

COMP2610/6261 - Information Theory

Lecture 15: Arithmetic Coding

Mark Reid and Aditya Menon

Research School of Computer Science
The Australian National University



Australian
National
University

September 23rd, 2014

1 The Trouble with Huffman Coding

2 Guessing Game

3 Interval Coding

- Shannon-Fano-Elias Coding

Huffman Coding: Advantages and Disadvantages

Advantages:

- Huffman Codes are provably optimal
- Algorithm is simple and efficient

Huffman Coding: Advantages and Disadvantages

Advantages:

- Huffman Codes are provably optimal
- Algorithm is simple and efficient

Disadvantages:

- Assumes a fixed distribution of symbols
- The extra bit in the SCT
 - ▶ If $H(X)$ is large – not a problem
 - ▶ If $H(X)$ is small (e.g., ~ 1 bit for English) codes are $2\times$ optimal

Huffman codes are the best possible symbol code
but symbol coding is not always the best type of code

1 The Trouble with Huffman Coding

2 Guessing Game

3 Interval Coding

- Shannon-Fano-Elias Coding

A Guessing Game

Let's play!

An Idealised Guessing Game

Encoding: Given message \mathbf{x} and guesser G :

For i from 1 to $|\mathbf{x}|$:

- 1 Set count $n_i = 1$
- 2 While G guesses x_i incorrectly:
 - 1 $n_i \leftarrow n_i + 1$
- 3 Output n_i

An Idealised Guessing Game

Encoding: Given message \mathbf{x} and guesser G :

For i from 1 to $|\mathbf{x}|$:

- 1 Set count $n_i = 1$
- 2 While G guesses x_i incorrectly:
 - 1 $n_i \leftarrow n_i + 1$
- 3 Output n_i

Decoding: Given counts \mathbf{n} and guesser G :

For i from 1 to $|\mathbf{n}|$ and guesser G :

- 1 While G has made fewer than n_i guesses:
 - 1 $x_i \leftarrow$ next guess from G
- 2 Output x_i

An Idealised Guesser

If the guesser G is *deterministic* (i.e., its next output depends only on the history of values it has seen), the same guesser can be used to **encode** and **decode**.

An Idealised Guesser

If the guesser G is *deterministic* (i.e., its next output depends only on the history of values it has seen), the same guesser can be used to **encode** and **decode**.

Advantages

- Scheme works **regardless of how the sequence x was generated**
- Only need to compute codes for **observed** sequence
(not all possible blocks of some size)

An Idealised Guesser

If the guesser G is *deterministic* (i.e., its next output depends only on the history of values it has seen), the same guesser can be used to **encode** and **decode**.

Advantages

- Scheme works **regardless of how the sequence x was generated**
- Only need to compute codes for **observed** sequence
(not all possible blocks of some size)

How can we use this?

- Have the guesser guess **distributions** rather than symbols (repeatedly)
- **Use bits** instead of counts (with fewer bits for lower counts)
- Define a **clever guesser** (one that “learns”)
- **Prove** that this scheme is close to optimal
(at least, not much worse than Huffman on probabilistic sources)

1 The Trouble with Huffman Coding

2 Guessing Game

3 Interval Coding

- Shannon-Fano-Elias Coding

Real Numbers in Binary

Real numbers are commonly expressed in **decimal**:

$$12_{10} \rightarrow 1 \times 10^1 + 2 \times 10^0$$

$$3.7_{10} \rightarrow 3 \times 10^0 + 7 \times 10^{-1}$$

$$0.94_{10} \rightarrow 9 \times 10^{-1} + 4 \times 10^{-2}$$

Real Numbers in Binary

Real numbers are commonly expressed in **decimal**:

$$12_{10} \rightarrow 1 \times 10^1 + 2 \times 10^0$$

$$3.7_{10} \rightarrow 3 \times 10^0 + 7 \times 10^{-1}$$

$$0.94_{10} \rightarrow 9 \times 10^{-1} + 4 \times 10^{-2}$$

Some real numbers have infinite, repeating decimal expansions:

$$\frac{1}{3} = 0.33333 \dots_{10} = 0.\overline{3}_{10} \quad \text{and} \quad \frac{22}{7} = 3.14285714 \dots_{10} = 3.\overline{142857}_{10}$$

