

Asymmetric Error Correction and Flash-Memory Rewriting Using Polar Codes

Eyal En Gad, *Member, IEEE*, Yue Li, Jörg Kliewer, *Senior Member, IEEE*,
Michael Langberg, *Senior Member, IEEE*, Anxiao (Andrew) Jiang, *Senior Member, IEEE*,
and Jehoshua Bruck, *Fellow, IEEE*

Abstract—We propose efficient coding schemes for two communication settings: 1) asymmetric channels and 2) channels with an informed encoder. These settings are important in non-volatile memories, as well as optical and broadcast communication. The schemes are based on non-linear polar codes, and they build on and improve recent work on these settings. In asymmetric channels, we tackle the exponential storage requirement of previously known schemes that resulted from the use of large Boolean functions. We propose an improved scheme that achieves the capacity of asymmetric channels with polynomial computational complexity and storage requirement. The proposed non-linear scheme is then generalized to the setting of channel coding with an informed encoder using a multicoding technique. We consider specific instances of the scheme for flash memories that incorporate error-correction capabilities together with rewriting. Since the considered codes are non-linear, they eliminate the requirement of previously known schemes (called polar write-once-memory codes) for shared randomness between the encoder and the decoder. Finally, we mention that the multicoding scheme is also useful for broadcast communication in Marton’s region, improving upon previous schemes for this setting.

Index Terms—Polar codes, Gelfand-Pinsker channel, write-once-memory codes (WOMs).

I. INTRODUCTION

IN THIS paper we make several contributions to the design and analysis of error-correcting codes in two important communication settings: 1. asymmetric channel coding, and 2. channel coding with an informed encoder. Asymmetric channel coding is important for applications such as non-volatile memories, in which the electrical mechanisms are dominantly asymmetric [5]. Another important application

is in optical communication, where photons may fail to be detected ($1 \rightarrow 0$) but a false detection when no photon was sent ($0 \rightarrow 1$) is much less likely [15, Sec. IX]. Channel coding with an informed encoder is also important for non-volatile memories, since the memory state in these devices affects the fate of writing attempts. Channel coding with an informed encoder is also useful in broadcast communication, where it is used in Marton’s coding scheme to achieve high communication rates (see [7, p. 210]).

The focus of this paper is on polar coding techniques, as they are both highly efficient in terms of communication rate and computational complexity, and are relatively easy to analyze and understand. Polar codes were introduced by Arikan in [1], achieving the symmetric capacity of binary-input memoryless channels. The first task that we consider in this paper is that of point-to-point communication over asymmetric channels. Several polar coding schemes for asymmetric channels were proposed recently, including a pre-mapping using Gallager’s scheme [11, p. 208] and a concatenation of two polar codes [31]. A more direct approach was proposed in [17], which we consider in this paper. A similar approach is also considered in [22]. The scheme in [17] achieves the capacity of asymmetric channels using non-linear polar codes, but it uses large Boolean functions that require storage space that is exponential in the block length. We propose a modification for this scheme, that removes the requirement for the Boolean functions, and thus reduces the storage requirement of the encoding and decoding tasks to a linear function of the block length.

The second contribution of this paper is a generalization of the non-linear polar-coding scheme to the availability of channel side information at the encoder. We call this scheme a polar multicoding scheme, and we prove that it achieves the capacity of channels with informed encoders. The capacity of such channels was characterized by Gelfand and Pinsker in [12]. This scheme is useful for non-volatile memories such as flash memories and phase change memories, and for broadcast channels. We focus mainly on the flash memory application.

A prominent characteristic of flash memories is that the response of the memory cells to a writing attempt is affected by the previous content of the memory. This complicates the design of error correcting schemes, and thus motivates flash systems to “erase” the content of the cells before writing, and by that to eliminate its effect. However, the erase operation

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E. En Gad was with the California Institute of Technology, Pasadena, CA 91125 USA. He is now with the University of Southern California, Los Angeles, CA 90089 USA (e-mail: engad@usc.edu).

Y. Li and J. Bruck are with the California Institute of Technology, Pasadena, CA 91125 USA (e-mail: yli@caltech.edu; bruck@caltech.edu).

J. Kliewer is with the New Jersey Institute of Technology, Newark, NJ 07102 USA (e-mail: jkliewer@njit.edu).

M. Langberg is with the University at Buffalo, The State University of New York, Buffalo, NY 14260 USA (e-mail: mikel@buffalo.edu).

A. Jiang is with Texas A&M University, College Station, TX 77840 USA (e-mail: ajiang@cse.tamu.edu).

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in flash memories is expensive, and therefore a simple coding scheme that does not require erasures could improve the performance of solid-state drives significantly. We show two instances of the proposed polar multicoding scheme that aim to achieve this goal.

A. Relation to Previous Work

The study of channel coding with an informed encoder was initiated by Kusnetsov and Tsybakov [19], with the channel capacity derived by Gel'fand and Pinsker [12]. The informed encoding technique of Gel'fand and Pinsker was used earlier by Marton to establish an inner bound for the capacity region of broadcast channels [21]. Low-complexity capacity-achieving codes were first proposed for continuous channels, using lattice codes [33]. In discrete channels, the first low-complexity capacity-achieving scheme was proposed using polar codes, for the symmetric special case of information embedding [18, Sec. VIII.B]. A modification of this scheme for the application of flash memory rewriting was proposed in [4], considering a model called write-once memory. An additional scheme for the application of flash memory, based on randomness extractors, was also proposed recently [10].

Our work is concerned with a setup that is similar to those considered in [4] and [10]. An important contribution of the current paper compared to [4] and [10] is that our scheme achieves the capacity of a rewriting model that also includes noise, while the schemes in [4] and [10] address only the noiseless case. Indeed, error correction is a crucial capability in flash memory systems. Our low-complexity achievability of the noisy capacity is done using a multicoding technique. Comparing with [10], the current paper allows an input cost constraint, which is important in rewriting models for maximizing the sum of the code rates over multiple rewriting rounds. Comparing with [4], the current paper also improves by removing the requirement for shared randomness between the encoder and the decoder, which limits the practical coding performance. The removal of the shared randomness is done by the use of non-linear polar codes. An additional coding scheme was proposed during the writing of this paper, which also does not require shared randomness [20]. However, the scheme in [20] considers only the noiseless case, and it is in fact a special case of the scheme in the current paper.

Polar coding for channels with informed encoders was implicitly studied recently in the context of broadcast channels, as the Marton coding scheme for broadcast communication contains an informed encoding instance as an ingredient. In fact, a multicoding technique similar to the one presented in this paper was recently presented for broadcast channels, in [13]. While we were unaware of the result of [13] and developed the scheme independently, this paper also has three contributions that were not shown in [13]. First, by using the modified scheme of non-linear polar codes, we reduce the storage requirement from an exponential function in the block length to a linear function. Secondly, we connect the scheme to the application of data storage and flash memory rewriting, that was not considered in the previous work. And thirdly,

the analysis in [13] holds only for channels whose capacity-achieving distribution forms a certain degraded structure. In this paper we consider a specific noisy rewriting model, whose capacity-achieving distribution forms the required degraded structure, and by that we show that the scheme achieves the capacity of the considered flash-memory model.

Another recent paper on polar coding for broadcast channels was published recently by Mondelli *et al.* [23]. That paper proposed a method, called “chaining”, that allows to bypass the degraded structure requirement. In this paper we connect the chaining method to the flash-memory rewriting application and to our new non-linear polar coding scheme, and apply it to our proposed multicoding scheme. This allows for a linear storage requirement, together with the achievability of the informed encoder capacity and Marton’s inner bound, eliminating the degraded structure requirement. Finally, we show an important instance of the chaining scheme for a specific flash-memory model, and explain the applicability of this instance in flash-memory systems.

The rest of the paper is organized as follows. Section II proposes a new non-linear polar coding scheme for asymmetric channels, which does not require an exponential storage of Boolean functions. Section III proposes a new polar multicoding scheme for channels with informed encoders, including two special cases for the rewriting of flash memories. Finally, Section IV summarizes the paper.

II. ASYMMETRIC POINT-TO-POINT CHANNELS

Notation: For positive integers $m \leq n$, let $[m : n]$ denote the set $\{m, m + 1, \dots, n\}$, and let $[n]$ denote the set $[1 : n]$. Given a subset \mathcal{A} of $[n]$, let \mathcal{A}^c denote the complement of \mathcal{A} with respect to $[n]$, where n is clear from the context. Let $x_{[n]}$ denote a vector of length n , and let $x_{\mathcal{A}}$ denote a vector of length $|\mathcal{A}|$ obtained from $x_{[n]}$ by deleting the elements with indices in \mathcal{A}^c .

Throughout this section we consider only channels with binary input alphabets, since the literature on polar codes with non-binary codeword symbols is relatively immature. However, the results of this section can be extended to non-binary alphabets without much difficulty using the methods described in [24]–[29]. The main idea of polar coding is to take advantage of the polarization effect of the Hadamard transform on the entropies of random vectors. Consider a binary-input memoryless channel model with an input random variable (RV) $X \in \{0, 1\}$, an output RV $Y \in \mathcal{Y}$ and a pair of conditional probability mass functions (pmfs) $p_{Y|X}(y|0)$, $p_{Y|X}(y|1)$ on \mathcal{Y} . Let n be a power of 2 that denotes the number of channel uses, also referred to as the block length. The channel capacity is the tightest upper bound on the code rate in which the probability of decoding error can be made as small as desirable for large enough block length. The channel capacity is given by the mutual information of X and Y .

Theorem 1 (Channel Coding Theorem [6, Ch. 7]): *The capacity of a discrete memoryless channel defined by $p_{X|Y}$ is*

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

The Hadamard transform is a multiplication of the random vector $X_{[n]}$ over the field of cardinality 2 with the matrix $G_n = G^{\otimes \log_2 n}$, where $G = \begin{pmatrix} 1 & 0 \\ 1 & 1 \end{pmatrix}$ and \otimes denotes the Kronecker power. In other words, G_n can be described recursively for $n \geq 4$ by the block matrix

$$G_n = \begin{pmatrix} G_{n/2} & 0 \\ G_{n/2} & G_{n/2} \end{pmatrix}.$$

The matrix G_n transforms $X_{[n]}$ into a random vector $U_{[n]} = X_{[n]}G_n$, such that the conditional entropy $H(U_i|U_{[i-1]}, Y_{[n]})$ is *polarized*. That means that for a fraction of close to $H(X|Y)$ of the indices $i \in [n]$, the conditional entropy $H(U_i|U_{[i-1]}, Y_{[n]})$ is close to 1, and for almost all the rest of the indices, $H(U_i|U_{[i-1]}, Y_{[n]})$ is close to 0. This result was shown by Arikan in [1] and [2].

