A Shannon Approach to Secure Multi-party Computations

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Abstract—In secure multi-party computations (SMC), parties wish to compute a function on their private data without revealing more information about their data than what the function reveals. In this paper, we investigate two Shannon-type questions on this problem. We first consider the traditional one-shot model for SMC which does not assume a probabilistic prior on the data. In this model, private communication and randomness are the key enablers to secure computing, and we investigate a notion of randomness cost and capacity. We then move to a probabilistic model for the data, and propose a Shannon model for discrete memoryless SMC. In this model, correlations among data are the key enablers for secure computing, and we investigate a notion of dependency which permits the secure computation of a function. While the models and questions are general, this paper focuses on summation functions, and relies on polar code constructions.

I. INTRODUCTION

Consider a group of $m$ parties, each with a private bit $x_i$, $i \in [m] = \{1, \ldots, m\}$, which are interested in computing jointly a function $f(x_1, \ldots, x_m)$, without revealing any other information (than what the function reveals) about their inputs to anybody else. For example, the parties want to vote between two candidates for presidency without revealing their vote, i.e., $f(x_1, \ldots, x_m) = \sum_{i=1}^{n} x_i$. Can this be achieved?

Note that we are asking here for an exact computation of the function $f$, with an arbitrary number of parties $m$ (possibly low), and no information leakage. The latter requirement means that no additional information about the inputs must be shared than what would be shared in a model with a trusted party, which takes care of the computation. Hence, even in the case of a summation function, a noise-perturbation approach will not work in this framework. Of course, the above cannot be achieved without leveraging some “security primitive”. With secure multi-party computations (SMC), this goal is achieved by assuming that the parties have access to private communication. The ideas of SMC were first introduced by Yao in [16], in a two-party setup, in particular with the millionaire problem. General multiparty protocols were then obtained by Goldreich, Micali and Wigderson [3] for computational security, and by Ben-Or, Goldwasser and Wigderson [4] and by Chaum, Crépeau and Damgård [2] for information-theoretic security, using in particular secret-sharing [13]. This paper focuses on the latter setting.

Information-theoretic (IT) security does not rely on the computational power of the adversary, i.e., on hardness assumptions. The models and questions in IT SMC are however very different than the ones studied in the Shannon information theory models. In this paper, we consider the following problems. First, we consider a traditional model for SMC (with private communication, private access to randomness and honest-but-curious parties) and investigate a notion of randomness cost needed to compute a given function securely. Identifying the least amount of randomness is primarily a question which we find mathematically interesting and which connects to information theory subjects, in particular to the study of entropy vectors. It is however also a notion which captures the complexity of a function $f$ for its secure computation. In the second part of the paper, we propose a Shannon model for SMC, assuming the parties input to be drawn from a discrete memoryless source, and requiring the function computation and the security requirement to hold up to a vanishing error probability in an asymptotic regime. In this model, the correlation among the data can be leveraged to obtain secure computations. This model departs significantly from the traditional SMC models discussed above, on the other hand, it is defined in a similar setting as for traditional information theory problems such secrecy [2], [11], [6] or wire-tap channels [15]. Along these lines, a Shannon type model was recently proposed in [14] for a notion of “secure computation”, which is however different than SMC and the notions discussed in this paper. In [14], the parties wish to compute a function on their inputs using communication links which are eavesdropped, and the goal is to compute $f$ without allowing an eavesdropper to compute it. This is different from our setting, where the communication links between parties are secured, and where the parties themselves are the eavesdropper toward one another. Other works relevant to our setting are the interactive source compression [10] and the compress and compute problems [9], [12], but again, these do not take into account the privacy of the inputs among the parties.

II. NOTATION

In what follows, $[n] = \{1, \ldots, n\}$, $|A|$ denotes the cardinality of a set $A$, $X^n$ denotes a vector of length $n$ and $X_i$ represents the $i^{th}$ element of the vector $X^n$. For $x \in \{0, 1\}^n$ and $S \in [n]$, $x[S] = \{x_i : i \in S\}$. Finally, for two vectors $X^n$ and $Y^n$, $X^n \oplus Y^n$ represents the component-wise XOR addition.

