## Chapter 3 Source Coding

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## § 3.1 An Introduction to Source Coding

- Entropy (e.g., in bits per symbol) implies the average number of bits that are required to represent a source symbol. This indicates a mapping between the source symbols and bits.
- Source coding can be seen as a mapping mechanism between source symbols and e.g., bits.
- For a string of symbols, how can we use less bits to represent them?

Intuition: Use short description to represent the most frequently occurred symbols; Use necessarily long description to represent the less frequently occurred symbols.

## § 3.1 An Introduction to Source Coding

Symbols: 1 |  | 2 | 4 | 4 | 3 | 1 | 4 | 4 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |

bits: 00 |  | 01 | 11 | 11 | 10 | 00 | 11 | 11 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |

Or can this be a shorter string of bits?

- Expected Length : Let $x$ denote a source symbol and $C(x)$ denote a codeword of $x$. If the length of $C(x)$ is $l(x)$ (e.g., in bits) and $x$ occurs with a probability of $p(x)$, the expected length $L(C)$ of source code $C$ is:

$$
L(C)=\sum_{x} p(x) \cdot l(x)
$$

- It implies the average number of bits that are required to represent a source symbol in source coding scheme $C$.


## § 3.1 An Introduction to Source Coding

Let us look at the following example:
Example 3.1 Let $X$ be a random variable with an alphabet of $\{1,2,3,4\}$, it has a distribution of

$$
P(x=1)=\frac{1}{2}, P(x=2)=\frac{1}{4}, P(x=3)=\frac{1}{8}, P(x=4)=\frac{1}{8}
$$

Entropy of $X$ is:

$$
\begin{aligned}
H(X) & =\sum_{x \in\{1,2,3,4\}} P(x) \log _{2} P(x)^{-1} \\
& =1.75 \text { bits/sym. }
\end{aligned}
$$

## § 3.1 An Introduction to Source Coding

Source Coding 1 (C):

$$
\begin{aligned}
& C(1)=00, C(2)=01, C(3)=10, C(4)=11 \\
& L(C)=\frac{1}{2} \cdot 2+\frac{1}{4} \cdot 2+\frac{1}{8} \cdot 2+\frac{1}{8} \cdot 2=2 \text { bits }
\end{aligned}
$$

On average, we use 2 bits to represent a symbol.
$\square L(C)>H(X)$.
Source Coding $2\left(C^{*}\right)$ :

$$
\begin{aligned}
& C^{*}(1)=0, C^{*}(2)=10, C^{*}(3)=110, C^{*}(4)=111 \\
& L\left(C^{*}\right)=\frac{1}{2} \cdot 1+\frac{1}{4} \cdot 2+\frac{1}{8} \cdot 3+\frac{1}{8} \cdot 3=1.75 \text { bits }
\end{aligned}
$$

On average, we use 1.75 bits to represent a symbol.
$\square L\left(C^{*}\right)=H(X)$.
Observation: $C^{*}$ should be a better source coding scheme than $C$.

## § 3.1 An Introduction to Source Coding

Memoryless Source: Given a source symbol sequence $s_{1}, s_{2}, \ldots, s_{n}$. It is memoryless if

$$
P\left(s_{j}\right)=P\left(s_{j} \mid s_{1}, s_{2}, \ldots, s_{j-1}\right), \forall j=1,2, \ldots, n
$$

The source symbols are statistically independent.

Theorem 3.1 Shannon's Source Coding Theorem Given a memoryless source $X$ whose symbols are chosen from the alphabet $\left\{x_{1}, x_{2}, \ldots, x_{U}\right\}$ with the alphabet symbol probabilities of $P\left(x_{1}\right)=p_{1}, P\left(x_{2}\right)=p_{2}, \ldots, P\left(x_{U}\right)=p_{U}$, and $\sum_{i=1}^{U} p_{i}=1$. If the source is of length $n$, when $n \rightarrow \infty$, it can be encoded with $H(X)$ bits per symbol. The coded sequence will be of $n H(X)$ bits.

