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BSC Thresholds for Code Ensembles based on "Typical Pairs" Decoding.*

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Abstract.
In this paper, we develop a method for closely estimating noise threshold values for ensembles of binary linear codes on the binary symmetric channel. Our method, based on the "typical pairs" decoding algorithm pioneered by Shannon, completely decouples the channel from the code ensemble. In this, it resembles the classical union bound, but unlike the union bound, our method is powerful enough to prove Shannon's theorem for the ensemble of random linear codes. We apply our general method to find numerical thresholds for the ensembles of low-density parity-check codes, and "repeat-accumulate" codes.

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1. Introduction.

In this paper, we consider the performance of ensembles of codes on the binary symmetric channel. Our particular focus is on the question as to whether or not a given ensemble is "good," in the sense of MacKay [7]. In short, an ensemble of codes is said to be good, if there is a $p > 0$ such that the ensemble word error probability (with maximum-likelihood decoding) on a BSC with crossover probability p approaches zero as the block length approaches infinity. The largest such p for a given ensemble is called the (noise) *threshold* for the ensemble. Our main result (Theorem 4.1) is a technique for finding a lower bound on the ensemble threshold, which is based on the ensemble's weight enumerator.

Of course the classical union bound provides one way of using weight enumerators to estimate ensemble thresholds, but the estimates are poor. On the other hand Gallager [4, Chapter 3] gave a powerful methodology for upper bounding the probability of maximum-likelihood decoding error for an arbitrary binary code, or ensemble of codes, on a general class of binary-input channels. Gallager's technique, however, is quite complex, and even in the special case of the BSC it is difficult to apply to the problem of finding ensemble thresholds.[1]

In this paper we abandon the full maximum-likelihood decoder, and instead focus on a slightly weaker decoding algorithm, which is much easier to analyze, the *typical pairs* decoder. This technique was pioneered by Shannon [10, Theorem 11], but as far as we can tell was not used to analyze ensembles other than the ensemble of all codes (which we call the Shannon ensemble in Section 5, below) until the 1999 paper of MacKay [7], in which it was used to analyze certain ensembles of low-density-parity check codes. In brief, when presented with a received word $\boldsymbol{y}$, the typical pairs decoder seeks a unique codeword $\boldsymbol{x}$ such that the pair $(\boldsymbol{x}, \boldsymbol{y})$ belongs to the set T of "typical pairs." (We give a precise definition of T in section 2, which follows.) In Section 3, we develop an upper bound on the T-decoder's error probability (Theorem 3.1) which, like the classical union bound, decouples the code's weight enumerator from the channel, but unlike the union bound, when combined with the law of large numbers, gives good estimates for code thresholds (Theorem 4.1).

We then apply Theorem 4.1 to three families of binary code ensembles: (1) The Shannon ensemble, consisting of all linear codes of rate R, (2) The Gallager ensemble, consisting of (j, k) low-density parity-check codes, and (3) the ensemble of Repeat-Accumulate codes introduced by Divsalar, Jin and McEliece [2]. In the case of the Shannon ensembles, we show that our method yields thresholds identical to those implied by Shannon's theorem. Thus the typical sequence method, despite its suboptimality, loses nothing (in terms of coding thresholds) for the Shannon ensemble.

Finally, we compare our thresholds to the *iterative* thresholds for the Gallager and RA ensembles recently obtained by Richarson and Urbanke [9], in order to estimate the price paid in coding threshold for the benefits of iterative decoding. In most cases, this loss is quite small, and in the case of $j = 2$ LDPC codes, there is no penalty at all.

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[1] We have been able to show that the thresholds obtained by our method are the same as the best obtainable by the Gallager methodology.

The method described in this paper can be readily extended to many other channel models, including channels with memory (cf. [7, Section II]). This extension will be developed in a forthcoming paper, where the emphasis will be on the binary erasure channel and the additive Gaussian noise channel.

2. Typical Pairs.

The basic idea of the typical set decoder (the T-decoder) is this. When the T-decoder is given a garbled codeword $\boldsymbol{y}$ to decode, for each possible codeword $\boldsymbol{x}_i$, it calculates the difference $\boldsymbol{z}_i = \boldsymbol{y} - \boldsymbol{x}_i$, which represents the channel noise if $\boldsymbol{x}_i$ was the transmitted codeword. If $\boldsymbol{z}_i$ is in some sense typical of what the channel noise is expectd to be, the decoder accepts the hypothesis $\boldsymbol{x}_i$. The set of typical noise samples is denoted by T. Roughly speaking, T consists of those sequences in which the fraction of 1's is approximately p, the channel crossover probability. However, to prove our first main theorem (Theorem 3.1), we only need to assume that T is invariant under coordinate permutations.