There are various other complexity measures, such as the number of communication rounds and the computational complexity.
III. ONE-SHOT MODEL

In this section, secure multi-party computation protocols are studied in the one-shot setting, where the parties’ inputs have no probabilistic prior (equivalently a uniform prior) and where the function computation is done once.

Definition 1. In the honest-but-curious-network (HCN) model,
1) any pair of parties can communicate on a secured channel,
2) each party has access to randomness privately,
3) every party is honest-but-curious, i.e., the parties follow the protocol without deviating from it. However, collecting all the information exchanged in the protocol, the parties may try to learn additional information about other parties’ inputs,
4) the parties have access to a synchronized clock.

A protocol Π in this model is a predetermined sequence of actions taken by the parties on a finite time scale T, where T ≥ 1 is odd. At time t = 0, each party possesses its own input. At an odd time t ∈ {1, 3, . . . , T}, each party P_i possesses Y_{i,t}(Π), and can take the following actions:

- a) draw a discrete random number R_{i,t}(Π),
- b) make a computation using Y_{i,t}(Π) and R_{i,t}(Π),

and at even time t ∈ {2, 4, . . . , T − 1}, each party can transmit information to some other parties. Finally, we define the view of party P_i from the protocol by Y_i(Π) = (Y_{i,1}(Π), R_{i,1}(Π), Y_{i,3}(Π), R_{i,3}(Π), . . . , Y_{i,T}(Π), R_{i,T}(Π)).

In SMCs, the notion of security is defined with the ideal vs. real model paradigm. In the ideal model, trusted parties provide securely their inputs to a trusted party which computes and sends back the output to other parties in a final round of the protocol. The techniques are based on traditional one-time pad and secret sharing steps.

Proposition 1. For any m ≥ 3,
\[ \rho(0, \ldots, 0, X_1 \oplus \cdots \oplus X_m) = 1. \]

Note that for m = 2 the problem is trivial, the party with XOR function can always recover the other input.

Proof: We start by the converse. To show that \[ \rho(0, \ldots, 0, X_1 \oplus \cdots \oplus X_m) \geq 1, \] it is enough to show \[ \rho(0, 0, X_1 \oplus X_2 \oplus X_3) \geq 1, \] since increasing the number of parties only increases the randomness required by the protocol. Clearly, since P_3 has input X_3, we have \[ \rho(0, 0, X_1 \oplus X_2 \oplus X_3) = \rho(0, 0, X_1 \oplus X_2). \] Denote by A_1 all the information that was exchanged between P_1 and P_3 throughout the protocol, and denote by A_2 all the information that was exchanged between P_2 and P_3 throughout the protocol.

From the accuracy requirement, we have \[ H(X_1 \oplus X_2|A_1, A_2) = 0, \] in addition to this, from the security requirement on P_3, we have \[ H(X_1|A_1, A_2) = 1 \] and \[ H(X_2|A_1, A_2) = 1, \] which is equivalent to
\[ H(X_1, X_2|A_1, A_2) = 1 \]
\[ H(X_1|A_1, A_2) = 1 \]
\[ H(X_2|A_1, A_2) = 1. \]

From the security requirement on P_1 and P_2, we have
\[ H(X_2|A_1, X_1) = 1 \] and \[ H(X_1|A_2, X_2) = 1. \]

Finally, from the independence of the inputs
\[ H(X_1|X_2) = 1 \] and \[ H(X_2|X_1) = 1. \]

Since A_1 and A_2 are only a part of all information transmitted and received,
\[ \rho(0, 0, X_1 \oplus X_2 \oplus X_3) \geq H(A_1, A_2|X_1, X_2). \]