Note: $H(X)=\sum_{i=1}^{U} p_{i} \log _{2} p_{i}^{-1}$ bits/sym.

## § 3.1 An Introduction to Source Coding

## Important Features of Source Coding:

1. Non-singularity: Unambiguous representation of source symbols.

That says if $x_{i} \neq x_{j}, c\left(x_{i}\right) \neq c\left(x_{j}\right)$.

| $X$ | $C(X)$ |
| :---: | :---: |
| 1 | 0 |
| 2 | 010 |
| 3 | 01 |
| 4 | 10 |

Problem: When we try to decode ' 010 ', it can be 2 or 14 or 31 .
The decoding is NOT unique.
2. Uniquely decodable: A codeword can only be uniquely decoded into a source symbol.

| $X$ | $C(X)$ |
| :---: | :---: |
| 1 | 10 |
| 2 | 00 |
| 3 | 11 |
| 4 | 110 |

Problem: When we try to decode '001011000', we have $21<32 \ldots$
We will have to wait and see the end of the bit string. The decoding is NOT instantaneous.

## § 3.1 An Introduction to Source Coding

3. Instantaneous decoding: The decoding (demapping) happens once a codeword is read.

Instantaneous codes: For an instantaneous code, no codeword is a prefix of any other codeword.

| $X$ | $C(X)$ |
| :---: | :---: |
| 1 | 0 |
| 2 | 10 |
| 3 | 110 |
| 4 | 111 |

Observation: If you try to decode '111110101100111', you would notice that the puncturing positions are determined by the instances you have reached a source codeword. The decoding is instantaneous, and the decoding output is '432314'.

Source Codes:


Non-singular codes
Uniquely decodable codes
Instantaneous codes

## § 3.2 Optimal Source Codes

How can we find an optimal source code?
An optimal source code :
(1) An instantaneous code (prefix code)
(2) The smallest expected length $L=\sum_{i} p_{i} l_{i}$

Theorem 3.2 Kraft Inequality For an instantaneous code over an alphabet of size $D$ (e.g.,
$D=2$ for binary codes), the codeword lengths $l_{1}, l_{2}, \cdots, l_{U}$ must satisfy

$$
\sum_{i} D^{-l_{i}} \leq 1
$$

Remark: An instantaneous code $\rightleftarrows \sum_{i} D^{-l_{i}} \leq 1$

Example 3.2 For the source code $C^{*}$ of Example 3.1.

$$
2^{-1}+2^{-2}+2^{-3}+2^{-3}=1
$$

## § 3.2 Optimal Source Codes

Proof:


- Assume $D=2$, and the above binary tree illustrates the assignment of binary source codeword. A complete solid path represents a source codeword.
- Based on property of instantaneous codes, if the first source codeword goes the ' 0 ' path, the next source codeword should not go the ' 0 ' path. Such a source codeword symbol assignment process repeats as the number of data symbols increases.


## § 3.2 Optimal Source Codes



- At level $l_{\max }$ of the tree (source codeword length is $l_{\max }$ ), there are at most $D^{l_{\text {max }}}$ codewords. Similarly, at level $l_{i}$ of the tree, there are at most $D^{l_{i}}$ codewords. A codeword at level $l_{i}$ has $D^{l_{\max }-l_{i}}$ descendants at level $l_{\text {max }}$.
- The descendent sets of all codewords should be disjoint. Consider all codewords, this property implies

$$
\sum_{i} D^{l_{\max }-l_{i}} \leq D^{l_{\max }} \quad \longrightarrow \quad \sum_{i} D^{-l_{i}} \leq 1 .
$$

## § 3.2 Optimal Source Codes

- The tree represents an instantaneous source code.

- The expected length of this tree is

$$
\mathbb{E}[l]=\sum_{i} l_{i} p_{i}
$$

$l_{i}$ : length of a source codeword for symbol $x_{i}$
$p_{i}$ : probability of symbol $x_{i}$

- Expected length of the tree is the expected length of the source code.