Thus let T be a set of binary vectors of length n which is closed under coordinate permutations, and let $\boldsymbol{Z} = (Z_1, Z_2, \ldots, Z_n)$ be the BSC noise vector, i.e., the Z_i's are i.i.d. random variables with common density

$$\Pr\{Z = 0\} = 1 - p, \qquad \Pr\{Z = 1\} = p.$$

Because T is invariant under coordinate permutations, if $\boldsymbol{x}$ is an n-vector, the probability $\Pr\{\boldsymbol{Z} \in T \cap (T + \boldsymbol{x})\}$ depends only on the weight of $\boldsymbol{x}$. Thus we define, for $h = 0, 1, \ldots, n$,

$$P_h(T) = \Pr\{\boldsymbol{Z} \in T \cap (T + \boldsymbol{x})\}, \tag{2.1}$$

where $\boldsymbol{x}$ is any vector of weight h. For example,

$$P_0(T) = \Pr\{\boldsymbol{Z} \in T\}. \tag{2.2}$$

Since any set T which is invariant under coordinate permutations must consist of all vectors of weight $k \in K$, where K is a subset of $\{0, 1, \ldots, n\}$, the probabilities $P_h(T)$ depend only on the set K. A short combinatorial calculation

$$P_h(T) = \sum_{k_1 \in K} p^{k_1}(1-p)^{n-k_1} \sum_{k_2 \in K} \binom{h}{(h + k_1 - k_2)/2} \binom{n-h}{(k_1 - h + k_2)/2}. \tag{2.3}$$

This is because a vector of weight k_1 has probability $p^{k_1}(1-p)^{n-k_1}$, and there are exactly $\binom{h}{(h+k_1-k_2)/2}\binom{n-h}{(k_1-h+k_2)/2}$ vectors of weight k_1, which have the property that when the first h components are complemented, the resulting vector has weight k_2. Applying (2.3) to the case $h = 0$, we obtain

$$P_0(T) = \sum_{k \in K} p^k (1-p)^{n-k} \binom{n}{k},$$

in agreement with (2.2).

In our main application (Theorem 4.1) the set T will depend on n and so will be denoted by T_n. The definition of T_n is

$$T_n = \left\{ \boldsymbol{z} : \left| \frac{\mathrm{wt}(\boldsymbol{z})}{n} - p \right| \le \epsilon_n \right\}, \tag{2.4}$$

where ϵ_n is a sequence of real numbers approaching zero more slowly than $n^{-1/2}$, i.e., $\epsilon_n \sqrt{n} \to \infty$. Then by a straightforward extension of the weak law of large numbers,

$$\lim_{n\to\infty} \Pr\{\boldsymbol{Z} \in T_n\} = 1. \tag{2.5}$$

Furthermore, by defining $K_n = \{k : n(p - \epsilon_n) \le k \le n(p + \epsilon_n)\}$, and using the formula (2.3), it is relatively easy to prove that for any δ in the range $0 < \delta < 1$, we have

$$\lim_{n\to\infty} -\frac{1}{n} \log P_{\delta n}(T_n) = K(\delta, p), \tag{2.6}$$

where $K(\delta, p)$ is given by the equivalent formulas

$$K(\delta, p) = H(p) - \delta \log 2 - (1-\delta) H\left(\frac{p - \delta/2}{1-\delta}\right) \tag{2.7}$$

$$= H(\delta) - pH\left(1 - \frac{\delta}{2p}\right) - (1-p)H\left(\frac{\delta}{2p}\right), \tag{2.8}$$

where $H(x)$ is the entropy function, i.e., $H(x) = -x \log x - (1-x)\log(1-x)$. (In fact, these formulae are true only for $\delta < 2p$; for $\delta \ge 2p$, $K(\delta, p)$ is infinite, since $P_h(T_n) = 0$ for $h > 2n(p + \epsilon_n)$.) In Figure 1, we have plotted the function $K(\delta, p)$ for several values of p.

