

情報理論的暗号の最近の発展と未解決問題

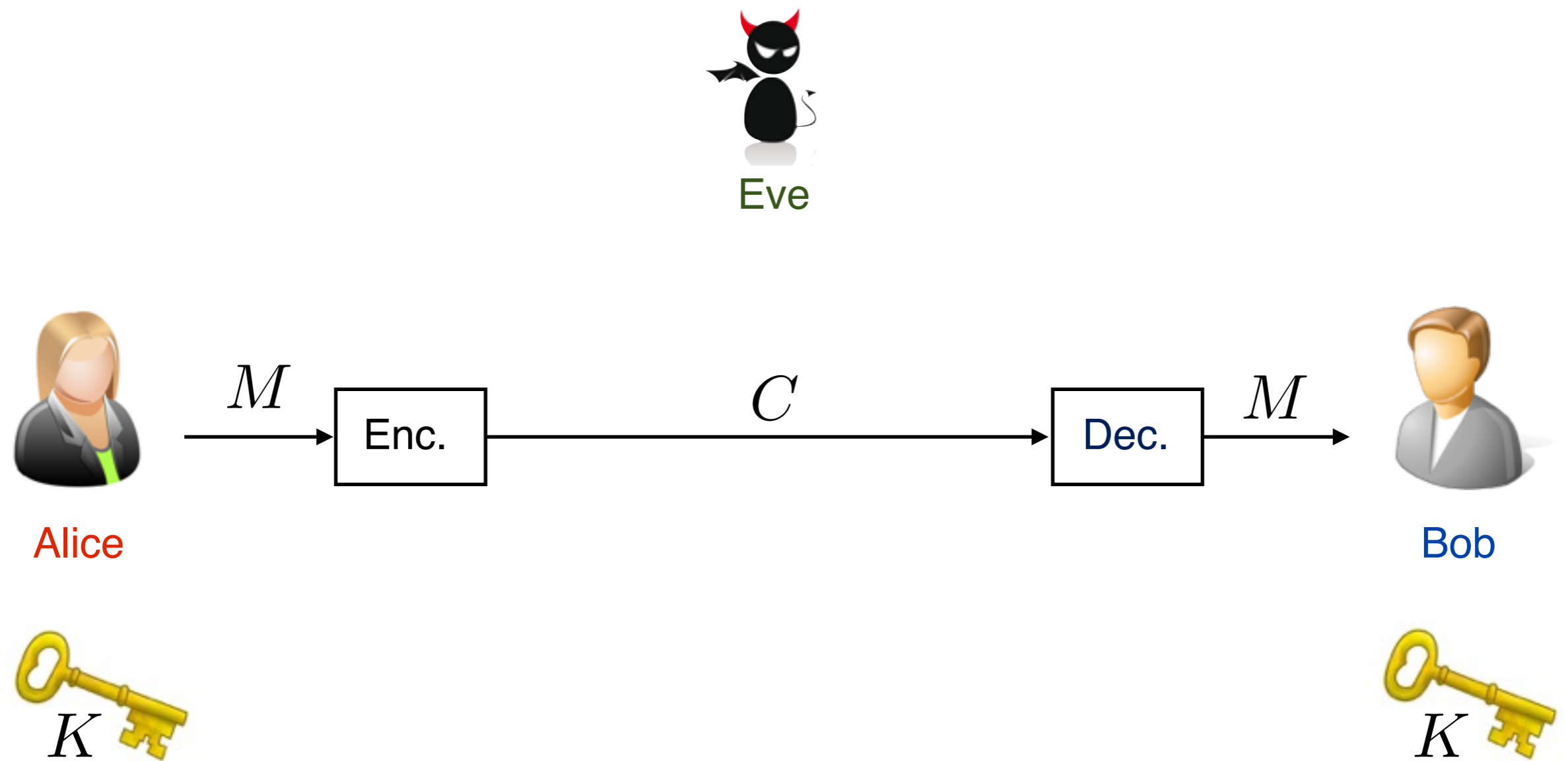
IT研究会@泉慶

November, 2017

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joint work with Himanshu Tyagi (IISc Bangalore)

Secret Key Cryptography



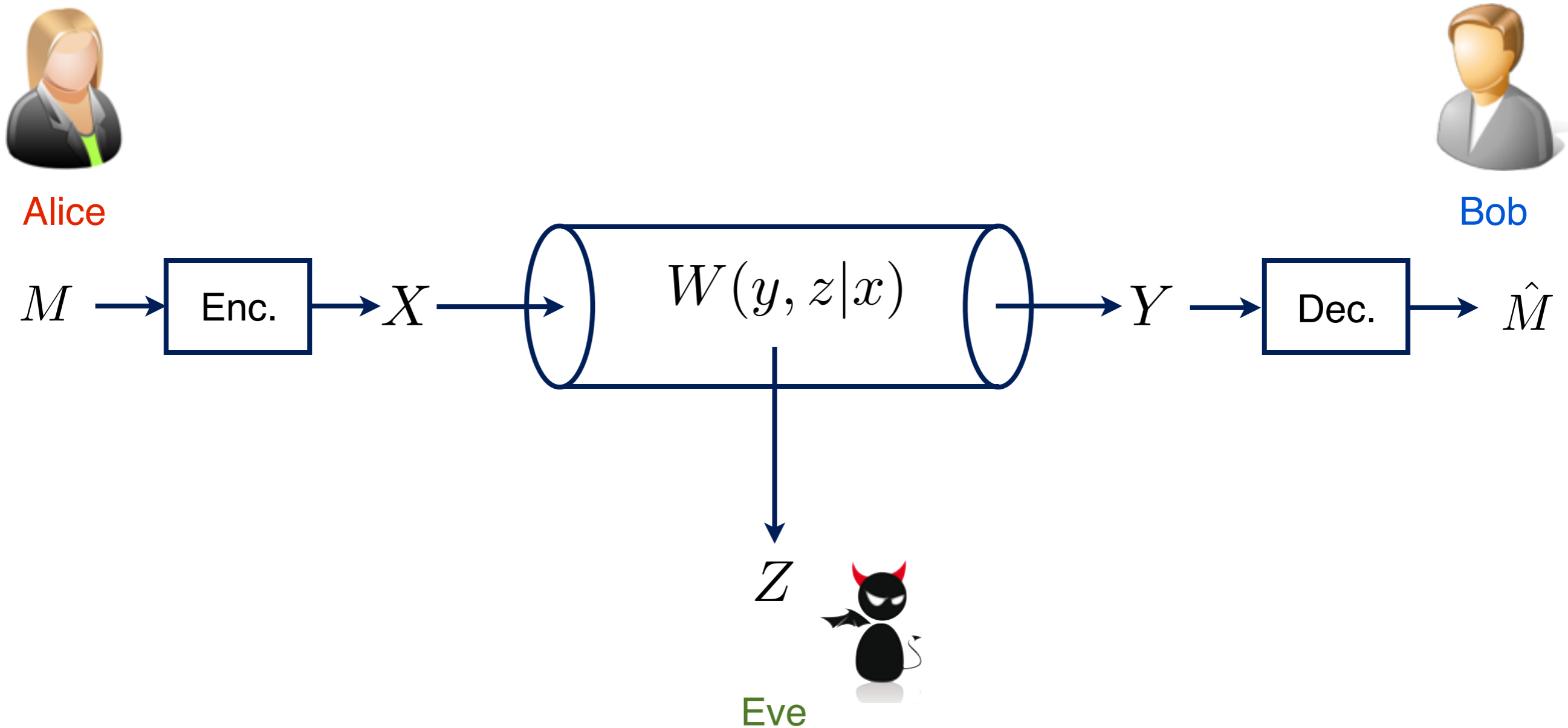
Shannon's Pessimistic Result

A secret key crypto system is secure only if

$$H(K) \geq H(M)$$

Key length must be as large as message length...

Wyner's Wiretap Channel



$W(y, z|x) = W_1(y|x)W_2(z|y)$: Degraded Wiretap Channel [Wyner 75]

General wiretap channel [Csiszár-Körner]

Secret Key Agreement: Model

[Maurer 93, Ahlswede-Csiszár 93]

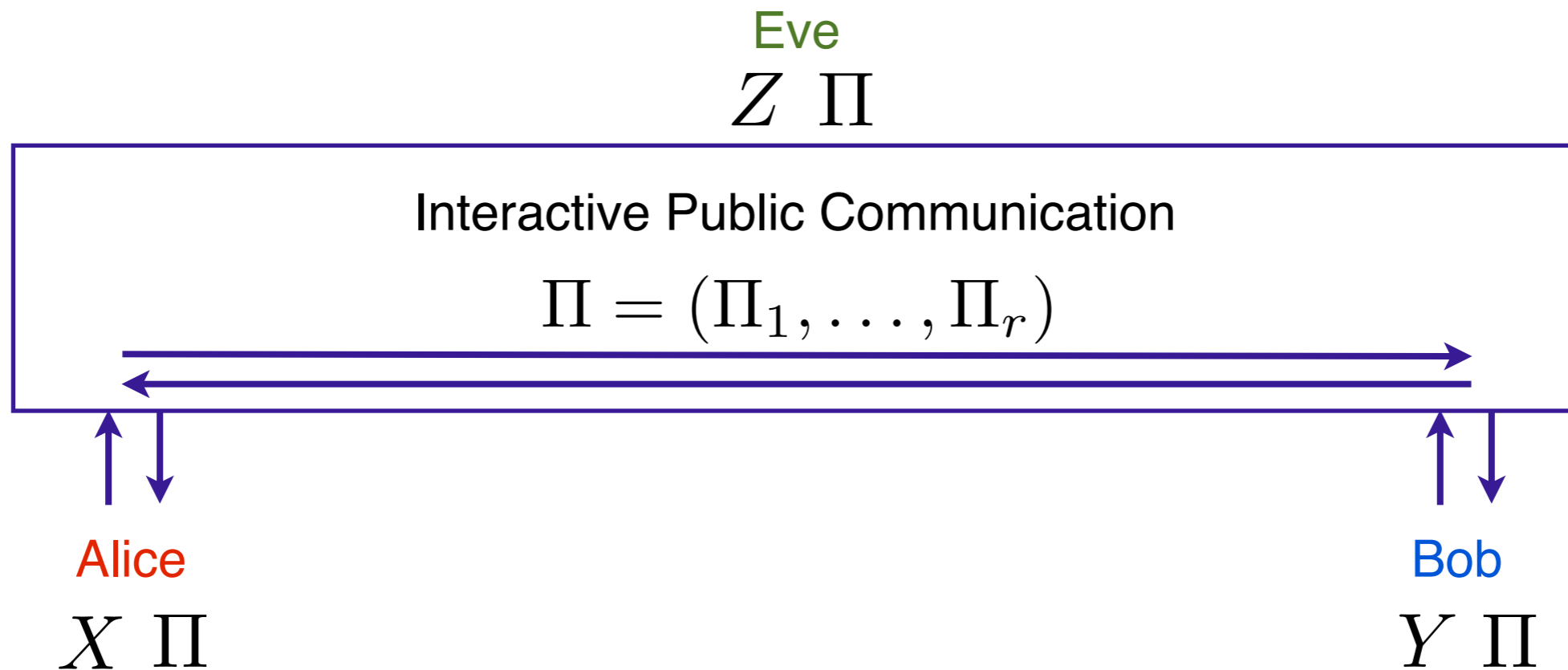
Eve
 Z

Alice
 X

Bob
 Y

Secret Key Agreement: Protocol

[Maurer 93, Ahlswede-Csiszár 93]



