Deterministic list codes for state-constrained arbitrarily varying channels

Anand D. Sarwate Student Member, IEEE, and Michael Gastpar Member, IEEE

Abstract

The capacity for the discrete memoryless arbitrarily varying channel (AVC) with cost constraints on the jammer is studied using deterministic list codes under both the maximal and average probability of error criteria. For a cost function $l(\cdot)$ on the state set and constraint Λ on the jammer it is shown that under maximal error a rate $\max_{P(x)} \min_{W \in \bar{\mathcal{W}}_{dep}(P,\Lambda)} I\left(X \wedge Y\right) - O(L^{-1})$ is achievable with list codes of list size L, where $\bar{\mathcal{W}}_{dep}(P,\Lambda)$ is a subset of the row-convex closure of the AVC. For average error, an integer $L_{\mathrm{sym}}(\Lambda)$, called the *symmetrizability*, is defined. It is shown that any rate below $C_r(\Lambda)$ is achievable under average error using list codes of list size $L > L_{\mathrm{sym}}$, where $C_r(\Lambda)$ is the randomized coding capacity of the AVC. An example is given for a class of discrete additive AVCs.

I. Introduction

The arbitrarily varying channel (AVC) is a model for communication subject to time-varying interference. The channel is specified by a set of channels $\{W(y|x,s):s\in\mathcal{S}\}$ indexed by the state variable s. The effect of the interference is captured by the state s and can vary arbitrarily across time. Coding schemes for these channels are required to give a guarantee on the probability of error for all possible channel state sequences. We can think of the AVC as an adversarial model in which the channel state is controlled by a malicious *jammer* who wishes to foil the communication between the encoder and decoder.

Because reliable communication over AVCs is defined using the worst case channel behavior, the coding problem for deterministic codes with the maximal probability of error criterion is quite difficult. The best bounds on the capacity for deterministic coding under maximal error C_d are due to Csiszár and Körner [15]. In some cases [6], [9], [15], it can be shown that $C_d = C^{\text{dep}}$, given by

$$C^{\text{dep}} = \max_{P(x)} \min_{U(s|x)} I(X \land Y) . \tag{1}$$

By relaxing the error criterion or expanding the coding strategies, results sometimes become easier to prove and the corresponding capacities can be shown to coincide in some cases. The first results on AVCs were proved for the case where the encoder and decoder share a source of common randomness that they can use to perform randomized coding [10]. The largest rate for which the probability of decoding error can be driven to 0 for any message and any state sequence is called the random coding capacity under maximal error and is given by the formula

$$C_r = \max_{P(x)} \min_{Q(s)} I(X \land Y) . \tag{2}$$

Part of this work was presented at the 2007 International Symposium on Information Theory in Nice, France [27]

The authors are with the Department of Electrical Engineering and Computer Sciences, University of California, Berkeley, Berkeley CA 94720-1770 USA.

The work of A.D. Sarwate and M. Gastpar was supported in part by the National Science Foundation under award CCF-0347298.

By requiring deterministic coding but allowing the error probability to be the averaged over all messages, Ahlswede [4] proved the following dichotomy: the deterministic coding capacity for average error \bar{C}_d is either 0 or $\bar{C}_d = C_r$. A condition for \bar{C}_d to be positive, called *symmetrizability*, was shown to be necessary by Ericson [22] and sufficient by Csiszár and Narayan [18].

Another way of relaxing the coding problem for these channels is to consider *list coding* [21], in which the decoder is allowed to output a list of codewords of size no more than L and an error occurs if the transmitted codeword is not in the list. For deterministic coding, list coding capacities C_L and \bar{C}_L for AVCs have been investigated for both maximal and average error. For maximal error, Ahlswede [2], [8] found that for any rate $R < C^{\text{dep}}$ there exists a constant list size L(R) such that R is achievable with list codes of list size L(R). The minimization in (1) is over all input-dependent state selection strategies U(s|x), so in general $C^{\text{dep}} \le C_r$. For the average probability of error criterion, the list coding capacity was found independently by Blinovsky, Narayan, and Pinsker [11], [12] and Hughes [26]. They proposed an extended notion of symmetrizability and showed that for non-symmetrizable channels there is a constant list size L so that all rates $R < C_r$ are achievable with list codes of list size L.

A simple modification to the standard AVC model is defining a cost function $l(\cdot)$ on the possible states and constraining the jammer to be arbitrary subject to a total budget Λn . For example, the inputs and outputs may be binary and the jammer can flip a fraction Λ of the bits. The random coding capacity for maximal error $C_r(\Lambda)$ and the deterministic coding capacity for average error $\bar{C}_d(\Lambda)$ under this model were found by Csiszár and Narayan [17], [18]. Deterministic codes for maximal error are intimately connected to algebraic coding theory, as the bit-flipping example shows. The minimum distance of a linear code provides a bound on the number of errors that can be corrected in a constrained AVC setting.

The purpose of this paper is to extend the results on list decoding to the case of constrained AVCs. Our primary results are the following:

- For maximal error, for any rate $R = C^{\text{dep}}(\Lambda) \epsilon$ there exists list codes of size $L(\epsilon) = O(\epsilon^{-1})$ that achieve the rate R.
- For average error there exists a number $L_{\mathrm{sym}}(\Lambda)$, called the *symmetrizability* of the channel, such that the list coding capacity is $C_r(\Lambda)$ for lists larger than $L_{\mathrm{sym}}(\Lambda)$. In addition, for lists smaller than $L_{\mathrm{sym}}(\Lambda)$, the list coding capacity may be positive but smaller than $C_r(\Lambda)$.

We follow the line of argument used by Ahlswede [8] for the maximal error case and by Hughes [26] for the average error case. In the maximum probability of error model, the result for constrained channels is similar to that in the unconstrained scenario. However, our average error result is qualitatively different from the unconstrained case, where the capacity is 0 for lists codes with lists smaller than $L_{\rm sym}$ and C_r for lists larger than $L_{\rm sym}$. An example of this difference is given in Figures 3 and 4 for the example in Section V.

In the next section we will describe the channel model in more detail. In Section III we prove the maximal error result and in Section IV the average error result. In Section V we discuss an example of a binary-input AVC with additive noise that is inspired by binary-input channels with continuous noise and quantized output.

II. CHANNEL MODELS AND MAIN RESULTS

A. Notation and basic facts of life

The proofs of AVC results tend to generate a surfeit of notation. Let $[N] = \{1, 2, ..., N\}$ and $\Sigma_L = \{J \subset [N] : |J| = L\}$. Let $\Sigma_L(-\{i\}) = \{J \in \Sigma_L : i \notin J\}$ and A^c denote the complement of a set A. We will use boldface symbols to denote tuples, so $\mathbf{z} = (z_1, z_2, ..., z_n)$. We will denote sets by calligraphic letters, such as \mathcal{Z} , and the set of all distributions on a set \mathcal{Z} by $\mathcal{P}(\mathcal{Z})$ and channels from $\mathcal{Z} \to \mathcal{Y}$ by

 $\mathcal{P}(\mathcal{Y}|\mathcal{Z})$. The distribution (channel) P^n (V^n) is the product distribution of P (V) with itself n times. For $P \in \mathcal{P}(\mathcal{Z})$ we write H(P) for the entropy under distribution P. The symbols \mathbb{P} and \mathbb{E} stand for probability and expectation, respectively.

Given a sequence $\mathbf{z} \in \mathcal{Z}^n$, let $N(\zeta|\mathbf{z}) = |\{i : z_i = \zeta\}|$, the number of times ζ appears in \mathbf{z} . We denote the type of \mathbf{z} by

$$T_{\mathbf{z}} = \frac{1}{n} (N(\zeta_1 | \mathbf{z}), N(\zeta_2 | \mathbf{z}), \dots, N(\zeta_{|\mathcal{Z}|} | \mathbf{z})) .$$
(3)

The set of all sequences of a fixed type P will be denoted by

$$\mathcal{T}(P) = \{ \mathbf{z} \in \mathcal{Z}^n : T_{\mathbf{z}} = P \} . \tag{4}$$

The set of all types of sequences of length n will be denoted by $\mathcal{P}_n(\mathcal{Z}) \subset \mathcal{P}(\mathcal{Z})$. We denote the maximum variation between two distributions P and Q by

$$d_m(P,Q) = \max_{\zeta \in \mathcal{Z}} |P(\zeta) - Q(\zeta)| . \tag{5}$$

For a distribution $P \in \mathcal{P}(\mathcal{Z})$, the set

$$T_P^{\epsilon} = \{ \mathbf{z} \in \mathcal{Z}^n : d_m(P, T_{\mathbf{z}}) \le \epsilon \}$$
 (6)

is the ϵ -(strongly) typical set.

Let V(Y|Z) be a channel. Then we denote the (V,ϵ) -shell of ${\bf z}$ by

$$T_V^{\epsilon}(\mathbf{z}) = \{ \mathbf{y} \in \mathcal{Y}^n : d_m(T_{\mathbf{y}\mathbf{z}}, VT_{\mathbf{z}}) < \epsilon \} . \tag{7}$$

We know from standard textbooks [16] that

$$V^{n}\left(\left\{\mathbf{y}: T_{\mathbf{v}\mathbf{z}} = P_{YZ}\right\} \middle| \mathbf{x}\right) \le \exp\left(-nD\left(P_{XZ} \parallel V \times P_{Z}\right)\right) . \tag{8}$$

$$V^{n}\left(\left\{\mathbf{y}: T_{\mathbf{x}\mathbf{y}\mathbf{z}} = P_{XYZ}\right\}|\mathbf{x}\right) \le \exp\left(-nI\left(X \wedge Y|Z\right)\right) . \tag{9}$$

B. Channel Model

An arbitrarily varying channel (AVC) is a collection of $\mathcal{W} = \{W(\cdot|\cdot,s) : s \in \mathcal{S}\}$ of channels from an input alphabet \mathcal{X} to an output alphabet \mathcal{Y} parameterized by a state $s \in \mathcal{S}$. Here we will assume the sets \mathcal{X} , \mathcal{Y} and \mathcal{S} are finite. If $\mathbf{x} = (x_1, x_2, \dots, x_n)$, $\mathbf{y} = (y_1, y_2, \dots, y_n)$ and $\mathbf{s} = (s_1, s_2, \dots, s_n)$ are length n vectors, the probability of \mathbf{y} given \mathbf{x} and \mathbf{s} is given by:

$$W(\mathbf{y}|\mathbf{x},\mathbf{s}) = \prod_{i=1}^{n} W(y_i|x_i,s_i) . \tag{10}$$

We think of the state as being controlled by a malicious adversary, called the *jammer*, whose objective is to maximize the probability of decoder error and thereby minimize the capacity.

We are interested in the case where there is a cost function $l: \mathcal{S} \to \mathbb{R}^+$ on the jammer. We will assume $\max_s l(s) \leq l_{\max} < \infty$. The cost of an *n*-tuple is

$$l(\mathbf{s}) = \sum_{k=1}^{n} l(s_k) . \tag{11}$$

The state obeys a state constraint Λ if

$$l(\mathbf{s}) \le n\Lambda \qquad a.s.$$
 (12)

The set $S^n(\Lambda) = \{ \mathbf{s} : l(\mathbf{s}) \leq n\Lambda \}$ is the set of allowable sequences. Note that if $\Lambda = l_{\text{max}}$ then the state constraint is inoperative and the AVC is unconstrained.

As an example, take the AVC given by $y = x \oplus s$ with $\mathcal{X} = \mathcal{Y} = \mathcal{S} = \{0, 1\}$ and l(s) = s, so $\mathcal{S}^n(\Lambda)$ contains all length-n binary sequences of weight $n\Lambda$. This is similar to a binary symmetric channel (BSC) with flip probability Λ . In a BSC the channel will flip close to Λn bits with high probability and the decoder error must be small for most error patterns. For this AVC, however, the channel is constrained to flip no more than Λn bits but the decoder error must be small for any error pattern of weight Λn .

