

## Lecture 14: October 17

Lecturer: Eshan Chattopadhyay

Scribe: Ke Wu

## 14.1 Preliminary and Notation

**Definition 14.1 (Shannon entropy)** Shannon Entropy of random variable  $X$  is defined as:

$$H(X) := \sum_{x \in \text{supp}(x)} p(x) \log\left(\frac{1}{p(x)}\right), p(x) := \Pr[X = x]$$

**Definition 14.2 (Conditional entropy)** The conditional Entropy of random variable  $Y$  given  $X$  is defined as:

$$H(Y|X) := \sum_{x \in \text{supp}(x), y \in \text{supp}(y)} p(x, y) \log\left(\frac{p(x)}{p(x, y)}\right), p(x) := \Pr[X = x], p(x, y) = \Pr[X = x, Y = y]$$

Denote the Shannon entropy of a Bernoulli random variable  $X$  as  $H(p)$ , where  $X$  equals to 1 with probability  $p$ , and 0 with probability  $1 - p$ . Then  $H(p) = p \log\left(\frac{1}{p}\right) + (1 - p) \log\left(\frac{1}{1-p}\right)$ .

**Theorem 14.3 (Chain rule of Shannon entropy)**

$$H(X, Y) = H(X) + H(Y|X)$$

**Proof:** Let  $p(x) = \Pr[X = x]$ ,  $p(x, y) = \Pr[X = x, Y = y]$  and  $p(y|x) = \Pr[Y = y|X = x]$ . Then we have:

$$\begin{aligned} H(X, Y) &= \sum p(x, y) \log\left(\frac{1}{p(x, y)}\right) \quad (\text{by definition}) \\ &= \sum p(x)p(y|x) \left(\log\left(\frac{1}{p(x)}\right) + \log\left(\frac{1}{p(y|x)}\right)\right) \\ &= \sum_x p(x) \left(\sum p(y|x)\right) \log\left(\frac{1}{p(x)}\right) + \sum_x p(x) \left(\sum p(y|x)\right) \log\left(\frac{1}{p(y|x)}\right) \\ &= H(X) + H(Y|X) \end{aligned}$$

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**Corollary 14.4 (Chain rule of  $n$  random variables)**

$$H(X_1, \dots, X_n) = \sum_{i=1}^n H(X_i|X_{<i})$$

where  $X_{<i} = (X_1, \dots, X_{i-1})$ .

**Proof:** By induction on  $n$ .

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## 14.2 Existence of Codes

What kinds of codes exist? We will analyze binary codes. Informally, we want to show that

**Theorem 14.5 (Informal)**  $\exists(n, k, d)_2$  codes where  $k = \Omega(n)$ ,  $d = \Omega(n)$ . That is, there exists binary codes with constant relative rates and constant relative distances.

More formally,

**Theorem 14.6 (Gilbert-Varshamov bound)**  $\forall 0 < \delta < \frac{1}{2}, 0 < \varepsilon \leq 1 - H(\delta)$ , there exists an  $(n, k, d)_2$  code where  $\frac{k}{n} \geq 1 - H(\delta) - \varepsilon$ ,  $\frac{d}{n} \geq \delta$ .

**Proof:** We will use a greedy algorithm to show the existence of claimed binary codes:

### Greedy Algorithm

- $\mathcal{C} \leftarrow \emptyset$
- while  $\exists v \in \{0, 1\}^n$  s.t.  $\Delta(v, \mathcal{C}) \geq d$ , add  $v$  to  $\mathcal{C}$ .
- Output  $\mathcal{C}$ .

**Definition 14.7 (Hamming Ball)**  $\forall v \in \{0, 1\}^n, r \geq 0$ , define  $Ball(v, r) := \{w \mid \Delta(v, w) \leq r\}$ .

**Definition 14.8 (Volume of Ball)**  $\forall n \in \mathbb{N}, r \leq n$ , define  $Vol(n, r) := |Ball(0^n, r)|$ . Notice that  $\forall v \in \{0, 1\}^n, |Ball(v, r)| = |Ball(0^n, r)|$ .

**Claim 14.9**

$$\bigcup_{c \in \mathcal{C}} Ball(c, d-1) = \{0, 1\}^n$$

**Proof of:**[14.9]

Suppose  $v \in \{0, 1\}^n$  is not in this union, then  $\Delta(v, \mathcal{C}) \geq d$ . The greedy algorithm would thus add  $v$  to  $\mathcal{C}$ , which indicates that  $v$  should then be included in this union. And we get a contradiction.  $\square$

Using claim 14.9 we know that  $Vol(n, d-1) \cdot |\mathcal{C}| \geq 2^n$ , which means that  $Vol(n, d-1) \cdot 2^k \geq 2^n$ . Now we are left with the evaluation  $Vol(n, d-1)$ . We'll show the following bound.