$$\Pi_1 = \Pi_1(X)$$

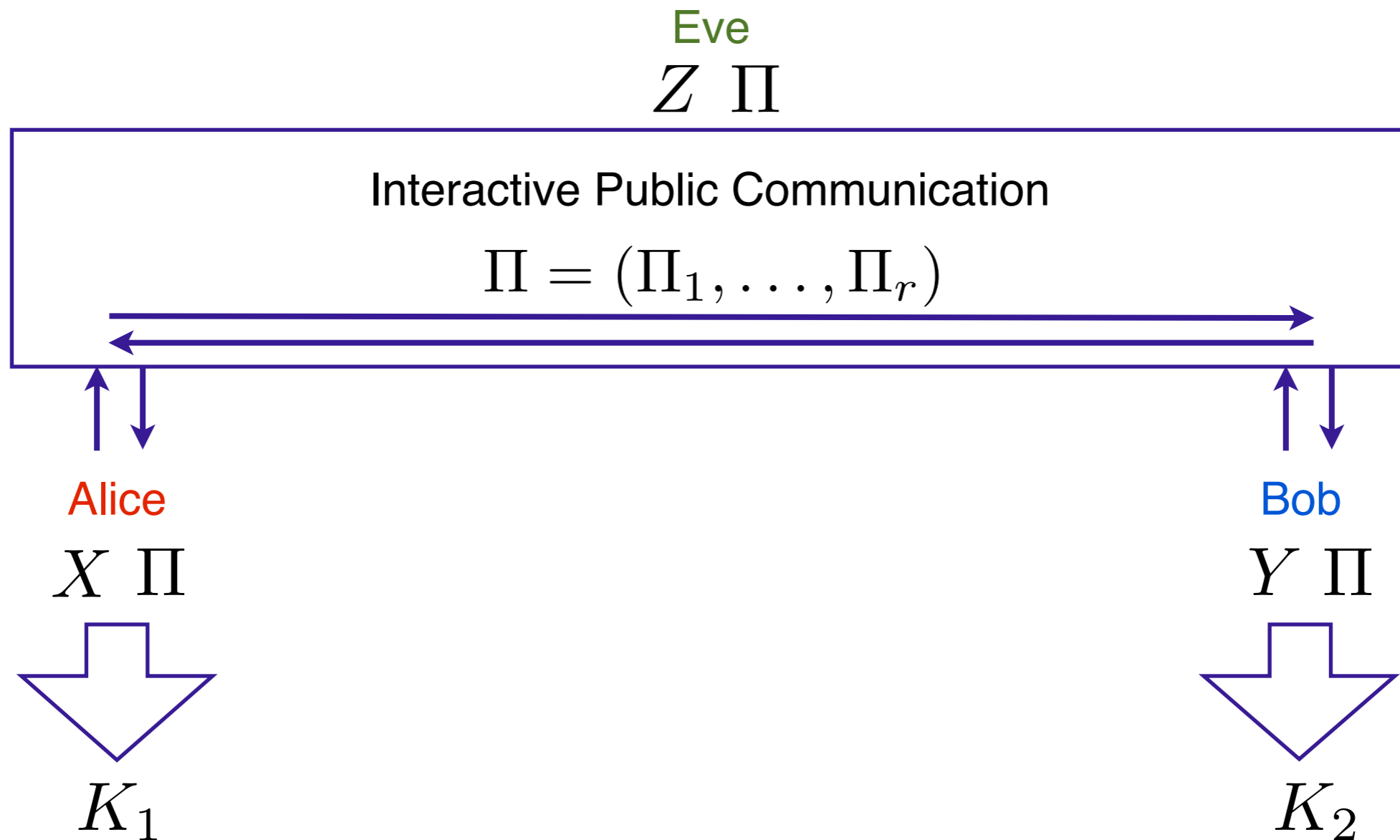
$$\Pi_2 = \Pi_2(Y, \Pi_1)$$

\vdots

$$\Pi_r = \Pi_r(Y, \Pi_1, \dots, \Pi_{r-1})$$

Secret Key Agreement: Protocol

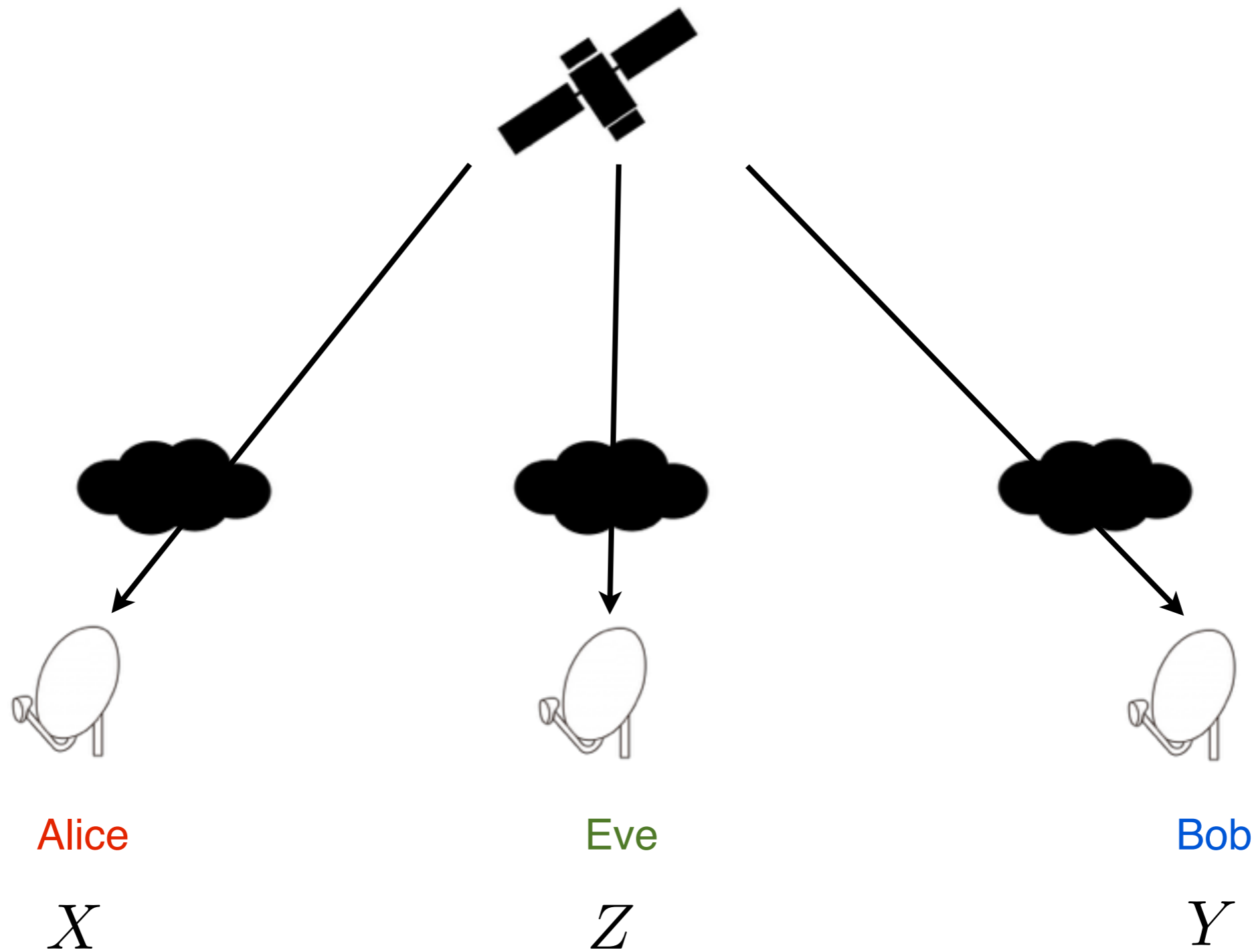
[Maurer 93, Ahlswede-Csiszár 93]



