Code Theory

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1. Memoryless resources

1.1. Sources and average word length

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

If $P(X_n = \mathcal{S}_i)$ 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 $\mathfrak{C} : \mathbb{S} \longrightarrow \mathbb{U}_{n\geq 1} T^n$ 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-lenght** 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 $\mathfrak{C}_0 = \mathfrak{C}$:

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

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 $l_1, l_2, .., l_q \iff$

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

proof: Insert proof here

insert example here

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

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

proof: Insert proof here

1.3. Optimal codes

Let be $\mathcal{S}$ 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 $\mathcal{S}$ 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

Construct the r-arg Huffman code we sum together (at each step) the r smallest probabilities.

For this to work we need $q \equiv 1(r-1)$. Recall q is the number of symbols in the source. If not, then we add symbols with probabilities zero so that it is.

insert example here

Lemma 1: Every source $\mathcal{S}$ has an optimal binary code $\mathfrak{D}$ in which two of the longest codewords are **siblings**, ie. $\exists x$ (a string) such that $x_0, x_1 \in \mathfrak{D}$.

proof: Insert proof here

Theorem 4: The Huffman code is an optimal code.

proof: Insert proof here

1.4. Extension of sources

Given a source $\mathcal{S}$ we define $\mathcal{S}^n$ the source with $|\mathcal{S}|^n$ symbols, typically $s_1, ..., s_n$, emitted with $p_1, ..., p_n$ probabilities.

insert example here

2. Information and entropy

2.1. Definitions

Definition 1: the **information** coveyed by a source is a function $I : S \to [0, \infty)$ where S is a **source** [1] 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

2.2. 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

2.3. 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: $\sum_{i=1}^{q} r^{-l_i} \leq \sum r^{-\log_r 1/p_i} = \sum p_i = 1$

[1] A **source** is a finite set S together with a sequence of random variables X_i whose range is S

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

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

2.4. 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

2.5. 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 $u_0 P^r$.

Theorem 5: if $\exists r \in \mathbb{N}$ such that P^r has no zero entries, then $u_0 P^r \longrightarrow u$, 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**.

2.6. 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 $u = (u_1, ..., u_)$. 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

3. Information channels

3.1. Channel matrix

Let $\mathcal{A}$ be a stationary memoryless source with random variables $X_1, X_2, \ldots$ where $P(X_n = a_i) = p_i$ for $a_i \in \mathcal{A}$.

Suppose we transmit $\mathcal{A}$ through a channel Γ.

Let $\mathcal{B}$ be a source with random variables $Y_1, Y_2, \ldots$ where $P(Y_n = b_j) = q_j$

For b_j emerging from the channel:

$$\mathcal{A} \overset{\Gamma}{\overbrace{\longrightarrow}} \mathcal{B}$$

Definition 1: The **channel** is defined by a matrix (p_{ij}) where $p_{ij} = P(X_n = b_j | X_n = a_i)$ the probability we recieve b_j given that a_i was sent, p_{ij}**-forward probabilities**. The **backwards probabilities** are $q_{ij} = P(X_n = a_i | Y_n = b_j)$ and **joint prababilities** $r_{ij} = P(X_n = a_i, Y_n = b_j)$

insert example here

inser example here (binary eraure channel)

3.2. System Entropies and mutual information

Definition 2: We define the **input entropy** as:

$$H(\mathcal{A}) := -\sum_i p_i \log(p_i)$$

Definition 3: We define the **output entropy** as:

$$H(\mathcal{B}) := -\sum_j q_j \log(q_j)$$

We suppress the r (base) in the $\log_r$ but it's always the same for every one.

Given that we have recived $b_j \in \mathcal{B}$, $H(\mathcal{A}|Y_n = b_j) = -\sum_i q_{ij} \log(q_{ij})$.

This is relling us the average information of $\mathcal{A}$ knowing that $Y_n = b_j$.

If $H(\mathcal{A}|Y_n = b_j) = 0$ then $\exists m$ such that $q_{ij} = 0$ for all $i \neq m$ and $q_{ij} = 1$ if $i = m$, ie. $P(X_n = a_m | Y_n = b_j) = 1$, ie. if we recieve b_j then we know that a_m was sent.