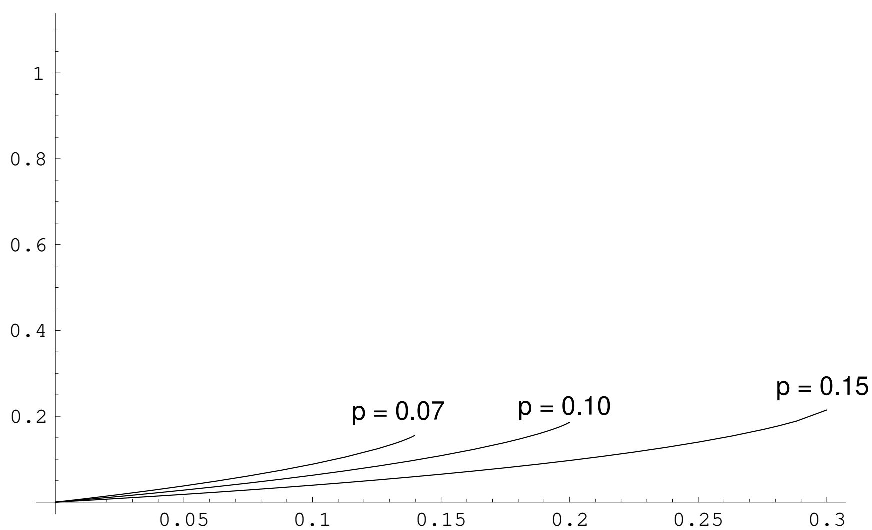

Figure 1. The Function $K(\delta, p)$ for $p = 0.07, 0.10., 0.15$.

We summarize eqs. (2.6)–(2.8) by writing

$$P_h(T_n) = e^{-n(K(\delta,p)+o(1))}, \tag{2.9}$$

where $\delta = h/n$.

3. The Typical Pairs Decoding Method.

Suppose C is an (n,k) binary linear code, with weight enumerator $(A_0, A_1, \ldots, A_n)$, i.e., C contains exactly A_h words of Hamming weight h, for $h = 1, \ldots, n$. We suppose that at the transmitter, a codeword $\boldsymbol{x} \in \mathcal{C}$ is selected at random, transmitted over a BSC with crossover probability p, and received at the destination, possibly garbled, as $\boldsymbol{y}$. The T-decoder tries to infer $\boldsymbol{x}$ based on knowledge of the code $\mathcal{C}$, the garbled codeword $\boldsymbol{y}$, and the channel noise parameter p. The T-decoder works as follows.

For every codeword $\boldsymbol{x}_i$, the ith "pseudonoise" $\boldsymbol{z}_i = \boldsymbol{y} - \boldsymbol{x}_i$ is computed. If there is exactly one index i such that $\boldsymbol{z}_i \in T$, then the decoder declares that $\boldsymbol{x}_i$ was the transmitted codeword. Otherwise, the decoder fails. In what follows we do not distinguish between decoder error and failure, and denote the probability of decoder (error or failure) by P_E.

3.1 Theorem. *If P_E denotes the probability that the T-decoder does not correctly identify the transmitted codeword, then*

$$P_E \leq (1 - P_0(T)) + \sum_{h=1}^{n} A_h P_h(T). \tag{3.1}$$

Proof: Let $(\boldsymbol{x}_0, \boldsymbol{x}_1, \ldots, \boldsymbol{x}_{M-1})$ be an ordering of the code with $\boldsymbol{x}_0$ being the all-zeros word, and suppose $\boldsymbol{x}_0$ is transmitted. Then the T-decoder will fail if and only if at least one of the events $\{\boldsymbol{z}_0 \in T'\}, \{\boldsymbol{z}_1 \in T\}, \ldots, \{\boldsymbol{z}_{M-1} \in T\}$ occurs. Thus if $\mathcal{E}$ denotes the event "T-decoder fails, given that $\boldsymbol{x}_0$ was transmitted," and T_i denotes the set $\{\boldsymbol{z}_i \in T\}$,

$$\begin{aligned}
\mathcal{E} &= T_0' \cup \left(\bigcup_{i=1}^{M-1} T_i \right) \\
&= T_0' \cup \left(T_0 \cap \bigcup_{i=1}^{M-1} T_i \right) \\
&= T_0' \cup \left(\bigcup_{i=1}^{M-1} (T_0 \cap T_i) \right).
\end{aligned} \tag{3.2}$$

