

ECI750 Multimedia Data Compression

Lecture 5 Huffman Coding – 2

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- In this lecture, we will study
 - How can we generate Huffman codes when the probability model of the source is unknown (Adaptive Huffman Codes)?
 - What are other related approaches?
 - How can Huffman coding be used for image compression, audio compression, and text compression?



• Adaptive Huffman Codes

- Huffman coding requires knowledge of the probabilities of the source sequence.
- If this knowledge is not available, Huffman coding becomes a two-pass procedure:
 - Statistics are collected in the first pass
 - Source is encoded in the second pass
- Faller [1] and Gallagher [2] developed adaptive algorithms to construct the Huffman code based on the statistics of the symbols already encountered.
 - These were later improved by Knuth [3] and Vitter [4].

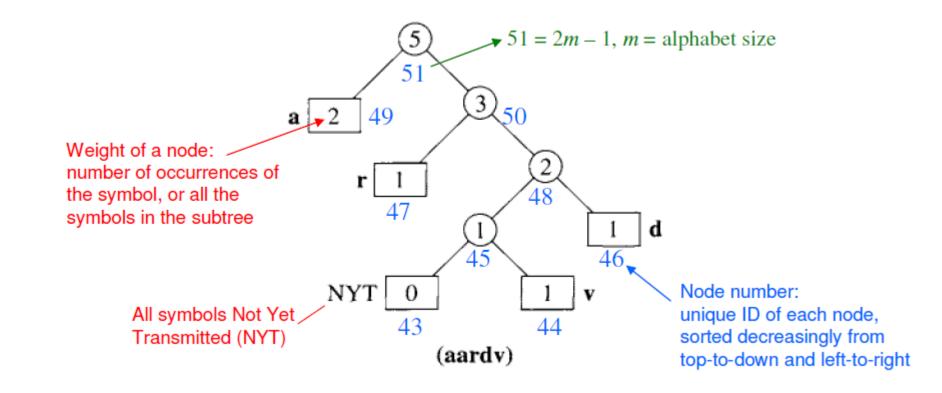


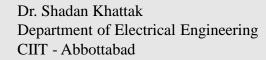
<u>Adaptive Huffman Codes</u>

- In adaptive Huffman Codes, we add two new parameters to the binary tree:
 - Weight:
 - The weight of each external node is the number of times the symbol corresponding to the leaf has been encountered.
 - The weight of each internal node is the sum of the weights of its offspring.
 - Node number:
 - The node number y_i is a unique number assigned to each internal and external node.
- If we have an alphabet of size n, then the number of internal and external nodes is 2n 1 with node numbers: y_1, \dots, y_{2n-1}
- If x_j is the weight of the node y_j , we have $x_1 \le x_2 \le \dots \le x_{2n-1}$
- Sibling property:
 - The nodes y_{2j-1} and y_{2j} are offspring of the same parent node, or siblings, for $1 \le j < n$
 - the node number for the parent node is greater than y_{2j-1} and y_{2j}
 - Any tree that possesses this property is a Huffman tree.
- *Block*: The set of nodes with the same weight makes up a block.



• Adaptive Huffman Codes (3)







• Adaptive Huffman Codes

- Neither transmitter nor receiver knows anything about the statistics of the source sequence at the start of transmission.
- The tree at both the transmitter and the receiver consists of a single node that corresponds to all symbols not yet transmitted (NYT) and has a weight zero.
- Before transmission, a fixed code for each symbol is agreed upon between transmitter and receiver.

