ECE 515 Information Theory

- Consider a binary discrete memoryless source (DMS) X = {0,1} with symbol probabilities p(1) = 1/4 p(0) = 3/4
- Sequences of *N* = 20 symbols

 - 2. 1,0,1,0,1,0,0,0,0,0,0,0,0,0,1,1,0,0,0,1

Tchebycheff Inequality

$$\eta_X \equiv E[X] = \sum_{k=1}^K p(x_k) \times x_k$$

$$\sigma_X^2 \equiv E[(X - \eta_X)^2] = \sum_{k=1}^K p(x_k) \times (x_k - \eta_X)^2$$

$$Pr\{|X - \eta_X| \ge \delta\} \le \frac{\sigma_X^2}{\delta^2}$$

Weak Law of Large Numbers

• Sequence of *N* i.i.d. RVs

$$\overline{X} = X_1, \dots, X_n, \dots, X_N$$

• Define a new RV

$$Y_N \equiv \frac{1}{N} \sum_{n=1}^N X_n$$

$$\eta_{Y_N} = \eta_X \quad \sigma_{Y_N}^2 = \frac{\sigma_X^2}{N}$$

Weak Law of Large Numbers

$$\lim_{N \to \infty} \Pr\left\{ \left| \left[\frac{1}{N} \sum_{n=1}^{N} X_n \right] - \eta_X \right| \ge \delta \right\} = 0$$

$$\lim_{N \to \infty} \Pr\left\{ \left| \left[\frac{1}{N} \sum_{n=1}^{N} X_n \right] - \eta_X \right| < \delta \right\} = 1$$

The sample average approaches the statistical mean

Asymptotic Equipartition Property

• *N* i.i.d. random variables X₁, ..., X_N

$$p(X_1, X_2, ..., X_N) = p(X_1)p(X_2)...p(X_N)$$

$$-\frac{1}{N}\log p(X_1, X_2, \dots, X_N) = -\frac{1}{N} \sum_{n=1}^N \log p(X_n) \to -E[\log p(X)] = H(X)$$

as $N \to \infty$

- RV X where $p(x_k) = p_k$
- Consider a sequence x of length N where x_k appears approximately Np_k times

$$p(\mathbf{x}) \approx p_1^{Np_1} p_2^{Np_2} \cdots p_k^{Np_k}$$

= $\prod_{k=1}^{K} p_k^{Np_k} = \prod_{k=1}^{K} ((2^{\log_2 p_k})^{Np_k})$
= $\prod_{k=1}^{K} 2^{Np_k \log_2 p_k} = 2^{N \sum_{k=1}^{K} p_k \log_2 p_k}$
= $2^{-NH(X)}$

- Binary RV X where $p(x_1) = p$ and $p(x_2) = 1-p$
- The number of sequences **x** of length N with $Np x_1$'s is $\binom{N}{Np} = \frac{N!}{(Np)!(N(1-p))!}$
- Stirling's approximation

$$n! \approx \sqrt{2\pi n} n^n e^{-n}$$

$$\binom{N}{Np} \approx \frac{N^{N} e^{-N}}{(Np)^{Np} e^{-Np} (N(1-p))^{N(1-p)} e^{-N(1-p)}}$$

$$= \frac{1}{p^{Np} (1-p)^{N(1-p)}}$$

$$= p^{-Np} (1-p)^{-N(1-p)}$$

$$= 2^{-Np \log p - N(1-p) \log(1-p)}$$

$$= 2^{N(-p \log p - (1-p) \log(1-p))}$$

$$= 2^{NH(X)}$$

- Consider a binary discrete memoryless source (DMS) X = {0,1} with symbol probabilities p(1) = 1/4 p(0) = 3/4
- H(X) = 0.811 bit
- Sequences of *N* = 20 symbols
- $2^{-NH(X)} = 1.3050 \times 10^{-5}$
- $2^{NH(X)} = 76627$

