

# Video Compression

# 視訊壓縮

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with slides by Wen-Hsiao Peng,

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and Aggelos K. Katsaggelos

Week	Date	Topic	Assignments
1	2025-09-01		
2	2025-09-08	Introduction to Image and Video Processing	
3	2025-09-16	Signals and Systems	#1 – Color Transform, due: 2025-09-29 1:19pm
4	2025-09-22	Fourier Transform and Sampling	
5	2025-09-29	教師節補假	
6	2025-10-06	中秋節	
7	2025-10-13	Fourier Transform and Sampling	#2 – 2D-DCT, due: 2025-10-27 1:59pm
8	2025-10-20	Motion Estimation	Final project assigned (group together in fours)
9	2025-10-27	Lossless Compression	#3 – MEMC, due: 2025-11-10 1:59pm
10	2025-11-03	Image Compression	
11	2025-11-10	Video Compression	#4 – Entropy coding, due: 2025-11-24 1:59pm
12	2025-11-17	Learning-based Image/Video Compression	
13	2025-11-24	Paper Presentation	
14	2025-12-01	Guest Lecturer –   	
15	2025-12-08	Guest Lecturer –   	
16	2025-12-15	Final Project Presentation	

# Lossless Compression

with slides by Wen-Hsiao Peng, Shao-Yi Chien, Hsueh-Ming Hang, and Aggelos K. Katsaggelos

# Lossless Compression

- Introduction
- Elements of Information Theory – Part I
- Elements of Information Theory – Part II
- Huffman Coding
- Run-Length Coding and Fax
- Arithmetic Coding
- Dictionary Techniques
- Predictive Coding

# Lossless Compression

- **Introduction**
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# Definition

- What is Compression?
  - The minimization of the number of bits in representing an image or video, while
    - Being able to exactly reconstruct the original data (**lossless compression**) or
    - Maintaining an acceptable quality of the reconstructed original data (**lossy compression**)

# Why Compress?

Telephony (220-3,400 Hz)	$8,000 \text{ samples/s} \times 12 \text{ b/sample} = 96 \text{ kbps}$
Wideband speech (50-7,000 Hz)	$16,000 \text{ samples/s} \times 14 \text{ b/sample} = 224 \text{ kbps}$
Wideband audio (20-20,000 Hz)	$44,100 \text{ samples/s} \times 2 \text{ channels} \times 16 \text{ b/sample} = 1.412 \text{ Mbps}$
Color images	$512 \times 512 \text{ pixels} \times 24 \text{ bpp} = 6.3 \text{ Mbits} = 786 \text{ Kbytes}$
Video (CCIR601)	$720 \times 480 \text{ gray pixels} \times 8 \text{ bpp} \times 30 \text{ frames/s} +$ $2 \times 360 \times 480 \text{ chroma pixels} \times 8 \text{ bpp} \times 30 \text{ frames/s} = 166 \text{ Mbps}$
HDTV	$1280 \times 720 \text{ color pixels} \times 24 \text{ bpp} \times 60 \text{ frames/s} = 1.3 \text{ Gbps}$

CCIR601: Without compression we could store

- 31 s of videos on a CD-ROM (650 Mbytes)
- 4 minutes of video on a DVD-5 (40 Gbits)

HDTV Terrestrial Broadcasting:

- 19.3 Mbits/s (6 MHz channel)
- Need compression ratio ~70

# Why are Signals Compressible?

- Statistical redundancy or structure in the data (spatial, temporal, spectral)
- Existence of perceptually irrelevant information

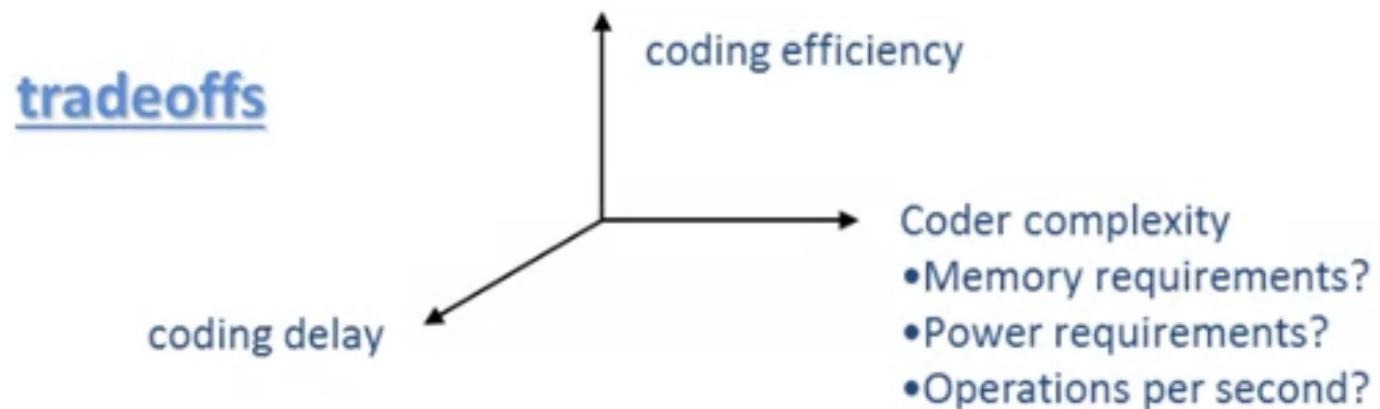
Compression is one of the **enabling technologies** behind the multimedia revolution we are experiencing

# Proliferation of Compression Application

- Over 50 years of extraordinary theoretical results on compression
- Use of perceptually based distortion measures
- Successful standards
- Unparalleled DSP capabilities
- Technological advances in computer, networks, and telecommunications

# Lossless Compression

- **OBJECTIVE:** Exact reconstruction of original data from compressed data, i.e., a **reversible** process
- **Compression ratio** (input size over output size) is determined by the **entropy** of the source
- Low Compression ratios
- Application examples: text, medical images, **lossy codecs**



# Lossless Source Coding

## **Statistical Methods (source statistics known)**

- Huffman
- Extended Huffman
- Other (Gilbert, Fano)

## **Universal Methods (source statistics unknown)**

- Arithmetic Coding
- Dictionary Techniques (LZxx, LZW)
- Other (adaptive Huffman)

## Applications

- Group 3 FAX
- Group 4 FAX

## Applications

- JBIG (arithmetic)
- Unix Compress, GIF, V.42 bis (LZW)

# Lossless Compression

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- Elements of Information Theory – Part II
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- Predictive Coding

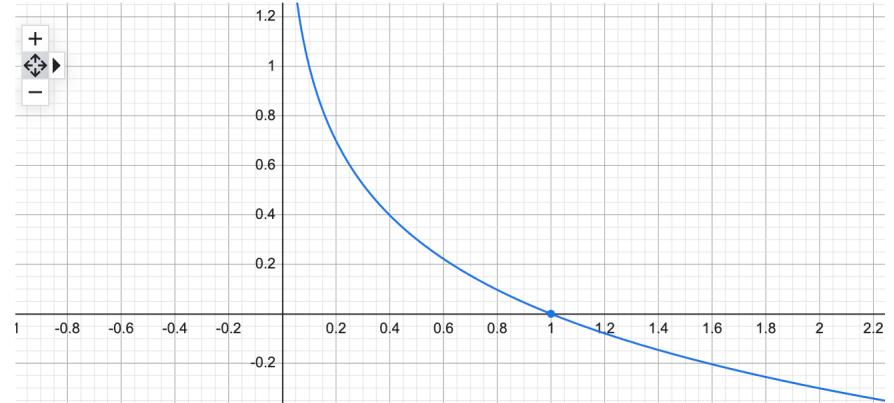
# Elements from Information Theory

- Any information generating process can be viewed as a source that emits a sequence of symbols randomly chosen from a finite alphabet
  - Example: natural written language;  $n$ -bit images ( $2^n$  symbols)
- Simplest case: discrete memoryless source (DMS) – successive symbols produced by the source are statistically independent (and identically distributed)
- A DMS is completely specified by the source alphabet  $S = \{s_1, s_2, \dots, s_n\}$  and the associated probabilities  $\{p_1, p_2, \dots, p_n\}$