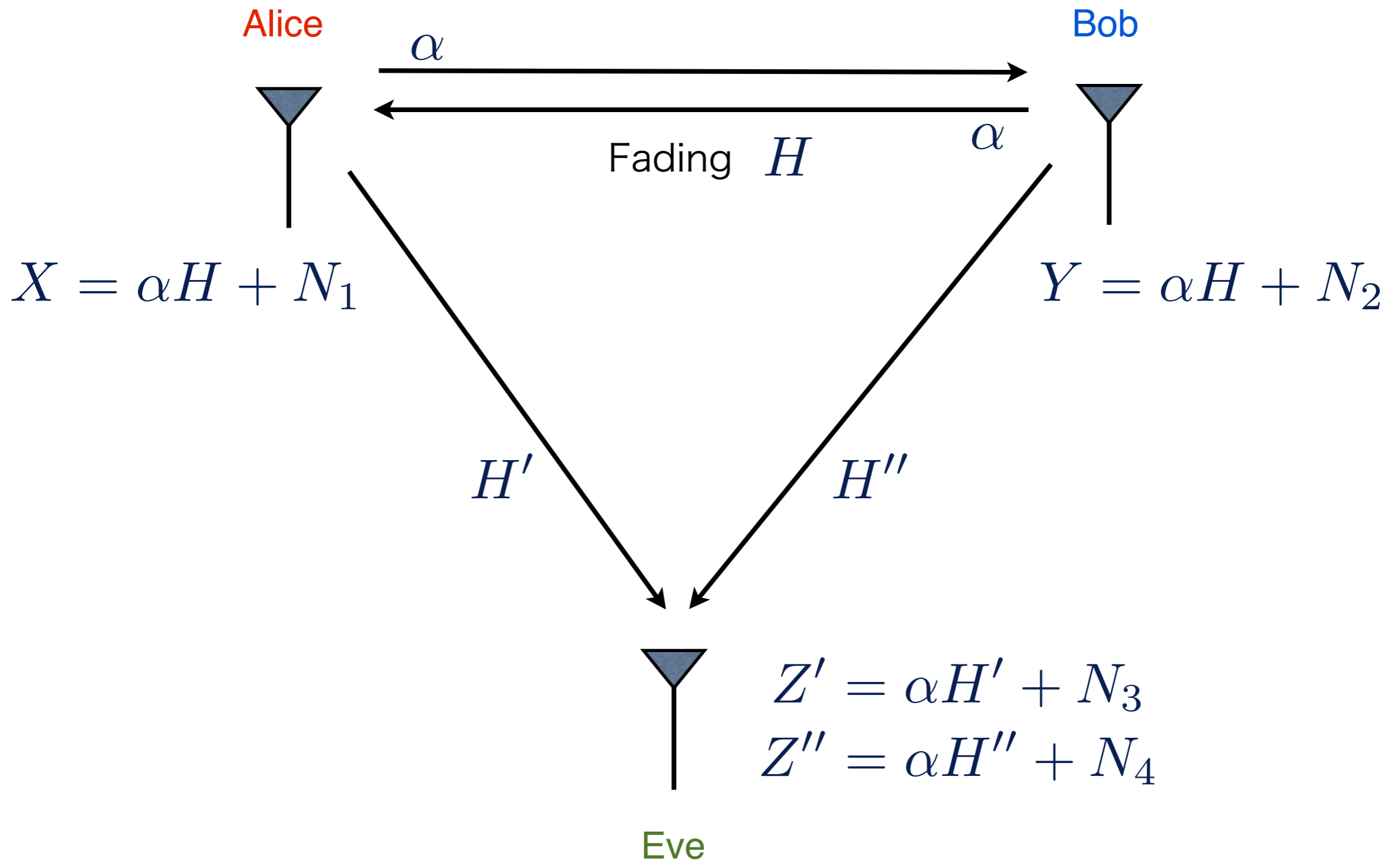
$$K_1 = K_1(X, \Pi)$$

$$K_2 = K_2(Y, \Pi)$$

Example 1: Maurer's Satellite Model

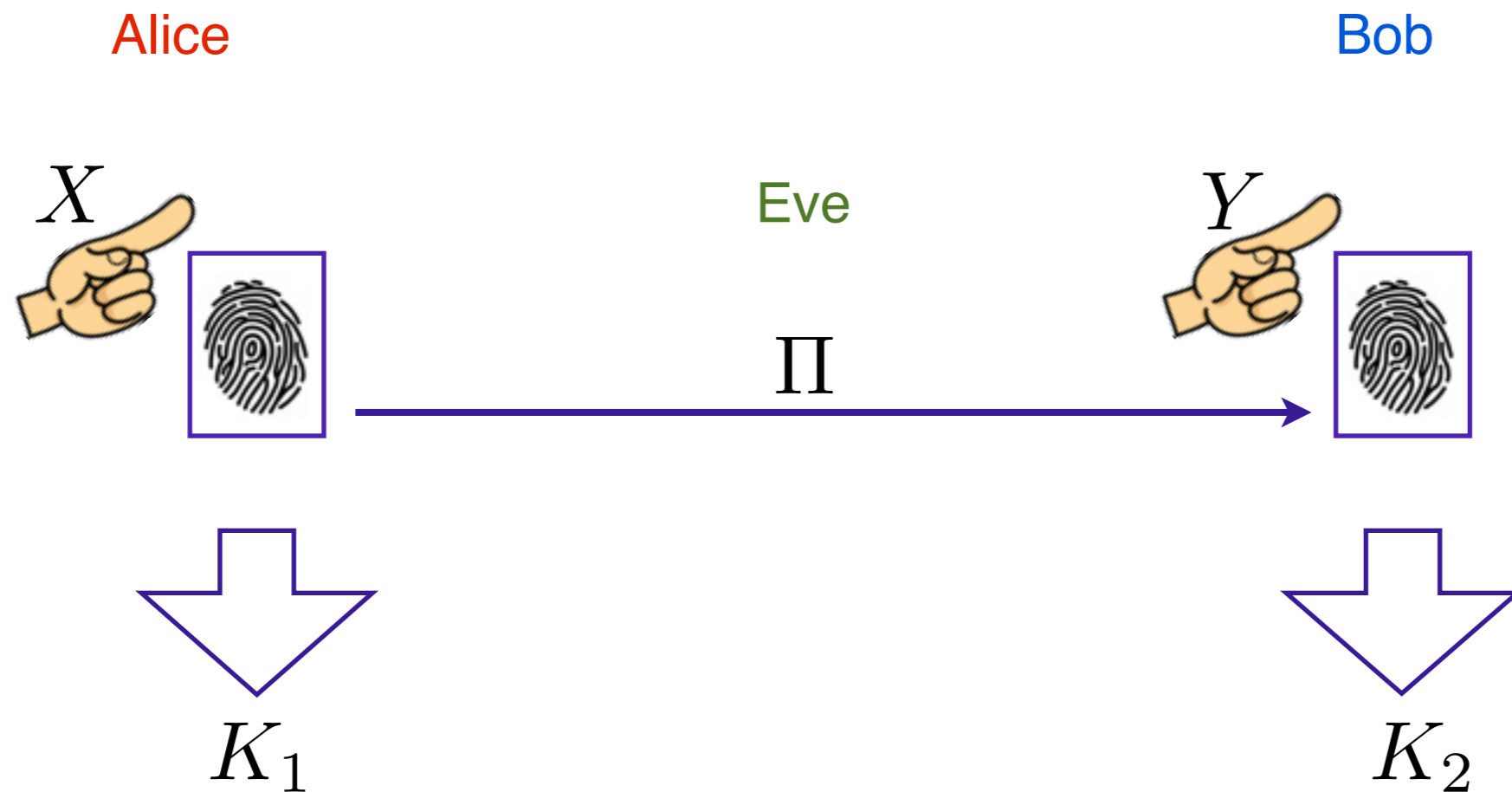


Example 2: Fading of Wireless Communication



[Hassan et. al. '96]

Example 3: Fuzzy Extractor (Biometric Security)



Problem Formulation of SK

The generate key is (ε, δ) -SK $(0 \leq \varepsilon, \delta < 1)$ if there exists K such that

Reliability $\Pr\{K_1 = K_2 = K\} \geq 1 - \varepsilon$

Security $d(P_{K\Pi Z}, P_{\text{unif}} \times P_{\Pi Z}) \leq \delta$

$$d(P, Q) := \frac{1}{2} \sum_a |P(a) - Q(a)| \quad P_{\Pi Z} : \text{marginal of } P_{K\Pi Z}$$

$$P_{\text{unif}}(k) = \frac{1}{|\mathcal{K}|}$$

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$S_{\varepsilon, \delta}(X, Y|Z)$: maximum $\log |\mathcal{K}|$ such that a protocol generating (ε, δ) -SK exists

Secret Key Capacity

For i.i.d. observations $\{(X^n, Y^n, Z^n)\}_{n=1}^{\infty}$,

$$C(X, Y|Z) := \lim_{\varepsilon, \delta \rightarrow 0} \liminf_{n \rightarrow \infty} \frac{1}{n} S_{\varepsilon, \delta}(X^n, Y^n|Z^n)$$

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Basic lower (achievability) bound:

$$C(X, Y|Z) \geq H(X|Z) - H(X|Y)$$

Basic upper (converse) bound:

$$C(X, Y|Z) \leq I(X \wedge Y|Z)$$

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Theorem [Maurer 93, Ahlswede-Csiszár 93]

When $X \circ\!\!-\!\!-\! Y \circ\!\!-\!\!-\! Z$ holds,

$$C(X, Y|Z) = I(X \wedge Y|Z)$$

In particular,

$$C(X, Y) = I(X \wedge Y)$$

Idea of achievability

- Information reconciliation

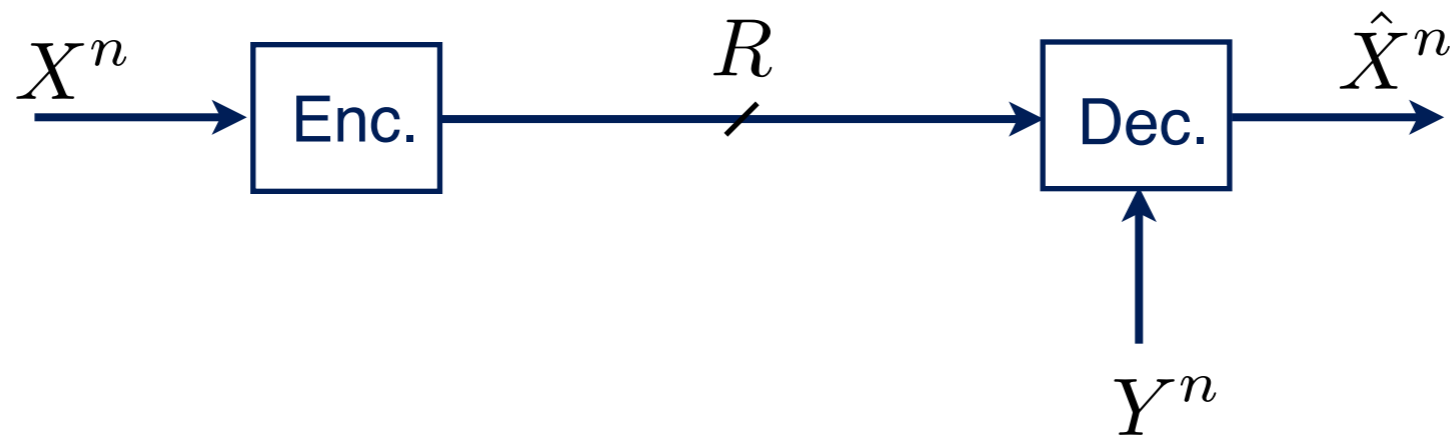
share a common random variable

- Privacy amplification

extract a secret key

Information Reconciliation

Use Slepian-Wolf coding:



If $R > H(X|Y)$, there exists a code such that $\Pr\{X^n \neq \hat{X}^n\} \rightarrow 0$

Privacy Amplification

Alice and Bob shall generate secret key from X when Z is known to Eve.

Definition (2-Universal hash family)

A random function $F : \mathcal{X} \rightarrow \{0, 1\}^l$ is called **2-UHF** if

$$\mathbb{P}(F(x) = F(x')) \leq \frac{1}{2^l}, \quad \forall x \neq x' \in \mathcal{X}$$

eg)

- the set of all functions from \mathcal{X} to $\{0, 1\}^l$
- the set of all linear functions from \mathcal{X} to $\{0, 1\}^l$

Privacy Amplification

Definition (Conditional min-entropy)

For P_{XZ} and Q_Z , the **conditional min-entropy of P_{XZ} given Q_Z** is

$$H_{\min}(P_{XZ}|Q_Z) := \min_{x \in \mathcal{X}, z \in \text{supp}(Q_Z)} \log \frac{Q_Z(z)}{P_{XZ}(x, z)}$$

Then, the **conditional min-entropy of P_{XZ} given Z** is

$$H_{\min}(P_{XZ}|Z) := \max_{Q_Z} H_{\min}(P_{XZ}|Q_Z)$$

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$$H_{\min}(P_{XZ}|Z) := \max_{Q_Z} H_{\min}(P_{XZ}|Q_Z)$$

The closed form (-log of **success guessing probability**):

$$H_{\min}(P_{XZ}|Z) = -\log \sum_z P_Z(z) \max_x P_{X|Z}(x|z)$$

$$Q_Z^*(z) \propto P_Z(z) \max_x P_{X|Z}(x|z)$$

Leftover Hash Lemma

The following bound is useful (cf. [Impagliazzo-Levin-Luby 89, Renner 05]).

Theorem (Leftover Hash Lemma)

For 2-UHF F , $K = F(X)$ satisfies

$$d(P_{KZF}, P_{\text{unif}} \times P_Z \times P_F) \leq \frac{1}{2} \sqrt{2^{l - H_{\min}(P_{XZ}|Z)}}$$

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δ -secure secret key of length

$$H_{\min}(P_{XZ}|Z) - 2 \log(1/2\delta)$$

can be generated.