Thus the probabiliity of T-decoder error, given that $\boldsymbol{x}_0$ was transmitted, can be upper bounded as follows:

$$\Pr\{\mathcal{E}|\boldsymbol{x}_0\} \leq \Pr\{T_0'|\boldsymbol{x}_0\} + \sum_{i=1}^{M-1} \Pr\{T_0 \cap T_i|\boldsymbol{x}_0\}. \tag{3.3}$$

But $\Pr\{T_0'|\boldsymbol{x}_0\} = 1 - \Pr\{T_0|\boldsymbol{x}_0\}$, and $\Pr\{T_0|\boldsymbol{x}_0\} = \Pr\{\boldsymbol{Z} \in T\} = P_0(T)$, from (2.2). Thus

$$\Pr\{T_0'|\boldsymbol{x}_0\} = 1 - P_0(T). \tag{3.4}$$

Also note that by definition $\boldsymbol{z}_i = \boldsymbol{y} - \boldsymbol{x}_i$, and so we have, for $i = 1, \ldots, M-1$, $\boldsymbol{z}_i = \boldsymbol{z}_0 + (\boldsymbol{x}_0 - \boldsymbol{x}_i) = \boldsymbol{z}_0 - \boldsymbol{x}_i$, since $\boldsymbol{x}_0$ is the all-zeros word. Thus $T_i = \{\boldsymbol{z}_0 \in T + \boldsymbol{x}_i\}$, and so

$$\begin{aligned} \Pr\{T_0 \cap T_i|\boldsymbol{x}_0\} &= \Pr\{\boldsymbol{Z} \in T \cap (T + \boldsymbol{x}_i)\} \\ &= P_{h_i}(T) \end{aligned}$$

where h_i is the Hamming weight of $\boldsymbol{x}_i$. Hence

$$\begin{aligned} \sum_{i=1}^{M-1} \Pr\{T_0 \cap T_i|\boldsymbol{x}_0\} &= \sum_{i=1}^{M-1} P_{h_i}(T), \\ &= \sum_{h=1}^{n} A_h P_h(T), \end{aligned} \tag{3.5}$$

since there are exactly A_h words of Hamming weight h in $\mathcal{C}$. Combining (3.3) with (3.4) and (3.5), gives (3.1). ▪

4. Code Ensembles.

By an *ensemble* of linear codes we mean a sequence $\mathcal{C}_{n_1}, \mathcal{C}_{n_2}, \ldots$ of sets of linear codes of a common rate R, where $\mathcal{C}_{n_i}$ is a set of (n_i, k_i) codes with $k_i/n_i = R$. We assume that the sequence $n_1, n_2, \ldots$ approaches infinity. If C is an (n,k) code in the ensemble, we denote the weight enumerator of C by the list $A_0(C), A_1(C), \ldots, A_n(C)$. The *average weight enumerator* for the set $\mathcal{C}_n$ is defined as the list

$$\overline{A}_0^{(n)}(C), \overline{A}_1^{(n)}(C), \ldots, \overline{A}_n^{(n)}(C),$$

where

$$\overline{A}_h^{(n)} \triangleq \frac{1}{|\mathcal{C}_n|} \sum_{C \in \mathcal{C}_n} A_h(C) \qquad \text{for } h = 0, 1, \ldots, n. \tag{4.1}$$

Also, we define the *ensemble spectral shape* :

$$r(\delta) \triangleq \lim_{n \to \infty} \frac{1}{n} \log \overline{A}_{\lfloor \delta n \rfloor}^{(n)} \qquad \text{for } 0 < \delta < 1, \tag{4.2}$$

assuming that the limit exists. In this case, we may write

$$\overline{A}_h^{(n)} = e^{n(r(\delta) + o(1))}, \tag{4.3}$$

where $\delta = h/n$.