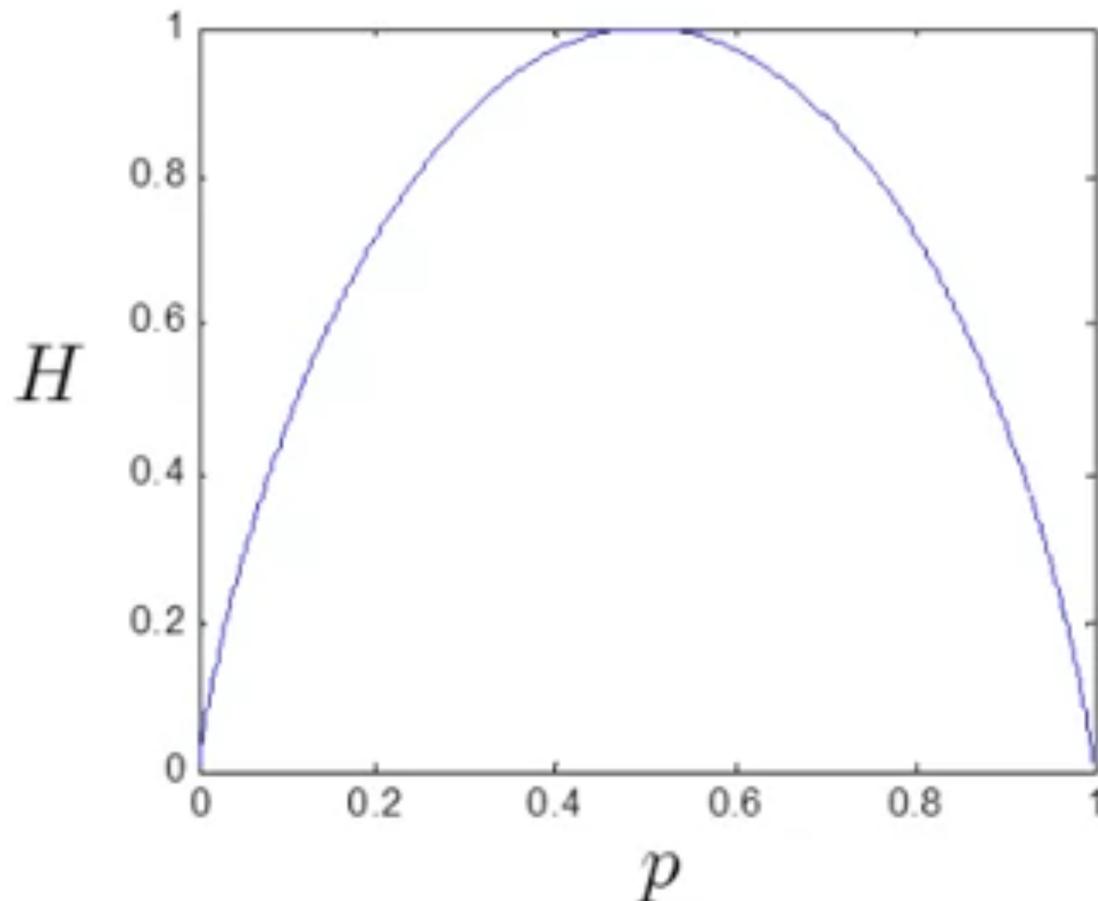
# Entropy

- Self Information  $I(s_i) = \log \frac{1}{p_i} = -\log p_i$ 
  - Base of log: 2  $\rightarrow$  unit: bits; e  $\rightarrow$  nats; 10  $\rightarrow$  Hartleys
  - The occurrence of a less probable event provides more information
  - The information of independent events taken as a single equals the sum of the information
  - $I(s_1 s_2) = \log \frac{1}{p(s_1 s_2)} = \log \frac{1}{p(s_1)p(s_2)} = -\log(p(s_1)p(s_2)) = -\log p_1 - \log p_2 = I(s_1) + I(s_2)$
- Entropy of a DMS: Average information per symbol

$$H(S) = \sum_{i=1}^n p_i I(s_i) = - \sum_{i=1}^n p_i \log_2 p_i$$



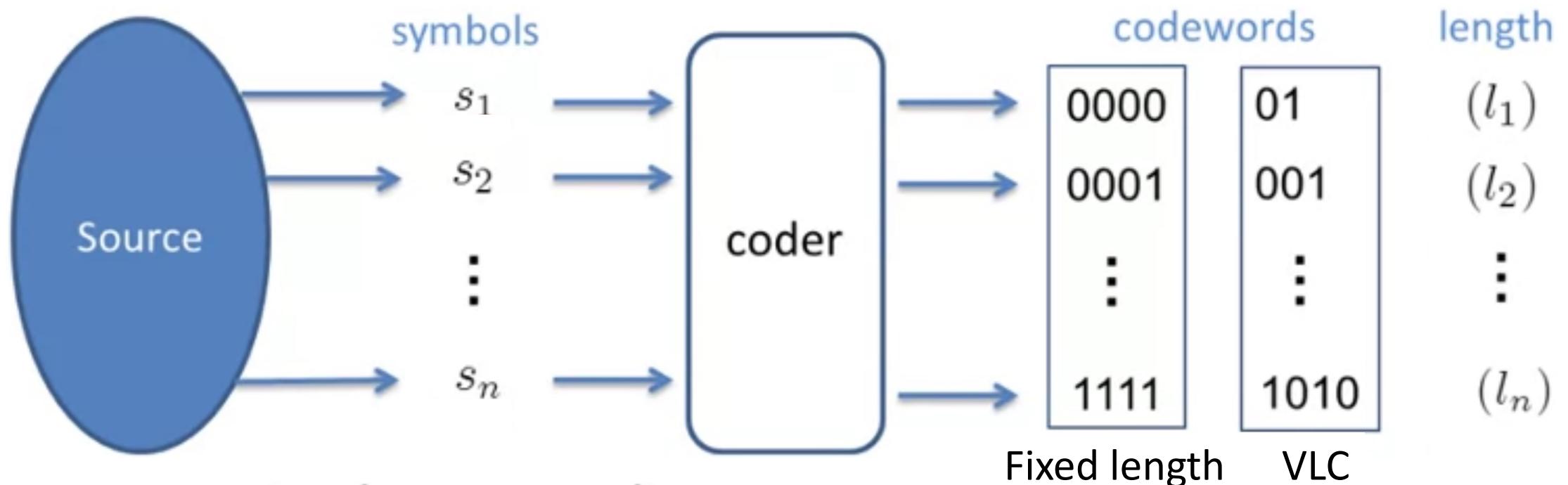
# Plot of Entropy



$n$  symbols  
 $H$  is maximum  
When  $p_i = 1/n$   
 $H_{\max} = \log_2 n$

$$H = -p \log_2 p - (1-p) \log_2 (1-p)$$

# Coding



Alphabet:  $A = \{s_1, s_2, \dots, s_n\}$

$$\begin{matrix} \downarrow \\ p_1 \end{matrix} \quad \begin{matrix} \downarrow \\ p_2 \end{matrix} \quad \begin{matrix} \downarrow \\ p_n \end{matrix}$$

Average Codeword Length:

$$l_{avg} = \sum_{i=1}^n l_i p_i$$

ASCII  
a(1000011)  
A(1000001)

Morse principle  
e( $\cdot$ )  
a( $\cdot -$ )  
q( $-- \cdot -$ )

Fixed length

codewords

length

# Coding

- **First order coders:** encode one symbol at a time, independently of other symbols
- **Block codes:** Group source into blocks of symbols; each block  $N$  considered as a single source symbol generated by a source  $S_N$  with alphabet size  $n^N$ .

In this case:  $H(S_N) = N \times H(S)$

- **Non-block codes:** arithmetic

# Source Coding Theorem

- Let  $S$  be a source with alphabet size  $n$  and entropy  $H(S)$ . Consider coding blocks of  $N$  source symbols into binary codewords. For any  $\delta > 0$ , it is possible by choosing  $N$  large enough to construct a code in such a way that the average number of bits per original source symbol  $l_{\text{avg}}$  satisfies

$$H(S) \leq l_{\text{avg}} < H(S) + \delta$$

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# Entropy of a Source

- Entropy of the English language
  - DMS, equal probabilities:  $H(S) = 4.70 \text{ bits / letter}$  ( $4.76 \text{ bits / letter}$  for 27 letters)
  - DMS:  $H(S) = 4.14 \text{ bits / letter}$
  - Taking co-dependencies up to 8 letters:  $H(S) = 2.3 \text{ bits / letter}$
- Knowledge about the structure of the data

Example #1: consider data: 1234323456

- $P(2) = P(4) = 0.2, P(3) = 0.3, P(1) = P(5) = P(6) = 0.1 \rightarrow H = 2.44 \text{ bits / s}$
- Predictor:  $x_n = x_{n-1} + r_n$
- $r_n = 1111-1-11111: P(1) = 0.8, P(-1) = 0.2 \rightarrow H = 0.7 \text{ bits / s}$

Example #2: consider data: 334533334545

- $P(3) = \frac{1}{2}, P(4) = P(5) = \frac{1}{4} \rightarrow H = 1.5 \text{ bits / symbol}$
- $P(33) = P(45) = \frac{1}{2} \rightarrow H = 1 \text{ bit / new symbol} \rightarrow 0.5 \text{ bits / original symbol}$

