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7

Text Compression

25 November 2024

Prof. Dr. Sebastian Wild

Learning Outcomes

Unit 7: *Text Compression*

1. Understand the necessity for encodings and know *ASCII* and *UTF-8 character encodings*.
2. Understand (qualitatively) the *limits of compressibility*.
3. Know and understand the algorithms (encoding and decoding) for *Huffman codes*, *RLE*, *Elias codes*, *LZW*, *MTF*, and *BWT*, including their *properties* like running time complexity.
4. Select and *adapt* (slightly) a *compression* pipeline for a specific type of data.

Outline

7 Text Compression

- 7.1 Context
- 7.2 Character Encodings
- 7.3 Huffman Codes
- 7.4 Entropy
- 7.5 Run-Length Encoding
- 7.6 Lempel-Ziv-Welch
- 7.7 Lempel-Ziv-Welch Decoding
- 7.8 Move-to-Front Transformation
- 7.9 Burrows-Wheeler Transform
- 7.10 Inverse BWT

7.1 Context

Overview

- ▶ Unit 6 & 13: How to *work* with strings
 - ▶ finding substrings
 - ▶ finding approximate matches \rightsquigarrow Unit 8
 - ▶ finding repeated parts \rightsquigarrow Unit 8
 - ▶ ...
 - ▶ assumed character array (random access)!
- ▶ Unit 7 & 8: How to *store/transmit* strings
 - ▶ computer memory: must be binary
 - ▶ how to compress strings (save space)
 - ▶ how to robustly transmit over noisy channels \rightsquigarrow Unit 8

Clicker Question



What compression methods do you know?



→ *sli.do/cs566*

Terminology

- ▶ **source text:** string $S \in \Sigma_S^*$ to be stored / transmitted
 Σ_S is some alphabet
- ▶ **coded text:** encoded data $C \in \Sigma_C^*$ that is actually stored / transmitted
usually use $\Sigma_C = \{0, 1\}$
- ▶ **encoding:** algorithm mapping source texts to coded texts $S \rightsquigarrow C$
- ▶ **decoding:** algorithm mapping coded texts back to original source text $C \rightsquigarrow S$

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- ▶ **Lossy vs. Lossless**
 - ▶ **lossy compression** can only decode **approximately**;
the exact source text S is lost
 - ▶ **lossless compression** always decodes S exactly
- ▶ For media files, lossy, logical compression is useful (e. g. JPEG, MPEG)
- ▶ We will concentrate on lossless compression algorithms.
These techniques can be used for any application.

What is a good encoding scheme?

- ▶ Depending on the application, goals can be
 - ▶ efficiency of encoding/decoding
 - ▶ resilience to errors/noise in transmission
 - ▶ security (encryption)
 - ▶ integrity (detect modifications made by third parties)
 - ▶ size

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- ▶ Focus in this unit: **size of coded text**

Encoding schemes that (try to) minimize the size of coded texts perform *data compression*.

- ▶ We will measure the compression ratio:
$$\frac{|C| \cdot \lg |\Sigma_C|}{|S| \cdot \lg |\Sigma_S|} \stackrel{\Sigma_C = \{0,1\}}{=} \frac{|C|}{|S| \cdot \lg |\Sigma_S|}$$
 - < 1 means successful compression
 - = 1 means no compression
 - > 1 means “compression” made it bigger!? (yes, that happens ...)

Clicker Question



Do you know what uncomputable/undecidable problems (halting problem, Post's correspondence problem, ...) are?

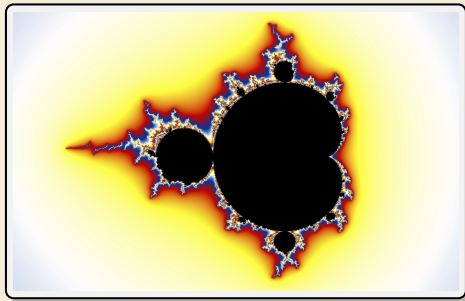
- ☐ A Sure, I could explain what it is.
- ☐ B Heard that in a lecture, but don't quite remember
- ☐ C No, never heard of it



→ *sli.do/cs566*

Limits of algorithmic compression

Is this image compressible?