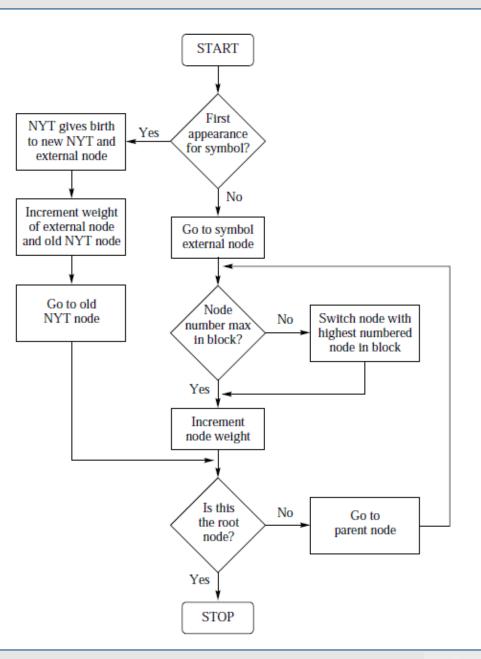


- <u>Adaptive Huffman Codes</u>
 - Initial Codewords
 - For an alphabet $(a_1, a_2, ..., a_m)$ of size m,
 - Pick *e* and *r* such that:
 - $m = 2^e + r$
 - $0 \le r < 2^e$
 - A letter a_k is encoded as:
 - the (e + 1)-bit binary representation of k 1, if $1 \le k \le 2r$
 - else, the *e*-bit binary representation of k r 1.
 - For example, for m = 26:
 - e = 4, r = 10

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$$a_1 = 00000, a_2 = 00001, a_{22} = 1011$$

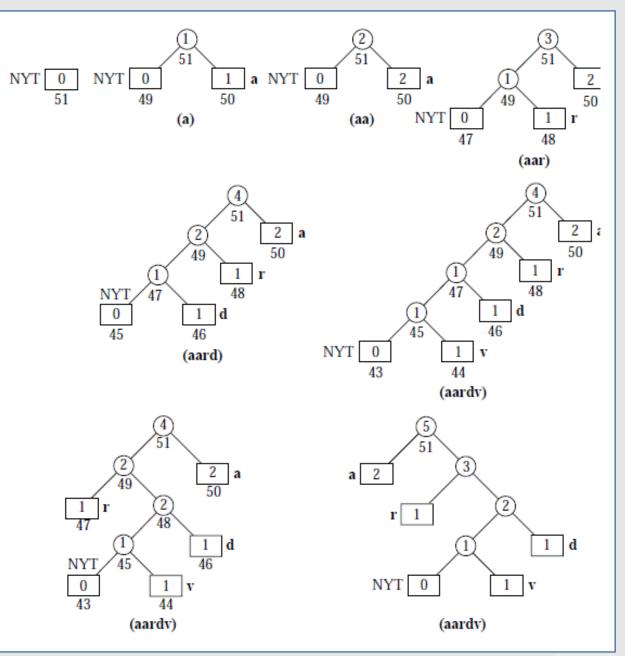


- Adaptive Huffman Codes
 - Update Procedure:



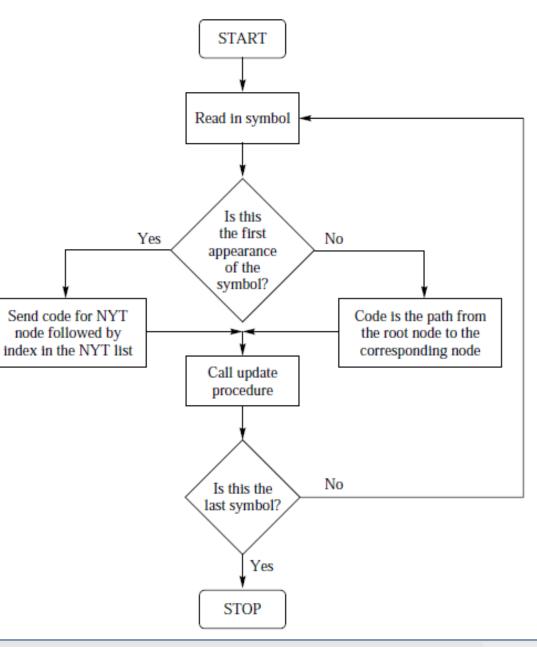


- Adaptive Huffman Codes
 - Update Procedure:
 - Example: aardv





- <u>Adaptive Huffman Codes</u>
 - Encoding Procedure:



