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# 1. Basic knowledge of coding

#### 1.1. Introduction

**Definition 1:** a **source** is a finite set S together with a set of random variables  $(X_1, X_2, ...)$  whose range is S.

If  $P(X_n = S_i)$  only depends on i and not on n then we say the source is **stationary** and if the  $X_n$  are independent then it's **memoryless**.

Insert example here

**Definition 2:** Let  $\mathcal{T}$  be a finite set called **alphabet**. A map  $\mathfrak{C}: \mathbb{S} \longrightarrow \bigcup_{n \geq 1} T^n$  is called a **code**.

If |T| = r then  $\mathfrak{C}$  is a r-ary code.

A code extends from  $\mathbb{S}$  to  $T \cup T^2 \cup ...$  to  $\mathbb{S} \cup \mathbb{S}^2 \cup ...$  to  $T \cup T^2 \cup ...$  in obvious way.

insert example here

**Definition 3:** The average word-length of a code  $\mathfrak{C}$  is  $L(\mathfrak{C}) := \sum_{i=1}^{n} p_i l_i$  where  $l_i$  is the length of the image of the symbol of  $\mathbb{S}$ , which is emitted with probability  $p_i$ .

For now, we write  $\mathfrak{C}$  to be the image of  $\mathfrak{C}$ .

### 1.2. Uniquely decodeable codes

**Definition 4:** If for any sequencies  $u_1...u_n = v_1...v_m$  in  $\mathfrak{C}$  implies m = n and  $u_i = v_i$  for i = 1, ..., n then we say that  $\mathfrak{C}$  is **uniquely decodeable**.

insert example here

insert example here

insert example here

Let  $\mathfrak{C}_0 = \mathfrak{C}$ :

- $\mathfrak{C}_n := \{ \omega \in T \cup T^2 \cup ... | u\omega = v \text{ for some } u \in \mathfrak{C}_{n-1}, v \in \mathfrak{C} \text{ or } u\omega = v \text{ for some } u \in \mathfrak{C}, v \in \mathfrak{C}_{n-1} \}$
- ullet  $\mathfrak{C}_{\infty}:=\bigcup_{k\geq 1}\mathfrak{C}_k$

Since everythig is finite either  $\mathfrak{C}_m = \emptyset$  for some m and then  $\mathfrak{C}_n = \emptyset$  for  $n \geq m$  or it will be periodic and start repeating.

**Theorem 1:**  $\mathfrak{C}$  is uniquely decodeable  $\iff \mathfrak{C} \cap \mathfrak{C}_{\infty} = \emptyset$ .

proof: Insert proof here

insert example here

insert example here

insert example here

**Definition 5:** A code is a **prefix-code** if no codeword is prefix of another (ie.  $\mathfrak{C}_1 = \emptyset$ ).

A prefix code is uniquely decodeable.

**Theorem 2:** (Kraft's inequality)  $\exists r$ -ary prefix code with word lengths  $l_1, l_2, ..., l_q \iff$ 

$$\sum_{i=1}^{q} r^{-l_i} \le 1$$

proof: Insert proof here

insert example here

**Theorem 3:** (McMillan's inequality)  $\exists$  r-ary uniquely decodeable code with word lengths  $l_1, l_2, ..., l_q \iff$ 

$$\sum_{i=1}^{q} r^{-l_i} \le 1$$

proof: Insert proof here

#### 1.3. Optimal codes

Let be  $\mathbb S$  a source with symbols  $s_1,...,s_q$  emitted with probabilities  $p_1,...,p_q$  and  $\mathfrak C$  is a code which encodes  $s_i$  with a codeword length  $l_i$ . Recall  $L(\mathfrak C) = \sum_{i=1}^q p_i l_i$ .

**Definition 6:** An **optimal code** for  $\mathbb S$  is an uniquely decodeable code  $\mathfrak D$  such that  $L(\mathfrak C) \geq L(\mathfrak D)$  for all uniquel decodeable code  $\mathfrak C$ .

inset example here

insert example here

**Definition 7:** A code constructed in this way is called a **Hoffman code**.

insert example here

#### 1.4. Extension of sources

## 2. Introduction

**Definition 1:** the **information** coveyed by a source is a function  $I: S \to [0, \infty)$  where S is a **source** <sup>1</sup> with the properties:

- $I(s_i)$  is a decreasing function of the propability  $p_i$ , with  $I(s_i) = 0$  if  $p_i = 1$ .
- $I(s_i s_j) = I(s_i) + I(s_j)$ , ie.the information geined by two symbols is the sum of the information obtained from each where the source has symbols  $s_1, ..., s_q$  emitted with probabilities  $p_1, ..., p_q$ .