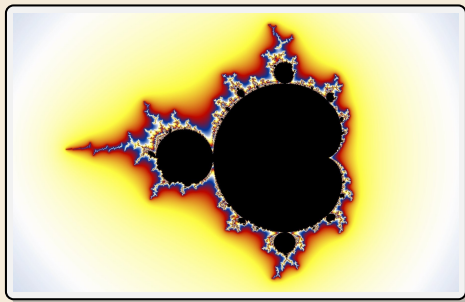


Limits of algorithmic compression

Is this image compressible?

visualization of Mandelbrot set

- ▶ Clearly a complex shape!
 - ▶ Will not compress (too) well using, say, PNG.
 - ▶ but:
 - ▶ completely defined by mathematical formula
- ~> can be generated by a very small program!

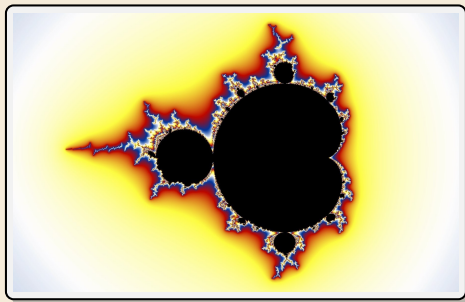


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~> *Kolmogorov complexity*

- ▶ $C =$ any program that outputs S

self-extracting archives!

needs fixed machine model, but compilers transfer results

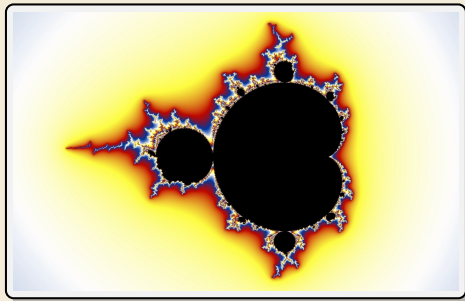
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~> *Kolmogorov complexity*

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needs fixed machine model, but compilers transfer results

- ▶ Kolmogorov complexity = length of smallest such program

- ▶ **Problem:** finding smallest such program is *uncomputable*.

~> No optimal encoding algorithm is possible!

~> must be inventive to get efficient methods

What makes data compressible?

- ▶ Lossless compression methods mainly exploit two types of redundancies in source texts:

- 1. uneven character frequencies**

some characters occur more often than others → Part I

- 2. repetitive texts**

different parts in the text are (almost) identical → Part II

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There is no such thing as a free lunch!

Not *everything* is compressible (→ tutorials)

~> focus on versatile methods that often work

Part I

Exploiting character frequencies

7.2 Character Encodings

Character encodings

- ▶ Simplest form of encoding: Encode each source character individually

↪ encoding function $E: \Sigma_S \rightarrow \Sigma_C^*$

- ▶ typically, $|\Sigma_S| \gg |\Sigma_C|$, so need several bits per character
- ▶ for $c \in \Sigma_S$, we call $E(c)$ the codeword of c
- ▶ **fixed-length code:** $|E(c)|$ is the same for all $c \in \Sigma_S$
- ▶ **variable-length code:** not all codewords of same length

Fixed-length codes

- ▶ fixed-length codes are the simplest type of character encodings
- ▶ Example: **ASCII** (American Standard Code for Information Interchange, 1963)

