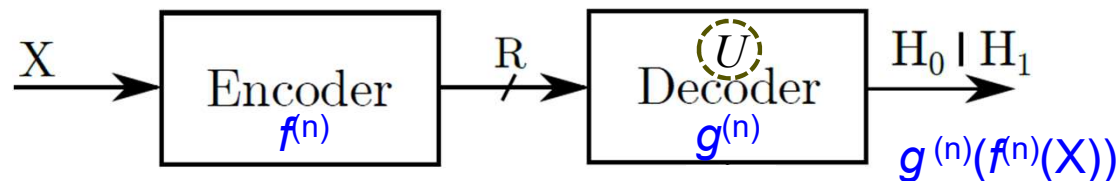


$$\alpha_n = \mathbb{P} \left[g^{(n)} \left(f^{(n)} (\mathbf{X}^n) \right) = H_1 \mid H_0 \text{ is true} \right]$$

$$\beta_n = \mathbb{P} \left[g^{(n)} \left(f^{(n)} (\mathbf{X}^n) \right) = H_0 \mid H_1 \text{ is true} \right]$$

$$H_0: X \sim P_{0,X}$$

$$H_1: X \sim P_{1,X}$$



under constraint the rate R being given.

Note: Tradeoff: $\alpha_n \uparrow$, $\beta_n \downarrow$

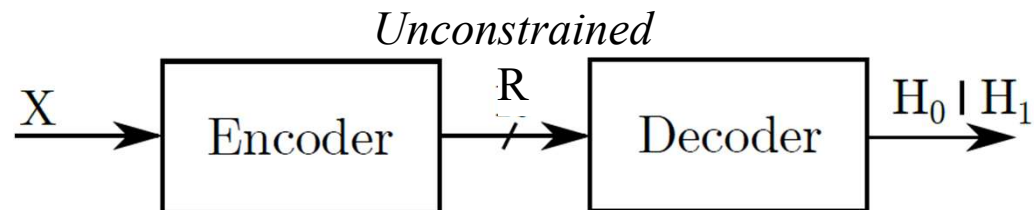
Note further: Decoder does NOT have to really “decode” to obtain U .
e.g., by Syndrome check only.

Nyman Pearson Test

With unconstrained R , the decision problem boils down to traditional Nyman Pearson test using Likelihood:

$$\frac{P_0(X_1, X_2, \dots, X_n)}{P_1(X_1, X_2, \dots, X_n)} > T, \quad X_1, X_2, \dots, X_n \in X, \text{ and } H_0: X \sim P_{0,X} \quad H_1: X \sim P_{1,X}$$

Unconstrained

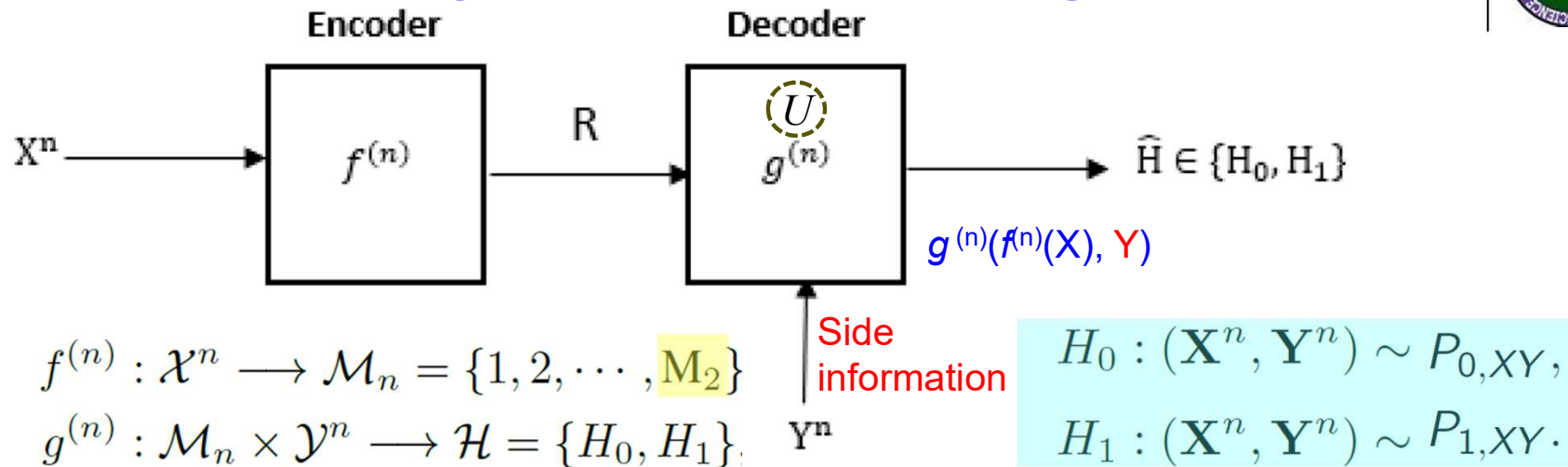


α_n and β_n are given by $\alpha^* = P_0^n(A_n^c(T)), \quad \beta^* = P_1^n(A_n(T)),$

with the likelihood test function $A_n(T) = \left\{ \frac{F_0(x_1, x_2, \dots, x_n)}{P_1(x_1, x_2, \dots, x_n)} > T \right\}.$

Note: Tradeoff $\alpha_n \uparrow, \beta_n \downarrow$ still holds with the threshold T and observation length n

Distributed Hypothesis Testing, DHT



Decoder $g^{(n)}$ does NOT have to really “decode” to obtain U ,
because the objective is to make a decision under the constraint on rate R .

- **Objective** : find the type-II error exponent θ such that type-I error probability α_n smaller than or equal to ε with the rate constraint satisfied.

$$\alpha_n = \mathbb{P} \left[g^{(n)} \left(f^{(n)} (\mathbf{X}^n), \mathbf{Y}^n \right) = H_1 \mid H_0 \text{ is true} \right],$$

$$\beta_n = \mathbb{P} \left[g^{(n)} \left(f^{(n)} (\mathbf{X}^n), \mathbf{Y}^n \right) = H_0 \mid H_1 \text{ is true} \right].$$

The objective is that minimize β_n , subject to $\alpha_n \leq \varepsilon$. Tradeoff: $\alpha_n \uparrow$, $\beta_n \downarrow$

DHT Problems:

(1) In the same way as HT, again, a DHT problem is a Code Design problem:
Design $f^{(n)}$ and $g^{(n)}$ such that

Minimize Type II Error Probability β_n subject to

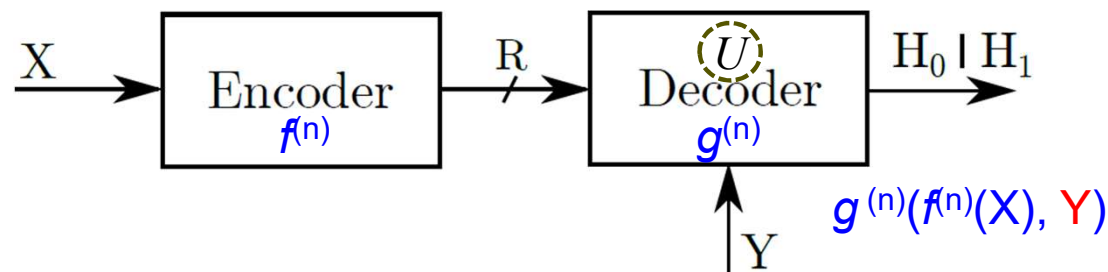
Type I Error Probability $\alpha_n \leq \varepsilon$ under constraint on the rate R given.

$$\alpha_n = \mathbb{P} \left[g^{(n)} \left(\underline{f^{(n)}}(\mathbf{X}^n), \mathbf{Y}^n \right) = H_1 \mid H_0 \text{ is true} \right]$$

$$\beta_n = \mathbb{P} \left[g^{(n)} \left(\underline{f^{(n)}}(\mathbf{X}^n), \mathbf{Y}^n \right) = H_0 \mid H_1 \text{ is true} \right]$$

$$H_0 : (\mathbf{X}^n, \mathbf{Y}^n) \sim P_{0,XY},$$

$$H_1 : (\mathbf{X}^n, \mathbf{Y}^n) \sim P_{1,XY}.$$



(2) Find Type-II Error Exponent θ

$$\limsup_{n \rightarrow \infty} \frac{1}{n} \log \frac{1}{\beta_n} \geq \theta$$

$$\beta_n \leq \exp(-n\theta)$$

Subject to $\alpha_n \leq \epsilon$

and $\limsup_{n \rightarrow \infty} \frac{1}{n} \log M_2 \leq R$

DHT: Type-II Error Exponent θ

$$\limsup_{n \rightarrow \infty} \frac{1}{n} \log \frac{1}{\beta_n} \geq \theta$$

It has already been known that:

$$\theta = \min \left\{ \underbrace{G(P_{0,UXY}, R)}_{\text{binning-error}}, \underbrace{D(P_{0,UXY} \| P_{1,UXY})}_{\text{testing-error}} \right\}$$

with the *binning-error* part being:

$$G(P_{0,UXY}, R) = R - [I(X; U) - I(U; Y)]$$

and

$D(P_{0,UXY} \| P_{1,UXY})$ is the KL divergence

We rewrite the *binning-error* part:

$$G(R, R(D)) = R - R(D)$$

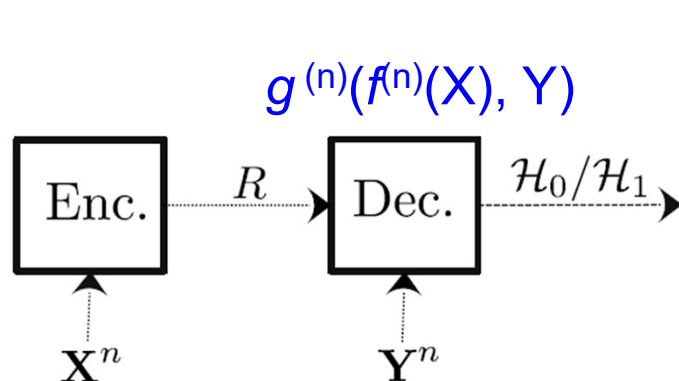
with

$$R(D) = \min \{ I(X; U) - I(U; Y) \} = \min I(X; U | Y) \text{ ---(1)}$$

being Wyner Ziv $R(D)$ function! \rightarrow The DHT Problem (1) boils down to **WZ Coding Problem**, because $U \rightarrow X \rightarrow Y$ forms a Markov Chain.

So far up to this point, formulations are **generic**, and hence distributions are **not specified**.

Binary DHT against Independence



$$Y \triangleq X \oplus W$$

$$\mathcal{H}_0 : W \sim \text{Bern}(p_0),$$

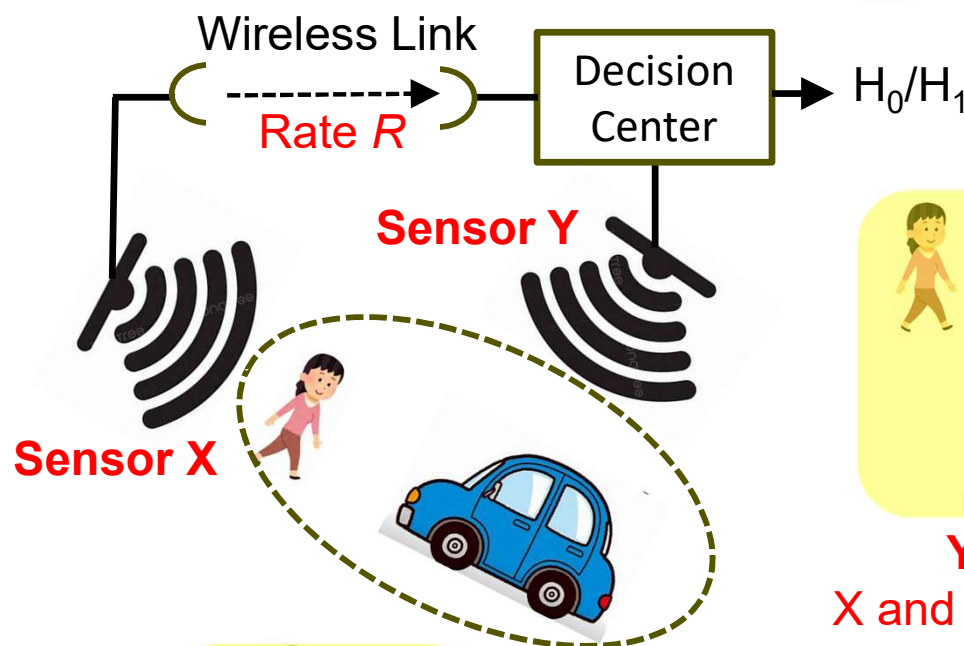
$$\mathcal{H}_1 : W \sim \text{Bern}(p_1),$$

\mathbf{X} and \mathbf{Y} are independent when $p_1=1/2$.