We now show that the last term is more than 1. We have
\[ H(A_1, A_2|X_1, X_2) \geq H(A_2|X_1, X_2) = H(A_2) \geq 1. \]
follows by \( \mathbf{5} \) and \( \mathbf{7} \), because
\[
H(X_1|A_2, X_2) = H(X_1|X_2)
\]
\[
\iff H(A_2|X_1, X_2) = H(A_2|X_2),
\]
and \( \mathbf{10} \) follows by \( \mathbf{5} \) because \( X_2 \) and \( (A_1, A_2) \) are independent, so in particular, \( X_2 \) and \( A_2 \) are independent. With the same argument, we notice that \( \mathbf{3} \) implies \( H(X_1|A_1) = 1 \). Finally, \( \mathbf{11} \) follows by \( \mathbf{3} \) and \( \mathbf{4} \) because
\[
H(X_1, X_2|A_1, A_2) = H(X_1|A_1)
\]
\[
\iff H(X_2, A_2|X_1, A_1) = H(A_2|A_1),
\]
and with \( \mathbf{5} \)
\[
H(A_2) \geq H(A_2|A_1)
\]
\[
= H(X_2, A_2|X_1, A_1)
\]
\[
\geq H(X_2|X_1, A_1) = 1.
\]

We now move to the direct part. The achievability of the lower bound is obtained with the following protocol. Consider a multi-party computation protocol for \( X_1 \oplus \cdots \oplus X_m \). Let \( A_1, \ldots, A_{m-1} \) be information that \( P_m \) receives during the protocol from \( P_1, \ldots, P_{m-1}, \) respectively.

1) \( P_1 \) draws a random number \( Z \in \{0, 1\} \) uniformly at random and sends \( Z \) to \( P_m \), \( Y_2 = Z \oplus X_1 \) to \( P_2 \).
2) For \( k \in \{2, \ldots, m - 1\} \), \( P_k \) receives \( Y_k \) from \( P_{k-1} \), computes \( Y_{k+1} = Y_k \oplus X_k = Z \oplus X_1 \oplus \cdots \oplus X_k \) and sends \( Y_{k+1} \) to \( P_{k+1} \).
3) \( P_m \) receives \( Y_m \) from \( P_{m-1} \) and computes the addition and subtraction in modulo \( m \)
\[
Y_m + X_m - Z = Z + X_1 + \cdots + X_m - Z = X_1 + \cdots + X_m.
\]

In this example, \( A_1 = Z \), \( A_2 = \cdots = A_{m-2} = 0 \), and \( A_{m-1} = Z + X_1 + \cdots + X_{m-1} \). Thus,
\[
H(A_1, \ldots, A_{m-1}|X_1, \ldots, X_{m-1})
\]
\[
= H(Z, X_1 + \cdots + X_{m-1}|X_1, \ldots, X_{m-1})
\]
\[
= H(Z) = \log_2 m.
\]

Conjecture 1. For any \( m \geq 3 \),
\[
\rho(\emptyset, \ldots, \emptyset, X_1 + \cdots + X_m) = \log_2 (m).
\]

While showing that \( \log_2 (m) \) is necessary is not established, we believe that a logarithmic bound in \( m \) can be obtained with similar argument as for the XOR function. In particular, this can be written as an inequality over entropic vectors, for which Shannon-type inequalities may or may not suffice.

Remark 1. While this paper focuses on summation functions, similar methods can be used for multiplications. Consider for example the case where three parties wish to compute \((X_1X_2, X_1X_3, X_2X_3)\), i.e., the product of the first two parties’ bits. This can be achieved with a protocol requiring 4 bits of randomness. One possibility is to break each number into three shares, two of which being uniformly distributed, i.e., \(X_1 = X_1(1) + X_1(2) + X_1(3)\) and \(X_2 = X_2(1) + X_2(2) + X_2(3)\), and requiring party \(P_1\) and \(P_2\) to exchange all the bits \(X_i(j)\) for \(i, j \in \{1, 2\}\) and to provide the bit \(X_1(3), X_2(3)\) to party \(3\). Then each party has a component of the product \(X_1X_2\) which can be transmitted to \(P_3\) for the function computation.