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Typically, this bound is loose...; for i.i.d.,

$$\frac{1}{n} H_{\min}(P_{XZ}^n | Z^n) = H_{\min}(P_{XZ}|Z) < H(X|Z)$$

Smoothing

Smoothing: $P_{XZ} \rightarrow \tilde{P}_{XZ}$ under the condition $d(\tilde{P}_{XZ}, P_{XZ}) \leq \delta$
(allow sub-normalized distribution)

We allow sub-normalized distribution since we typically choose **truncated** distribution

$$\tilde{P}_{XZ}(x, z) = P_{XZ}(x, z) \mathbf{1}[(x, z) \in \mathcal{T}]$$

for some \mathcal{T} with

$$P_{XZ}(\mathcal{T}) \geq 1 - 2\delta$$

Smooth Conditional Min-Entropy

Definition (Smooth conditional min-entropy)

For P_{XZ} and Q_Z , the **smooth conditional min-entropy of P_{XZ} given Q_Z** is

$$H_{\min}^{\delta}(P_{XZ}|Q_Z) := \max_{\tilde{P}_{XZ} \in \mathcal{B}_{\delta}(P_{XZ})} H_{\min}(\tilde{P}_{XZ}|Q_Z)$$

$$\mathcal{B}_{\delta}(P_{XZ}) := \{\tilde{P}_{XZ} \in \mathcal{P}_{\text{sub}}(\mathcal{X} \times \mathcal{Z}) : d(\tilde{P}_{XZ}, P_{XZ}) \leq \delta\}$$

Then, the **smooth conditional min-entropy of P_{XZ} given Z** is

$$H_{\min}^{\delta}(P_{XZ}|Z) := \max_{Q_Z} H_{\min}^{\delta}(P_{XZ}|Q_Z)$$

Leftover Hash Lemma with Smoothing

Apply triangular inequality for smoothed distribution...

Theorem (Leftover Hash Lemma with smoothing)

For 2-UHF F , $K = F(X)$ satisfies

$$d(P_{KZF}, P_{\text{unif}} \times P_Z \times P_F) \leq 2\delta + \frac{1}{2} \sqrt{2^{l - H_{\min}^{\delta}(P_{XZ|Z})}}$$

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$$H_{\min}^{(\delta-\eta)/2}(P_{XZ|Z}) - 2 \log(1/2\eta) - 1$$

can be generated for $0 < \eta \leq \delta$.

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can be generated for $0 < \eta \leq \delta$.

For i.i.d. observation,

$$\lim_{n \rightarrow \infty} \frac{1}{n} H_{\min}^{(\delta-\eta)/2}(P_{XZ}^n|Z^n) = H(X|Z)$$

for $0 < \eta < \delta$.

Leftover Hash Lemma with Extra Message

The following variant of LHL for P_{XZV} is useful for later application:

Theorem (Leftover Hash Lemma with extra message)

For 2-UHF F , $K = F(X)$ satisfies

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δ -secure secret key of length

$$H_{\min}^{(\delta-\eta)/2}(P_{XZ}|Z) - 2 \log(1/2\delta) - 1 - \log |\mathcal{V}|$$

for $0 < \eta \leq \varepsilon$; **extra message reduces key length at most $\log |\mathcal{V}|$.**

Composition of IR and PA

When message of rate R is revealed to Eve in IR

Alice and Bob can generate SK at rate

$$H(X|Z) - R$$

$\implies H(X|Z) - H(X|Y)$ is attainable

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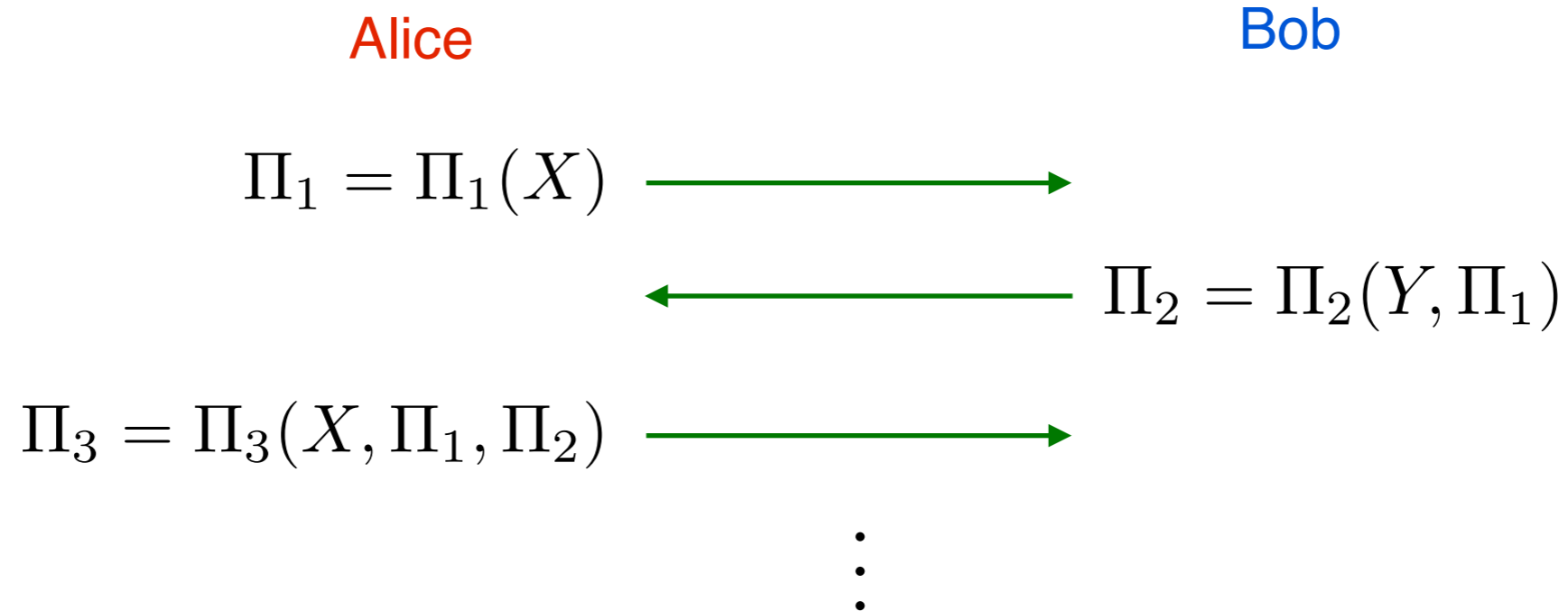
$\implies H(X|Z) - H(X|Y)$ is attainable

More generally,

(Randomness unknown to Eve initially) — (Rate revealed in IR)

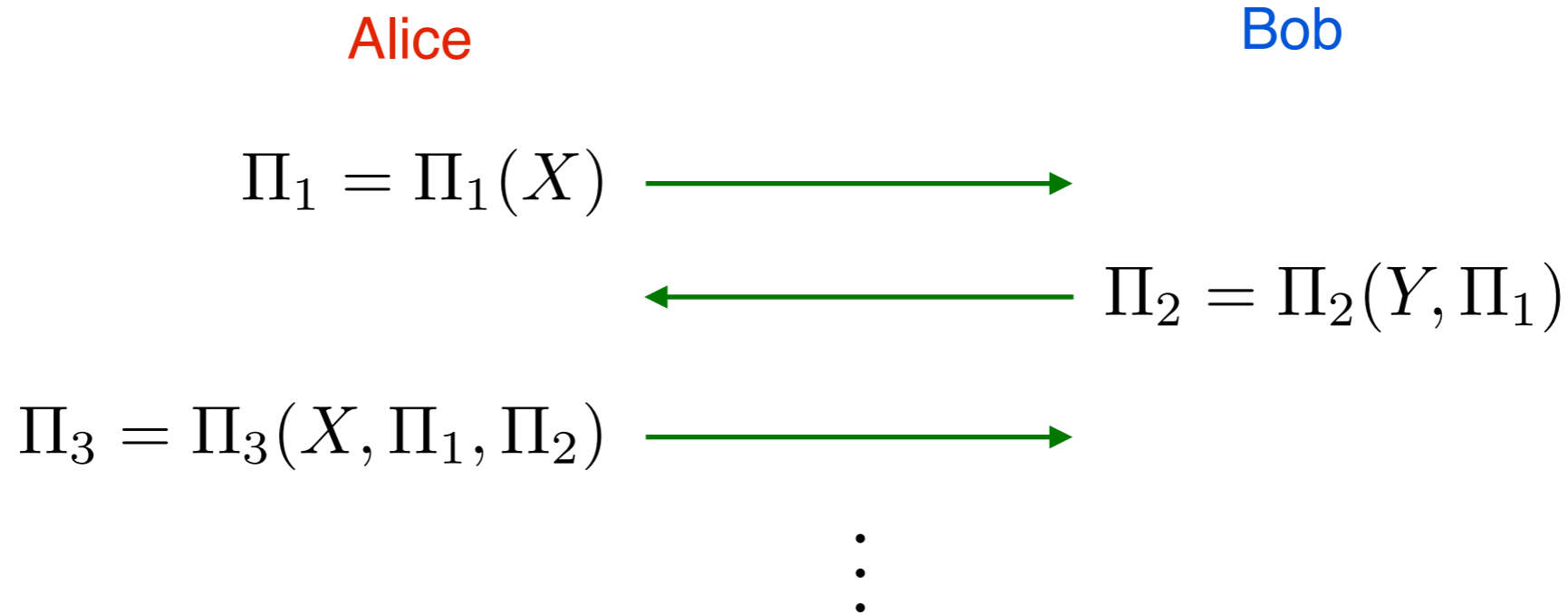
Idea of Converse: a property of interactive communication

Interactive communication



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Lemma [Maurer 93, Ahlswede-Csiszár 93]

For any protocol $\Pi = (\Pi_1, \dots, \Pi_r)$,

$$I(X \wedge Y | Z, \Pi) \leq I(X \wedge Y | Z)$$

In particular,

$$P_{XYZ} = P_{X|Z}P_{Y|Z}P_Z \implies P_{XYZ\Pi} = P_{X|Z\Pi}P_{Y|Z\Pi}P_{Z\Pi}$$

A Basic Converse Bound

By the Fano inequality argument,...

Theorem [Maurer 93, Ahlswede-Csiszár 93]

For every $0 \leq \varepsilon, \delta < 1$ with $\varepsilon + \delta < 1$,

$$S_{\varepsilon, \delta}(X, Y|Z) \leq \frac{I(X \wedge Y|Z) + h(\varepsilon) + h(\delta)}{1 - \varepsilon - \delta}$$

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For i.i.d. observations,

$$C(X, Y|Z) = \lim_{\varepsilon, \delta \rightarrow 0} \liminf_{n \rightarrow \infty} \frac{1}{n} S_{\varepsilon, \delta}(X^n, Y^n|Z^n) \leq I(X \wedge Y|Z)$$

It is tight when (X, Y, Z) form Markov chain (**degraded**):

$$I(X \wedge Y|Z) = H(X|Z) - H(X|Y)$$

Conditional Independence Testing Bound

By relating SK and hypothesis testing,...

Theorem [Tyagi-W. 14]

For every $0 \leq \varepsilon, \delta < 1$ and $0 < \eta < 1 - \varepsilon - \delta$, we have

$$S_{\varepsilon, \delta}(X, Y|Z) \leq -\log \beta_{\varepsilon + \delta + \eta}(P_{XYZ}, Q_{XYZ}) + 2 \log(1/\eta)$$

for any $Q_{XYZ} = Q_{X|Z}Q_{Y|Z}Q_Z$.