Type-I error and Type-II error:

$$\alpha_n = \Pr(\mathcal{H}_1 | \mathcal{H}_0)$$

$$\beta_n = \Pr(\mathcal{H}_0 | \mathcal{H}_1)$$



X's view



Y's view:
X and Y Independent



Y's view:
X and Y Correlated

H_0 : Correlated=Dangerous!

H_1 : Independent=Safe!

Objective: Minimize Type II Error Probability β_n subject to Type I Error Probability $\alpha_n \leq \varepsilon$ under constraint on the rate R given.

Binary DHT

- Compression of \mathbf{X} by Short Linear Block Code
- \mathbf{Y} is not compressed.
- Nayman-Pearson Test

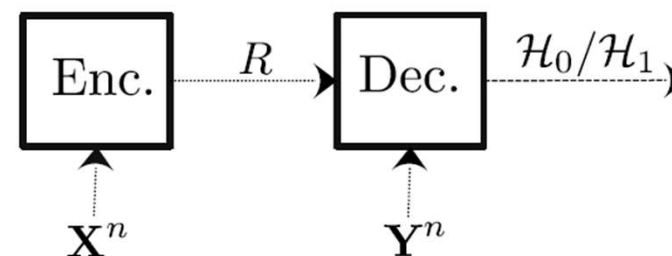
Consider a binary linear code \mathcal{C} defined by a $k \times n$ generator matrix \mathbf{G} with a rate of $R = \frac{k}{n}$ as the binary quantizer component [17]. According to the standard array concept [18], the minimum Hamming weight vector $d_H(\cdot)$ in each *coset* \mathcal{C}_s associated to the syndrome s is referred to as the *coset leader* defined as

$$L(\mathcal{C}_s) \triangleq \arg \min_{\mathbf{z} \in \mathcal{C}_s} d_H(\mathbf{z}),$$

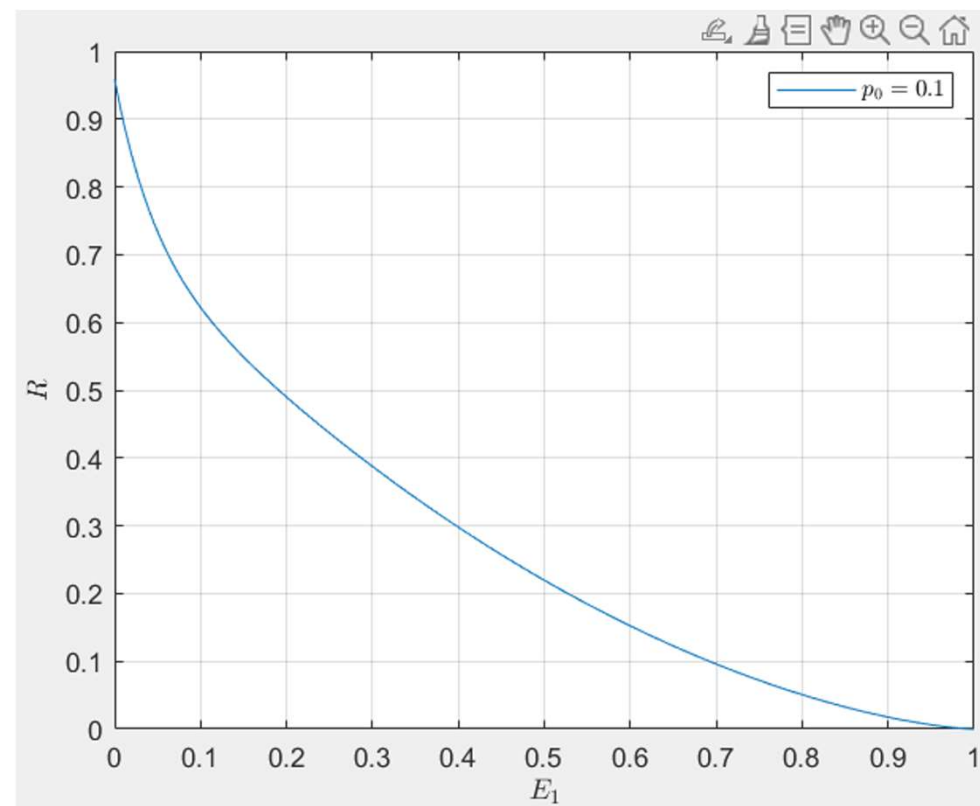
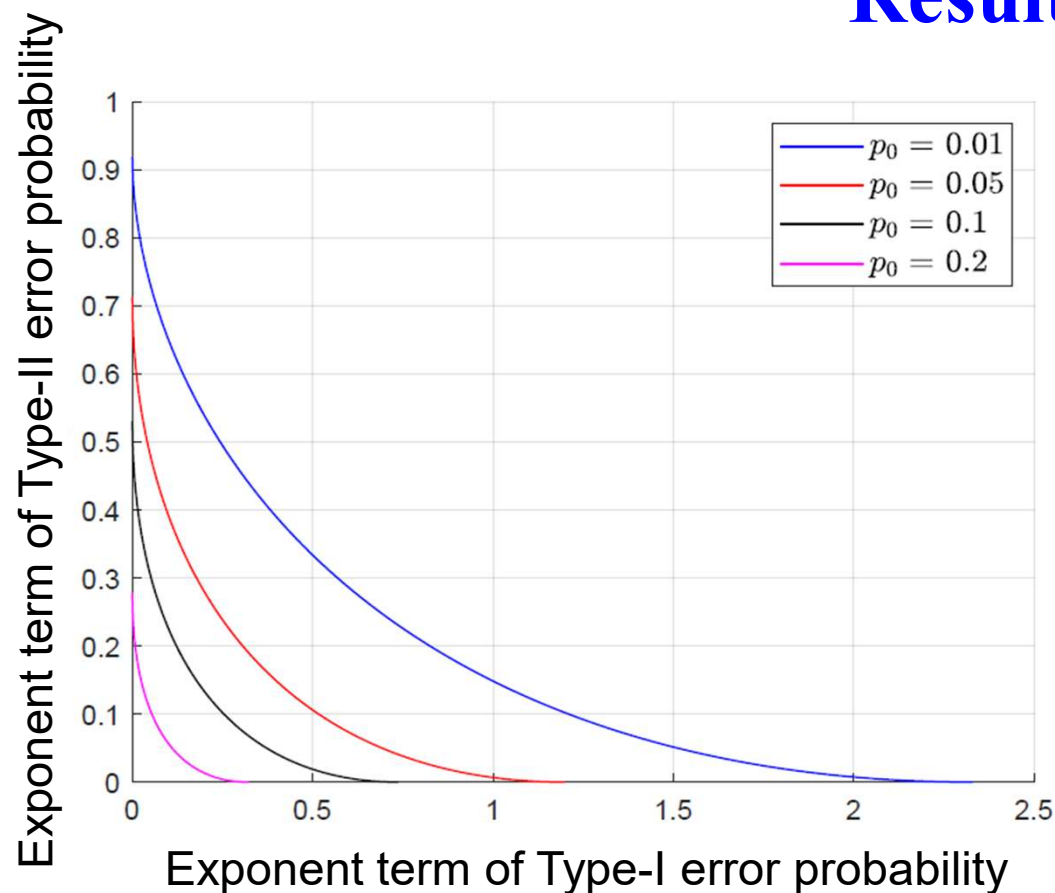
Encoding: $\mathbf{u}_q^k = \arg \min_{\mathbf{u}^k \in \{0,1\}^k} d_H(\mathbf{x}^n, \mathbf{x}_q^n)$

Neyman Pearson Test: $\sum_{j=1}^n (x_{q,j} \oplus y_j) \leq \gamma_t$, where $\mathbf{x}_q^n = \mathbf{u}^k \mathbf{G}$

γ_t is the threshold that determines the α_n and the β_n values.



Binary DHT against Orthogonality: Recent Results



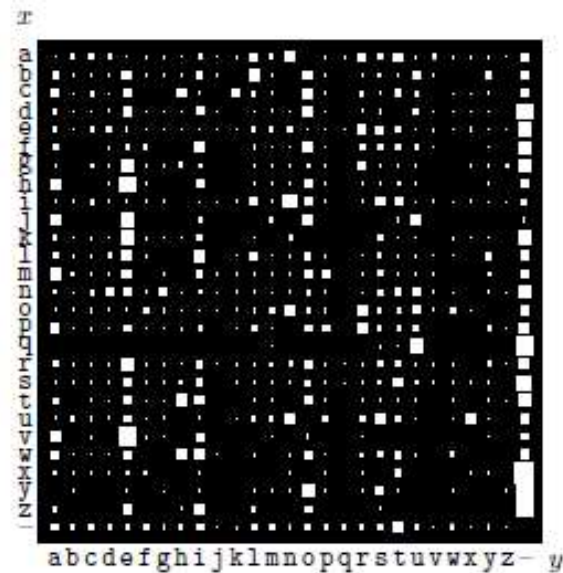
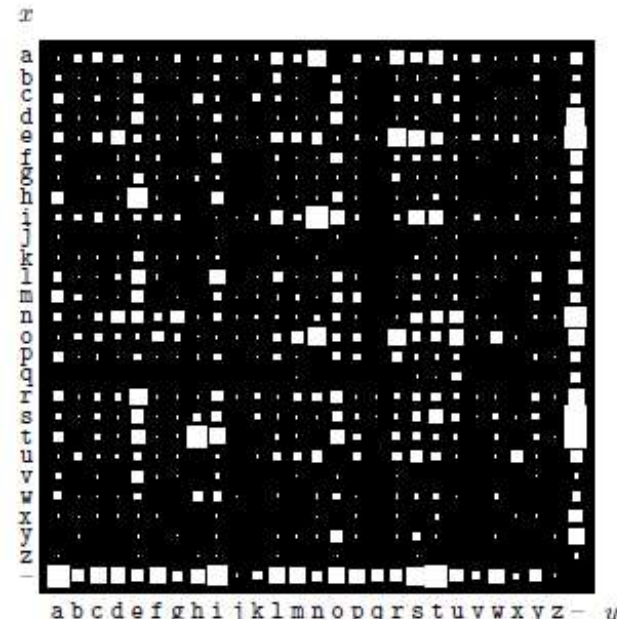
English Letters Appearance Probabilities