## § 3.2 Optimal Source Codes

- Finding the smallest expected length $L$ becomes

$$
\begin{array}{rc}
\hline \text { minimize: } & L=\sum_{i} p_{i} l_{i} \\
\text { s.t. } & \sum_{i} D^{-l_{i}} \leq 1 \\
\hline
\end{array}
$$

- The constrained minimization problem can be interpreted through the Lagrange multipliers as:

$$
\text { minimize: } \quad J=\sum_{i} p_{i} l_{i}+\lambda\left(\sum_{i} D^{-l_{i}}\right)
$$

- Calculus: $\frac{\partial J}{\partial l_{i}}=p_{i}-\lambda D^{-l_{i}} \log _{e} D$. To enable $\frac{\partial J}{\partial l_{i}}=0$, we need $D^{-l_{i}}=\frac{p_{i}}{\lambda \log _{e} D}$.
- To satisfy the Kraft Inequality, we have $\lambda=\frac{1}{\log _{e} D}$. Hence, $p_{i}=D^{-l_{i}}$.
- To minimized $L$, we need $l_{i}^{*}=\log _{D} p_{i}^{-1}$.
- With $l_{i}^{*}=\log _{D} p_{i}^{-1}$, we have

$$
L=\sum_{i} p_{i} l_{i}^{*}=\sum_{i} p_{i} \log _{D} p_{i}^{-1}=H_{D}(X) \quad \text { Entropy of the source symbols }
$$

## § 3.2 Optimal Source Codes

Theorem 3.3 (Lower Bound of the Expected Length) The expected length $L$ of an instantaneous $D$-ary code for a random variable $X$ is lower bounded by

$$
L \geq H_{D}(X)
$$

Proof:

$$
\begin{aligned}
L-H_{D}(X) & =\sum_{i} l_{i} p_{i}+\sum_{i} p_{i} \log _{D} p_{i} \\
& =-\sum_{i} p_{i} \log _{D} D^{-l_{i}}+\sum_{i} p_{i} \log _{D} p_{i} \\
& =\sum_{i} p_{i} \log _{D} \frac{p_{i}}{D^{-l_{i}}} .
\end{aligned}
$$

Let $p_{i}^{\prime}=D^{-l_{i}}$,

$$
\begin{aligned}
L-H_{D}(X) & =\sum_{i} p_{i} \log _{D} \frac{p_{i}}{p_{i}^{\prime}} \\
& =D\left(p_{i} \| p_{i}^{\prime}\right) \geq 0 .
\end{aligned}
$$

Remark: Since $l_{i}$ can only be an integer,

$$
\begin{aligned}
& L=H_{D}(X), \text { if } l_{i}=-\log _{D} p_{i} \\
& L>H_{D}(X), \text { if } l_{i}=\left\lceil-\log _{D} p_{i}\right\rceil .
\end{aligned}
$$

## § 3.2 Optimal Source Codes

Corollary 3.4 (Upper Bound of the Expected Length) The expected length $L$ of an instantaneous $D$-ary code for a random variable $X$ is upper bounded by

$$
L<H_{D}(X)+1
$$

Proof: Since $-\log _{D} p_{i} \leq l_{i}<-\log _{D} p_{i}+1$.
By multiplying $p_{i}$ to the above inequality and performing summation over $i$ as

$$
\begin{gathered}
\sum_{i}-p_{i} \log p_{i} \leq \sum_{i} p_{i} l_{i}<\sum_{i}-p_{i} \log p_{i}+\sum_{i} p_{i} \\
H_{D}(X) \leq L<H_{D}(X)+1
\end{gathered}
$$

## § 3.3 Shannon-Fano Code

- Given a source that contains symbols $x_{1}, x_{2}, \ldots, x_{U}$ with probabilities of $p_{1}, p_{2}, \ldots, p_{U}$, respectively.
- Determine the source codeword length for symbol $x_{i}$ as

$$
l_{i}=\left\lceil\log _{2} \frac{1}{p_{i}}\right] \text { bits. }
$$

- Further determine $l_{\max }=\max \left\{l_{i}, \forall i\right\}$.
- Shannon-Fano Code Construction:

Step 1: Construct a binary tree of depth $l_{\text {max }}$.
Step 2: Choose a node of depth $l_{i}$ and delete its following paths and nodes. The path from root to the node represents the source codeword for source symbol $x_{i}$.