Real Numbers in Binary

Real numbers are commonly expressed in **decimal**:

$$12_{10} \rightarrow 1 \times 10^1 + 2 \times 10^0$$

$$3.7_{10} \rightarrow 3 \times 10^0 + 7 \times 10^{-1}$$

$$0.94_{10} \rightarrow 9 \times 10^{-1} + 4 \times 10^{-2}$$

Some real numbers have infinite, repeating decimal expansions:

$$\frac{1}{3} = 0.33333\dots_{10} = 0.\overline{3}_{10} \quad \text{and} \quad \frac{22}{7} = 3.14285714\dots_{10} = 3.\overline{142857}_{10}$$

Real numbers can also be similarly expressed in **binary**:

$$11_2 \rightarrow 1 \times 2^1 + 1 \times 2^0$$

$$1.1_2 \rightarrow 1 \times 2^0 + 1 \times 2^{-1}$$

$$0.01_2 \rightarrow 0 \times 2^{-1} + 1 \times 2^{-2}$$

$$\frac{1}{3} = 0.010101\dots_2 = 1.\overline{01}_2 \quad \text{and} \quad \frac{22}{7} = 11.001001\dots_2 = 11.\overline{001}_2$$

Real Numbers in Binary

Real numbers are commonly expressed in **decimal**:

$$12_{10} \rightarrow 1 \times 10^1 + 2 \times 10^0$$

$$3.7_{10} \rightarrow 3 \times 10^0 + 7 \times 10^{-1}$$

$$0.94_{10} \rightarrow 9 \times 10^{-1} + 4 \times 10^{-2}$$

Some real numbers have infinite, repeating decimal expansions:

$$\frac{1}{3} = 0.33333\dots_{10} = 0.\overline{3}_{10} \quad \text{and} \quad \frac{22}{7} = 3.14285714\dots_{10} = 3.\overline{142857}_{10}$$

Real numbers can also be similarly expressed in **binary**:

$$11_2 \rightarrow 1 \times 2^1 + 1 \times 2^0$$

$$1.1_2 \rightarrow 1 \times 2^0 + 1 \times 2^{-1}$$

$$0.01_2 \rightarrow 0 \times 2^{-1} + 1 \times 2^{-2}$$

$$\frac{1}{3} = 0.010101\dots_2 = 1.\overline{01}_2 \quad \text{and} \quad \frac{22}{7} = 11.001001\dots_2 = 11.\overline{001}_2$$

Question: 1) What is 0.1011_2 in decimal? 2) What is $\frac{7}{5}$ in binary?

Intervals in Binary

An **interval** $[a, b)$ is the set of all the numbers at least as big as a but smaller than b . That is,

$$[a, b) = \{x : a \leq x < b\}.$$

Examples: $[0, 1)$, $[0.3, 0.6)$, $[0.2, 0.4)$.

Intervals in Binary

An **interval** $[a, b)$ is the set of all the numbers at least as big as a but smaller than b . That is,

$$[a, b) = \{x : a \leq x < b\}.$$

Examples: $[0, 1)$, $[0.3, 0.6)$, $[0.2, 0.4)$.

The set of numbers in $[0, 1)$ that start with a given sequence of bits $b = b_1 \dots b_n$ form the interval $[0.b_1 \dots b_n, 0.(b_1 \dots b_n + 1))$.

- $1 \rightarrow [0.1, 1.0)$ $[0.5, 1]_{10}$
- $01 \rightarrow [0.01, 0.10)$ $[0.25, 0.5]_{10}$
- $1101 \rightarrow [0.1101, 0.1110)$ $[0.8125, 0.875]_{10}$

Intervals in Binary

An **interval** $[a, b)$ is the set of all the numbers at least as big as a but smaller than b . That is,

$$[a, b) = \{x : a \leq x < b\}.$$

Examples: $[0, 1)$, $[0.3, 0.6)$, $[0.2, 0.4)$.

The set of numbers in $[0, 1)$ that start with a given sequence of bits $\mathbf{b} = b_1 \dots b_n$ form the interval $[0.b_1 \dots b_n, 0.(b_1 \dots b_n + 1))$.

- $1 \rightarrow [0.1, 1.0)$ $[0.5, 1]_{10}$
- $01 \rightarrow [0.01, 0.10)$ $[0.25, 0.5]_{10}$
- $1101 \rightarrow [0.1101, 0.1110)$ $[0.8125, 0.875]_{10}$

If \mathbf{b}' is a **prefix** of \mathbf{b} the interval for \mathbf{b} is **contained** in the interval for \mathbf{b}' .

$$\mathbf{b}' = 01 \text{ is prefix of } \mathbf{b} = 0101 \text{ so } \underbrace{[0.0101, 0.0110)}_{[0.3125, 0.375]_{10}} \subset \underbrace{[0.01, 0.10)}_{[0.25, 0.5]_{10}}$$

Cumulative Distribution

Suppose $\mathbf{p} = (p_1, \dots, p_K)$ is a distribution over $\mathcal{A} = \{a_1, \dots, a_K\}$.