# Example

Symbols	Probability	Code 1	Code 2	Code 3	Code 4
$s_1$	1/2	0	0	0	0
$s_2$	1/4	0	1	10	01
$s_3$	1/8	1	00	110	011
$s_4$	1/8	10	11	111	0111
Average length		1.125	1.25	1.75	1.875

010110

Entropy  $H(S) = 1.75$  bits / symbol

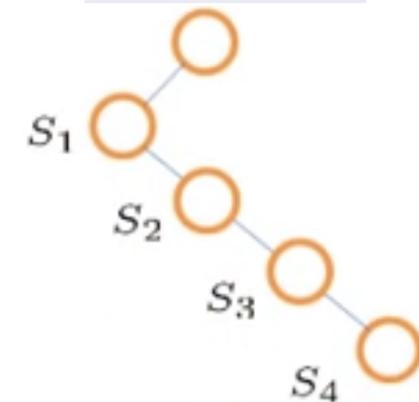
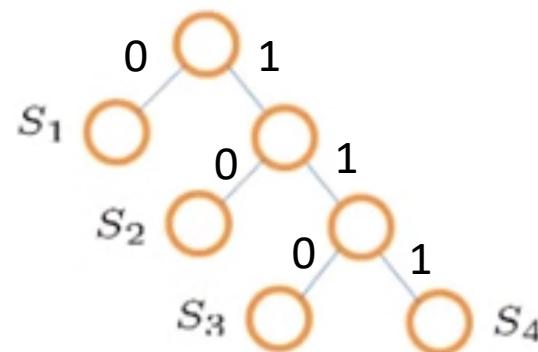
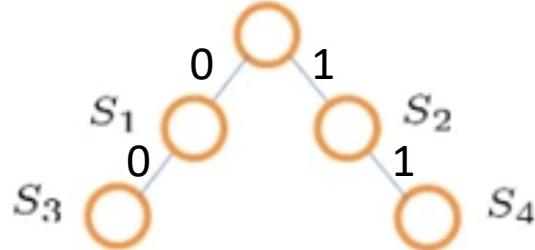
- **Uniquely decodable (UD)** or uniquely decipherable: any finite sequence of codewords corresponds to only one message sequence
- **Prefix(-free) code:** no codeword is prefix to another

# Binary Tree Representation

Code 2
0
1
00
11

Code 3
0
10
110
111

Code 4
0
01
011
0111



- Base of the tree: **root node**
- Point at which a branch divides: **branch node**
- Termination point: **leaf (or external) node**
- In a prefix code, codewords are **only** associated with leaves

# Prefix and UD Codes

- In general, it is hard to tell if a code is UD (systematic procedure exists to determine if a code is UD in finite number of steps)
- Prefix codes are UD (the converse is not true)
- Prefix codes are instantaneously decodable
- Prefix codes: easy to design, easy to decode
- No loss of performance: For any UD code that is not prefix, we can find a prefix with the same rate.

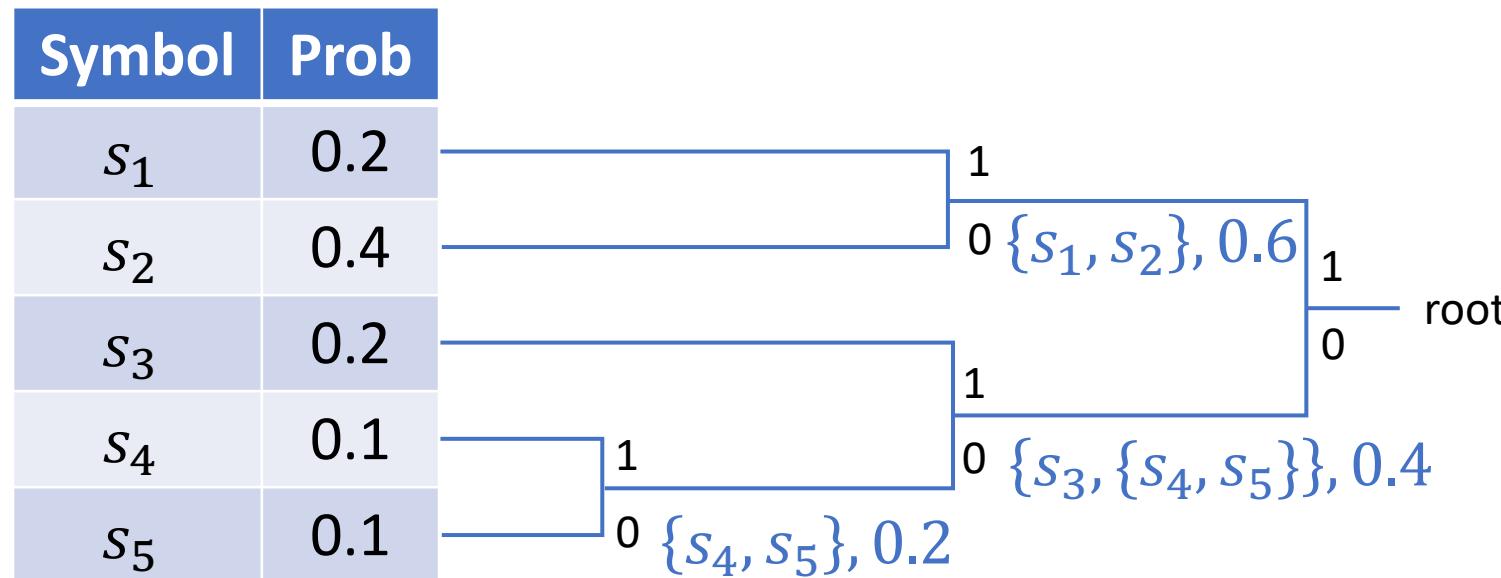
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# Huffman Coding Algorithm (1951)

- Symbols that occur more often will have shorter codewords
- The two symbols that occur least frequently will have the same length
- Design procedure:
  - Sort the symbols according to probability
  - Combine the least probable symbols to form a composite symbol, with probability equal to the sum of the respective symbol probabilities (with this step the size of the alphabet is reduced by one).
  - Repeat procedure for remaining symbols
  - Extract the codewords from the resulting binary tree representation of the code

# Huffman Code Example



$s_1: 11$   
 $s_2: 10$   
 $s_3: 01$   
 $s_4: 001$   
 $s_5: 000$

↑  
Huffman code

$$H \approx 2.122 \text{ b/s}$$
$$l_{avg} \cong 2.2 \text{ b/s}$$

# Properties of Huffman Codes

$$H(S) \leq R < H(S) + 1$$
$$\begin{cases} p_{\max} < 0.5 \Rightarrow R < H(S) + p_{\max} \\ p_{\max} \geq 0.5 \Rightarrow R < H(S) + p_{\max} + 0.086 \end{cases}$$

- Best possible code when  $p_i = 2^{-i}$ : in such a case:  $R = H(S)$
- If alphabet size is large,  $p_{\max}$  is generally small, and Huffman codes perform quite well
- If alphabet size is small and  $p_{\max}$  is large, the Huffman codes can be quite inefficient

# Huffman Code for Extended Source

- Block codes: Group source into blocks of symbols; each block  $N$  considered as a single source symbol generated by a source  $S_N$  with alphabet size  $n^N$ . Then  $H(S_N) = N \cdot H(S)$
- Therefore
$$\begin{aligned} H(S_N) \leq R_N < H(S_N) + 1 &\Rightarrow N \cdot H(S) \leq N \cdot R < N \cdot H(S) + 1 \\ &\Rightarrow H(S) \leq R < H(S) + \frac{1}{N} \end{aligned}$$
- Tradeoff: blocking increases number of possible codewords (e.g., for  $n = 3$  and  $N = 8$ ,  $3^8 = 6561$  codewords)
  - Storage, computation, delay

# Example of Extended Source: Case that Works

Symbols	Probability	Code
$s_1$	0.8	0
$s_2$	0.02	11
$s_3$	0.18	10

Huffman code: entropy = 0.816 bits / symbol;  
 average length = 1.2 bits / symbol;  
 redundancy = 0.384 bits / symbol, or 47% of entropy

Symbols	Probability	Code
$s_1s_1$	0.64	0
$s_1s_2$	0.016	10101
$s_1s_3$	0.144	11
$s_2s_1$	0.016	101000
$s_2s_2$	0.0004	10100101
$s_2s_3$	0.0036	1010011
$s_3s_1$	0.1440	100
$s_3s_2$	0.0036	10100100
$s_3s_3$	0.0324	1011

The extended alphabet and corresponding Huffman code;  
 average length = 1.7516 bits / new symbol;  
 or average length = 0.8758 bits / original symbol;  
 redundancy = 0.06 bits / symbol, or 7% of entropy