## § 3.3 Shannon-Fano Code

- Example 3.3 Given a source with symbols $x_{1}, x_{2}, x_{3}, x_{4}$, they occur with a probability of $p_{1}=0.4, p_{2}=0.3, p_{3}=0.2, p_{4}=0.1$, respectively. Construct its Shannon-Fano code.
We can determine

$$
l_{1}=\left\lceil\log _{2} \frac{1}{p_{1}}\right\rceil=2, l_{2}=\left\lceil\log _{2} \frac{1}{p_{2}}\right\rceil=2, l_{3}=\left\lceil\log _{2} \frac{1}{p_{3}}\right\rceil=3, l_{4}=\left\lceil\log _{2} \frac{1}{p_{4}}\right\rceil=4
$$

and $l_{\text {max }}=4$.
Construct a binary tree of depth 4 .
The source codewords are


$$
\begin{aligned}
& x_{1}: 00 \\
& x_{2}: 01 \\
& x_{3}: 100 \\
& x_{4}: 1010 .
\end{aligned}
$$

Note: $L=2.4$ bits/sym., $H(X)=1.85$ bits/sym.,

$$
\text { and } H(X)<L<H(X)+1
$$

## § 3.4 Huffman Code

- Given a source that contains symbols $x_{1}, x_{2}, \ldots, x_{U}$ with probabilities of $p_{1}, p_{2}, \ldots, p_{U}$, respectively.
- Huffman Code Construction:

Step 1: Merge the 2 smallest symbol probabilities;
Step 2: Assign the 2 corresponding symbols with 0 and 1, then go back to Step 1;
Repeat the above process until two probabilities are merged into a probability of 1 .

- Huffman code is the shortest prefix code, i.e., an optimal code.


## § 3.4 Huffman Code

Example 3.4 Given a source with symbols $x_{1}, x_{2}, x_{3}, x_{4}, x_{5}$. They occur with probabilities of $P_{1}=0.25, P_{2}=0.25, P_{3}=0.2, P_{4}=0.15, P_{5}=0.15$, respectively. Construct its Huffman code.


## § 3.4 Huffman Code

| Codeword | $x_{i}$ | $P_{i}$ |  |
| :---: | :---: | :---: | :---: |
|  | $x_{1}$ | 0.25 | 0.3 |
| 0 | $x_{2}$ | 0.25 | 0.25 |
| 1 | $x_{3}$ | 0.2 | 0.25 |
| 0 | $x_{4}$ | 0.15 | 0.2 |
| 1 | $x_{5}$ | 0.15 | 0.25 |
|  |  |  |  |


| Codeword | $x_{i}$ | $P_{i}$ |  |  |
| :---: | :---: | :--- | :--- | :--- |
| 1 | $x_{1}$ | 0.25 | 0.3 | 0.45 |
| 0 | $x_{2}$ | 0.25 | 0.25 | 0.3 |
| 1 | $x_{3}$ | 0.2 | 0.25 | 0.25 |
| 0 | 0 | $x_{4}$ | 0.15 | 0.2 |
| 0 | 1 | $x_{5}$ | 0.15 |  |