0000000 NUL	0010000 DLE	0100000	0110000 0	1000000 @	1010000 P	1100000 ‘	1110000 p
0000001 SOH	0010001 DC1	0100001 !	0110001 1	1000001 A	1010001 Q	1100001 a	1110001 q
0000010 STX	0010010 DC2	0100010 "	0110010 2	1000010 B	1010010 R	1100010 b	1110010 r
0000011 ETX	0010011 DC3	0100011 #	0110011 3	1000011 C	1010011 S	1100011 c	1110011 s
0000100 EOT	0010100 DC4	0100100 \$	0110100 4	1000100 D	1010100 T	1100100 d	1110100 t
0000101 ENQ	0010101 NAK	0100101 %	0110101 5	1000101 E	1010101 U	1100101 e	1110101 u
0000110 ACK	0010110 SYN	0100110 &	0110110 6	1000110 F	1010110 V	1100110 f	1110110 v
0000111 BEL	0010111 ETB	0100111 '	0110111 7	1000111 G	1010111 W	1100111 g	1110111 w
0001000 BS	0011000 CAN	0101000 (0111000 8	1001000 H	1011000 X	1101000 h	1111000 x
0001001 HT	0011001 EM	0101001)	0111001 9	1001001 I	1011001 Y	1101001 i	1111001 y
0001010 LF	0011010 SUB	0101010 *	0111010 :	1001010 J	1011010 Z	1101010 j	1111010 z
0001011 VT	0011011 ESC	0101011 +	0111011 ;	1001011 K	1011011 [1101011 k	1111011 {
0001100 FF	0011100 FS	0101100 ,	0111100 <	1001100 L	1011100 \	1101100 l	1111100
0001101 CR	0011101 GS	0101101 -	0111101 =	1001101 M	1011101]	1101101 m	1111101 }
0001110 SO	0011110 RS	0101110 .	0111110 >	1001110 N	1011110 ^	1101110 n	1111110 ~
0001111 SI	0011111 US	0101111 /	0111111 ?	1001111 O	1011111 _	1101111 o	1111111 DEL

- ▶ 7 bit per character
- ▶ just enough for English letters and a few symbols (plus control characters)

Fixed-length codes – Discussion



Encoding & Decoding as fast as it gets



Unless all characters equally likely, it wastes a lot of space



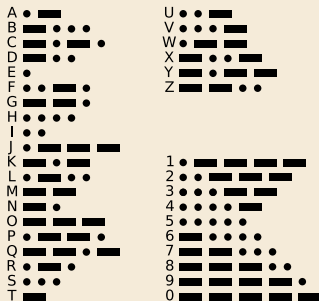
inflexible (how to support adding a new character?)

Variable-length codes

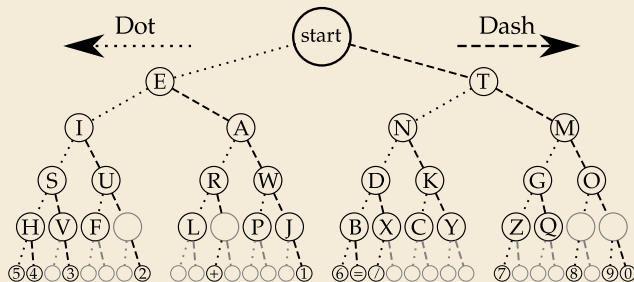
- ▶ to gain more flexibility, have to allow different lengths for codewords
- ▶ actually an old idea: **Morse Code**

International Morse Code

1. The length of a dot is one unit,
2. A dash is three units,
3. The space between parts of the same letter is one unit,
4. The space between letters is three units,
5. The space between words is seven units,



https://commons.wikimedia.org/wiki/File:International_Morse_Code.svg



<https://commons.wikimedia.org/wiki/File:Morse-code-tree.svg>

Clicker Question

How many characters are there in the alphabet of the coded text in Morse Code, i. e., what is $|\Sigma_C|$?



A 1

B 2

C 3

D 4

E 26

F 36

G 256



→ sli.do/cs566

Clicker Question

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A ~~1~~

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C 3 ✓

D 4

E ~~26~~

F ~~36~~

G ~~256~~



→ sli.do/cs566

Variable-length codes – UTF-8

► Modern example: UTF-8 encoding of Unicode:

 default encoding for text-files, XML, HTML since 2009

- Encodes any Unicode character (154 998 as of Nov 2024, and counting)
- uses 1–4 bytes (codeword lengths: 8, 16, 24, or 32 bits)
- Every ASCII character is encoded in 1 byte with leading bit 0, followed by the 7 bits for ASCII
- Non-ASCII characters start with 1–4 1s indicating the total number of bytes, followed by a 0 and 3–5 bits.