IV. DISCRETE MEMORYLESS SECURE MULTIPARTY COMPUTATIONS

We now define a probabilistic model for the parties’ inputs, and leverage the correlations among these inputs to obtain protocols which are secure with high probability in the limit of large sequences, without requiring private communication channels between all parties.

Definition 4. Let \( n \geq 1 \) and \((X_{n(1)}, \ldots, X_{n(m)})\) be i.i.d. sequences with a joint distribution \(\mu\) on \(\mathbb{F}_m^n\). Let \(P_1, \ldots, P_m\) be parties, where party \(P_i\) possesses the input sequence \(X_{n(i)}\) and the distribution \(\mu\), for \(i \in [m]\).

We are now interested in sequences of deterministic protocols, defined on the HCN model without item 2), where parties exchange only deterministic functions of their inputs (no action \(a\)). A sequence of deterministic protocols \(\{\Pi_n\}_{n \geq 1}\) computes asymptotically accurately and privately the deterministic and discrete function sequence \(\{(f_{n(i)}^{(1)}, \ldots, f_{n(i)}^{(m)})\}_{n \geq 1}\) if

- [Asymptotic accuracy] Each party \(P_i\) can compute \(f_{n(i)}^{(1)}(X_{n(i)}^{(1)}, \ldots, X_{n(i)}^{(m)})\) with a vanishing error probability,
i.e., from the view of the protocol $Y(i) | (\Pi_n)$ and its input $X^{n}_i$, party $i$ can compute an estimate $\hat{f}_i^n$ such that
\[ \mathbb{P}\{\hat{f}_i^n \neq f_i^n(X^{n}_1, \ldots, X^{n}_n)\} \rightarrow 0, \quad \text{as } n \rightarrow \infty, \] (15)

- **[Asymmetric security]** Each party $P_i$ cannot recover the input of another party, i.e., for any $j \neq i$, there is no function $\tilde{X}_j$ of $Y(i) | (\Pi_n)$ and $X_i^n$ such that
\[ \lim_{n \rightarrow \infty} \mathbb{P}\{\tilde{X}^n_j \neq X^{n}_j\} \rightarrow 0. \] (16)

Note that the above definition of security is weaker than its counterpart in the one-shot setting by more than just its asymptotic nature: it is not forbidden to just leak some information, but to actually recover an input sequence.

Given a set of functions $\{f_1^n, \ldots, f_m^n\}$, our goal is to study for which distributions $\mu$ on $\mathbb{F}_2^n$ it is possible to obtain a protocol computing the functions accurately and securely in the above asymptotic sense.

A. The XOR function

In this section, we introduce an asymptotically accurate and secure protocol for the modulo-2 sum of three parties inputs. Namely $f_i^n = X^n \oplus Y^n \oplus Z^n$ for $i = 1, 2, 3$.

**Definition 5.** Let $X$ and $Y$ be binary random variables with a joint distribution $\mu$ on $\mathbb{F}_2^n$. We call the distribution additively-correlated if
\[ H(X, Y) = 2H(X \oplus Y) > 0. \] (17)

Let $X, Y, Z$ be binary random variables with a joint distribution $\mu$ on $\mathbb{F}_2^n$. We call the distribution additively-correlated if at least one pair of the random variables is additively-correlated.

For example, $X \sim \text{Ber}(0.5)$, $Z \sim \text{Ber}(p)$, and $Y = X \oplus Z$, where $p < 0.5$ satisfies (17).

**Proposition 3.** Let $n \geq 1$ and $(X^n, Y^n, Z^n)$ be i.i.d. sequences with a joint distribution $\mu$ on $\mathbb{F}_2^n$ which is pair-wise-additively correlated. Then the ASP protocol defined below allows to compute asymptotically accurately and securely the function $X^n \oplus Y^n \oplus Z^n$.

This provides an achievability result.

**Remark 2.** The ASP protocol is based on polar codes. The linearity of the code is crucial to compute the XOR function. The protocol could probably be adapted with other linear codes, such as random linear codes, however, polar codes provide in addition a low-complexity protocol, and are also insightful as a proof technique.