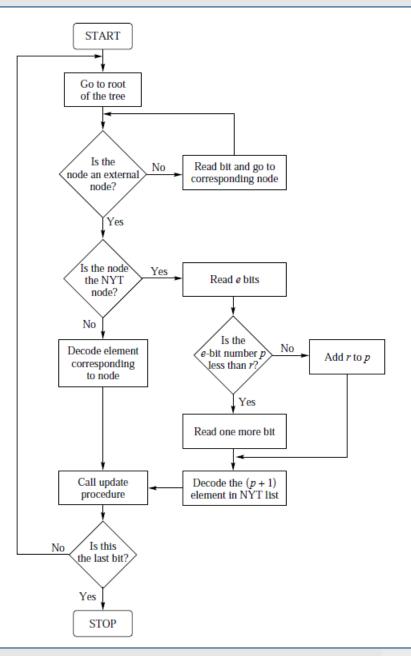


- Adaptive Huffman Codes
 - Encoding Procedure:
 - Example: aardva
 - *a* = 00000
 - *a* = 1
 - r = 010001
 - d = 0000011
 - v = 0001011
 - *a* = 0

Code to transmit: 000001010001000001100010110



- <u>Adaptive Huffman Codes</u>
 - Decoding Procedure:





- Adaptive Huffman Codes
 - Decoding Procedure:
 - *Example:* 000001010001000001100010110
 - 00000 = a
 - 1 = a
 - 010001 = r
 - 0000011 = d
 - 0001011 = v

•
$$0 = a$$

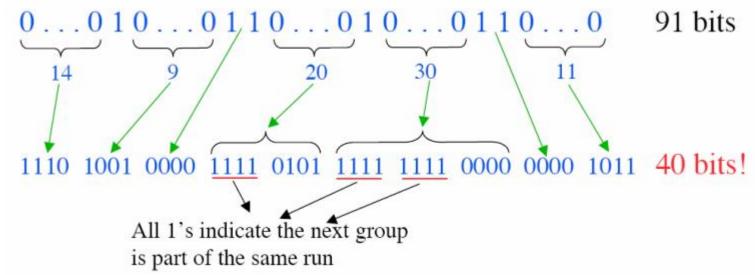


• <u>Run-Length Coding (RLE)</u>

- In many sources, it is possible to have consecutive identical symbols.
- It is not efficient to encode each of these symbols separately.
- Hence, the repeated value is generally coded once along with the number of times it appears.
- For example, in a binary sequence, if 0's are more probable, then we can code the run length of 0's using k-bits and transmit the code.
- In this case, we will not transmit the runs of 1's.



- <u>Run-Length Coding (RLE)</u>
 - Suppose k = 4.



- Is there a more efficient way of encoding the run lengths?
 - Why fixed length codes?



• <u>Unary Codes</u>

- A simple code for integers which uses the following coding scheme:
 - Codeword for an integer *n* is *n* number of 1s followed by a 0.
 - E.g., codeword for 4 is 11110 and for 7 is 11111110.
- Unary code is optimal when $A = \{1, 2, 3, ...\}$ and $P[k] = \frac{1}{2^k}$



Golomb Codes

- A family of codes parameterized by an integer m > 0.
- In the Golomb code with parameter m, we represent an integer n > 0 using two parameters q and r, where

$$q = \left\lfloor \frac{n}{m} \right\rfloor$$

and

$$r = n - qm$$
,

- q is the quotient and r is the remainder when n is divided by m.
- q can take on values 0,1,2, ... and is represented by the unary code of q.
- r can take on values 0, 1, 2, ..., m 1.
 - If m is a power of 2, we use the $\log_2 m$ -bit binary representation of r.
 - If m is not a power of 2, we could still use $\lceil \log_2 m \rceil$ bits,
 - We can reduce the number of bits required if we use the $\lfloor \log_2 m \rfloor$ -bit binary representation of r for the first $2^{\lfloor \log_2 m \rfloor} m$ values and the $\lfloor \log_2 m \rfloor$ -bit binary representation of $r + 2^{\lfloor \log_2 m \rfloor} m$ for the rest of the values.



