

Common Randomness Principles of Secrecy

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Correlated Data, Distributed in Space and Time

Sensor Networks



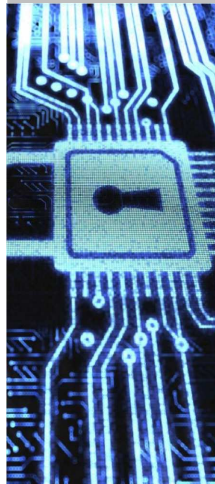
Cloud Computing



Biometric Security



Hardware Security



Secure Processing of Distributed Data

Three classes of problems are studied:

1. Secure Function Computation with Trusted Parties
2. Communication Requirements for Secret Key Generation
3. Querying Eavesdropper

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Our Approach

- ▶ Identify the underlying *common randomness*
- ▶ Decompose common randomness into *independent components*

Outline

1. Basic Concepts
2. Secure Computation
3. Minimal Communication for Optimum Rate Secret Keys
4. Querying Common Randomness
5. Principles of Secrecy Generation

Basic Concepts

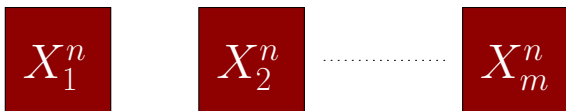
Multiterminal Source Model

Interactive Communication Protocol

Common Randomness

Secret Key

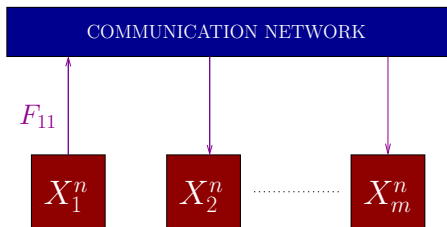
Multiterminal Source Model



Assumption on the data

- ▶ $X_i^n = (X_{i1}, \dots, X_{in})$
 - Data observed at time instance t : $X_{\mathcal{M}t} = (X_{1t}, \dots, X_{mt})$
 - Probability distribution of X_1, \dots, X_m is known.
- ▶ Observations are i.i.d. across time:
 - $X_{\mathcal{M}1}, \dots, X_{\mathcal{M}n}$ are i.i.d. rvs.
- ▶ Observations are finite-valued.

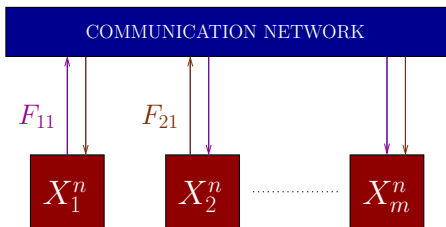
Interactive Communication Protocol



Assumptions on the protocol

- ▶ Each terminal has access to all the communication.
- ▶ Multiple rounds of interactive communication are allowed.
- ▶ Communication from terminal 1: $F_{11} = f_{11}(X_1^n)$

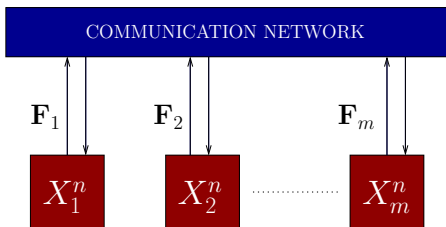
Interactive Communication Protocol



Assumptions on the protocol

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- ▶ Communication from terminal 2: $F_{21} = f_{21}(X_2^n, F_{11})$

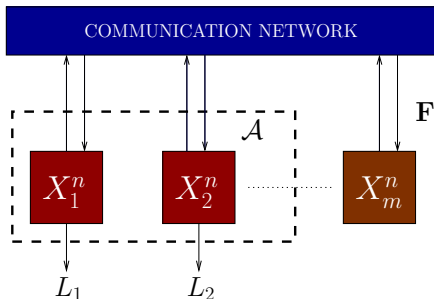
Interactive Communication Protocol



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- ▶ r rounds of interactive communication: $\mathbf{F} = \mathbf{F}_1, \dots, \mathbf{F}_m$