3.3 Semantic Communications

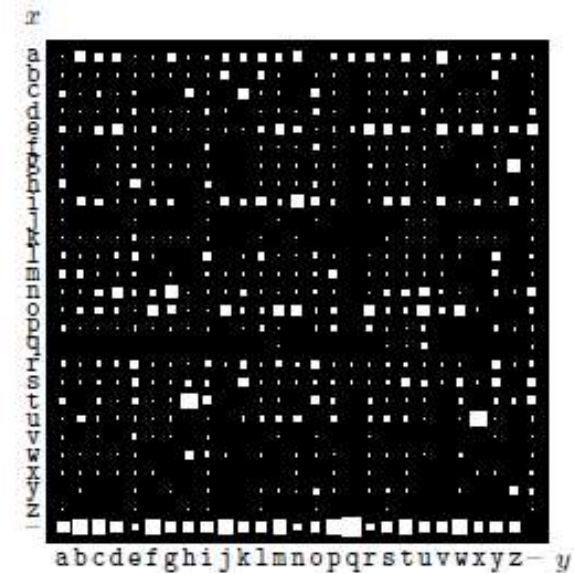
Copied from:

| i | a_i | p_i | |
|-----|-------|--------|---|
| 1 | a | 0.0575 | a |
| 2 | b | 0.0128 | b |
| 3 | c | 0.0263 | c |
| 4 | d | 0.0285 | d |
| 5 | e | 0.0913 | e |
| 6 | f | 0.0173 | f |
| 7 | g | 0.0133 | g |
| 8 | h | 0.0313 | h |
| 9 | i | 0.0599 | i |
| 10 | j | 0.0006 | j |
| 11 | k | 0.0084 | k |
| 12 | l | 0.0335 | l |
| 13 | m | 0.0235 | m |
| 14 | n | 0.0596 | n |
| 15 | o | 0.0689 | o |
| 16 | p | 0.0192 | p |
| 17 | q | 0.0008 | q |
| 18 | r | 0.0508 | r |
| 19 | s | 0.0567 | s |
| 20 | t | 0.0706 | t |
| 21 | u | 0.0334 | u |
| 22 | v | 0.0069 | v |
| 23 | w | 0.0119 | w |
| 24 | x | 0.0073 | x |
| 25 | y | 0.0164 | y |
| 26 | z | 0.0007 | z |
| 27 | - | 0.1928 | - |

$P(x, y)$

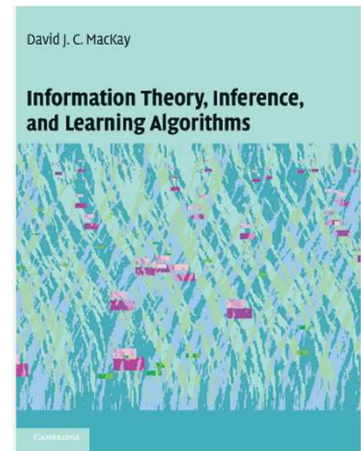


(a) $P(y|x)$



(b) $P(x|y)$

Figure 2.1. Probability distribution over the 27 outcomes for a randomly selected letter in an English language document



Conditioned English Letter Appearance

If we can evaluate conditional probabilities $p(x_i|x_{i-1})$, $p(x_i|x_{i-1}, x_{i-2})$, ..., $p(x_i|x_{i-1}, x_{i-2}, \dots, x_{i-n})$, empirically or theoretically and create a Markov model of the letter appearances, we can reduce the rate required to encode English.

Shannon's landmark paper presents artificially created English sentences!

Using empirical
knowledge $p(x_i)$

1. *Zero-order approximation.* (The symbols are independent and equiprobable.)

XFOML RXKHRJFFJUJ ZLPWCFWKCYJ
FFJEYVKCQSGXYD QPAAMKBZAACIBZLHJQD

$p(x_i|x_{i-1})$

2. *First-order approximation.* (The symbols are independent. Frequency of letters matches English text.)

OCRO HLI RGWR NMIELWIS EU LL NBNESBYA TH EEI
ALHENTIITPA OOBTTVA NAH BRL

$p(x_i|x_{i-1}, x_{i-2})$

3. *Second-order approximation.* (The frequency of pairs of letters matches English text.)

ON IE ANTSOUTINYS ARE T INCTORE ST BE S DEAMY
ACHIN D ILONASIVE TUCCOOWE AT TEASONARE FUSO
TIZIN ANDY TOBE SEACE CTISBE

4. *Third-order approximation.* (The frequency of triplets of letters matches English text.)

IN NO IST LAT WHEY CRATICT FROURE BERS GROCID
PONDENOME OF DEMONSTURES OF THE REPTAGIN IS
REGOACTIONA OF CRE

Higher-order Conditioning: Letter and Word Levels

Using empirical
knowledge of
 $p(x_i|x_{i-1}, x_{i-2}, x_{i-3})$

5. *Fourth-order approximation.* (The frequency of quadruplets of letters matches English text. Each letter depends on the previous three letters. This sentence is from Lucky's book, *Silicon Dreams* [183].)

THE GENERATED JOB PROVIDUAL BETTER TRAND THE
DISPLAYED CODE, ABOVERY UPONDULTS WELL THE
CODERST IN THESTICAL IT DO HOCK BOTHE MERG.
(INSTATES CONS ERATION. NEVER ANY OF PUBLE AND TO
THEORY. EVENTIAL CALLEGAND TO ELAST BENERATED IN
WITH PIES AS IS WITH THE)

Instead of continuing with the letter models, we jump to word models.

Using empirical
knowledge of the
word appearance
probability $p(w_i)$

6. *First-order word model.* (The words are chosen independently but with frequencies as in English.)

REPRESENTING AND 3PEEDILY I3 AN GOOD APT OR COME
CAN DIFFERENT NATURAL HERE HE THE A IN CAME THE TO
OF TO EXPERT GRAY COME TO FURNISHES THE LINE
MESSAGE HAD BE THESE.

$p(w_i|w_{i-1}, w_{i-2})$

7. *Second-order word model.* (The word transition probabilities match English text.)

THE HEAD AND IN FRONTAL ATTACK ON AN ENGLISH
WRITER THAT THE CHARACTER OF THIS POINT IS
THEREFORE ANOTHER METHOD FOR THE LETTERS THAT THE
TIME OF WHO EVER TOLD THE PROBLEM FOR AN
UNEXPECTED

With the 4th order model, Shannon showed that 2.8 bits are enough to express one English letter!

Adaptive Morse Code

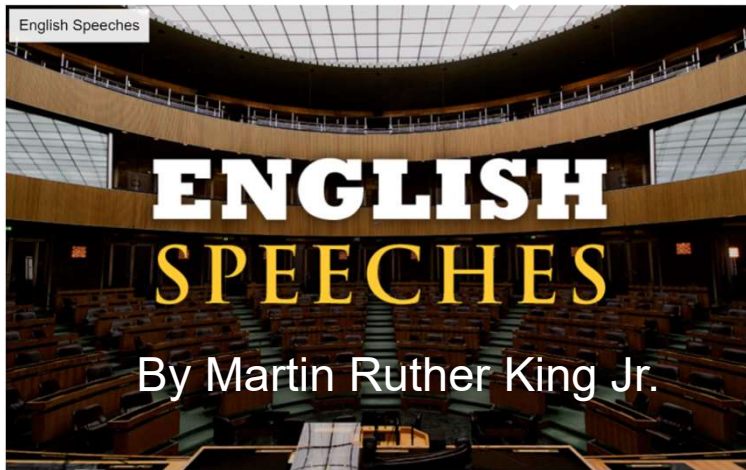
Semantic Communications

Morse Code Alphabet

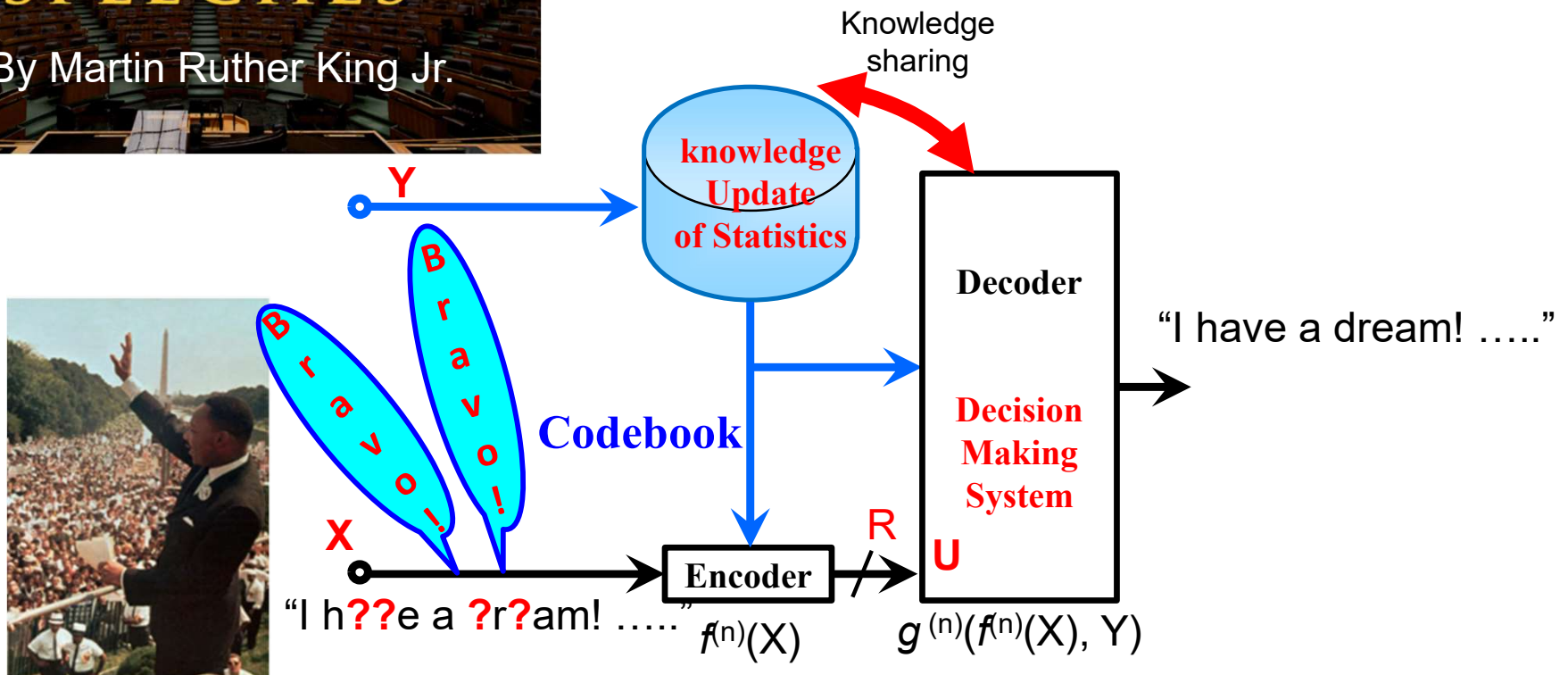
| | | | | | |
|---|--------|---|-------|---|---------|
| A | •- | N | -• | 0 | ----- |
| B | -...• | O | --- | 1 | •----- |
| C | -...• | P | •...• | 2 | ••---- |
| D | -...• | Q | --•- | 3 | •••--- |
| E | • | R | •-• | 4 | ••••- |
| F | ••...• | S | ••• | 5 | ••••• |
| G | --• | T | - | 6 | -•••• |
| H | •••• | U | ••- | 7 | --••• |
| I | •• | V | •••- | 8 | ----•• |
| J | •---- | W | •-- | 9 | ----• |
| K | -•- | X | -••- | . | •-•-•- |
| L | •...• | Y | -•-- | , | --••--- |
| M | -- | Z | --•• | ? | ••••• |

- The higher the appearance probability, the shorter the code length, following the **Huffman coding rule**.
- However, the appearance probabilities should change according to the sources, such as Book, Video, File type,, situation, person, ... ← **Semantic Dependency**.
- **Joint Source and Channel Coding and Adaptive**, to exploit higher order **Markov Source Memory Structure** and **Error Correction Capability**, depending on **“Semantics”** → Learning needed to construct **Corpus** for *Natural Language Processing*!

Knowledge updating for Semantic Communications: a WZ Problem



Share the updated knowledge of pdf, dynamics, Share the updated knowledge of pdf, dynamics,, representing “Personality”.