Now we apply Theorem 3.1, using the set T_n, defined in (2.4), to a code $C \in \mathcal{C}_n$:

$$P_E \leq \delta_n + \sum_{h=1}^{n} A_h(C) P_h(T_n), \tag{4.4}$$

where $\delta_n = \Pr\{T'_n\} \to 0$ by (2.5). If we average (4.4) over all codes in the ensemble $\mathcal{C}_n$, we obtain the following upper bound on $\overline{P}_E^{(n)}$, the ensemble decoder error probability:

$$\overline{P}_E^{(n)} \leq \delta_n + \sum_{h=1}^{n} \overline{A}_h^{(n)} P_h(T_n). \tag{4.5}$$

Replacing $\overline{A}_h^{(n)}$ with the right side of (4.3), and $P_h(T_n)$ with the right side of (2.9), (4.5) becomes

$$\overline{P}_E^{(n)} \leq \delta_n + \sum_{h=1}^{n} e^{-n(K(\delta,p)-r(\delta)+o(1))}. \tag{4.6}$$

It now appears that if p is chosen so that the function $K(\delta, p) - r(\delta)$ is positive for all $0 < \delta < 1$, so that the exponent in the sum in (4.6) is always negative, the ensemble word error probability $\overline{P}_E^{(n)}$ will approach zero, as $n \to \infty$. This is in fact true, provided we make the following two technical assumptions about the behavior of $\overline{A}_h^{(n)}$, for $h = o(n)$. (Both assumptions say, roughly, that there are not too many words of low weight in the ensemble.)

- *Assumption 1*: There exist a sequence of integers d_n such that $d_n \to \infty$ and

$$\lim_{n\to\infty} \sum_{h=1}^{d_n} \overline{A}_h^{(n)} = 0. \tag{4.7}$$

- *Assumption 2*:

$$\lim_{\delta\to 0} \frac{r(\delta)}{\delta} \leq 0. \tag{4.8}$$

Omitting further details, we now state our main result:

4.1 Theorem. *Suppose the code ensemble has spectral shape $r(\delta)$, and also that it satisfies Assumptions 1 and 2. Then if the crossover probability p of the channel satisfies*

$$K(\delta, p) > r(\delta) \qquad \text{for } 0 < \delta < 2p,$$

the ensemble is "good," i.e., $\overline{P}_E^{(n)} \to 0$ as $n \to \infty$.

In the following three sections, we will apply Theorem 4.1 to three different ensembles of binary linear codes: (1) The Shannon ensemble, consisting of all linear codes of rate R,

(2) The Gallager ensemble, consisting of (j, k) low-density parity-check codes, and (3) the ensemble of Repeat-Accumulate codes introduced by Divsalar, Jin and McEliece [2].

5. The Shannon Ensemble.

For the set of random linear codes of rate R, we have

$$\overline{A}_h^{(n)} = \binom{n}{h} 2^{-n(1-R)}, \tag{5.1}$$

from which it follows via a routine calculation that

$$r(\delta) = H(\delta) - (1-R)\log 2. \tag{5.2}$$

This function is shown for $R = 1/3$ in Figure 2.

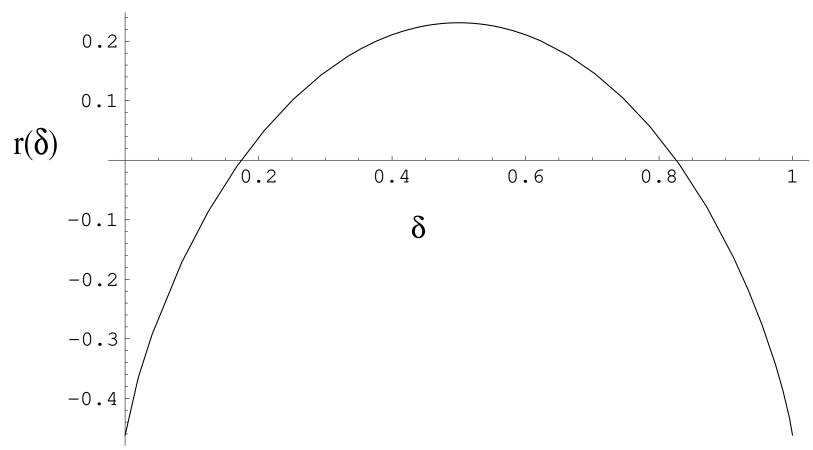

Figure 2. The function $r(\delta)$ for the ensemble of $R = 1/3$ linear codes.