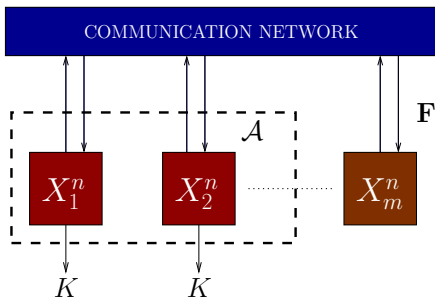
Common Randomness



Definition. L is an ϵ -common randomness for \mathcal{A} from \mathbf{F} if

$$\mathbb{P}(L = L_i(X_i^n, \mathbf{F}), i \in \mathcal{A}) \geq 1 - \epsilon$$

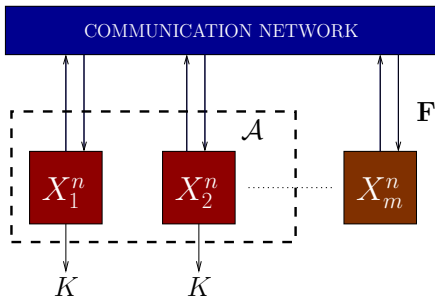
Secret Key



Definition. An rv $K \in \mathcal{K}$ is an ϵ -secret key for \mathcal{A} from \mathbf{F} if

1. *Recoverability:* K is an ϵ -CR for \mathcal{A} from \mathbf{F}
2. *Security:* K is concealed from an observer of \mathbf{F}

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$$P_{KF} \approx U_{\mathcal{K}} \times P_{\mathbf{F}}$$

Notions of Security

- ▶ Kullback-Leibler Divergence

$$\begin{aligned} s_{in}(K, \mathbf{F}) &= D(P_{K\mathbf{F}} \| U_{\mathcal{K}} \times P_{\mathbf{F}}) \\ &= \log |\mathcal{K}| - H(K) + I(K \wedge \mathbf{F}) \approx 0 \end{aligned}$$

- ▶ Variational Distance

$$s_{var}(K, \mathbf{F}) = \|P_{K\mathbf{F}} - U_{\mathcal{K}} \times P_{\mathbf{F}}\|_1 \approx 0$$

- ▶ Weak

$$s_{weak}(K, \mathbf{F}) = \frac{1}{n} s_{in}(K, \mathbf{F}) \approx 0$$

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$$s_{weak}(K, \mathbf{F}) = \frac{1}{n} s_{in}(K, \mathbf{F}) \approx 0$$

$$2 s_{var}(K, \mathbf{F})^2 \leq s_{in}(K, \mathbf{F}) \leq s_{var}(K, \mathbf{F}) \log \frac{|\mathcal{K}|}{s_{var}(K, \mathbf{F})}$$

Secret Key Capacity

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Rate of $K \equiv \frac{1}{n} \log |\mathcal{K}|$

- ▶ ϵ -SK capacity $C(\epsilon) =$ supremum over the rates of ϵ -SKs
- ▶ SK capacity $C = \inf_{0 < \epsilon < 1} C(\epsilon)$

Secret Key Capacity

Theorem (Csiszár-Narayan '04)

The SK capacity is given by

$$C = H(X_{\mathcal{M}}) - R_{CO},$$

where

$$R_{CO} = \min \sum_{i=1}^m R_i,$$

such that $\sum_{i \in B} R_i \geq H(X_B | X_{B^c})$, for all $A \not\subseteq B \subseteq \mathcal{M}$.

Secret Key Capacity

$R_{CO} \equiv$ min. rate of "communication for omniscience" for \mathcal{A}

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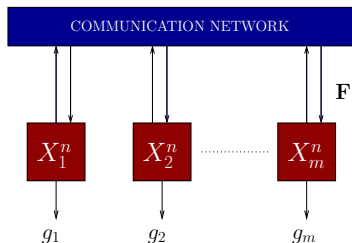
(Maurer '93, Ahlswede-Csiszár '93)

For $m = 2$:

$$C = I(X_1 \wedge X_2)$$

Secure Computation

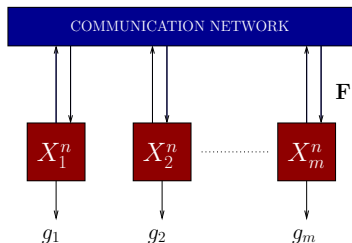
Computing Functions of Distributed Data



Function computed at terminal i : $g_i(x_1, \dots, x_m)$

- Denote the random value of $g_i(x_1, \dots, x_m)$ by G_i

Computing Functions of Distributed Data

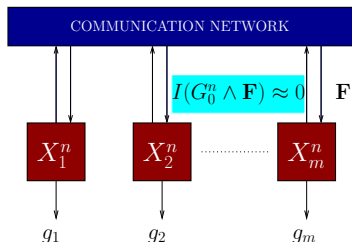


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$$\mathbb{P} \left(G_i^n = \hat{G}_i^{(n)}(X_i^n, \mathbf{F}), \text{ for all } 1 \leq i \leq m \right) \geq 1 - \epsilon$$