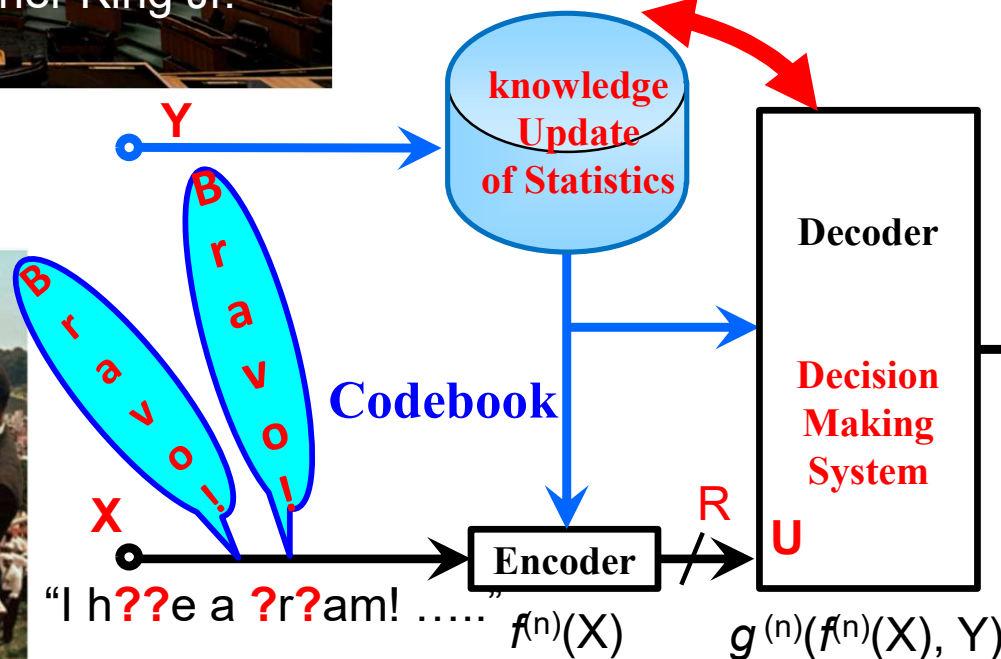
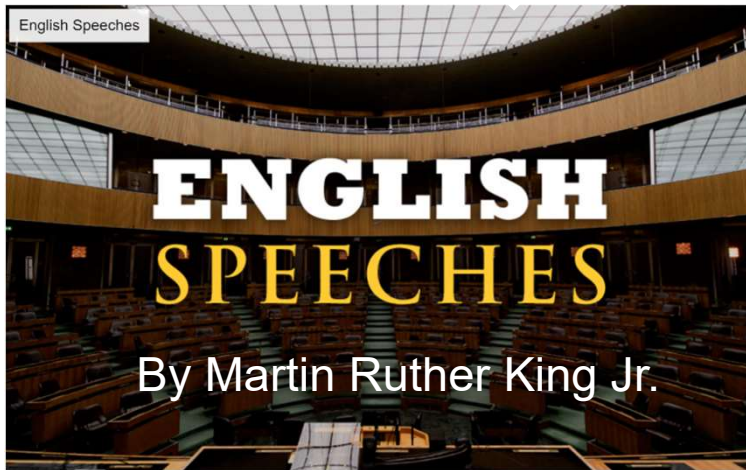
Knowledge updating for Semantic Communications: a WZ Problem

Updating the knowledge to
under the rate R given, so that:

β_n , minimized subject to $\alpha_n \leq \varepsilon$

$\text{Min } I(X; U) - I(Y; U) = \text{Min } I(X; U|Y)$

Share the updated knowledge of
pdf, dynamics,, representing
“**Personality**”.



Combining SC with DHT

$H_0|H_1$

“I have a dream!”

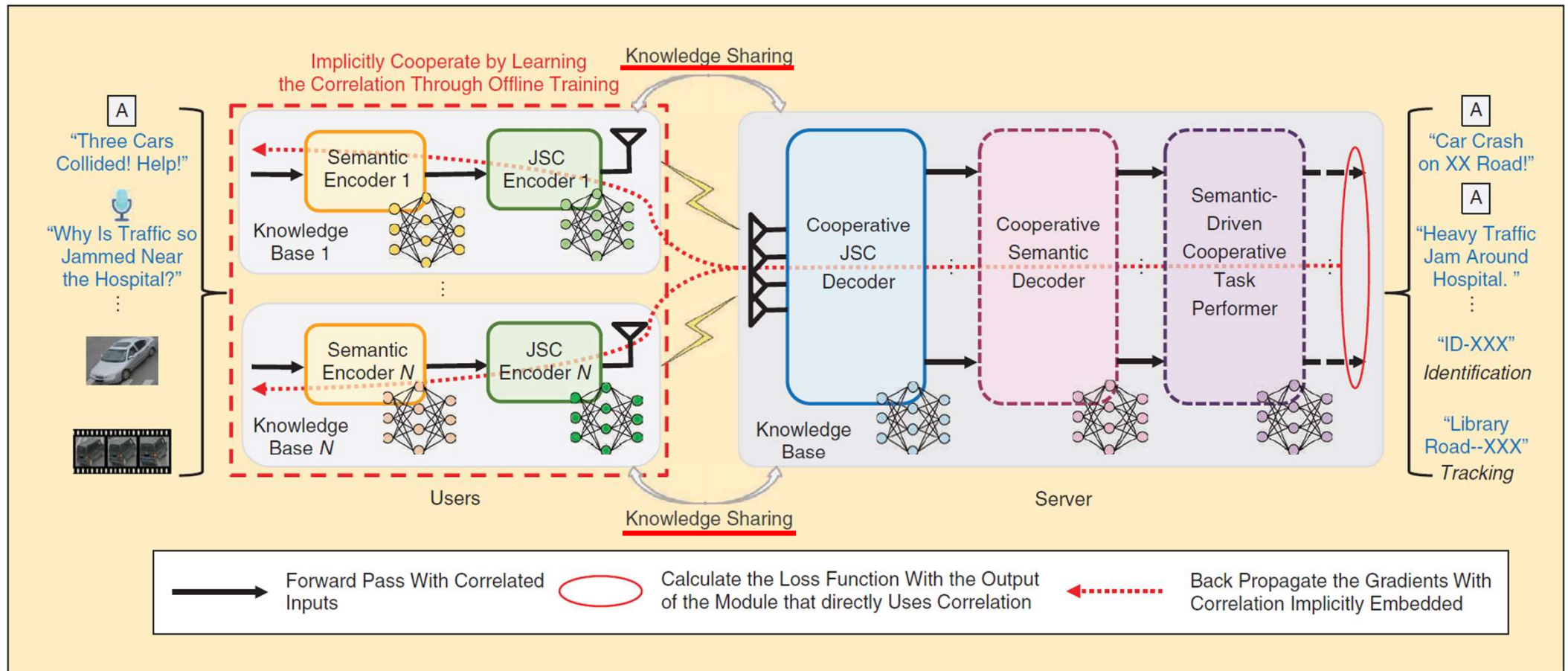
β_n , minimized subject
to $\alpha_n \leq \varepsilon$

SEMANTIC COMMUNICATION FOR THE INTERNET OF VEHICLES

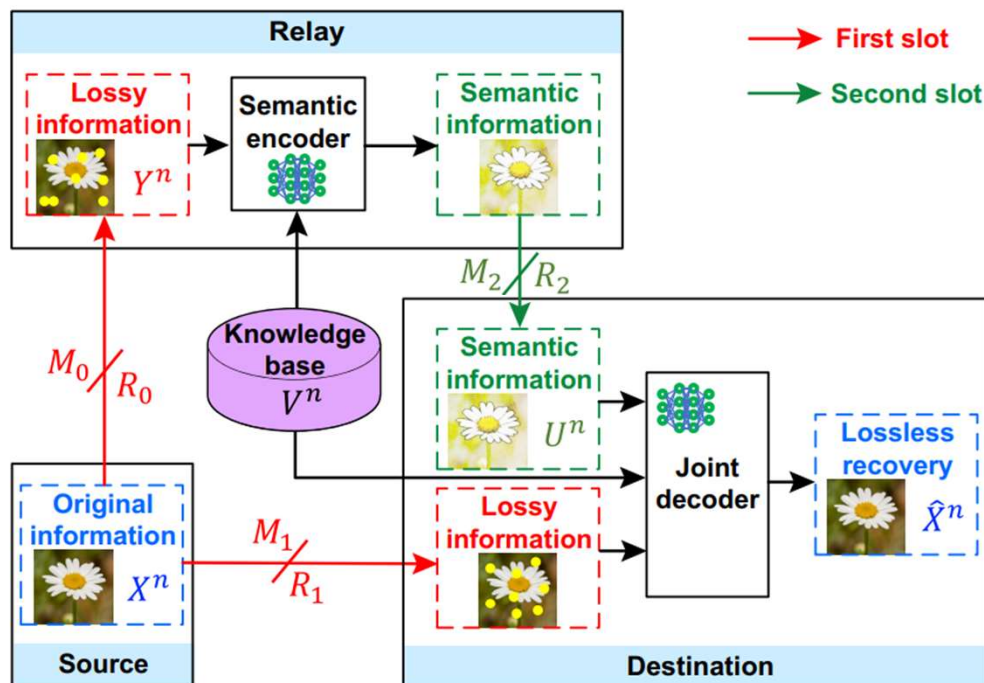
A Multiuser Cooperative Approach

Wenjun Xu¹, Yimeng Zhang¹, Fengyu Wang¹, Zhijin Qin¹,
Chenyao Liu², and Ping Zhang²

IEEE VTS Magazine Volume 18, No. 1, pp. 100-109



Semantic Forward



We know already (see *Lossless Relaying*)