The remaining bytes each start with 10 followed by 6 bits.

Char. number range (hexadecimal)	UTF-8 octet sequence (binary)
0000 0000 – 0000 007F	0xxxxxxx
0000 0080 – 0000 07FF	110xxxxx 10xxxxxx
0000 0800 – 0000 FFFF	1110xxxx 10xxxxxx 10xxxxxx
0001 0000 – 0010 FFFF	11110xxx 10xxxxxx 10xxxxxx 10xxxxxx



For English text, most characters use only 8 bit,
but we can include any Unicode character, as well. 🤖

Pitfall in variable-length codes

- Suppose we have the following code:

c	a	n	b	s
$E(c)$	0	10	110	100
- Happily encode text $S = \text{banana}$ with the coded text $C = \underline{1100}\underline{100}\underline{100}$

b
a
n
a
n
a

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a
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⚡ C = 1100100100 decodes **both** to banana and to bass: $\frac{1100100100}{\text{b a s s}}$

→ not a valid code ... (cannot tolerate ambiguity)

but how should we have known?

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$E(n) = 10$ is a (proper) **prefix** of $E(s) = 100$

↪ Leaves decoder wondering whether to stop after reading 10 or continue!

⇒ Usually require a *prefix-free* code: No codeword is a prefix of another.

prefix-free \Rightarrow instantaneously decodable \Rightarrow uniquely decodable

Code tries

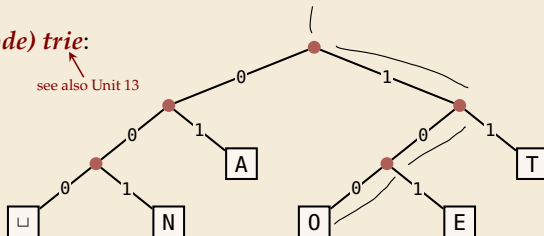
- From now on only consider prefix-free codes E :
 $E(c)$ is not a proper prefix of $E(c')$ for any $c, c' \in \Sigma_S$.

► **Example:**

c	A	E	N	O	T	\sqcup
$E(c)$	01	101	<u>001</u>	100	11	000

Any prefix-free code corresponds to a **(code) trie**:

- binary tree
- one **leaf** for each characters of Σ_S
- path from root to leaf = codeword
 left child = 0; right child = 1



- Example for using the code trie:

- Encode $AN\sqcup ANT$
- Decode $\boxed{11}\boxed{100}0001010111$
 $\quad \quad \quad \tau \quad o$

Code tries

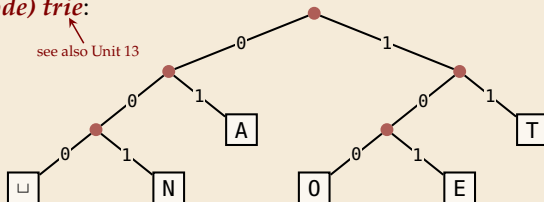
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- ▶ Example for using the code trie:
 - ▶ Encode $AN\sqcup ANT \rightarrow 010010000100111$
 - ▶ Decode $111000001010111 \rightarrow T0\sqcup EAT$

The Codeword Supermarket

0	00	000	0000	00000
			0001	00001
		001	0010	00010
			0011	00011
	01	010	0100	00100
			0101	00101
		011	0110	00110
			0111	00111
1	10	100	1000	01000
			1001	01001
		101	1010	01010
			1011	01011
	11	110	1100	01100
			1101	01101
		111	1110	01110
			1111	01111
	10	100	1000	10000
			1001	10001
		101	1010	10010
			1011	10011
	11	110	1100	10100
			1101	10101
		111	1110	10110
			1111	10111
	11	110	1100	11000
			1101	11001
		111	1110	11010
			1111	11011
	11	110	1100	11100
			1101	11101
		111	1110	11110
			1111	11111