Secure Function Computation



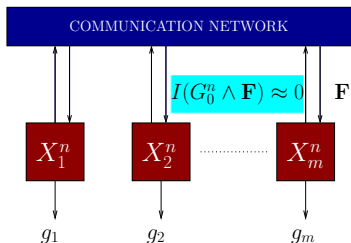
Value of *private function* g_0 must not be revealed

Definition. Functions g_0, g_1, \dots, g_m are **securely computable** if

1. *Recoverability:* $\mathbb{P} \left(G_i^n = \hat{G}_i^{(n)}(X_i^n, \mathbf{F}), i \in \mathcal{M} \right) \rightarrow 1$
2. *Security:* $I(G_0^n \wedge \mathbf{F}) \rightarrow 0$

Secure Function Computation

When are functions g_0, g_1, \dots, g_m securely computable?



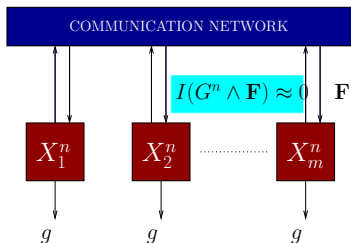
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Secure Function Computation

When is a function g securely computable?



Value of Private function $g_0 = g$

Definition. Function g is **securely computable** if

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2. *Security:* $I(G^n \wedge \mathbf{F}) \rightarrow 0$

A Necessary Condition

If g is securely computable, then it constitutes an SK for \mathcal{M} .

Therefore,

rate of $G \leq$ SK Capacity,

i.e.,

$$H(G) \leq C.$$

When is g securely computable?

Theorem

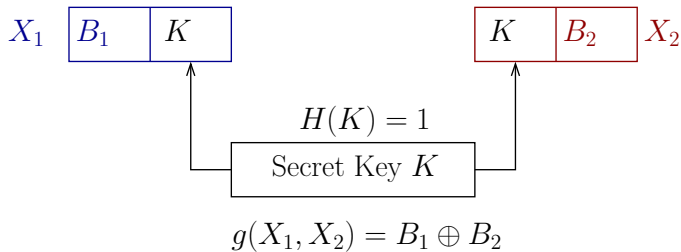
If g is securely computable, then $H(G) \leq C$.

Conversely, g is securely computable if $H(G) < C$.

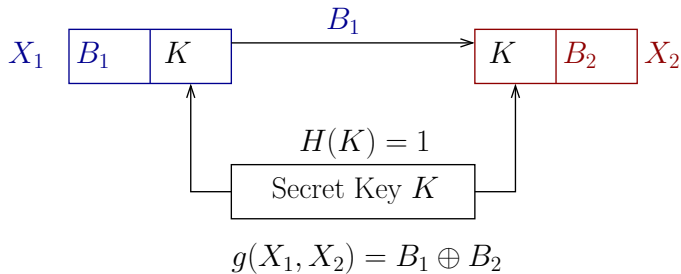
For a securely computable function g :

- ▶ *Omniscience can be obtained using $\mathbf{F} \stackrel{\sim}{\perp\!\!\!\perp} G^n$.*
- ▶ *Noninteractive communication suffices.*
- ▶ *Randomization is not needed.*

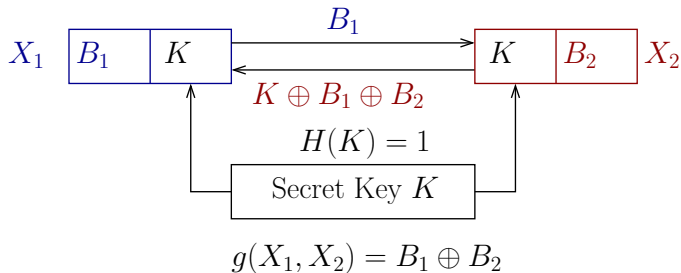
Example: Secure Computation using Secret Keys



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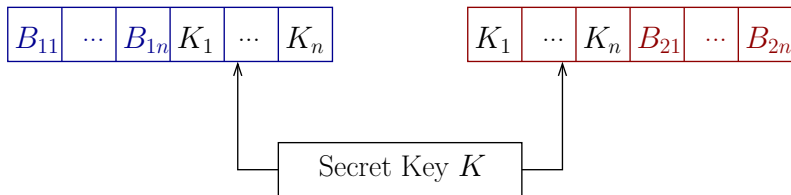