If $H(\mathcal{A}|Y_n = b_j) = H(\mathcal{A})$ then we learn nothing about $\mathcal{A}$ when we recieve b_j and this occurs when $q_{ij} = P(X_n = a_i | Y_n = b_j) = P(X_n = a_i) = p_i$.

Definition 4: Averaging over $b_j \in \mathcal{B}$ we get the **condicional entropy**:

$$H(\mathcal{A}|\mathcal{B}) := -\sum_j P(Y_n = b_j) H(\mathcal{A}|Y_n = b_j) = -\sum_{i,j} q_j q_{ij} \log q_{ij}$$

Similary:

$$H(\mathcal{B}|\mathcal{A}) := -\sum_{i,j} p_i p_{ij} \log p_{ij}$$

Definition 5: The **joint entropy**:

$$H(\mathcal{A}, \mathcal{B}) := -\sum_{i,j} r_{ij} \log r_{ij}$$

insert example here

Theorem 1: For sources $\mathcal{A}$ and $\mathcal{B}$:

$$H(\mathcal{A}, \mathcal{B}) = H(\mathcal{A}|\mathcal{B}) + H(\mathcal{B}) = H(\mathcal{B}|\mathcal{A}) + H(\mathcal{A})$$

proof: Insert proof here

Definition 6: We define the **mutual information** as the amount of information about $\mathcal{A}$ we have learnt from $\mathcal{B}$ and vice-versa:

$$I(\mathcal{A}, \mathcal{B}) := H(\mathcal{B}) - H(\mathcal{B}|\mathcal{A}) = H(\mathcal{A}) - H(\mathcal{A}|\mathcal{B})$$

If $H(\mathcal{A}) = H(\mathcal{A}|\mathcal{B})$ then $\mathcal{B}$ tells us nothing about $\mathcal{A}$, so $I(\mathcal{A}, \mathcal{B}) = 0$. This is an unrialiable channel and useless as a mean of communication.

If $H(\mathcal{A}|\mathcal{B}) = 0$ then knowing $\mathcal{B}$ we know everythin about $\mathcal{A}$, so $I(\mathcal{A}, \mathcal{B}) = H(\mathcal{A})$. This is the perfect situation because when we recive something, we know exactly what was sent.

insert example here

3.3. Extension of noiseless coding theorem to information channels

We have proved that given a source $\mathcal{A}$ we can find an encoding of $\mathcal{A}^n$ such that the average word lenght L_n satisfies $\frac{L_n}{n} \longrightarrow H(\mathcal{A})$.

$\mathcal{A} \longrightarrow \mathcal{B}$, imagine we know $\mathcal{B}$.

Lemma 1: $H(\mathcal{A}^n|\mathcal{B}^n) = nH(\mathcal{A}|\mathcal{B})$

proof: EXERCISE

Theorem 2: if $\mathcal{B}$ is know then we can find encodings of $\mathcal{A}^n$ such that the average word length L_n satisfies $\frac{L_n}{n} \longrightarrow H(\mathcal{A}|\mathcal{B})$.

proof: Insert proof here

3.4. Decision rules

$$\mathcal{A} \overset{\Gamma}{\hookrightarrow} \mathcal{B}$$

Where $\mathcal{A}$ is the **input**, $\mathcal{B}$ is the **output** and Γ is the **channel**.

The channel is given by a matrix (p_{ij}), $p_{ij} = P(Y_n = b_j | X_n = a_i)$. We defined $r_{ij} = P(X_n = a_i | X_n = b_j)$.

So if we recive b_J we should "decode" b_j as a_{j*} where $r_{j*j} \geq r_{ij}$ for all i.

Definition 7: We would define our decision $\Delta : \mathcal{B} \longrightarrow \mathcal{A}$ as $\Delta(b_j) := a_{j*}$, this is called the **ideal observer rule**.

Howecer, most likely we only know p_{ij}'s.

Definition 8: In **maximun likelihood decoding** we use the decision rule $\Delta(b_j) := a_{j*}$, where $p_{j*j} \geq p_{ij}$ for all i.