Summary

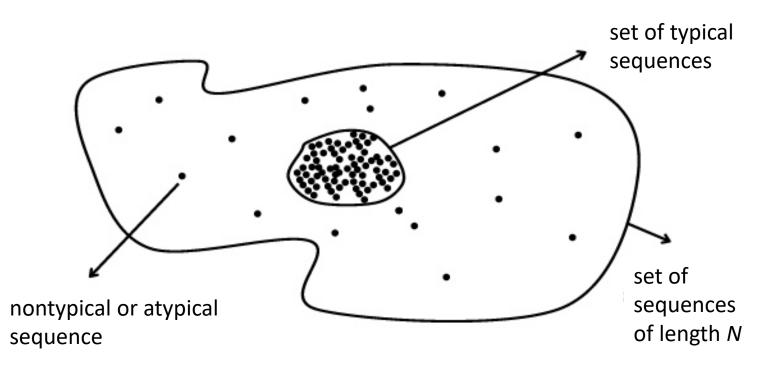
• The Tchebycheff inequality was used to prove the weak law of large numbers (WLLN)

– the sample average approaches the statistical mean as $N \rightarrow \infty$

- The WLLN was used to prove the AEP $-\frac{1}{N}\sum_{n=1}^{N} \log p(X_n) \rightarrow H(X) \text{ as } N \rightarrow \infty$
- A typical sequence has probability $p(\mathbf{x}) \approx 2^{-NH(X)}$
- There are about $2^{NH(X)}$ typical sequences of length N

$$\mathcal{T}_X(\delta) \equiv \{\mathbf{x} \colon |-\frac{1}{N}\log_b p(\mathbf{x}) - H(X)| < \delta\}$$

$$\mathcal{T}_X^c(\delta) \equiv \{\mathbf{x} : \left| -\frac{1}{N} \log_b p(\mathbf{x}) - H(X) \right| \ge \delta \}$$



Interpretation

- Although there are very many results that may be produced by a random process, the one actually produced is most probably from a set of outcomes that all have approximately the same chance of being the one actually realized.
- Although there are individual outcomes which may have a higher probability than outcomes in this set, the vast number of outcomes in the set almost guarantees that the outcome will come from the set.
- ``Almost all events are almost equally surprising" Cover and Thomas

• From the definition, the probability of occurrence of a typical sequence p(**x**) is

$$b^{-N[H(X)+\delta]} < p(\mathbf{x}) < b^{-N[H(X)-\delta]}$$

- $p(x_1) = p(1) = 1/4$ $p(x_2) = p(0) = 3/4$
- H(X) = 0.811 bit
- *N* = 3
- $p(x_1, x_1, x_1) = 1/64$
- $p(x_1, x_1, x_2) = p(x_1, x_2, x_1) = p(x_2, x_1, x_1) = 3/64$
- $p(x_1, x_2, x_2) = p(x_2, x_2, x_1) = p(x_2, x_1, x_2) = 9/64$
- $p(x_2, x_2, x_2) = 27/64$

• $H(X) = 0.811 \text{ bit } N = 3 \quad b = 2$

$$2^{-3[.811+\delta]} < p(x_1, x_2, x_3) < 2^{-3[.811-\delta]}$$

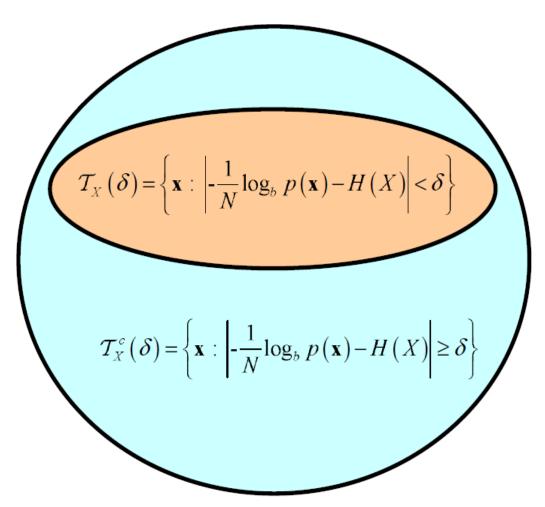
- x_1, x_1, x_1 1/64 = 2^{-3[.811+1.199]}
- x_1, x_1, x_2 3/64 = 2^{-3[.811+0.661]}
- x_1, x_2, x_2 9/64 = 2^{-3[.811+0.132]}
- x_2, x_2, x_2 27/64 = 2^{-3[.811-0.395]}

• If $\delta = 0.2$ the typical sequences are

 $-(x_1, x_2, x_2), (x_2, x_1, x_2), (x_2, x_2, x_1)$ with probability 0.422 (1,0,0), (0,1,0), (0,0,1)

- If $\delta = 0.4$ the typical sequences are
 - $-(x_1,x_2,x_2), (x_2,x_1,x_2), (x_2,x_2,x_1), (x_2,x_2,x_2)$ with probability 0.844 (1,0,0), (0,1,0), (0,0,1), (0,0,0)