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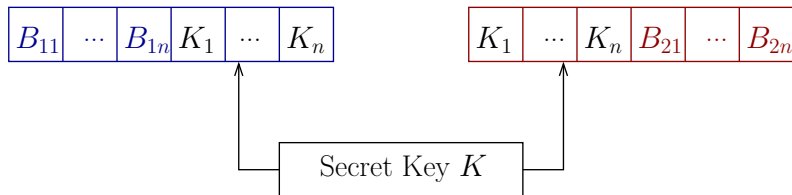
Do fewer than n bits suffice?



$$g(X_1^n, X_2^n) = B_{11} \oplus B_{21}, \dots, B_{1n} \oplus B_{2n}$$

Example: Secure Computation using Secret Keys

Do fewer than n bits suffice?



$$g(X_1^n, X_2^n) = B_{11} \oplus B_{21}, \dots, B_{1n} \oplus B_{2n}$$

- ▶ If parity is securely computable:

$$1 = H(G) \leq C = H(K)$$

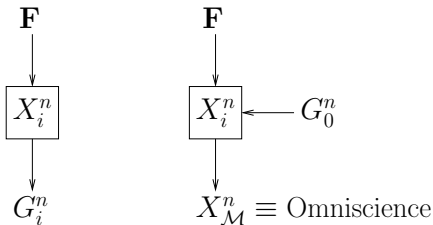
Characterization of Secure Computability

Theorem

The functions g_0, g_1, \dots, g_m are secure computable if ($>$) and only if (\geq)

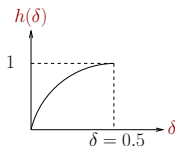
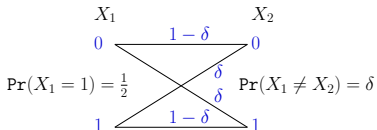
$$H(X_{\mathcal{M}} | G_0) \geq R^*.$$

R^* : minimum rate of \mathbf{F} such that



A data compression problem with no secrecy

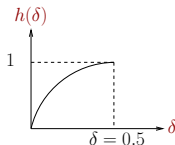
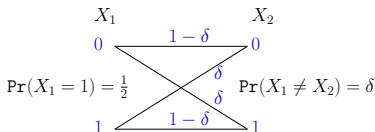
Example: Functions of Binary Sources



Functions are securely computable iff(!) $h(\delta) \leq \tau$

| g_0 | g_1 | g_2 | τ |
|---------------------------------|---------------------------------|------------------|-------------|
| $X_1 \oplus X_2$ | $X_1 \oplus X_2$ | ϕ | 1 |
| $X_1 \oplus X_2$ | $X_1 \oplus X_2$ | $X_1 \cdot X_2$ | $2/3$ |
| $X_1 \oplus X_2$ | $X_1 \oplus X_2$ | $X_1 \oplus X_2$ | $1/2$ |
| $X_1 \oplus X_2, X_1 \cdot X_2$ | $X_1 \oplus X_2, X_1 \cdot X_2$ | $X_1 \cdot X_2$ | $2\delta/3$ |

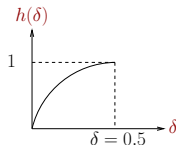
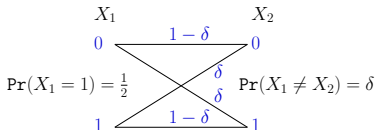
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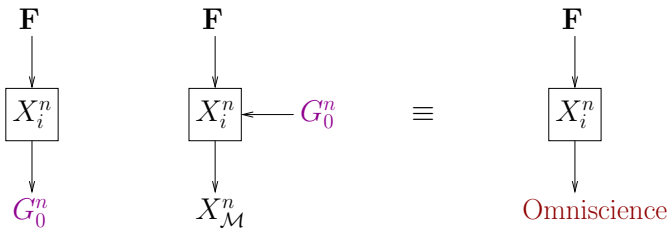
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| $X_1 \oplus X_2, X_1 \cdot X_2$ | $X_1 \oplus X_2, X_1 \cdot X_2$ | $X_1 \cdot X_2$ | $\frac{2\delta}{3}$ |

Computing the Private Function

$$H(X_{\mathcal{M}} | G_0) \geq R^*$$

- Suppose $g_i = g_0$

R^* : minimum rate of \mathbf{F} such that

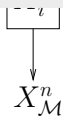
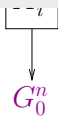