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strong converse can be proved.

It is also tight up to the second-order term for degraded case.

Second-Order Rate of Secret Key Agreement

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The standard protocol with

- information reconciliation
- privacy amplification

no interaction

achieves the secrecy capacity: $H(X|Z) - H(X|Y) = I(X \wedge Y|Z)$

The standard protocol is always optimal? Does interaction help in some case?

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Theorem [Hayashi-Tyagi-W. 14]

For $0 < \varepsilon, \delta < 1$ with $\varepsilon + \delta < 1$,

$$S_{\varepsilon, \delta}(X^n, Y^n | Z^n) = nI(X \wedge Y | Z) - \sqrt{nV} Q^{-1}(\varepsilon + \delta) + \mathcal{O}(\log n)$$

where

$$V := \text{Var} \left[\log \frac{P_{XY|Z}(X, Y | Z)}{P_{X|Z}(X | Z) P_{Y|Z}(Y | Z)} \right]$$

$$Q(a) := \int_a^\infty \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{t^2}{2}\right) dt$$

Does Standard Protocol Work?

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$$nH(X|Y) + \sqrt{nV_{X|Y}}Q^{-1}(\varepsilon) + \mathcal{O}(\log n)$$

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The standard protocol does not achieve the optimal second-order rate.

The optimal second-order rate is achieved by an **interactive** protocol.

Achievability Idea

Use interactive Slepian-Wolf coding (cf. [Draper 04, Feder-Schulman 02, Yang-He 10])

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- Alice should communicate at small rate if $h_{P_{X|Y}}(X|Y) = \log \frac{1}{P_{X|Y}(X|Y)}$ is small;

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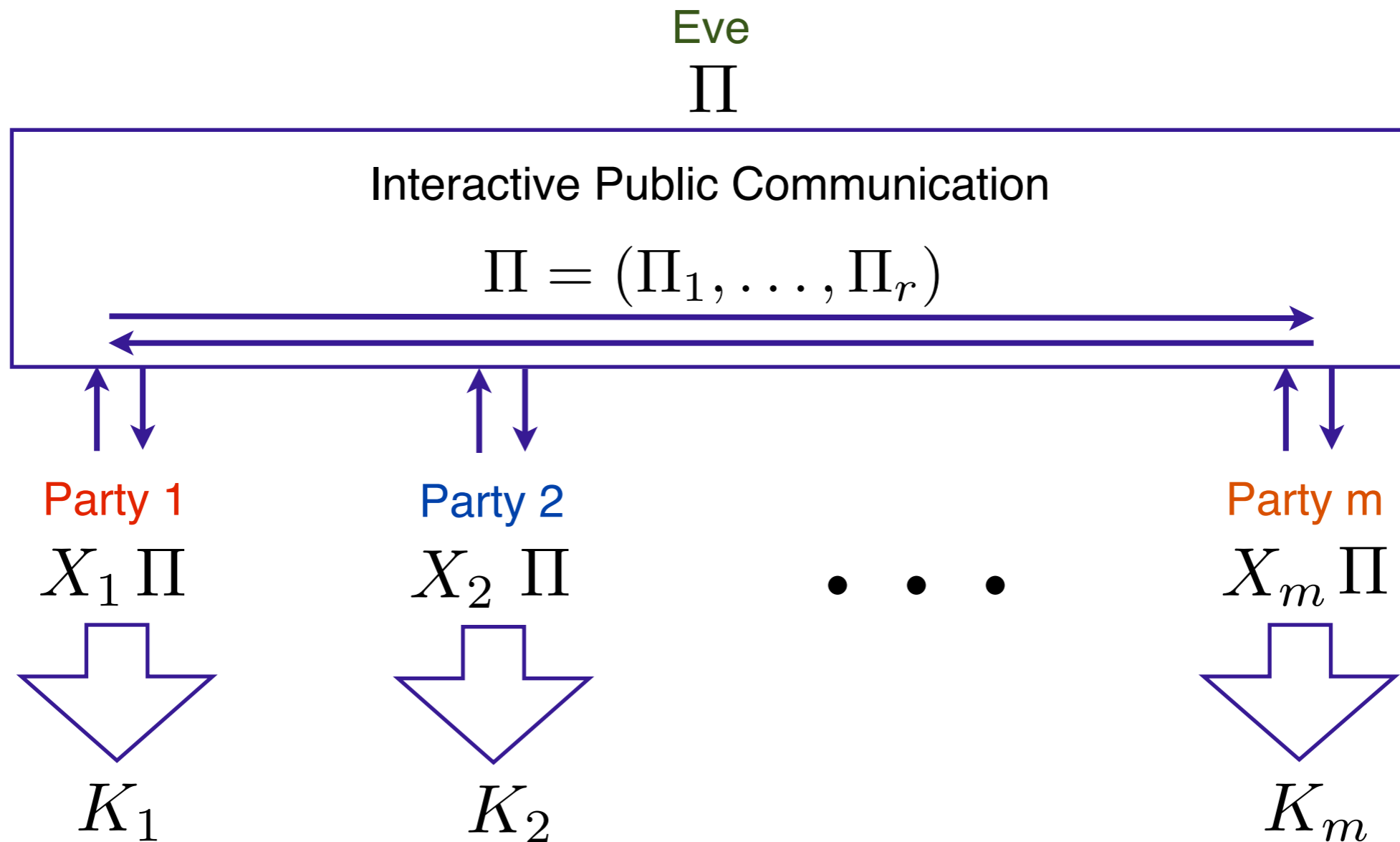
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- Alice gradually increase rate until Bob is able to decode X ;
- Bob return **Ack/Nack** until it decode X .

The usage of interaction decreases information revealed to Eve...

Multi-Party Secret Key Agreement

Multi-Party Setting

[Csiszár-Narayan 04]



$$A \subset \mathcal{M} := \{1, \dots, M\}$$

$$X_A := (X_i : i \in A)$$

$$X_{\mathcal{M}} := (X_1, \dots, X_m)$$

$$K_{\mathcal{M}} := (K_1, \dots, K_m)$$

Problem Formulation of Multi-Party SK

The generate key is (ε, δ) -SK $(0 \leq \varepsilon, \delta < 1)$ if there exists K such that

Reliability $\Pr\{K_1 = \dots = K_m = K\} \geq 1 - \varepsilon$

Security $d(P_{K\Pi Z}, P_{\text{unif}} \times P_{\Pi Z}) \leq \delta$

$S_{\varepsilon, \delta}(X_{\mathcal{M}})$: maximum $\log |\mathcal{K}|$ such that a protocol generating (ε, δ) -SK exists

$$C(X_{\mathcal{M}}) := \lim_{\varepsilon, \delta \rightarrow 0} \liminf_{n \rightarrow \infty} \frac{1}{n} S_{\varepsilon, \delta}(X_{\mathcal{M}}^n)$$

2 Party Revisited

(Randomness unknown to Eve initially) — (Rate revealed in IR)

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$$\begin{aligned} C(X_1, X_2) &= I(X_1 \wedge X_2) \\ &= H(X_1) - H(X_1|X_2) \end{aligned}$$

it is asymmetric...

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$$= H(X_1) - H(X_1|X_2)$$

it is asymmetric...

$$= H(X_1, X_2) - H(X_1|X_2) - H(X_2|X_1)$$

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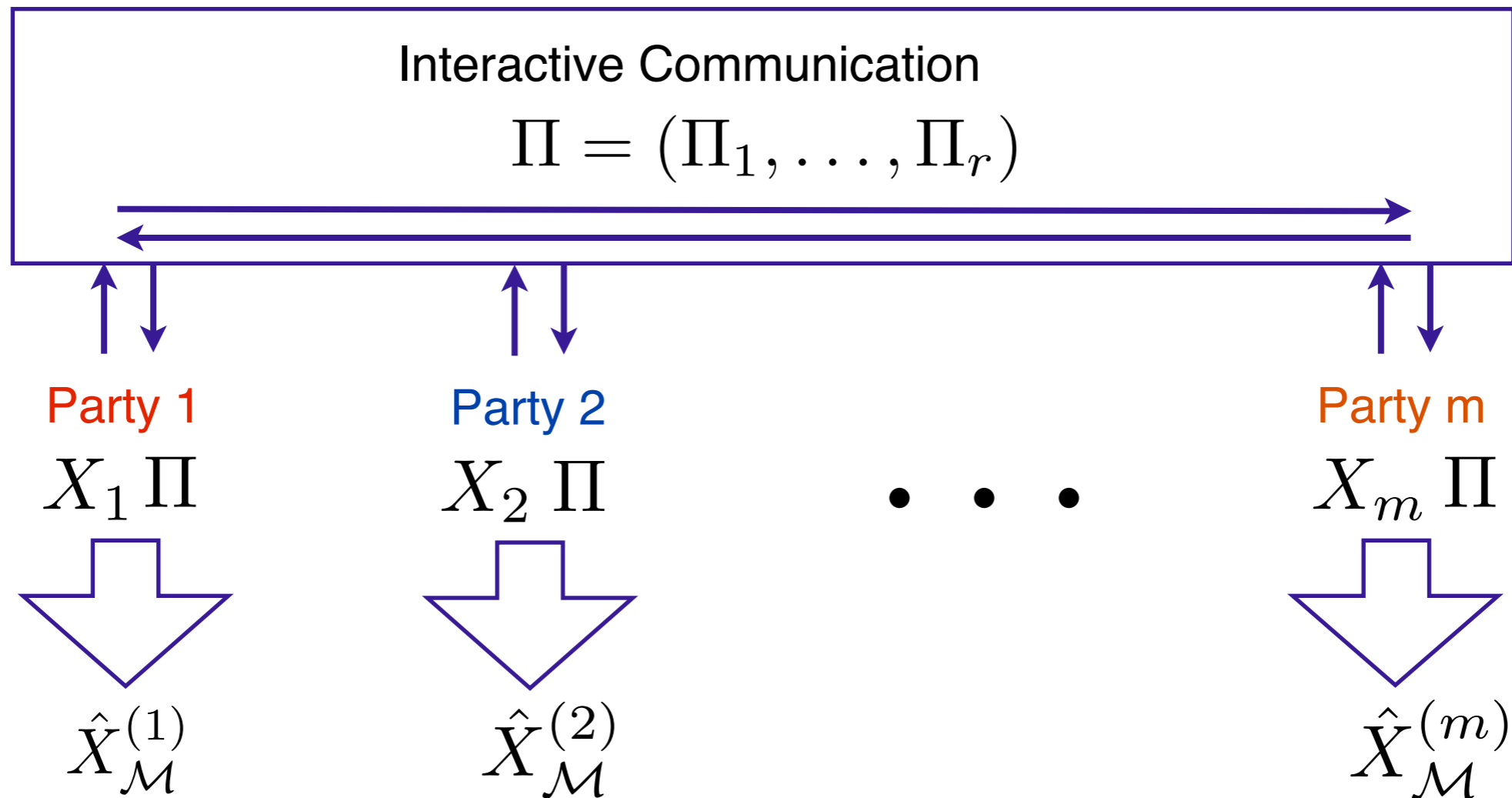
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$$= H(X_1, X_2) - H(X_1|X_2) - H(X_2|X_1)$$

