

Lecture #6 – Compression

ESE 1500 – DIGITAL AUDIO BASICS

Based on slides © 2009–2023 DeHon
Additional Material © 2014 Farmer

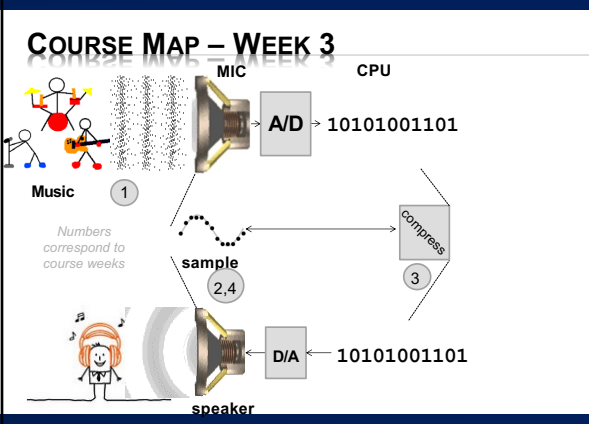
1

LECTURE TOPICS

- × Where are we on course map?
- × **Preclass**
- × **Compression: Lossy and Lossless**
- × **Lossless Compression**
 - + Probability-based lossless compression
 - × Huffman Encoding
- × **Part 2:**
 - + Common case
 - + Entropy
 - × Shannon Limits
- × **Next Lab**
- × **References**

2

COURSE MAP – WEEK 3



Music (1) → MIC → A/D → 10101001101 → CPU → compress (3) → sample (2,4) → D/A → 10101001101 → speaker

Numbers correspond to course weeks

3

PRECLASS

5

PRECLASS

- × Tell me and I forget, teach me and I may remember, involve me and I learn
 - + -- Benjamin Franklin
- × **73 symbols** (fancy, more general term for letters)
- × **19 unique (ignoring case)**
 - + (A, B, C, D, E, F, G, H, I, L, M, N, O, R, T, V, Y, space, comma)
 - + How many bits to represent each symbol?
- × **How many bits to encode quote?**

6

PRECLASS

- × Tell me and I forget, teach me and I may remember, involve me and I learn
 - + -- Benjamin Franklin
- × **73 symbols**
- × **19 unique (ignoring case)**
- × **If symbols occurrence equally likely, how many occurrences of each symbol should we expect in quote?**
- × **How many E's are there in the quote?**

7

PRECLASS

- × **Tell me and I forget, teach me and I may remember, involve me and I learn**
 - + -- Benjamin Franklin
- × **73 symbols**
- × **19 unique (ignoring case)**
- × **Conclude**
 - + Symbols do not occur equally
 - + Symbol occurrence is not uniformly random

8

PRECLASS

- × **Tell me and I forget, teach me and I may remember, involve me and I learn**
 - + -- Benjamin Franklin
- × **Using uniform encoding (from question 1)**
 - + How many bits to encode first 24 symbols?
- × **How many bits using encoding given (Q5a)?**

$$TotalBits = \sum_{i=1}^{24} bits[quote[i]]$$

9

PRECLASS

- × **Tell me and I forget, teach me and I may remember, involve me and I learn**
 - + -- Benjamin Franklin
- × **Using uniform encoding (question 1)**
 - + How many bits to encode all 73 symbols?
- × **How many bits using encoding given (Q5c)?**

$$TotalBits = \sum_{i=1}^{73} bits[quote[i]]$$

10

CONCLUDE

- × **Can encode with (on average) fewer bits than $\log_2(\text{unique-symbols})$**

11

INTRO TO COMPRESSION

12

DATA COMPRESSION

- × **What is compression?**
 - + Encoding information using fewer bits than the original representation
- × **Why do we need compression?**
 - + Most digital data is not sampled/quantized/represented in the most compact form
 - × It takes up more space on a hard drive/memory
 - × It takes longer to transmit over a network
 - + Why? Because data is represented so that it is easiest to use
- × **Two broad categories of compression algorithms:**
 - + **Lossless** – when data is un-compressed, data is its original form
 - × No data is lost or distorted
 - + **Lossy** – when data is un-compressed, data is in **approximate** form
 - × Some of the original data is lost

13

12

13

RECALL ADC PROCESS?