Assume the alphabet \mathcal{A} is ordered and define $a_i \leq a_j$ to mean $i \leq j$. Consider F the *cumulative distribution* for \mathbf{p} :

$$F(a) = P(x \leq a) = \sum_{a_i \leq a} p_i$$

Each symbol $a_i \in \mathcal{A}$ is associated with the interval $[F(a_{i-1}), F(a_i))$. (The value of $F(a_0) = 0$).

Cumulative Distribution

Suppose $\mathbf{p} = (p_1, \dots, p_K)$ is a distribution over $\mathcal{A} = \{a_1, \dots, a_K\}$.

Assume the alphabet \mathcal{A} is ordered and define $a_i \leq a_j$ to mean $i \leq j$. Consider F the *cumulative distribution* for \mathbf{p} :

$$F(a) = P(x \leq a) = \sum_{a_i \leq a} p_i$$

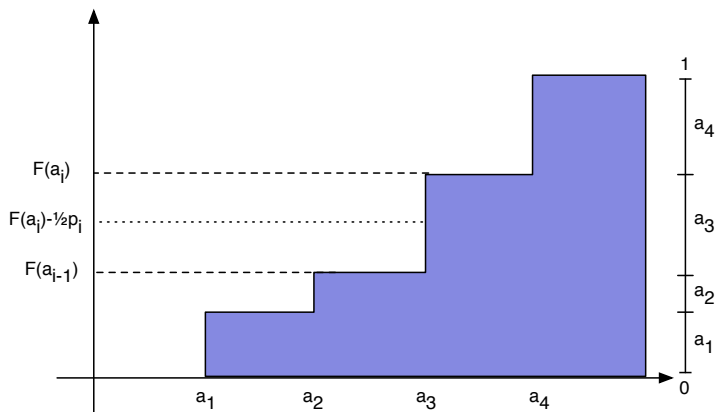
Each symbol $a_i \in \mathcal{A}$ is associated with the interval $[F(a_{i-1}), F(a_i))$. (The value of $F(a_0) = 0$).

Example:

$\mathcal{A} = \{r, g, b\} \implies a_1 = r, a_2 = g, a_3 = b \implies r \leq b$ since $1 \leq 3$.
If $\mathbf{p} = (\frac{1}{2}, \frac{1}{4}, \frac{1}{4})$ then $F(r) = \frac{1}{2}$, $F(g) = \frac{3}{4}$, $F(b) = 1$.

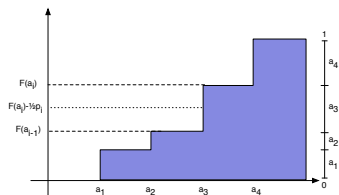
Cumulative Distribution

Example



Cumulative distribution for $\mathbf{p} = \left(\frac{2}{9}, \frac{1}{9}, \frac{1}{3}, \frac{1}{3}\right)$

Shannon-Fano-Elias Coding



$$\left[0, \frac{2}{9}\right)_{10}$$

$$\left[\frac{2}{9}, \frac{1}{3}\right)_{10}$$

$$\left[\frac{1}{3}, \frac{2}{3}\right)_{10}$$

$$\left[\frac{2}{3}, 1\right)_{10}$$

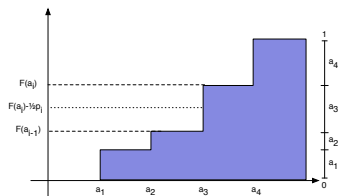
$$\left[0, 0.\overline{0011110}\right)_2$$