We will denote the set of all s that satisfy the cost constraint by $S^n(\Lambda)$:

$$S^{n}(\Lambda) = \{ \mathbf{s} : l(\mathbf{s}) \le \Lambda \} . \tag{13}$$

We will also define the sets of all distributions and channels on S satisfying the constraint.

$$Q(\Lambda) = \left\{ Q \in \mathcal{P}(\mathcal{S}) : \sum_{s} Q(s)l(s) \le \Lambda \right\}$$
(14)

$$\mathcal{U}(P,\Lambda) = \left\{ U \in \mathcal{P}(\mathcal{S}|\mathcal{X}) : \sum_{s,x} U(s|x)P(x)l(s) \le \Lambda \right\} . \tag{15}$$

For an AVC $W = \{W(Y|X,S) : s \in \mathcal{S}\}$ with state constraint Λ we can define two sets of channels $\bar{\mathcal{W}}(\Lambda)$ by

$$\bar{\mathcal{W}}(\Lambda) = \left\{ V(Y|X) : V(y|x) = \sum_{s} W(y|x,s)Q(s), \quad Q(s) \in \mathcal{Q}(\Lambda) \right\}$$
(16)

$$\bar{\mathcal{W}}_{dep}(P,\Lambda) = \left\{ V(Y|X) : V(y|x) = \sum_{s} W(y|x,s)U(s|x), \quad U(s|x) \in \mathcal{U}(P,\Lambda) \right\} . \tag{17}$$

We will suppress the explicit dependence on Λ . The set in (16) is called the *convex closure* of W, and the set in (17) is the *row-convex closure* of W. In earlier works $\bar{W}_{dep}(P,\Lambda)$ is sometimes written as \bar{W} .

An (n, N, L) deterministic list code C for the AVC is a pair of maps (ψ, ϕ) where the encoding function is $\psi : [N] \to \mathcal{X}^n$ and the decoding function is $\phi : \mathcal{Y}^n \to [N]^L$. The rate of the code is $R = \log(N/L)$. The codebook is the set of vectors $\{\mathbf{x}_i : 1 \le i \le N\}$, where $\mathbf{x}_i = \psi(i)$. The decoding region for message i is $D_i = \{\mathbf{y} : i \in \phi(\mathbf{y})\}$. We will often specify a code by the pairs $\{(\mathbf{x}_i, D_i) : i = 1, 2, \dots, N\}$, with the encoder and decoder defined implicitly.

We have two notions of error probability, maximal and average. The maximal error is given by:

$$\varepsilon(\mathcal{C}) = \max_{\mathbf{s}: l(\mathbf{s}) \le \Lambda} \max_{i} \mathbb{P}(i \notin \phi(\mathbf{y}) | \mathbf{x}_i, \mathbf{s}) = \max_{\mathbf{s}: l(\mathbf{s}) \le \Lambda} \max_{i} W(D_i^c | X^n = \mathbf{x}_i, \mathbf{s}) . \tag{18}$$

The average probability of error is given by

$$\bar{\varepsilon}(\mathcal{C}) = \max_{\mathbf{s}: l(\mathbf{s}) \le \Lambda} \bar{\varepsilon}(\mathbf{s}) = \max_{\mathbf{s}: l(\mathbf{s}) \le \Lambda} \frac{1}{N} \sum_{i=1}^{N} W(D_i^c | \mathbf{x}_i, \mathbf{s}) . \tag{19}$$

A rate R is called *achievable* under maximal (average) error with list size L if there exists of sequence of (n,N,L) codes of rate greater than R whose maximal (average) error converges to 0 as $n \to \infty$. The supremum of all achievable rates is the list-L capacity. We will denote the list-L capacity for maximal error by $C_L(\Lambda)$ and for average error by $\bar{C}_L(\Lambda)$.

In some cases the capacity $\bar{C}_L(\Lambda) = 0$. A necessary and sufficient condition for this is if the AVC is L-symmetrizable. We say an AVC is m-symmetrizable if there is channel $U: \mathcal{X}^m \to \mathcal{S}$ such that

$$V(y|x, x_1, \dots, x_m) = \sum_{s} W(y|x, s) U(s|x_1, x_2, \dots, x_m)$$
(20)

is a symmetric function in (x, x_1, \dots, x_m) . For a distribution $P \in \mathcal{P}(\mathcal{X})$ let us define the quantity

$$\Lambda_m(P) = \min_{U:\mathcal{X}^m \to \mathcal{S}} \sum_{x^m} \sum_{s} P(x^m) U(s|x^m) l(s) . \tag{21}$$

We define the symmetrizability $L_{\text{sym}}(P,\Lambda)$ of the channel to be the largest integer such that

$$\Lambda_{L_{\text{sym}}(P,\Lambda)}(P) \le \Lambda \tag{22}$$

$$\Lambda_{L_{\text{sym}}(P,\Lambda)+1}(P) > \Lambda . \tag{23}$$

Intuitively, the jammer can "simulate $L_{\text{sym}}(P,\Lambda)$ codewords of type P" within its cost constraint Λ , but simulating $L_{\mathrm{sym}}(P,\Lambda)+1$ codewords will make it exceed the constraint. When it is clear from context we will suppress the dependence on Λ and write $L_{\text{sym}}(P)$ for $L_{\text{sym}}(P,\Lambda)$.

C. Main Results

Our main results on list coding are analogous to those in [8], [11], [26] for unconstrained discrete AVCs. The primary contribution of this work is an extension of these results to the constrained AVC setting. Let us define the following quantities:

$$C^{\operatorname{dep}}(\Lambda) = \max_{P(x)} \min_{U(s|x): \mathbb{E}_{PU}[l(s)] < \Lambda} I(X \wedge Y)$$
(24)

$$C^{\text{dep}}(\Lambda) = \max_{P(x)} \min_{U(s|x): \mathbb{E}_{PU}[l(s)] \le \Lambda} I(X \wedge Y)$$

$$C_r(\Lambda) = \max_{P(x)} \min_{Q(s): \mathbb{E}_{Q}[l(s)] \le \Lambda} I(X \wedge Y) .$$
(24)

In the first case, the minimization is over all channels U(s|x) from $\mathcal{X} \to \mathcal{S}$ such that the expected cost under the joint distribution P(x)U(s|x) is no more than Λ , and in the second case it is over all iid distributions Q(s) on S such that the expected cost under Q(s) is less than Λ . In both cases the maximization is over all distributions on \mathcal{X} .

For maximal error, we prove that a rate $R = C^{\text{dep}}(\Lambda) - \epsilon$ is achievable using list codes of list size $L > O(\epsilon^{-1})$. Here the size of the list grows as we approach capacity, but does not scale with the blocklength. To prove this result, we first construct a code with nearly $\exp(nH(X))$ codewords that is list-decodable with lists of size $\exp(n \max_{U \in \bar{\mathcal{W}}_{dep}} H(X|Y))$. We then subsample this list code to obtain a code with finite list size and rate $C^{\text{dep}} - \epsilon$. It is not clear that this list size is necessary – matching converse bounds are not shown.

For average error, we show that if P^* is the maximizing input distribution in (25) and $L_{\text{sym}}(P^*) < \infty$, any rate below $C_r(\Lambda)$ is achievable using lists of size larger than $L_{\text{sym}}(P^*)$. Hughes [26] proved that for the unconstrained AVC there is a single L_{sym} that acts as a threshold for list decoding, so $C_L = 0$ for $L \leq L_{\mathrm{sym}}$ and $\bar{C}_L = C_r(\Lambda)$ for $L > L_{\mathrm{sym}}$. For constrained jammers we do not have such a dichotomy for list coding. Since each input distribution P has a corresponding symmetrizability $L_{\text{sym}}(P)$, we may have the case that $L_{\mathrm{sym}}(P) < L_{\mathrm{sym}}(P^*)$, in which case we can achieve

$$I(P) = \min_{Q(s): \mathbb{E}_{Q}[l(s)] \leq \Lambda)} I(X \wedge Y) , \qquad (26)$$

with lists of size smaller than $L_{\text{sym}}(P^*)$. We will define $L_{\text{sym}}(\Lambda) = L_{\text{sym}}(P^*, \Lambda)$ to be the symmetrizability of the channel. Csiszár and Narayan observed in [18] that the deterministic coding capacity for constrained AVCs may be positive but smaller than the corresponding random code capacity. The analogous statement for list codes is that the capacity for list codes with list size smaller than $L_{\text{sym}}(\Lambda)$ may be positive but smaller than the random coding capacity. However, if $C_r(\Lambda) > 0$ we can choose a list size large enough so that $\bar{C}_L(\Lambda) = C_r(\Lambda)$.

The proof closely follows that of Hughes (who in turn follows Csiszár and Narayan [18]) with some modifications to deal with the state constraint. We note that the proof by Blinovsky, Narayan, and Pinsker [11] relies on the elimination technique [4], which is not applicable to cost-constrained AVCs [18].

III. LIST DECODING FOR MAXIMAL ERROR

The arbitrarily varying channel with deterministic codes and maximal error is directly related to the channel model used in the design of algebraic error correcting codes. In the bit-flipping example given in the previous section, a trivial list code of list size 1 under maximal error must correct every error pattern of weight Λn for every codeword. It is sometimes easier to prove the existence of list codes with small but constant list size that perform well under maximal error. For unconstrained AVCs, the list coding capacity was investigated by Ahlswede [3], [8] using hypergraph coloring arguments [5], [7]. In this section we use constant composition codes to recover and generalize his result without using the hypergraphs formalism.

Theorem 1 (List decoding for maximal error): Let $W = \{W(\cdot|\cdot,s) : s \in \mathcal{S}\}$ be an arbitrarily varying channel with constraint function l(s) and state constraint Λ . Fix a rate $R < C^{\text{dep}}(\Lambda)$. Then R is achievable under maximal error with deterministic list codes of list size

$$L = O\left(\frac{1}{C^{\text{dep}}(\Lambda) - R}\right) . (27)$$

In other words,

$$C_L(\Lambda) \ge C^{\text{dep}}(\Lambda) - O(L^{-1})$$
 (28)

The result is proved in two steps – first we show that constant-composition list codes of exponential list size exist, and then we construct a code of finite list size by sampling codewords from the larger list code. We first need some results on types and jointly typical sets.

A. Preliminaries

We need to define some more sets. First we define an AVC-version of a shell:

$$T_W^{\epsilon}(\mathbf{x}|\mathbf{s}) = \left\{ \mathbf{y} \in \mathcal{Y}^n : d_m \left(T_{\mathbf{x}, \mathbf{y}}, \frac{1}{n} \sum_{k: x_k = a} W(y|a, s_k) \right) < \epsilon \right\}$$
 (29)

We can take the union over all s satisfying the state constraint Λ to get the set of all y sequences that could have been generated from x and some permissible state s:

$$T_{\mathcal{W}}^{\epsilon}(\mathbf{x}) = \bigcup_{\mathbf{s} \in \mathcal{S}^{n}(\Lambda)} T_{W}^{\epsilon}(\mathbf{x}|\mathbf{s})$$
(30)

For a received sequence y, we must find the possible x sequences for which there exists a state vector s such that x and s could have generated y. For an input distribution P(x) and channel V(y|x) we can define an output distribution P'(y) and "reverse channel" V'(x|y) by

$$P'(y) = \sum_{x} P(x)V(y|x)$$
(31)

$$V(y|x)P(x) = V'(x|y)P'(y)$$
 (32)

The decoder can use the empirical output type T_y to find a candidate set of channels V(y|x) consistent with the observed sequence. We define

$$\mathcal{V}_{P}^{\epsilon}(\mathbf{y}) = \{ V \in \bar{\mathcal{W}}_{dep}(P, \Lambda) : d_{m}(P', T_{\mathbf{y}}) < \epsilon \} . \tag{33}$$

For a fixed \mathbf{y} we will bound the size of the set $T_{V'}^{\epsilon}(\mathbf{y})$ for $V \in \mathcal{V}_{P}^{\epsilon}(\mathbf{y})$, and the union of all $T_{V'}^{\epsilon}(\mathbf{y})$ for $V \in \mathcal{V}_{P}^{\epsilon}(\mathbf{y})$.