- × **Analog-to-Digital (ADC) Conversion**
 - We have 7 discrete voltages, # of bits to represent 7 things?
 - 3-bits! Why? $2^3\text{-bits} = 8$ (1 unused state)

Encoding: mapping data from one form to another (not always conversion) 14

14

EXAMPLE OF LOSSY COMPRESSION

- × Sample Rate: 1000 samples/sec, Resolution: 3-bits per sample
- × Our Sampled Signal: {0, 2.2V, 3V, 2.2V, 0, -2.2V, -3, -2.2V, 0}
- × Our Quantized Signal: {0, 2V, 3, 2V, 0, -2, -3, -2, 0}
- × Our 3-bit Digitized Data: {011, 101, 110, 101, 011, 001, 000, 001, 011}
 - space required to store/transmit: 27 bits
- × ADC related compression algorithm:
 - CS&Q (Coarser Sampling AND/OR Quantization)
 - Either reduce number of bits per sample AND/OR discard a sample completely
 - Example with our digitized data:
 - Our 3-bit Digitized Data: {011, 101, 110, 101, 011, 001, 000, 001, 011}
 - If we drop the sampling rate by a factor of 2, how impact number of bits needed?
 - **Lossy** because we cannot restore exact original

15

15

DE-COMPRESSION OF SIGNAL:

- × **Decompression & DAC Process**
 - Original digital signal: {011, 101, 110, 101, 011, 001, 000, 001, 011}
 - Original Sampling Rate: 1000 samples/sec

Original Signal (recall ADC/DAC is approximation at best anyway!) 16

16

DE-COMPRESSION OF SIGNAL:

- × **Decompression & DAC Process**
 - Original compressed signal: {011, , 110, , 011, , 000, , 011}
 - New Sampling Rate Due to Compression: 500 samples/sec

Effect of CS&Q compression:
Lowered Sampling Rate
Added "noise" to signal
Listeners might not notice!

Lossy Compression:
One can achieve high
Compression ratios

Frequently used for Audio:
MP3 format uses lossy
compression algorithm

Lossy: Compression removed every other sample 17

17

TWO FORMS OF CLASSIFICATION

```

    Compression Algorithms
    /      \
  Lossy    Lossless

  Compression Algorithms
  /      \
Fixed Group Size  Variable Group Size
  
```

Examples of **Fixed** Group Size:
Take in 2 samples: (6-bits) always spit out: (3-bits)
Take in 8-bit ASCII character (group), spit out 7-bit ASCII character (group)

18

18

PROBABILITY-BASED LOSSLESS COMPRESSION

19

19

INFORMATION CONTENT

- × Does each character contain the same amount of “information”?

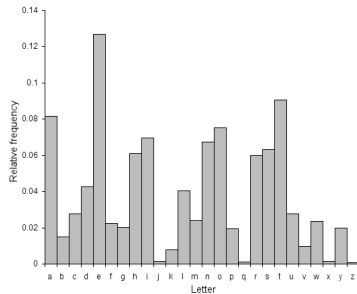
20

STATISTICS

- How often does each character occur?
 - Capital letters versus non-capitals?
 - How many e's in preclass quote?
 - How many z's?
 - How many q's?

21

ENGLISH LETTER FREQUENCY



<http://en.wikipedia.org/wiki/File:English-slf.png>

22

HUFFMAN ENCODING

- × Developed in 1950's (D.A. Huffman)
- × Takes advantage of frequency of stream of bits occurrence in data
 - Can be done for ASCII (8-bits per character)
 - × Characters do not occur with equal frequency.
 - × How can we exploit statistics (frequency) to pick character encodings?
 - But can also be used for anything with symbols occurring frequently
 - × E.g., Music (drum beats...frequently occurring data)
 - Example of **variable length** compression algorithm
 - × Takes in fixed size group – spits out variable size replacement

23

HOW MANY BITS TO REPRESENT ALL LETTERS?

Letter	Binary Encoding	Letter	Binary Encoding
A	00000	N	01101
B	00001	O	01110
C	00010	P	01111
D	00011	Q	10000
E	00100	R	10001
F	00101	S	10010
G	00110	T	10011
H	00111	U	10100
I	01000	V	10101
J	01001	W	10110
K	01010	X	10111
L	01011	Y	11000
M	01100	Z	11001

Including upper and lower case?
...and numbers, how many bits?

