



On the Communication Complexity for SK Generation in the Multiterminal Source Model

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EECS Divisional Symposium

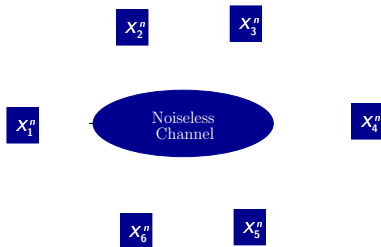


Outline

- 1 The Multiterminal Source Model
- 2 Lower Bound on R_{SK}
- 3 R_{SK} -maximal Sources



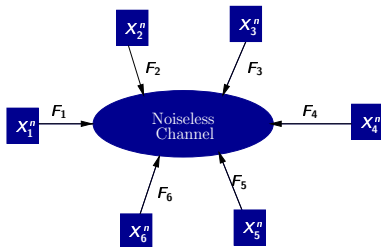
Preliminaries



- A set of terminals $\mathcal{M} = \{1, 2, \dots, m\}$ wants to generate a group secret key.
- Each terminal has a component of a **discrete memoryless multiple source**, X_i^n , $\forall 1 \leq i \leq m$.



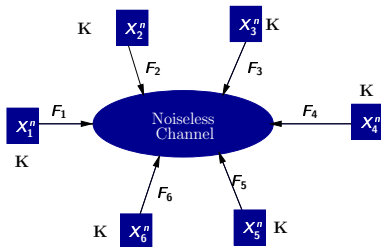
Preliminaries



- **Interactive communication** is allowed among the terminals.
- $\mathbf{F} = \{F_1, F_2, \dots, F_r\}$ is the *interactive communication* taking values in \mathcal{F} .
Here F_j sent by some terminal i is a function of X_i^n and all the previous communication.
- **Communication rate** $= \frac{1}{n} \log |\mathcal{F}|$.
- After the communication the terminals compute a group **secret key** (SK) $\mathbf{K}^{(n)} = \mathbf{K}^{(n)}(X_{\mathcal{M}}^n)$.



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 $K^{(n)} = K^{(n)}(X_{\mathcal{M}}^n)$.



Preliminaries(contd.)

- The secret key $\mathbf{K}^{(n)}$ satisfies the following property:
for any $\epsilon > 0$ and for all sufficiently large n ,
 - \exists some function $\mathbf{g}_i^{(n)}(\mathbf{X}_i^n, \mathbf{F})$ such that
 $\Pr(\mathbf{K}^{(n)} \neq \mathbf{g}_i^{(n)}(\mathbf{X}_i^n, \mathbf{F})) \leq \epsilon, \forall 1 \leq i \leq m$. (*Recoverability*)
 - $I(\mathbf{K}^{(n)}; \mathbf{F}) \leq \epsilon$ (*Strong secrecy*)
 - $\log|\mathcal{K}^{(n)}| - H(\mathbf{K}^{(n)}) \leq \epsilon$, where $\mathcal{K}^{(n)}$ is the range of $\mathbf{K}^{(n)}$. (*Uniformity*)
- If $\frac{1}{n}H(\mathbf{K}^{(n)}) \rightarrow R$ as $n \rightarrow \infty$, then R is an *achievable secret key rate*.
- *Secret key capacity* $\mathcal{C}(\mathcal{M}) = \sup R$.



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Evaluating SK Capacity

- $\mathcal{C}(\mathcal{M}) = H(X_{\mathcal{M}}) - \min_{(R_1, R_2, \dots, R_m) \in \mathcal{R}_{CO}} \sum_{i=1}^m R_i$.
 [Csiszár & Narayan, 2004]

- Here

$$\mathcal{R}_{CO} = \left\{ (R_1, R_2, \dots, R_m) : R_i \geq 0, \forall 1 \leq i \leq m, \right. \\ \left. \sum_{j \in B} R_j \geq H(X_B | X_{B^c}), \forall B \subsetneq \mathcal{M}, B \neq \phi \right\}$$

is the achievable communication rate region for all terminals to recover $X_{\mathcal{M}}^n$.

- $R_{CO} = \min_{(R_1, R_2, \dots, R_m) \in \mathcal{R}_{CO}} \sum_{i=1}^m R_i$ is called the minimum rate of communication for omniscience.



Evaluating SK Capacity

- $\mathcal{C}(\mathcal{M}) = \min_{\mathcal{P}} \Delta(\mathcal{P})$. [Chan & Zheng, 2010]

- $$\Delta(\mathcal{P}) = \frac{1}{\ell-1} \left[H(X_{A_1}) + H(X_{A_2}) + \cdots + H(X_{A_\ell}) - H(X_{\mathcal{M}}) \right].$$

- Here $\mathcal{P} = \{A_1, A_2, \dots, A_\ell\}$, $\ell \geq 2$, is a partition of \mathcal{M} and $X_A = (X_i : i \in A)$.

- The quantity $\min_{\mathcal{P}} \Delta(\mathcal{P})$ is called **multipartite information**.