B. List codes with exponential list size

Lemma 1: For $P \in \mathcal{P}_n(\mathcal{X})$ with $\min_a P(a) > 0$ and $0 < \epsilon < \min_a P(a)$ and n sufficiently large the following statements all hold:

1) We can bound the size of the typical set by

$$|T_P| \ge (n+1)^{|\mathcal{X}|} \exp(nH(P))$$
 (34)

2) For $\mathbf{x} \in \mathcal{X}^n$ and \mathbf{s} such that $l(\mathbf{s}) \leq \Lambda$ we have for some $E(\epsilon) > 0$:

$$\mathbb{P}\left(T_W^{\epsilon}(\mathbf{x}|\mathbf{s})|\mathbf{x},\mathbf{s}\right) \ge 1 - \exp\left(-nE(\epsilon)\right) . \tag{35}$$

3) For $P \in \mathcal{P}_n(\mathcal{X})$, channel $V \in \overline{\mathcal{W}}_{dep}(P)$, $\mathbf{y} \in \mathcal{Y}^n$, and $\epsilon > 0$,

$$|T_{V'}^{\epsilon}(\mathbf{y})| \le \exp\left(n\left(\sum_{y} H\left(V'(x|y)\right)T_{\mathbf{y}}(y) + O(\epsilon\log\epsilon^{-1})\right)\right)$$
 (36)

$$\left| \bigcup_{V \in \mathcal{V}_{P}^{\epsilon}(\mathbf{y})} T_{V'}^{\epsilon}(\mathbf{y}) \right| \leq \exp \left(n \left(\max_{V \in \mathcal{V}_{P}^{\epsilon}(\mathbf{y})} \sum_{y} H\left(V'(x|y)\right) P'(y) + O(\epsilon \log \epsilon^{-1}) \right) \right) . \tag{37}$$

4) For sufficiently small $\epsilon > 0$, $\mathbf{x} \in T_P$, and $\mathbf{y} \in T_W^{\epsilon}(\mathbf{x})$ we have

$$\mathbf{x} \in \bigcup_{V \in \mathcal{V}_P^{\epsilon}(\mathbf{y})} T_{V'}^{(|\mathcal{X}|+1)\epsilon}(\mathbf{y}) \tag{38}$$

$$\mathbf{y} \in \bigcup_{V \in \mathcal{V}_P^{|\mathcal{X}|\epsilon}(\mathbf{y})}^{V \in \mathcal{V}_P^{|\mathcal{X}|\epsilon}(\mathbf{y})} T_V^{\epsilon}(\mathbf{x})$$
(39)

Proof: We take up the different items in turn.

- 1) This is obvious from the definition of types.
- 2) Fix sequences \mathbf{x} and \mathbf{s} and let $\{Y_i: i \in [n]\}$ be independent random variables with distribution $\{W(\cdot|x_i,s_i)\}$. Let $g_{(a,b)}(Y_1,\ldots,Y_n)=N(a,b|\mathbf{x},Y_1^n)$. Then

$$\mathbb{E}[g_{(a,b)}(Y_1,\ldots,Y_n)] = \sum_{k:x_k=a} W(\cdot|a,s_k)$$

If $\{\tilde{Y}_i\}$ are independent copies of $\{Y_i: i=1,\ldots,n\}$, then we have

$$\left| g_{(a,b)}(Y_1, \dots, Y_i, \dots, Y_n) - g_{(a,b)}(Y_1, \dots, \tilde{Y}_i, \dots, Y_n) \right| \le 1$$

almost surely, so by standard concentration inequalities [20, Corollary 2.4.14], for any $\epsilon > 0$

$$\mathbb{P}\left(\left|g_{(a,b)}(Y_1^n) - \mathbb{E}[g_{(a,b)}(Y_1^n)]\right| \ge \epsilon\right) \le \exp\left(-nD\left(\frac{1+\epsilon}{2} \parallel \frac{1}{2}\right)\right)$$

Taking a union bound over all $(a, b) \in \mathcal{X} \times \mathcal{Y}$ shows that there exists an $E(\epsilon) > 0$ so that for n sufficiently large

$$\mathbb{P}\left(T_W^{\epsilon}(\mathbf{x}|\mathbf{s})|\mathbf{x}.\mathbf{s}\right) \ge 1 - \exp\left(-nE(\epsilon)\right)$$
.

3) For input distribution P and channel V we can define V' via (32). Equation (36) then follows from [16, Lemma 2.13].

To prove (37) we consider only the set $\mathcal{V}_{P}^{\epsilon}(\mathbf{y}) \cap \mathcal{P}_{n}(\mathcal{Y}|\mathcal{X})$. For any V in this set we have the bound (36), and there are at most $(n+1)^{|\mathcal{X}||\mathcal{Y}|}$ elements in $\mathcal{V}_P^{\epsilon}(\mathbf{y}) \cap \mathcal{P}_n(\mathcal{Y}|\mathcal{X})$. This gives

$$\left| \bigcup_{V \in \mathcal{V}_{P}^{\epsilon}(\mathbf{y})} T_{V'}^{\epsilon}(\mathbf{y}) \right| \leq \exp \left(n \left(\max_{V \in \mathcal{V}_{P}^{\epsilon}(\mathbf{y}) \cap \mathcal{P}_{n}(\mathcal{Y}|\mathcal{X})} \sum_{y} H\left(V'(x|y)\right) T_{\mathbf{y}}(y) + O(\epsilon \log \epsilon^{-1}) \right) \right) . \tag{40}$$

Since $V \in \mathcal{V}_P^{\epsilon}(\mathbf{y})$ implies $|P'(y) - T_{\mathbf{y}}(y)| \leq \epsilon$, we have the bound in (37).

4) Since $\mathbf{y} \in T_{\mathcal{W}}^{\epsilon}(\mathbf{x})$, from (30) we know there exists an $\mathbf{s} \in \mathcal{S}^{n}(\Lambda)$ such that $\mathbf{y} \in T_{W,\mathbf{s}}^{\epsilon}(\mathbf{x})$ with high probability. Let us define the channel

$$V(b|a) = \frac{1}{N(a|\mathbf{x})} \sum_{k:x_k=a} W(y|a, s_k)$$
$$= \sum_{s} W(y|a, s) \frac{N(a, s|\mathbf{x}, \mathbf{s})}{N(a|\mathbf{x})}.$$

Therefore $V \in \bar{\mathcal{W}}_{dep}$ and $\mathbf{y} \in T_V^{\epsilon}(\mathbf{x})$. We claim that $V \in \mathcal{V}_P^{|\mathcal{X}|\epsilon}(\mathbf{y})$. We can now bound $d_m(T_{\mathbf{x},\mathbf{y}},P(x)V(y|x))$ by using (29) and the fact that $P(a)=n^{-1}N(a|\mathbf{x})$:

$$d_m(T_{\mathbf{x},\mathbf{y}}, P(x)V(y|x)) = d_m\left(T_{\mathbf{x},\mathbf{y}}, \frac{1}{n} \sum_{k:x_k=a} W(y|a, s_k)\right)$$
(41)

(42)

This proves that $\mathbf{y} \in T_V^{\epsilon}(\mathbf{x})$. We must also show that $V \in \mathcal{V}_P^{|\mathcal{X}|\epsilon}(\mathbf{y})$. Marginalizing (42) we obtain:

$$d_m\left(T_{\mathbf{y}}, P'(y)\right) \le |\mathcal{X}|\epsilon , \qquad (43)$$

So $V \in \mathcal{V}_{P}^{|\mathcal{X}|\epsilon}(\mathbf{y})$ and thus we have (39).

To show (38), let V be a channel such that $\mathbf{y} \in T_V^{\epsilon}(\mathbf{x})$.

$$d_m(T_{\mathbf{x},\mathbf{y}}, P(x)V(y|x)) = d_m(T_{\mathbf{x},\mathbf{y}}, T_{\mathbf{x}}V(y|x))$$

$$\leq \epsilon . \tag{44}$$

Now, marginalizing this allows us to bound the distance between $T_{x,y}$ and $T_yV'(x|y)$:

$$d_m(T_{\mathbf{x},\mathbf{y}}, T_{\mathbf{y}}V'(x|y)) \le d_m(T_{\mathbf{x},\mathbf{y}}, P'(y)V'(x|y)) + d_m(P'(y)V'(x|y), T_{\mathbf{y}}V'(x|y))$$

$$\le \epsilon + |\mathcal{X}|\epsilon.$$
(45)

Thus we have shown $\mathbf{x} \in T_{V'}^{(|\mathcal{X}|+1)\epsilon}(\mathbf{y})$.

Lemma 2: Let $(W, l(\cdot), \Lambda)$ be a constrained AVC. For any $\epsilon > 0$ there is an n sufficiently large and an (n, N, L) list code C with

$$N \ge \exp\left(n\left(H(P(x)) - o(\epsilon)\right)\right) \tag{46}$$

$$L \le \exp\left(n\left(\max_{V \in \bar{\mathcal{W}}_{dep}(\Lambda)} H(V'(x|y)|P'(y)) + O(\epsilon \log \epsilon^{-1})\right)\right)$$
(47)

$$\varepsilon(\mathcal{C}) \le \exp(-nE(\epsilon))$$
 (48)

Proof: Let the codewords of the code be $\mathbf{x} \in T_P$. For each channel output \mathbf{y} let the decoder output the list

$$\bigcup_{V \in \mathcal{V}_P^{\epsilon}(\mathbf{y})} T_{V'}^{(|\mathcal{X}|+1)\epsilon}(\mathbf{y}) . \tag{49}$$

Equation (46) follows from Lemma 1 part 1. The bound (47) on the list size follows from Lemma 1 part 3. To bound the error in (48) note that with probability $\exp(-nE(\epsilon))$ we have $\mathbf{y} \in T_{\mathcal{W}}^{\epsilon}(\mathbf{x})$ (by Lemma 1 part 2) and hence by Lemma 1 part 4 we have $\mathbf{x} \in T_{\mathcal{V}'}^{(|\mathcal{X}|+1)\epsilon}(\mathbf{y})$ for some $V \in \mathcal{V}_P^{\epsilon}(\mathbf{y})$.

C. List reduction

We can now prove our main result on list coding for constrained AVCs under maximal error. Given a small gap ϵ from capacity, we subsample the previous code with exponential list sizes to obtain a code with finite list size $O(\epsilon^{-1})$ that can achieve rates ϵ away from capacity.

Lemma 3: Let $(W, l(\cdot), \Lambda)$ be a constrained AVC. For any $\epsilon' > 0$ there exists a list code of rate $R \geq C^{\text{dep}}(\Lambda) - \epsilon'$, list size

$$L' < \left\lceil \frac{4 \log |\mathcal{Y}|}{C^{\text{dep}}(\Lambda) - R} \right\rceil + 1. \tag{50}$$
 Proof: By Lemma 2 there exists N , L , and δ satisfying (46) – (48) for any ϵ so that there exists an

Proof: By Lemma 2 there exists N, L, and δ satisfying (46) – (48) for any ϵ so that there exists an (n, N, L) list code $C_L = \{(\mathbf{u}_i, D_i) : i \in [N]\}$. Note that $N/L = \exp(n(C^{\text{dep}} - 2\epsilon))$. We will subsample this codebook to find our code of constant list size.

Let $N' = \exp(nR)$ and $\mathcal{C}_{L'} = \{(\mathbf{x}_j, D_j) : j \in [N']\}$ be a collection of N' codewords selected uniformly from \mathcal{C}_L . We will prove that there exists a constant L' such that no $\mathbf{y} \in \mathcal{Y}^n$ is in more than L' decoding sets D_j with high probability. Fix $\mathbf{y} \in \mathcal{Y}^n$ and note that from the definition of \mathcal{C}_L we have

$$\mathbb{E}\left(\mathbf{1}(\mathbf{y} \in D_j)\right) = \mathbb{P}\left(\mathbf{y} \in D_j\right) \le \frac{L}{N} . \tag{51}$$

For a fixed y, the chance that more than L' decoding regions contain y out of N' choices can be bounded above using Sanov's Theorem [14, Theorem 12.4.1]. That is, for $\nu = (N'+1)^2 < \exp(n3R) \le \exp(n3\log|\mathcal{Y}|)$ we can choose n large enough so that

$$\mathbb{P}\left(\frac{1}{N'}\sum_{j=1}^{N'}\mathbf{1}(\mathbf{y}\in D_j) > \frac{L'}{N'}\right) \le \nu \cdot \exp\left(-N'\left(D\left(\frac{L'}{N'} \parallel \frac{L}{N}\right)\right)\right) . \tag{52}$$

We will upper bound the exponent:

$$-N'D\left(\frac{L'}{N'} \parallel \frac{L}{N}\right) + \log \nu = -L' \log \frac{L'/N'}{L/N} - N' \left(1 - \frac{L'}{N'}\right) \log \frac{1 - L'/N'}{1 - L/N} + \log \nu . \tag{53}$$

To deal with the second term we use the inequality $-(1-a)\log(1-a) \le 2a$ (for small a) on the term $(1-L'/N')\log(1-L'/N')$ and discard the small positive term $-(1-L'/N')\log(1-L/N)$.

$$-N'D\left(\frac{L'}{N'} \parallel \frac{L}{N}\right) + \log \nu \le -L' \log \frac{L'/N'}{L/N} + N' \left(2\frac{L'}{N'}\right) + \log \nu$$

$$= -nL'(C^{\text{dep}} - R - 2\epsilon) - L' \log L' + 2L' + \log \nu$$

$$\le -nL'(C^{\text{dep}} - R - 2\epsilon) + 3\log |\mathcal{Y}|$$
(54)

The last inequality follows from taking L' > 4 and the bound on ν .