24

ASCII ENCODING (7-BIT ENCODING)

Letter	ASCII Code	Binary	Letter	ASCII Code	Binary
a	097	01100001	A	065	01000001
b	098	01100010	B	066	01000010
c	099	01100011	C	067	01000011
d	100	01100100	D	068	01000100
e	101	01100101	E	069	01000101
f	102	01100110	F	070	01000110
g	103	01100111	G	071	01000111
h	104	01101000	H	072	01001000
i	105	01101001	I	073	01001001
j	106	01101010	J	074	01001010
k	107	01101011	K	075	01001011
l	108	01101100	L	076	01001100
m	109	01101101	M	077	01001101
n	110	01101110	N	078	01001110
o	111	01101111	O	079	01001111
p	112	01110000	P	080	01010000
q	113	01110001	Q	081	01010001
r	114	01110010	R	082	01010010
s	115	01110011	S	083	01010011
t	116	01110100	T	084	01010100
u	117	01110101	U	085	01010101
v	118	01110110	V	086	01010110
w	119	01110111	W	087	01010111
x	120	01111000	X	088	01011000
y	121	01111001	Y	089	01011001
z	122	01111010	Z	090	01011010

ASCII:
American Standard Code for Information Interchange
 $2^7=128$ combinations

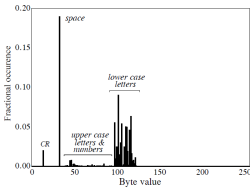
Standard encoding, developed in the 1960's

Didn't take into account international standards!

UNICODE
8-bit encoding
 $2^8=256$ possibilities!

25

HUFFMAN ENCODING – THE BASICS



- * Example: more than 96% of file consists of 31 characters
- * Idea: Assign frequently used characters fewer bits
 - + 31 common characters get 5b codes 00000-11110
 - + Rest get 13b: 11111+original 8b code
- * How many bits do we need on average per original byte?

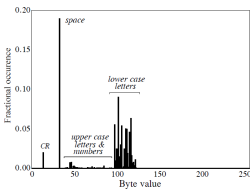
26

CALCULATION

- * Bits = #5b-characters * 5 + #13b-character * 13
- * Bits=#bytes*0.96*5 + #bytes*0.04*13
- * Bits/original-byte = 0.96*5+0.04*13
- * Bits/original-byte = 5.32

27

HUFFMAN ENCODING – MORE ADVANCED



Example Encoding Table

letter	probability	Huffman code
A	.154	1
B	.110	01
C	.072	0010
D	.063	0011
E	.059	0001
F	.015	000010
G	.011	000011

- * Huffman goes further: Assign MOST used characters least # of bits:
 - + Most frequent: A= 1, least frequent: G=000011, etc.
 - + Example: original data stream: C E G A D F B E A...
- Huffman encoded: 0010 0001 000011 1 0011 000010 01 0001 1...

28

PRECLASS ENCODING

symbol	encode	occur
(space)	00	15
A	1110	
B	100100	
C	100101	
D	10110	
E	110	11
F	011010	
G	011011	
H	011000	
I	0111	

symbol	encode	occur
L	0100	
M	1111	
N	1010	
O	10011	
R	0101	
T	10111	
V	10000	
Y	011001	
,	10001	

29

PRECLASS ENCODING

symbol	encode	occur
(space)	00	15
A	1110	6
B	100100	
C	100101	
D	10110	
E	110	11
F	011010	
G	011011	
H	011000	
I	0111	4

symbol	encode	occur
L	0100	4
M	1111	6
N	1010	5
O	10011	
R	0101	4
T	10111	
V	10000	
Y	011001	
,	10001	

30

30

PRECLASS ENCODING

symbol	encode	occur
(space)	00	15
A	1110	6
B	100100	
C	100101	
D	10110	3
E	110	11
F	011010	
G	011011	
H	011000	
I	0111	4

symbol	encode	occur
L	0100	4
M	1111	6
N	1010	5
O	10011	2
R	0101	4
T	10111	3
V	10000	2
Y	011001	
,	10001	2

31

31

PRECLASS ENCODING

symbol	encode	occur
(space)	00	15
A	1110	6
B	100100	1
C	100101	1
D	10110	3
E	110	11
F	011010	1
G	011011	1
H	011000	1
I	0111	4

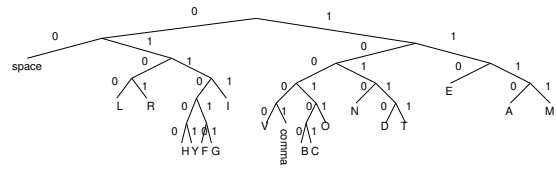
symbol	encode	occur
L	0100	4
M	1111	6
N	1010	5
O	10011	2
R	0101	4
T	10111	3
V	10000	2
Y	011001	1
,	10001	2

See how variable length encoding saved bits?
Questions?

