Information Theory Chapter3: Source Coding

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Communication Channel

from an information theoretic point of view

Variable Length Encoding

Given some source alphabet $\mathcal{X} = \{x_1, \ldots, x_m\}$, code alphabet $\mathcal{Y} = \{y_1, \ldots, y_d\}$.

Aim:

For each character x_1, \ldots, x_m find a code word formed over \mathcal{Y} .

Formally: Map each character $x_i \in \mathcal{X}$ uniquely onto a "word" over \mathcal{Y} .

Definition 3.1.

An injective mapping

$$
g: \mathcal{X} \to \bigcup_{\ell=0}^{\infty} \mathcal{Y}^{\ell}: x_i \mapsto g(x_i) = (w_{i1}, \ldots, w_{in_i})
$$

is called *encoding.* $g(x_i) = (w_{i1}, \ldots, w_{in_i})$ is called *code word* of character x_i, n_i is called *length* of code word *i*.

Variable Length Encoding

Example:

Hence, separability of concatenated words over $\mathcal Y$ is important.

Variable Length Encoding

Definition 3.2.

An encoding g is called uniquely decodable $(u.d.)$ or uniquely decipherable, if the mapping

$$
G:\bigcup_{\ell=0}^{\infty}\mathcal{X}^{\ell}\rightarrow\bigcup_{\ell=0}^{\infty}\mathcal{Y}^{\ell}:\big(a_1,\ldots,a_k\big)\mapsto\big(g(a_1),\ldots,g(a_k)\big)
$$

is injectiv.

Example:

Use the previous encoding g_3

 $(g_3$ is a so called prefix code)

Prefix Codes

Definition 3.3.

A code is called *prefix code*, if no complete code word is prefix of some other code word, i.e., no code word evolves from continuing some other.

Formally: $\boldsymbol{a}\in\mathcal{Y}^k$ is called prefix of $\boldsymbol{b}\in\mathcal{Y}^l,\ k\leq l,$ if there is some $c\in\mathcal{Y}^{l-k}$ such that $b = (a, c)$.

Theorem 3.4.

Prefix codes are uniquely decodable.

More properties:

- \triangleright Prefix codes are easy to construct based on the code word lengths.
- \triangleright Decoding of prefix codes is fast and requires no memory storage.

Next aim: characterize uniquely decodable codes by their code word lengths.

Kraft-McMillan Theorem

Theorem 3.5. (a) McMillan (1959), b) Kraft (1949))

a) All uniquely decodable codes with code word lengths n_1, \ldots, n_m satisfy

b) Conversely, if $n_1, \ldots, n_m \in \mathbb{N}$ are such that $\sum_{j=1}^m d^{-n_j} \leq 1$, then there exists a u.d. code (even a prefix code) with code word lengths n_1, \ldots, n_m .

Example:

For g_3 : $2^{-1} + 2^{-2} + 2^{-3} + 2^{-3} = 1$ For g_4 : $2^{-1} + 2^{-2} + 2^{-2} + 2^{-2} = 5/4 > 1$

 g_4 is not u.d., there is no u.d. code with code word lengths 1,2,2,2.

Kraft-McMillan Theorem, Proof of b)

Assume $n_1 = n_2 = 2$, $n_3 = n_4 = n_5 = 3$, $n_6 = 4$. Then $\sum i = 1^6 = 15/16 < 1$

Construct a prefix code by a binary code tree as follows.

The corresponding code is given as

x_i	x_1	x_2	x_3	x_4	x_5	x_6
$g(x_i)$	11	10	011	010	001	0001

Average Code Word Length

Given a code $g(x_1), \ldots, g(x_m)$ with code word lengths n_1, \ldots, n_m . Question: What is a reasonable measure of the "length of a code"?

Definition 3.6.

The *expected code word length* is defined as

$$
\bar{n} = \bar{n}(g) = \sum_{j=1}^{m} n_j p_j = \sum_{j=1}^{m} n_j P(X = x_j)
$$

Example:

Noiseless Coding Theorem, Shannon (1949)

Theorem 3.7.