Now we take a union bound over all y to get

$$\mathbb{P}\left(\frac{1}{N'}\sum_{j=1}^{N'}\mathbf{1}(\mathbf{y}\in D_j) > \frac{L'}{N'} \ \forall \mathbf{y}\right) \le \exp\left(-n\left(L'(C^{\text{dep}} - R - 2\epsilon) + 4\log|\mathcal{Y}|\right)\right) . \tag{55}$$

Then we have for

$$L' > \left| \frac{4 \log |\mathcal{Y}|}{C^{\text{dep}} - R - 2\epsilon} \right| + 1 , \qquad (56)$$

have an $(n, \exp(nR), L')$ codebook. Letting $\epsilon' = 3\epsilon$ and $R = C^{\text{dep}} - \epsilon'$, we have a list code with lists of size $O(1/\epsilon')$, as desired.

Theorem 1 now follows from the preceding Lemma.

IV. LIST DECODING FOR AVERAGE ERROR

In the case where we simultaneously allow list codes and measure performance by the average error over the codebook, we can also achieve all rates below the randomized coding capacity with finite list sizes. We need to first relate the symmetrizability $L_{\text{sym}}(P)$ to the rate I(P) defined in (26). The following theorem shows that if I(P) is positive, then $L_{\text{sym}}(P)$ is finite. In particular, since $I(P^*)$ is finite, the theorem implies that if $C_r(\Lambda) > 0$, we have $L_{\text{sym}}(\Lambda) < \infty$.

Theorem 2 (Finite symmetrizability): Let $\mathcal{W} = \{W(\cdot|\cdot,s) : s \in \mathcal{S}\}$ be an arbitrarily varying channel with cost function l(s) and cost constraint Λ . If the randomized coding capacity $C_r(\Lambda) = 0$ then $L_{\mathrm{sym}}(P) = \infty$ for all P. If $C_r(\Lambda) > 0$ then

$$L_{\text{sym}}(P) \le \frac{\log(\min(|\mathcal{Y}|, |\mathcal{S}|))}{I(P)} \ . \tag{57}$$

Proof: Suppose $C_r(\Lambda) = 0$. Then for all P we know I(P) = 0. Without loss of generality, we may take P(x) > 0 for all $x \in \mathcal{X}$. For such P there exists a distribution $Q(s) \in \mathcal{P}(\mathcal{S}, \Lambda)$ so that

$$\sum_{s} W(y|x,s)Q(s) = P_Y(y) .$$

That is, the input and output are independent under Q(s). If we define $U(s|x^L) = Q(s)$ it is clear that

$$V(x, x^L) = \sum_{s} W(y|x, s)U(s|x^L)$$

is symmetric in (x, x_1, \ldots, x_L) and that

$$\Lambda_L(P) = \sum_{s,x^L} P^L(x^L) U(s|x^L) l(S) = \sum_s Q(s) l(s) \le \Lambda .$$

Since this holds for all L, the channel is L-symmetrizable for all L and thus $L_{\text{sym}}(P) = \infty$.

Suppose now that $C_r(\Lambda) > 0$. Let P be an input distribution for which I(P) > 0. Suppose that under P the channel is L-symmetrizable. Therefore there is a channel $U(S|X^L)$ that symmetrizes W. Let X_1, X_2, \ldots, X_L be independent with distribution P and let (S, X^L) be distributed according to $U(S|X^L)P(X_1)\cdots P(X_L)$. Then $(X, X^L) \to (X, S) \to Y$ is a Markov chain, so by the Data Processing inequality we have

$$\begin{split} I\left(XS \ \wedge \ Y\right) &\geq I\left(XX^L \ \wedge \ Y\right) \\ &\geq I\left(X \ \wedge \ Y\right) + \sum_{j=1}^L I\left(X_j \ \wedge \ Y\right) \\ &= (L+1)I\left(X \ \wedge \ Y\right) \ , \end{split}$$

where the last line follows from the symmetrizability. Now, subtracting $I(X \land Y)$ from both sides, we obtain the bound

$$I(S \land Y|X) \ge L \cdot I(X \land Y)$$
.

This gives us a bound on the list size:

$$L \leq \frac{I(S \land Y|X)}{I(X \land Y)}$$
$$\leq \frac{\log(\min(|\mathcal{Y}|, |\mathcal{S}|))}{I(P)}$$

Substituting $L_{\text{sym}}(P)$ for L we obtain the result.

The P^* maximizing I(P) may not have the smallest symmetrizability. This implies that rates below $C_r(\Lambda)$ may be achievable using list codes with lists smaller than $L_{\mathrm{sym}}(P^*)$. An example of this is given in Section V. A similar issue arises in the non-list coding case, which can be thought of as list coding with list size 1. There, the capacity may be positive but strictly less than the random coding capacity. However, for lists larger than $L_{\mathrm{sym}}(P^*)$ the capacity of the constrained AVC for deterministic coding and average error is equal to the random coding capacity, as shown in the following theorem.

Theorem 3 (List decoding for average error): Let $\mathcal{W} = \{W(\cdot|\cdot,s) : s \in \mathcal{S}\}$ be an arbitrarily varying channel with constraint function l(s) and state constraint Λ . Let $L_{\mathrm{sym}} = L_{\mathrm{sym}}(P^*)$ be the symmetrizability of the AVC for the input distribution P^* that maximizes I(P). Then the deterministic-coding capacity of \mathcal{W} for list size $M > L_{\mathrm{sym}}$ and average error is given by

$$\bar{C}_M(\Lambda) = C_r(\Lambda) \tag{58}$$

The proof of this theorem parallels that of Hughes [26], whose proof is in turn based on the original proof by Csiszár and Narayan [18]. The converse follows from the fact that the jammer can simulate up to $L_{\rm sym}$ codewords via its state input, so there is a constant probability that the decoder will not be able to construct a list containing the correct codeword whose size is smaller than $L_{\rm sym}$.

The decoding rule we use is an extension of the Hughes rule to the case with constraints. To show that C_r is achievable for $L_{\rm sym}$, we use the fact the a random codebook with fixed type P enjoys certain properties (Lemma 5). We then show that nonsymmetrizability for $M > L_{\rm sym}$ implies a certain "separation" of probability distributions (Lemma 6), which we can use to show that the decoding rule will be unambiguous (Lemma 7). The codebook properties plus this unambiguous decoding allows us to show that I(P) is achievable with fixed input type P (Lemma 8). Maximizing over P gives the result.

A. The converse

The converse argument is a combination of the converse arguments for deterministic coding for constrained AVCs [18, Lemma 1] and list coding for unconstrained AVCs [26, Lemma 4]. The result is that error will be large for list codes with list size smaller than the symmetrizability of the channel.

Lemma 4: For an AVC $\{W, l(\cdot), \Lambda\}$ with symmetrizability $L_{\text{sym}}(P)$, every list-L code with blocklength n and codewords of fixed type P with $N \geq 2$ codewords satisfies

$$\max_{\mathbf{s} \in \mathcal{S}^n(\Lambda)} \bar{\varepsilon}(\mathbf{s}) \ge \left(1 - \frac{L}{K+1}\right) \left(\frac{N-K}{N}\right) - \frac{1}{n} \cdot \frac{l_{\max}^2}{(\Lambda - \Lambda_K(P))^2}$$
 (59)

where $K = \min(N - 1, L_{\text{sym}}(P))$.

Proof: Fix a codebook with codewords $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N$ and list-L decoder ϕ . Since the channel is K-symmetrizable we know there is a channel $U: \mathcal{X}^K \to \mathcal{S}$ such that

$$V(y|x_0^K) = \sum_{s \in S} W(y|x_0, s)U(s|x_1^K)$$
(60)

is symmetric in (x_0, \ldots, x_K) .

For any $J \subset [N]$ with |J| = K let S_J be a random variable distributed according to

$$Q^{n}(\mathbf{s}_{J}) = \prod_{k=1}^{n} U(s_{J,k} | \{x_{j,k} : j \in J\})$$
(61)

That is, the k-th element of S_J is formed by passing the k-th elements of the codewords $\{x_J : j \in J\}$ through the channel U. Then we have

$$\mathbb{E}\left[W^{n}(\mathbf{y}|\mathbf{x}_{i},\mathbf{S}_{J})\right] = \sum_{\mathbf{s}} W^{n}(\mathbf{y}|\mathbf{x}_{i},\mathbf{s})U^{n}(\mathbf{s}|\{\mathbf{x}_{j}: j \in J\})$$
(62)

We will use the symmetry of this function to obtain our bound.

Pick now a set $G \subset [N]$ with |G| = K + 1. We have for $i \in G$ that

$$\sum_{i \in G} \mathbb{E}\left[\varepsilon(i, \mathbf{S}_{G-\{i\}})\right] = \sum_{i \in G} \left(1 - \sum_{\mathbf{y}: i \in \phi(\mathbf{y})} \mathbb{E}\left[W^{n}(\mathbf{y}|\mathbf{x}_{i}, \mathbf{S}_{G-\{i\}})\right]\right)$$

$$= K + 1 - \sum_{i \in G} \sum_{\mathbf{y}: i \in \phi(\mathbf{y})} \mathbb{E}\left[W^{n}(\mathbf{y}|\mathbf{x}_{i_{0}}, \mathbf{S}_{G-\{i_{0}\}})\right]$$

$$\geq K + 1 - L \sum_{\mathbf{y} \in \mathcal{Y}^{n}} \mathbb{E}\left[W^{n}(\mathbf{y}|\mathbf{x}_{i_{0}}, \mathbf{S}_{G-\{i_{0}\}})\right]$$

$$= K + 1 - L.$$
(63)

Suppose the jammer chooses the following strategy: it randomly chooses a subset J uniformly from all subsets of size K, generates an S_J and sends that. The expected error for this strategy is

$${\binom{N}{K}}^{-1} \sum_{J \in \Sigma_{K}} \mathbb{E}\left[\bar{\varepsilon}\mathbf{S}_{J}\right] = {\binom{N}{K}}^{-1} \sum_{J} \frac{1}{N} \sum_{i=1}^{N} \mathbb{E}\left[\varepsilon(i, \mathbf{S}_{J})\right]$$

$$\geq \frac{1}{N} {\binom{N}{K}}^{-1} \sum_{G} \sum_{i \in G} \mathbb{E}\left[\varepsilon(i, \mathbf{S}_{G-\{i\}})\right]$$

$$\geq \frac{{\binom{N}{K+1}}(K+1-L)}{N \cdot {\binom{N}{K}}}$$

$$= \left(1 - \frac{L}{K+1}\right) \left(\frac{N-K}{N}\right) . \tag{64}$$

We now turn to the state constraint. Note that

$$\mathbb{E}\left[\bar{\varepsilon}(\mathbf{S}_J)\right] \le \max_{\mathbf{s}: \mathbf{s} \in \mathcal{S}^n(\Lambda)} \bar{\varepsilon}(\mathbf{s}) + \mathbb{P}\left(l(\mathbf{S}_J) > \Lambda\right) , \tag{65}$$

so

$$\max_{\mathbf{s} \in \mathcal{S}^{n}(\Lambda)} \bar{\varepsilon}(\mathbf{s}) \ge \mathbb{E}\left[\bar{\varepsilon}(\mathbf{S}_{J})\right] - \mathbb{P}\left(l(\mathbf{S}_{J}) > \Lambda\right) . \tag{66}$$

Suppose $\Lambda_K(P) < \Lambda$ and U attains the minimum in the definition of $\Lambda_K(P)$. Then by expanding out the expectation we can see that

$$\mathbb{E}\left[l(\mathbf{S}_J)\right] = \Lambda_K(P) \ . \tag{67}$$

Furthermore,

$$Var(l(\mathbf{S}_J) = \frac{1}{n^2} \sum_{k=1}^n Var(l(s_{J,k}) \le \frac{l_{\max}^2}{n} .$$
 (68)

Therefore Chebyshev's bound gives us

$$\mathbb{P}(l(\mathbf{S}_{j}) \leq \Lambda) = \mathbb{P}\left(l(\mathbf{S}_{J}) - \mathbb{E}[l(\mathbf{S}_{J})] > \Lambda - \Lambda_{K}(P)\right)$$

$$\geq \frac{l_{\max}^{2}}{n} \cdot \frac{1}{(\Lambda - \Lambda_{K}(P))^{2}}.$$
(69)

From (64) and (68) we obtain

$$\max_{\mathbf{s} \in \mathcal{S}^n(\Lambda)} \bar{\varepsilon}(\mathbf{s}) \ge \left(1 - \frac{L}{K+1}\right) \left(\frac{N-K}{N}\right) - \frac{1}{n} \cdot \frac{l_{\max}^2}{(\Lambda - \Lambda_K(P))^2} , \tag{70}$$

as desired.