## § 3.4 Huffman Code

| Codeword | $x_{i}$ | $P_{i}$ |
| :---: | :---: | :---: |
| 01 | $x_{1}$ | $0.25 / /^{0.3} / 0^{0.45}>{ }^{0.55}{ }^{1}$ |
| 10 | $x_{2}$ | $0.25 \times 0.25 \times 0.3 \times 0.45$ |
| 11 | $x_{3}$ | $0.2 \times 0.25 \times 0.25$ |
| $0 \quad 00$ | $x_{4}$ | 0.15 0.2 |
| $0 \quad 01$ | $x_{5}$ | 0.15 |

Validations:
$l_{1}=2, l_{2}=2, l_{3}=2, l_{4}=3, l_{5}=3$
$L=\sum_{i} l_{i} \cdot P_{i}=2.3 \mathrm{bits} / \mathrm{symbol}$
$H_{2}(X)=\sum_{i} P_{i} \log _{2} P_{i}^{-1}=2.3$ bits $/ \mathrm{sym}$.

Q: Try to construct a Shannon-Fano code and see if it is also optimal.

## § 3.4 Huffman Code

So now, let us look back at the problem proposed at the beginning.
How to represent the source vector $\left\{\begin{array}{llllllll}1 & 2 & 4 & 4 & 3 & 1 & 4 & 4\end{array}\right\} ?$

| Codeword | $x$ | $P(x)$ |  |
| :---: | :---: | :---: | :---: |
|  | 0 | 1 | 1 |
| 0 | 0 | 0 | 2 |
| 0 | 0 | 1 | 3 |
|  |  | 1 | 4 |

It should be represented as $\{01000110010111\}$ and $L=1.75$ bits/symbol.

Q: How if the source vector becomes $\{12434421$ ? ?

Remark: The source coding depends on the source vector.

## § 3.4 Huffman Code

- Huffman code can also be defined as a $D$-ary code.
- A $D$-ary Huffman code can be similarly constructed following the binary construction.

Step 1: Merge the $D$ smallest symbol probabilities;
Step 2: Assign the corresponding symbols with $0,1, \ldots, D-1$, then go back to Step 1; Repeat the above process until $D$ probabilities are merged into a probability of 1 .

## § 3.4 Huffman Code

Example 3.5 Consider a source with symbols $x_{1}, x_{2}, x_{3}, x_{4}, x_{5}, x_{6}$. They occur with probabilities of $P_{1}=0.25, P_{2}=0.25, P_{3}=0.2, P_{4}=0.1, P_{5}=0.1, P_{6}=0.1$, respectively. Construct a ternary ( $\{0,1,2\}$ ) Huffman code.

| Codeword | $\chi_{i}$ | $P_{i}$ |
| :---: | :---: | :---: |
| 0 | $x_{1}$ | $0.25-0.25-0.25 \pi^{1}$ |
| 1 | $x_{2}$ | $0.25-0.25-0.25 /$ |
| 20 | $x_{3}$ | $0.2-0.2 \longrightarrow 0.5$ |
| 21 | $x_{4}$ | $0.1-0.1$ |
| 220 | $x_{5}$ | $0.1 \longrightarrow 0.2$ |
| $\begin{array}{lll}2 & 2 & 1\end{array}$ | $x_{6}$ | $0.1 /$ |
| 222 | Dummy | 0 |

Note: A dummy symbol is created such that 3 probabilities can merge into a probability of 1 in the end.

## § 3.4 Huffman Code

Properties on an optimal $\boldsymbol{D}$-ary source code (Huffman code)
(1) If $p_{j}>p_{k}$, then $l_{j} \leq l_{k}$;
(2) The $D$ longest codewords have the same length;
(3) The $D$ longest codewords differ only at the last symbol and correspond to the $D$ least likely source symbols.

Theorem 3.5 (Optimal Source Code) A source code $\left(C^{*}\right)$ is optimal if giving any other source code $C^{\prime}$, we have $L\left(C^{*}\right) \leq L\left(C^{\prime}\right)$.

Note: Huffman codes are optimal.

References:
[1] Elements of Information Theory, by T. Cover and J. Thomas.
[2] Scriptum for the lectures, Applied Information Theory, by M. Bossert.