total symbol codeword budget

The Codeword Supermarket

0	00	000	0000	000000
			0001	000001
		001	0010	000100
			0011	000101
	01	010	0100	001000
			0101	001001
		011	0110	001100
			0111	001101
1	10	100	1000	010000
			1001	010001
		101	1010	010100
			1011	010101
	11	110	1100	011000
			1101	011001
		111	1110	011100
			1111	011101
	10	100	1000	100000
			1001	100001
		101	1010	100100
			1011	100101
		110	1100	101000
			1101	101001
	11	110	1110	101100
			1111	101101
		111	1110	110000
			1111	110001

total symbol codeword budget

- ▶ Can “spend” at most budget of 1 across all codewords
 - ▶ Codeword with ℓ bits costs $2^{-\ell}$
- ▶ *Kraft-McMillan inequality*:
any uniquely decodable code with codeword lengths $\ell_1, \dots, \ell_\sigma$ satisfies

$$\sum_{i=1}^{\sigma} 2^{-\ell_i} \leq 1$$

and for any such lengths there is a prefix-free code

The Codeword Supermarket

0	00	000	0000	000000
			0001	000001
		001	0010	000100
			0011	000101
			0011	000110
	01	010	0100	001000
			0101	001001
		011	0110	001010
			0111	001011
			0111	001100
1	10	100	1000	001101
			1001	001110
		101	1010	001111
			1011	010000
			1011	010001
			1011	010010
	11	110	1100	010011
			1101	010100
		111	1110	010101
			1111	010110
			1111	010111
			1111	011000
			1111	011001
			1111	011010
			1111	011011
			1111	011100
			1111	011101
			1111	011110
			1111	011111

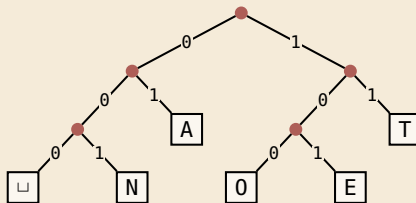
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any uniquely decodable code with codeword lengths $\ell_1, \dots, \ell_\sigma$ satisfies

$$\sum_{i=1}^{\sigma} 2^{-\ell_i} \leq 1 \quad \text{and for any such lengths there is a prefix-free code}$$



Who decodes the decoder?

- ▶ Depending on the application, we have to **store/transmit** the **used code**!
- ▶ We distinguish:
 - ▶ **fixed coding:** code agreed upon in advance, not transmitted (e. g., Morse, UTF-8)
 - ▶ **static coding:** code depends on message, but stays same for entire message; it must be transmitted (e. g., Huffman codes → next)
 - ▶ **adaptive coding:** code depends on message and changes during encoding; implicitly stored withing the message (e. g., LZW → below)

7.3 Huffman Codes

Character frequencies

- **Goal:** Find character encoding that produces short coded text
- Convention here: fix $\Sigma_C = \{0, 1\}$ (binary codes), abbreviate $\Sigma = \Sigma_S$,
- **Observation:** Some letters occur more often than others.

Typical English prose:

e	12.70%	████████	d	4.25%	██	p	1.93%	█
t	9.06%	██████	l	4.03%	██	b	1.49%	█
a	8.17%	██████	c	2.78%	█	v	0.98%	█
o	7.51%	██████	u	2.76%	█	k	0.77%	█
i	6.97%	██████	m	2.41%	█	j	0.15%	
n	6.75%	██████	w	2.36%	█	x	0.15%	
s	6.33%	██████	f	2.23%	█	q	0.10%	
h	6.09%	██████	g	2.02%	█	z	0.07%	
r	5.99%	██████	y	1.97%	█			

~> Want shorter codes for more frequent characters!