Observe for the case of $m = 2$ the quantity $\min_{\mathcal{P}} \Delta(\mathcal{P})$ equals $I(X_1; X_2)$.

- There exists a unique finest partition \mathcal{P}^* of \mathcal{M} which minimizes $\Delta(\mathcal{P})$.

We shall refer to \mathcal{P}^* as the **fundamental partition**.



Communication Complexity

- $R_{SK} =$ Communication complexity,
is the minimum rate of communication required to achieve SK capacity.
- $R_{SK} \leq R_{CO}$. [Csiszár & Narayan, 2004]
- If $R_{SK} = R_{CO}$, we call the source R_{SK} -maximal.
These are thus the worst-case sources in terms of communication rates.
- Can we compute R_{SK} ?



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Lower Bound on Communication Complexity

Theorem (Mukherjee & Kashyap, '16)

$$R_{SK} \geq CI(\mathbf{X}_{\mathcal{M}}) - I(\mathbf{X}_{\mathcal{M}}).$$

- The result is an extension of Tyagi's earlier work for two terminals, i.e., $m = 2$.
- $CI(\mathbf{X}_{\mathcal{M}})$ is the minimum rate of interactive common information.
- Fact: $H(\mathbf{X}_{\mathcal{M}}) \geq CI(\mathbf{X}_{\mathcal{M}}) \geq I(\mathbf{X}_{\mathcal{M}})$
and hence the lower bound is non-negative.
- $CI(\mathbf{X}_{\mathcal{M}})$ is difficult to compute in general.
Exact computation of $CI(\mathbf{X}_{\mathcal{M}})$ is possible for the special case of the hypergraphical source.



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Evaluating $CI(X_{\mathcal{M}})$: The Hypergraphical Source

- Consider a **hypergraph** $\mathcal{H} = (\mathcal{V}, \mathcal{E})$.
- $\mathcal{V} = \mathcal{M}$.
- Associate with each hyperedge $e \in \mathcal{E}$ an i.i.d. sequence of n Bernoulli ($1/2$) random variables ξ_e^n .
- Random variables associated with distinct hyperedges in \mathcal{E} are independent.
- Define a multiterminal source as follows:
 $X_i^n = (\xi_e^n : e \in \mathcal{E} \text{ such that } i \in e)$.
- The multiterminal source $X_{\mathcal{M}}^n$ is known as the **hypergraphical source**.

Theorem

For a hypergraphical source we have $CI(X_{\mathcal{M}}) = |\mathcal{E}_{\mathcal{P}^}|$, where $\mathcal{E}_{\mathcal{P}^*}$ is the set of hyperedges intersecting with at least two parts of \mathcal{P}^* .*



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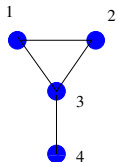
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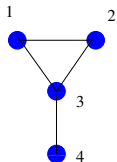
The Lower Bound is Loose



- Consider the following hypergraphical model.
 - $m = 4$ and $\mathcal{E} = \{\{1, 2\}, \{1, 3\}, \{2, 3\}, \{3, 4\}\}$.
 - The random variables $(\xi_e)_{e \in \mathcal{E}}$ are Bernoulli $(1/2)$ random variables.
 - $\mathcal{P}^* = \{\{1, 2, 3\}, \{4\}\}$ and $\mathbf{I}(\mathbf{X}_{\mathcal{M}}) = 1$.
- Therefore, $\text{CI}(\mathbf{X}_{\mathcal{M}}) = 1$ and hence, $\text{CI}(\mathbf{X}_{\mathcal{M}}) - \mathbf{I}(\mathbf{X}_{\mathcal{M}}) = 0$.
- However, $R_{SK} > 0$ as (X_1, X_2) is independent of X_4 .



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 - The random variables $(\xi_e)_{e \in \mathcal{E}}$ are Bernoulli $(1/2)$ random variables.
 - $\mathcal{P}^* = \{\{1, 2, 3\}, \{4\}\}$ and $I(\mathbf{X}_{\mathcal{M}}) = 1$.

- Therefore, $Cl(\mathbf{X}_{\mathcal{M}}) = 1$ and hence, $Cl(\mathbf{X}_{\mathcal{M}}) - I(\mathbf{X}_{\mathcal{M}}) = 0$.
- However, $R_{SK} > 0$ as (X_1, X_2) is independent of X_4 .



When is a Source R_{SK} -maximal?

Theorem

A multiterminal source $X_{\mathcal{M}}$ with fundamental partition \mathcal{P}^* is R_{SK} -maximal if for all $A \in \mathcal{P}^*$ we have $H(X_A | X_{A^c}) = 0$.

Theorem

A hypergraphical source $\mathcal{H} = (\mathcal{M}, \mathcal{E})$ is R_{SK} -maximal iff $\mathcal{E} = \mathcal{E}_{\mathcal{P}^*}$.

- **Example:** Hypergraphical source defined on the complete t -uniform hypergraph $K_{m,t}$:

$$\mathcal{V} = \mathcal{M}.$$

\mathcal{E} is the set of all t -subsets of \mathcal{M} .