# Example of Extended Source: Case that does not Work

Symbols	Probability	Code
$s_1$	0.95	0
$s_2$	0.02	11
$s_3$	0.03	10

Huffman code: entropy = 0.335 bits / symbol;  
average length = 1.05 bits / symbol;  
redundancy = 0.715 bits / symbol, or 213% of entropy

Symbols	Probability	Code
$s_1s_1$	0.9025	0
$s_1s_2$	0.0190	111
$s_1s_3$	0.0285	100
$s_2s_1$	0.0190	1101
$s_2s_2$	0.0004	110011
$s_2s_3$	0.0006	110001
$s_3s_1$	0.0285	101
$s_3s_2$	0.0006	110010
$s_3s_3$	0.0009	110000

Huffman code for the extended alphabet;  
average length = 1.222 bits / new symbol;  
or average length = 0.611 bits / original symbol;  
redundancy = 72% of entropy;  
redundancy drops to acceptable values for N = 8 (alphabet size = 6561)

# Lossless Compression

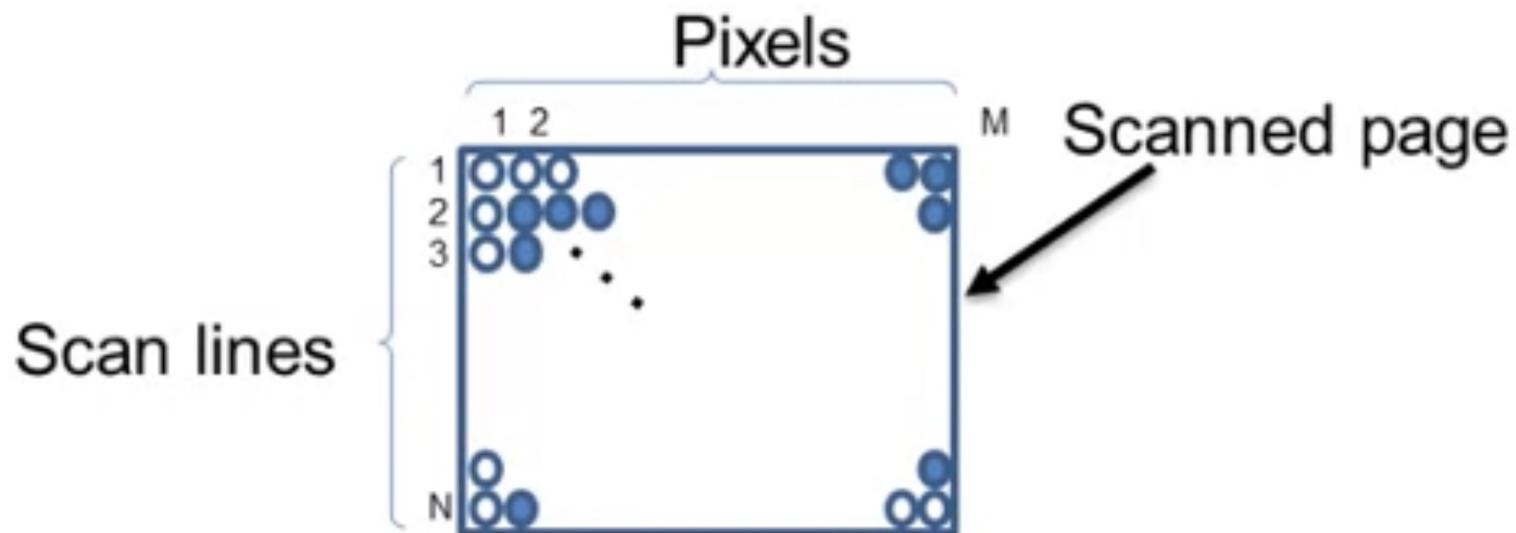
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# Facsimile Encoding

Page being scanned



Printed digital image

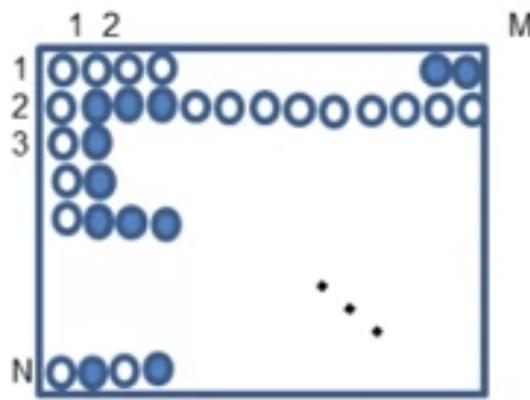


Resolution =  $M \times N$   
Pixel resolution = 8 per mm  
Line resolution =  $3.85/7.7$  per mm  
=  $100/200$  per inch  
A4 document: 210x297 mm

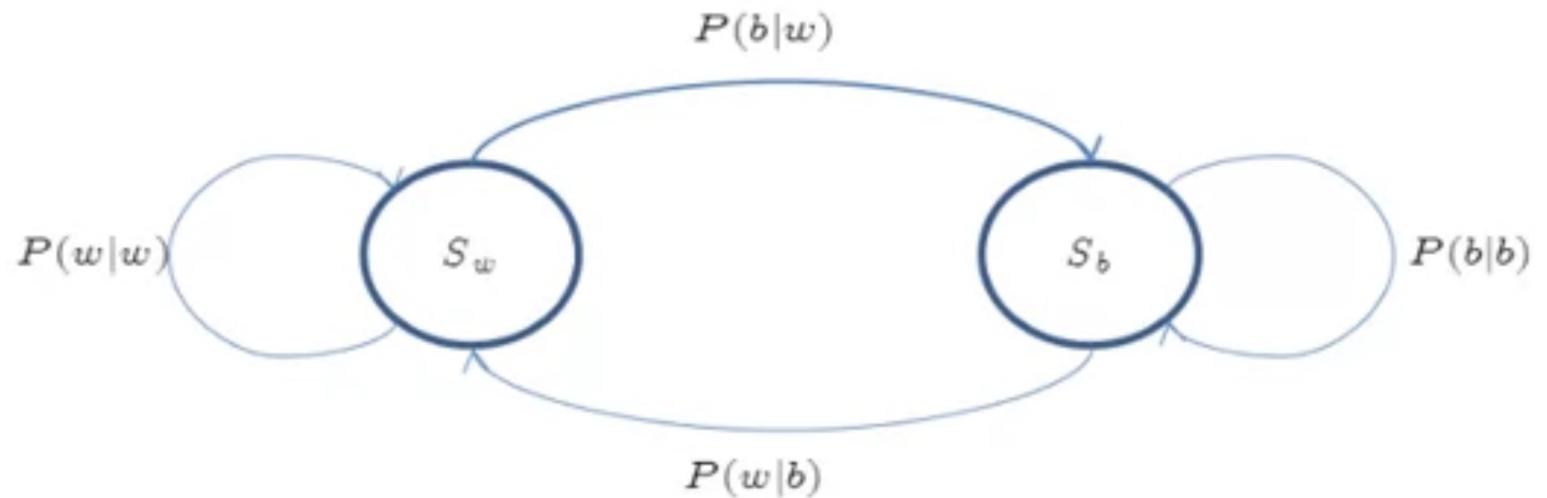
# G3, G4 Facsimile Standards

- Developed for text documents
  - Do not work as well for tables, charts, etc.
  - Efficiency drop dramatically for halftone images
- G3: digital operation with analog modems
  - **Run length coding** (1-D and 2-D)
  - **Huffman** compression for black and white runs (static Huffman tables)
  - 2-D: current line predicted from previous line
  - 1-D/2-D mixed to prevent error propagation
- G4: all-digital for digital networks (e.g., ISDN)
  - 2-D run length only (no error protection necessary)

# Run Length Coding



A two-state Markov model for binary images



$$H = P(S_w)H(S_w) + P(S_b)H(S_b)$$

# G3 Facsimile Standards

- Designing 1-D Huffman codes
  - Estimate probabilities of runs of white pixels and runs of black pixels
  - Follow Huffman encoding procedure
- 1-D scheme (Modified Huffman – MH):
  - Must limit the number of possible lengths
  - $r_l = 64m + t, t = 0, 1, \dots, 63, m = 1, 2, \dots, 27$
  - Use codes for m (*make-up codes*) and t (*terminating codes*)
  - Maximum length 1728 (A4-size document)
  - Optional codes for wider documents