Let random variable X describe a source with distribution $P(X = x_i) = p_i$, $i = 1, ..., m$. Let the code alphabet $\mathcal{Y} = \{y_1, ..., y_d\}$ have size d.

a) Each u.d. code g with code word lengths n_1, \ldots, n_m satisfies

 $\bar{n}(g)$ > $H(X)$ /log d.

b) Conversely, there is a prefix code, hence a u.d. code g with

 $\overline{n}(g) \leq H(X)/\log d + 1.$

Proof of a)

For any u.d. code it holds by McMillan's Theorem that

$$
\frac{H(X)}{\log d} - \bar{n}(g) = \frac{1}{\log d} \sum_{j=1}^{m} p_j \log \frac{1}{p_j} - \sum_{j=1}^{m} p_j n_j
$$
\n
$$
= \frac{1}{\log d} \sum_{j=1}^{m} p_j \log \frac{1}{p_j} + \sum_{j=1}^{m} p_j \frac{\log d^{-n_j}}{\log d}
$$
\n
$$
= \frac{1}{\log d} \sum_{j=1}^{m} p_j \log \frac{d^{-n_j}}{p_j}
$$
\n
$$
= \frac{\log e}{\log d} \sum_{j=1}^{m} p_j \ln \frac{d^{-n_j}}{p_j}
$$
\n
$$
\leq \frac{\log e}{\log d} \sum_{j=1}^{m} p_j \left(\frac{d^{-n_j}}{p_j} - 1\right)
$$
\n
$$
\leq \frac{\log e}{\log d} \sum_{j=1}^{m} \left(d^{-n_j} - p_j\right) \leq 0
$$

Proof of b) Shannon-Fano Coding

W.l.o.g. assume that $p_i > 0$ for all j.

Choose integers n_j such that $d^{-n_j} \leq p_j < d^{-n_j+1}$ for all j . Then

$$
\sum_{j=1}^m d^{-n_j} \leq \sum_{j=1}^m p_j \leq 1
$$

such that by Kraft's Theorem a u.d. code g exists. Furthermore,

$$
\log p_j<(-n_j+1)\log d
$$

holds by construction. Hence

$$
\sum_{j=1}^m p_j \log p_j < (\log d) \sum_{j=1}^m p_j(-n_j+1),
$$

equivalently,

$$
H(X) > (\log d) \left(\bar{n}(g) - 1 \right).
$$

Compact Codes

Is there always a u.d. code g with

$$
\bar{n}(g) = H(X)/\log d?
$$

No! Check the previous proof. Equality holds if and only if $p_j = 2^{-n_j}$ for all $i = 1, \ldots, m$.

Example. Consider binary codes, i.e., $d = 2$. $\mathcal{X} = \{a, b\}$, $p_1 = 0.6$, $p_2 = 0.4$. The shortest possible code is $g(a) = (0), g(b) = (1).$

$$
H(X) = -0.6 \log_2 0.6 - 0.4 \log_2 0.4 = 0.97095
$$

$$
\bar{n}(g) = 1.
$$

Definition 3.8.

Any code of shortest possible average code word length is called compact.

How to construct compact codes?

Huffman Coding

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Huffman Coding

A compact code g^* is given by:

It holds (log to the base 2):

 $\bar{n}(g^*) = 5 \cdot 0.05 + \cdots + 2 \cdot 0.3 = 2.75$ $H(X) = -0.05 \cdot \log_2 0.05 - \cdots - 0.3 \cdot \log_2 0.3 = 2.7087$

Block Codes for Stationary Sources

Encode blocks/words of length N by words over the code alphabet \mathcal{Y} . Assume that blocks are generated by a stationary source, a stationary sequence of random variables $\{X_n\}_{n\in\mathbb{N}}$. Notation for a block code:

$$
g^{(N)}:\mathcal{X}^N\rightarrow \bigcup_{\ell=0}^\infty \mathcal{Y}^\ell
$$

Block codes are "normal" variabel length codes over the extended alphabet \mathcal{X}^N .

A fair measure of the "length" of a block code is the average code word length per character

$$
\bar{n}(g^{(N)})/N.
$$

The lower Shannon bound, namely the entropy of the source, is asymptotically $(N \to \infty)$ attained by suitable block codes, as is shown in the following.

Noiseless Coding Theorem for Block Codes

Theorem 3.9.