Computing the Private Function

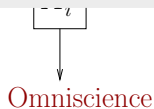
$$H(X_{\mathcal{M}} | G_0) \geq R^*$$

- ▶ Suppose $g_i = g_0$

If g_0 is securely computable at a terminal then the entire data can be recovered securely at that terminal

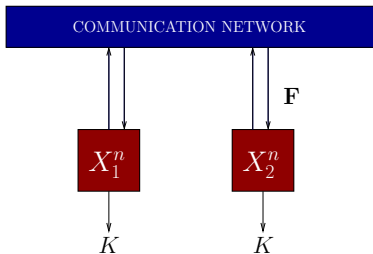


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Minimal Communication for an
Optimum Rate Secret Key

Secret Key Generation for Two Terminals



Weak secrecy criterion: $\frac{1}{n} s_{in}(K, \mathbf{F}) \rightarrow 0$.

Secret key capacity $C = I(X_1 \wedge X_2)$

Common Randomness for SK Capacity

What is the form of CR that yields an optimum rate SK?

► Maurer-Ahlsvede-Csiszár

Common randomness generated

$$X_1^n \text{ or } X_2^n$$

Rate of communication required

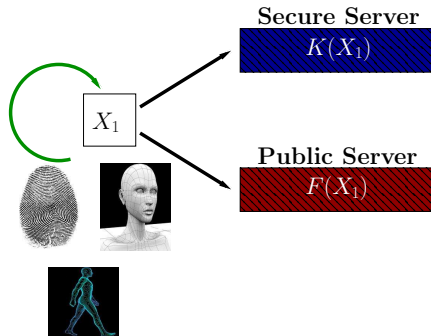
$$\min\{H(X_1|X_2), H(X_2|X_1)\}$$

Decomposition

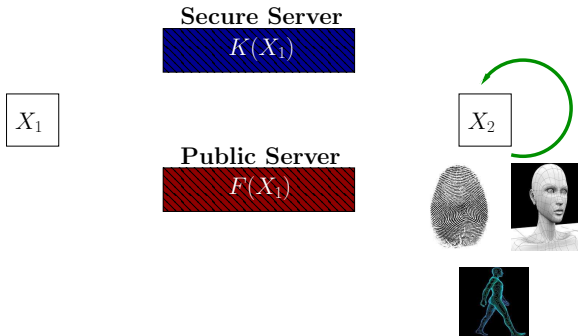
$$H(X_1) = H(X_1|X_2) + I(X_1 \wedge X_2)$$

$$H(X_2) = H(X_2|X_1) + I(X_1 \wedge X_2)$$

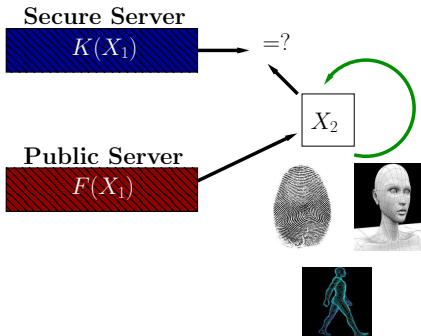
Digression: Secret Keys and Biometric Security



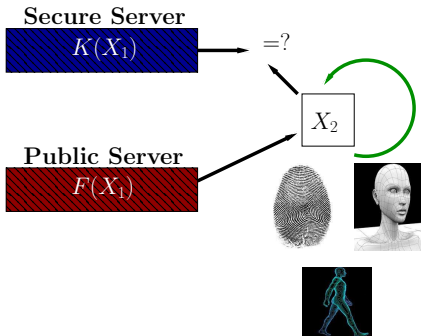
Digression: Secret Keys and Biometric Security



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Digression: Secret Keys and Biometric Security



Similar approach can be applied for **physically uncloneable functions**

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$$X_1^n \text{ or } X_2^n$$

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$$\min\{H(X_1|X_2), H(X_2|X_1)\}$$