Theorem 2 (Polarization Theorem [2, Th. 1]): Let $n, U_{[n]}, X_{[n]}, Y_{[n]}$ be defined as above. For any $\delta \in (0, 1)$, let

$$H_{X|Y} \triangleq \{i \in [n] : H(U_i|U_{[i-1]}, Y_{[n]}) \in (1 - \delta, 1)\},$$

and

$$L_{X|Y} \triangleq \{i \in [n] : H(U_i|U_{[i-1]}, Y_{[n]}) \in (0, \delta)\}.$$

Then

$\lim_{n \rightarrow \infty} |H_{X|Y}|/n = H(X|Y)$ and $\lim_{n \rightarrow \infty} |L_{X|Y}|/n = 1 - H(X|Y)$. Note that $H(X|Y)$ denotes a conditional entropy, while $H_{X|Y}$ denotes a subset of $[n]$. It is also shown in [1] that the transformation G_n is invertible with $G_n^{-1} = G_n$, implying $X_{[n]} = U_{[n]}G_n$. This polarization effect can be used quite simply for the design of a coding scheme that achieves the capacity of symmetric channels with a running time that is polynomial in the block length. The capacity of symmetric channels is achieved by a uniform distribution on the input alphabet, i.e. $p_X = 1/2$ [6, Th. 7.2.1]. Since the input alphabet in this paper is binary, the capacity-achieving distribution gives $H(X) = 1$, and therefore we have

$$\begin{aligned} \lim_{n \rightarrow \infty} (1/n)|L_{X|Y}| &= 1 - H(X|Y) \\ &= H(X) - H(X|Y) \\ &= I(X; Y) = C. \end{aligned} \quad (1)$$

Furthermore, for each index in $L_{X|Y}$, the conditional probability $p(u_i|u_{[i-1]}, y_{[n]})$ must be close to either 0 or 1 (since the conditional entropy is small by the definition of the set $L_{X|Y}$). It follows that the RV U_i can be estimated reliably given $u_{[i-1]}$ and $y_{[n]}$. This fact motivates the capacity-achieving coding scheme that follows. The encoder creates a vector $u_{[n]}$ by assigning the subvector $U_{L_{X|Y}}$ with the source message, and the subvector $U_{L_{X|Y}^c}$ with uniformly distributed random bits that are shared with the decoder. The randomness sharing is useful for the analysis, but is in fact unnecessary for using the scheme (the proof of this fact is described in [1, Sec. VI]). The set $U_{L_{X|Y}^c}$ is called the *frozen set*. Equation (1) implies that this coding rate approaches the channel capacity. The decoding is performed iteratively, from index 1 up to n . In each iteration, the decoder estimates the bit u_i using the shared information or using a maximum likelihood estimation, according to the set membership of the iteration. The estimates of u_i are denoted

by \hat{u}_i . The estimates \hat{u}_i for which i is in $L_{X|Y}^c$ are always successful, since these bits were known to the decoder in advance. The rest of the bits (those in $L_{X|Y}$) are estimated correctly with high probability (as explained in the beginning of the paragraph), leading to a successful decoding of the entire message with high probability.

However, this reasoning does not translate directly to asymmetric channels. Remember that the capacity-achieving input distribution of asymmetric channels is in general not uniform (see, for example, [14]), i.e. $p_X(1) \neq 1/2$. Since the Hadamard transform is bijective, it follows that the capacity-achieving distribution of the polarized vector $U_{[n]}$ is non uniform as well. The problem with this fact is that assigning uniform bits of message or shared randomness changes the distribution of $U_{[n]}$, and consequentially also changes the conditional entropies $H(U_i|U_{[i-1]}, Y_{[n]})$. To manage this situation, the approach proposed in [17], which we adopt in this work, is to make sure that the change in the distribution of $U_{[n]}$ is kept to be minor, and thus its effect on the probability of decoding error is also minor. To do this, consider the conditional entropies $H(U_i|U_{[i-1]})$, for $i \in [n]$. Since the polarization happens regardless of the channel model, we can consider a channel for which the output Y is a deterministic variable, and conclude by Theorem 2 that the entropies $H(U_i|U_{[i-1]})$ also polarize. For this polarization, a fraction of $H(X)$ of the indices admit a high $H(U_i|U_{[i-1]})$. To ensure a minor change in the distribution of $U_{[n]}$, we restrict the assignments of uniform bits of message and shared randomness to the indices with high $H(U_i|U_{[i-1]})$.

The insight of the last paragraph motivates a modified coding scheme. The locations with high entropy $H(U_i|U_{[i-1]})$ are assigned with uniformly distributed bits, while the rest of the locations are assigned with the pmf $p(u_i|u_{[i-1]})$. Note that $p(u_{[n]}, x_{[n]})$ and $H(U_{[n]})$ refer to the capacity-achieving distribution of the channel, which does not equal to the distribution that the encoding process induces. Similar to the notation of Theorem 2, we denote the set of indices with high entropy $H(U_i|U_{[i-1]})$ by H_X . To achieve a reliable decoding, we place the message bits in the indices of H_X that can be decoded reliably, meaning that their entropies $H(U_i|U_{[i-1]}, Y_{[n]})$ are low. So we say that we place the message bits in the intersection $H_X \cap L_{X|Y}$. The value of $u_{L_{X|Y}^c}$ must be known by the decoder in advance for a reliable decoding. Previous work suggested to share random Boolean functions between the encoder and the decoder, drawn according to the pmf $p(u_i|u_{[i-1]})$, and to assign the value of $u_{(H_X \cap L_{X|Y})^c} = u_{H_X^c \cup L_{X|Y}^c}$ according to these functions [13], [17]. However, we note that the storage required for those Boolean functions is exponential in n , and therefore we propose an alternative method.

To avoid the Boolean function, we divide the complement of $H_X \cap L_{X|Y}$ into three disjoint sets. First, the indices in the intersection $H_X \cap L_{X|Y}^c$ are assigned with uniformly distributed random bits that are shared between the encoder and the decoder. As in the symmetric case, this randomness sharing will in fact not be necessary, and a deterministic frozen vector could be shared instead. The rest of the bits of $U_{[n]}$

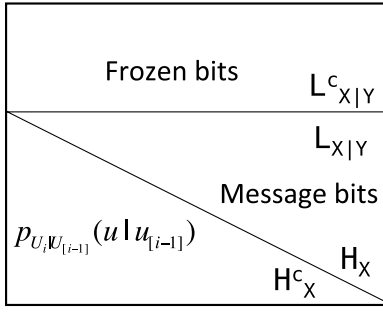


Fig. 1. Encoding the vector $u_{[n]}$. The message bits are assigned in the set $H_X \cap L_{X|Y}$. The set $H_X^c \cap L_{X|Y}^c$ is vanishingly small, and shown as empty in the figure.

(those in the set H_X^c), are assigned *randomly* at the encoder to a value u with probability $p_{U_i|U_{[i-1]}}(u|u_{[i-1]})$ (where $p_{U_i|U_{[i-1]}}$ is calculated according to the pmf $p_{U_{[n]},X_{[n]},Y_{[n]}}$, the capacity-achieving distribution of the channel). The indices in $H_X^c \cap L_{X|Y}$ could be decoded reliably, but not those in $H_X \cap L_{X|Y}^c$. Fortunately, the set $H_X^c \cap L_{X|Y}^c$ can be shown to be small (as we will show later), and thus we could transmit those locations separately with a vanishing effect on the code rate. The encoding of the vector $u_{[n]}$ is illustrated in Figure 1.

We note that an alternative method to avoid the Boolean functions was implied in [17]. According to this method, a seed of uniformly random bits is shared in advance between the encoder and the decoder. During encoding and decoding, the bits whose indices are in the set $(H_X \cap L_{X|Y})^c$ are generated as pseudorandom bits from the shared seed, such that each bit is distributed according to $p_{U_i|U_{[i-1]}}(u|u_{[i-1]})$. Such scheme could be used in many practical scenarios. However, the use of pseudorandomness might lead to error propagation in some applications. Therefore, we describe the constructions in the rest of the paper according to the approach of the previous paragraph.

To see the reason of why the code rate approaches the channel capacity, notice that the source message is placed in the indices in the intersection $H_X \cap L_{X|Y}$. The asymptotic fraction of this intersection can be derived as following.

$$\begin{aligned} |H_X \cap L_{X|Y}|/n &= 1 - |H_X^c \cup L_{X|Y}^c|/n \\ &= 1 - |H_X^c|/n - |L_{X|Y}^c|/n + |H_X^c \cap L_{X|Y}^c|/n. \end{aligned} \quad (2)$$

The Polarization Theorem (Theorem 2) implies that $|H_X^c|/n \rightarrow 1 - H(X)$ and $|L_{X|Y}^c|/n \rightarrow H(X|Y)$. Since the fraction $|H_X^c \cap L_{X|Y}^c|$ vanishes for large n , we get that the asymptotic rate is $|H_X \cap L_{X|Y}|/n \rightarrow H(X) - H(X|Y) = I(X; Y)$, achieving the channel capacity.

For a more precise definition of the scheme, we use the so called Bhattacharyya parameter in the selection of subsets of $U_{[n]}$, instead of the conditional entropy. The Bhattacharyya parameters are polarized in a similar manner as the entropies, and are more useful for bounding the probability of decoding error. For a discrete RV Y and a Bernoulli RV X , the Bhattacharyya parameter is defined by

$$Z(X|Y) \triangleq 2 \sum_y \sqrt{p_{X,Y}(0, y)p_{X,Y}(1, y)}. \quad (3)$$

Note that most of the polar coding literature is using a slightly different definition of the Bhattacharyya parameter, that coincides with Equation (3) when the RV X is distributed uniformly. We use the following relations between the Bhattacharyya parameter and the conditional entropy.

Proposition 3 [2, Proposition 2]:

$$(Z(X|Y))^2 \leq H(X|Y), \quad (4)$$

$$H(X|Y) \leq \log_2(1 + Z(X|Y)) \leq Z(X|Y). \quad (5)$$

We now define the set of high and low Bhattacharyya parameters, and work with them instead of the sets $H_{X|Y}$ and $L_{X|Y}$. For $\delta \in (0, 1)$, define

$$\begin{aligned} \mathcal{H}_{X|Y} &\triangleq \{i \in [n] : Z(U_i|U_{[i-1]}, Y_{[n]}) \geq 1 - 2^{-n^{1/2-\delta}}\}, \\ \mathcal{L}_{X|Y} &\triangleq \{i \in [n] : Z(U_i|U_{[i-1]}, Y_{[n]}) \leq 2^{-n^{1/2-\delta}}\}. \end{aligned}$$

As before, we define the sets \mathcal{H}_X and \mathcal{L}_X for the parameter $Z(U_i|U_{[i-1]})$ by letting $Y_{[n]}$ be a deterministic vector. Using Proposition 3, it is shown in [17, combining Proposition 2 with Theorem 2] that Theorem 2 holds also if we replace the sets $H_{X|Y}$ and $L_{X|Y}$ with the sets $\mathcal{H}_{X|Y}$ and $\mathcal{L}_{X|Y}$. That is, we have

$$\lim_{n \rightarrow \infty} |\mathcal{H}_{X|Y}|/n = H(X|Y) \quad \text{and} \quad \lim_{n \rightarrow \infty} |\mathcal{L}_{X|Y}|/n = 1 - H(X|Y). \quad (6)$$

We now define our coding scheme formally. Let $m_{[|\mathcal{H}_X \cap \mathcal{L}_{X|Y}|]} \in \{0, 1\}^{|\mathcal{H}_X \cap \mathcal{L}_{X|Y}|}$ be the realization of a uniformly distributed source message, and $f_{[|\mathcal{H}_X \cap \mathcal{L}_{X|Y}^c|]} \in \{0, 1\}^{|\mathcal{H}_X \cap \mathcal{L}_{X|Y}^c|}$ be a deterministic frozen vector known to both the encoder and the decoder. We discuss how to find a good frozen vector in Appendix C-C. For a subset $\mathcal{A} \subseteq [n]$ and an index $i \in \mathcal{A}$, we use a function $r(i, \mathcal{A})$ to denote the *rank* of i in an ordered list of the elements of \mathcal{A} . The probabilities $p_{U_i|U_{[i-1]}}(u|u_{[i-1]})$ and $p_{U_i|U_{[i-1]}, Y_{[n]}}(u|u_{[i-1]}, y_{[n]})$ can be calculated efficiently by a recursive method described in [17, Sec. III.B].