$$R_0 \geq I(X; Y)$$

$$R_1 \geq H(X|U),$$

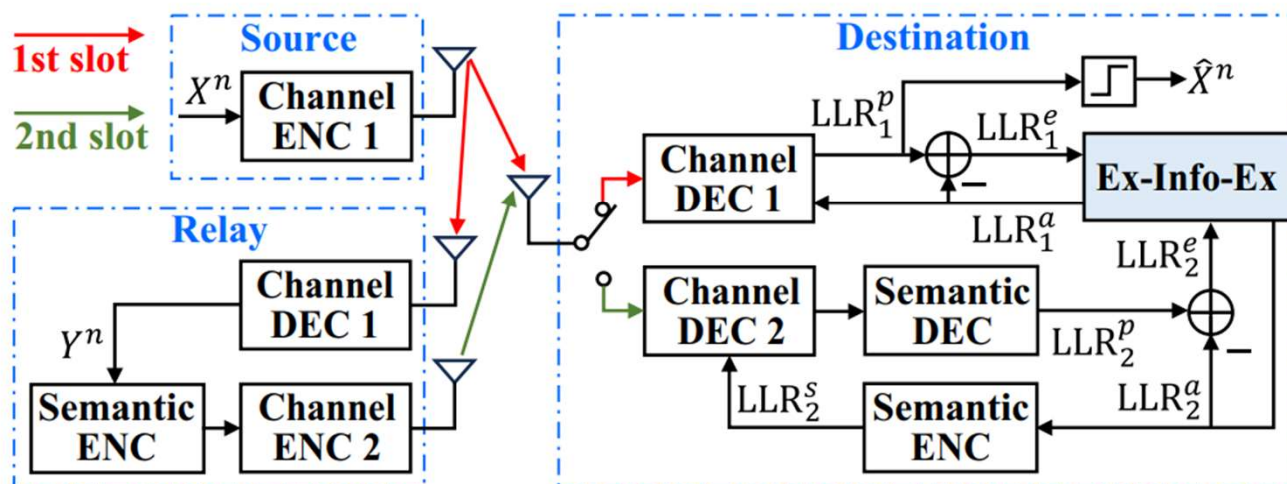
$$R_2 \geq I(Y; U).$$

With *Semantic* encoder and decoder,

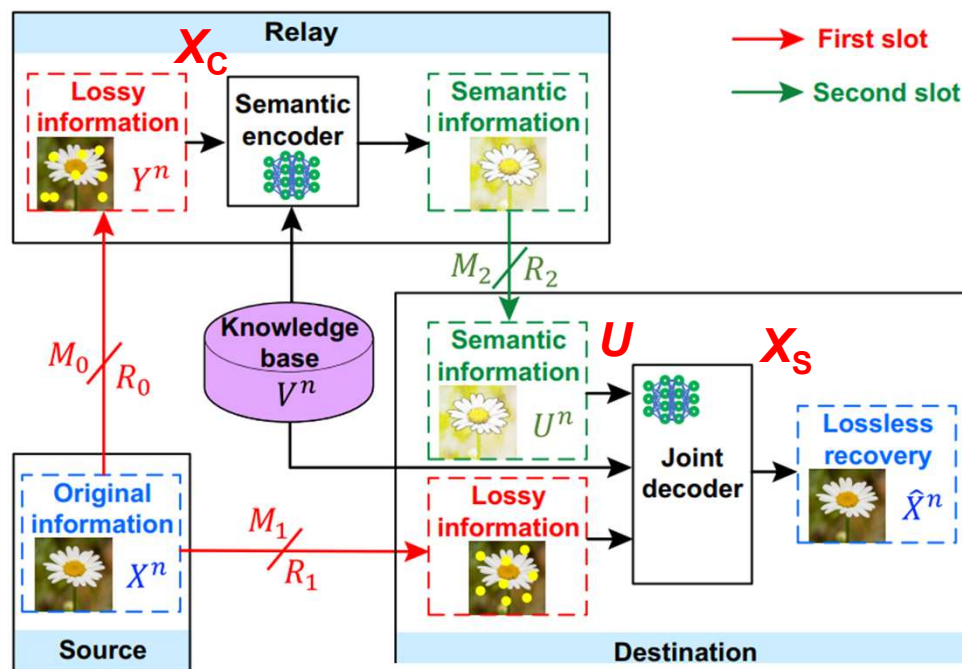
$$R_1 \geq H(X|U, V)$$

$$R_2 \geq I(Y; U|V).$$

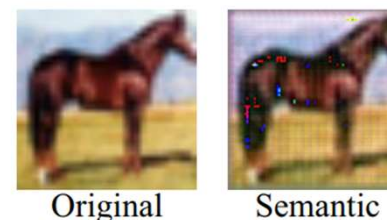
V reduces the required rate \rightarrow Compression



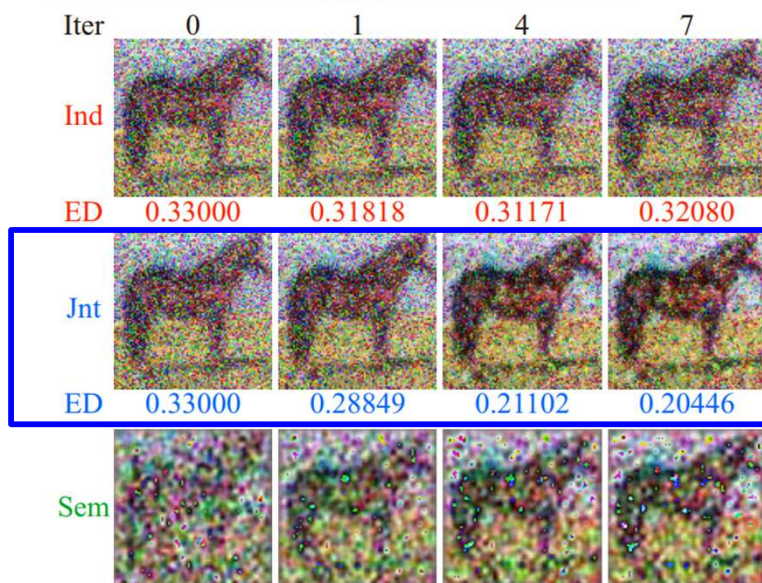
Semantic Forward



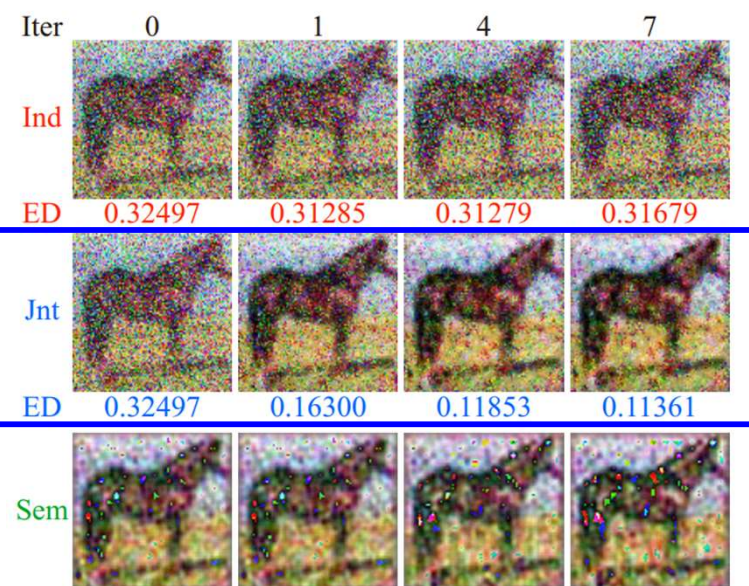
$$Y = X \oplus E, \text{ where } E \sim \text{Bern}(\rho)$$



(a) Example with $\rho = 0$.

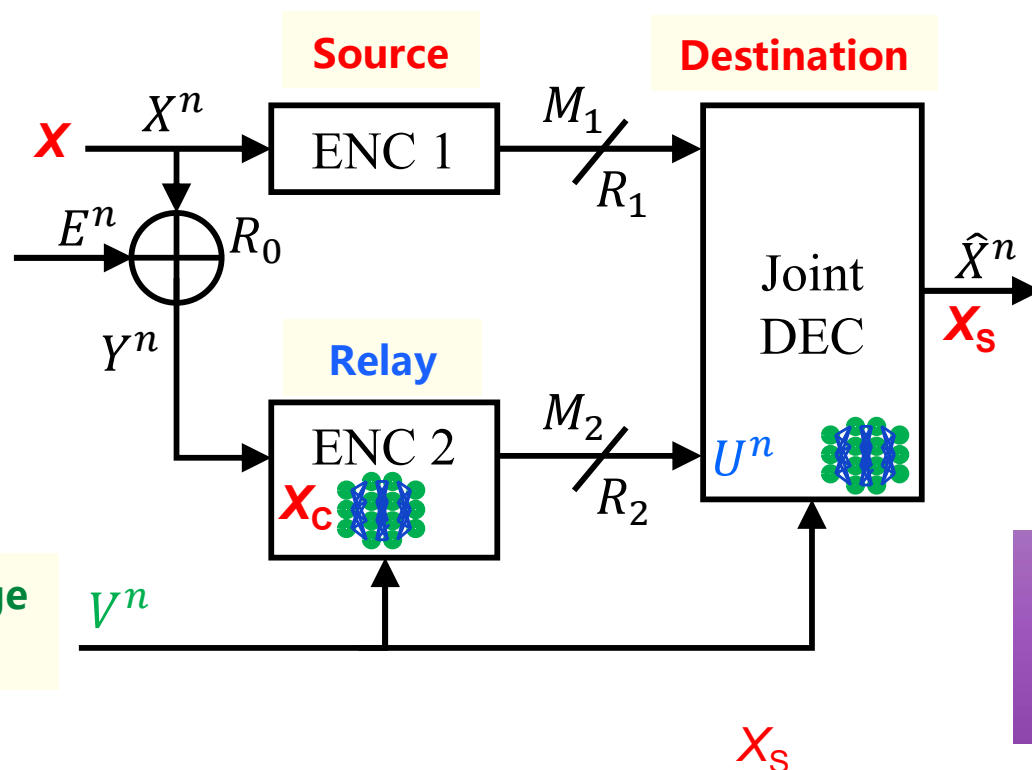


(c) $\gamma_1 = -5$ dB, $\rho = 0.35$.



(b) $\gamma_1 = -5$ dB, $\rho = 0.1$.

Semantic Forward



Slepian Wolf (Lossless) Formulation

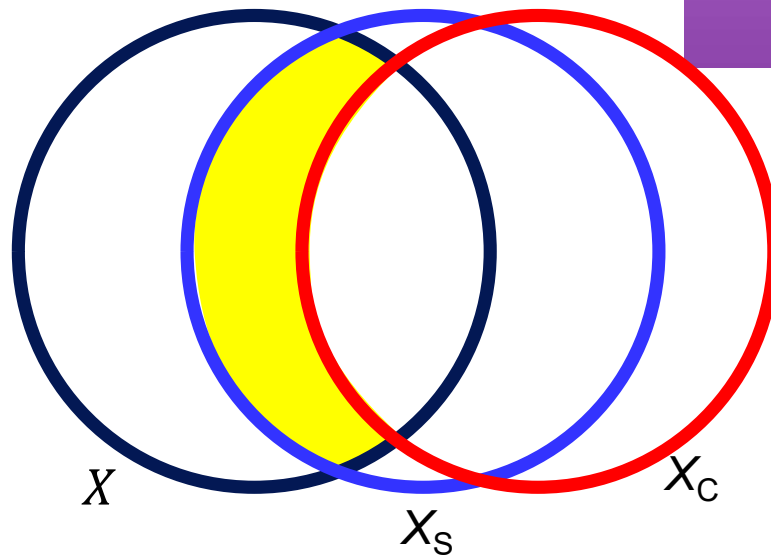
$$R_0 \geq I(X; Y)$$

$$R_1 \geq H(X|U, V)$$

$$R_2 \geq I(Y; U|V)$$

Rate requirement is reduced by the side information V

Optimal neural network forms Markov chain by making adjustment of codebook pdf to the observations!.

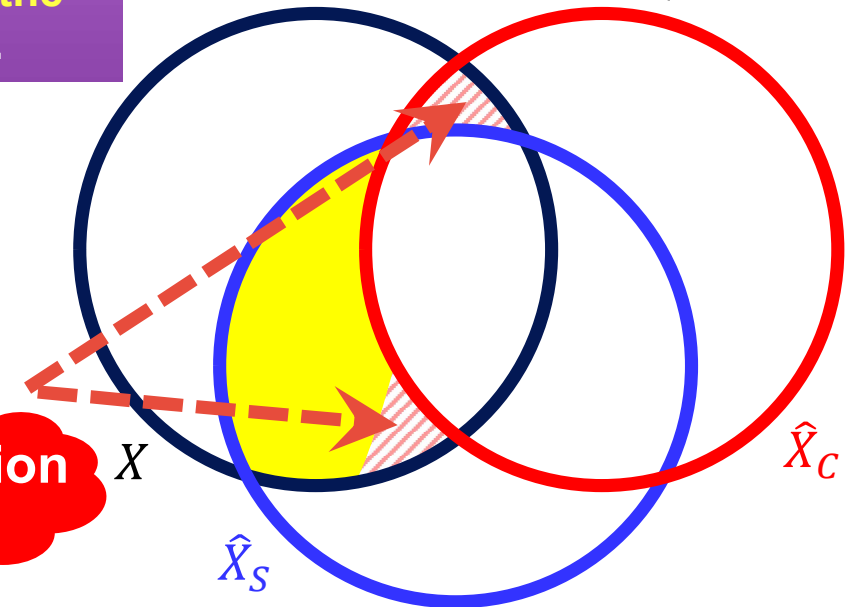


Wyner Ziv Formulation

Markov chain

$$X \rightarrow X_C \rightarrow X_S$$

$$I(X; X_C) - I(X; X_S) = I(X; X_C | X_S)$$



Not Markov chain

$$X \rightarrow \hat{X}_C \rightarrow \hat{X}_S$$

$$0 < I(X; X_C | X_S) < I(X; \hat{X}_C) - I(X; \hat{X}_S)$$

NN may lose some information while it introduce more side information, V, by training.
The gain achieved by semantic encoder-decoder chain can be positive.