$H(X_{\mathcal{M}})$ — communication rate needed to agree on $X_{\mathcal{M}}$

Omniscience (Data Exchange) Problem

[Csiszár-Narayan 04]



$L_\epsilon(X_{\mathcal{M}})$: minimum sum-rate for omniscience with

$$\mathbb{P}(X_{\mathcal{M}}^{(i)} = X_{\mathcal{M}}, \forall 1 \leq i \leq m) \geq 1 - \epsilon$$

Asymptotic Omniscience Rate

$$R(P_{X_{\mathcal{M}}}) = \lim_{\epsilon \rightarrow 0} \limsup_{n \rightarrow \infty} \frac{1}{n} L_{\epsilon}(X_{\mathcal{M}}^n)$$

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$$\stackrel{\text{red}}{\geq} \max_{\sigma \in \Sigma(\mathcal{M})} \mathbb{H}_{\sigma}(\mathcal{M} | \mathbb{P}_{X_{\mathcal{M}}})$$

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$$\mathbb{H}_{\sigma}(\mathcal{M} | \mathbb{P}_{X_{\mathcal{M}}}) := \frac{1}{|\sigma| - 1} \sum_{i=1}^{|\sigma|} H(X_{\mathcal{M}} | X_{\sigma_i}) \quad \sigma : \text{partition of } \mathcal{M}$$

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$$m = 2 \quad \Sigma(\mathcal{M}) = \{\{1|2\}\}$$

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$$m = 3 \quad \Sigma(\mathcal{M}) = \{\{1|23\}, \{12|3\}, \{23|1\}, \{1|2|3\}\}$$

$$R(\mathbb{P}_{X_{\mathcal{M}}}) = \max \left\{ H(X_1 | X_2, X_3) + H(X_2, X_3 | X_1), H(X_3 | X_1, X_2) + H(X_1, X_2 | X_3), \right. \\ \left. H(X_2 | X_1, X_3) + H(X_1, X_3 | X_2), \frac{H(X_2, X_3 | X_1) + H(X_1, X_3 | X_2) + H(X_1, X_2 | X_3)}{2} \right\}$$

Multi-Party Secrecy Capacity

Theorem [Csiszár-Narayan 04]

$$C(X_{\mathcal{M}}) = H(X_{\mathcal{M}}) - R(P_{X_{\mathcal{M}}})$$

Multi-Party Secrecy Capacity

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Multi-Party Secrecy Capacity

Theorem [Csiszár-Narayan 04, Chan 08]

$$\begin{aligned} C(X_{\mathcal{M}}) &= H(X_{\mathcal{M}}) - R(P_{X_{\mathcal{M}}}) \\ &= \min_{\sigma \in \Sigma(\mathcal{M})} \frac{1}{|\sigma| - 1} D \left(P_{X_{\mathcal{M}}} \parallel \prod_{i=1}^{|\sigma|} P_{X_{\sigma_i}} \right) \end{aligned}$$

A single-shot converse can be proved via hypothesis testing [Tyagi-W. 14]

Universal Protocol

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We shall construct a SK/Data exchange protocol that does not rely on knowledge of $P_{X_{\mathcal{M}}}$.

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It suffices to construct a universal data exchange protocol.

In fact, it works for a given individual sequence...

Theorem [Tyagi-W. 16]

There exists a universal data exchange protocol such that, for a given $\mathbf{x}_{\mathcal{M}}$, it communicates

$$nR^*(P_{\mathbf{x}_{\mathcal{M}}}) + \mathcal{O}(\sqrt{n})$$

where $P_{\mathbf{x}_{\mathcal{M}}}$ is the joint type.

The universal protocol is called **recursive data exchange (RDE)** protocol.

Universal RDE Protocol

Two-step coding for single-terminal source coding:

(1) Send the type $\mathcal{O}(\log n)$

(2) Send the index among the type class $nH(P_{\mathbf{x}}) + \mathcal{O}(\log n)$

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The decoder looks for joint type $P_{\overline{XY}}$ s.t. there exists a unique $\hat{\mathbf{X}}$ satisfying

- 1) $P_{\hat{\mathbf{x}}\mathbf{y}} = P_{\overline{XY}}$
- 2) $R_t \geq H(\overline{X}|\overline{Y}) + \Delta$
- 3) Hash values (bin indices) of $\hat{\mathbf{X}}$ up to round t are compatible.

Decoding Rule for Local Omniscience

Local omniscience region for $A \subseteq \mathcal{M}$:

$$\mathcal{R}_{\text{CO}}^{\Delta}(A|P_{\bar{X}_A}) = \left\{ (R_i : i \in A) : \sum_{i \in B} R_i \geq H(\bar{X}_B | \bar{X}_{A \setminus B}) + |B|\Delta, \forall B \subseteq A \right\}$$

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i th party looks for maximal $i \in A \subseteq \mathcal{M}$ and $P_{\overline{X}_A}$ s.t. there exists a unique $\hat{\mathbf{x}}_A$ satisfying

1) $\hat{\mathbf{x}}_i = \mathbf{x}_i$, $P_{\hat{\mathbf{x}}_A} = P_{\overline{X}_A}$

2) $(R_i^{(t)} : i \in A) \in \mathcal{R}_{\text{CO}}^{\Delta}(A|P_{\overline{X}_A})$

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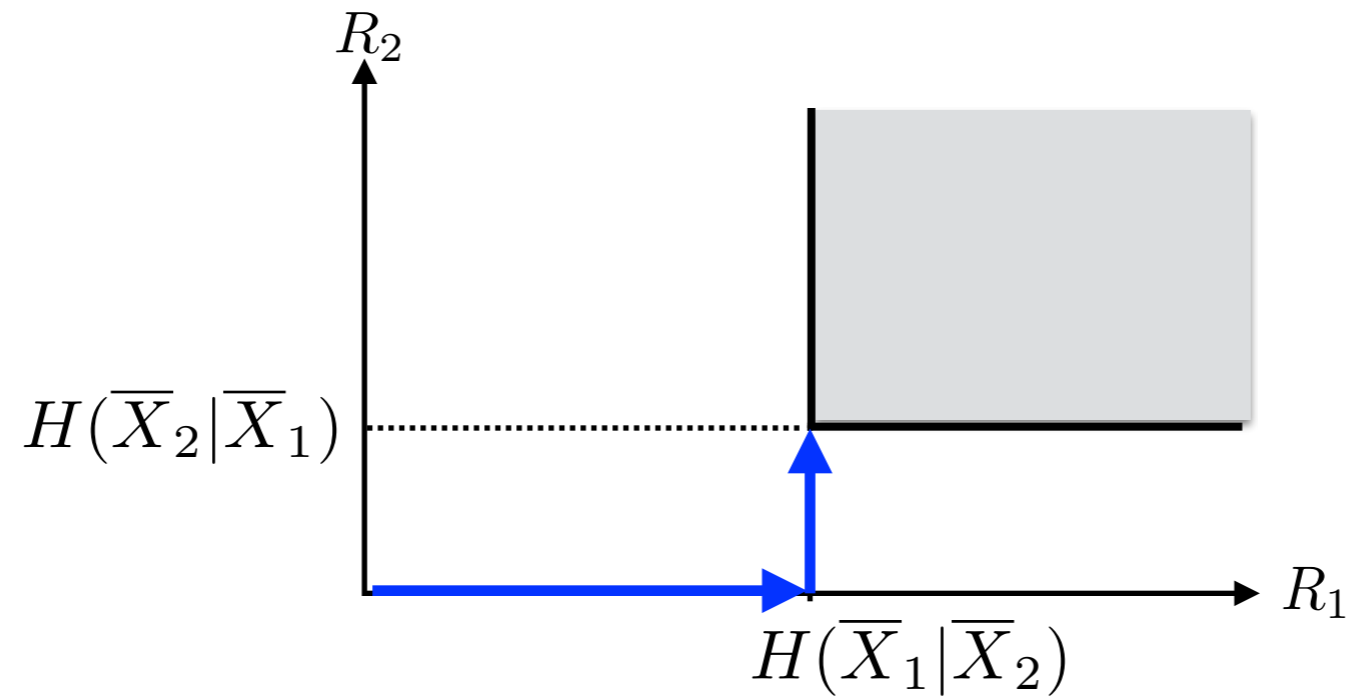
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Once accumulated rate vector enters a local omniscience region, local omniscience occur automatically. Difficulty is how to increment rates...

Rate Increment Rule

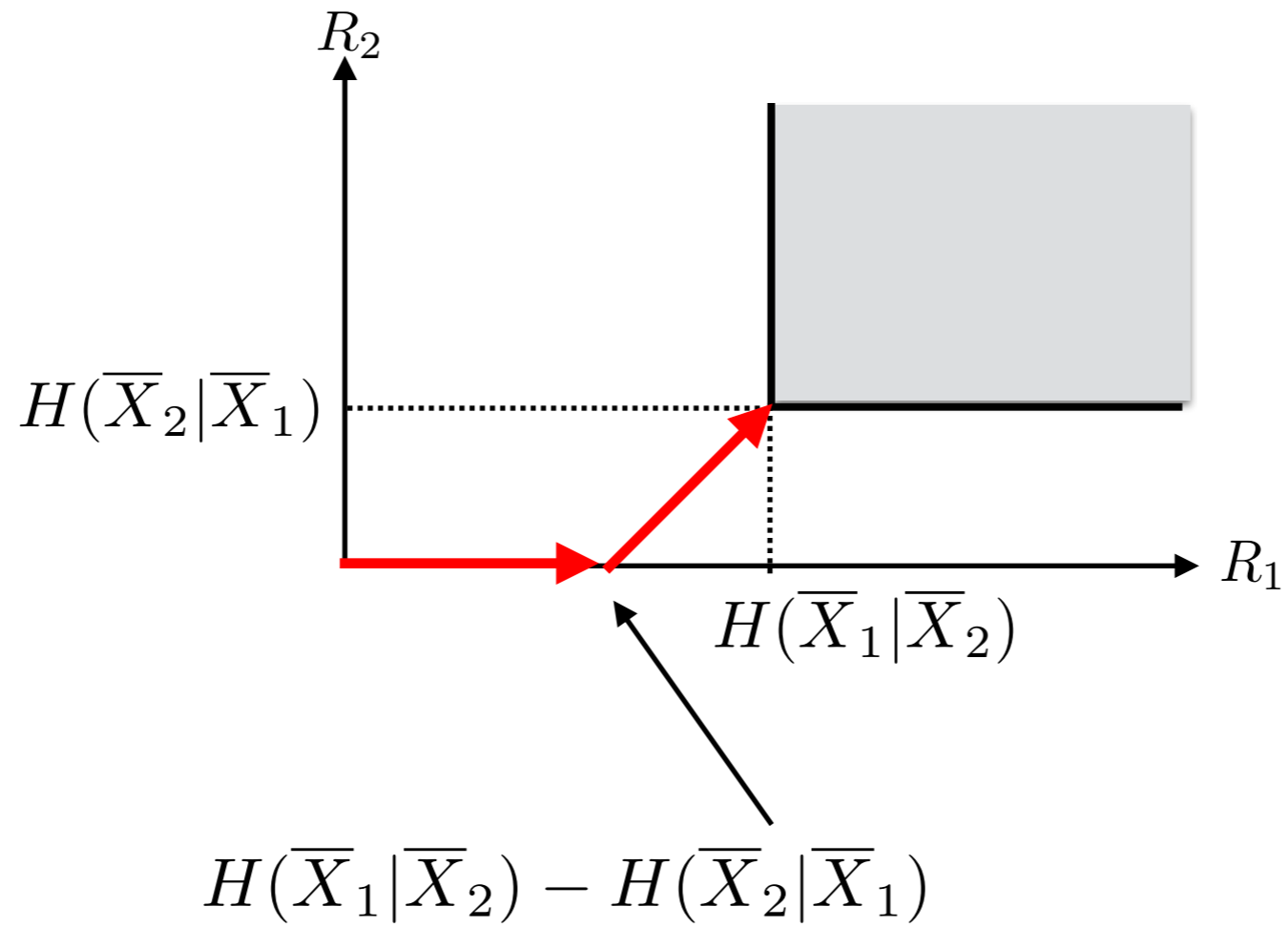
Two-party case:



It is asymmetric...