**Lemma 1:**  $I(s_i) = -\log_r p_i$  for some r.

proof: Insert proof here

**Definition 2:** The r-ary entropy  $H_r(S)$  of a source S is the average information coveyed by S.

$$H_r(S) := -\sum_{i=1}^q p_i \log_r p_i$$

, by convenction  $x \log_r x$  evaluated at 0 is 0.

Insert five examples

## 3. Properties of the entropy funcion

**Theorem 1:**  $H_r(S) \leq \log_r q$  with equality if and only iff S is the source where each symbol is emitted with probability 1/q.

proof: Insert proof here

**Theorem 2:**  $H_r(S) \leq L(C)$  for unique decodeable code C.

proof: Insert proof here

## 4. Shannon-Fano Code

Let S be the source with symbols  $s_i$  and probabilities  $p_i$ . Let  $l_i := \lceil \log_r 1/p_i \rceil$ .

Then: 
$$\sum_{i=1}^{q} r^{-l_i} \le \sum r^{-\log_r 1/p_i} = \sum p_i = 1$$

**Definition 3:** by Kraft exists a prefix code with woed length  $l_1, l_2, ..., l_1$ . This code is called **Shannon-Fano code**.

<sup>&</sup>lt;sup>1</sup>A **source** is a finite set S together with a sequence of random variables  $X_i$  whose range is S

Inert example here

**Lemma 2:** For the Shannon-Fano code  $C: H_r(S) \leq L(C) < H_r(S) + 1$ .

proof: Insert proof here

#### 5. Product of sources

Let S and T be two memoryless sources, S with symbols  $s_i$  and probabilities  $p_i$  and T with symbols  $t_j$  and probabilities  $q_j$ .

**Definition 4:** The **product source**  $S \times T$  is a source with symbols  $s_i t_j$  and probabilities  $p_i q_j$ .

Theorem 3:  $H_r(S \times T) = H_r(S) + H_r(T)$ .

proof: Insert proof here

Corollary 1:  $H_r(S^n) = nH_r(S)$ .

**Theorem 4: Noiseless Coding** The average word length  $L_n$  of an optiml code of  $S^n$  satisfies:

$$\frac{L_n}{n} \longrightarrow H_r(S), n \to \infty$$

proof: Insert proof here

some examples

### 6. Markov Chains

**Definition 4:** A Markov Chain is a sequency of random variables where  $X_{n+1}$  depends only for  $X_n$ .

$$P(X_{n+1} = s_j | X_n = s_j) = p_{i,j}$$

This can be represented in a direct graph and also by a matrix  $P := (p)_{i,j}$ .

Suppose  $u_0$  is the vector which describes the initial distribution, ie. the *i*-th coordinate of  $u_0$  is probability we start at  $s_i$ . Probability of beeing in the *i*-th state after r steps is the *i*-th coordinate of  $u_0P^r$ .

**Theorem 5:** if  $\exists r \in \mathbb{N}$  such that  $P^r$  has no zero entries, then  $u_0P^r \longrightarrow u$ , as  $n \to \infty$ .

**Definition 5:** This vector u is called the **stationary distribution**. It is normalised eigenvector of  $P^t$  with eigenvalue 1, ie.  $u_j = \sum_i p_{i,j} u_i$  and  $\sum_j u_j = 1$ .

**Definition 6:** If P is the matrix of a Markov Chain and  $\exists r$  such that  $P^r$  has non zero entries then we say that the Markov Chain is **regular**.

## 7. Sources with memory

Suppose S is a Markov Chain source with random variables  $X_1, X_2, ...$  such that

$$P(X_{n+1} = s_j | X_n = s_j) = p_{i,j}$$

**Definition 7:** *S* is **not memoryless**, but it is stationary.

**Theorem 6:** suppose S is a regular Markov Chain source with stationary distribution  $u = (u_1, ..., u_j)$ . Let S' be the stationary memoryless source with the same source elements as S (where  $s_i$  is emmitted with probability  $w_i$ ). Then:

$$H_r(S) \leq H_r(S')$$

*proof:* Insert proof here