# ITU-T G3, G4 Fax Huffman Codes

Terminating codes →

$$r_l = 64 \cdot m + t$$

Runlength of 12 white pixels

0010000

Runlength of 140 black pixels

$$140 = 2 \times 64 + 12$$

0000110010000000111

White run length	Code-word	Black run length	Code-word
0	00110101	0	0000110111
1	000111	1	010
2	0111	2	11
3	1000	3	10
4	1011	4	011
5	1100	5	0011
6	1110	6	0010
7	1111	7	00011
8	10011	8	000101
9	10100	9	000100
10	00111	10	0000100
11	01000	11	0000101
12	00000	12	0000111
13	000011	13	0000000
14	110100	14	00000111
15	110101	15	000011000
16	101010	16	0000010111
17	101011	17	0000011000
18	010111	18	00000010000
19	0001100	19	0000110111
20	0001000	20	00001101000
21	0010111	21	0000110100
22	0000011	22	00000110111
23	0000100	23	00000101000
24	0101000	24	00000010111
25	0101011	25	00000011000
26	0010011	26	000011001010
27	0100100	27	000011001011
28	0011000	28	00001100100
29	00000010	29	00001100101
30	00000011	30	00001100100
31	00011010	31	000001101001
32	00011011	32	000001101010
33	0010010	33	000001101011
34	00010011	34	0000011010010
35	00010100	35	0000011010011
36	00010101	36	0000011010100
37	00010110	37	0000011010101
38	00010111	38	0000011010110
39	00101000	39	0000011010111
40	00101001	40	000001101100
41	00101011	41	000001101101
42	00101011	42	0000011011010
43	00101100	43	0000011011011
44	00101101	44	000001101100
45	00000100	45	0000011011011
46	00000101	46	0000011011010
47	00000110	47	000001101111
48	00000111	48	000001101100
49	01010010	49	00000110101
50	01010011	50	000001101010
51	01010100	51	000001101011
52	01010101	52	000001101000
53	00100100	53	000000110111
54	00100101	54	000000111000
55	01011000	55	000000100111

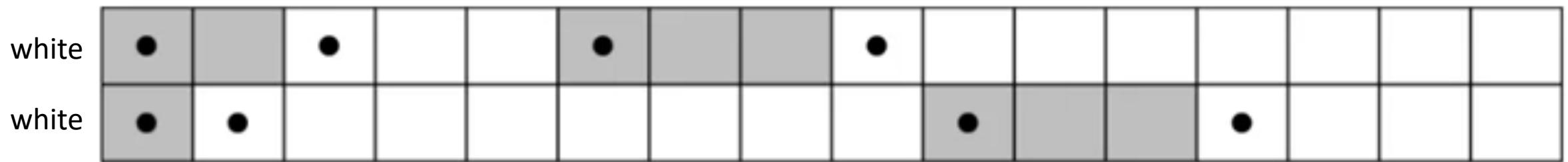
White run length	Code-word	Black run length	Code-word
56	01011001	56	0000000101000
57	01011010	57	0000010111000
58	01011011	58	0000010111001
59	01001010	59	0000001010111
60	01001011	60	0000001011100
61	00110010	61	0000010111010
62	00110011	62	000001100110
63	00110100	63	0000011001111

White run length	Code-word	Black run length	Code-word
64	11011	64	00000011111
128	10010	128	000011001000
192	010111	192	000011001001
256	0110111	256	0000010111011
320	00110110	320	0000001100111
384	00100111	384	000000110100
448	0100000	448	000000110101
512	01000103	512	0000001101100
576	01101000	576	0000001101101
640	01000111	640	00000011001010
704	010001100	704	00000011001011
768	010001101	768	00000011001100
832	01100010	832	00000011001101
896	01100011	896	0000001100010
960	01100100	960	0000001110011
1024	01100101	1024	0000001110100
1088	01100110	1088	0000001110101
1152	01100111	1152	0000001110110
1216	011011000	1216	0000001110111
1280	011011001	1280	00000011010010
1344	011011010	1344	00000011010011
1408	011011011	1408	00000011010100
1472	010011000	1472	0000001010101
1536	010011001	1536	00000010101010
1600	010011010	1600	00000010101011
1664	011000	1664	0000001100100
1728	01100111	1728	0000001100101
1792	00000001000	1792	00000001000
1856	00000001100	1856	00000001100
1920	00000001101	1920	00000001101
1984	000000010010	1984	000000010010
2048	000000010011	2048	000000010011
2112	000000010100	2112	000000010100
2176	000000010101	2176	000000010101
2240	000000010110	2240	000000010110
2304	000000010111	2304	000000010111
2368	000000011100	2368	000000011100
2432	000000011101	2432	000000011101
2496	000000011110	2496	000000011110
2560	000000011111	2560	000000011111
EOT	000000000001	EOT	000000000001

← Make-up codes

# G3, G4 Facsimile Standards

## 2-D codes



1<sup>st</sup> row: 0, 2, 3, 3, 8      1, 3, 6, 9

2<sup>nd</sup> row: 0, 1, 8, 3, 4      1, 2, 10, 13

- 2-D scheme (modified READ – MR)
  - READ: Relative Element Address Designate
  - Exploit heavy correlation of image rows
  - Code transition points with reference to previous line, or distance from previous point is same line

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# Arithmetic Coding

- It is more efficient to generate codewords for groups or sequences of symbols rather than generating a separate codeword for each symbol in the sequence
- With Huffman encoding, in finding a codeword for a *particular* sequence of length m, we need codewords for all possible sequences of length m
- A way to assign codewords to *particular* sequences without having to generate codes for all sequences of that length, is offered by **arithmetic coding**
- In arithmetic coding a unique identifier (or **tag**) is generated for the sequence to be encoded, which corresponds to a binary fraction, which becomes the binary code for the sequence

# Generating a Tag

$A = \{a_1, a_2, \dots, a_m\}; P(a_i)$

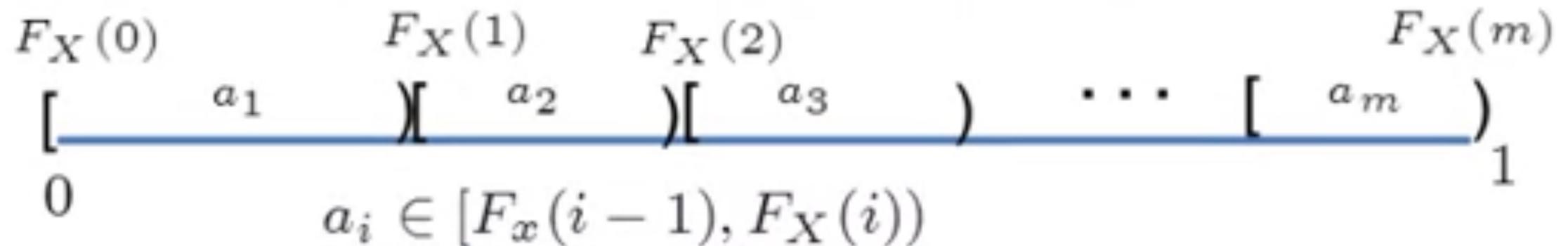
Random variable:  $X(a_i) = i$

Probability density function (pdf):  $P(X = i) = P(a_i)$

Cumulative distribution function (cdf):  $F_X(i) = \sum_{k=1}^i P(X = k)$

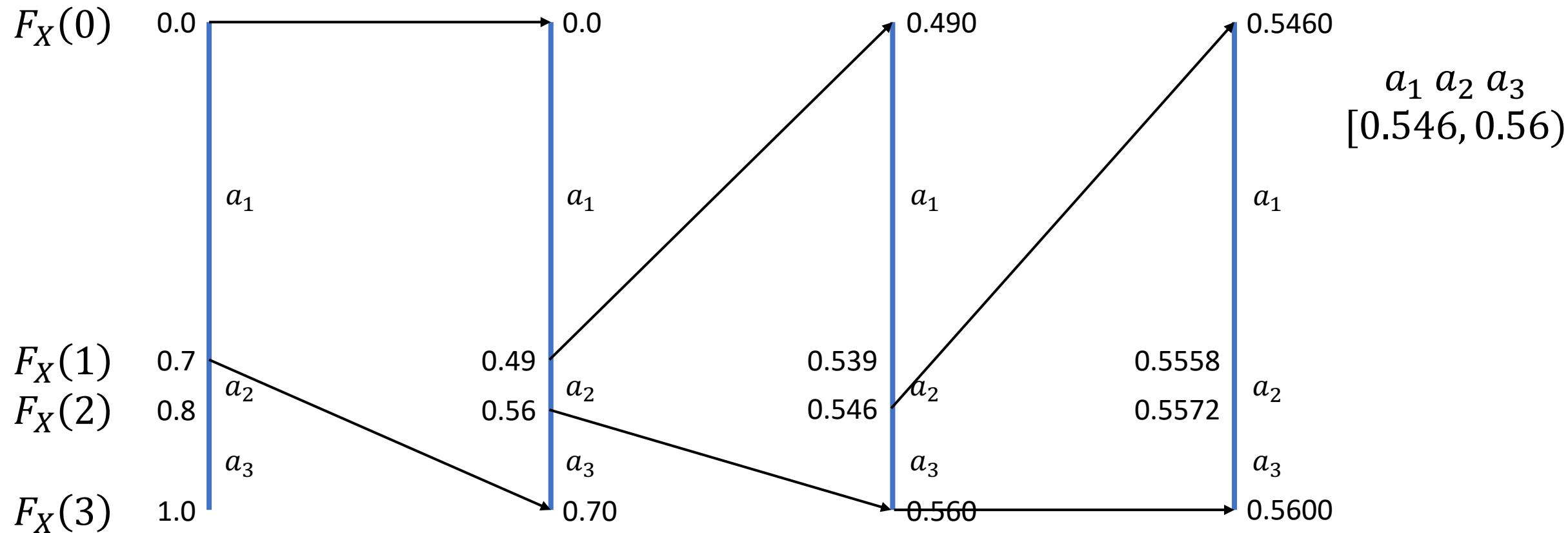
**IDEA:** Reduce the size of the interval in which the tag resides as more and more elements of the sequence are received