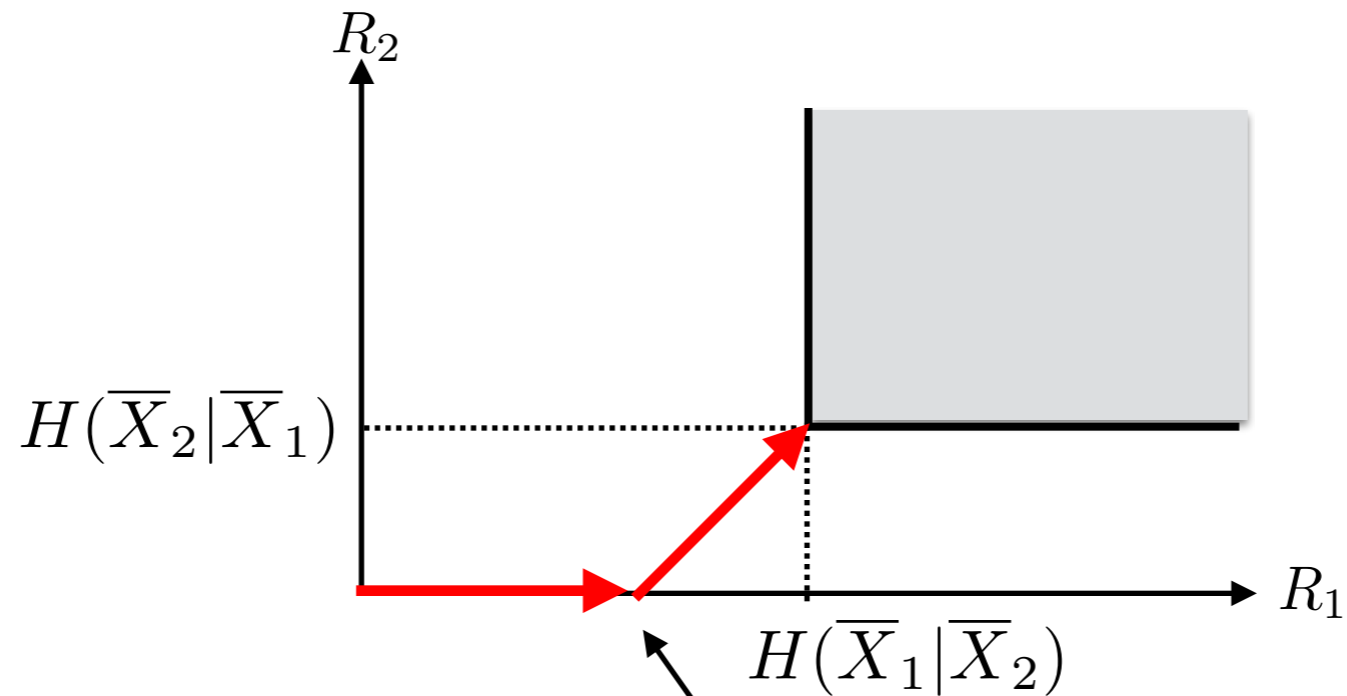
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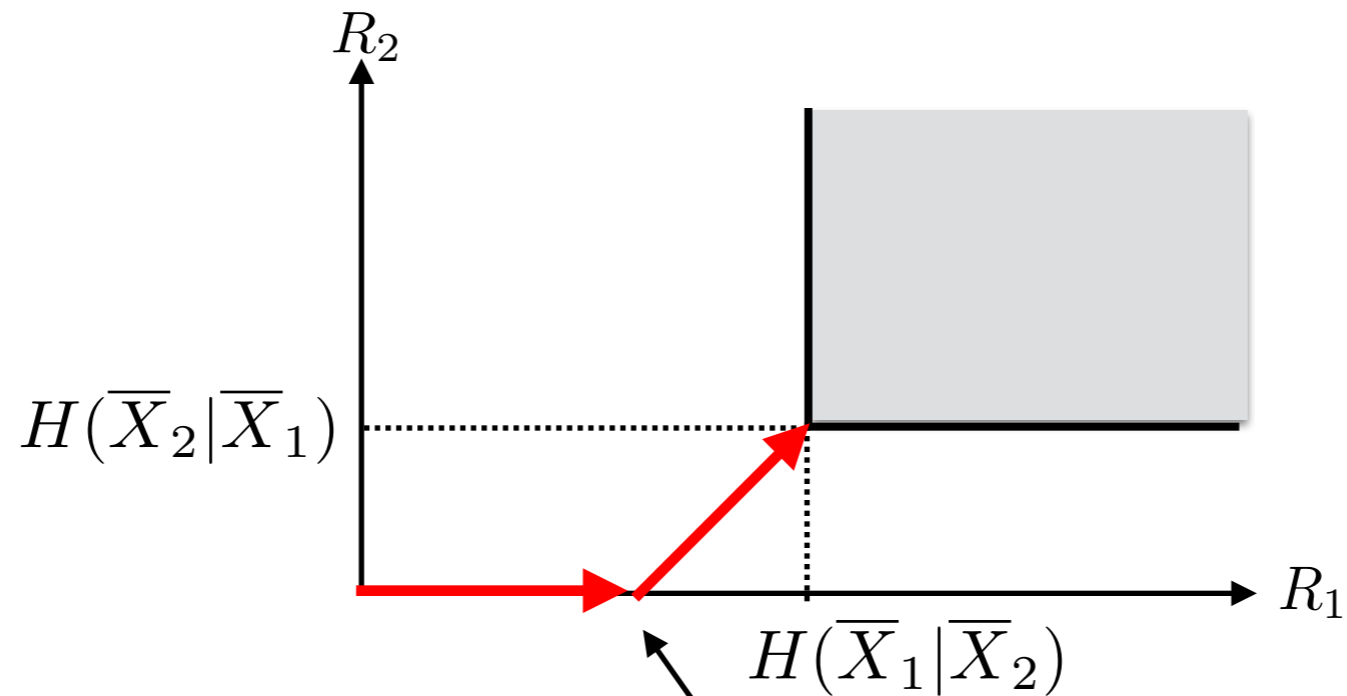
$$H(\bar{X}_1|\bar{X}_2) - H(\bar{X}_2|\bar{X}_1) = H(\bar{X}_1) - H(\bar{X}_2)$$

W.L.G., assume $H(\bar{X}_1) \geq H(\bar{X}_2)$

Party 1: $R_1^{(0)} = 0$; $R_1^{(t+1)} := R_1^{(t)} + \Delta$

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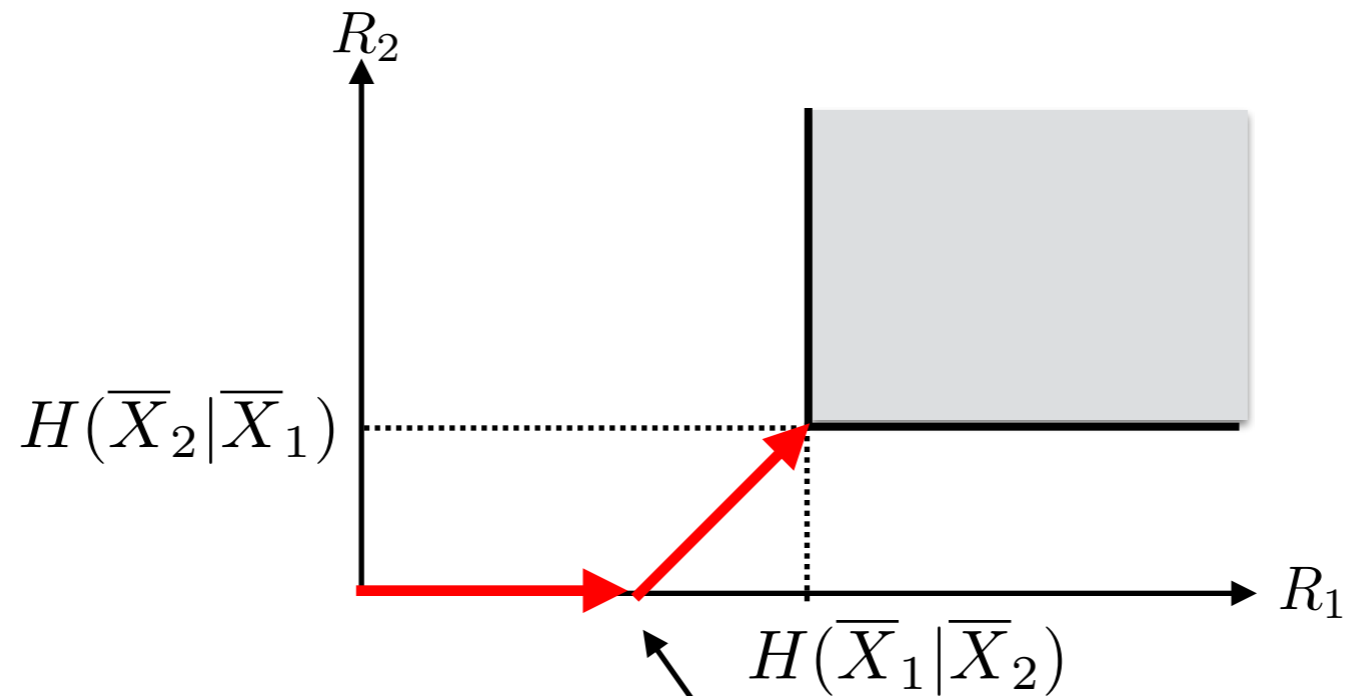
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⋮

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⋮

Rate assignment for the tipping

$$\sum_{i \in A \setminus \{j\}} R_i^*(A) = H(\bar{X}_A | \bar{X}_j), \quad j \in A$$

Property:

$$R_i^*(A) - R_j^*(A) = H(\bar{X}_i) - H(\bar{X}_j)$$

Recursive Structure

Theorem (rough statement)

At some point, $(R_i^{(t)} : i \in A)$ for some $A \subseteq \mathcal{M}$ reaches $\mathcal{R}_{\text{co}}^\Delta(A | \mathbb{P}_{\overline{X}_A})$ at

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Parties in A attain **local omniscience**.