We next recall the source polarization results and then describe the protocol.

B. Preliminaries on polar codes

For $n$ a power of 2, define $G_n = \begin{pmatrix} 1 & 0 \\ 1 & 1 \end{pmatrix}^\otimes \log_2(n)$, where $A^\otimes k$ denotes the matrix obtained by taking $k$ Kronecker products of matrix $A$ with itself.

**Theorem 1.** Let $X^n = [X_1, \ldots, X_n] \text{ iid Bernoulli}(p)$, where $n$ is a power of 2, and let $\tilde{X}^n = X^n \oplus G_n$. Then, for any $\epsilon \in (0, 1/2]$, $|\{j \in [n] : H(\tilde{X}_j | \tilde{X}^{j-1}) \in (\epsilon, 1 - \epsilon)\}| = o(n)$, where $H(\tilde{X}_j | \tilde{X}^{j-1})$ represents the conditional Shannon entropy of $\tilde{X}_j$ given $\tilde{X}^{j-1} = [X_1, \ldots, X_{j-1}]$. The above still holds if $\epsilon = O(2^{-n^\beta})$, $\beta < 1/2$.

Theorem 1 says that, except for a vanishing fraction, all conditional entropies $H(\tilde{X}_j | \tilde{X}^{j-1})$ tend to either 0 or 1. Also, notice that since $G_n$ is invertible, hence $nH(p) = H(X^n) = H(\tilde{X}_n)$, and defining
\[ R_{\epsilon, n}(X) := \{i \in [n] : H(\tilde{X}_i | \tilde{X}^{i-1}) \geq \epsilon\}, \] (18)
we have
\[ \frac{1}{n} |R_{\epsilon, n}(X)| \rightarrow H(p), \] (19)
where $H(p)$ is the entropy of the Bernoulli$(p)$ distribution.

**C. The asymptotically secure polar (ASP) protocol**

All the parties know $\mu$ and set $\epsilon = \epsilon_n = 2^{-n^{0.45}}$. Since $\mu$ is additively-correlated, assume w.l.o.g. that the inputs of $P_1$ and $P_2$ are additively-correlated.

1) Inputs at time 0:
- party 1: $X^n$, party 2: $Y^n$, party 3: $Z^n$

2) At time 1:
- $P_1$ computes $\tilde{X}^n = X^n \oplus G_n$ and $R_{\epsilon, n}(X \oplus Y)$
- $P_2$ computes $\tilde{Y}^n = Y^n \oplus G_n$ and $R_{\epsilon, n}(X \oplus Y)$

3) At time 2:
- $P_1$ sends $\tilde{X}[R_{\epsilon, n}(X \oplus Y)]$ to $P_3$
- $P_2$ sends $\tilde{Y}[R_{\epsilon, n}(X \oplus Y)]$ to $P_3$

4) At time 3: $P_3$ computes $\tilde{X}[R_{\epsilon, n}(X \oplus Y)] \oplus Y[R_{\epsilon, n}(X \oplus Y)] = (\tilde{X} \oplus \tilde{Y})[R_{\epsilon, n}(X \oplus Y)]$ and decodes $\tilde{X}^n \oplus \tilde{Y}^n$ from $(\tilde{X} \oplus \tilde{Y})[R_{\epsilon, n}(X \oplus Y)]$ using the polar decoding algorithm in [3]. Let $\tilde{X}^n \oplus \tilde{Y}^n$ be the decoded vector.
- $P_3$ computes $\tilde{X}^n \oplus \tilde{Y}^n = (\tilde{X} \oplus \tilde{Y}^n)G_n^{-1}$
- At time 4: $P_3$ sends $\tilde{X}^n \oplus \tilde{Y}^n + Z^n$ to $P_1$ and $P_2$.