Construction 4:

Encoding

Input: a message

$$m_{[|\mathcal{H}_X \cap \mathcal{L}_{X|Y}|]} \in \{0, 1\}^{|\mathcal{H}_X \cap \mathcal{L}_{X|Y}|}.$$

Output: a codeword $x_{[n]} \in \{0, 1\}^n$.

1) For i from 1 to n , successively, set

$$u_i = \begin{cases} u \in \{0, 1\} & \text{w.p. } p_{U_i|U_{[i-1]}}(u|u_{[i-1]}) \\ & \text{if } i \in \mathcal{H}_X^c \\ m_{r(i, \mathcal{H}_X \cap \mathcal{L}_{X|Y})} & \text{if } i \in \mathcal{H}_X \cap \mathcal{L}_{X|Y} \\ f_{r(i, \mathcal{H}_X \cap \mathcal{L}_{X|Y}^c)} & \text{if } i \in \mathcal{H}_X \cap \mathcal{L}_{X|Y}^c. \end{cases}$$

2) Transmit the codeword $x_{[n]} = u_{[n]}G_n$.

3) Transmit the vector $u_{\mathcal{H}_X^c \cap \mathcal{L}_{X|Y}^c}$ separately using a linear, non-capacity-achieving polar code with a uniform input distribution (as in [1]). In practice, other error-correcting codes could be used for this vector as well.

Decoding

Input: a noisy vector $y_{[n]} \in \{0, 1\}^n$.

Output: a message estimation

$$\hat{m}_{[|\mathcal{H}_X \cap \mathcal{L}_{X|Y}|]} \in \{0, 1\}^{|\mathcal{H}_X \cap \mathcal{L}_{X|Y}|}.$$

- 1) Estimate the vector $u_{\mathcal{H}_X^c \cap \mathcal{L}_{X|Y}^c}$ by $\hat{u}_{\mathcal{H}_X^c \cap \mathcal{L}_{X|Y}^c}$.
- 2) For i from 1 to n , set

$$\hat{u}_i = \begin{cases} \arg \max_{u \in \{0,1\}} p_{U_i|U_{[i-1]}, Y_{[n]}}(u|u_{[i-1]}, Y_{[n]}) & \text{if } i \in \mathcal{L}_{X|Y} \\ \hat{u}_{r(i, \mathcal{H}_X^c \cap \mathcal{L}_{X|Y}^c)} & \text{if } i \in \mathcal{H}_X^c \cap \mathcal{L}_{X|Y}^c \\ f_{r(i, \mathcal{H}_X \cap \mathcal{L}_{X|Y}^c)} & \text{if } i \in \mathcal{H}_X \cap \mathcal{L}_{X|Y}^c. \end{cases}$$

- 3) Return the estimated message

$$\hat{m}_{[\mathcal{H}_X \cap \mathcal{L}_{X|Y}]} = \hat{u}_{\mathcal{H}_X \cap \mathcal{L}_{X|Y}}.$$

We say that a sequence of coding schemes achieves the channel capacity if the probability of decoding error vanishes with the block length for any rate below the capacity.

Theorem 5: Construction 4 achieves the channel capacity (Theorem 1) with a encoding and decoding complexity of $O(n \log n)$ and a probability of decoding error of at most $2^{-n^{1/2-\delta}}$ for any $\delta > 0$ and large enough n .

In the next section we show a generalized construction and prove its capacity-achieving property. Theorem 5 thus will follow as a corollary of the more general Theorem 15. We note here two differences between Construction 4 and the construction in [23, Sec. III.B]. First, in the encoding of Construction 4, the bits in the set \mathcal{H}_X^c are set randomly, while in [23, Sec. III.B], those bits are set according to a maximum likelihood rule. And second, the vector $u_{\mathcal{H}_X^c \cap \mathcal{L}_{X|Y}^c}$ is being sent through a side channel in Construction 4, but not in [23, Sec. III.B]. These two features of Construction 4 allow an alternative analysis and proof that the scheme achieves the channel capacity.

III. CHANNELS WITH NON-CAUSAL ENCODER STATE INFORMATION

In this section we generalize Construction 4 to the availability of channel state information at the encoder. We consider mainly the application of rewriting in flash memories, and present two special cases of the channel model for this application. In flash memory, information is stored in a set of n memory cells. We mainly focus on a flash memory type that is called Single-Level Cell (SLC), in which each cell stores a single information bit, and its value is denoted by either 0 or 1. We first note that the assumption of a memoryless channel is not exactly accurate in flash memories, due to a mechanism of cell-to-cell interference. However, we keep using this assumption, as it is nonetheless useful for the design of coding schemes with valuable practical performance. The main limitation of flash memories that we consider in this work is the high cost of changing a cell level from 1 to 0 (in SLC memories). To perform such a change, an expensive operation, called “block erasure”, is required. To avoid this block erasure operation, information is rewritten over existing memory in the sense that no cell is changed from value 1 to 0. We thus consider the use of the information about the previous state of the cells in the encoding process. We model the memory cells as a channel with a discrete state, and we also assume that the state is memoryless, meaning that the states of different cells are distributed independently.

We assume that the state of the entire n cells is available to the writer prior to the beginning of the writing process. In communication terminology this kind of state availability is referred to as “non causal”. We note that this setting is also useful in the so called *Marton-coding* method for communication over broadcast channels. Therefore, the multicoding schemes that will follow serve as a contribution also in this important setting. One special case of the model which we consider is the noiseless write-once memory model. This model also serves as an ingredient for a type of codes called “rank-modulation rewriting codes” [9]. Therefore, the schemes proposed in this section can also be useful for the design of rank-modulation rewriting codes.

We represent the channel state as a Bernoulli random variable S with parameter β , which equals the probability $p_S(S = 1)$. A cell of state 1 can only be written with the value 1. Note that, intuitively, when β is high, the capacity of the memory is small, since only a few cells are available for modification in the writing process, and thus only a small amount of information could be stored. This also means that the choice of codebook has a crucial effect on the capacity of the memory in *future writes*. A codebook that contains many codewords of high Hamming weight (number of 1’s in the codeword) would make the parameter β of future writes high, and thus the capacity of the future writes would be low. However, forcing the expected Hamming weight of the codebook to be low would reduce the capacity of the current write. To settle this trade-off, previous work suggested to optimize the sum of the code rates over multiple writes. It was shown that in many cases, constraints on the codebook Hamming weight (henceforth just weight) strictly increase the sum rate (see, for example, [16]). Therefore, we consider an input cost constraint in the model.

The most general model that we consider is a discrete memoryless channel (DMC) with a discrete memoryless (DM) state and an input cost constraint, where the state information is available non causally at the encoder. The channel input, state and output are denoted by x, s and y , respectively, and their respective finite alphabets are denoted by \mathcal{X}, \mathcal{S} and \mathcal{Y} . The random variables are denoted by X, S and Y , and the random vectors by $X_{[n]}, S_{[n]}$ and $Y_{[n]}$, where n is the block length. The state is distributed according to the pmf $p(s)$, and the conditional pmfs of the channel are denoted by $p(y|x, s)$. The input cost function is denoted by $b(x)$, and the input cost constraint is

$$\sum_{i=1}^n \mathbb{E}[b(X_i)] \leq nB,$$

where B is a real number representing the normalized constraint. The channel capacity with an informed encoder and an input cost constraint is given by an extension of the Gelfand-Pinsker Theorem.¹

Theorem 6 (Gelfand-Pinsker Theorem With Cost Constraint [7, eq. (7.7) on p. 186]): Consider a DMC with a DM state where $p(y|x, s)$ denotes the channel transition probability and $p(s)$ denotes the state probability. Under an

¹The cost constraint is defined slightly differently in this reference, but the capacity is not affected by this change.

input cost constraint B , where the state information is available non causally only at the encoder, the capacity of the channel is

$$C = \max_{p(v|s), x(v,s): E(b(X)) \leq B} (I(V; Y) - I(V; S)), \quad (7)$$

where V is an auxiliary random variable with a finite alphabet \mathcal{V} , $|\mathcal{V}| \leq \min\{|\mathcal{X}| \cdot S, \mathcal{Y} + S - 1\}$.

The main coding scheme that we present in this section achieves the capacity in Theorem 6.² The proof of Theorem 6 considers a virtual channel model, in which the RV V is the channel input and Y is the channel output. Similar to the previous section, we limit the treatment to the case in which the RV V is binary. In flash memory, this case would correspond to a single-level cell (SLC) type of memory. As mentioned in Section II, an extension of the scheme to a non-binary case is not difficult. The non-binary case is useful for flash memories in which each cell stores 2 or more bits of information. Such memories are called Multi-Level Cell (MLC). We also mention that the limitation to binary random variables does not apply on the channel output Y . Therefore, the cell voltage in flash memory could be read more accurately at the decoder to increase the coding performance, similarly to the soft decoding method that is used in flash memories with LDPC codes. Another practical remark is that the binary-input model can be used in MLC memories by coding separately on the MSB and the LSB of the cells, as in fact is the coding method in current MLC flash systems.

The scheme that achieves the capacity of Theorem 6 is called Construction 16, and it will be described in Subsection III-C. The capacity achieving result is summarized in the following theorem, which will be proven in Subsection III-C.

Theorem 7: Construction 16 achieves the capacity of the Gelfand-Pinsker Theorem with Cost Constraint (Theorem 6) with a encoding and decoding complexity of $O(n \log n)$ and a probability of decoding error of at most $2^{-n^{1/2-\delta}}$ for any $\delta > 0$ and large enough n .

Note that the setting of Theorem 7 is a generalization of the asymmetric channel-coding setting of Theorem 5, and therefore Construction 16 and Theorem 7 are in fact a generalization of Construction 4 and Theorem 5. We note also that polar codes were constructed for a symmetric case of the Gelfand-Pinsker channel by Korada and Urbanke in [18]. As the key constraint of flash memories is notably asymmetric, the important novelty of this work is in providing the non-trivial generalization that cover the asymmetric case.

Before we describe the code construction, we first show in Subsection III-A two special cases of the Gelfand-Pinsker model that are useful for the rewriting of flash memories. Afterwards, in subsections III-B and III-C, we will show two versions of the construction that correspond to generalizations of the two special cases.

²More precisely, the scheme achieves the mentioned capacity for channels in which the capacity remains strictly positive even if the encoder does not have access to the state information (See [30]). Such channels include flash memory applications.

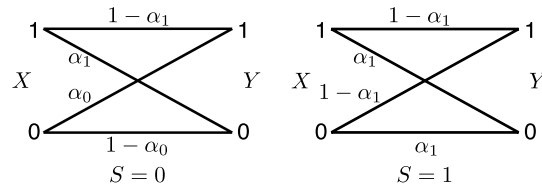


Fig. 2. Example 8: A binary noisy WOM model.

A. Special Cases

We start with a special case that is quite a natural model for flash memory rewriting.

