EECE 523

Ch. 1 Introduction & Lossless Example

I. Introduction

Wht is Dta Cmprsn? The systematic removal and, later, reintroduction of redundancy from data, and possibly also the removal of insignificant data.



Similar to Orange Juice Concentrate:



II. Lossless Vs. Lossy

There are two broad categories of data compression:

- Lossless Compression
- Lossy Compression

<u>Lossless Compression</u>: Original digital data can be <u>exactly</u> reconstructed from the compressed data

Generally applied to:
≻text files (documents, source code, etc.)
>program files

•Can achieve modest compression ratios:

>2:1 to 8:1 depending on type of content of file

•Examples:

≻UNIX "compress" command

≻PKZIP

≻Ram Doublers, Stacker, etc.

<u>Lossy Compression</u>: Original digital data can only be <u>approximately</u> reconstructed from the compressed data

•Generally applied to:

Signals (speech, music, sensor signals, etc.)

Images (digitized photos, digitized video)

•Can achieve large compression ratios:

≻up to (many tens): 1 depending on type & content to data

•Examples:

➢JPEG (for digitized photos)

➢MPEG (for digitized video)

Speech compression used in digital cell phones

➢Digital answering machines

► MP3 (for music)

Lossless Example to Motivate Needed Theory Consider a source with alphabet $\{A, B, C, D\}$ Suppose this is a typical source sequence:

DAABCAAABADBAAABBAAACDBC

The # of occurances of symbols in this sequence are: $N_A = 12$ $N_B = 6$ $N_C = 3$ $N_D = 3$

Total # *of symbols in sequence* = 24

 $\underline{\Delta}^N$

Say we have a binary code for the symbols such that length in bits of code word $A = \ell_A$ length in bits of code word $B = \ell_B$ length in bits of code word $D = \ell_D$

 $\underbrace{Total \ \# \ of \ bits \ to \ code \ sequence}_{\underline{\Delta}^{B_T}} = N_{A}\ell_{A} + N_{B}\ell_{B} + N_{C}\ell_{C} + N_{D}\ell_{D}$ $= 12\ell_{A} + 6\ell_{B} + 3\ell_{C} + 3\ell_{D}$

Avg # Bits/symbol
$$= \frac{B_T}{N}$$
$$= \frac{N_A}{N} \ell_A + \frac{N_B}{N} \ell_B + \frac{N_C}{N} \ell_C \frac{N_D}{N} \ell_D$$
$${}^{\ell_A} \text{"Freq. of Occurance"}$$
$$= 0.5 \ell_A + 0.25 \ell_B$$

 $\Rightarrow Want \ \ell_A \text{ to be smallest code length} \\ \text{ then } \ \ell_B \\ \text{ then } \ \ell_C \ and \ \ell_D$

 \Rightarrow Most likely symbols get fewer bits

Prob. Theory Says:

$$\lim_{N\to\infty}\frac{N_i}{N} = P_i$$

Prob. of ith event

 \Rightarrow Base on our theory on probability

⇒Avg. # Bits/Symbol uses probability average (not data average)

So, to study lossless <u>theory</u> we need to "specify" a probability <u>model</u> for the source: $P_{A1}, P_{B1}, P_{C1}, P_{D2}$

$$\Rightarrow \text{Avg Bits/symbol} = E\{\ell\}$$

$$\Rightarrow \text{Rv representing} \text{code word length} \text{of coded random symbols}$$

$$= P_A \ell_A + P_B \ell_B + P_C \ell_C + P_D \ell_D$$

So, for this example we want ℓ_A smallest, then ℓ_B , then $\ell_C = \ell_D$

So try: A = 0 B = 1 C = 01 D = 10

Code #1

Does that work? NO!

Can't decode sequences uniquely:

Original:
Coded:D A A B C ...
1 0 0 0 | 0 |Decoded:BAAABA...
DACAB...
etc.No unique decoding
etc.







Note this property: No other codeword is a prefix

Yes, this works! <Verify!>

So optimal lossless coding is a <u>constrained</u> <u>optimization</u> problem

minimize Avg. Bits/symbol subject to decodability



To study this \rightarrow Need some theory

Prob. Theory + Decodability

Information Theory (at least <u>part</u> of it)

Role of Info Theory Here:

•Determine conditions need for decodability

- •Determine lower bounds for avg. bits/symbol
- Provide understanding of how structure of the Source prob. Model impacts lower bounds
 Provide basis/structure on which practical codes can be built