$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	Occurrences of x_1 n	Number of sequences $\binom{N}{n}$	Probability of each sequence $p(x_1)^n \ p(x_2)^{N-n}$	Probability of all sequences $\binom{N}{n} p(x_1)^n p(x_2)^{N-n}$
$ \begin{vmatrix} 10 \\ 14 \\ 38760 \\ 15 \\ 15 \\ 15 \\ 16 \\ 16 \\ 16 \\ 17 \\ 1140 \\ 2,456 \times 10^{-10} \\ 2,210 \times 10^{-11} \\ 2,210$	$ \begin{array}{c} 1\\2\\3\\4\\5\\6\\7\\8\\9\\10\\11\\12\\13\\14\\15\\16\\17\\18\end{array} $	$\begin{array}{c} 20\\ 190\\ 1140\\ 4845\\ 15504\\ 38760\\ 77520\\ 125970\\ 167960\\ 184756\\ 167960\\ 125970\\ 77520\\ 38760\\ 125970\\ 77520\\ 38760\\ 15504\\ 4845\\ 1140\\ 190\end{array}$	$\begin{array}{rrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrr$	$\begin{array}{c cccccc} 0 \times 0,494 & 0,021141 \\ 0 \times 0,574 & 0,066948 \\ 0 \times 0,653 & 0,133896 \\ 0 \times 0,732 & 0,189685 \\ 0 \times 0,811 & 0,202331 \\ 0 \times 0,891 & 0,168609 \\ 0 \times 0,970 & 0,112406 \\ 0 \times 1,049 & 0,060887 \\ 0 \times 1,128 & 0,027061 \\ 0 \times 1,208 & 0,009922 \\ 0 \times 1,287 & 0,003007 \\ 0 \times 1,366 & 0,000752 \\ 0 \times 1,445 & 0,000154 \\ 0 \times 1,525 & 0,000026 \\ 0 \times 1,604 & 0,000003 \\ 0 \times 1,683 & 0,000000 \\ 0 \times 1,842 & 0,000000 \\ 0 \times 1,921 & 0,000000 \\ \end{array}$



- Random variable X
- Alphabet size K
- Entropy H(X)
- Arbitrary number δ >0
- Sequences x of blocklength N≥N₀ and probability p(x)

•
$$\left\|\mathcal{T}_{X}(\partial)\right\| + \left\|\mathcal{T}_{X}^{c}(\partial)\right\| = K^{N}$$

Shannon-McMillan Theorem

a) The probability that a particular sequence \mathbf{x} of blocklength N belongs to the set of atypical sequences $\mathcal{T}_X^c(\delta)$ is upperbounded as:

$$Pr[\mathbf{x} \in \mathcal{T}_X^c(\delta)] < \epsilon$$

b) If a sequence \mathbf{x} is in the set of typical sequences $\mathcal{T}_X(\delta)$ then its probability of occurrence $p(\mathbf{x})$ is approximately equal to $b^{-NH(X)}$, that is:

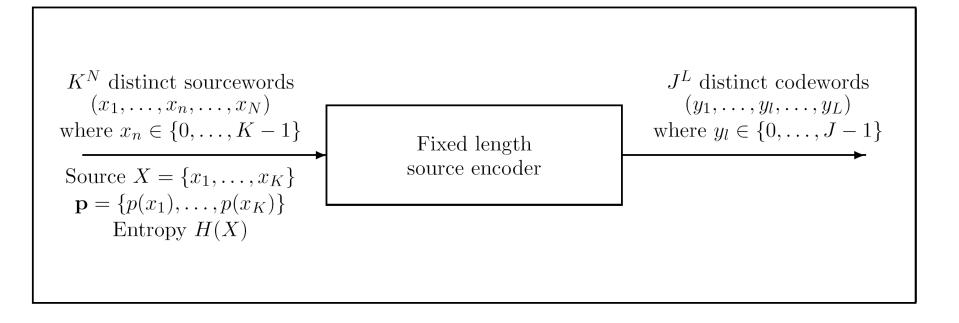
$$b^{-N[H(X)+\delta]} < p(\mathbf{x}) < b^{-N[H(X)-\delta]}$$

c) The number of typical, or likely, sequences $\|\mathcal{T}_X(\delta)\|$ is bounded by:

$$(1-\epsilon)b^{N[H(X)-\delta]} < \|\mathcal{T}_X(\delta)\| < b^{N[H(X)+\delta]}$$

- The essence of source coding or data compression is that as N→∞, atypical sequences almost never appear as the output of the source.
- Therefore, one can focus on representing typical sequences with codewords and ignore atypical sequences.
- Since there are only about 2^{NH(X)} typical sequences of length N, and they are approximately equiprobable, it takes about NH(X) bits to represent them.
- On average it takes H(X) bits to represent a source symbol.