B. Decoding rule

In order to describe the decoding rule we will use, we define the set

$$\mathcal{G}_{\eta}(\Lambda) = \{ P_{XSY} : D(P_{XSY} || P_X \times P_S \times W) \le \eta, \ \mathbb{E}[l(s)] \le \Lambda \}$$
(71)

We can think of $\mathcal{G}_{\eta}(\Lambda)$ as those joint types which are close to those generated from the AVC \mathcal{W} via independent inputs of type P_X and P_S .

Definition 1 (Decoding rule): Let $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N$ be a given codebook and suppose \mathbf{y} was received. Let $\mathcal{L}(\mathbf{y})$ denote the list decoded from \mathbf{y} . Then put $i \in \mathcal{L}(\mathbf{y})$ if and only if

- 1) there exists an $\mathbf{s} \in \mathcal{S}^n$ such that $T_{\mathbf{x},\mathbf{s}\mathbf{y}} \in \mathcal{G}_{\eta}(\Lambda)$.
- 2) for every choice of L other distinct codewords $\{\mathbf{x}_j : j \in J, |J| = L\}$ such that $T_{\mathbf{x}_j \mathbf{s}_j \mathbf{y}} \in \mathcal{C}_{\eta}$ for some $\mathbf{s}_j \in \mathcal{S}^n$ and all $j \in J$ we have

$$I\left(YX \ \wedge \ X^L \middle| S\right) \le \eta \tag{72}$$

where P_{YXX^LS} is the joint type of $(\mathbf{y}, \mathbf{x}_i, {\mathbf{x}_j : j \in J}, \mathbf{s})$.

This is the decoding rule used by Hughes in [26] modified in the natural way suggested by Csiszár and Narayan [18].

C. Codebook generation

We use Lemma 1 from Hughes [26], wherein the proof may be found. The proof requires some large deviations results [6], [18] that have proved useful in many other coding problems for AVCs under average error [19], [23], [24], [26]. We note that these properties do not depend on the presence of the state constraint.

Lemma 5 (Codebook existence): For any $L \ge 1$, $\epsilon > 0$, $n \ge n_0(\epsilon, L)$, $N \ge L \exp(n\epsilon)$, and type P, there exist codewords $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N$, each of type P, such that for every $\mathbf{x} \in \mathcal{X}^n$, $\mathbf{s} \in \mathcal{S}^n$, and joint type P_{XX^LS} we have the following for $k = 1, 2, \dots, L$:

1) If $I(X \wedge S) \ge \epsilon$ then

$$\frac{1}{N} |\{i : (\mathbf{x}_i, \mathbf{s}) \in T_{XS}\}| \le \exp(-n\epsilon/2) . \tag{73}$$

2) If $I(X \wedge X_k S) \ge |R - I(X_k \wedge S)|^+ + \epsilon$ then

$$\frac{1}{N} |\{i : (\mathbf{x}_i, \mathbf{x}_j, \mathbf{s}) \in T_{XX_kS} \text{ for some } j \neq i\}| \le \exp(-n\epsilon/2) . \tag{74}$$

3) Also, for any x

$$|\{j: (\mathbf{x}, \mathbf{x}_j, \mathbf{s}) \in T_{XX_k S}\}| \le \exp\left(n\left(|R - I(X_k \wedge XS)|^+ + \epsilon\right)\right) . \tag{75}$$

4) Moreover, if $R < \min_k I(X_k \wedge S)$, then $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N$ can be selected to further satisfy

$$|\{J \in \Sigma_L : (\mathbf{x}_i, \mathbf{x}_J, \mathbf{s}) \in T_{XX^LS}\}| \le \exp(n\epsilon) . \tag{76}$$

5) If $R < \min_k I(X_k \wedge S)$ and $I(X \wedge X^L S) \ge \epsilon$ then

$$\frac{1}{N} |\{i : (\mathbf{x}_i, \mathbf{x}_J, \mathbf{s}) \in T_{XX^LS} \text{ for some } J \in \Sigma_L(-\{i\})\}| \le \exp(-n\epsilon/2) . \tag{77}$$

D. Nonsymmetrizability and separation

We need to prove that using lists longer than the symmetrizability of the AVC will lead to a sufficient "distance" property for us to use in our decoding rule for the AVC. The proof is given in Appendix I.

Lemma 6: Let $\beta > 0$, W be an AVC with cost function $l(\cdot)$ and constraint Λ , $P \in \mathcal{P}(\mathcal{X})$ with I(P)>0 and $\min_x P(x)\geq \beta$, and $M=L_{\mathrm{sym}}(P)+1$. Then there exists a $\zeta>0$ such that every collection of distributions $\{U_i \in \mathcal{P}(\mathcal{X}^M \times \mathcal{S}) : i = 1, 2, \dots, M\}$ satisfies

$$\max_{j \neq i} \sum_{y, x^{M+1}} \left| \sum_{s} W(y|x_i, s) U_i(x_{-\{i\}}^{M+1}, s) P(x_i) - \sum_{s} W(y|x_j, s) U_j(x_{-\{j\}}^{M+1}, s) P(x_j) \right| \ge \zeta$$
 (78)

Furthermore, for any AVC and $\alpha > 0$ there exists a $\zeta > 0$ such that (78) holds for any collection of U_i 's for which a P can be found with

$$\sum_{x^{M+1},s} P(x_i) U_i(x_{-\{i\}}^M, s) l(s) \le \Lambda_M(P) - \alpha$$
(79)

for all $i = 1, 2, \dots, M + 1$.

E. Non ambiguity of decoding

We must ensure that our decoding rule will not output a list of size larger than $L_{\text{sym}}(P) + 1$. The next lemma shows that for sufficiently small η there are no random variables that can force the decoding rule to output a list that is too large.

 $\textit{Lemma 7: } \text{ Let } M = L_{\text{sym}}(P) + 1 \text{ for the AVC } \{\mathcal{W}, l(\cdot), \Lambda\}. \text{ If } \beta > 0 \text{ then no tuple of rv's } (Y, X^{M+1}, S^{M+1}) = 0 \text{ then no tuple of rv's } (Y, X^{M+1}, S^{M+1}) = 0 \text{ then no tuple of rv's } (Y, X^{M+1}, S^{M+1}) = 0 \text{ then no tuple of rv's } (Y, X^{M+1}, S^{M+1}) = 0 \text{ then no tuple of rv's } (Y, X^{M+1}, S^{M+1}) = 0 \text{ then no tuple of rv's } (Y, X^{M+1}, S^{M+1}) = 0 \text{ then no tuple of rv's } (Y, X^{M+1}, S^{M+1}) = 0 \text{ then no tuple of rv's } (Y, X^{M+1}, S^{M+1}) = 0 \text{ then no tuple of rv's } (Y, X^{M+1}, S^{M+1}) = 0 \text{ then no tuple of rv's } (Y, X^{M+1}, S^{M+1}) = 0 \text{ then no tuple of rv's } (Y, X^{M+1}, S^{M+1}) = 0 \text{ then no tuple } (Y, Y, X^{M+1}, S^{M+1}) = 0 \text{ then no tuple } (Y, Y, X^{M+1}, S^{M+1}) = 0 \text{ then no tu$ can satisfy

$$\min P(x) \ge \beta \tag{80}$$

$$P_{X} = P \tag{81}$$

$$P_{YX_iS_i} \in \mathcal{G}_n(\Lambda) \tag{82}$$

$$P_{YX_{i}S_{i}} \in \mathcal{G}_{\eta}(\Lambda)$$

$$I\left(YX_{i} \wedge X_{-\{i\}}^{M+1} \middle| S_{i}\right) \leq \eta \quad 1 \leq i \leq M+1$$

$$(83)$$

Proof: Assume, to the contrary, that there does exist a tuple of random variables (Y, X^{M+1}, S^{M+1}) satifying (80)–(83). This will lead to a bound on a certain KL-divergence which, via Pinsker's inequality, becomes a bound on total variational distance that contradicts the conclusion of Lemma 6.

Let $W_i = W(\cdot|\cdot, S_i)$. For every i we then have the following divergence bound:

$$\begin{split} D\left(P_{YX^{M+1}S_{i}} \ \left\| \ W_{i} \times P_{X_{i}} \times P_{X_{-\{i\}}^{M+1}S_{i}} \right) \\ &= D\left(P_{YX_{i}S_{i}} \ \left\| \ W_{i} \times P_{X_{i}} \times P_{S_{i}} \right) + D\left(P_{X_{-\{i\}}^{M+1}|YX_{i}S_{i}} \ \left\| \ P_{X_{-\{i\}}^{M+1}|S_{i}} \right| P_{YX_{i}S_{i}} \right) \\ &= D\left(P_{YX_{i}S_{i}} \ \left\| \ W_{i} \times P_{X_{i}} \times P_{S_{i}} \right) + I\left(YX_{i} \ \wedge \ X_{-\{i\}}^{M+1} \left| S_{i} \right) \right. \\ &\leq 2\eta \ , \end{split}$$

where the last line follows from (82), (71) and (83).

Projecting the distributions onto $\mathcal{Y} \times \mathcal{X}^{M+1}$ cannot increase the divergence, so if we define

$$W_{i}P_{X_{-\{i\}}^{M+1}}(y|x_{-\{i\}}^{M+1}|x_{i}) = \sum_{s} W(y|x_{i},s)P_{X_{-\{i\}}^{M+1}S_{i}}(x_{-\{i\}}^{M+1},s) , \qquad (84)$$

we get

$$D\left(P_{YX^{M+1}} \mid \mid W_i P_{X_{-\{i\}}^{M+1}} \times P_{X_i}\right) < 2\eta$$

To use Lemma 6 we must turn this divergence bound into a bound on a total variational distance. We can use Pinsker's inequality [16, p. 58, Problem 17] to show that the KL-divergence is an upper bound on the variational distance:

$$\sum_{y,x^{L+1}} \left| P_{YX^{M+1}}(y, x^{L+1}) - W_i P_{X_{-\{i\}}^{M+1}}(y | x_{-\{i\}}^{M+1} | x_i) P_{X_i}(x_i) \right| < \sqrt{(2\ln 2)\eta} \quad \forall i \in [M+1]$$
 (85)

Since the bound holds for all i, we know that the second terms must be close to each other, and by using (84)

$$\max_{i \neq j} \sum_{y,x^{L+1}} \left| W_{i} P_{X_{-\{j\}}^{M+1}}(y | x_{-\{j\}}^{M+1} | x_{j}) P_{X_{j}}(x_{j}) - W_{i} P_{X_{-\{i\}}^{M+1}}(y | x_{-\{i\}}^{M+1} | x_{i}) P_{X_{i}}(x_{i}) \right| \\
= \max_{i \neq j} \sum_{y,x^{L+1}} \left| \sum_{s} W(y | x_{j}, s) P_{X_{-\{j\}}^{M+1}}(x_{-\{j\}}^{M+1}, s | x_{j}) P_{X_{j}}(x_{j}) - \sum_{s} W(y | x_{j}, s) P_{X_{-\{i\}}^{M+1}}(x_{-\{i\}}^{M+1}, s | x_{i}) P_{X_{i}}(x_{i}) \right| \\
< 2\sqrt{(2 \ln 2)\eta} \tag{86}$$

By choosing η small enough we violate the conclusion of Lemma 6, which is the desired contradiction. Therefore no tuple of random variables can satisfy the conditions given in (80) - (83).

F. Achievability of rates

The statement of the following lemma is identical to Lemma 3 of Hughes, and a proof is included for completeness in Appendix II.

Lemma 8: For any $\delta > 0$, $\beta > 0$ and $P \in \mathcal{P}(\mathcal{X})$ with I(P) > 0 and $\min_x P(x) \geq \beta$, for $M = L_{\text{sym}}(P) + 1$ there exists a list-M code of constant type P such that

$$R = \frac{1}{n} \log \left(\frac{N}{M} \right) > I(P) - \delta, \tag{87}$$

$$\max_{\mathbf{s} \in \mathcal{S}^n(\Lambda)} \bar{\varepsilon}(\mathbf{s}) < \exp(-n\gamma) , \qquad (88)$$

for all $n \geq n_2(\beta, \delta, \mathcal{W})$ and $\gamma(\beta, \delta, \mathcal{W})$.

G. Putting it all together

We now provide the proof of Theorem 3.