$$\left[0.\overline{0011110}, 0.\overline{01}\right)_2$$

$$\left[0.\overline{01}, 0.\overline{10}\right)_2$$

$$\left[0.\overline{10}, 1\right)_2$$

Shannon-Fano-Elias Coding



$$\left[0, \frac{2}{9}\right)_{10}$$

$$\left[\frac{2}{9}, \frac{1}{3}\right)_{10}$$

$$\left[\frac{1}{3}, \frac{2}{3}\right)_{10}$$

$$\left[\frac{2}{3}, 1\right)_{10}$$

$$[0, 0.\overline{0011110})_2$$

$$[0.\overline{0011110}, 0.\overline{01})_2$$

$$[0.\overline{01}, 0.\overline{10})_2$$

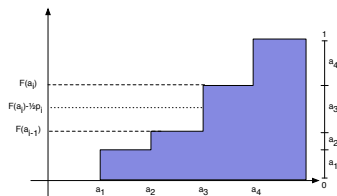
$$[0.\overline{10}, 1)_2$$

Define the midpoint $\bar{F}(a_i) = F(a_i) - \frac{1}{2}p_i$ and length $\ell(a_i) = \left\lceil \log_2 \frac{1}{p_i} \right\rceil + 1$.

Code $x \in \mathcal{A}$ using first $\ell(x)$ bits of $\bar{F}(x)$.

| x | $p(x)$ | $F(x)$ | $\bar{F}(x)$ | $\bar{F}(x)_2$ | $\ell(x)$ | Code |
|-------|--------|--------|--------------|----------------------------|-----------|-------|
| a_1 | $2/9$ | $2/9$ | $1/9$ | $0.\overline{0001111}_2$ | 4 | 0001 |
| a_2 | $1/9$ | $1/3$ | $5/18$ | $0.01\overline{0001111}_2$ | 5 | 01000 |
| a_3 | $1/3$ | $2/3$ | $1/2$ | 0.1_2 | 3 | 100 |
| a_4 | $1/3$ | 1 | $5/6$ | $0.1\overline{10}_2$ | 3 | 110 |

Shannon-Fano-Elias Coding



$$\left[0, \frac{2}{9}\right)_{10}$$

$$\left[\frac{2}{9}, \frac{1}{3}\right)_{10}$$

$$\left[\frac{1}{3}, \frac{2}{3}\right)_{10}$$

$$\left[\frac{2}{3}, 1\right)_{10}$$

$$[0, 0.\overline{001110})_2$$

$$[0.\overline{001110}, 0.\overline{01})_2$$

$$[0.\overline{01}, 0.\overline{10})_2$$

$$[0.\overline{10}, 1)_2$$

Define the midpoint $\bar{F}(a_i) = F(a_i) - \frac{1}{2}p_i$ and length $\ell(a_i) = \left\lceil \log_2 \frac{1}{p_i} \right\rceil + 1$.

Code $x \in \mathcal{A}$ using first $\ell(x)$ bits of $\bar{F}(x)$.

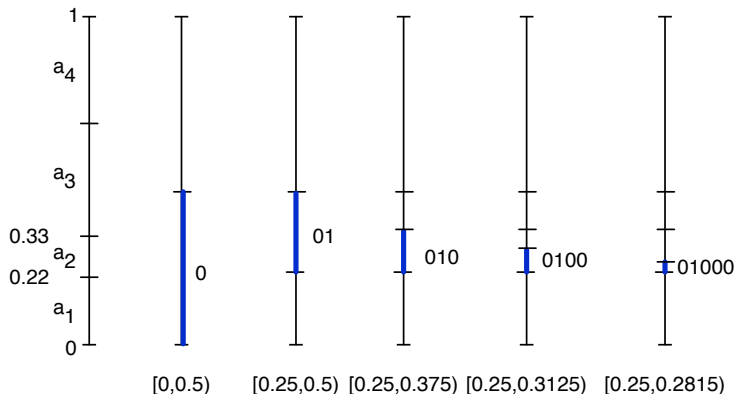
| x | $p(x)$ | $F(x)$ | $\bar{F}(x)$ | $\bar{F}(x)_2$ | $\ell(x)$ | Code |
|-------|--------|--------|--------------|---------------------------|-----------|-------|
| a_1 | $2/9$ | $2/9$ | $1/9$ | $0.\overline{000111}_2$ | 4 | 0001 |
| a_2 | $1/9$ | $1/3$ | $5/18$ | $0.01\overline{000111}_2$ | 5 | 01000 |
| a_3 | $1/3$ | $2/3$ | $1/2$ | 0.1_2 | 3 | 100 |
| a_4 | $1/3$ | 1 | $5/6$ | $0.1\overline{10}_2$ | 3 | 110 |

Example: Sequence $\mathbf{x} = a_3 a_3 a_1$ coded as 100 100 0001.

