

Audio and Video Coding

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Student Information Processing Board

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Overview

1. Mathematical preliminaries
2. Lossless compression
3. Audio coding
4. Video coding

The problems:

- ▶ **Representing information digitally.** We have Dvorak's "New World Symphony." How should we represent this inside a computer? ⇒ *Clearly a domain-specific problem...*
- ▶ **Lossless compression.** We have a set of bitstrings, like the great works of English literature represented in UTF-16LE. What's the most efficient way to represent them?
- ▶ **Lossy compression.** We have a set of bitstrings, and we want to represent them efficiently, but we're willing to tolerate some distortion. Given a "distortion function" that relates two bitstrings, and a maximum tolerance for distortion, what's the most efficient way to represent the strings? Or the constraint can be on maximum bits, trying to minimize distortion.

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These are inevitably domain-specific too!

Say we want to transmit a sequence of numbers.

9	11	11	11	14	13	15	17	16	17	20	21	...
---	----	----	----	----	----	----	----	----	----	----	----	-----

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One possibility: send five bits per symbol.

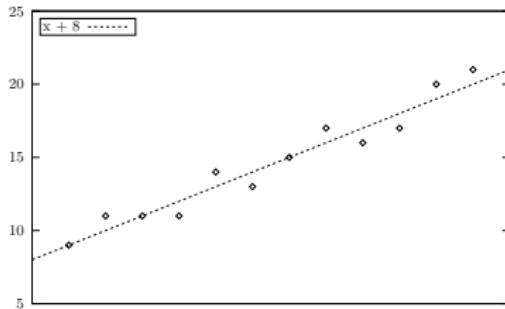
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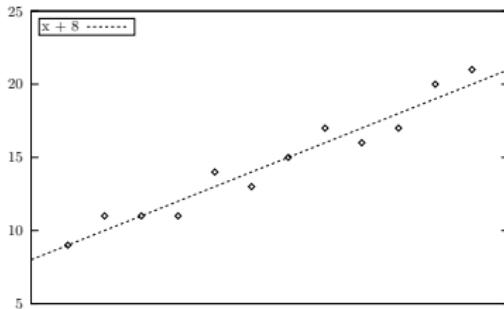


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Or:



0	1	0	-1	1	-1	0	1	-1	-1	1	1	...
---	---	---	----	---	----	---	---	----	----	---	---	-----

Subtract $x + 8$, then send just two bits per symbol!

Sayood, 1996

Another example:

27	28	29	28	26	27	29	28	30	32	34	36	38	...
----	----	----	----	----	----	----	----	----	----	----	----	----	-----

Send six bits per symbol?

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----	----	----	----	----	----	----	----	----	----	----	----	----	-----

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This time we can subtract $f[x - 1]$:

♡	1	1	-1	-2	1	2	-1	2	2	2	2	2	...
---	---	---	----	----	---	---	----	---	---	---	---	---	-----

Sayood, 1996

So **modeling** the source of data to let us **predict** symbols is important to finding an efficient representation.

How low can we go?

Shannon (1948) showed that the best that lossless compression can do, on average, is to match the *entropy* of the data source.

Let X be a discrete random variable, which outputs symbol $x \in \mathcal{X}$ with probability $p(x)$. Then the *entropy* $H(X)$ is:

$$H(X) = \sum_{x \in \mathcal{X}} p(x) \log \frac{1}{p(x)}.$$

Self-information

Entropy:

$$H(X) = \sum_{x \in \mathcal{X}} p(x) \log \frac{1}{p(x)} = - \sum_{x \in \mathcal{X}} p(x) \log p(x) \quad (1)$$

Each possible output $x \in \mathcal{X}$ will occur with a certain probability. The more probable outputs are not that surprising. The less probable outputs have a high “surprise factor,” also known as *self-information*.

We define the self-information of symbol x as $\log \frac{1}{p(x)}$.

Entropy is just the expected “surprise” per symbol! In other words, the entropy of the source is the average self-information per symbol.

Benefits of a logarithmic measure.

- ▶ Why do we define entropy *logarithmically*, as
– $\sum p(x) \log p(x)$?