Example 8: Let the sets \mathcal{X} , \mathcal{S} and \mathcal{Y} be all equal to $\{0, 1\}$, and let the state pmf be $p_S(1) = \beta$. This model corresponds to a single level cell flash memory. We describe the cell behaviour after a bit x is attempted to be written. When $s = 0$, the cell behaves as a binary asymmetric channel with input x , since the cell state does not interfere with the writing attempt. When $s = 1$, the cell behaves as if a value of 1 was attempted to be written, regardless of the actual value x attempted. However, an error might still occur, during the writing process or anytime afterwards (for example, due to charge leakage). Thus, we can say that when $s = 1$, the cell behaves as a binary asymmetric channel with input 1. Formally, the channel pmfs are given by

$$p_{Y|XS}(1|x, s) = \begin{cases} \alpha_0 & \text{if } (x, s) = (0, 0) \\ 1 - \alpha_1 & \text{if } (x, s) = (0, 1) \\ 1 - \alpha_1 & \text{if } (x, s) = (1, 0) \\ 1 - \alpha_1 & \text{if } (x, s) = (1, 1) \end{cases} \quad (8)$$

The error model is also presented in Figure 2. The cost constraint is given by $b(x_i) = x_i$, since it is desirable to limit the amount of cells written to a value of 1.

Our coding-scheme construction for the setting of Theorem 6 is based on a more limited construction, which serves as a building block. We will start by describing the limited construction, and then show how to extend it for the model of Theorem 6. We will prove that the limited construction achieves the capacity of channels whose capacity-achieving distribution forms a certain stochastically degraded structure. We first recall the definition of stochastically degraded channels.

Definition 9 [7, p. 112]: A discrete memoryless channel (DMC) $W_1 : \{0, 1\} \rightarrow \mathcal{Y}_1$ is stochastically degraded (or simply degraded) with respect to a DMC $W_2 : \{0, 1\} \rightarrow \mathcal{Y}_2$, denoted as $W_1 \leq W_2$, if there exists a DMC $W : \mathcal{Y}_2 \rightarrow \mathcal{Y}_1$ such that W satisfies the equation $W_1(y_1|x) = \sum_{y_2 \in \mathcal{Y}_2} W_2(y_2|x)W(y_1|y_2)$.

Next, we bring the required property of channels whose capacity is achieved by the limited construction to be proposed.

Property 10: There exist functions $p(v|s)$ and $x(v, s)$ that maximize the Gelfand-Pinsker capacity in Theorem 6 which satisfy the condition $p(y|v) \geq p(s|v)$.

It is an open problem whether the model of Example 8 satisfies the degradation condition of Property 10. However, we can modify the model such that it will satisfy Property 10. Specifically, we study the following model:

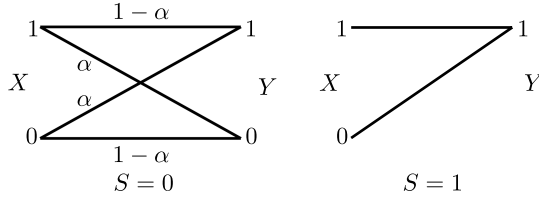


Fig. 3. Example 11: A binary WOM with writing noise.

Example 11: Let the sets \mathcal{X} , \mathcal{S} and \mathcal{Y} be all equal to $\{0, 1\}$. The channel and state pmfs are given by $p_S(1) = \beta$ and

$$p_{Y|XS}(1|x, s) = \begin{cases} \alpha & \text{if } (x, s) = (0, 0) \\ 1 - \alpha & \text{if } (x, s) = (1, 0) \\ 1 & \text{if } s = 1. \end{cases} \quad (9)$$

In words, if $s = 1$ the channel output is always 1, and if $s = 0$, the channel behave as a binary symmetric channel. The cost function is given by $b(x_i) = x_i$. The error model is also presented in Figure 3. This model can represent a writing noise, as a cell of state $s = 1$ is not written on and it never suffers errors.

We claim that the model of Example 11 satisfies the degradation condition of Property 10. To show this, we need first to find the functions $p(v|s)$ and $x(v, s)$ that maximize the Gelfand-Pinsker capacity in Theorem 6. Those functions are established in the following theorem of Heegard.

Theorem 12 [16, Th. 4]: *The capacity of the channel in Example 11 is*

$$C = (1 - \beta)[h(\epsilon * \alpha) - h(\alpha)],$$

where $\epsilon = B/(1 - \beta)$ and $\epsilon * \alpha \equiv \epsilon(1 - \alpha) + (1 - \epsilon)\alpha$. The selections $\mathcal{V} = \{0, 1\}$, $x(v, s) = v \wedge \neg s$ (where \wedge is the logical AND operation, and \neg is the logical negation), and

$$p_{V|S}(1|0) = \epsilon, \quad p_{V|S}(1|1) = \frac{\epsilon(1 - \alpha)}{\epsilon * \alpha} \quad (10)$$

achieve this capacity.

We provide an alternative proof for Theorem 12 in Appendix A. Intuitively, the upper bound is obtained by assuming that the state information is available also at the decoder, and the lower bound is obtained by setting the functions $x(v, s)$ and $p(v|s)$ according to the statement of the theorem. The proof that the model in Example 11 satisfies the degradation condition of Property 10 is completed by the following lemma.

Lemma 13: *The capacity achieving functions of Theorem 12 for the model of Example 11 satisfy the degradation condition of Property 10. That is, the channel $p(s|v)$ is degraded with respect to the channel $p(y|v)$.*

Lemma 13 is proven in Appendix B, and consequently, the capacity of the model in Example 11 can be achieved by our limited construction. In the next subsection we describe the construction for channel models which satisfy Property 10, including the model in Example 11.

B. Multicoding Construction for Degraded Channels

Notice first that the capacity-achieving distribution of the asymmetric channel in Section II actually satisfies Property 10. In the asymmetric channel-coding case, the state can be

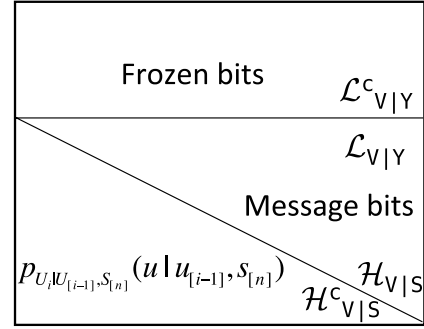


Fig. 4. Encoding the vector $u_{[n]}$ in Construction 14. The message bits are assigned in the set $\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}$. The set $\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c$ is vanishingly small, and shown as empty in the figure.

thought of as a degenerate random variable (a RV which only takes a single value), and therefore we can choose W in Definition 9 to be degenerate as well, and by that satisfy Property 10. We will see that the construction that we present in this subsection is a generalization of Construction 4.

The construction has a similar structure as the achievability proof of the Gelfand-Pinsker Theorem (Theorem 6). The encoder first finds a vector $v_{[n]}$ in a similar manner to Construction 4, where the RV $X|Y$ in Construction 4 is replaced with $V|Y$, and the RV X is replaced with $V|S$. The vector $U_{[n]}$ is now the polarization of the vector $V_{[n]}$, meaning that $U_{[n]} = V_{[n]}G_n$. The RV V is taken according to the pmfs $p(v|s)$ that maximize the rate expression in Equation (7). The selection of the vector $u_{[n]}$ is illustrated in Figure 4. After the vector $u_{[n]}$ is chosen, each bit $i \in [n]$ in the codeword $x_{[n]}$ is calculated by the function $x_i(v_i, s_i)$ that maximizes Equation (7). To use the model of Example 11, one should use the functions $p(v|s)$ and $x(v, s)$ according to Theorem 12. The key to showing that the scheme achieves the channel capacity is that the fraction $|\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c|/n$ can be shown to vanish for large n if the channel satisfies Property 10. Then, by the same intuition as in Equation (2) and using Equation (6), the replacements imply that the asymptotic rate of the codes is

$$\begin{aligned} & |\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}|/n \\ &= 1 - |\mathcal{H}_{V|S}^c|/n - |\mathcal{L}_{V|Y}^c|/n + |\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c|/n \\ &\rightarrow 1 - (1 - H(V|S)) - H(V|Y) + 0 \\ &= I(V; Y) - I(V; S), \end{aligned}$$

achieving the Gelfand-Pinsker capacity of Theorem 6. We now describe the coding scheme formally.

Construction 14:

Encoding

Input: a message

$$m_{[|\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}|]} \in \{0, 1\}^{|\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}|}$$

and a state $s_{[n]} \in \{0, 1\}^n$.

Output: a codeword $x_{[n]} \in \{0, 1\}^n$.

1) For each i from 1 to n , assign

$$u_i = \begin{cases} u \in \{0, 1\} \text{ w.p. } p_{U_i|U_{[i-1], S_{[n]}}}(u|u_{[i-1], S_{[n]}}) & \text{if } i \in \mathcal{H}_{V|S}^c \\ m_r(i, \mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}) & \text{if } i \in \mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y} \\ f_r(i, \mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}^c) & \text{if } i \in \mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}^c. \end{cases} \quad (11)$$

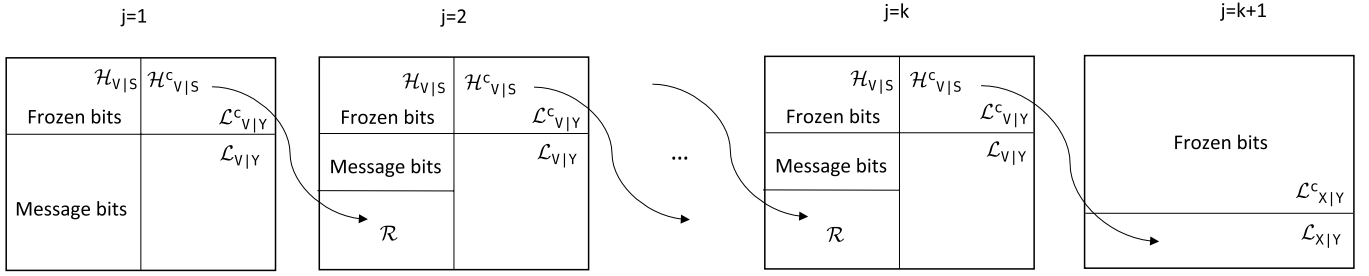


Fig. 5. The chaining construction.

- 2) Calculate $v_{[n]} = u_{[n]}G_n$ and for each $i \in [n]$, store the value $x_i(v_i, s_i)$.
- 3) Store the vector $u_{\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c}$ separately using a point-to-point linear non-capacity-achieving polar code with a uniform input distribution. The encoder here does not use the state information in the encoding process, but rather treat it as an unknown part of the channel noise.

Decoding

Input: a noisy vector $y_{[n]} \in \{0, 1\}^n$.

Output: a message estimation

$$\hat{m}_{[|\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}|]} \in \{0, 1\}^{|\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}|}.$$

- 1) Estimate the vector $u_{\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c}$ by $\hat{u}_{\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c}$.
- 2) Estimate $u_{[n]}$ by $\hat{u}_{[n]}(y_{[n]}, f_{[|\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}|]})$ as follows: For each i from 1 to n , assign

$$\hat{u}_i = \begin{cases} \arg \max_{u \in \{0,1\}} p_{U_i|U_{[i-1]}, Y_{[n]}}(u|u_{[i-1]}, y_{[n]}) & \text{if } i \in \mathcal{L}_{V|Y} \\ \hat{u}_{r(i, \mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c)} & \text{if } i \in \mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c \\ f_{r(i, \mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y})} & \text{if } i \in \mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}. \end{cases} \quad (12)$$

- 3) Return the estimated message

$$\hat{m}_{[|\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}|]} = \hat{u}_{\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}}.$$

The asymptotic performance of Construction 14 is stated in the following theorem.

Theorem 15: *If Property 10 holds, then Construction 14 achieves the capacity of Theorem 6 with a encoding and decoding complexity of $O(n \log n)$ and a probability of decoding error of at most $2^{-n^{1/2-\delta}}$ for any $\delta > 0$ and large enough n .*

The proof of Theorem 15 is shown in Appendix C. The next subsection describes a method to remove the degradation requirement of Property 10. This allows to achieve also the capacity of the more realistic model of Example 8.