To apply Theorem 4.1 to the Shannon ensemble, for a given rate R we must find the largest p such that $K(\delta, p) > H(\delta) - (1-R)\log 2$ for all $0 < \delta < 2p$. Using (5.2) and (2.8), this inequality becomes

$$pH\left(1 - \frac{\delta}{2p}\right) + (1-p)H\left(\frac{\delta}{2p}\right) < (1-R)\log 2. \tag{5.3}$$

The maximum of the left side of (5.3) in the range $0 < \delta < 2p$ occurs at $\delta = 2p(1-p)$, and is $H(p)$. Thus the inequality $K(\delta, p) > H(\delta) - (1-R)\log 2$ required by Theorem 4.1 becomes simply $H(p) < (1-R)\log 2$, or $H_2(p) < 1 - R$, where $H_2(p)$ is the binary entropy function. Thus we have proved

5.1 Theorem. *The ensemble of random linear codes of rate R is good on a BSC with crossover probability p if $H_2(p) < 1 - R$.*

The idea of the proof is illustrated in Figure 3, where we see the function $K(\delta, 0.174)$ just touching the $r(\delta)$ curve of Figure 2. This shows that the threshold for the ensemble of $R = 1/3$ linear codes is $p = 0.174$, which reflects the fact that $H_2(0.174) = 1 - 2/3$.

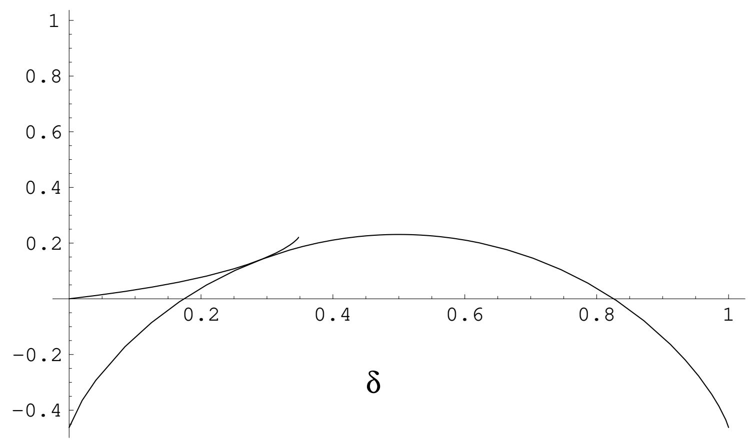

Figure 3. The function $r(\delta)$ for the ensemble of $R = 1/3$ linear codes, together with the function $K(\delta, p)$ for $p = 0.174$.

Of course, Theorem 5.1 is just Shannon's theorem for linear codes on the BSC. We have included it only to demonstrate that Theorem 4.1 is powerful enough to reproduce Shannon's theorem. In the next two sections we will apply it to more interesting ensembles.

6. The Gallager Ensemble.

In this section, we discuss the application of Theorem 4.1 to the ensemble of (j, k) low-density parity-check codes defined by Gallager [4].[2] In brief, every code in Gallager's (j, k) ensemble is defined by a parity-check matrix which has j ones in each column and k ones in each row. The rate of each code in the ensemble is at least $R_{j,k} = 1 - (j/k)$.

The spectral shape $r_{j,k}(\delta)$ for the (j, k) ensemble was determined by Gallager. It can be expressed in parametric form, as follows:

$$\delta_{j,k}(s) = \frac{1}{k}\frac{\partial \mu}{\partial s}(s, k)$$

$$r_{j,k}(s) = \frac{j}{k}\left(\mu(s, k) - s\frac{\partial \mu}{\partial s}(s, k) + (k-1)\log 2\right) - (j-1)H\left(\frac{1}{k}\frac{\partial \mu}{\partial s}(s, k)\right)$$

[2] There are numerous ways to define this ensemble. The definiton we follow was given by Gallager [4, Section 2.2], and differs, e.g. from the ensemble analyzed by MacKay in [7, Section II].

where the parameter s ranges from $-\infty$ to $+\infty$, $H(x)$ is the entropy function $-(x \log x + (1-x)\log(1-x))$, and the function $\mu(s,k)$ is defined by

$$\mu(s,k) \triangleq \log \frac{(1+e^s)^k + (1-e^s)^k}{2^k}.$$

Figure 4 shows the function $r_{j,k}$ for $(j,k) = (3,6)$.