Partition the unit into sub-interval of the form



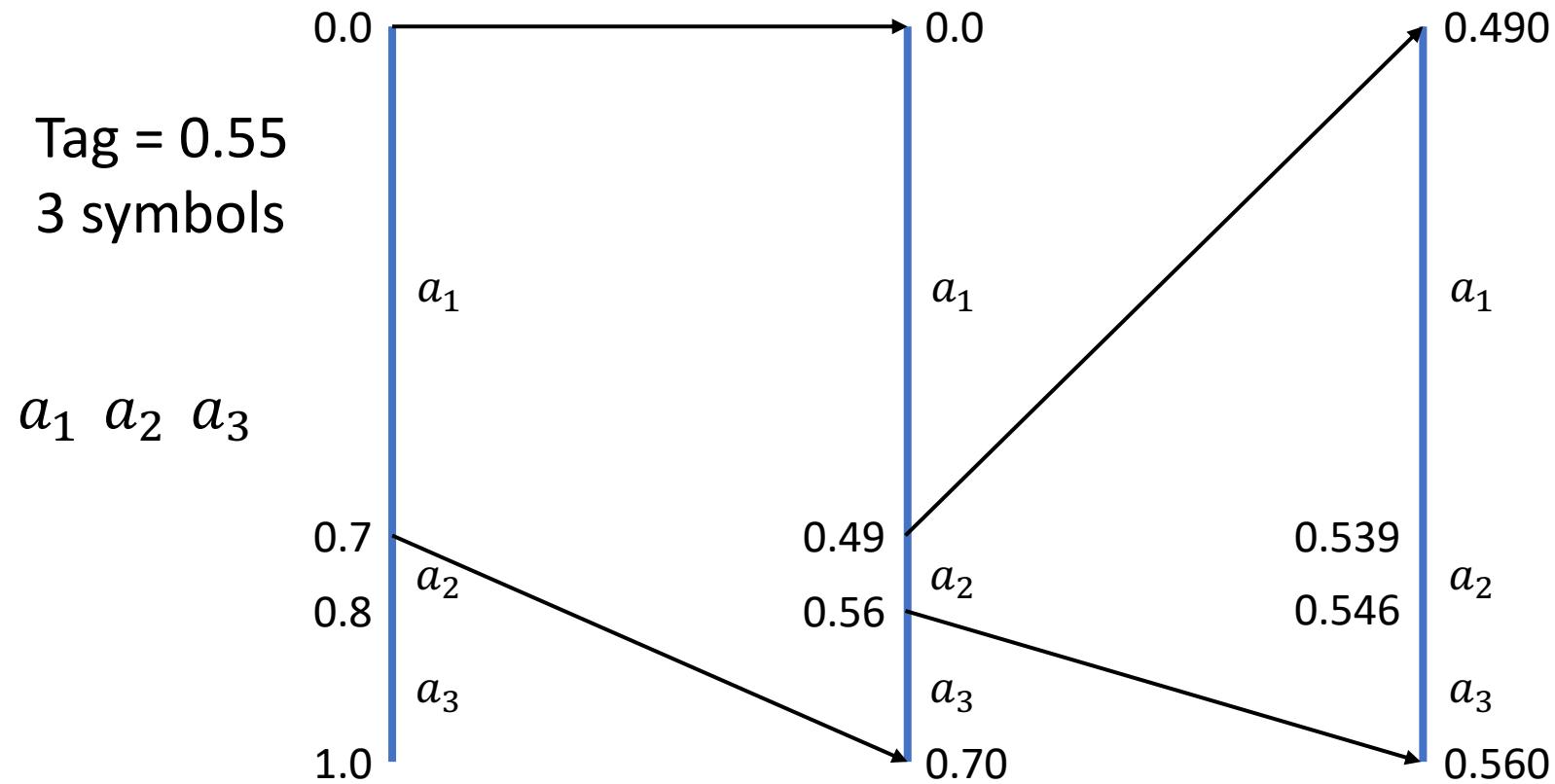
# Arithmetic Coding Example

$$A = \{a_1, a_2, a_3\}; P(a_1) = 0.7, p(a_2) = 0.1, P(a_3) = 0.2; F_X(1) = 0.7, F_X(2) = 0.8, F_X(3) = 1$$



# Deciphering the Tag

$$A = \{a_1, a_2, a_3\}; P(a_1) = 0.7, p(a_2) = 0.1, P(a_3) = 0.2; F_X(1) = 0.7, F_X(2) = 0.8, F_X(3) = 1$$



Mimic the encoder for decoding

# AC vs Huffman

$$H(S) \leq R_{\text{Huffman}} < H(S) + \frac{1}{N}$$

$$H(S) \leq R_{\text{AC}} < H(S) + \frac{2}{N}$$

Scaling and incremental coding

# Taking Context into Account

Assume a given document has:  $P(B) = 0.2, P(W) = 0.8$

$$H = -0.2 \log 0.2 - 0.8 \log 0.8 = 0.722 \text{ bpp}$$

Divide document into 2 regions:

Region 1 includes 80% of pixels

$$P(W) = 0.95, P(B) = 0.05$$

$$H_1 = 0.286 \text{ bpp}$$

Region 2 includes 20% of pixels

$$P(B) = 0.7, P(W) = 0.3$$

$$H_2 = 0.881 \text{ bpp}$$

Total Entropy:  $H = 0.8H_1 + 0.2H_2 = 0.405 \text{ bpp}$

# JBIG

- Joint Bi-Level Image Processing Group (JBIG)
- Standard for the progressive transmission of bi-level images

	o	o	o	
o	o	o	o	A
o	o	x		

	o	o	o	o	o	A
o	o	o	o	x		

10-pixel neighborhoods

	0	0	0	
1	0	0	0	1
1	0	0		

	0	0	1	1	1	0
0	0	0	1	1		

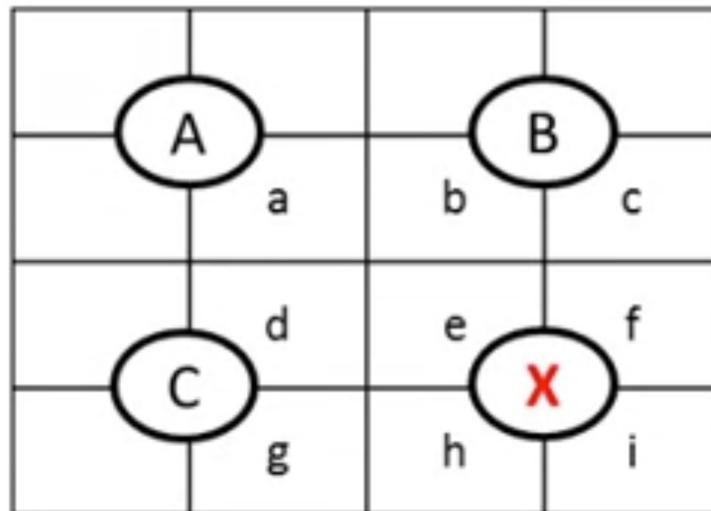
# JBIG-Progressive Transmission

0	0
0	1

$1/4 \rightarrow 0$

0	0
1	1

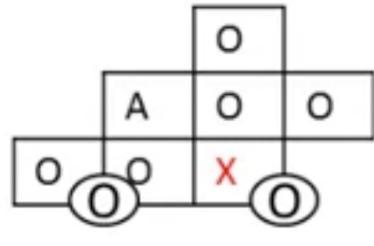
$1/2 \leftarrow 0?$   
 $1?$



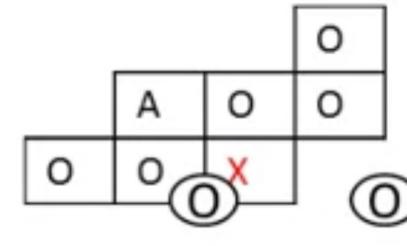
Pixels used for downsampling

$$4e + 2(b + d + f + h) + (a + c + g + i) - 3(B + C) - A \begin{cases} > 4.5 \Rightarrow X = 1 \\ < 4.5 \Rightarrow X = 0 \end{cases}$$