32

PRECLASS ENCODING

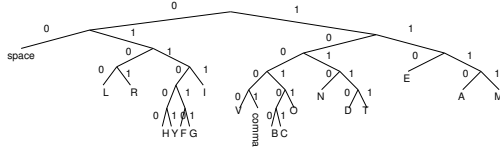
× Prefix decodable on tree



33

PRECLASS ENCODING

× Prefix decodable on tree



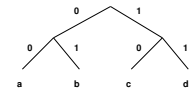
- × Cannot have 4 length 2 codes and longer codes
- × Each length 2 code consumes 25% of code space
- × Each length n code consumes 2⁻ⁿ of space
- × Having some short codes means some things get longer encodings

34

PREFIX DECODABLE

× Consider small 4 symbol case

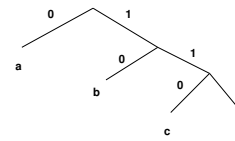
+ Uniform 2b each



+ Can give one symbol 1b code: say 0

+ But then must code remaining 3 cases start with 1

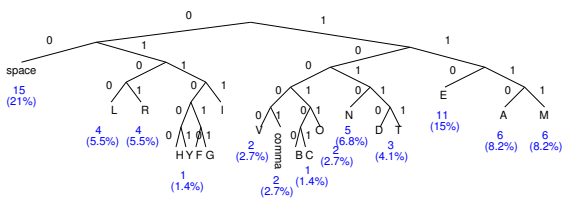
× 3 cases left – need at least 2 more bits for some to differentiate



35

PRECLASS ENCODING

× Probability, encoding, length



36

36

INTERLUDE

37

37

INTERLUDE

- × **SNL – 5 minute University**
 - + Father Guido Sarducci
- × <https://www.youtube.com/watch?v=kO8x8eoU3L4>
- × **What form of compression here?**

38

38

FOR COMPUTER ENGINEERING?

- × **Make the common case fast**
- × **Make the frequent case small**

39

39

PART 2

40

40

COMMON CASE

- × **Big idea in optimization engineering**
 - + **Make the common case inexpensive**
- × **Shows up throughout computer systems**
 - + Computer architecture
 - × Caching, instruction selection, branch prediction, ...
 - + Networking and communication, data storage
 - × Compression, error-correction/retransmission
 - + Algorithms and software optimization
 - + User Interfaces
 - × Where things live on menus, shortcuts, ...
 - × How you organize your apps on screens

41

41

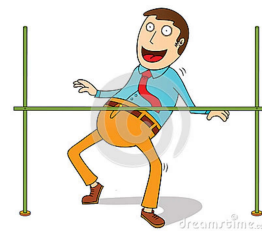
ENTROPY

Is there a lower bound for compression?

42

42

HOW LOW CAN WE GO WITH COMPRESSION?



What is the least # of bits required to encode information?

43

43

CLAUDE SHANNON



- × **Father of Information Theory, brilliant mathematician**
- × **While at AT&T Bell Labs, landmark paper in 1948**
- × **Determined exactly how low we can go with compression!**

44

SHANNON'S ENTROPY

- × **What is entropy?**
 - + Chaos/Disorganization/Randomness/Uncertainty
- × **Shannon's Famous Entropy Formula:**

$$H = - \sum p(x) \log_2 p(x)$$

Shannon's Entropy (measured in bits) Negative Sum Of: Probability of each outcome X
 \log_2 of (probability of each outcome)

45

ESTIMATING ENTROPY OF ENGLISH LANGUAGE

- × **Example: 32 Characters**
- × **If we assume all characters are equally probable:**

$$p(\text{each character}) = \frac{1}{32}$$

- × **Information Entropy per character:**

$$H = - \sum p(x) \log_2 p(x)$$

$$H = -32 \left(\frac{1}{32} \right) \log_2 \left(\frac{1}{32} \right) = -\log_2 \left(\frac{1}{32} \right) = +5 \text{ bits}$$

Same thing we got when we said we needed $\log_2(\text{unique_things})$ bits

46

46

ESTIMATING ENTROPY OF ENGLISH LANGUAGE

- × **27 Characters (26 letters + space)**
- × **If we assume all characters are equally probable:**

$$p(\text{each character}) = \frac{1}{27}$$

- × **Information Entropy per character:**

$$H = - \sum p(x) \log_2 p(x)$$

$$H = -27 \left(\frac{1}{27} \right) \log_2 \left(\frac{1}{27} \right) = -\log_2 \left(\frac{1}{27} \right) = +4.75 \text{ bits}$$