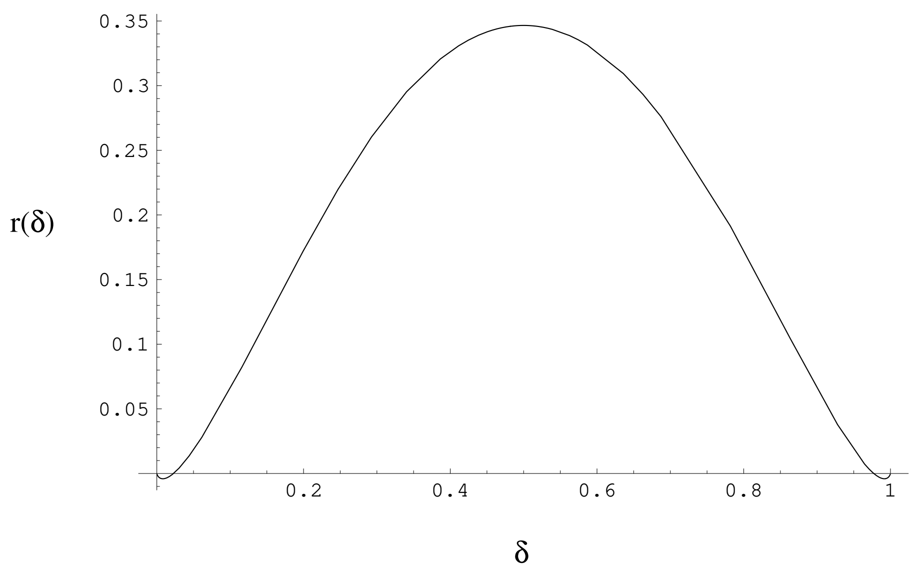

Figure 4. The function $r(\delta)$ for the ensemble of $(3,6)$ LDPC codes.

Given the spectral shape, it is an easy task to apply Theorem 4.1 to find the corresponding BSC ensemble thresholds. A short table of these thresholds, together with the corresponding Shannon limit, is given below.

(j,k)	$R_{j,k}$	$p_{j,k}$	RU limit	Shannon limit
$(3,6)$	1/2	0.0915	0.084	0.109
$(3,5)$	2/5	0.129	0.113	0.145
$(4,6)$	1/3	0.170	0.116	0.174
$(3,4)$	1/4	0.205	0.167	0.214
$(2,3)$	1/3	0.0670	0.0670	0.174
$(2,4)$	1/2	0.0286	0.0286	0.109

For example, consider the "$(3,5)$" line in the table. The corresponding Gallager ensemble consists of codes which have parity-check matrices with 3 ones per column and 5 ones per row. The common rate of the codes in the ensemble is $R = 1 - (3/5) = 2/5$. Using Theorem 4.1, it is calculated that for any BSC with crossover probability $p < 0.129$, the $(3,5)$ ensemble is good, i.e., the average word error probability of the T-decoder approaches 0, as $n \to \infty$. This should be compared to the Shannon limit for the ensemble of all linear codes of rate 2/5 (cf. Theorem 5.1), which is $p = 0.145$, which indicates the price which is paid for having the $(3,5)$ structure. Finally, we note that the Richardson-Urbanke limit [9] for the $(3,5)$ ensemble is $p = 0.113$, i.e., with belief propagation–style iterative decoding, the ensemble decoder error probability approaches 0 if and only if $p < 0.113$.

(The values $p_{j,k}$ for $(j,k) = (3,6)$, $(3,5)$, $(4,6)$, and $(3,4)$ given in the above table appear to agree with the values given by Gallager [4] in his Figure 3.5, although he gave no numerical values. However, as we mentioned above, we have been able to show that the thresholds obtained from our Theorem 4.1 are the same as the best obtainable using Gallager's methodology, so we can be sure they are the same.)

We conclude this section with some remarks on the ensemble of $(2,k)$ LDPC codes. Originally dismissed by Gallager because their minimum distance is $O(\log n)$ [4, Theorem 2.5], they are nevertheless quite interesting. Variously called "graph-theoretic," "circuit," or "cycle" codes [8, Section 5.8], [6] because of their close connection to finite undirected graphs, it was shown by Decreusefond and Zémor [3] that the ensemble of $(2,k)$ cycle codes has exact maximum-likelihood BSC coding threshold equal to

$$p^*(k) = \frac{1}{2}\left(1 - \sqrt{1 - \frac{1}{(k-1)^2}}\right). \tag{6.1}$$

Thus for $p < p^*(k)$, the ensemble is good, but for $p > p^*(k)$, the ensemble word error probability approaches 1. Independently, Wiberg [11, Example 5.1] showed that with iterative decoding, the ensemble of $(2,k)$ cycle codes is good for $p < p^*(k)$. Combining these two results, we see that for $(2,k)$ cycle codes, the iterative and maximum-likelihood thresholds are the same, and are given by the formula (6.1). For a complete summary of iterative decoding of cycle codes, including the Gaussian channel, see [5]. In any case, the thresholds obtained from Theorem 4.1 gives thresholds which agree numerically with (6.1), but we have not yet proved this analytically.