Decomposition

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

Common Randomness for SK Capacity

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► Maurer-Ahlsvede-Csiszár

Csiszár-Narayan

Common randomness generated

$$X_1^n \text{ or } X_2^n \quad (X_1^n, X_2^n)$$

Rate of communication required

$$\min\{H(X_1|X_2), H(X_2|X_1)\} \quad H(X_1|X_2) + H(X_2|X_1)$$

Decomposition

$$H(X_1) = H(X_1|X_2) + I(X_1 \wedge X_2)$$

$$H(X_2) = H(X_2|X_1) + I(X_1 \wedge X_2)$$

$$H(X_1, X_2) = H(X_1|X_2) + H(X_2|X_1) + I(X_1 \wedge X_2)$$

Characterization of CR for Optimum Rate SK

Theorem

A CR J recoverable from \mathbf{F} yields an optimum rate SK iff

$$\frac{1}{n} I(X_1^n \wedge X_2^n | J, \mathbf{F}) \rightarrow 0.$$

Examples: X_1^n or X_2^n or (X_1^n, X_2^n)

Interactive Common Information

► Interactive Common Information

Let J be a CR from communication \mathbf{F} .

$CI_i^r(X_1; X_2) \equiv$ min. rate of $L = (J, \mathbf{F})$ such that

$$\frac{1}{n} I(X_1^n \wedge X_2^n | L) \rightarrow 0 \quad (*)$$

$$CI_i(X_1 \wedge X_2) := \lim_{r \rightarrow \infty} CI_i^r(X_1; X_2)$$

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► Wyner's Common Information

$CI(X_1 \wedge X_2) \equiv$ min. rate of $L(X_1^n, X_2^n)$ s.t. $(*)$ holds

Minimum Communication for Optimum Rate SK

R_{SK}^r : min. rate of an r -round communication \mathbf{F} needed to generate an optimum rate SK

Theorem

The minimum rate R_{SK}^r is given by

$$R_{SK}^r = CI_i^r(X_1; X_2) - I(X_1 \wedge X_2).$$

It follows upon taking the limit $r \rightarrow \infty$ that

$$R_{SK} = CI_i(X_1 \wedge X_2) - I(X_1 \wedge X_2)$$

A single letter characterization of CI_i^r is available.

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Binary symmetric rvs: $CI_i^1 = \dots = CI_i^r = \min\{H(X_1), H(X_2)\}$

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There is an example with $CI_i^1 > CI_i^2 \Rightarrow$ Interaction does help!

Common Information Quantities

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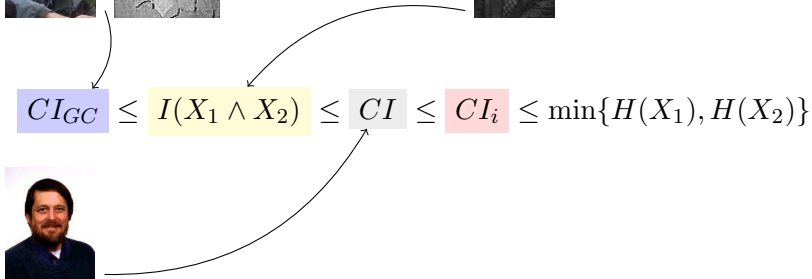
Common Information Quantities



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The diagram shows three arrows pointing from the images above to the terms in the inequality. One arrow points from the color photo to CI_{GC} , another from the grayscale photo to $I(X_1 \wedge X_2)$, and a third from the black and white photo to CI_i .

Common Information Quantities



Common Information Quantities

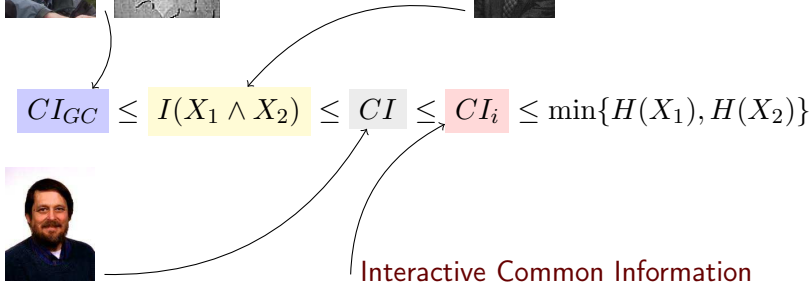


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Interactive Common Information

Common Information Quantities

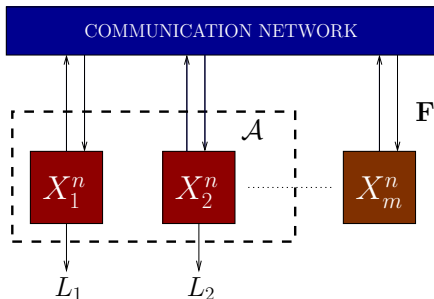


- ▶ CI_i is indeed a new quantity

Binary symmetric rvs: $CI < \min\{H(X_1), H(X_2)\} = CI_i$.