It is reasonable to evaluate the Loss = $I(X; \hat{X}_C) - I(X; \hat{X}_S) - \min I(X; X_C | X_S)$

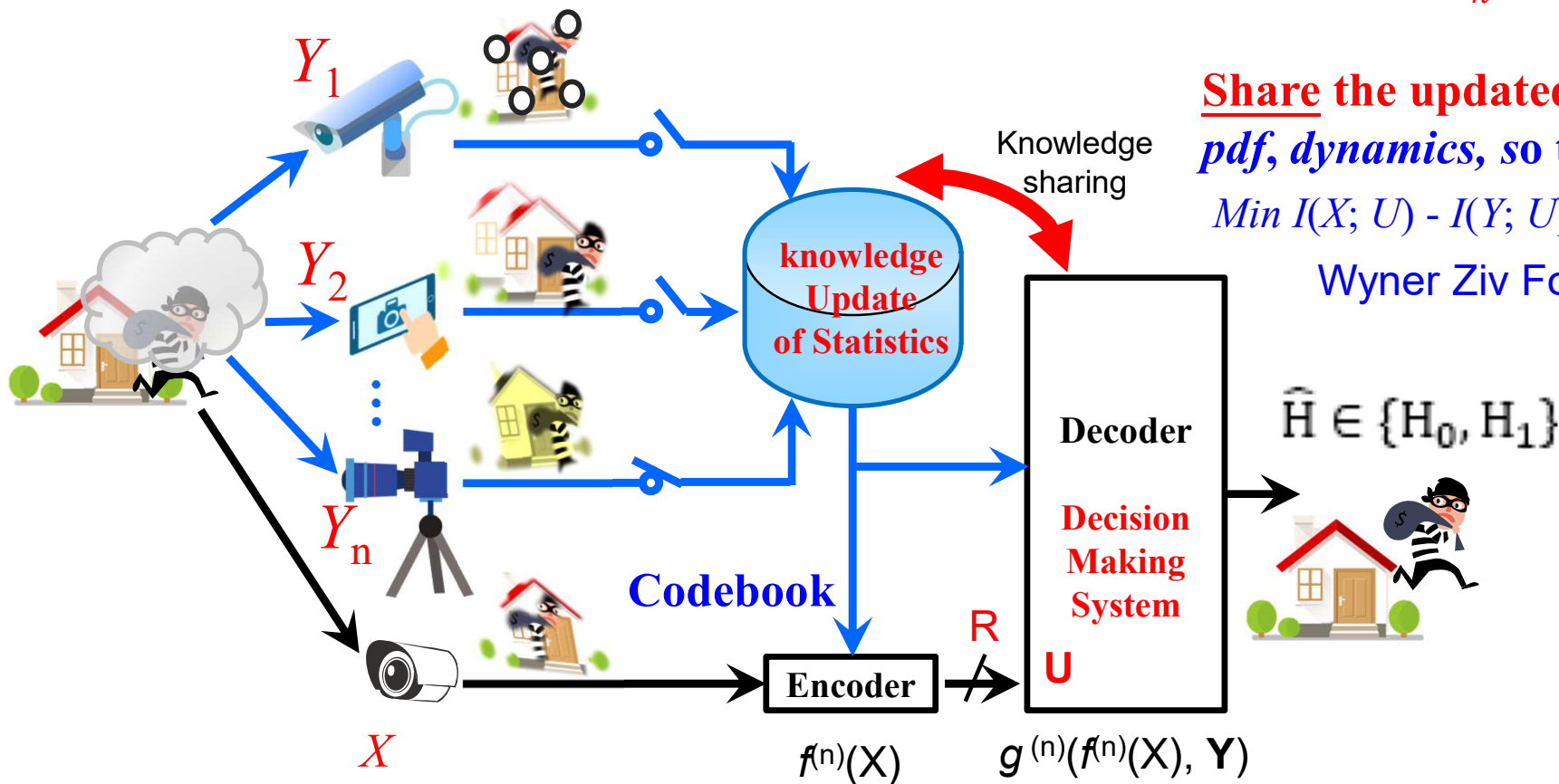
3.4 Training Process in Machine Learning

Updating the knowledge to minimize β_n under the constraints $\alpha_n \leq \varepsilon$ and rate= R :

Share the updated knowledge of *pdf, dynamics*, so that $U \rightarrow X \rightarrow Y$

$$\text{Min } I(X; U) - I(Y; U) = \text{Min } I(X; U|Y)$$

Wyner Ziv Formulation



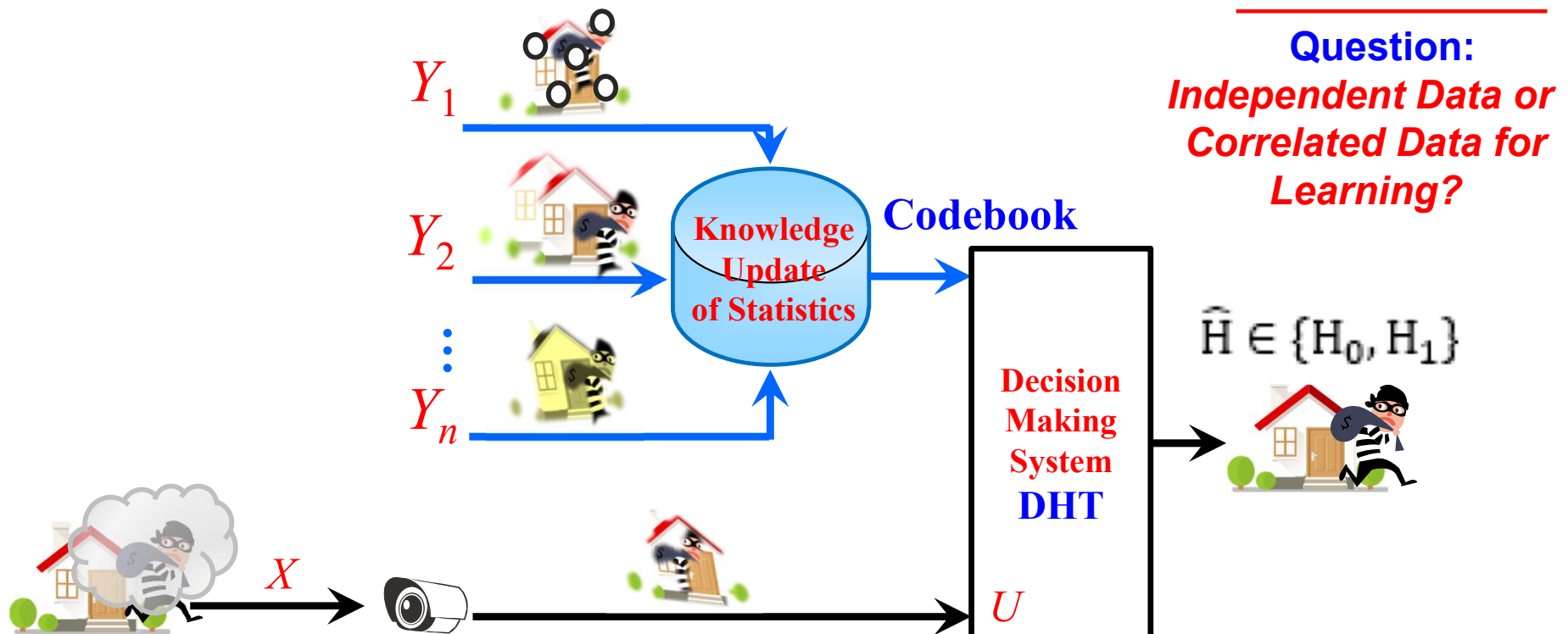
Learning, in the WZ framework

X corresponding to the Current Observation, U to the Lossy Reconstruction, and Y to Data Set for the Learning of Probability Distribution for knowledge updating followed by Codebook generation!

$$Y = (Y_1, Y_2, \dots, Y_n)$$

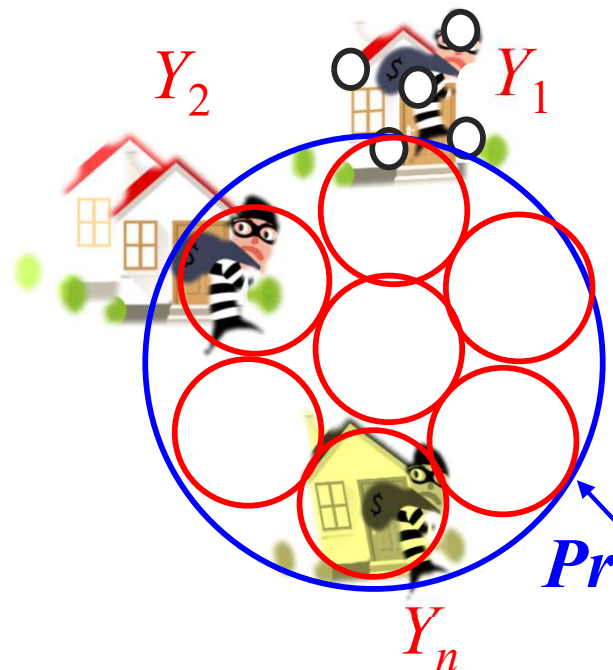
Wyner Ziv Formulation

$$R(D) = \min \{ I(X; U) - I(U; Y_1, Y_2, \dots, Y_n) \} = \min I(X; U | \underbrace{Y_1, Y_2, \dots, Y_n}_{\text{Question:}})$$

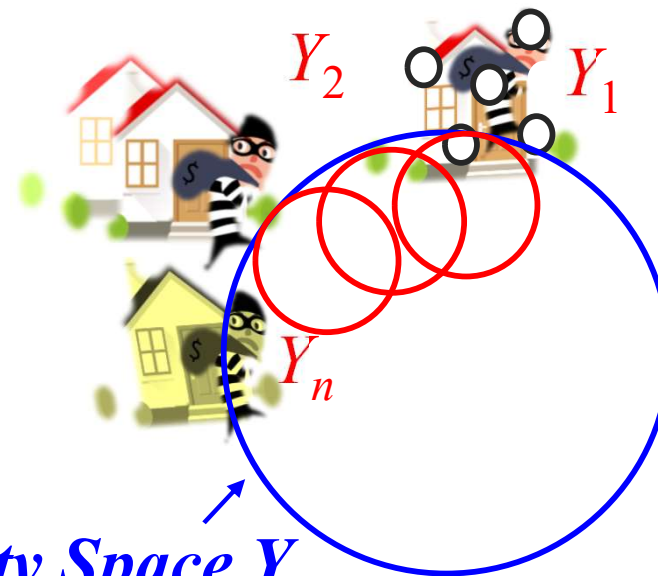


Learning in the WZ framework: Open Questions

(1) Y is fully covered by sub-
 probability space Y_i without
 overlapping. → **Global Optimization**



(2) Y is NOT fully covered.
 Y_i are overlapping. → **Partial Optimization**



Decision on the observation $X =$  being correct or incorrect
 depends on the generated learning data by (1) or (2).

Ergodic vs. Instantaneous

(Global) (Partial)

(1) is suitable when *decision* is *Ergodic* (time average).

→ Learning requires **Large size of training data**. *Suitable for pre-training, such as ML.*

(2) is suitable when *decision* is *Instantaneous*. Learning data may require only **partial** data.

→ *Suitable for online-training by introducing a forgetting factor.*
A similarity to Information Bottleneck!

Connection to *Information Bottleneck*

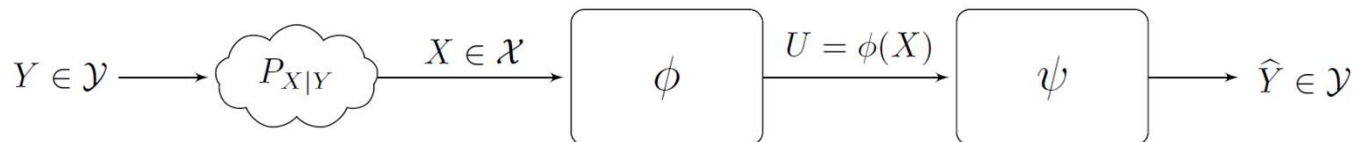


Tutorial

On the Information Bottleneck Problems: Models, Connections, Applications and Information Theoretic Views

Abdellatif Zaidi ^{1,2,*} and Iñaki Estella-Aguerri ² and Shlomo Shamai (Shitz) ³

Specifically, IB formulates the problem of extracting the relevant information that some signal $X \in \mathcal{X}$ provides about another one $Y \in \mathcal{Y}$ that is of interest as that of finding a representation U that is maximally informative about Y (i.e., large mutual information $I(U; Y)$) while being minimally informative about X (i.e., small mutual information $I(U; X)$).