D. Proof of Proposition 3

**Lemma 1.** The SPC protocol is asymptotically accurate.

**Proof:** Since $Z^n$ is not encoded during the protocol, it is enough to prove that
\[ \text{Pr}(\tilde{X}_i \oplus \tilde{Y}_i \neq X_i \oplus Y_i) \xrightarrow{n \rightarrow \infty} 0. \] (20)
This is a direct application of Theorem [1] as in [3].

**Lemma 2.** The SPC is asymptotically secure.

**Proof:** Since $P_1$ receives only $X^n \oplus Y^n \oplus Z^n$ during the protocol, it is clear that it cannot estimate $Y^n$ or $Z^n$ with a vanishing error probabilities. Similarly, $P_2$ cannot estimate $X^n$ or $Z^n$ with a vanishing error probability. Therefore, to prove that the protocol 2 is asymptoticlly secure for all parties, it is enough to prove that for $P_3$,

$$Pr(\tilde{X}^n \neq X^n) \geq 0 \tag{21}$$

where $a_n \rightarrow 0$ means $\lim \inf_{n \rightarrow \infty} a_n > 0$, and

$$Pr(\tilde{Y}^n \neq Y^n) \geq 0, \tag{22}$$

where $\tilde{X}^n$ and $\tilde{Y}^n$ are $P_3$'s estimations of $X^n$ and $Y^n$ given $X[R_{\epsilon,n}(X \oplus Y)]$ and $\tilde{Y}[R_{\epsilon,n}(X \oplus Y)]$.

During the protocol, $P_3$ receives $\tilde{X}[R_{\epsilon,n}(X \oplus Y)]$ and $\tilde{Y}[R_{\epsilon,n}(X \oplus Y)]$ and knows $X^n \oplus Y^n$ with the vanishing error probability by Theorem [1]. Thus, for $P_3$, knowing $X^n$ with the vanishing error probability guarantees recovery of $Y^n = X^n \oplus (X^n \oplus Y^n)$, and vice verse. Then,

$$Pr(\tilde{X}^n \neq X^n) \rightarrow 0 \cup Pr(\tilde{Y}^n \neq Y^n) \rightarrow 0 \iff Pr(\tilde{X}^n, \tilde{Y}^n \neq X^n, Y^n) \rightarrow 0.$$

Therefore, it is enough to show $Pr(\tilde{X}^n, \tilde{Y}^n \neq X^n, Y^n) \rightarrow 0$. Notice that $X^n, Y^n \rightarrow \tilde{X}[R_{\epsilon,n}(X \oplus Y)], \tilde{Y}[R_{\epsilon,n}(X \oplus Y)] \rightarrow \tilde{X}^n, \tilde{Y}^n$ forms a Markov chain. Then, by Fano’s inequality,

$$Pr(\tilde{X}^n, \tilde{Y}^n \neq X^n, Y^n) \geq H(X^n, Y^n | \tilde{X}[R_{\epsilon,n}(X \oplus Y)], \tilde{Y}[R_{\epsilon,n}(X \oplus Y)]) - 1$$

$$\geq H(X^n, Y^n) - H(\tilde{X}[R_{\epsilon,n}(X \oplus Y)], \tilde{Y}[R_{\epsilon,n}(X \oplus Y)]) - 1$$

$$\geq H(X^n, Y^n) - 2H(\tilde{X}[R_{\epsilon,n}(X \oplus Y)]) - 1$$

$$\geq H(X^n, Y^n) - 2|R_{\epsilon,n}(X \oplus Y)| - 1$$

$$\geq \frac{nH(X^n, Y^n) - 2H(X^n) - 1}{n}$$

where (23) follows from (19). Then, since $X^n$ and $Y^n$ are additively-correlated,

$$\lim \inf_{n \rightarrow \infty} Pr(\tilde{X}^n, \tilde{Y}^n \neq X^n, Y^n) > 0. \tag{25}$$

**Remark 3.** Note that since the ASP protocol is asymptotically secure, it must be that $H(X,Y) - 2H(X \oplus Y) > 0$ implies $H(X) - H(\tilde{X}) > 0$ and $H(Y) - H(\tilde{Y}) > 0$. The reason for that is due to the nested property of source polar codes, see for example [1], which implies that if $H(X+Y) > H(X)$, then $R_{\epsilon,n}(X + Y)$ contains $R_{\epsilon,n}(X)$ and hence observing $\tilde{X}[R_{\epsilon,n}(X + Y)]$ allows to decode $X^n$ correctly. In fact the above implication is true since

$$H(X,Y) - 2H(X \oplus Y) > 0 \iff H(X|X+Y) > H(X)$$

and $H(X|X+Y) \leq H(X)$.