Proof: Let $P \in \mathcal{P}(\mathcal{X})$ with $\min P(x) > \beta$ for some $\beta > 0$ and I(P) > 0. Suppose $M \leq L_{\mathrm{sym}}(P)$. For any rate R > 0, we know that for n large enough $L_{\mathrm{sym}} < N - 1$. Then from Lemma 4 the error is lower bounded by

$$\max_{\mathbf{s} \in \mathcal{S}^n} \bar{\varepsilon}(\mathbf{s}) \ge \left(1 - \frac{M}{L_{\text{sym}}(P) + 1}\right) \left(\frac{N - L_{\text{sym}}(P)}{N}\right) - \frac{1}{n} \cdot \frac{l_{max}^2}{(\Lambda - \Lambda_{L_{\text{sym}}(P)}(P))^2}$$
(89)

So for large n the first term is strictly positive and not decreasing with n, which establishes that no positive rate is achievable if $M \leq L_{\text{sym}}(P)$.

Suppose now that $M = L_{\text{sym}}(P) + 1$. Then Lemma 8 shows that codebooks of type P can achieve rates arbitrarily close to I(P). Maximizing over P and choosing $M = L_{\text{sym}}(P^*) + 1$, we see that for any $\delta > 0$, rates

$$R > \max_{P \in \mathcal{P}(\mathcal{X})} \min_{Q \in \mathcal{P}(\mathcal{S}, \Lambda)} I(X \land Y) - \delta = C_r(\Lambda) - \delta$$
(90)

are achievable. Therefore $C_L(\Lambda)=C_r(\Lambda)$ for $L>L_{\mathrm{sym}}(P^*)$.

V. EXAMPLES

We now turn to an example of an additive cost-constrained AVC. Let $\mathcal{X} = \{-1, 1\}$ and let $\mathcal{S} = \{-\sigma, -\sigma + 1, \dots, \sigma\}$ for some integer σ . The output Y of this channel is given by

$$Y = X + S (91)$$

that is, the real addition of the input and state. This is similar in spirit to the example given by Hughes [26], but is more closely related to [28], which analyzes a game between power constrained noise and an encoder with binary inputs.

We will consider two kinds of cost constraints on the jammer for this AVC. The first is an L_1 constraint:

$$l_1(s) = |s| (92)$$

The second is an L_2 constraint:

$$l_2(s) = s^2 (93)$$

For each of these constraints we will compute capacities for different values of Λ .

The first question to settle is that of the randomized coding capacity $C_r(\Lambda)$ for this channel, given by (25). By symmetry, we may assume that the input distribution P^* is uniform on the set $\{-1,1\}$. Therefore we can write:

$$C_r(\Lambda) = \min_{Q(s) \in \mathcal{P}(S, \Lambda)} I(X \wedge X + S)$$

$$= \min_{Q(s) \in \mathcal{P}(S, \Lambda)} H(X + S) - H(S) . \tag{94}$$

This minimization can be carried out numerically by convex optimization methods. Some details are given in Appendix III. Capacities for the L_1 case are shown in Figure 1 and for L_2 are shown in Figure 2. As the cost constraint Λ is increased, the randomized coding capacity decreases, and for smaller alphabet sizes the constraint becomes inactive.

For coding under average probability of error, we can achieve the randomized coding capacity with list codes of constant list size. To find this critical list size, we would also like to know the symmetrizability of these channels. For each candidate list size L, we must determine if there exists a channel $U: \mathcal{X}^L \to \mathcal{S}$ satisfying (20). The channel $U(S|X^L)$ itself must be symmetric, so it is only a function of the type of X^L . We can rewrite the averaged channel as

$$\sum_{s} W(y|x,s)U(s|t) \tag{95}$$

where $t \in [0, 1, \dots, L]$ counts the number of 1's in X^L . The condition that V be symmetric can be rewritten as:

$$\sum_{s} W(y|-1,s)U(s|t) - \sum_{s} W(y|+1,s)U(s|t-1) \qquad \forall y,t$$
(96)

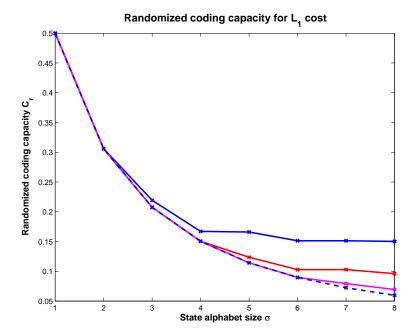


Fig. 1. Randomized coding capacity $C_r(\Lambda)$ versus σ for $\Lambda = 1.5$, 2, and 2.5 with loss function $l_1(s)$. The dashed line is the randomized coding capacity for the unconstrained case.

where U must satisfy

$$\sum_{s} l(s) \sum_{t=0}^{L} {L \choose t} 2^{-L} U(s|t) \le \Lambda . \tag{97}$$

To obtain a convex objective function, note that (96) holds if and only if

$$f(U) = \sum_{y} \sum_{t=1}^{L} \left(\sum_{s} W(y|-1, s) U(s|t) - \sum_{s} W(y|+1, s) U(s|t-1) \right)^{2} = 0$$
 (98)

To determine if the channel is L-symmetrizable, we minimize the function f(U). If $\min f(U) = 0$ then the channel is symmetrizable, and if $\min f(U) > 0$ it is not. If we replace the square in (98) with an absolute value function, then we obtain a function similar to that in Lemma 6.

The plot in Figure 3 shows $\max I(P)$ versus Λ for $l_2(\cdot)$ and $\sigma=8$ under with list codes of fixed list sizes. As Λ increases, the capacity-achieving input distribution with P(X=1)=1/2 becomes L-symmetrizable for small L. However, suboptimal input distributions are not L-symmetrizable, and list codes of size L can still achieve some rates below C_r . In Figure 4 we show $\arg\max I(P)$ for the distributions P that are not L-symmetrizable. This shows the main difference between the constrained and unconstrained AVC problems – for some values of L and Λ the capacity may be positive but strictly less than the random coding capacity.

The extensive analysis in [28] found that the worst case power-constrained *noise* for binary modulation had support only on integer points. In this example, we are interested in the interplay between the list size, achievable rates, and cost constraint. In order to compute the random coding capacity we need to find the worst-case noise distribution, but this capacity is not in necessarily realizable with deterministic codes. List coding relaxes the coding problem and, as we have shown here, approaches the performance of randomized coding for small list sizes.

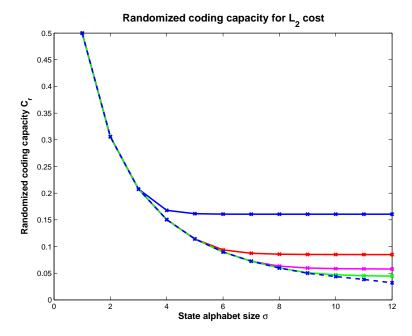


Fig. 2. Randomized coding capacity $C_r(\Lambda)$ versus σ for $\Lambda=4,\,8,\,12,\,16$ with loss function $l_2(s)$. The dashed line is the randomized coding capacity for the unconstrained case.

VI. CONCLUSIONS

In this paper we have extended the earlier results [8], [11], [26] on list coding for arbitrarily varying channels to the case in which the state is subject to a cost constraint. The proof structures parallel those for the unconstrained case. Although somewhat technical, these results on list decoding for cost-constrained AVCs are useful for constructing codes for adversarial communication models and demonstrate some of the differences between unconstrained AVCs and constrained AVCs.

For maximal error, we first construct list codes of exponential list size and subsample them to show that rates approaching $C^{\mathrm{dep}}(\Lambda)$ can be achieved with increasing list sizes. For average error, the symmetrizability of the channel for an input distribution P gives a criterion under which list decoding can be successful. For the P^* that is capacity-achieving for randomized coding, we can show that $\bar{C}_L(\Lambda) = C_r(\Lambda)$ for $L > L_{\mathrm{sym}}(P^*)$.

For maximal error we have shown that lists of size $O(\epsilon^{-1})$ are sufficient to achieve rates $R = C^{\text{dep}}(\Lambda) - \epsilon$. In general we have $C_d \leq C^{\text{dep}} \leq C_r$, which means that the list coding capacity may lie between the list-1 capacities for deterministic and randomized coding. For deterministic codes, this implies that the state sequence can depend on the *codeword* as well as the message. Agarwal, Sahai, and Mitter [1] proposed a model of a distortion-constrained attacker that knows the transmitted codeword, and proved a capacity result using randomized coding. In a subsequent paper we will use a list code to construct randomized codes with small key size for AVC models in which the codeword is known to the jammer.

For average error it may be the case that $L_{\mathrm{sym}}(P) < L_{\mathrm{sym}}(P^*)$ for some P with I(P) > 0. In this case the rate I(P) is achievable with lists smaller than $L_{\mathrm{sym}}(P^*)$. However, if achieving the randomized coding capacity is our goal, we require lists larger than $L_{\mathrm{sym}}(P^*)$. As for non-list codes, Ahlswede's dichotomy theorem does not hold for constrained AVCs, and list coding shows one qualitative difference between constrained and unconstrained AVCs – the set of achievable rates increases with the list size until it reaches the randomized coding capacity in the constrained case, whereas for unconstrained AVCs

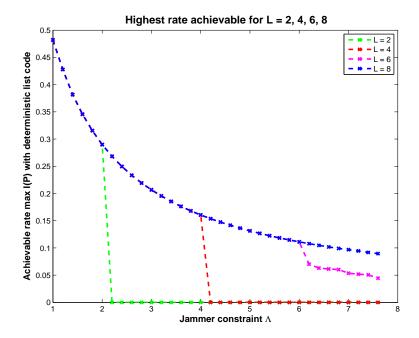


Fig. 3. The largest value of I(P) achievable versus Λ for $l(s) = |s|^2$, $\sigma = 8$, and for different list sizes.

there is an abrupt jump from 0 to C_r .

If we restrict our attention to linear codes, a connection between the notion of symmetrizability for list codes and generalized Hamming weights [29], [30] has been shown by Guruswami [25] for the case of list decoding from erasures. The r-th generalized Hamming weight $d_r(\mathcal{C})$ of a code \mathcal{C} is the minimum weight for the basis of an r-dimensional subcode of \mathcal{C} . For erasure channels, a list code \mathcal{C} can correct Λn errors with a list of size L if and only if $d_r(\mathcal{C}) > \Lambda n$ for $r = 1 + \lfloor \log n \rfloor$. The converse argument is similar to that for the average-error AVC – the error pattern can simulate r codewords if $d_r(\mathcal{C}) < \Lambda n$. It would be interesting to see how strong this connection is for more general AVCs.

APPENDIX I PROOF OF LEMMA 6

Proof: Note that the outer sum in (78) is over all x^{M+1} . Define the joint distribution V_i by:

$$V_i(x^{M+1}, s) = U_i(x_{-\{i\}}^{M+1}, s) . (99)$$

Let Π_{M+1} be the set of all permutations of [M+1] and for $\pi \in \Pi_{M+1}$ let π_i be the image of i under π . Then

$$\max_{j \neq i} \sum_{y,x^{M+1}} \left| \sum_{s} W(y|x_{i},s) V_{i}(x^{M+1},s) P(x_{i}) - \sum_{s} W(y|x_{j},s) V_{j}(x^{M+1},s) P(x_{j}) \right| \\
= \max_{j \neq i} \sum_{y,x^{M+1}} \left| \sum_{s} W(y|x_{i},s) V_{\pi_{i}}(x^{M+1},s) P(x_{i}) - \sum_{s} W(y|x_{j},s) V_{\pi_{j}}(x^{M+1},s) P(x_{j}) \right| . (100)$$

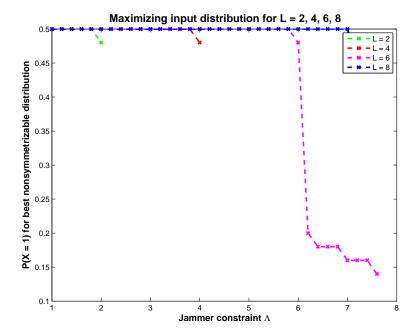


Fig. 4. The value of P(X=1) which is non-symmetrizable and achieves the highest rate versus Λ for $l(s)=|s|^2$, $\sigma=8$, and different list sizes.