Information Bottleneck as a classification problem

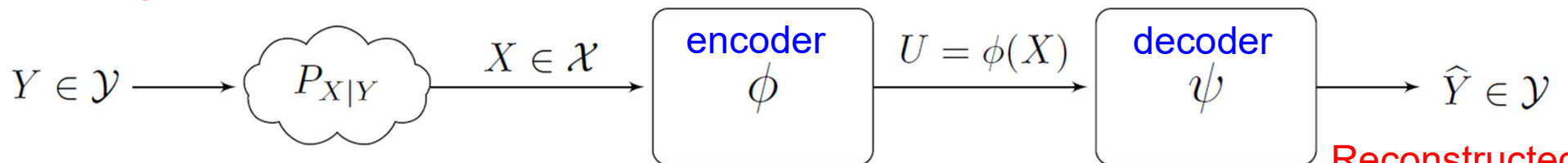
Specifically, IB formulates the problem of extracting the relevant information that some signal $X \in \mathcal{X}$ provides about another one $Y \in \mathcal{Y}$ that is of interest as that of finding a representation U that is maximally informative about Y (i.e., large mutual information $I(U; Y)$) while being minimally informative about X (i.e., small mutual information $I(U; X)$). In the IB framework, $I(U; Y)$ is referred

Medical Data Analysis: an Example

What is happening
in the **Organ/Tissue**

What we observe

Compressed data including
as much information Y as possible
while minimizing the rate.



Reconstructed

information
 Y , NOT X ,

But it may be **Lossy**

Notice; $U \rightarrow X \rightarrow Y$. However,

$$\mathcal{L}_{\beta}^{\text{IB},*} := \max_{P_{U|X}} I(U; Y) - \beta I(U; X).$$

Balancing factor

This term can not be **ZERO** because X has some information about Y .

The encoder and decoder need to **share** some **invisible** medical factors.

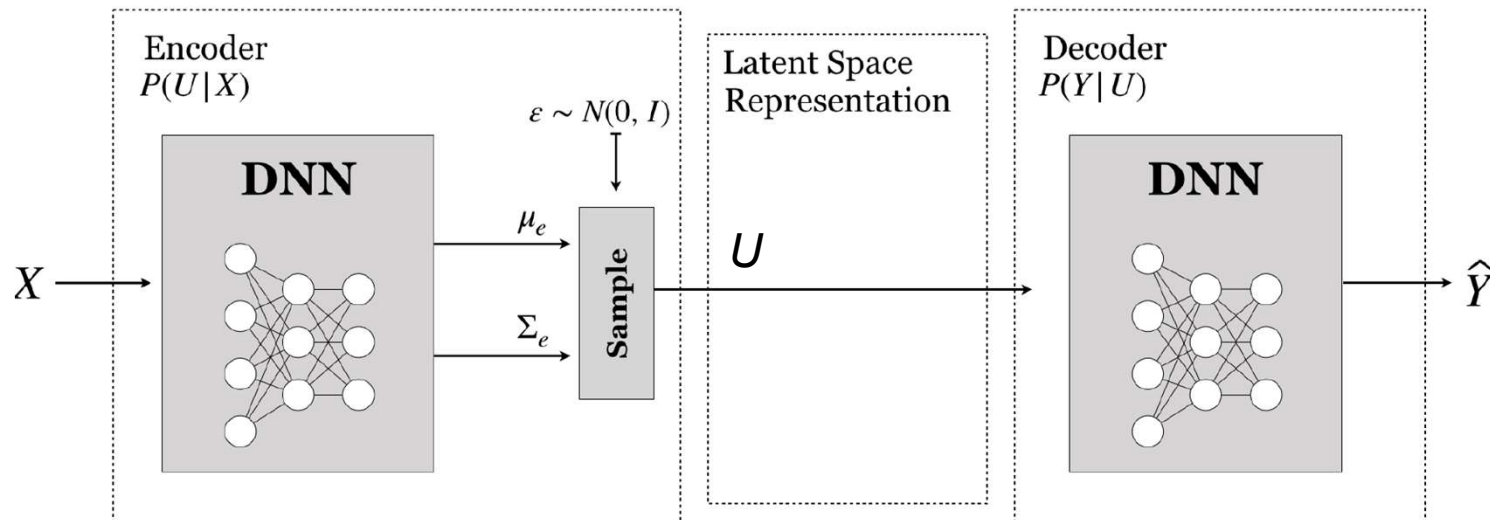
The roles can be performed by **DNN** which needs to be **"trained"**.

Information Bottleneck: Formulation under WZ Framework!

Accordingly, for a given β and source distribution $P_{X,Y}$, the optimal mapping of the data, denoted by $P_{U|X}^{*,\beta}$, is found by solving the IB problem, defined as

$$\mathcal{L}_{\beta}^{\text{IB}}(P_{U|X}) := I(U; Y) - \beta I(U; X)$$

with $U \rightarrow X \rightarrow Y$ and Lagrange Multiplier β . \longrightarrow We can use some optimization tools.



ITW 2024 Category

Welcome to ITW 2024 (<https://IEEE-ITW2024.org>)

Register a paper for 2024 IEEE Information Theory Workshop

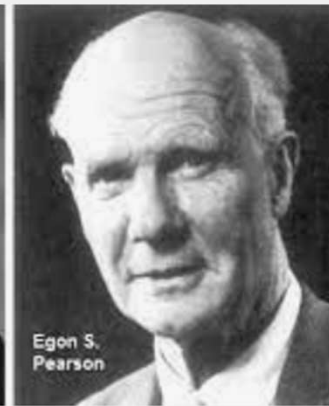
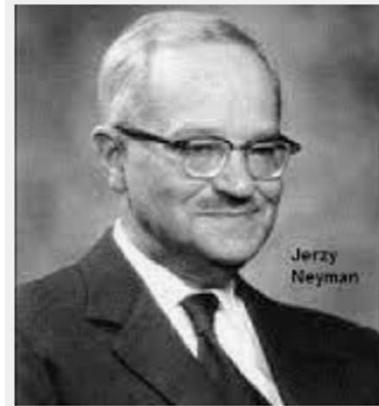
Topics

- ☐ Deep Learning for Communication Networks
- ☐ Detection and Estimation
- ☐ Distributed Storage and Computing
- ☐ Emerging Applications of Information Theory
- ☐ Information Theory and Statistics
- ☐ Information Theory for Decision and Control
- ☐ Information Theory in Biology
- ☐ Information Theory in Computer Science



ITW'2024

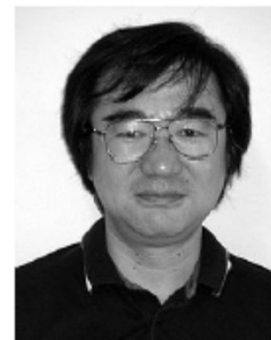
Any Questions?



My **SISU** Continues.
Thank you!

Do they meet
in 6G Networks?

See you soon again somewhere in the world!



Achievable Error Exponent [Ismaila, Elsa, Tad, 2023]

$$\theta \leq \min \{ \theta_{\text{test}}, \theta_{\text{bin}} \} , \text{ Tradeoff!} \longrightarrow \text{Random coding}$$

► $\theta_{\text{bin}} = R - \{ I(\mathbf{X}; \mathbf{U}) - I(\mathbf{U}; \mathbf{Y}) \}$

(~~U~~X~~Y~~), Markov chain

► $\theta_{\text{test}} = D(P_{\mathbf{U}|\mathbf{Y}} \| P_{\mathbf{U}|\mathbf{Y}}) + \{ I(\mathbf{X}; \mathbf{U}) - \bar{I}(\mathbf{X}; \mathbf{U}) \}$

$$\bar{I}(\mathbf{X}; \mathbf{U}) = \limsup_{n \rightarrow \infty} \frac{1}{n} \log \frac{P_{\mathbf{U}^n | \mathbf{X}^n}(\mathbf{U}^n | \mathbf{X}^n)}{P_{\mathbf{U}^n}(\mathbf{U}^n)}$$

For a sequence $\{Z_n\}_{n=1}^{\infty}$:

$$\limsup_{n \rightarrow \infty} Z_n = \inf \left\{ \alpha \mid \lim_{n \rightarrow +\infty} \mathbb{P}(Z_n > \alpha) = 0 \right\},$$



A) Quantized-and-binning scheme

A) General source of \mathbf{X} , \mathbf{U} and

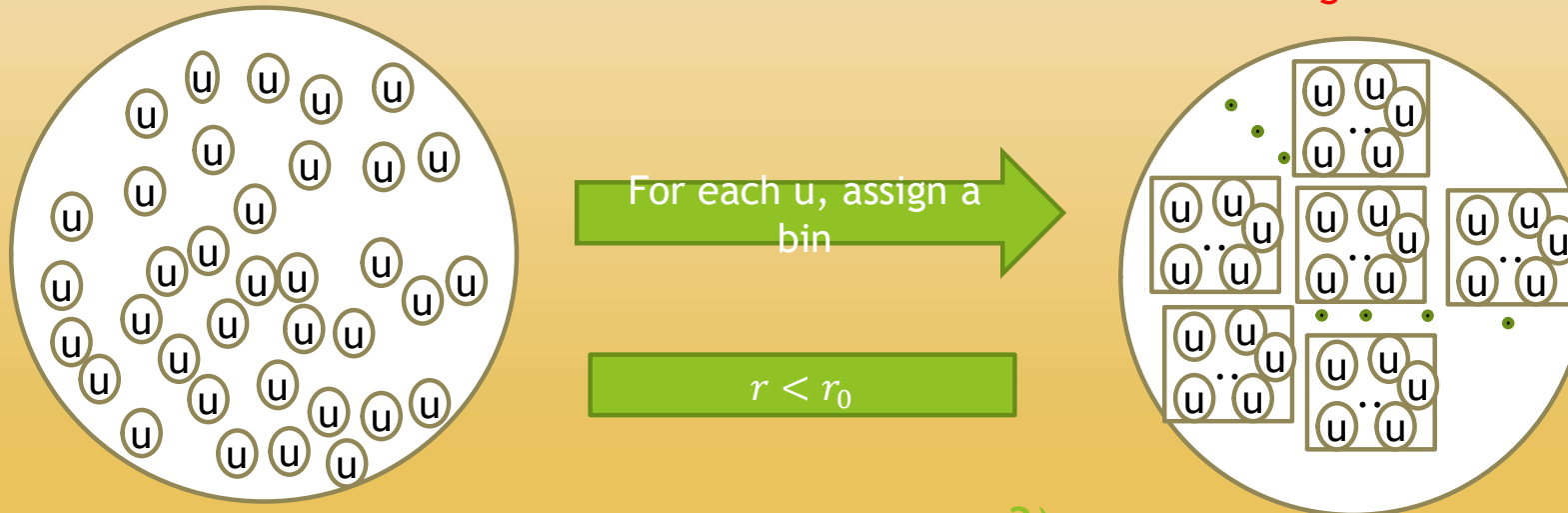
B) Quantized-and-binning coding scheme [Katz 2015]

1) Random codebook generation

○ Quantization
□ Binning

Quantization: generate e^{nr_0} u uniformly

Binning : e^{nr} bins



2)

Encoder

For a given x , the encoder sends the index of the bin to which u belongs to s.t (x,u) belongs to a certain set.