C. Multicoding Construction Without Degradation

A technique called ‘‘chaining’’ was proposed in [23] that allows to achieve the capacity of models that do not exhibit the degradation condition of Property 10. The chaining idea was presented in the context of broadcast communication and point-to-point universal coding. We connect it here to the application of flash memory rewriting through Example 8. We note also that the chaining technique that follows comes with a price of a slower convergence to the channel capacity, and thus a lower non-asymptotic code rate.

The requirement of Construction 14 for degraded channels comes from the fact that the set $\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c$ needs to be

communicated to the decoder in a side channel. If the fraction $(1/n)|\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c|$ vanishes with n , Construction 14 achieves the channel capacity. In this subsection we deal with the case that the fraction $(1/n)|\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c|$ does not vanish. In this case we have

$$\begin{aligned} |\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}|/n &= 1 - |\mathcal{H}_{V|S}^c \cup \mathcal{L}_{V|Y}^c|/n \\ &= 1 - |\mathcal{H}_{V|S}^c|/n - |\mathcal{L}_{V|Y}^c|/n + |\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c|/n \\ &\rightarrow I(V; Y) - I(V; S) + |\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c|/n. \end{aligned}$$

The idea is then to store the subvector $u_{\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c}$ in a subset of the indices $\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}$ of an *additional code block* of n cells. The additional block is using the same coding technique as the original block. Therefore, it can use about $I(V; Y) - I(V; S)$ of the cells to store additional message bits, and by that to approach the channel capacity. We denote the by \mathcal{R} the subset of $\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}$ in which we store the the subvector $u_{\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c}$ of the previous block. Note that the additional block also faces the same difficulty as the original block with the set $\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c$. To solve this, we use the same solution, recursively, sending a total of k blocks, each of length n . Each block can store a source message of fraction that approaches the channel capacity. The ‘‘problematic’’ bits of block k (the last block) will then be stored using yet another block, but this block will be coded without taking the state information into account, and thus will not face the same difficulty. The last block is thus causing a rate loss, but this loss is of a fraction $1/k$, which vanishes for large k . The decoding is performed ‘‘backwards’’, starting from the last block and ending with the first block. The chaining construction is illustrated in Figure 5. In the following formal description of the construction we denote the index i of the j -th block of the message by $m_{i,j}$, and similarly for other vectors. The vectors themselves are also denoted in two dimensions, for example $x_{[n],[k]}$.

Construction 16: *Let \mathcal{R} be an arbitrary subset of $\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}$ of size $|\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c|$.*

Encoding

Input: a message

$$\begin{aligned} m_{(|\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}| - |\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c|, [k])} \\ \in \{0, 1\}^{k(|\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}| - |\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c|)} \end{aligned}$$

and a state $s_{[n],[k]} \in \{0, 1\}^{kn}$.

Output: a codeword $x_{[n],[k]} \in \{0, 1\}^{kn}$.

- 1) Let $u_{[n],0} \in \{0, 1\}^n$ be an arbitrary vector. For each j from 1 to k , and for each i from 1 to n ,

assign

$$u_{i,j} = \begin{cases} u \in \{0, 1\} \text{ w.p. } p_{U_i|U_{[i-1]}, S_{[n]}}(u|u_{[i-1]}, s_{[n]}) & \text{if } i \in \mathcal{H}_{V|S}^c \\ m_{r(i, \mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}), j} & \text{if } i \in (\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}) \setminus \mathcal{R} \\ u_{r(i, \mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c), j-1} & \text{if } i \in \mathcal{R} \\ f_{r(i, \mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}^c), j} & \text{if } i \in \mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}^c. \end{cases} \quad (13)$$

- 2) For each j from 1 to k calculate $v_{[n],j} = u_{[n],j} G_n$, and for each $i \in [n]$, store the value $x_{i,j}(v_{i,j}, s_{i,j})$.
- 3) Store the vector $u_{\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c, k}$ separately using a point-to-point linear non-capacity-achieving polar code with a uniform input distribution. The encoder here does not use the state information in the encoding process, but rather treat it as an unknown part of the channel noise.

Decoding

Input: a noisy vector $y_{[n],[k]} \in \{0, 1\}^k n$.

Output: a message estimation

$$\hat{m}_{[|\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}| - |\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c|, [k]} \in \{0, 1\}^{k|\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}| - |\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c|}.$$

- 1) Estimate the vector $u_{\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c, k}$ by $\hat{u}_{\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c, k}$, and let $\hat{u}_{\mathcal{R}, k+1} = \hat{u}_{\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c, k}$.
- 2) Estimate $u_{[n],[k]}$ by

$$\hat{u}_{[n],[k]}(y_{[n],[k]}, f_{[|\mathcal{L}_{V|Y}^c \cap \mathcal{H}_{V|S}|, [k]})$$

as follows: For each j down from k to 1, and for each i from 1 to n , assign

$$\hat{u}_i^j = \begin{cases} \arg \max_{u \in \{0, 1\}} p_{U_i|U_{[i-1]}, Y_{[n]}}(u|u_{[i-1],j}, y_{[n],j}) & \text{if } i \in \mathcal{L}_{V|Y} \\ \hat{u}_{r(i, \mathcal{R}), j+1} & \text{if } i \in \mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y} \\ f_{r(i, \mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}^c), j} & \text{if } i \in \mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}^c. \end{cases} \quad (14)$$

- 3) Return the estimated message

$$\begin{aligned} \hat{m}_{[|\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}| - |\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c|, [k]} \\ = \hat{u}_{(\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}) \setminus \mathcal{R}, [k]}. \end{aligned}$$

Constructions 14 and 16 can also be used for communication over broadcast channels in Marton's region, as described in [13] and [23]. Constructions 14 and 16 improve on these previous results since they provably achieve the capacity with linear storage requirement.

Construction 16 achieves the capacity of Theorem 6 with low complexity, without the degradation requirement of Property 10. This result was stated in Theorem 7. The proof of Theorem 7 follows from Theorem 15 and the fact that the rate loss vanishes with large k . Construction 16 is useful for the realistic model of flash memory-rewriting of Example 8, using the appropriate capacity-achieving functions $p(v|s)$ and $x(v, s)$.

IV. CONCLUSION

In this paper we proposed three capacity-achieving polar coding schemes, for the settings of asymmetric channel coding and flash memory rewriting. The scheme for asymmetric channels improves on the scheme of [17] by reducing the exponential storage requirement into a linear one. The idea for this reduction is to perform the encoding randomly instead of using Boolean functions, and to transmit a vanishing fraction of information on a side channel.

The second proposed scheme is used for the setting of flash memory rewriting. We propose a model of flash memory rewriting with writing noise, and show that the scheme achieves its capacity. We also describe a more general class of channels whose capacity can be achieved using the scheme. The second scheme is derived from the asymmetric-channel scheme by replacing the Shannon random variables X and $X|Y$ with the Gelfand-Pinsker random variables $V|S$ and $V|Y$.

The last proposed scheme achieves the capacity of any channel with non-causal state information at the encoder. We bring a model of noisy flash memory rewriting for which the scheme would be useful. The main idea in this scheme is the code chaining proposed in [23]. Another potential application could be in an asymmetric version of information embedding, which can be modeled as another special case of the Gelfand-Pinsker problem (as in [3]).

APPENDIX A

In this appendix we provide an alternative proof for Theorem 12, which was originally proven in [16, Th. 4]. We find the proof in this Appendix to be somewhat more intuitive. Theorem 12 states that the capacity of the channel in Example 11 is

$$C = (1 - \beta)[h(\epsilon * \alpha) - h(\alpha)],$$

where $\epsilon = B/(1 - \beta)$ and $\epsilon * \alpha \equiv \epsilon(1 - \alpha) + (1 - \epsilon)\alpha$. An upper bound on the capacity can be obtained by assuming that the state information is available also to the decoder. In this case, the best coding scheme would ignore the cells with $s_i = 1$ (about a fraction β of the cells), and the rest of the cells would be coded according to a binary symmetric channel with an input cost constraint. It is optimal to assign a channel input $x_i = 0$ for the cells with state $s_i = 1$, such that those cells who do not convey information do not contribute to the cost. We now focus on the capacity of the binary symmetric channel with cost constraint. To comply with the expected input cost constraint B of the channel of Example 11, the expected cost of the input to the binary symmetric channel (BSC) must be at most $\epsilon = B/(1 - \beta)$. To complete the proof of the upper bound, we show next that the capacity of the BSC with cost constraint is equals to $h(\alpha * \epsilon) - h(\alpha)$. For this channel, we have

$$H(Y|X) = h(\alpha)p_X(0) + h(\alpha)p_X(1) = h(\alpha).$$

We are left now with maximizing the entropy $H(Y)$ over the input pmfs $p_X(1) \leq \epsilon$. We have

$$\begin{aligned} p_Y(1) &= p_{Y|X}(1|0)p_X(0) + p_{Y|X}(1|1)p_X(1) \\ &= \alpha(1 - p_X(1)) + (1 - \alpha)p_X(1) \\ &= \alpha * p_X(1). \end{aligned}$$

Now since $p_X(1) \leq \epsilon \leq 1/2$ and $\alpha * p_X(1)$ is increasing in $p_X(1)$ below $1/2$, it follows that $p_Y(1) \leq \alpha * \epsilon \leq 1/2$ and therefore also that $H(Y) \leq h(\alpha * \epsilon)$. So we have

$$\begin{aligned} \max_{p_X(1) \leq \epsilon} I(X; Y) &= \max_{p_X(1) \leq \epsilon} (H(Y) - H(Y|X)) \\ &= h(\alpha * \epsilon) - h(\alpha). \end{aligned}$$

This completes the proof of the upper bound.

The lower bound is obtained by considering the selections $\mathcal{V} = \{0, 1\}$, $x(v, 0) = v$, $x(v, 1) = 0$ and

$$p_{V|S}(1|0) = \epsilon, \quad p_{V|S}(1|1) = \frac{\epsilon(1-\alpha)}{\epsilon * \alpha}, \quad (15)$$

and calculating the rate expression directly. Notice first that the cost constraint is met since

$$\begin{aligned} p_X(1) &= p_{X|S}(1|0)p_S(0) \\ &= p_{V|S}(1|0)p_S(0) = \epsilon(1-\beta) = B. \end{aligned}$$

We need to show that $H(V|S) - H(V|Y) = (1-\beta)[h(\alpha * \epsilon) - h(\alpha)]$. Given the distributions p_S and $p_{V|S}$, the conditional entropy $H(V|S)$ is

$$\begin{aligned} H(V|S) &= \sum_{s \in \{0,1\}} p_S(s)H(V|S=s) \\ &= p_S(0)H(V|S=0) + p_S(1)H(V|S=1) \\ &= (1-\beta)h(\epsilon) + \beta h\left(\frac{\epsilon(1-\alpha)}{\epsilon * \alpha}\right) \end{aligned}$$

To compute the conditional entropy $H(V|Y)$, we first compute the probability distribution of the memory output Y as follows:

$$\begin{aligned} p_Y(0) &= \sum_{v \in \{0,1\}} p_{Y|V,S}(0|v,0)p_{V|S}(v|0)p_S(0) \\ &= (1-\beta)((1-\alpha)(1-\epsilon) + \alpha\epsilon) \\ &= (1-\beta)(\alpha * (1-\epsilon)), \\ p_Y(1) &= 1 - p_Y(0) \\ &= (1-\beta)(\alpha * \epsilon) + \beta. \end{aligned}$$