Querying Common Randomness

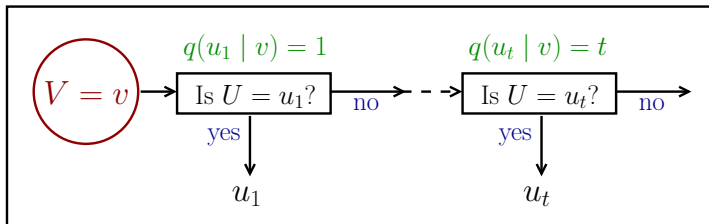
Common Randomness



Definition. L is an ϵ -common randomness for \mathcal{A} from \mathbf{F} if

$$\mathbb{P}(L = L_i(X_i^n, \mathbf{F}), i \in \mathcal{A}) \geq 1 - \epsilon$$

Query Strategy



Query strategy for U given V

Massey '94, Arıkan '96, Arıkan-Merhav '99, Hanawal-Sundaresan '11

Query Strategy

Given rvs U, V with values in the sets \mathcal{U}, \mathcal{V} .

Definition. A **query strategy** q for U given $V = v$ is a bijection

$$q(\cdot|v) : \mathcal{U} \rightarrow \{1, \dots, |\mathcal{U}|\},$$

where the querier, upon observing $V = v$, asks the question

"Is $U = u$?"

in the $q(u|v)^{\text{th}}$ query.

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$$|\{u : q(u | v) < \gamma\}| < \gamma$$

Optimum Query Exponent

Definition. $E \geq 0$ is an ϵ -achievable *query exponent* if there exists ϵ -CR L_n for \mathcal{A} from \mathbf{F}_n such that

$$\sup_q \mathbb{P} (q(L_n | \mathbf{F}_n) < 2^{nE}) \rightarrow 0 \quad \text{as } n \rightarrow \infty,$$

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$$E^*(\epsilon) \triangleq \sup \{ E : E \text{ is an } \epsilon\text{-achievable query exponent} \}$$

$$E^* \triangleq \inf_{0 < \epsilon < 1} E^*(\epsilon) : \text{optimum query exponent}$$

Characterization of Optimum Query Exponent

Theorem

For $0 < \epsilon < 1$, the optimum query exponent E^ equals*

$$E^* = E^*(\epsilon) = C.$$

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Converse: $E^*(\epsilon) \leq C$ - Main contribution

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Proof.

Achievability: $E^*(\epsilon) \geq C(\epsilon)$ - Easy

Converse: $E^*(\epsilon) \leq C$ - Main contribution

Theorem (Strong converse for SK capacity)

For $0 < \epsilon < 1$, the ϵ -SK capacity is given by

$$C(\epsilon) = E^* = C.$$

A Single-Shot Converse

For rvs Y_1, \dots, Y_k , let L be an ϵ -CR for $\{1, \dots, k\}$ from \mathbf{F} .

Theorem

Let θ be such that

$$\mathbb{P} \left(\left\{ (y_1, \dots, y_k) : \frac{\mathbb{P}_{Y_1, \dots, Y_k}(y_1, \dots, y_k)}{\prod_{i=1}^k \mathbb{P}_{Y_i}(y_i)} \leq \theta \right\} \right) \approx 1.$$

Then, there exists a query strategy q_0 for L given \mathbf{F} such that

$$\mathbb{P} \left(q_0(L | \mathbf{F}) \lesssim \theta^{\frac{1}{k-1}} \right) \geq (1 - \sqrt{\epsilon})^2 > 0.$$

Small Cardinality Sets with Large Probabilities

Rényi entropy of order α of a probability measure μ on \mathcal{U} :

$$H_\alpha(\mu) \triangleq \frac{1}{1-\alpha} \log \sum_{u \in \mathcal{U}} \mu(u)^\alpha, \quad 0 \leq \alpha \neq 1$$

Lemma. There exists a set $\mathcal{U}_\delta \subseteq \mathcal{U}$ with $\mu(\mathcal{U}_\delta) \geq 1 - \delta$ s.t.

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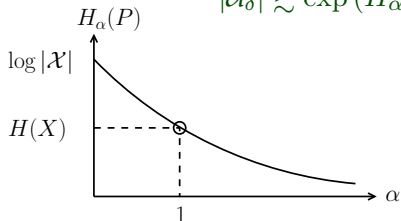
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In Closing ...