V. OPEN PROBLEMS

Concerning the first part, it would interesting to set conjecture [1] We believe that a logarithmic bound can be obtained with the approach of this paper. As mentioned in Remark [1] it is possible to obtain achievability results on $\rho$ for multivariate polynomials. The scaling of the $\rho$ can then be analyzed. For the second part, it would be interesting to establish converse results for XOR function, and any result for other type of functions, starting perhaps with the real-addition.

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REFERENCES

[1] E. Abbe, Randomness and dependencies extraction via polarization, Information Theory and Applications Workshop (ITA), 2011, 2011, pp. 1–7.
[2] R. Ahlswede and I. Csiszar, Common randomness in information theory and cryptography, i. secret sharing, Information Theory, IEEE Transactions on 39 (1993), no. 4, 1121–1132.
[3] E. Arikan, Source polarization, Information Theory Proceedings (ISIT), 2010 IEEE International Symposium on, 2010, pp. 899–903.
[4] M. Ben-Or, S. Goldwasser, and A. Wigderson, Completeness theorems for non-cryptographic fault-tolerant distributed computation, ACM Symposium on Theory of Comput. (STOC) (New York, NY), 1988, pp. 1–10.
[5] D. Chaum, C. Cr´epeau, and I. Damgard, Multiparty unconditionally secure protocols, Proceedings of the twentieth annual ACM symposium on Theory of computing, STOC’88, 1988, pp. 11–19.
[6] I. Csiszar and P. Narayan, Secrecy capacities for multiterminal channel models, Information Theory, IEEE Transactions on 54 (2008), no. 6, 2437–2452.
[7] O. Goldreich, Secure multi-party computation (working draft), Available from http://www.wisdom.weizmann.ac.il/home/oded/
/public.html/foc.html (1998).
[8] O. Goldreich, S. Micali, and A. Wigderson, How to play any mental game, ACM Sympos. on Theory of Comput. (STOC) (New York, NY), 1987, pp. 218–229.
[9] J. Korner and K. Marton, How to encode the module-two sum of binary sources (corresp.), Information Theory, IEEE Transactions on 25 (1979), no. 2, 219–221.
[10] Nan Ma and Prakash Ishwar, Infinite-message distributed source coding for two-terminal interactive computing, Proceedings of the 47th Annual Allerton Conference on Communication, Control, and Computing (Piscataway, NJ, USA), Allerton’09, IEEE Press, 2009, pp. 1510–1517.
[11] Ueli Maurer and Stefan Wolf, Information-theoretic key agreement: From weak to strong secrecy for free, Proceedings of the 19th International Conference on Theory and Application of Cryptographic Techniques (Berlin, Heidelberg), EUROCRYPT’00, Springer-Verlag, 2000, pp. 351–368.
[12] A. Orlitsky and J.R. Roche, Coding for computing, Information Theory, IEEE Transactions on 47 (2001), no. 3, 903–917.
[13] A. Shamir, How to share a secret, Communications of the ACM 22 (1979), 612–613.
[14] H. Tyagi, P. Narayan, and P. Gupta, When is a function securely computable?, Information Theory, IEEE Transactions on 57 (2011), no. 10, 6337–6350.
[15] Aaron D. Wyner, The Wire-tap Channel, Bell Systems Technical Journal 54 (1975), no. 8, 1355–1387.
[16] A. C. Yao, Protocols for secure computations, 23rd Annual Symposium on Foundations of Computer Science (FOCS), 1982, pp. 160–164.