Let $X = \{X_n\}_{n \in \mathbb{N}}$ be a stationary source. Let the code alphabet $\mathcal{Y} = \{y_1, \ldots, y_d\}$ have size d.

a) Each u.d. block code $g^{(N)}$ satisfies

$$
\frac{\bar{n}(g^{(N)})}{N}\geq \frac{H(X_1,\ldots,X_N)}{N\,\log d}.
$$

b) Conversely, there is a prefix block code, hence a u.d. block code $g^{(N)}$ with

$$
\frac{\bar{n}(g^{(N)})}{N}\leq \frac{H(X_1,\ldots,X_N)}{N\,\log d}+\frac{1}{N}.
$$

Hence, in the limit as $N \to \infty$: There is a sequence of u.d. block codes $g^{(N)}$ such that

$$
\lim_{N\to\infty}\frac{\bar{n}(g^{(N)})}{N}=\frac{H_{\infty}(X)}{\log d}.
$$

Huffman Block Coding

In principle, Huffman encoding can be applied to block codes. However, problems include

- \blacktriangleright The size of the Huffman table is m^N , thus growing exponentially with the block length.
- \blacktriangleright The code table needs to be transmitted to the receiver.
- \blacktriangleright The source statistics are assumed to be stationary. No adaptivity to to changing probabilities.
- \blacktriangleright Encoding and decoding only per block. Delays occur at the beginning and end. Padding may be necessary.

"Arithmetic coding" avoids these shortcomings.

Assume that

- ▶ Message $(x_{i_1},...,x_{i_N})$, $x_{i_j} \in \mathcal{X}$, $j = 1,...,N$ is generated by some source $\{X_n\}_{n\in\mathbb{N}}$.
- \blacktriangleright All (conditional) probabilities

$$
P(X_n = x_{i_n} | X_1 = x_{i_1}, \ldots, X_{n-1} = x_{i_{n-1}}) = p(i_n | i_1, \ldots, i_{n-1}),
$$

 $x_{i_1}, \ldots, x_{i_n} \in \mathcal{X}, n = 1, \ldots, N$, are known to the encoder and decoder, or can be estimated.

Then,

$$
P(X_1 = x_{i_1}, \ldots, X_n = x_{i_n}) = p(i_1, \ldots, i_n)
$$

can be easily computed as

$$
p(i_1,\ldots,i_n)=p(i_n|i_1,\ldots,i_{n-1})\cdot p(i_1,\ldots,i_{n-1})
$$

Iteratively construct intervals

Initialization, $n = 1$: $(c(1) = 0, c(m + 1) = 1)$

$$
I(j) = [c(j), c(j + 1)), \quad c(j) = \sum_{i=1}^{j-1} p(i), \ j = 1, \ldots, m
$$

(cumulative probabilities)

RWT

Recursion over $n = 2, \ldots, N$:

$$
I(i_1, ..., i_n)
$$

= $\left[c(i_1, ..., i_{n-1}) + \sum_{i=1}^{i_n-1} p(i_n | i_1, ..., i_{n-1}) \cdot p(i_1, ..., i_{n-1})\right)$

$$
c(i_1, ..., i_{n-1}) + \sum_{i=1}^{i_n} p(i_n | i_1, ..., i_{n-1}) \cdot p(i_1, ..., i_{n-1})\right)
$$

Program code available from Togneri, deSilva, p. 151, 152

Example.

Encode message (x_{i_1},\ldots,x_{i_N}) by the binary representation of some binary number in the interval $I(i_1, \ldots, i_n)$.

A scheme which usually works quite well is as follows.

Let $l = l(i_1, \ldots, i_n)$ and $r = r(i_1, \ldots, i_n)$ denote the left and right bound of the corresponding interval. Carry out the binary expansion of l and r until until they differ. Since $l < r$, at the first place they differ there will be a 0 in the expansion of l and a 1 in the expansion of r . The number $0.a_1a_2... a_{t-1}1$ falls within the interval and requires the least number of bits.

$$
(a_1 a_2 \ldots a_{t-1} 1)
$$
 is the encoding of $(x_{i_1}, \ldots, x_{i_N})$.

The probability of occurrence of message (x_{i_1},\ldots,x_{i_N}) is equal to the length of the representing interval. Approximately

$$
-\log_2 p(i_1,\ldots,i_n)
$$

bits are needed to represent the interval, which is close to optimal.

Example. Assume a memoryless source with 4 characters and probabilities

x_i	a	b	c	d
$P(X_n = x_i)$	0.3	0.4	0.1	0.2

Encode the word (bad):

$$
(bad) = [0.396, 0.42)
$$

0.396 = 0.01100... 0.420 = 0.01101...
(bad) = (01101)