Fixed Length Source Compaction Codes



Fixed Length Source Compaction Codes

- If J^L < K^N we cannot uniquely encode all source words with length L codewords
- Two questions
 - 1. How small can J^{L} be such that performance is acceptable?
 - 2. How should sourcewords be encoded to length *L* codewords for unique decodability?

The number of typical sequences satisfies

$$\left\|T_{X}(\delta)\right\| < b^{N[H(X)+\delta]}$$

so encoding all typical sequences with length *L* codewords requires that

$$J^{L} \geq b^{N[H(X)+\delta]}$$

 Although the set of atypical sequences may be large, the Shannon-McMillan Theorem ensures that

 $Pr[\mathbf{x} \in \mathcal{T}_X^c(\delta)] < \epsilon$

- Thus it is possible to encode sourcewords with an arbitrarily small block decoding failure probability P_e provided that
 - $-L\log_{b}J > NH(X)$
 - N is sufficiently large

- K = J = 2
- $p(x_1) = 0.1$ $p(x_2) = 0.9$ H(X) = 0.469 bit
- Choose *N* = 4, *L* = 3

$$R = \frac{L}{N} = \frac{3}{4} > H(X)$$

Partition the 16 sourcewords into 7 typical sequences and 9 atypical sequences

$$p(x_1)^4 = 0.0001 \qquad \binom{4}{4} = 1 \text{ sourceword}$$

$$p(x_1)^3 p(x_2) = 0.0009 \qquad \binom{4}{3} = 4 \text{ sourcewords}$$

$$p(x_1)^2 p(x_2)^2 = 0.0081 \qquad \binom{4}{2} = 6 \text{ sourcewords}$$

$$p(x_1) p(x_2)^3 = 0.0729 \qquad \binom{4}{1} = 4 \text{ sourcewords}$$

$$p(x_2)^4 = 0.6561 \qquad \binom{4}{0} = 1 \text{ sourceword}$$

The Code

Typical	
Sequence	Codeword
$x_{2}x_{2}x_{2}x_{2}x_{2}$	000
$x_1 x_2 x_2 x_2$	100
$x_2 x_1 x_2 x_2$	010
$x_{2}x_{2}x_{1}x_{2}$	001
$x_{2}x_{2}x_{2}x_{1}$	110
$x_1 x_1 x_2 x_2$	101
$x_1 x_2 x_1 x_2$	011

The Code

Atypical Sequence Codeword 111 0000 $x_1 x_2 x_2 x_1$ 111 1000 $X_{2}X_{1}X_{1}X_{2}$ 111 0100 $X_2 X_1 X_2 X_1$ 111 0010 $X_{2}X_{2}X_{1}X_{1}$ 111 0001 $X_1 X_1 X_1 X_2$ 111 1100 $X_1 X_1 X_2 X_1$ 111 1010 $X_1 X_2 X_1 X_1$ 111 1001 $x_2 x_1 x_1 x_1$ 111 0110 $x_1 x_1 x_1 x_1$

Code Rate

• The actual code rate is

$$R = \frac{.9639 \times 3 + .0361 \times 7}{4} = \frac{3}{4} + .0361 = .7861$$

- K = J = 2
- $p(x_1) = 0.1$ $p(x_2) = 0.9$ H(X) = 0.469 bit
- Choose *N* = 8, *L* = 6

$$R = \frac{L}{N} = \frac{6}{8} = \frac{3}{4} > H(X)$$

Partition the 256 sourcewords into 63 typical sequences and 193 atypical sequences

