

# Decoding bounds

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# 1 Typical Set decoding

The decoding strategy is to only decode defective sets if the defective set is typical. Write  $\Sigma_{n,k}$ , for the collection of sets of size  $k$  out of  $n$  items and  $\theta(S)$  for the vector of all test outcomes then:

$$A_y = \theta^{-1}(S) = \{S \in \Sigma_{n,k} : \theta(S) = \mathbf{y}\} \quad (1)$$

As the probabilities are not equal, we can do better than picking amongst the  $A_y$  with equal probability. Define:

$$\tilde{A}_y = A_y \cap \{\epsilon\text{-typical set}\} \quad (2)$$

for some  $\epsilon$ .

Then decode the largest in probability. I.e.

$$\mathbb{P}(\text{succ}) = \frac{q_i}{\sum_{j=1}^n q_j} \quad (3)$$

Where

$$q_i \leq 2^{N(H-\epsilon)} \quad (4)$$

and:

$$q_j \geq 2^{-N(H+\epsilon)} \quad (5)$$

so,

$$\sum q_j \geq |\tilde{A}_y| 2^{-N(H+\epsilon)} \quad (6)$$

Putting these together:

$$\mathbb{P}(\text{succ}) \leq \frac{2^{-N(H-\epsilon)}}{|\tilde{A}_y| 2^{-N(H+\epsilon)}} = 2^{-N(H-\epsilon)} 2^{N(H+\epsilon)} \quad (7)$$

$$= 2^{-N(H+\epsilon)+N(H+\epsilon)} \quad (8)$$

$$= 2^{-NH+N\epsilon+NH+N\epsilon} \quad (9)$$

$$= \frac{2^{2N\epsilon}}{|\tilde{A}_y|} \quad (10)$$

## 2 AEP for non-iid sequences

**Definition 2.1.** *Given a sequence of  $n$  random variables  $X_1 \dots X_n$  s.t.  $\mathbb{P}(X_i = 1) = p_i$ , and a random variable  $X$  s.t.  $\mathbb{E}X = \frac{k}{n}$ , let  $S_n = n^{-1} \sum_{i=1}^n X_i$ . Then the weak law of large numbers implies:*

$$S_n \rightarrow \mathbb{E}X \quad (11)$$

in probability

Define the random variable,  $Z_i = \log p_i$  with expectation

$$\mathbb{E}Z_i = -p_i \log p_i - (1 - p_i) \log (1 - p_i) = h_2(p_i) \quad (12)$$

and variance:

$$\mathbb{V}Z_i = p_i z_i^2 - \mathbb{E}Z_i \quad (13)$$

$$= p_i (-\log p_i)^2 + (1 - p_i) (-\log 1 - p_i)^2 - \mathbb{E}Z_i \quad (14)$$

$$= (1 - p_i) p_i (\log 1 - p_i - \log p_i)^2 \quad (15)$$

$$= g(p_i) \quad (16)$$

This isn't so surprising as the sequence  $\{X_i\}$  has a Poisson limit (Le Cam's theorem).

Then the WLLN implies:

$$\frac{1}{n} \sum_{i=1}^n Z_i \rightarrow \sum_{i=1}^n h_2(p_i) \quad (17)$$

This result can be refined a little, note that for the sequence  $X_1 \dots X_n$ ,  $\mathbb{E}X_i = p_i$  and that  $\mathbb{V}X_i = p_i(1 - p_i)$ , where  $\mathbb{V}$  denotes the variance. Let  $S_n$  be defined as above, and

$$\mathbb{E}S_n = \frac{1}{n} (p_1 \dots p_n) = \bar{p} \quad (18)$$

$$\mathbb{V}S_n = \frac{1}{n^2} (\mathbb{V}X_1 \dots \mathbb{V}X_n) = \frac{1}{n^2} \sum_{i=1}^n p_i (1 - p_i) \quad (19)$$

Note that  $\mathbb{V}X_i = p_i(1 - p_i) \leq 0.25$  for all  $i$ , and that  $\mathbb{V}S_n \leq 0.25n$ . Using Chebyshev's inequality we have:

$$\mathbb{P}(|S_n - \bar{p}| \leq \epsilon) \leq \frac{\mathbb{V}S_n}{\epsilon^2} \leq \frac{1}{4n\epsilon^2} \quad (20)$$

where  $\epsilon \in (0, 1)$ .

Using the sequence  $\{Z_i\}$ , and defining  $Y_n = n^{-1} \log S_n$  s.t.  $\mathbb{E}Y_n = \sum_{i=1}^n h_2(p_i)$  and  $\mathbb{V}Y_n = n^{-2} \sum \mathbb{V}Z_i = n^{-2} \sum g(p_i)$ , the AEP can be stated as:

$$\mathbb{P}\left(\left|Y_n - \sum_{i=1}^n h_2(p_i)\right| \leq \epsilon\right) \leq \frac{\mathbb{V}Y_n}{\epsilon^2} \quad (21)$$

$$\leq \frac{1}{n^2} \frac{\sum_{i=1}^n g(p_i)}{\epsilon^2} \quad (22)$$

**Theorem 2.1** (Bernstein). *Let  $\{X_i\}_{i=1}^n$  be independent rvs with zero mean and finite variance s.t.  $|X_i| \leq M \forall i$ , write  $L := \sum_{j=1}^N$  then for  $t \geq 0$ :*

$$\mathbb{P}\left(\sum_{i=1}^N X_i \geq t\right) \leq \exp\left(-\frac{t^2}{4L}\right) \quad (23)$$

This using this inequality and equation (16) on the rvs  $\{Z_i\}$ :

$$\mathbb{P}\left(\left(\sum_{i=1}^N Z_i - H(p)\right) \geq t\right) \leq \exp\left(-\frac{t^2}{4 \sum_{i=1}^N g(p_i)}\right) \quad (24)$$

This implies that instead of conditioning over equiprobable sets of size  $\binom{n}{k}$ , we can bound the success probability by:

$$\mathbb{P}(\text{succ}) = \frac{2^T}{2^{\sum \theta(p_i)}} \quad (25)$$

with the conjecture that

$$\theta(\circ) = h_2(\circ) \quad (26)$$

Putting this together with the results from the previous section (after marginalising out all possible sets  $A_y$ ) we get:

$$\mathbb{P}(\text{succ}) \leq 2^{T - \sum \theta(p_i) + 2N\varepsilon} \quad (27)$$

Choosing  $\varepsilon = 1/2N$  gives us:

$$\mathbb{P}(\text{succ}) \leq 2^{T - H(\mathbf{p}) + 1} \quad (28)$$