• Golomb Codes

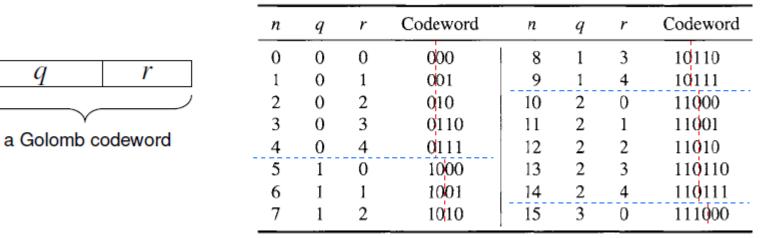
- Example:
- $m = 5, \lceil \log_2 5 \rceil = 3, \lfloor \log_2 5 \rfloor = 2, 2^{\lceil \log_2 5 \rceil} = 8$
- So the first 8 5 = 3 values of *r* where (*r* = 0, 1, 2) will be represented by the 2 bit binary representation of *r*.
- The next two values (r = 3, 4) will be represented by the 3-bit representation of r + 3.
- The quotient q is represented by the unary code for q.
- So the codeword for 3 is 0110 and for 21 is 1111001.



q

• Golomb Codes

Example:







• Golomb Codes

Example: Encoding Run Lengths using Golomb Codes

17 bits \rightarrow 9 bits



• Golomb Codes

Optimality of Golomb Codes and Choosing "m":

- Suppose that 0 has the probability p and 1 has probability 1-p
- Golomb code is optimal for the probability model:

$$P(n) = p^{n-1}q, \qquad q = 1-p$$

when

$$m = \left[-\frac{1}{\log_2 p} \right]$$

For example, if p=127/128
$$m = \left[-\frac{1}{\log_2 \left(\frac{127}{128}\right)} \right] = 89$$

- Golomb Codes
 - Useful for binary compression when one symbol is much more likely than the other.



<u>Tunstall Codes</u>

- All codewords are of equal length
- Each codeword represents a different number of letters

TABLE 3.18

- The main advantages is that errors in codewords do not propagate
- Example: Alphabet $\mathcal{A} = \{A, B\}$

Sequence	Codeword
AAA	00
AAB	01
AB	10
В	11

A 2-bit Tunstall code.



• <u>Tunstall Codes</u>

- Coded String: 001101010100
- Entropy?
- Average Codeword Length using FLC?
- Average Codeword Length using Huffman?
- Average Codwowrd Length using Tunstall?



• <u>Tunstall Codes</u>

<u>Algorithm:</u>

- Tunstall Code: n-bit, Source: iid, Alphabet Size: N, Number of codewords: 2ⁿ.
 - Start with the N letters of the source alphabet
 - Remove the entry in the codebook that has the highest probability
 - Add the N strings obtained by concatenating this letters with every letter in the alphabet (including itself).
- Repeat the above steps



<u>Tunstall Codes</u>

Example 2:

• Tunstall Code: 3-bit, Source: iid, Alphabet: $\mathcal{A} = \{A, B, C\}, P(A) = 0.6, P(B) = 0.3, P(C) = 0.1.$

		TABLE 3.21	The codebook after	TABLE 3.22	A 3-bit Tunstall code.
	Source alphabet and associated probabilities.		one iteration.	Sequence	Probability
	_	Sequence	Probability	R	000
Letter	Probability	В	0.30	C D	001
Α	0.60	С	0.10	AB	010
В	0.30	AA	0.36	AC	011
С	0.10	AB	0.18	AAA	100
		AC	0.06	AAB	101
				AAC	110



- Application of Huffman Coding
 - Lossless Image compression:
 - Test Images





• Application of Huffman Coding

• Lossless Image compression:

Image Name	Bits/Pixel	Total Size (bytes)	Compression Ratio
Sena	7.01	57,504	1.14
Sensin	7.49	61,430	1.07
Earth	4.94	40,534	1.62
Omaha	7.12	58,374	1.12

TABLE 3.23 Compression using Huffman codes on pixel values.