- If yes, send the bin index
- Otherwise, send an error message

3)

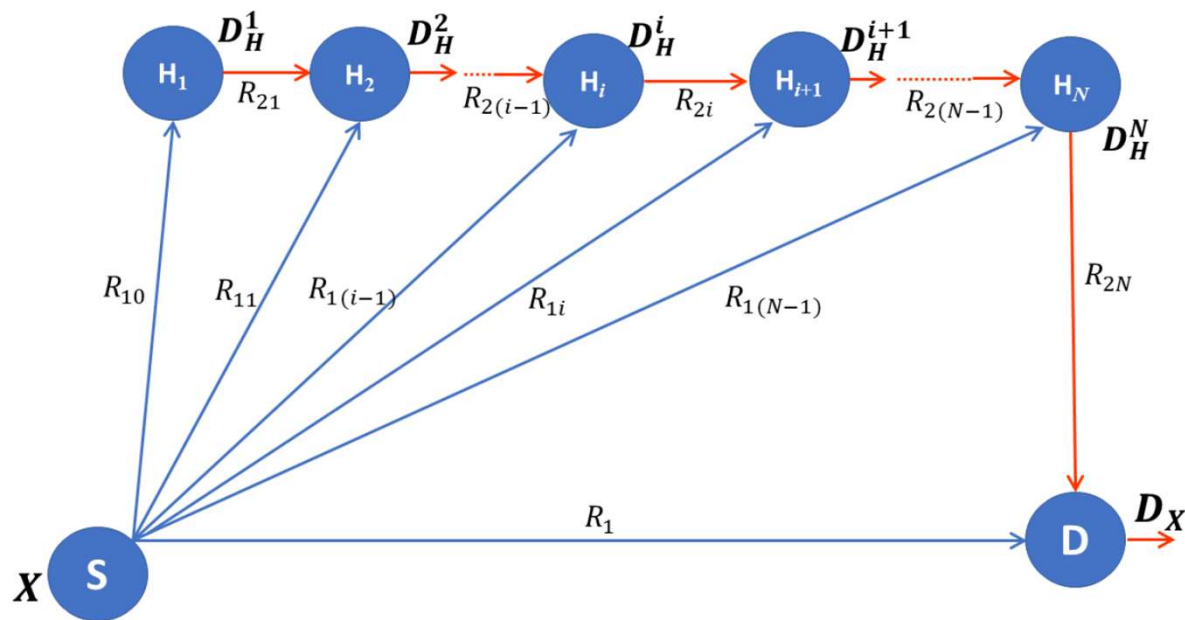
Decoder

a) Decoding: given the received index and y , pick u s.t (y,u) belongs to a certain set

b) Testing: checks if (u,y) belongs to the testing set

On the connected structure of lossy wireless communication

- ▶ DTF applications: solving connected lossy networks
 - ▶ Multi-hops serial relaying
 - ▶ Extension of the two-stages WZ to N stages



Stage N admissible rates

$$R_{2N} \geq 1 - H_b(p_{2N})$$

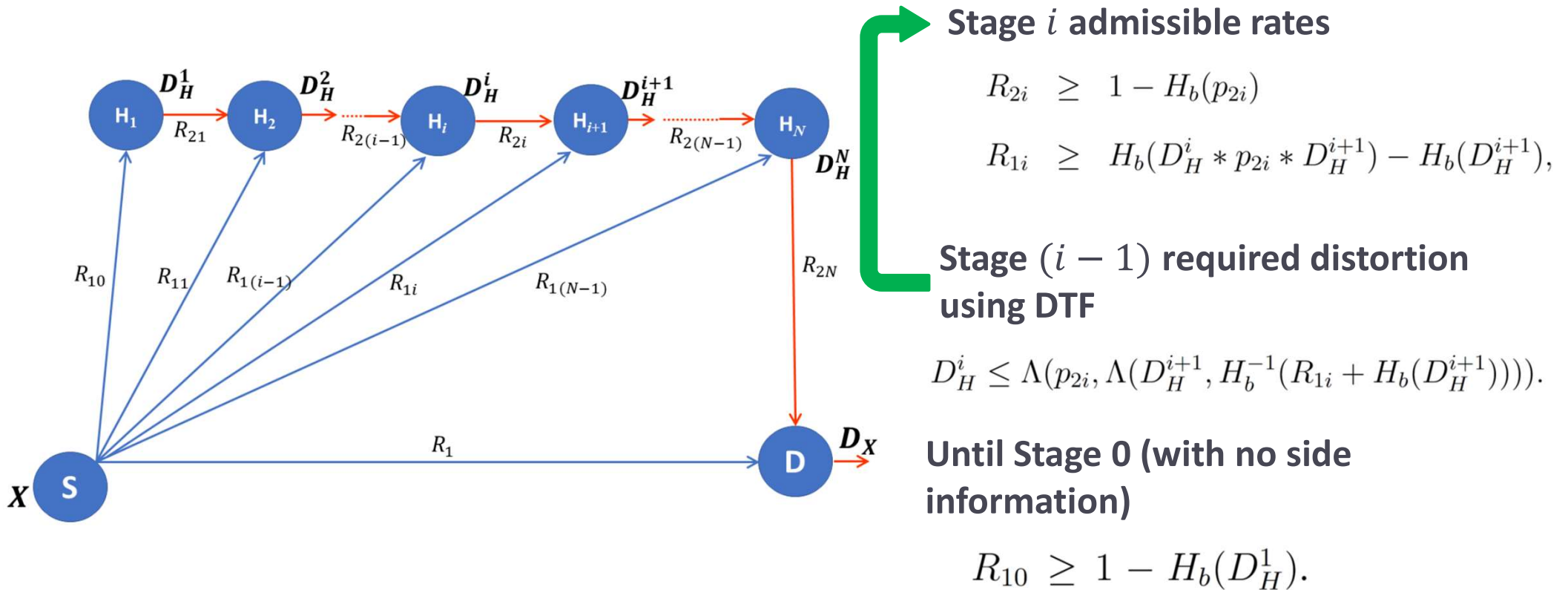
$$R_1 \geq H_b(D_H^N * p_{2N} * D_X) - H_b(D_X),$$

Stage $(N - 1)$ required distortion using DTF

$$D_H^N \leq \Lambda(p_{2N}, \Lambda(D_X, H_b^{-1}(R_1 + H_b(D_X)))).$$

On the connected structure of lossy wireless communication

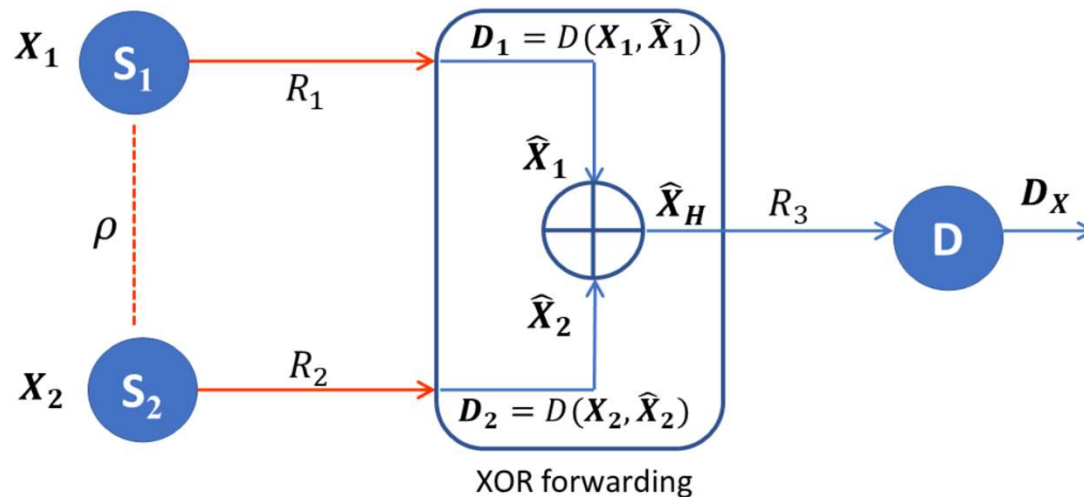
- ▶ DTF applications: solving connected lossy networks
 - ▶ Multi-hops serial relaying
 - ▶ Extension of the two-stages WZ to N stages



On the connected structure of lossy wireless communication

► DTF applications: solving connected lossy networks

► Two hops XOR lossy data forwarding



Stage 2 admissible rate

$$R_3 \geq 1 - H_b(p_3)$$

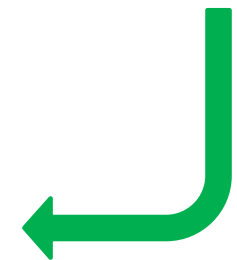
Stage 1 distortions constraint using DTF

$$D_H * p_3 \leq D_X$$

$$D_H \leq D_H^* = \Lambda(p_3, D_X).$$

From the XORed distortion to the sources' distortion

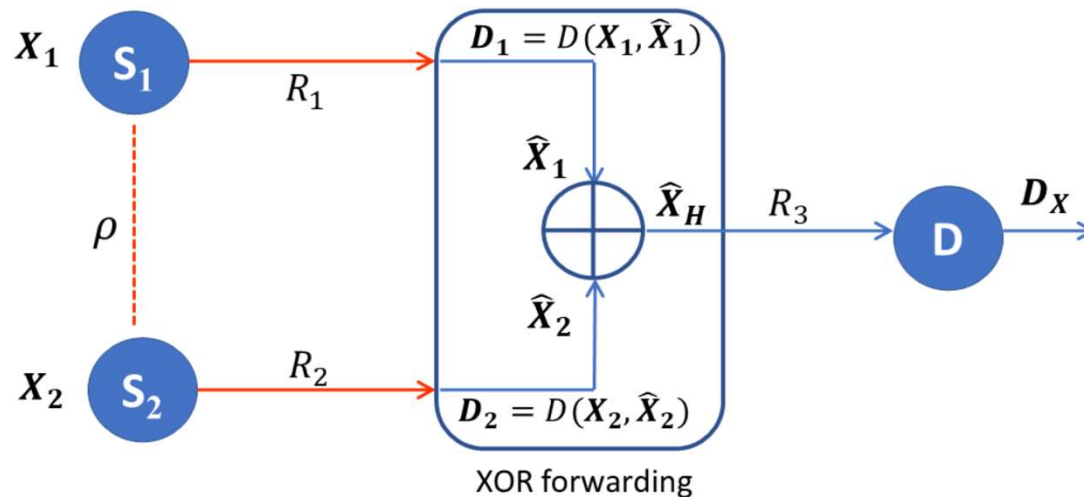
$$\begin{aligned} D_H &= P(\hat{X}_H \neq X) = P(\hat{X}_1 \oplus \hat{X}_2 \neq X_1 \oplus X_2) \\ &= P(\hat{X}_1 \oplus \hat{X}_2 \oplus X_1 \oplus X_2 = 1) \\ &= P((\hat{X}_1 \oplus X_1) \oplus (\hat{X}_2 \oplus X_2) = 1) = D_1 * D_2 \end{aligned}$$



On the connected structure of lossy wireless communication

► DTF applications: solving connected lossy networks

► Two hops XOR lossy data forwarding



By taking

$$D_1 * D_2 = D_H = D_H^*$$

$$\hookrightarrow D_2 = \Lambda(D_1, D_H^*)$$

Stage 1 admissible rate using distributed lossy multi-terminal source coding

$$R_1 \geq H_b(D_1 * D_2 * \rho) - H_b(D_1),$$

$$R_2 \geq H_b(D_1 * D_2 * \rho) - H_b(D_2),$$

$$R_1 + R_2 \geq 1 + H_b(D_1 * D_2 * \rho) - H_b(D_1) - H_b(D_2).$$

$$R_1 \geq H_b(D_H^* * \rho) - H_b(D_1),$$

$$R_2 \geq H_b(D_H^* * \rho) - H_b(\Lambda(D_1, D_H^*)),$$

$$R_1 + R_2 \geq 1 + H_b(D_H^* * \rho) - H_b(D_1) - H_b(\Lambda(D_1, D_H^*))$$