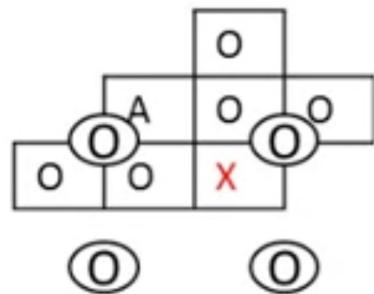
# JBIG-Lossless Compression Revisited



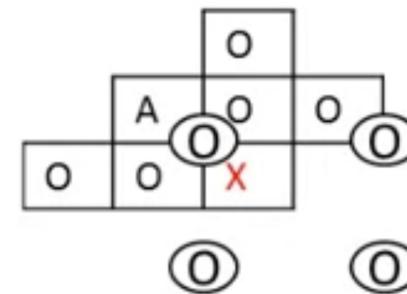
○ ○



○ ○



○ ○



○ ○

Context templates used in the coding of higher-resolution layers

# Lossless Compression

- Introduction
- Elements of Information Theory – Part I
- Elements of Information Theory – Part II
- Huffman Coding
- Run-Length Coding and Fax
- Arithmetic Coding
- **Dictionary Techniques**
- Predictive Coding

# Dictionary Techniques

- In many applications, the output of the source consists of recurring patterns
- A very reasonable approach to encode such sources is to keep a list, or *dictionary*, of frequently occurring patterns.
- The input is split into two classes, frequently occurring and infrequently occurring patterns
- There are static and adaptive dictionary techniques
- Most adaptive techniques have their roots in two papers by Ziv and Lempel in 1977 (LZ77) and 1978 (LZ78)

# Static Dictionary

Code	Entry
000	a
001	b
010	c
011	d
100	r
101	ab
110	ac
111	ad

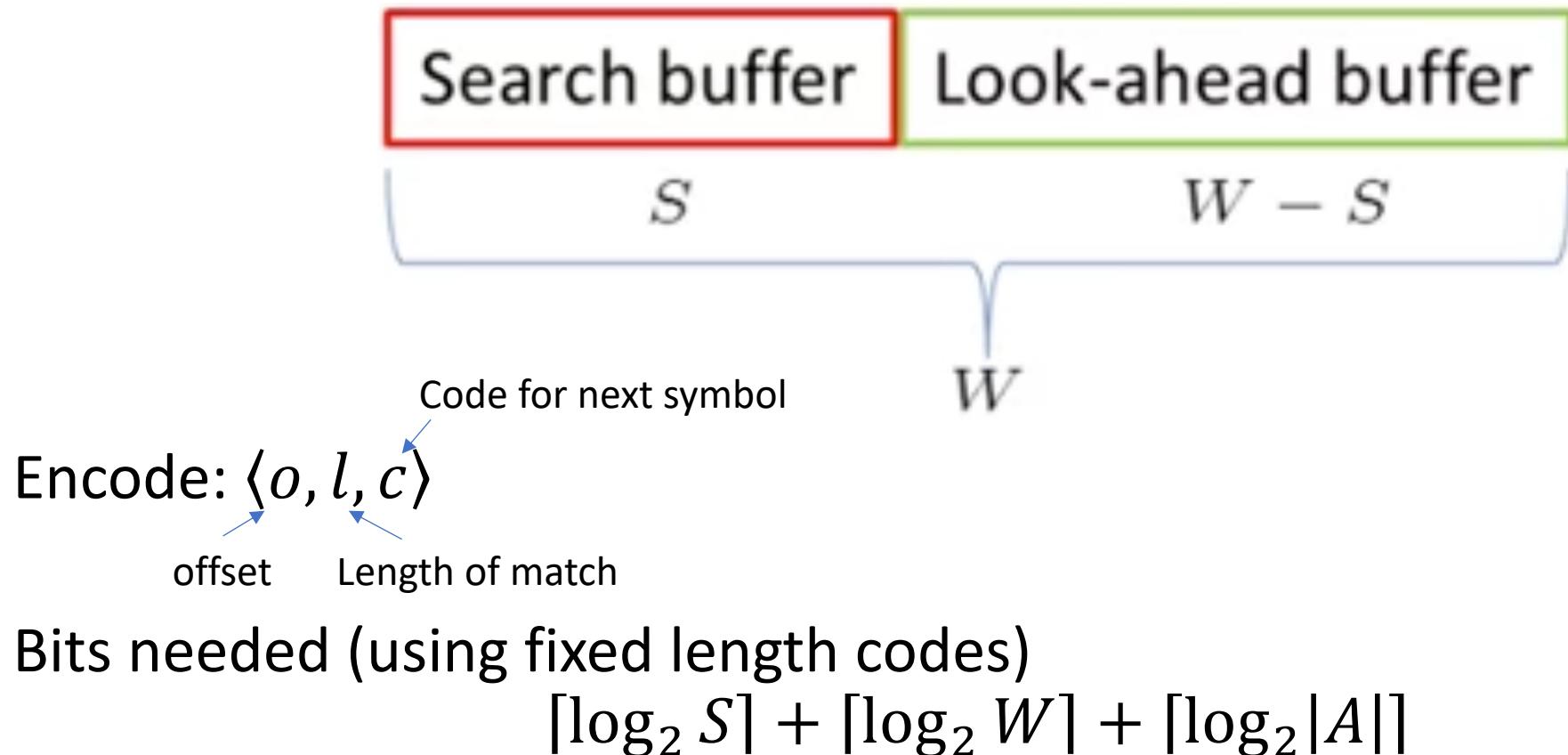
$$A = \{a, b, c, d, r\}$$

*a b r a c a d a b r a*

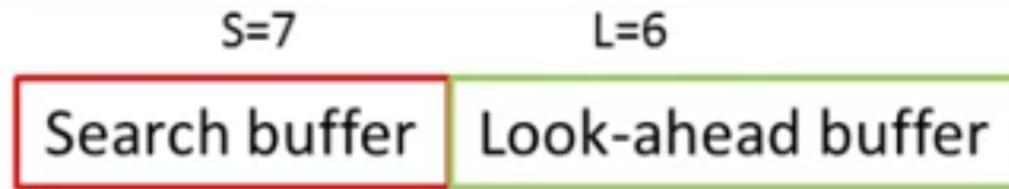
$$11 \times 3 = 33 \text{ bits}$$

$$7 \times 3 = 21 \text{ bits}$$

# LZ77 Approach



# LZ77 Example



cabracadabrar**rarrarrad**  
 $\langle o, l, c \rangle$

## Example: Encoding

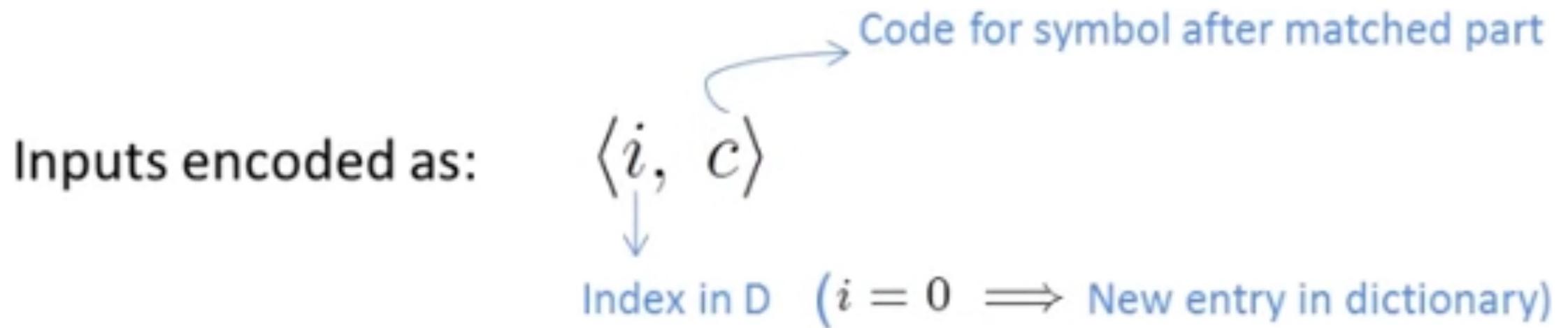
cabracadab**rarrarrad**  
cabracadab**rarrarrad**  
cabracadab**rarrarrad**