Because it works. We want the information in two independent sources to be the sum of the information in each independent source. With a logarithmic measure, $H(X, Y) = H(X) + H(Y)$ for independent sources.

- ▶ What do we call the measure of information?

With a base-2 logarithm, *bits*. A natural logarithm gives *nats*. Base 10 yields *hartleys* (nobody uses hartleys).

Huffman coding.

- ▶ In coding data from a source, we want the coded rate to match the entropy as closely as possible. Each symbol's code length should be close to its self-information. More “surprising” symbols should require more bits.

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- ▶ The code assigns rarer symbols more bits, and the most common symbols are coded with the fewest bits. The procedure is based on one rule, applied recursively:
 1. The two symbols that occur least frequently should have the same length and differ only in the last bit.

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 1. The two symbols that occur least frequently should have the same length and differ only in the last bit.
- ▶ As an added benefit, Huffman codes are *prefix codes*, meaning we can decode each symbol immediately, without having to “look ahead.”

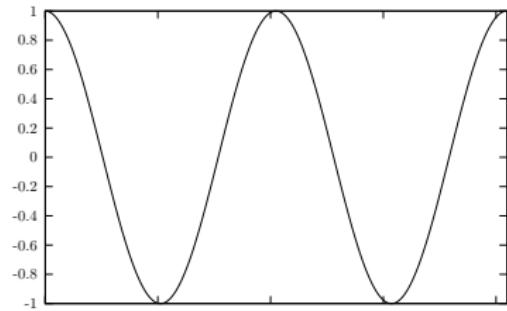
Huffman coding example.

'	\Rightarrow	111	E	\Rightarrow	000
T	\Rightarrow	1101	A	\Rightarrow	1011
I	\Rightarrow	1001	O	\Rightarrow	1000
R	\Rightarrow	0111	S	\Rightarrow	0110
N	\Rightarrow	0100	H	\Rightarrow	11001
C	\Rightarrow	10101	L	\Rightarrow	10100
D	\Rightarrow	01011	M	\Rightarrow	00111
U	\Rightarrow	00110	P	\Rightarrow	00100
F	\Rightarrow	110001	G	\Rightarrow	110000
B	\Rightarrow	010100	W	\Rightarrow	001011
Y	\Rightarrow	001010	V	\Rightarrow	0101010
K	\Rightarrow	01010110	X	\Rightarrow	010101110
Q	\Rightarrow	0101011110	J	\Rightarrow	01010111110
Z	\Rightarrow	01010111111			

Example by hand.

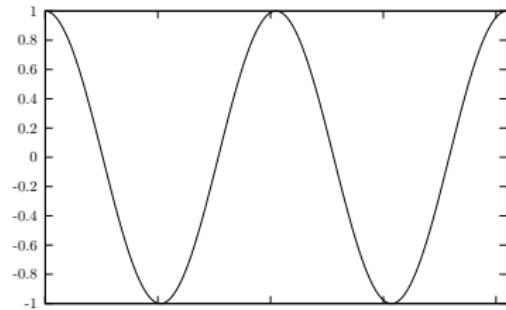
Coding audio.

What we want:

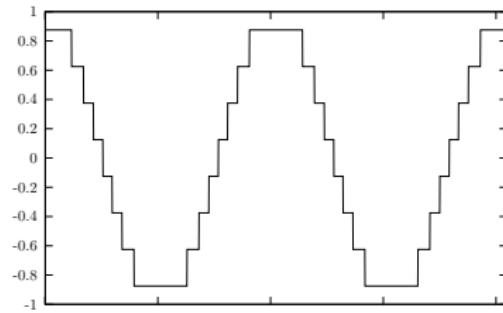


Coding audio.

What we want:



One way to compress:



Coding audio.

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- ▶ Nonlinear quantizer – pack output values closer together for more probable outputs.

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- ▶ Nonlinear quantizer – pack output values closer together for more probable outputs.
- ▶ Code multiple symbols at once to increase efficiency (vector quantization).
- ▶ **Use a smart distortion measure that makes use of the ear's weaknesses.**

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