We can lower bound this by averaging over all $\pi \in \Pi_{M+1}$:

$$\max_{j \neq i} \sum_{y, x^{M+1}} \frac{1}{(M+1)!} \sum_{\pi \in \Pi_{M+1}} \left| \sum_{s} W(y|x_i, s) V_{\pi_i}(x^{M+1}, s) P(x_i) - \sum_{s} W(y|x_j, s) V_{\pi_j}(x^{M+1}, s) P(x_j) \right| . \tag{101}$$

Now we use the convexity of $|\cdot|$ to pull the averaging inside to get a further lower bound:

$$F(\bar{V}, P) = \max_{j \neq i} \sum_{y \in \mathcal{X}_{-\{j\}}} \left| \sum_{s} W(y|x_i, s) \bar{V}(x_{-\{i\}}^{M+1}, s) P(x_i) - \sum_{s} W(y|x_j, s) \bar{V}(x_{-\{j\}}^{M+1}, s) P(x_j) \right| . (102)$$

where we define

$$\begin{split} \bar{V}(x_{-\{i\}}^{M+1},s) &= \frac{1}{(M+1)!} \sum_{\pi \in \Pi_{M+1}} V_{\pi_i}(x^{M+1},s) \\ &= \frac{1}{(M+1)!} \sum_{l=1}^{M+1} \sum_{\pi \in \Pi_{M+1}: \pi_i = l} U_l(\pi(x^{M+1})_{-\{\pi_i\}},s) \\ &= \frac{1}{(M+1)!} \sum_{l=1}^{M+1} \sum_{\sigma \in \Pi_M} U_l(\sigma(x_{-\{i\}}^{M+1}),s) \; . \end{split}$$

Now note that \bar{V} is a symmetric function for all s. The function $F(\bar{V},P)$ is continuous function on the compact set of symmetric distributions $\{\bar{V}\}$ and the set of distributions P with $\min_x P(x) \geq \beta$, so it has a minimum $\zeta = F(\bar{V}^*, P^*)$ for some (\bar{V}^*, P^*) .

We will prove that $\zeta>0$ by contradiction. Suppose $F(\bar{V}^*,P^*)=0$. Then

$$\sum_{s} W(y|x_{i}, s) \bar{V}^{*}(x_{-\{i\}}^{M+1}, s) P^{*}(x_{i}) = \sum_{s} W(y|x_{j}, s) \bar{V}^{*}(x_{-\{j\}}^{M+1}, s) P^{*}(x_{j}) .$$

So

$$\sum_{y} \sum_{s} W(y|x_{i}, s) \bar{V}^{*}(x_{-\{i\}}^{M+1}, s) P^{*}(x_{i}) = \sum_{y} \sum_{s} W(y|x_{j}, s) \bar{V}^{*}(x_{-\{j\}}^{M+1}, s) P^{*}(x_{j})$$
$$\bar{V}^{*}(x_{-\{i\}}^{M+1}) P^{*}(x_{i}) = \bar{V}^{*}(x_{-\{j\}}^{M+1}) P^{*}(x_{j}) ,$$

which implies (see [26, Lemma A3]) that for all j:

$$\bar{V}^*(x_{-\{j\}}^{M+1})P^*(x_j) = P^{*(M+1)}(x^{M+1})$$
.

Therefore

$$\sum_{s} W(y|x_1, s) \bar{V}^*(s|x^{M+1}) .$$

is symmetric in $(x_1, x_2, \dots, x_{M+1})$, which contradicts our assumption. Therefore $\zeta > 0$.

To bring in the state constraints, note that if (79) holds then

$$\sum_{x^{M+1},s} P(x_i)\bar{V}(x_{-\{i\}}^M,s)l(s) \le \Lambda_M(P) - \alpha$$
(103)

Again, because the AVC is not m-symmetrizable for m > M, the minimum of $F(\bar{V}, P)$ with the constraint (103) cannot be 0 or else $\Lambda_M(P) < \Lambda$. Thus we can still find a $\zeta > 0$ such that (78) holds.

APPENDIX II PROOF OF LEMMA 8

Proof: Choose N to so that

$$I(P) - \delta < R < I(P) - \delta/2 . \tag{104}$$

Let ϵ and η be parameters to be chosen later in the proof. Choose N codewords according to Lemma 5 using this ϵ . The decoding rule will be given by Definition 1. Lemma 7 proves that for small η the decoding rule is unambiguous and that the list size needed is at most $M = L_{\text{sym}}(P) + 1$.

We must now bound the average probability of error for a fixed s:

$$\varepsilon(\mathbf{s}) = \frac{1}{N} \sum_{i=1}^{N} \varepsilon(i, \mathbf{s}) .$$
 (105)

We must bound this error using the properties of the codebook guaranteed by Lemma 5.

Suppose that \mathbf{x}_i was transmitted, the state sequence was \mathbf{s} , and \mathbf{y} was received, $i \notin \mathcal{L}(\mathbf{y})$. From the definition of the decoder in Definition 1 we know that \mathbf{y} must violate either the first or second of the two conditions in the decoding rule. Correspondingly, we can define:

$$A_i(\mathbf{s}) = \{ \mathbf{y} : T_{\mathbf{x}_i \mathbf{s} \mathbf{y}} \in \mathcal{G}_{\eta}(\Lambda) \}$$
 (106)

$$B_{i}(\mathbf{s}) = \{\mathbf{y} : \mathbf{1}_{\mathbf{x}_{i}}\mathbf{s}\mathbf{y} \in \mathfrak{G}_{\eta}(\mathbf{1})\}$$

$$E(P_{YXX^{L}S})$$

$$E(P_{YXX^{L}S})$$

$$(107)$$

$$\mathcal{H}_{\eta}(i,\mathbf{s}) = \{ P_{YXX^{L}S} : \exists J \in \Sigma_{L}(-\{i\}), \ P_{YXX^{L}S} = T_{\mathbf{y}\mathbf{x}_{i}\mathbf{x}_{J}\mathbf{s}}, \ I\left(XY \land X^{L} \middle| S\right) > \eta \} \quad (108)$$

$$E(P_{YXX^{L}S}) = \{ \mathbf{y} : \exists (k, \mathbf{s}_{k}), k \in J, \mathbf{y} \in A_{k}(\mathbf{s}_{k}) \} \text{ for } P_{YXX^{L}S} \in \mathcal{H}_{\eta}(i, \mathbf{s}), J \text{ from (108)}$$
 (109)

$$F(\mathbf{s}) = \{i : I(X \land S) < \epsilon, \ P_{XS} = T_{\mathbf{x}, \mathbf{s}}\} \ . \tag{110}$$

An output $\mathbf{y} \in A_i^c(\mathbf{s})$ is atypical and fails the first criterion of the decoding rule. A joint distribution is in $\mathcal{H}_{\eta}(i,\mathbf{s})$ if is the type of $(\mathbf{y},\mathbf{x},\mathbf{x}_J,\mathbf{s})$, where J is a list of L codewords not containing i, and if the mutual information condition in the second part of the decoding rule is violated. An output \mathbf{y} is in $E(T_{\mathbf{y}\mathbf{x}_i\mathbf{x}_J\mathbf{s}})$ if there is a $k \in J$ and a state sequence \mathbf{s}_k so that \mathbf{x}_k is an alternate candidate for being the transmitted codeword. Putting this together, the $\mathbf{y} \in B_i(\mathbf{s})$ fail the second decoding rule. Therefore we can write the error as:

$$\varepsilon(\mathbf{s}) = \frac{1}{N} \left(\sum_{i \in F^{c}(\mathbf{s})} \varepsilon(i, \mathbf{s}) + \sum_{i \in F(\mathbf{s})} \varepsilon(i, \mathbf{s}) \right) \\
\leq \frac{1}{N} \left(\sum_{i \in F^{c}(\mathbf{s})} \varepsilon(i, \mathbf{s}) + \sum_{i \in F(\mathbf{s})} W^{n}(A_{i}^{c}(\mathbf{s}) | \mathbf{x}_{i}, \mathbf{s}) + \sum_{i \in F(\mathbf{s})} \sum_{P_{YXX^{L}S} \in \mathcal{H}_{\eta}} W^{n}(E(P_{YXX^{L}S}) | \mathbf{x}_{i}, \mathbf{s}) \right). \tag{111}$$

We must bound each of these three terms using the properties of our codebook guaranteed by Lemma 5 and some properties of types.

To bound the first term, note that for a joint type P_{XS} we can bound $|F^c(\mathbf{s})|$ using part 1 of Lemma 5:

$$\frac{1}{N} \sum_{i \in F^{c}(\mathbf{s})} \varepsilon(i, \mathbf{s}) \leq \frac{|F^{c}(\mathbf{s})|}{N}$$

$$\leq \sum_{P_{XS} \in \mathcal{P}_{n}(\mathcal{X}, \mathcal{S})} \exp(-n\epsilon/2)$$

$$\leq (n+1)^{|\mathcal{X}||\mathcal{S}|} \exp(-n\epsilon/2) . \tag{112}$$

To bound the second term, we use some facts about types. Note first that for $P_{XS} = T_{\mathbf{x}_i \mathbf{s}}$ and $I(X \wedge S) = D(P_{XS} \parallel P_X \times P_S)$ we have:

$$D(P_{XSY} \parallel P_{XS} \times W) + I(X \wedge S) = D(P_{XSY} \parallel P_X \times P_S \times W) . \tag{113}$$

For $i \in F(\mathbf{s})$ we have $I(X \land S) < \epsilon$ and for $\mathbf{y} \in A_i^c(\mathbf{s})$ we have $D(P_{XSY} \parallel P_X \times P_S \times W) > \eta$, so

$$D(P_{XSY} \parallel P_{XS} \times W) > \eta - \epsilon . \tag{114}$$

Now, the second sum can be rewritten using (113) and (8):

$$\sum_{i \in F(\mathbf{s})} W^{n}(A_{i}^{c}(\mathbf{s})|\mathbf{x}_{i}, \mathbf{s}) \leq \sum_{P_{XSY} \notin \mathcal{G}_{\eta}(\Lambda)} W^{n}\left(\{\mathbf{y} : P_{XSY} = T_{\mathbf{x}_{i}\mathbf{s}\mathbf{y}}\}|\mathbf{x}_{i}\mathbf{s}\right) \\
\leq (n+1)^{|\mathcal{X}||\mathcal{S}||\mathcal{Y}|} \exp(-nD\left(P_{XSY} \parallel P_{XS} \times W\right)) \\
\leq (n+1)^{|\mathcal{X}||\mathcal{S}||\mathcal{Y}|} \exp(-n(\eta - \epsilon)) . \tag{115}$$

To bound the last term, let us fix $P_{YXX^LS} \in \mathcal{H}_{\eta}$. We will consider the cases where R is greater then or less than $\min_k I(X_k \wedge S)$, where $k \in [L]$.

1) Suppose $R < \min_k I(X_k \wedge S)$. In this case $|R - I(X_k \wedge S)|^+ = 0$. We consider two sub-cases. If $I(X \wedge X^L S) \ge \epsilon$ then part 5 of Lemma 5 says that for all k

$$\frac{1}{N} \sum_{i \in F(\mathbf{s})} W^n(E(P_{YXX^LS}) | \mathbf{x}_i, \mathbf{s}) \le \frac{1}{N} | \{ i : (\mathbf{x}_i, \mathbf{x}_J, \mathbf{s}) \in T_{XX^LS} \text{ for some } J \in \Sigma_L(-\{i\}) \} |$$

$$\le \exp(-n\epsilon/2) . \tag{116}$$

If instead $I(X \wedge X^L S) < \epsilon$ we can bound

$$E(P_{YXX^LS}) \subset \bigcup_{J \in \Sigma_L(-\{i\}): T_{\mathbf{x}_i \mathbf{x}_J \mathbf{s}} = P_{XX^LS}} \{ \mathbf{y} : T_{\mathbf{y} \mathbf{x}_i \mathbf{x}_J \mathbf{s}} = P_{YXX^LS} \} . \tag{117}$$

Using a union bound, (9) and part 4 of Lemma 5 we obtain

$$\sum W^{n}(E(P_{YXX^{L}S})|\mathbf{x}_{i},\mathbf{s}) \leq \sum_{J \in \Sigma_{L}(-\{i\}):T_{\mathbf{x}_{i}\mathbf{x}_{J}\mathbf{s}}=P_{XX^{L}S}} W^{n}(\{\mathbf{y}:T_{\mathbf{y}\mathbf{x}_{i}\mathbf{x}_{J}\mathbf{s}}=P_{YXX^{L}S}\}|\mathbf{x}_{i},\mathbf{s})$$

$$\leq \sum_{J \in \Sigma_{L}(-\{i\}):T_{\mathbf{x}_{i}\mathbf{x}_{J}\mathbf{s}}=P_{XX^{L}S}} \exp\left(-nI\left(Y \wedge X^{L}|XS\right)\right)$$

$$\leq \exp\left(-n(I\left(Y \wedge X^{L}|XS\right)-\epsilon\right)\right)!. \tag{118}$$

To bound the exponent, note that since $P_{YXX^LS} \in \mathcal{H}_{\eta}(i, \mathbf{s})$ and $I(X \land X^LS) < \epsilon$,

$$I(Y \wedge X^{L}|XS) = I(YX \wedge X^{L}|S) - I(X \wedge X^{L}|S)$$

$$> \eta - I(X \wedge X^{L}S)$$

$$> \eta - \epsilon.$$
(119)