## Example: Decoding

cabraca  
cabracad  
cabracadab**rar**  
cabracadab**rarr****a**  
cabracadab**rarrarrad**

# LZ78

- Drops reliance on search buffer and keeps an EXPLICIT dictionary
- This dictionary has to be built as both the encoder and decoder, and therefore they have to be identical



# LZ78 Example

b a w w a / b a w w a / b a w w a / b a w w a / b o o / b o

Encoder output	Index	Entry
<0,c(b)>	1	b
<0,c(a)>	2	a
<0,c(w)>	3	w
<3,c(a)>	4	wa
<0,c(/)>	5	/
<1,c(a)>	6	ba
<3,c(w)>	7	ww
<2,c(/)>	8	a/
<6,c(w)>	9	baw
<4,c(/)>	10	wa/
<9,c(w)>	11	baww
<8,c(b)>	12	a/b
<0,c(o)>	13	o
<13,c(/)>	14	o/
<1,c(o)>	15	bo

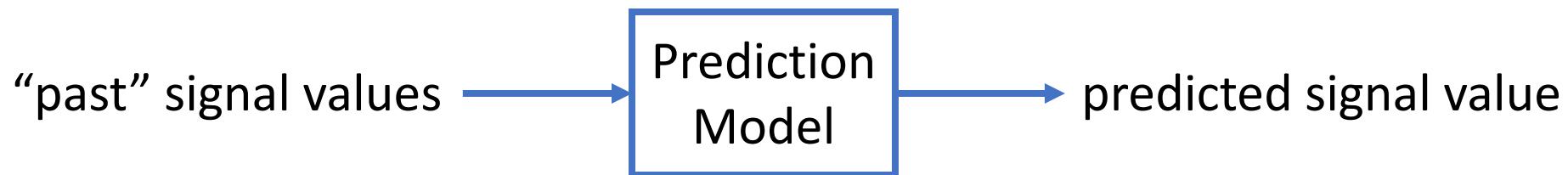
# Dictionary Techniques

- Variations of LZ77
  - Efficient encoding of the triplets
  - Variable size of S and L buffers
  - Eliminate 3<sup>rd</sup> element in triplet by adding a flag when a single symbol is encountered
- Variation of LZ78
  - LZW: encoder only sends index
- Applications of LZx
  - Unix *compress*
  - GIF (Graphics Interchange Format)
  - Compression over modems – V.42 bis

# Lossless Compression

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- **Predictive Coding**

# Predictive Coding



$$\text{Reconstruction} = \text{Prediction} + \text{Prediction Error}$$

- Context Adaptive Lossless Image Compression (CALIC)
- Joint Photographic Experts Group (JPEG)-LS

# Prediction Example

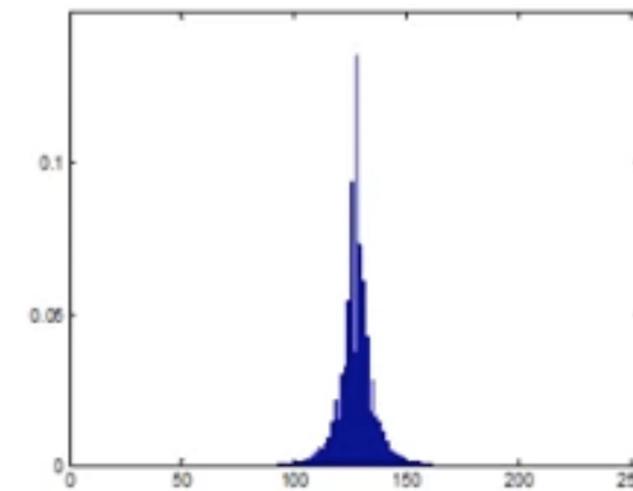
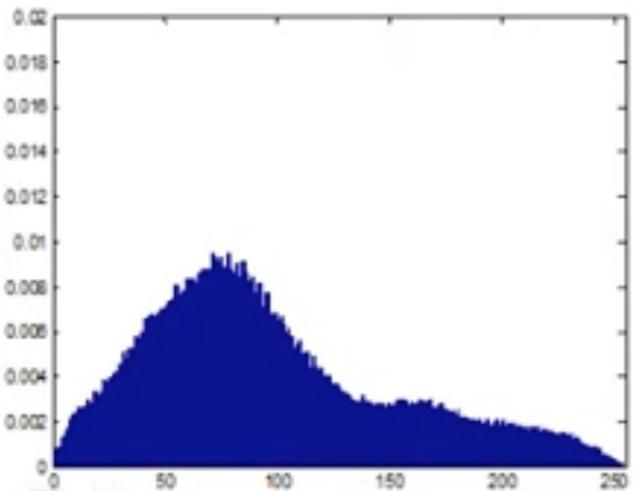


predicted value of  $x(n)$ :

$$x_p(n) = x(n - 1)$$

prediction error:

$$\begin{aligned} e(n) &= x(n) - x_p(n) \\ &= x(n) - x(n - 1) \end{aligned}$$



# JPEG-LS Predictors

Predictors:

0 No predictor

$$1 \hat{f}(i, j) = f(i - 1, j)$$

$$2 \hat{f}(i, j) = f(i, j - 1)$$

$$3 \hat{f}(i, j) = f(i - 1, j - 1)$$

$$4 \hat{f}(i, j) = f(i, j - 1) + f(i - 1, j) - f(i - 1, j - 1)$$

$$5 \hat{f}(i, j) = f(i, j - 1) + (f(i - 1, j) - f(i - 1, j - 1))/2$$

$$6 \hat{f}(i, j) = f(i - 1, j) + (f(i, j - 1) - f(i - 1, j - 1))/2$$

$$7 \hat{f}(i, j) = (f(i, j - 1) + f(i - 1, j))/2$$

Correction encoded by adaptive arithmetic coding

# JPEG-LS Example

Image	JPEG 0	JPEG 1	JPEG 2	JPEG 3	JPEG 4	JPEG 5	JPEG 6	JPEG 7
Sena	53,431	37,220	31,559	38,261	31,055	<b>29,742</b>	33,063	32,179
Sensin	58,306	41,298	37,126	43,445	<b>32,429</b>	33,463	35,965	36,428
Earth	38,248	32,295	<b>32,137</b>	34,089	33,570	33,057	33,072	32,672
Omaha	56,061	<b>48,818</b>	51,283	53,909	53,771	53,520	52,542	52,189

Compressed file size in bytes of the residual images obtained using the various JPEG prediction modes

Image	Best JPEG-LS	GIF
Sena	31,055	51,085
Sensin	32,429	60,649
Earth	32,137	34,276
Omaha	48,818	61,341

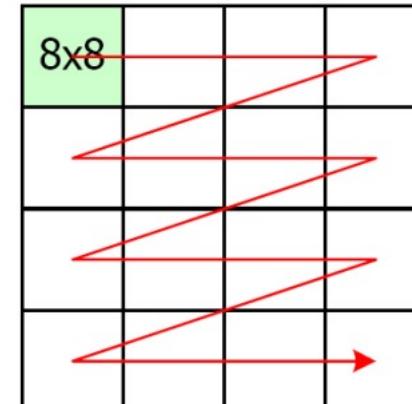
Comparison of the file sizes obtained using JPEG lossless compression and GIF

# Lossless Compression

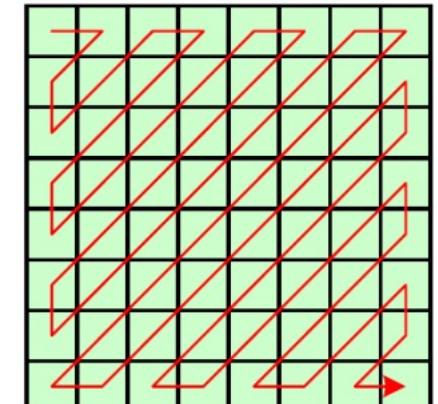
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# Homework #3 – Entropy Coding

- Run length encoding and run length decoding
  - 8x8 block-based DCT coefficients of “lena.png”.
  - Quantize the coefficients with 16-bit for DC and 8-bit for AC.
  - Use raster scan to visit all 8x8 blocks in these images.
  - Do the run length encoding by using zigzag scan to visit all pixels in one block.
  - Do the run length decoding and IDCT to recover the image.
- Deadline: 2023/04/10 11:59 PM
- Compressed as a single ZIP file.  
Upload to E3 with filename:  
`VC_HW3_[student_id].zip`
- Required files :
  - Report PDF
  - Source code (C/C++/Python/MATLAB)



Block level scan



Pixel level scan