Definition 9: The **average probability of a correct decoding** is:

$$P_{cor} := \sum_j q_j q_{j*j} - \sum_j r_{j*j}$$

Remind $q_{ij} = P(X_n = a_i | Y_n = b_j)$. Given that we recived b_j if we dcode it as a_{j*} then the probability we have decoded correctly is $P(X_n = a_{j*} | Y_n = b_j) = q_{j*j}$

3.5. Improving reliability

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$$\begin{pmatrix} hola & hola \\ hola & hola \end{pmatrix}$$

3.6. Rates of transmision and Hamming distance

noindent Suppose $\mathcal{A}$ is a source with r symbols. By extending the source, consider $\mathcal{C}$ to be a subset of $\mathcal{A}^n$.

Definition 10: The **(transmision) rate of** $\mathcal{C}$ is:

$$R := \frac{\log_r |\mathcal{C}|}{n}$$

By increasing n in the previous exercise we can make $P_{cor} \longrightarrow 1$. However $R \longrightarrow 0$ since $|\mathcal{C} = \frac{\log_2 2}{n} \longrightarrow 0$.

Definition 11: The **capacity of a channel** Γ is:

$$\Lambda = \max_{\mathcal{A},\mathcal{B}} I(\mathcal{A},\mathcal{B})$$

Maximising over $\mathcal{A},\mathcal{B}$ means we can vary p_i's and q_j's.

Since $\mathcal{C}$ is a subset of $\mathcal{A}^n$ the rate tell us how many bits od information we can send in n bits (it is Rn).

Lemma 2: The capacity of a binary symetric channel $\begin{pmatrix} \phi & 1-\phi \\ 1-\phi & \phi \end{pmatrix}$ is $\Lambda = 1 + \phi \log_2 \phi + (1-\phi)\log_2 (1-\phi)$.

proof: Insert proof here

Definition 12: For any $u, v \in \mathcal{A}^n$, the **Hamming distance** is $d(u,v) :=$ number of cordinates where u and v differ.

Lemma 3: The Hamming distande satisfies the triangle inequality $d(u,v) \leq d(u,w) + d(w,v)$

proof: Insert proof here

Lemma 4: Fot the binary symmetric channerl, maximun likelihood decoding is $\Delta(v) = u$, where u is the closest element of $\mathcal{C}$ with respect the Hamming distance.

proof: Insert proof here

Definition 13: in general this decoding is called **nearest neighbour decoding**.

Lemma 5: For $0 < \lambda < \frac{1}{2}$:

$$\sum_{i=0}^{\lambda n} \binom{n}{i} \leq 2^{n(-\lambda \log(\lambda) - (1-\lambda)\log(1-\lambda))}$$

proof: Insert proof here

Theorem 2: (**Shannon**) Let $\delta, \varepsilon > 0$. For all sufficiently large n there is a code of length n and rate R satisfying $\Lambda - \varepsilon < R < \Lambda$ together with a decision rule Δ such that $P_{cor} \longrightarrow 1 - \delta$.

proof: Insert proof here (ONLY FOR BINARY SYMETRIC CHANNEL)

Lemma 6: For an input source $\mathcal{A}$ and output source $\mathcal{B}$ and decision rule $\Delta(b_j) = a_{j*}$.

$$H(\mathcal{A}|\mathcal{B}) \leq -P_{cor}\log(P_{cor}) - (1-P_{cor})\log(1-P_{cor}) + (1-P_{cor})(\log|\mathcal{C}| - 1)$$

where $\mathcal{C}$ is the set of input source elements emitted with non zero probability.

Theorem 3: If $\Lambda^{`} > \Lambda$ and we fix the input probability distribution is uniform then ther is no sequence of codes $C_n$ of rate $R$ satisfying $\Lambda^{`} - \varepsilon < R < \Lambda^{`}$ such that $P_{cor} \longrightarrow 1$ as $n \to \infty$.

proof: Insert proof here

4. Finite fields

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5. Block codes

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7. Cyclic codes

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Decision problem, yes/no problem

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9. Alternant codes

10. Low density parity check codes

10.1. Bipartite graphs with the expander property

10.2. Low density parity check (LDPC) codes

10.3. Belief propagation

11. P-adic codes

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11.1. P-adic numbers

11.2. Polynomials over $\mathbb{Q}_p$