- We get a reduction of about $\frac{1}{2}$ to 1 bit/pixel.
- If we are storing 1000s of images, 1 bit/pixel saves many megabytes
- We can do even better by modelling the data first.



• Application of Huffman Coding

- Lossless Image compression:
- Using the model: $\hat{x}_n = x_{n-1}$

Image Name	Bits/Pixel	Total Size (bytes)	Compression Ratio
Sena	4.02	32,968	1.99
Sensin	4.70	38,541	1.70
Earth	4.13	33,880	1.93
Omaha	6.42	52,643	1.24

TABLE 3.24Compression using Huffman codes on pixel difference values.



• Application of Huffman Coding

- Lossless Image compression:
- Using the model: $\hat{x}_n = x_{n-1}$
- Using adaptive Huffman Coding

TABLE 3.25Compression using adaptive Huffman codes on pixel difference
values.

Image Name	Bits/Pixel	Total Size (bytes)	Compression Ratio
Sena	3.93	32,261	2.03
Sensin	4.63	37,896	1.73
Earth	4.82	39,504	1.66
Omaha	6.39	52,321	1.25



<u>Application of Huffman Coding</u>

• <u>Text compression:</u>

Letter	Probability	Letter	Probability
А	0.057305	N	0.056035
B	0.014876	0	0.058215
С	0.025775	Р	0.021034
D	0.026811	Q	0.000973
E	0.112578	R	0.048819
F	0.022875	S	0.060289
G	0.009523	Т	0.078085
Н	0.042915	U	0.018474
Ι	0.053475	v	0.009882
J	0.002031	W	0.007576
K	0.001016	Х	0.002264
L	0.031403	Y	0.011702
Μ	0.015892	Z	0.001502

TABLE 3.26 Probabilities of occurrence of the letters in the English alphabet in the U.S. Constitution.

TABLE 3.27 Probabilities of occurrence of the letters in the English alphabet in this chapter.

Letter	Probability	Letter	Probability
Α	0.049855	N	0.048039
в	0.016100	0	0.050642
C	0.025835	Р	0.015007
D	0.030232	Q	0.001509
E	0.097434	R	0.040492
F	0.019754	S	0.042657
G	0.012053	Т	0.061142
Н	0.035723	U	0.015794
Ι	0.048783	V	0.004988
J	0.000394	W	0.012207
K	0.002450	Х	0.003413
L	0.025835	Y	0.008466
Μ	0.016494	Z	0.001050

• For Chapter 3, the file size dropped from about 70,000 bytes to about 43,000 bytes with Huffman coding.



• Application of Huffman Coding

• Audio compression:

TABLE 3.28Huffman coding of 16-bit CD-quality audio.

File Name	Original File Size (bytes)	Entropy (bits)	Estimated Compressed File Size (bytes)	Compression Ratio
Mozart	939,862	12.8	725,420	1.30
Cohn	402,442	13.8	349,300	1.15
Mir	884,020	13.7	759,540	1.16

TABLE 3.29Huffman coding of differences of 16-bit CD-quality audio.

File Name	Original File Size (bytes)	Entropy of Differences (bits)	Estimated Compressed File Size (bytes)	Compression Ratio
Mozart	939,862	9.7	569,792	1.65
Cohn	402,442	10.4	261,590	1.54
Mir	884,020	10.9	602,240	1.47



References

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- R.G. Gallager. Variations on a theme by Huffman. *IEEE Transactions on Information Theory*, IT-24(6):668–674, November 1978.
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- [4] J.S. Vitter. Design and analysis of dynamic Huffman codes. *Journal of ACM*, 34(4):825–845, October 1987.