The conditional distribution $p_{V|Y}$ is given by

$$\begin{aligned} p_{V|Y}(1|0) &= \sum_{s \in \{0,1\}} p_{V,S|Y}(1,s|0) \\ &= \sum_{s \in \{0,1\}} \frac{p_{Y|V,S}(0|1,s)p_{V,S}(1,s)}{p_Y(0)} \\ &= \sum_{s \in \{0,1\}} \frac{p_{Y|V,S}(0|1,s)p_{V|S}(1|s)p_S(s)}{p_Y(0)} \\ &= \frac{\alpha\epsilon}{\alpha * (1-\epsilon)}, \\ p_{V|Y}(1|1) &= \sum_{s \in \{0,1\}} p_{V,S|Y}(1,s|1) \\ &= \sum_{s \in \{0,1\}} \frac{p_{Y|V,S}(1|1,s)p_{V,S}(1,s)}{p_Y(1)} \\ &= \sum_{s \in \{0,1\}} \frac{p_{Y|V,S}(1|1,s)p_{V|S}(1|s)p_S(s)}{p_Y(1)} \\ &= \frac{(1-\alpha)\epsilon(1-\beta) + \frac{\epsilon(1-\alpha)}{\epsilon * \alpha}\beta}{(1-\beta)(\alpha * \epsilon) + \beta} \\ &= \frac{\epsilon(1-\alpha)}{\epsilon * \alpha}. \end{aligned}$$

Therefore we have

$$\begin{aligned} H(V|Y) &= \sum_{y \in \{0,1\}} p_Y(y)H(V|Y=y) \\ &= (1-\beta)(\alpha * (1-\epsilon))h\left(\frac{\alpha\epsilon}{\alpha * (1-\epsilon)}\right) \\ &\quad + (\beta + (1-\beta)(\alpha * \epsilon))h\left(\frac{\epsilon(1-\alpha)}{\epsilon * \alpha}\right), \end{aligned}$$

and then

$$\begin{aligned} H(V|S) - H(V|Y) &= (1-\beta) \left[h(\epsilon) - (\alpha * (1-\epsilon))h\left(\frac{\alpha\epsilon}{\alpha * (1-\epsilon)}\right) \right. \\ &\quad \left. - (\alpha * \epsilon)h\left(\frac{\epsilon(1-\alpha)}{\epsilon * \alpha}\right) \right] \\ &= (1-\beta) \left[h(\epsilon) + \alpha\epsilon \log_2 \frac{\alpha\epsilon}{\alpha * (1-\epsilon)} \right. \\ &\quad \left. + (1-\alpha)(1-\epsilon) \log_2 \frac{(1-\alpha)(1-\epsilon)}{\alpha * (1-\epsilon)} \right. \\ &\quad \left. + \alpha(1-\epsilon) \log_2 \frac{\alpha(1-\epsilon)}{\alpha * \epsilon} \right. \\ &\quad \left. + \epsilon(1-\alpha) \log_2 \frac{\epsilon(1-\alpha)}{\alpha * \epsilon} \right] \\ &= (1-\beta)[h(\alpha * \epsilon) + h(\epsilon) + \alpha\epsilon \log_2(\alpha\epsilon) \\ &\quad + (1-\alpha)(1-\epsilon) \log_2(1-\alpha)(1-\epsilon) \\ &\quad + \alpha(1-\epsilon) \log_2 \alpha(1-\epsilon) \\ &\quad + \epsilon(1-\alpha) \log_2 \epsilon(1-\alpha)] \\ &= (1-\beta)[h(\alpha * \epsilon) + h(\epsilon) - h(\alpha) - h(\epsilon)] \\ &= (1-\beta)[h(\alpha * \epsilon) - h(\alpha)]. \end{aligned}$$

APPENDIX B

In this appendix we prove Lemma 13. We need to show that, using the functions of Theorem 12, there exists a DMC $W: \{0, 1\} \rightarrow \{0, 1\}$ such that

$$p_{S|V}(s|v) = \sum_{y \in \{0,1\}} p_{Y|V}(y|v)W(s|y). \quad (16)$$

To define such channel W , we first claim that

$$p_{Y|V,S}(1|v,0)p_{V|S}(v|0) = (\epsilon * \alpha)p_{V|S}(v|1). \quad (17)$$

Equation (17) follows directly from Equation (10) since

$$\begin{aligned} \frac{p_{Y|V,S}(1|0,0)p_{V|S}(0|0)}{p_{V|S}(0|1)} &= \frac{\alpha(1-\epsilon)}{\frac{\alpha(1-\epsilon)}{\epsilon * \alpha}} = \epsilon * \alpha, \\ \frac{p_{Y|V,S}(1|1,0)p_{V|S}(1|0)}{p_{V|S}(1|1)} &= \frac{(1-\alpha)\epsilon}{\frac{(1-\alpha)\epsilon}{\epsilon * \alpha}} = \epsilon * \alpha. \end{aligned}$$

Next, we claim that $\frac{p_{V,S}(v,1)}{p_{V,Y}(v,1)} = \frac{\beta}{(\epsilon * \alpha)(1-\beta) + \beta}$ for any $v \in \{0, 1\}$, and therefore that $\frac{p_{V,S}(v,1)}{p_{V,Y}(v,1)} \in [0, 1]$. This follows

from

$$\begin{aligned} \frac{p_{V,S}(v, 1)}{p_{V,Y}(v, 1)} &\stackrel{(a)}{=} \frac{p_{V|S}(v|1)p_S(1)}{p_{Y,V|S}(1, v|0)p_S(0) + p_{Y,V|S}(1, v|1)p_S(1)} \\ &\stackrel{(b)}{=} \frac{p_{V|S}(v|1)\beta / (p_{Y|V,S}(1|v, 0)p_{V|S}(v|0)(1 - \beta) \\ &\quad + p_{Y|V,S}(1|v, 1)p_{V|S}(v|1)\beta)}{(\epsilon * \alpha)p_{V|S}(v|1)(1 - \beta) + p_{V|S}(v|1)\beta} \\ &\stackrel{(c)}{=} \frac{\beta}{(\epsilon * \alpha)(1 - \beta) + \beta}, \end{aligned}$$

where (a) follows from the law of total probability, (b) follows from the definition of conditional probability, and (c) follows from Equations (9) and (17).

Since $\frac{p_{V,S}(v, 1)}{p_{V,Y}(v, 1)}$ is not a function of v and is in $[0, 1]$, we can define W as following:

$$W(s|y) \triangleq \begin{cases} 1 & \text{if } (s, y) = (0, 0) \\ 1 - \frac{p_{S|V}(1|v)}{p_{Y|V}(1|v)} & \text{if } (s, y) = (0, 1) \\ \frac{p_{S|V}(1|v)}{p_{Y|V}(1|v)} & \text{if } (s, y) = (1, 1) \\ 0 & \text{if } (s, y) = (1, 0). \end{cases}$$

We show next that Equation (16) holds for W defined above:

$$\begin{aligned} &\sum_{y \in \{0,1\}} p_{Y|V}(y|v)W(s|y) \\ &= p_{Y|V}(0|v)W(s|0) + p_{Y|V}(1|v)W(s|1) \\ &= \left[p_{Y|V}(0|v) + p_{Y|V}(1|v) \left(1 - \frac{p_{S|V}(1|v)}{p_{Y|V}(1|v)} \right) \right] \\ &\quad \cdot \mathbb{1}[s=0] + p_{S|V}(1|v) \mathbb{1}[s=1] \\ &= [1 - p_{S|V}(1|v)] \mathbb{1}[s=0] \\ &\quad + p_{S|V}(1|v) \mathbb{1}[s=1] \\ &= p_{S|V}(0|v) \mathbb{1}[s=0] + p_{S|V}(1|v) \mathbb{1}[s=1] \\ &= p_{S|V}(s|v). \end{aligned}$$

So the channel W satisfies Equation (16) and thus the lemma holds.

APPENDIX C

In this appendix we prove Theorem 15. The complexity claim of Theorem 15 is explained in [17, Sec. III.B]. We start with the asymptotic rate of Construction 14. We want to show that $\lim_{n \rightarrow \infty} (1/n)|\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c| = 0$. Since $p_{S|V}$ is degraded with respect to $p_{Y|V}$, it follows from [13, Lemma 4] that $\mathcal{L}_{V|S} \subseteq \mathcal{L}_{V|Y}$, and therefore that $\mathcal{L}_{V|S}^c \supseteq \mathcal{L}_{V|Y}^c$. So we have

$$\lim_{n \rightarrow \infty} (1/n)|\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|Y}^c| \leq \lim_{n \rightarrow \infty} (1/n)|\mathcal{H}_{V|S}^c \cap \mathcal{L}_{V|S}^c| = 0,$$

where the equality follows from the definition of the sets. To complete the proof of the theorem, we need to show that for some frozen vector, the input cost meets the design constraint, while the decoding error probability vanishes sub-exponentially fast in the block length. We show this result using the probabilistic method. That is, we first assume that the frozen vector is random, drawn uniformly, and analyze the input cost and error probability in this case, and then we show

the existence of a good vector using Markov's inequalities and the union bound. Denote the uniformly distributed random vector that represents the frozen vector by $F_{[|\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}^c|]}$. We show next that the expected input cost exceeds the design constraint B by a vanishing amount.

A. Expected Input Cost

Define

$$b^n(X_{[n]}) = \sum_{i=1}^n b(X_i).$$

For a state vector $s_{[n]}$ and the encoding rule (11) with uniform frozen vector $F_{[|\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}^c|]}$, each vector $u_{[n]}$ appears with probability

$$\left(\prod_{i \in \mathcal{H}_{V|S}^c} p_{U_i|U_{[i-1]}, S_{[n]}}(u_i | u_{[i-1]}, s_{[n]}) \right) 2^{-|\mathcal{H}_{V|S}|}.$$

Remember that the joint pmf $p_{S_{[n]}, U_{[n]}}$ refers to the capacity-achieving distribution of the channel. The expected cost is expressed as

$$\begin{aligned} &\mathbb{E}_{F_{[|\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}^c|]}}(b^n(X_{[n]})) \\ &= \sum_{u_{[n]}, s_{[n]}} p_{S_{[n]}}(s_{[n]}) \cdot \left(\prod_{i \in \mathcal{H}_{V|S}^c} p_{U_i|U_{[i-1]}, S_{[n]}}(u_i | u_{[i-1]}, s_{[n]}) \right) \\ &\quad \cdot 2^{-|\mathcal{H}_{V|S}|} b^n(u_{[n]} G_n). \end{aligned}$$

Define the joint pmf

$$q_{S_{[n]}, U_{[n]}} \equiv p_{S_{[n]}}(s_{[n]}) \left(\prod_{i \in \mathcal{H}_{V|S}^c} p_{U_i|U_{[i-1]}, S_{[n]}}(u_i | u_{[i-1]}, s_{[n]}) \right) \cdot 2^{-|\mathcal{H}_{V|S}|}. \quad (18)$$