$$p(x_1)^8 = 1.0000 \times 10^{-8}$$

$$p(x_1)^7 p(x_2) = 9.0000 \times 10^{-8}$$

$$p(x_1)^6 p(x_2)^2 = 8.1000 \times 10^{-7}$$

$$p(x_1)^5 p(x_2)^3 = 7.2900 \times 10^{-6}$$

$$p(x_1)^4 p(x_2)^4 = 6.5610 \times 10^{-5}$$

$$p(x_1)^3 p(x_2)^5 = 5.9049 \times 10^{-4}$$

$$p(x_1)^2 p(x_2)^6 = 5.3144 \times 10^{-3}$$

$$p(x_1) p(x_2)^7 = 4.7830 \times 10^{-2}$$

$$p(x_2)^8 = 4.3047 \times 10^{-1}$$

 $\binom{8}{8} = 1$ sourceword $\binom{8}{7} = 8$ sourcewords $\binom{8}{6} = 28$ sourcewords $\binom{8}{5} = 56$ sourcewords $\binom{8}{4} = 70$ sourcewords $\binom{8}{3} = 56$ sourcewords $\binom{8}{2} = 28$ sourcewords $\binom{8}{1} = 8$ sourcewords $\binom{8}{0} = 1$ sourceword

Code Rate

• For *N* = 8, *L* = 6 the actual code rate is

$$R = \frac{.9773 \times 6 + .0227 \times 14}{8} = \frac{3}{4} + .0227 = .7727$$

Theorem (Converse of the Source Coding Theorem)

Let $\epsilon > 0$. Given a memoryless source X of entropy H(X), a codeword alphabet size J and a codeword length L, if:

- a) $L \log_b J < NH(X)$ and
- b) $N \ge N_0$

then the probability of decoding failure P_e is lower bounded by:

 $P_e > 1-\epsilon$

- K = J = 2
- $p(x_1) = 0.3$ $p(x_2) = 0.7$ H(X) = 0.881 bit
- Choose *N* = 4, *L* = 3

$$R = \frac{L}{N} = \frac{3}{4} < H(X)$$

Partition the 16 sourcewords into 7 typical sequences and 9 atypical sequences

$$p(x_1)^4 = 2.4010 \times 10^{-1} \qquad \binom{4}{4} = 1 \text{ sourceword}$$

$$p(x_1)^3 p(x_2) = 1.0290 \times 10^{-1} \qquad \binom{4}{3} = 4 \text{ sourcewords}$$

$$p(x_1)^2 p(x_2)^2 = 4.4100 \times 10^{-2} \qquad \binom{4}{2} = 6 \text{ sourcewords}$$

$$p(x_1)p(x_2)^3 = 1.8900 \times 10^{-2} \qquad \binom{4}{1} = 4 \text{ sourcewords}$$

$$p(x_2)^4 = 8.1000 \times 10^{-3} \qquad \binom{4}{0} = 1 \text{ sourcewords}$$

- K = J = 2
- $p(x_1) = 0.3$ $p(x_2) = 0.7$ H(X) = 0.881 bit
- Choose *N* = 8, *L* = 6

$$R = \frac{L}{N} = \frac{6}{8} = \frac{3}{4} < H(X)$$

Partition the 256 sourcewords into 63 typical sequences and 193 atypical sequences

$$p(x_1)^8 = 6.5610 \times 10^{-5}$$

$$p(x_1)^7 p(x_2) = 1.5309 \times 10^{-4}$$

$$p(x_1)^6 p(x_2)^2 = 3.5721 \times 10^{-4}$$

$$p(x_1)^5 p(x_2)^3 = 8.3349 \times 10^{-4}$$

$$p(x_1)^4 p(x_2)^4 = 1.9448 \times 10^{-3}$$

$$p(x_1)^3 p(x_2)^5 = 4.5379 \times 10^{-3}$$

$$p(x_1)^2 p(x_2)^6 = 1.0588 \times 10^{-2}$$

$$p(x_1) p(x_2)^7 = 2.4706 \times 10^{-2}$$

$$p(x_2)^8 = 5.7648 \times 10^{-2}$$

 $\binom{8}{8} = 1$ sourceword $\binom{8}{7} = 8$ sourcewords $\binom{8}{6} = 28$ sourcewords $\binom{8}{5} = 56$ sourcewords $\binom{8}{4} = 70$ sourcewords $\binom{8}{3} = 56$ sourcewords $\binom{8}{2} = 28$ sourcewords $\binom{8}{1} = 8$ sourcewords $\binom{8}{0} = 1$ sourceword

Fixed Length Source Compaction Codes

- If R > H(X), as $N \rightarrow \infty P_e \rightarrow 0$
- If R < H(X), as $N \rightarrow \infty P_e \rightarrow 1$