**Claim 14.10**  $Vol(n, r) \leq 2^{nH(\frac{r}{n})}, \forall r \leq \frac{n}{2}$

**Proof of:**[14.10]

Let  $X = (X_1, \dots, X_n)$  be a random variable that is uniform over  $Ball(0^n, r)$ . Then the entropy of  $H(X) = \log(Vol(n, r))$ . Notice that

$$\begin{aligned} H(X_1, \dots, X_n) &= \sum_{i=1}^n H(X_i | X_{<i}) \\ &\leq \sum_{i=1}^n H(X_i) = nH(X_1) \\ &\leq n \cdot H\left(\frac{r}{n}\right) \end{aligned}$$

The last step holds because  $n \cdot \mathbb{E}[X_1] = \mathbb{E}[\sum_{i=1}^n X_i] \leq r$ , which means that  $\mathbb{E}[X_1] = \Pr[X_1 = 1] \leq \frac{r}{n}$ . Thus  $Vol(n, r) \leq 2^{nH(\frac{r}{n})}$ .  $\square$

Therefore we have  $2^{n-k} \leq Vol(n, d-1) \leq 2^{nH(\frac{d}{n})}$ , which means that  $1 - \frac{k}{n} \leq H(\frac{d}{n})$ . Thus we have  $\frac{k}{n} \geq 1 - H(\delta) - \varepsilon$ .  $\blacksquare$

### 14.3 Unique Decoding of RS Codes

**Definition 14.11** Define  $Poly_{\leq w} :=$  univariate polynomials over  $\mathbb{F}_q$  of degree less than or equal to  $w$ .

Then the message space of RS code is  $Poly_{\leq k-1} : p(x) = \sum_{i=0}^{k-1} \alpha_i x^i$  where  $(\alpha_0, \dots, \alpha_{k-1}) \in \mathbb{F}_q^k$ . The encoding is the evaluation of this polynomial on  $n$  distinct points:  $(p(\beta_1), \dots, p(\beta_n))$ . Observe that this is a linear code.

**Decoding question:** let  $(f(\beta_1), f(\beta_2), \dots, f(\beta_n))$  for some  $f : \mathbb{F}_q \mapsto \mathbb{F}_q$  be a corrupted codeword. If the number of errors is small, can we recover  $p$ ?

Information theoretically, we can recover up to  $\lfloor \frac{d-1}{2} \rfloor$  errors. The intuition is simple: if we have  $e$ , where  $\lfloor \frac{d-1}{2} \rfloor$ , then the corrupted codeword  $f$  might be within  $e$  distance from two codewords, which makes it impossible for the decoder to uniquely decode from  $f$ . As in the figure,  $f$  is within distance  $e$  to  $p_1$  and  $p_2$  if  $e > \lfloor \frac{d-1}{2} \rfloor$ :

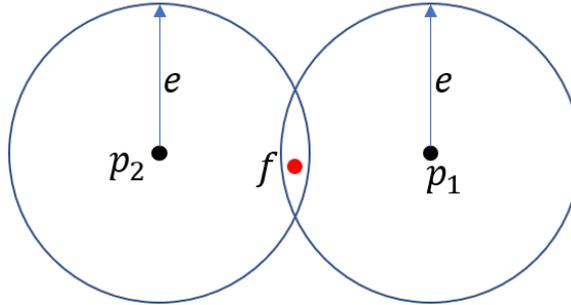


Figure 14.1:  $\Delta(p_1, p_2) = d, e > \lfloor \frac{d-1}{2} \rfloor, \Delta(f, p_1) \leq e, \Delta(f, p_2) \leq e$ , so the decoder doesn't know which one is being modified.

Formally, the decoding problem is defined as:

**Problem 14.12** given a function  $f : \mathbb{F}_q \mapsto \mathbb{F}_q$ , and the promise that  $\exists p \in Poly_{\leq k-1}$  s.t. the  $\frac{e}{q} = \Pr_{x \in \mathbb{F}_q} [f(x) \neq p(x)] \leq \lfloor \frac{d-1}{2} \rfloor \frac{1}{q}$ , can we recover  $p(x)$  in  $poly(n)$  time?

#### 14.3.1 Welch-Berlekamp Algorithm

For convenience, define  $T = \{\beta_i : f(\beta_i) \neq p(\beta_i)\}$  to be the set of all corrupted positions. Then  $|T| \leq e$ .

**Definition 14.13 (Error-locator polynomial)**  $E(x)$  is a polynomial over  $\mathbb{F}_q$  such that  $E(\beta_i) = 0$  iff  $\beta_i \in T$ .

For example, the error locator polynomial can be defined as  $E(x) = \prod_{\beta_i \in T} (x - \beta_i)$ .

**Observation 14.14**

$$\forall x \in \mathbb{F}_q, E(x)p(x) = E(x)f(x) \quad (*)$$

As  $E(x)$  is of degree  $e$  and the degree of  $p(x)$  is smaller than or equal to  $k-1$ ,  $(*)$  is a system of  $n$  equations on  $e+k-1 < n$  variables which are the unknown coefficients of  $E(x)$  and  $p(x)$ . Thus, solving this system would give us the error locator polynomial  $E(x)$  as well as the correct codeword  $p(x)$ . However,  $(*)$  is a quadratic system, which is a NP-hard problem in general. We need to figure out an alternative way of decoding in the next lecture.