7. The Ensemble of Repeat-Accumulate Codes.

In brief, for an integer $q \geq 2$, the ensemble of q-repeat accumulate codes, consists of those codes which can be encoded by the serial concatenation of a q-ary repetition encoder, followed by a pseudorandom permutation, followed by a rate 1 code with (square) generator matrix of generic shape

$$G = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix}.$$

The basic combinatorial fact about the ensemble of (qk,k) RA codes is the following formula for the average number of input words of weight w which are encoded into output words of weight h [2, eq. (5.4)]:

$$\overline{A}^{(qk)}_{w,h} = \frac{\binom{k}{w}\binom{qk-h}{\lfloor qw/2\rfloor}\binom{h-1}{\lceil qw/2\rceil-1}}{\binom{qk}{qw}}. \tag{7.1}$$

It follows then that if $\overline{A}^{(qk)}_h$ denotes the average number of words of weight h in the ensemble,

$$\overline{A}^{(qk)}_h = \sum_{w=1}^{N} \overline{A}^{(qk)}_{w,h}. \tag{7.2}$$

From (7.2), we find that the the spectral shape $r(\delta)$ for the ensemble of q-RA codes is as follows :

$$r(\delta) = \max_{0\le x\le 1/q}\left\{-\frac{q-1}{q}H(qx) + (1-\delta)H\left(\frac{qx}{2(1-\delta)}\right) + \delta H\left(\frac{qx}{2\delta}\right)\right\}. \tag{7.3}$$

Figure 5 shows the $r(\delta)$ curve for the ensemble of $q = 4$ RA codes.

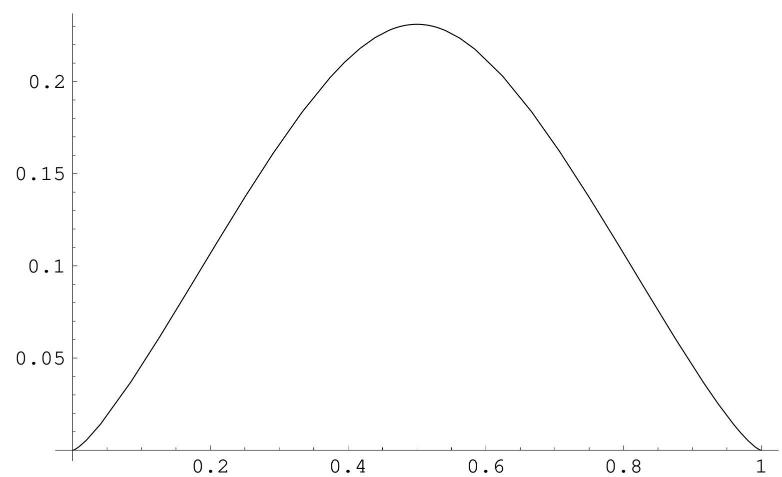

Figure 5. The function $r(\delta)$ for the ensemble of $R = 1/4$ RA codes.

Combining (7.3) with Theorem 4.1, it is a straightforward computation to obtain the thresholds in the following table.

q	R_q	p_q	RU limit	Shannon limit
3	1/3	0.132	0.142	0.174
4	1/4	0.191	0.188	0.215
5	1/5	0.228	0.216	0.243
6	1/6	0.254	0.235	0.264
7	1/7	0.274	0.250	0.281

For example, consider the $q = 3$ line of the table. It indicates that the common rate for all $q = 3$ RA codes is $R = 1/3$, and that this ensemble is good on any BSC with crossover probability $p < 0.132$. By way of comparison, the Shannon threshold for the ensemble of all rate 1/3 linear codes is seen to be $p < 0.174$. Finally, the Richardson-Urbanke iterative decoding threshold [Richardson and Urbanke, private commmunication] is $p < 0.142$. This rather surprising result shows that the T-decoding method does not always give the best possible threshold, which contradicts an otherwise attractive conjecture.

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