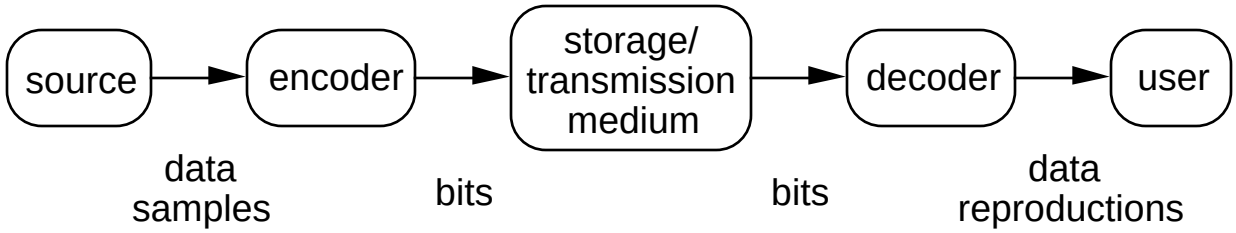
Introduction to Source Coding/Data Compression

Course is about the **Theory** and **Practice** of **Source Coding,** a.k.a. **Data Compression**

Data compression is process of **encoding** data from some **source** into **bits** in such a way that it can be **decoded** back into a **reproduction** of the original data.

Source code = data compressor = data compression system = **encoder + decoder**



encoder creates bits, decoder creates reproduction from bits

Goals:

efficiency: as few bits as possible

accuracy, fidelity: reproduction as much like original as possible

Source is assumed to produce **discrete-time samples or symbols**

e.g. text or samples of speech

we won't spend significant time on sampling issues; just assume the source is already sampled

source will be modelled as a **random process**, usually **stationary** and **ergodic**

why assume random?? because if not, why encode it? because can exploit statistical characteristics (what occurs more frequently. what values, what combinations of values (correlation))

autoregressive Gauss-Markov (AR) processes make nice tractable models of speech and image sources.

Rate is our measure of efficiency

rate = number of bits/sample

AVOID "compression ratio"

why encode into bits?? no big deal, just the most useful convention

Average Distortion wrt some distortion measure is our measure of fidelity

satisfactory human perception is usually the "ultimate" criteria

most commonly **MSE**

$$\text{empirical distortion} = D = \frac{1}{n}\sum_{i=1}^{n}(X_i - Y_i)^2$$

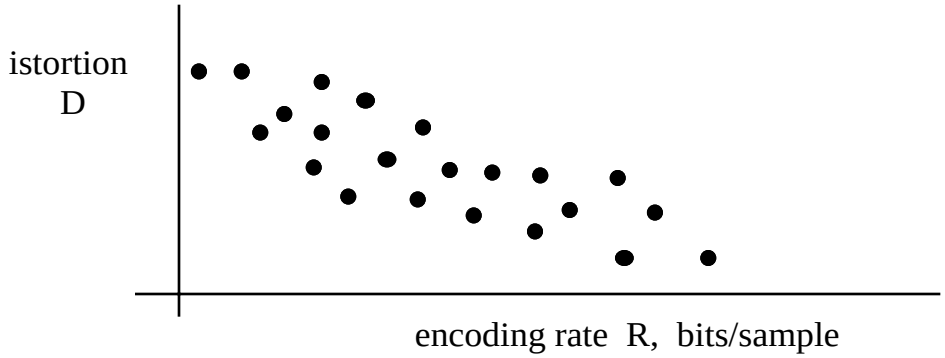
$$\text{statistical distortion} = D = E\left[\frac{1}{n}\sum_{i=1}^{n}(X_i - Y_i)^2\right] \text{ or } E(X-Y)^2$$

why MSE? pro's and cons

other distortion measures

usually emprical = statistical or else we're wasting our time with statistical

Summary: code performance on a given source is characterized by **rate and distortion**



Lossless coding is when $\hat{X}$ must equal X; i.e. D = 0

Lossy coding is the other case

course is 3/4's lossy, 1/4 lossless, projects are mostly lossy, so we begin with lossy

Complexity is other big issue

implementation complexity

number of arithmetic operations per sample

bytes of auxiliary storage, e.g. for tables

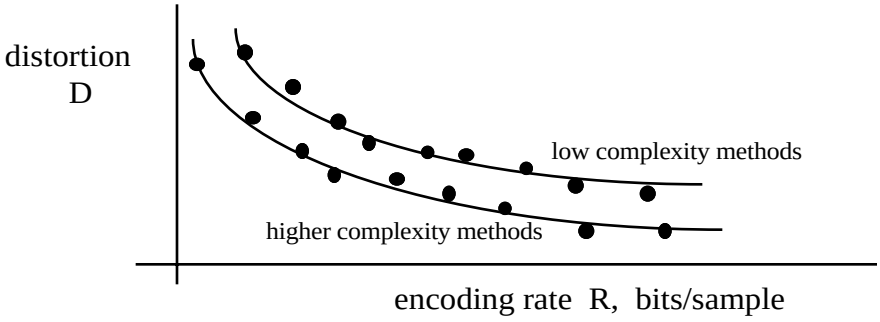
these influence:

building cost -- cost of building or buying hardware for computing and storing

running/operating cost -- cost of operating (depreciation, power, heat, rental, or sharing of resources)

design complexity is a lesser issue

performance vs. complexity



We're not concerned with **channel errors**

Though it's possible to build source codes that are terribly sensitive to channel errors, it is also possible to build them that are not. Any source code can be "fixed" so it is not too sensitive to errors, with only small loss. Typically, $p = 10^{-4}$ is small enough for speech and images, and even 10^{-3}.

Shannon says that an optimum communication system can have a separation of source code and channel code.

But there are many situations where we're just storing data and the storage medium is so reliable that it doesn't make sense to model it as a noisy channel.

Working through lossy coding (quantization) with channel errors makes interesting excercises.

Typical Examples of Lossy Compression

Source	Uncompressed	Compressed
Speech	64 Kbps	9.6K bps (CELP)
B/W Images	8 bpp	1 bpp (JPEG)
Color Images	24 bpp	1.25 bits/pixel
Video	100M bps	.01-20M bps
Audio	1.4M bps	256K bps (MPEG)

Typical Example of Lossless Compression

English Text	7 bits/symbol	3 bits/symbol