Our Approach

- ▶ Identify the underlying *common randomness*
- ▶ Decompose common randomness into *independent components*

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Secure Computing

Common Randomness

Omniscience with side information g_0 for decoding

Decomposition

The private function, the communication and the residual randomness

Our Approach

- ▶ Identify the underlying *common randomness*
- ▶ Decompose common randomness into *independent components*

Two Terminal Secret Key Generation

Common Randomness

Renders the observations conditionally independent

Decomposition

The secret key and the communication

Our Approach

- ▶ Identify the underlying *common randomness*
- ▶ Decompose common randomness into *independent components*

Querying Eavesdropper

*Requiring the number of queries to be as large as possible
– is tantamount to decomposition into independent parts*

Principles of Secrecy Generation

Computing the private function g_0 at a terminal is as difficult as securely recovering the entire data at that terminal.

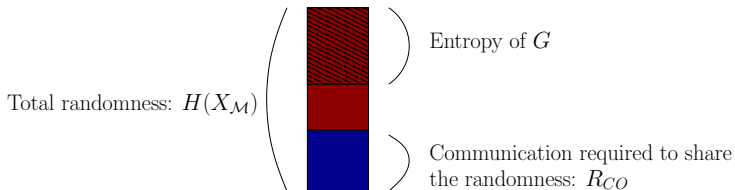
A CR yields an optimum rate SK iff it renders the observations of the two terminals (almost) conditionally independent.

Almost independence secrecy criterion is equivalent to imposing a lower bound on the complexity of a querier of the secret.

Supplementary Slides

Sufficiency

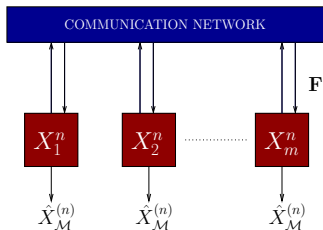
- ▶ Share all data to compute g : **Omniscience** $\equiv X_{\mathcal{M}}^n$
- ▶ Can we attain omniscience using $\mathbf{F} \stackrel{\perp\!\!\!\perp}{\sim} G^n$?



Claim: Omniscience can be attained using $\mathbf{F} \stackrel{\perp\!\!\!\perp}{\sim} G^n$ if:

$$H(G) < H(X_{\mathcal{M}}) - R_{CO}$$

Random Mappings For Omniscience



- ▶ $F_i = F_i(X_i^n)$: random mapping of rate R_i .
- ▶ With large probability, F_1, \dots, F_m result in omniscience if:

$$\sum_{i \in B} R_i \geq H(X_B | X_{B^c}), \quad B \subsetneq \mathcal{M}.$$

- ▶ $R_{CO} = \min \sum_{i \in \mathcal{M}} R_i$.

Independence Properties of Random Mappings

- ▶ \mathcal{P} be a family of N pmfs on \mathcal{X} s.t.

$$P \left(\left\{ x \in \mathcal{X} : P(x) > \frac{1}{2^d} \right\} \right) \leq \epsilon, \quad \forall P \in \mathcal{P}.$$

Balanced Coloring Lemma: Probability that a random mapping $F : \mathcal{X} \rightarrow \{1, \dots, 2^r\}$ fails to satisfy for some $P \in \mathcal{P}$

$$\sum_{i=1}^{2^r} \left| P(F(X) = i) - \frac{1}{2^r} \right| \leq 3\epsilon.$$

is less than $\exp \{ r + \log(2N) - (\epsilon^2/3) 2^{(d-r)} \}$.

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Generalized Privacy Amplification

Sufficiency of $H(G) < H(X_{\mathcal{M}}) - R_{CO}$

Consider random mappings $F_i = F_i(X_i^n)$ of rates R_i such that

$$\sum_{i \in B} R_i \geq H(X_B | X_{B^c}), \quad B \subsetneq \mathcal{M}.$$

- ▶ \mathbf{F} results in omniscience at all the terminals.
- ▶ \mathbf{F} is approximately independent of G^n .

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Note: $I(F_1, \dots, F_m \wedge G^n) \leq \sum_{i=1}^m I(F_i \wedge G^n, F_{\mathcal{M} \setminus i})$

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Show $I(F_i \wedge G^n, F_{\mathcal{M} \setminus i}) \approx 0$ with probability close to 1

- using an extension of the BC Lemma [Lemma 2.7]