Then (118) and (119) give

$$\sum_{i \in F(\mathbf{s})} W^n(E(P_{YXX^LS})|\mathbf{x}_i, \mathbf{s}) \le \exp(-n(\eta - 2\epsilon)) . \tag{120}$$

2) Suppose $R \ge \min_k I(X_k \land S)$, and pick k such that $R \ge I(X_k \land S)$. Then if $I(X \land X^L S) \ge |R - I(X_k \land S)|^+ + \epsilon$ then part 2 of Lemma 5 says that for this k

$$\frac{1}{N} \sum_{i \in F(\mathbf{s})} W^n(E(P_{YXX^LS})|\mathbf{x}_i, \mathbf{s}) \le \frac{1}{N} \left| \{i : (\mathbf{x}_i, \mathbf{x}_j, \mathbf{s}) \in T_{XX_kS} \text{ for some } j \neq i\} \right| \\
\le \exp(-n\epsilon/2) . \tag{121}$$

Suppose now that $I\left(X \wedge X^LS\right) < |R - I\left(X_k \wedge S\right)|^+ + \epsilon$. We may assume $P_{X_k} = P_X$, since X_k has the type of a codeword by the definition of $\mathcal{H}(i,\mathbf{s})$. Rewriting as before, the set $E(P_{YXX^LS})$ is a subset of those \mathbf{y} with $T_{\mathbf{y}\mathbf{x}_i\mathbf{x}_j\mathbf{s}} == P_{YXX_kS}$ for some $j \neq i$:

$$E(P_{YXX^LS}) \subset \bigcup_{j \neq i: T_{\mathbf{x}, \mathbf{x}, \mathbf{s}} = P_{XX_LS}} \{ \mathbf{y} : T_{\mathbf{y}\mathbf{x}_i\mathbf{x}_j\mathbf{s}} = P_{YXX_kS} \} . \tag{122}$$

Using a union bound, (9) and part 3 of Lemma 5 we obtain

$$W^{n}(E(P_{YXX^{L}S})|\mathbf{x}_{i},\mathbf{s}) \leq \sum_{j \neq i:T_{\mathbf{x}_{i}\mathbf{x}_{j}\mathbf{s}}} W^{n}(\{\mathbf{y}:T_{\mathbf{y}\mathbf{x}_{i}\mathbf{x}_{j}\mathbf{s}} = P_{YXX_{k}S}\}|\mathbf{x}_{i},\mathbf{s})$$

$$\leq \sum_{j \neq i:T_{\mathbf{x}_{i}\mathbf{x}_{j}\mathbf{s}}} \exp\left(-n(I(Y \land X_{k}|XS))\right)$$

$$\leq \exp\left(-n(I(Y \land X_{k}|XS) - |R - I(X_{k} \land XS)|^{+} - \epsilon)\right) . \quad (123)$$

Because $R \ge \min_k I(X_k \land S)$, we have

$$R > I(X \land X_k S) + I(X_k \land S) - \epsilon$$

$$\geq I(X \land X_k | S) + I(X_k \land S) - \epsilon$$

$$= I(X_k \land XS) - \epsilon . \tag{124}$$

Therefore

$$I(Y \wedge X_{k}|XS) - |R - I(X_{k} \wedge XS)|^{+} - \epsilon \ge I(Y \wedge X_{k}|XS) + I(X_{k} \wedge XS) - R - 2\epsilon$$
$$\ge I(YXS \wedge X_{k}) - R - 2\epsilon$$
$$\ge I(X_{k} \wedge Y) - R - 2\epsilon . \tag{125}$$

Since we have $P_{YXX^LS} \in \mathcal{H}_{\eta}(i, \mathbf{s})$, we must also have $P_{YX_kS_k} \in \mathcal{G}_{\eta}(\Lambda)$. This means

$$D\left(P_{YX_{k}S_{k}} \parallel P_{X} \times P_{S_{k}} \times W\right) < \eta , \qquad (126)$$

so projecting onto (Y, X_k) and using Pinsker's inequality [16, p. 58, Problem 17] we see the total variational distance between P_{X_kY} and P_XW is less than η . This in turn means that for any $\delta>0$ we can choose an η small enough so that $I(X_k \wedge Y)-I(P_X)<\delta/3$. This in turn means

$$I(X_k \wedge Y) - R \ge I(P_X) - R - \delta/3 \ge \delta/3. \tag{127}$$

From (123), (125), and (127)

$$W^{n}(E(P_{YXX^{L}S})|\mathbf{x}_{i},\mathbf{s}) \leq \exp\left(-n(I(X_{k} \wedge Y) - R - 2\epsilon)\right)$$

$$\leq \exp\left(-n(\delta/3 - 3\epsilon)\right). \tag{128}$$

Since the number of joint types in $\mathcal{H}_{\eta}(i,\mathbf{s})$ is at most polynomial in n and the bounds on the probability of $E(P_{YXX^LS})$ in (112), (115), (116), (120), (121), (128) are exponentially decreasing in all cases, we have an exponential bound on the third term in the error sum.

Thus all three terms can be bounded by terms exponentially decreasing in n and the average error can be made as small as we like by choosing the block length to be large enough. These bounds are uniform in s and hence hold for all s for which the decoding rule is valid. Since the rule is valid if the list size is greater than $L_{\rm sym}$, we are done.

APPENDIX III

OPTIMIZATION FOR THE EXAMPLE

To find the random coding capacity we must minimize the quantity $I(X \wedge X + S)$. This can be stated as the following optimization problem. Let $I(Q) = I(X \wedge X + S)$ with Q = Q(s) and P(X = 1) = P(X = -1) = 1/2. For a cost function $l(s) = |s|^{\theta}$, let $\Theta = (l(-A), l(-A+1), \dots l(A))^{T}$. The optimization is

$$minimize I(Q) (129)$$

subject to
$$\mathbf{1}^T Q = 1$$
 (130)

$$-Q(s) \le 0 \quad \forall s \tag{131}$$

$$\Theta^T Q - \Lambda < 0 , (132)$$

Since the mutual information is convex in the distribution Q, this is a convex optimization problem in the vector Q and can be solved using standard optimization techniques [13].

By performing an optimization for each value of σ and Λ we can create the plots shown in Figures 1 and 2.

In order to calculate the symmetrizability of the channel, we must solve the following program:

minimize
$$f(U) = \sum_{y} \sum_{t=1}^{L} \left(\sum_{s} W(y|-1, s) U(s|t) - \sum_{s} W(y|+1, s) U(s|t-1) \right)^{2}$$
 (133)

subject to
$$\sum_{s} U(s|t) = 1 \quad \forall t$$

$$-U(s|t) \leq 0 \quad \forall s, t$$
 (134)

$$-U(s|t) \le 0 \quad \forall s, t \tag{135}$$

$$\sum_{s} \sum_{t=0}^{L} {L \choose t} 2^{-L} l(s) U(s|t) - \Lambda \le 0.$$

$$(136)$$

This is a quadratic program in the channel U and we can again use standard techniques to find L_{sym} for different P and Λ .

REFERENCES

- [1] M. Agarwal, A. Sahai, and S. Mitter, "Coding into a source: a direct inverse rate-distortion theorem," in 45th Annual Allerton Conference on Communication, Control and Computation, 2006.
- [2] R. Ahlswede, "Channel Capacities for List Codes," Journal of Applied Probability, vol. 10, no. 4, pp. 824-836, 1973.
- [3] —, "Channels with Arbitrarily Varying Channel Probability Functions in the Presence of Noiseless Feedback," Zeitschrift für Wahrscheinlichkeit und verwandte Gebiete, vol. 25, pp. 239–252, 1973.
- [4] —, "Elimination of correlation in random codes for arbitrarily varying channels," Zeitschrift für Wahrscheinlichkeitstheorie und Verwandte Gebiete, vol. 44, no. 2, pp. 159-175, 1978.
- [5] —, "Coloring hypergraphs: A new approach fo multi-user source coding I," Journal of Combinatorics, Information, and System Sciences, vol. 4, no. 1, pp. 76-115, 1979.
- ----, "A method of coding and an application to arbitrarily varying channels," Journal of Combinatorics, Information and System Sciences, vol. 5, pp. 10-35, 1980.
- [7] —, "Coloring hypergraphs: A new approach fo multi-user source coding II," Journal of Combinatorics, Information and System Sciences, vol. 5, no. 3, pp. 220-268, 1980.
- ----, "The maximal error capacity of arbitrarily varying channels for constant list sizes," IEEE Transactions on Information Theory, vol. 39, no. 4, pp. 1416-1417, 1993.
- [9] R. Ahlswede and J. Wolfowitz, "The capacity of a channel with arbitrarily varying channel probability functions and binary output alphabet," Zeitschrift für Wahrscheinlichkeit und verwandte Gebiete, vol. 15, no. 3, pp. 186–194, 1970.
- [10] D. Blackwell, L. Breiman, and A. Thomasian, "The capacities of certain channel classes under random coding," Annals of Mathematical Statistics, vol. 31, pp. 558–567, 1960.
- [11] V. Blinovsky, P. Narayan, and M. Pinsker, "Capacity of the arbitrarily varying channel under list decoding," Problems of Information Transmission, vol. 31, no. 2, pp. 99-113, 1995.
- [12] V. Blinovsky and M. Pinsker, "Estimation of the size of the list when decoding over an arbitrarily varying channel," in Proceedings of 1st French-Israeli Workshop on Algebraic Coding, ser. Lecture Notes in Computer Science, G. Cohen, S. Litsyn, A. Lobstein, and G. Zémor, Eds., no. 781. Berlin: Springer-Verlag, July 1993.
- [13] S. Boyd and L. Vandenberghe, Convex Optimization. Cambridge, UK: Cambridge University Press, 2004.
- [14] T. Cover and J. Thomas, *Elements of Information Theory*. New York: Wiley, 1991.
- [15] I. Csiszár and J. Körner, "On the capacity of the arbitrarily varying channel for maximum probability of error," Zeitschrift für Wahrscheinlichkeitstheorie und Verwandte Gebiete, vol. 57, pp. 87–101, 1981.
- [16] —, Information Theory: Coding Theorems for Discrete Memoryless Systems. Budapest: Akadémi Kiadó, 1982.
- [17] I. Csiszár and P. Narayan, "Arbitrarily varying channels with constrained inputs and states," IEEE Transactions on Information Theory, vol. 34, no. 1, pp. 27–34, 1988.
- —, "The capacity of the arbitrarily varying channel revisited: Positivity, constraints," *IEEE Transactions on Information* Theory, vol. 34, no. 2, pp. 181–193, 1988.
- [19] —, "Capacity of the Gaussian arbitrarily varying channel," *IEEE Transactions on Information Theory*, vol. 37, no. 1, pp. 18-26, 1991.
- [20] A. Dembo and O. Zeitouni, Large Deviations Techniques and Applications. New York: Springer, 1998.
- [21] P. Elias, "List decoding for noisy channels," in Wescon Convention Record, Part 2. Institute of Radio Engineers (now IEEE), 1957, pp. 94-104.
- [22] T. Ericson, "Exponential error bounds for random codes on the arbitrarily carying channel," IEEE Transactions on Information Theory, vol. 31, no. 1, pp. 42–48, 1985.

- [23] J. Gubner, "On the deterministic-code capacity of the multiple-access arbitrarily varying channel," *IEEE Transactions on Information Theory*, vol. 36, no. 2, pp. 262–275, 1990.
- [24] —, "State constraints for the multiple-access arbitrarily varying channel," *IEEE Transactions on Information Theory*, vol. 37, no. 1, pp. 27–31, 1991.
- [25] V. Guruswami, "List decoding from erasures: Bounds and code constructions," *IEEE Transactions on Information Theory*, vol. 49, no. 11, pp. 2826–2833, 2003.
- [26] B. Hughes, "The smallest list for the arbitrarily varying channel," *IEEE Transactions on Information Theory*, vol. 43, no. 3, pp. 803–815, 1997.
- [27] A. Sarwate and M. Gastpar, "Channels with nosy "noise"," in *Proceedings of the 2007 IEEE International Symposium on Information Theory*, Nice, France, June 2007.
- [28] S. Shamai (Shitz) and S. Verdú, "Worst-case power-constrained noise binary-input channels," *IEEE Transactions on Information Theory*, vol. 38, no. 5, pp. 1494–1511, 1992.
- [29] M. A. Tsfasman and S. G. Vlăduţ, "Geometric approach to higher weights," *IEEE Transactions on Information Theory*, vol. 41, no. 6, pp. 1564–1588, 1995.
- [30] V. K. Wei, "Generalized hamming weights for linear codes," *IEEE Transactions on Information Theory*, vol. 37, no. 5, pp. 1412–1418, 1991.