Intuitively, $q_{U_{[n]}, S_{[n]}}$ refers to the distribution imposed by the encoding procedure of Construction 14. Then we have

$$\begin{aligned} &\mathbb{E}_{F_{[|\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}^c|]}}(b^n(X_{[n]})) \\ &= \mathbb{E}_{q_{U_{[n]}, S_{[n]}}}[b^n(U_{[n]} G_n)] \\ &\leq \mathbb{E}_{p_{U_{[n]}, S_{[n]}}}[b^n(U_{[n]} G_n)] \\ &\quad + \max_x b(x) \|p_{U_{[n]}, S_{[n]}} - q_{U_{[n]}, S_{[n]}}\| \\ &= nB + \max_x b(x) \|p_{U_{[n]}, S_{[n]}} - q_{U_{[n]}, S_{[n]}}\|, \end{aligned}$$

where $\|\cdot\|$ is the L_1 distance and the inequality follows from the triangle inequality. We will now prove that

$$\mathbb{E}_{F_{[|\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}^c|]}}(b^n(X_{[n]})) \leq nB + 2^{-n^{1/2-\delta}},$$

by showing that $\|p_{U_{[n]}, S_{[n]}} - q_{U_{[n]}, S_{[n]}}\| \leq 2^{-n^{1/2-\delta}}$. To do this, we will prove a slightly stronger relation that will be used also for the proof of the probability of decoding error. We first define the joint pmf

$$q_{U_{[n]}, S_{[n]}, Y_{[n]}} \equiv q_{U_{[n]}, S_{[n]}}(u_{[n]}, s_{[n]}) p_{Y_{[n]}|U_{[n]}, S_{[n]}}(y_{[n]} | u_{[n]}, s_{[n]}).$$

Then we notice that

$$\begin{aligned}
& \|pU_{[n],S_{[n]}} - qU_{[n],S_{[n]}}\| \\
&= \sum_{u_{[n],S_{[n]}}} |p(u_{[n]}, s_{[n]}) - q(u_{[n]}, s_{[n]})| \\
&= \sum_{u_{[n],S_{[n]}}} \left| \sum_{y_{[n]}} [p(u_{[n]}, s_{[n]}, y_{[n]}) - q(u_{[n]}, s_{[n]}, y_{[n]})] \right| \\
&\leq \sum_{u_{[n],S_{[n]},Y_{[n]}}} |p(u_{[n]}, s_{[n]}, y_{[n]}) - q(u_{[n]}, s_{[n]}, y_{[n]})| \\
&= \|pU_{[n],S_{[n]},Y_{[n]}} - qU_{[n],S_{[n]},Y_{[n]}}\|,
\end{aligned}$$

where the inequality follows from the triangle inequality. The proof of the expected cost is completed with the following lemma, which will be used also for analyzing the probability of decoding error.

Lemma 17:

$$\|pU_{[n],S_{[n]},Y_{[n]}} - qU_{[n],S_{[n]},Y_{[n]}}\| \leq 2^{-n^{1/2-\delta}}. \quad (19)$$

Proof: Let $D(\cdot\|\cdot)$ denote the relative entropy. Then the equality

$$\begin{aligned}
& \|pU_{[n],S_{[n]},Y_{[n]}} - qU_{[n],S_{[n]},Y_{[n]}}\| \\
&= \sum_{i \in \mathcal{H}_{V|S}} \sqrt{(2 \ln 2)[1 - H(U_i|U_{[i-1]}, S_{[n]})]},
\end{aligned}$$

is derived in Equation (20), as shown at the bottom of this page, where

- (a) follows from the fact that $p(s_{[n]}) = q(s_{[n]})$ and $p(y_{[n]}|u_{[n]}, s_{[n]}) = q(y_{[n]}|u_{[n]}, s_{[n]})$,
- (b) follows from the chain rule,
- (c) follows from the telescoping expansion

$$\begin{aligned}
B_{[n]} - A_{[n]} &= \sum_{i=1}^n A_{[i-1]}B_{[i:n]} - \sum_{i=1}^n A_{[i]}B_{[i+1:n]} \\
&= \sum_{i=1}^n (B_i - A_i)A_{[i-1]}B_{[i+1:n]},
\end{aligned}$$

$$\begin{aligned}
& \|pU_{[n],S_{[n]},Y_{[n]}} - qU_{[n],S_{[n]},Y_{[n]}}\| \\
&= \sum_{u_{[n],S_{[n]},Y_{[n]}}} |p(u_{[n]}, s_{[n]}, y_{[n]}) - q(u_{[n]}, s_{[n]}, y_{[n]})| \\
&\stackrel{(a)}{=} \sum_{u_{[n],S_{[n]},Y_{[n]}}} |p(u_{[n]}|s_{[n]}) - q(u_{[n]}|s_{[n]})| p(s_{[n]}) \cdot p(y_{[n]}|u_{[n]}, s_{[n]}) \\
&\stackrel{(b)}{=} \sum_{u_{[n],S_{[n]},Y_{[n]}}} \left| \prod_{i=1}^n p(u_i|u_{[i-1]}, s_{[n]}) - \prod_{i=1}^n q(u_i|u_{[i-1]}, s_{[n]}) \right| p(s_{[n]}) p(y_{[n]}|u_{[n]}, s_{[n]}) \\
&\stackrel{(c)}{=} \sum_{u_{[n],S_{[n]},Y_{[n]}}} \sum_{i=1}^n |[p(u_i|u_{[i-1]}, s_{[n]}) - q(u_i|u_{[i-1]}, s_{[n]})]| p(s_{[n]}) p(y_{[n]}|u_{[n]}, s_{[n]}) \\
&\quad \cdot \prod_{j=1}^{i-1} p(u_j|u_{[j-1]}, s_{[n]}) \prod_{j=i+1}^n q(u_j|u_{[j-1]}, s_{[n]}) \\
&\stackrel{(d)}{\leq} \sum_{i \in \mathcal{H}_{V|S}} \sum_{u_{[n],S_{[n]},Y_{[n]}}} |p(u_i|u_{[i-1]}, s_{[n]}) - q(u_i|u_{[i-1]}, s_{[n]})| p(s_{[n]}) \prod_{j=1}^{i-1} p(u_j|u_{[j-1]}, s_{[n]}) \\
&\quad \cdot \prod_{j=i+1}^n q(u_j|u_{[j-1]}, s_{[n]}) p(y_{[n]}|u_{[n]}, s_{[n]}) \\
&= \sum_{i \in \mathcal{H}_{V|S}} \sum_{u_{[i],S_{[n]}}} |p(u_i|u_{[i-1]}, s_{[n]}) - q(u_i|u_{[i-1]}, s_{[n]})| \prod_{j=1}^{i-1} p(u_j|u_{[j-1]}, s_{[n]}) p(s_{[n]}) \\
&\stackrel{(e)}{=} \sum_{i \in \mathcal{H}_{V|S}} \sum_{u_{[i-1],S_{[n]}}} p(u_{[i-1]}, s_{[n]}) \|pU_{[i-1],U_{[i-1]=u_{[i-1]},S_{[n]=s_{[n]}}} - qU_{[i-1],U_{[i-1]=u_{[i-1]},S_{[n]=s_{[n]}}}\| \\
&\stackrel{(f)}{\leq} \sum_{i \in \mathcal{H}_{V|S}} \sum_{u_{[i-1],S_{[n]}}} p(u_{[i-1]}, s_{[n]}) \sqrt{2 \ln 2} \sqrt{D(pU_{[i-1],U_{[i-1]=u_{[i-1]},S_{[n]=s_{[n]}}} \| qU_{[i-1],U_{[i-1]=u_{[i-1]},S_{[n]=s_{[n]}}})} \\
&\stackrel{(g)}{\leq} \sum_{i \in \mathcal{H}_{V|S}} \sqrt{(2 \ln 2) \sum_{u_{[i-1],S_{[n]}}} p(u_{[i-1]}, s_{[n]}) D(pU_{[i-1],U_{[i-1]=u_{[i-1]},S_{[n]=s_{[n]}}} \| qU_{[i-1],U_{[i-1]=u_{[i-1]},S_{[n]=s_{[n]}}})} \\
&= \sum_{i \in \mathcal{H}_{V|S}} \sqrt{(2 \ln 2) D(pU_i \| qU_i | U_{[i-1]}, S_{[n]})} \\
&\stackrel{(h)}{=} \sum_{i \in \mathcal{H}_{V|S}} \sqrt{(2 \ln 2)[1 - H(U_i|U_{[i-1]}, S_{[n]})]}, \tag{20}
\end{aligned}$$

where $A_{[j:k]}$ and $B_{[j:k]}$ denote the products $\prod_{i=j}^k A_i$ and $\prod_{i=j}^k B_i$, respectively,

- (d) follows from the triangular inequality and the fact that $p(u_i|u_{[i-1]}, s_{[n]}) = q(u_i|u_{[i-1]}, s_{[n]})$ for all $i \in \mathcal{H}_{V|S}^c$ (as defined in Equation (18)),
(e) follows from the chain rule again,
(f) follows from Pinsker's inequality (see, e.g., [6, Lemma 11.6.1]),
(g) follows from Jensen's inequality and
(h) follows from the facts that $q(u_i|u_{[i-1]}, s_{[n]}) = 1/2$ for $i \in \mathcal{H}_{V|S}$ and from [13, Lemma 10].

Now if $i \in \mathcal{H}_{V|S}$, we have

$$1 - H(U_i|U_{[i-1]}, S_{[n]}) \leq 1 - [Z(U_i|U_{[i-1]}, S_{[n]})]^2 \leq 2^{-2n^{1/2-\delta}}, \quad (21)$$

where the first inequality follows from Proposition 3, and the second inequality follows from the fact that i is in $\mathcal{H}_{V|S}$. This completes the proof of the lemma. ■

B. Probability of Decoding Error

Let \mathcal{E}_i be the set of pairs of vectors $(u_{[n]}, y_{[n]})$ such that $\hat{u}_{[n]}$ is a result of decoding $y_{[n]}$, and $\hat{u}_{[i]}$ satisfies both $\hat{u}_{[i-1]} = u_{[i-1]}$ and $\hat{u}_i \neq u_i$. The block decoding error event is given by $\mathcal{E} \equiv \cup_{i \in \mathcal{L}_{V|Y}} \mathcal{E}_i$. Under decoding given in (12) with an arbitrary tie-breaking rule, every pair $(u_{[n]}, y_{[n]}) \in \mathcal{E}_i$ satisfies

$$p_{U_i|U_{[i-1]}, Y_{[n]}}(u_i|u_{[i-1]}, y_{[n]}) \leq p_{U_i|U_{[i-1]}, Y_{[n]}}(u_i \oplus 1|u_{[i-1]}, y_{[n]}). \quad (22)$$

Consider the block decoding error probability $p_e(F_{[\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}^c]})$ for the random frozen vector $F_{[\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}^c]}$. For a state vector $s_{[n]}$ and the encoding rule (11), each vector $u_{[n]}$ appears with probability

$$\left(\prod_{i \in \mathcal{H}_{V|S}^c} p_{U_i|U_{[i-1]}, S_{[n]}}(u_i|u_{[i-1]}, s_{[n]}) \right) 2^{-|\mathcal{H}_{V|S}|}.$$

By the definition of conditional probability and the law of total probability, the probability of error $p_e(F_{[\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}^c]})$ is given by

$$\begin{aligned} & \mathbb{E}_{F_{[\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}^c]}}[p_e] \\ &= \sum_{u_{[n]}, s_{[n]}, y_{[n]}} p_{S_{[n]}}(s_{[n]}) \\ & \cdot \left(\prod_{i \in \mathcal{H}_{V|S}^c} p_{U_i|U_{[i-1]}, S_{[n]}}(u_i|u_{[i-1]}, s_{[n]}) \right) 2^{-|\mathcal{H}_{V|S}|} \\ & \cdot p_{Y_{[n]}|U_{[n]}, S_{[n]}}(y_{[n]}|u_{[n]}, s_{[n]}) \mathbb{1}[(u_{[n]}, y_{[n]}) \in \mathcal{E}]. \end{aligned}$$