Shannon-Fano-Elias Decoding

Let $\mathbf{p} = \{\frac{2}{9}, \frac{1}{9}, \frac{1}{3}, \frac{1}{3}\}$. Suppose we want to *decode* 01000:

Find symbol whose interval contains interval for 01000



Note: We did not need to know all the codewords in C .

Expected Code Length of SFE Code

The **extra bit** for the code lengths is because we code $\frac{p_i}{2}$ and

$$\log_2 \frac{2}{p_i} = \log_2 \frac{1}{p_i} + \log_2 2 = \log_2 \frac{1}{p_i} + 1$$

What is the **expected length** of a SFE code C for ensemble X with probabilities \mathbf{p} ?

$$\begin{aligned} L(C, X) &= \sum_{i=1}^K p_i \ell(a_i) = \sum_{i=1}^K p_i \left(\left\lceil \log_2 \frac{1}{p_i} \right\rceil + 1 \right) \\ &\leq \sum_{i=1}^K p_i \left(\log_2 \frac{1}{p_i} + 2 \right) \\ &= H(X) + 2 \end{aligned}$$

Similarly, $H(X) + 1 \leq L(C, X)$ for the SFE codes.

What does the extra bit buy us?

Let X be an ensemble, C_{SFE} be a Shannon-Fano-Elias code for X and C_H be a Huffman code for X .

$$\underbrace{H(X) \leq L(C_H, X) \leq H(X) + 1}_{\text{Source Coding Theorem}} \leq L(C_{SFE}, X) \leq H(X) + 2$$

What does the extra bit buy us?

Let X be an ensemble, C_{SFE} be a Shannon-Fano-Elias code for X and C_H be a Huffman code for X .

$$\underbrace{H(X) \leq L(C_H, X) \leq H(X) + 1}_{\text{Source Coding Theorem}} \leq L(C_{SFE}, X) \leq H(X) + 2$$

The extra bit *guarantees* that the interval for each code word lies entirely within the interval for each symbol. [Why?]

What does the extra bit buy us?

Let X be an ensemble, C_{SFE} be a Shannon-Fano-Elias code for X and C_H be a Huffman code for X .

$$\underbrace{H(X) \leq L(C_H, X) \leq H(X) + 1}_{\text{Source Coding Theorem}} \leq L(C_{SFE}, X) \leq H(X) + 2$$

The extra bit *guarantees* that the interval for each code word lies entirely within the interval for each symbol. [Why?]

Example: SFE Code for $\mathbf{p} = \{\frac{2}{9}, \frac{1}{9}, \frac{1}{3}, \frac{1}{3}\}$ is $C = \{0001, 0100, 100, 110\}$. Intervals for \mathbf{p} are

$$[0, 0.22), [0.22, 0.33), [0.33, 0.66), [0.66, 1)$$

Intervals for $\{000, 0100, 10, 11\}$ are

$$[0, 0.125), [0.25, 0.3125), [0.5, 0.75), [0.75, 1)$$

Main points:

- Problems with Huffman coding
- Guessing game for coding **without** assuming fixed symbol distribution
- Binary strings to/from intervals in $[0, 1]$
- Shannon-Fano-Elias Coding:
 - ▶ Code C via cumulative distribution function for p
 - ▶ $H(X) + 1 \leq L(C, X) \leq H(X) + 2$
- Extra bit guarantees interval containment

Summary and Reading

Main points:

- Problems with Huffman coding
- Guessing game for coding **without** assuming fixed symbol distribution
- Binary strings to/from intervals in $[0, 1]$
- Shannon-Fano-Elias Coding:
 - ▶ Code C via cumulative distribution function for p
 - ▶ $H(X) + 1 \leq L(C, X) \leq H(X) + 2$
- Extra bit guarantees interval containment

Reading:

- Guessing game and interval coding: MacKay §6.1 and §6.2
- Shannon-Fano-Elias Coding: Cover & Thomas §5.9

Summary and Reading

Main points:

- Problems with Huffman coding
- Guessing game for coding **without** assuming fixed symbol distribution
- Binary strings to/from intervals in $[0, 1]$
- Shannon-Fano-Elias Coding:
 - ▶ Code C via cumulative distribution function for p
 - ▶ $H(X) + 1 \leq L(C, X) \leq H(X) + 2$
- Extra bit guarantees interval containment

Reading:

- Guessing game and interval coding: MacKay §6.1 and §6.2
- Shannon-Fano-Elias Coding: Cover & Thomas §5.9

Next time:

Extending SFE Coding to sequences of symbols