From that point, the parties in A behaves as if one large party: increment rule is

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The protocol proceed as if A were one party from the begin with...

Recursive Structure

P1
 X_1

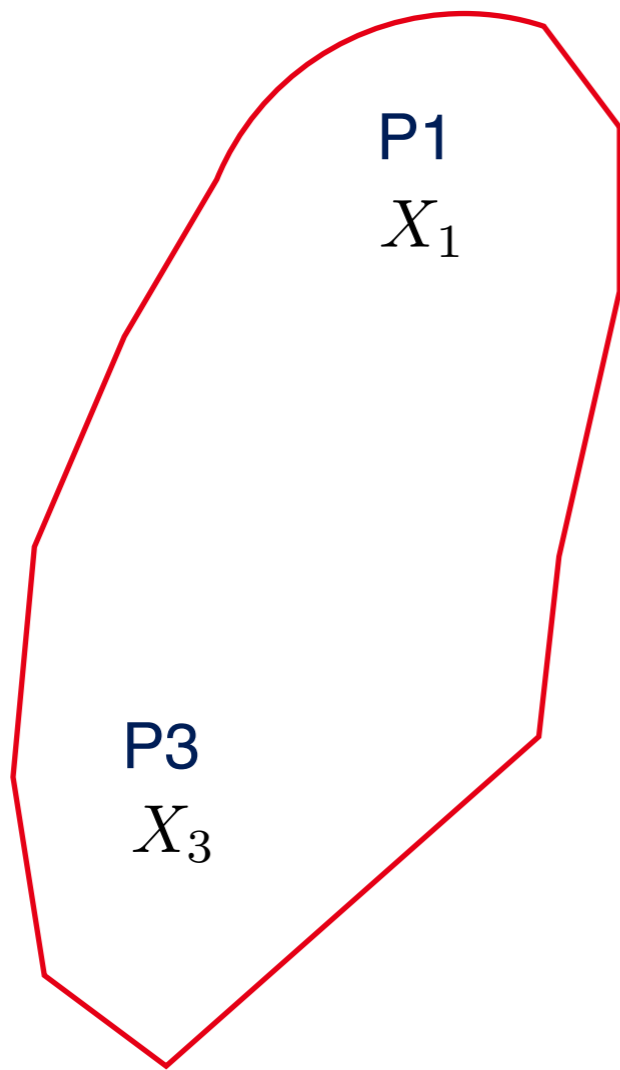
P2
 X_2

P3
 X_3

P5
 X_5

P4
 X_4

Recursive Structure

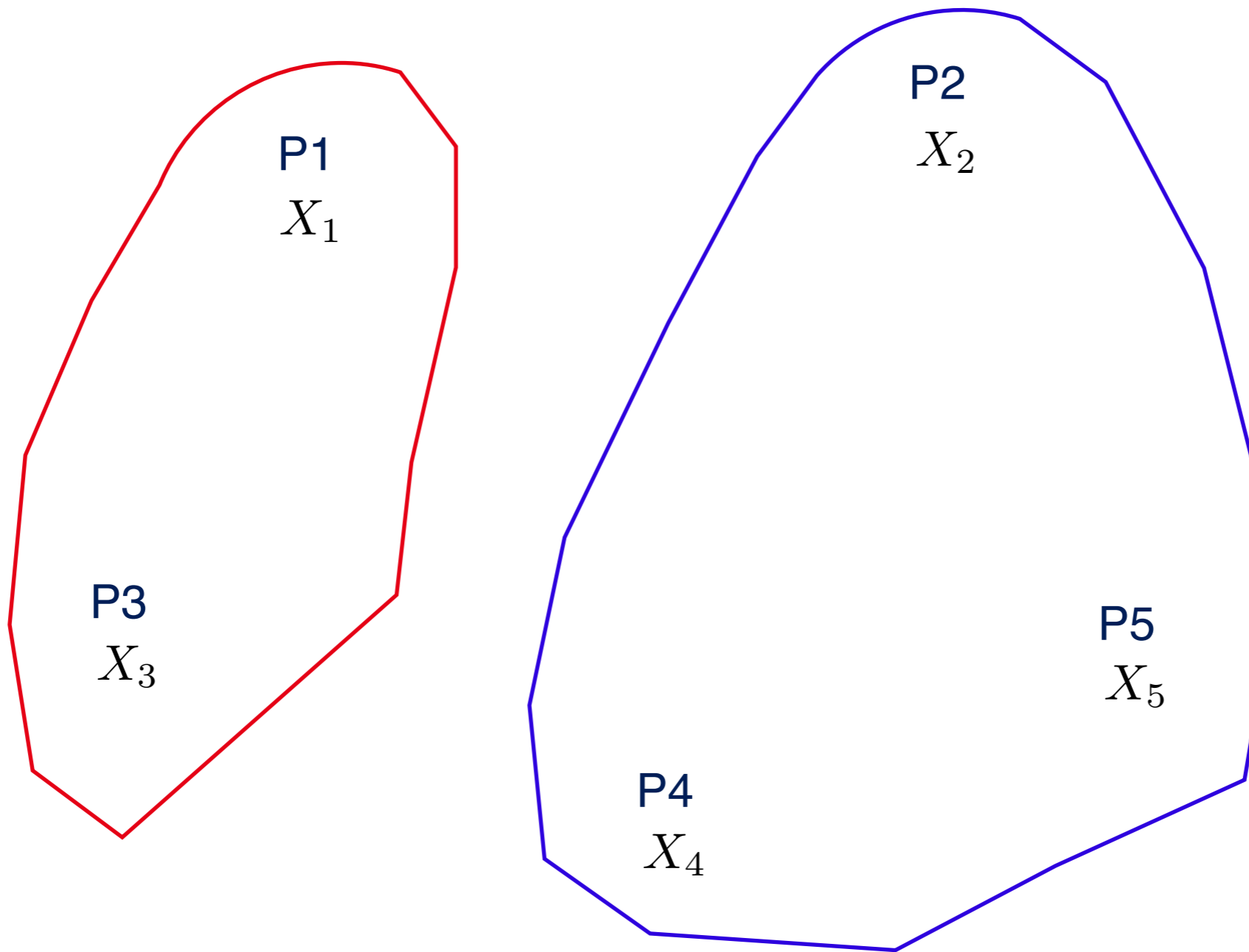


P2
 X_2

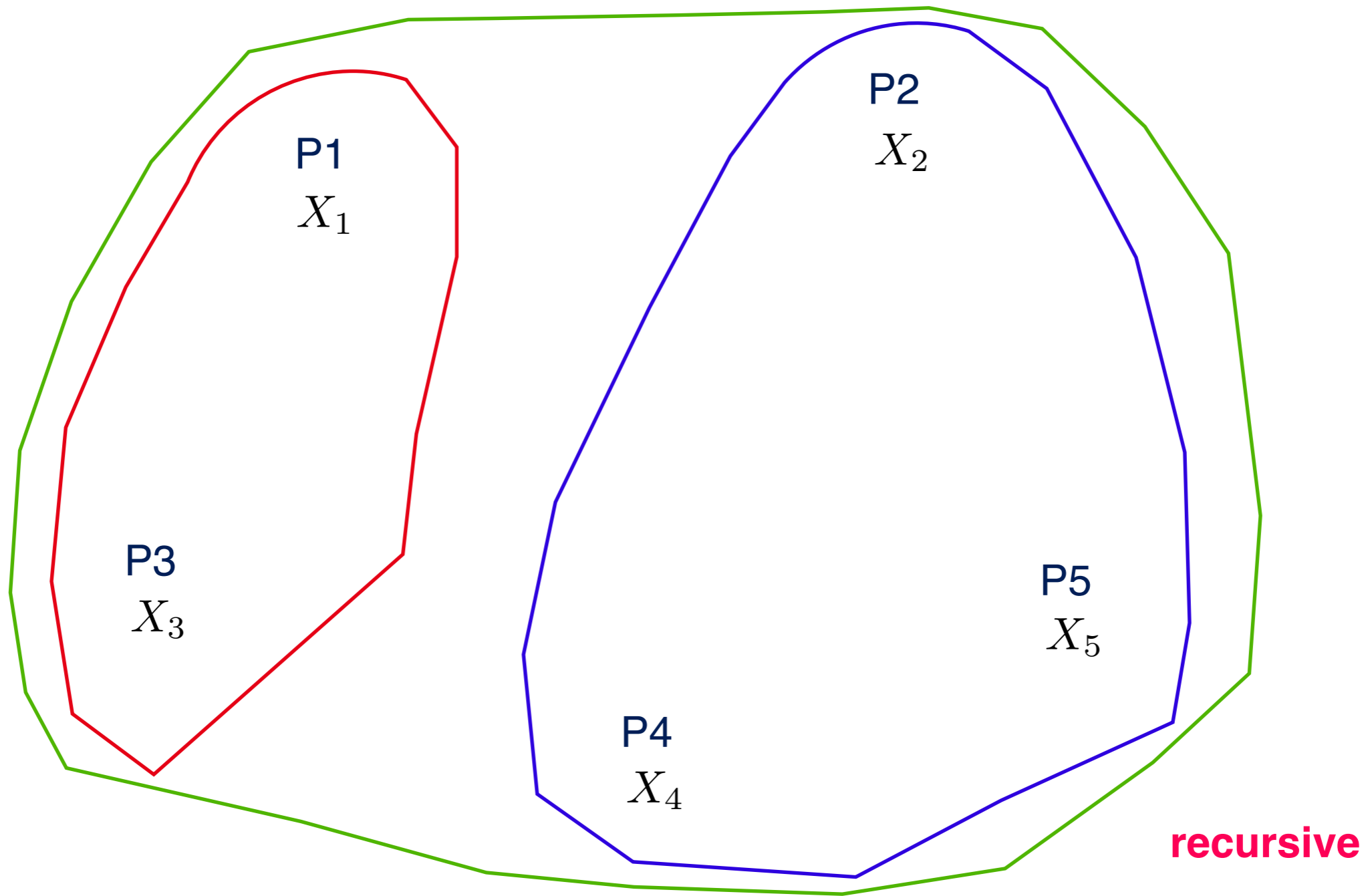
P5
 X_5

P4
 X_4

Recursive Structure



Recursive Structure



Performance of Universal RDE

Corollary (rough statement)

The protocol recursively attain omniscience with rate

$$R(P_{\mathbf{x}_M}) + \underline{\mathcal{O}(\Delta)} + \mathcal{O}\left(\frac{1}{n\Delta}\right) + \mathcal{O}\left(\frac{\log n}{n}\right)$$

slack of rate increment

rate for Ack/Nack

proportional to #rounds $\mathcal{O}(1/\Delta)$

Some Open Problems

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(1) Non-degraded case:

- Even the first-order capacity is not known in general.
- When interaction is not allowed, capacity is known but involves auxiliary RVs.
- What is the second-order rate when the capacity is known?

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(3) Universal protocol for the case with helpers

- When only subset $\mathcal{A} \subset \mathcal{M}$ try to attain omniscience, is there universal protocol?
- Slepian-Wolf coding is known to be optimal, but the rate formula is more involved.

Thank you for listening.