Then we have

$$\begin{aligned} \mathbb{E}_{F_{[\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}^c]}}[p_e] &= q_{U_{[n]}, Y_{[n]}}(\mathcal{E}) \\ &\leq \|q_{U_{[n]}, Y_{[n]}} - p_{U_{[n]}, Y_{[n]}}\| + p_{U_{[n]}, Y_{[n]}}(\mathcal{E}) \\ &\leq \|q_{U_{[n]}, Y_{[n]}} - p_{U_{[n]}, Y_{[n]}}\| + \sum_{i \in \mathcal{L}_{V|Y}} p_{U_{[n]}, Y_{[n]}}(\mathcal{E}_i), \end{aligned}$$

where the first inequality follows from the triangle inequality. Each term in the summation is bounded by

$$\begin{aligned} & p_{U_{[n]}, Y_{[n]}}(\mathcal{E}_i) \\ &\leq \sum_{u_{[i]}, y_{[n]}} p(u_{[i]}, y_{[n]}) \\ & \cdot \mathbb{1}[p(u_i|u_{[i-1]}, y_{[n]}) \leq p(u_i \oplus 1|u_{[i-1]}, y_{[n]})] \\ &\leq \sum_{u_{[i]}, y_{[n]}} p(u_{[i-1]}, y_{[n]}) p(u_i|u_{[i-1]}, y_{[n]}) \\ & \cdot \sqrt{\frac{p(u_i \oplus 1|u_{[i-1]}, y_{[n]})}{p(u_i|u_{[i-1]}, y_{[n]})}} \\ &= Z(U_i|U_{[i-1]}, Y_{[n]}) \\ &\leq 2^{-n^{1/2-\delta}}, \end{aligned}$$

where the last inequality follows from the fact that i belongs to the set $\mathcal{L}_{V|Y}$.

To prove that $\mathbb{E}_{F_{[\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}^c]}}[p_e] \leq 2^{-n^{1/2-\delta'}}$ for some $\delta' > \delta$, we are left with showing that $\|p_{U_{[n]}, Y_{[n]}} - q_{U_{[n]}, Y_{[n]}}\| \leq 2^{-n^{1/2-\delta}}$. Notice that

$$\begin{aligned} & 2\|p_{U_{[n]}, Y_{[n]}} - q_{U_{[n]}, Y_{[n]}}\| \\ &= \sum_{u_{[n]}, y_{[n]}} |p(u_{[n]}, y_{[n]}) - q(u_{[n]}, y_{[n]})| \\ &= \sum_{u_{[n]}, y_{[n]}} \left| \sum_{s_{[n]}} [p(u_{[n]}, s_{[n]}, y_{[n]}) - q(u_{[n]}, s_{[n]}, y_{[n]})] \right| \\ &\leq \sum_{u_{[n]}, s_{[n]}, y_{[n]}} |p(u_{[n]}, s_{[n]}, y_{[n]}) - q(u_{[n]}, s_{[n]}, y_{[n]})| \\ &= 2\|p_{U_{[n]}, S_{[n]}, Y_{[n]}} - q_{U_{[n]}, S_{[n]}, Y_{[n]}}\|, \end{aligned}$$

where the inequality follows from the triangle inequality. Lemma 17 now completes the proof that $\mathbb{E}_{F_{[\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}^c]}}[p_e] = 2^{-n^{1/2-\delta}}$.

C. Existence of a Good Frozen Vector

We showed that

$$\mathbb{E}_{F_{[\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}^c]}}(b^n(X_{[n]})) \leq nB + 2^{-n^{1/2-\delta}}.$$

In this subsection we will be interested to find a frozen vector which satisfies a slightly higher expected cost, namely

$$\mathbb{E}(b^n(X_{[n]})) \leq nB + 1/n^2.$$

Remember that B is a constant. We take a uniformly distributed frozen vector, and bound the probability that the expected cost exceeds $nB + 1/n^2$, using Markov's inequality. The following inequalities hold for large enough n , and we

are not concerned here with the exact values required.

$$\begin{aligned}
P(\mathbf{E}(b^n(X_{[n]})) \geq nB + 1/n^2) & \\
&\leq E_{F_{\|\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}^c\|}}(b^n(X))/(nB + 1/n^2) \\
&\leq (nB + 2^{-n^{1/2-\delta}})/(nB + 1/n^2) \\
&\leq (nB + n^{-3})/(nB + n^{-2}) \\
&= 1 - (n^{-2} - n^{-3})/(nB + n^{-2}) \\
&\leq 1 - (n^{-2.1})/(nB + n^{-2}) \\
&\leq 1 - 1/(Bn^{3.1} + n^{0.1}) \\
&\leq 1 - 1/(Bn^{3.2}) \\
&\leq 1 - 1/n^4.
\end{aligned}$$

We now apply Markov's inequality on the probability of decoding error:

$$\begin{aligned}
P(p_e \geq n^5 2^{-n^{1/2-\delta}}) &\leq \frac{E_{F_{\|\mathcal{H}_{V|S} \cap \mathcal{L}_{V|Y}^c\|}}(p_e)}{n^5 2^{-n^{1/2-\delta}}} \\
&\leq \frac{2^{-n^{1/2-\delta}}}{n^5 2^{-n^{1/2-\delta}}} = 1/n^5.
\end{aligned}$$

By the union bound, the probability that either $\mathbf{E}(b^n(X_{[n]})) \geq nB + 1/n^2$ or $p_e \geq n^5 2^{-n^{1/2-\delta}}$ is at most

$$1 - 1/n^4 + 1/n^5 \leq 1 - 1/n^5.$$

This implies that the probability that both $\mathbf{E}(b^n(X_{[n]})) \leq nB + 1/n^2$ and $p_e \leq n^5 2^{-n^{1/2-\delta}}$ is at least $1/n^5$. So there exists at least one frozen vector for which the desired properties for both the expected cost and the probability of error hold. Furthermore, such a vector can be found by repeatedly selecting a frozen vector uniformly at random, until the required properties hold. The properties can be verified efficiently with close approximations by the upgradation and degradation method proposed in [32]. The expected number of times until a good vector is found is polynomial in the block length (at most n^5). This completes the proof of Theorem 15.

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Eyal En Gad (S'09–M'15) is a postdoctoral researcher at the Electrical Engineering Department at the University of Southern California. He received the B.Sc. degree in electrical engineering from the Technion - Israel Institute of Technology, in 2008, and the M.Sc and Ph.D. degrees in electrical engineering from the California Institute of Technology, in 2012 and 2015, respectively. His research interests include information theory, data storage, and machine learning.

Yue Li (S'07) is a postdoctoral fellow at the Electrical Engineering Department at California Institute of Technology. He received the Ph.D. degree in computer science from Texas A&M University in 2014, and the B.Eng. degree in information security from Huazhong University of Science and Technology in 2008. His research interests include coding and signal processing for emerging non-volatile memories.

Jörg Kliewer (S'97–M'99–SM'04) received the Dipl.-Ing. (M.Sc.) degree in electrical engineering from Hamburg University of Technology, Hamburg, Germany, in 1993 and the Dr.-Ing. degree (Ph.D.) in electrical engineering from the University of Kiel, Germany, in 1999, respectively.

From 1993 to 1998, he was a research assistant at the University of Kiel, and from 1999 to 2004, he was a senior researcher and lecturer with the same institution. In 2004, he visited the University of Southampton, U.K., for one year, and from 2005 until 2007, he was with the University of Notre Dame, IN, as a Visiting assistant professor. From 2007 until 2013 he was with New Mexico State University, Las Cruces, NM, most recently as an associate professor. He is now with the New Jersey Institute of Technology, Newark, NJ, as an associate professor. His research interests span coding and information theory, graphical models, and statistical algorithms, which includes applications to networked communication and security, data storage, and biology.

Dr. Kliewer was the recipient of a Leverhulme Trust Award and a German Research Foundation Fellowship Award in 2003 and 2004, respectively. He was an Associate Editor of the IEEE TRANSACTIONS ON COMMUNICATIONS from 2008 until 2014, and since 2015 serves as an Area Editor for the IEEE TRANSACTIONS ON COMMUNICATIONS. He is also member of the editorial board of the IEEE INFORMATION THEORY SOCIETY NEWSLETTER since 2012.

Michael Langberg (M'07–S'15) received his B.Sc. in mathematics and computer science from Tel-Aviv University in 1996, and his M.Sc. and Ph.D. in computer science from the Weizmann Institute of Science in 1998 and 2003 respectively. Between 2003 and 2006, he was a postdoctoral scholar in the Electrical Engineering and Computer Science departments at the California Institute of Technology, and between 2007 and 2012 he was in the Department of Mathematics and Computer Science at The Open University of Israel. Prof. Langberg is currently an associate professor in the Department of Electrical Engineering at the State University of New York in Buffalo.

Prof. Langberg's research addresses the algorithmic and combinatorial aspects of information in communication, management, and storage; focusing on the study of information theory, coding theory, network communication and network coding, big data in the form of succinct data representation, and probabilistic methods in combinatorics. Prof. Langberg was an Associate Editor for the IEEE TRANSACTIONS ON INFORMATION THEORY during the years 2012-2015 and is currently the Editor of the IEEE INFORMATION THEORY SOCIETY NEWSLETTER.

Anxiao (Andrew) Jiang (S'00–M'05–SM'12) received the B.Sc. degree in electronic engineering from Tsinghua University, Beijing, China in 1999, and the M.Sc. and Ph.D. degrees in electrical engineering from the California Institute of Technology, Pasadena, California in 2000 and 2004, respectively.

He is currently an Associate Professor in the Computer Science and Engineering Department and the Electrical and Computer Engineering Department at Texas A&M University in College Station, Texas. He has been a visiting professor or associate at California Institute of Technology, University of California in San Diego, Ecole Polytechnique Federale de Lausanne (EPFL), Singapore Data Storage Institute (DSI) and Israel Institute of Technology (Technion), and a consulting researcher at HP Labs, EMC and Microsoft Research. His research interests include information theory, data storage, networks and algorithm design.

Prof. Jiang is a recipient of the NSF CAREER Award in 2008 for his research on information theory for flash memories and a recipient of the 2009 IEEE Communications Society Data Storage Technical Committee (DSTC) Best Paper Award in Signal Processing and Coding for Data Storage.

Jehoshua Bruck (S'86–M'89–SM'93–F'01) is the Gordon and Betty Moore Professor of computation and neural systems and electrical engineering at the California Institute of Technology (Caltech). His current research interests include information theory and its applications to memory systems, including molecular memories (DNA), associative memories (the brain), and nonvolatile memories (flash).

Dr. Bruck received the B.Sc. and M.Sc. degrees in electrical engineering from the Technion-Israel Institute of Technology, in 1982 and 1985, respectively, and the Ph.D. degree in electrical engineering from Stanford University, in 1989.

His industrial and entrepreneurial experiences include working with IBM Research where he participated in the design and implementation of the first IBM parallel computer; cofounding and serving as Chairman of Rainfinity (acquired in 2005 by EMC), a spin-off company from Caltech that created the first virtualization solution for Network Attached Storage; as well as cofounding and serving as Chairman of XtremIO (acquired in 2012 by EMC), a start-up company that created the first scalable all-flash enterprise storage system.

Dr. Bruck is a recipient of the Feynman Prize for Excellence in Teaching, the Sloan Research Fellowship, the National Science Foundation Young Investigator Award, the IBM Outstanding Innovation Award and the IBM Outstanding Technical Achievement Award.