Same thing we got when we said we needed $\log_2(\text{unique_things})$ bits

47

47

PRECLASS 5C

- × **Computed total bits as sum of bits**

$$\text{TotalBits} = \sum_i^73 \text{bits}[\text{quote}[i]]$$

- × **Per character**

- + Divide by total characters
- + Group by same symbols
- + $p_i = \# \text{occurrences} / \text{total_characters}$

$$\text{Average Bits} = \sum_i p_i \times \text{bits}(i)$$

48

48

SHANNON ENTROPY

- × **Essentially says**
 - + Should be able to encode symbol with $\log(1/p)$ bits

$$\text{Average Bits} = \sum_i p_i \times \text{bits}(i)$$

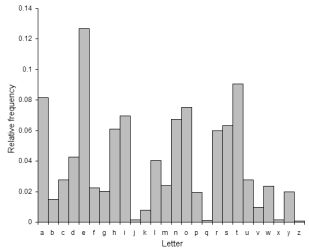
$$H = - \sum_i p_i \times \log_2(p_i)$$

49

49

RECALL:

Not all letters are equally probable in English Language



<http://en.wikipedia.org/wiki/File:English-slf.png>

50

SHANNON ENTROPY ENGLISH LETTERS

$$H = -\sum_i p_i \times \log_2(p_i)$$

letter	p	$-\log_2(p)$	$-p \times \log_2(p)$
a	8.17%	3.61	0.30
b	1.49%	6.07	0.09
c	2.78%	5.17	0.14
d	4.25%	4.56	0.19
e	12.70%	2.98	0.38
f	2.23%	5.49	0.12
z	0.07%	10.40	0.01
sum	100.00%		4.18

51

51

SHANNON ENTROPY PRECLASS QUOTE

$$H = -\sum_i p_i \times \log_2(p_i)$$

Symbol	Bits	Occur	P	$-\log_2(p)$	$-p \times \log_2(p)$	$p \times \text{bits}$
(space)	2	15	0.21	2.28	0.47	0.41
A	4	6	0.08	3.60	0.30	0.33
B	6	1	0.01	6.19	0.08	0.08
C	6	1	0.01	6.19	0.08	0.08
D	5	3	0.04	4.60	0.19	0.21
E	3	11	0.15	2.73	0.41	0.45
,	5	2	0.03	5.19	0.14	0.14
sum					3.74	3.77

52

52

ENCODING TARGET

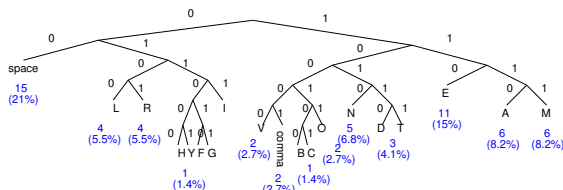
- × Right bits target is:
 - + $\text{Bits}(i) = -\log_2(p_i)$
 - + $2^{-\text{Bits}(i)} = p_i$
- × Symbol should take up fraction of encoding space matching probability of occurrence

53

53

PRECLASS ENCODING

- × Probability, encoding, length



54

54

SUMMING IT UP: SHANNON & COMPRESSION

- × **Shannon's Entropy represents a lower limit for lossless data compression**
 - + It tells us the minimum number of bits that can be used to encode a message without loss (according to a particular model)
- × **Shannon's Source Coding Theorem:**
 - + A lossless data compression algorithm cannot compress messages to have (on average) more than 1 bit of Shannon's Entropy per bit of encoded message

55

55

LEARN MORE

- × **ESE 3010– Probability**
 - + Central to understanding probabilities
 - × What cases are common and how common they are
- × **ESE 6740 – Information Theory**
- × **Most all computer engineering courses**
 - + Deal with common-case optimizations
 - + CIS2400, CIS4710, CIS3800, ESE4070,

56

56

BIG IDEAS

- × **Lossless Compression**
 - + Exploit non-uniform statistics of data
 - + Given short encoding to most common items
- × **Common Case**
 - + Make the common case inexpensive
- × **Shannon’s Entropy**
 - + Gives us a formal tool to define lower bound for compressibility of data

57

57

MONDAY IN LAB

- × **Implement Compression!**
 - + Implement Huffman Compression
 - + **Note:** longer prelab with MATLAB intro; plan accordingly
 - × Budget a few hours
- × **Remember**
 - + Feedback

58

58

REFERENCES

- × **S. Smith, “The Scientists and Engineer’s Guide to Digital Signal Processing,” 1997.**
- × **Shannon’s Entropy (excellent video)**
<http://www.youtube.com/watch?v=JnJq3Py0dyM>
 - + Used heavily in the creation of entropy slides

59

59