Huffman coding

e. g. frequencies / probabilities

- ▶ **Given:** Σ and weights $w : \Sigma \rightarrow \mathbb{R}_{\geq 0}$
- ▶ **Goal:** prefix-free code E (= code trie) for Σ that minimizes coded text length

i. e., a code trie minimizing $\sum_{c \in \Sigma} w(c) \cdot |E(c)|$

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i. e., a code trie minimizing $\sum_{c \in \Sigma} w(c) \cdot |E(c)|$

- ▶ Let's abbreviate $|S|_c = \text{\#occurrences of } c \text{ in } S$
- ▶ If we use $w(c) = |S|_c$,
this is the character encoding with smallest possible $|C|$

\rightsquigarrow **best possible *character-wise* encoding**

- ▶ Quite ambitious! *Is this efficiently possible?*

Huffman's algorithm

- ▶ Actually, yes! A greedy/myopic approach succeeds here.

Huffman's algorithm:

1. Find two characters a , b with lowest weights.
 - ▶ We will encode them with the same prefix, plus one distinguishing bit, i. e., $E(a) = u0$ and $E(b) = u1$ for a bitstring $u \in \{0, 1\}^*$ (u to be determined)
2. (Conceptually) replace a and b by a single character " \boxed{ab} " with $w(\boxed{ab}) = w(a) + w(b)$.
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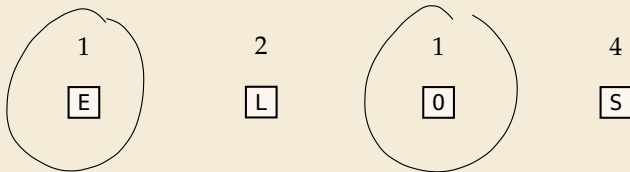
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- ▶ efficient implementation using a (min-oriented) *priority queue*
 - ▶ start by inserting all characters with their weight as key
 - ▶ step 1 uses two `deleteMin` calls
 - ▶ step 2 inserts a new character with the sum of old weights as key

Huffman's algorithm – Example

► Example text: $S = \text{LOSSLESS}$ $\rightsquigarrow \Sigma_S = \{E, L, O, S\}$

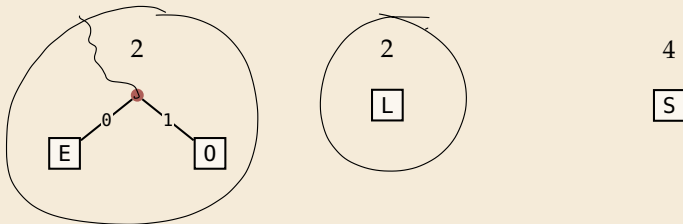
► Character frequencies: $E : 1, \quad L : 2, \quad O : 1, \quad S : 4$



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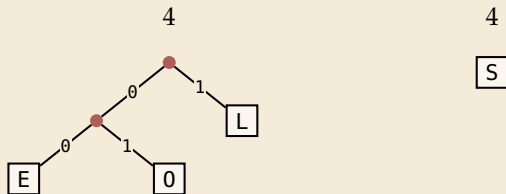
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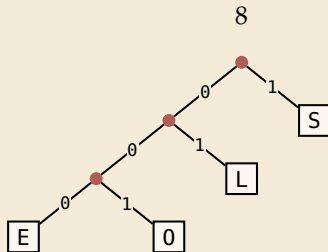
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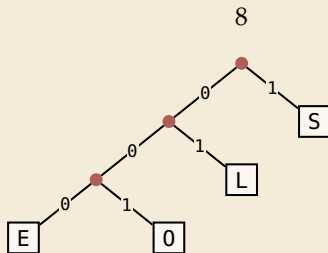
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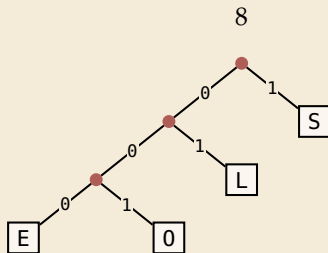


\rightsquigarrow *Huffman tree* (code trie for Huffman code)

Huffman's algorithm – Example

► Example text: $S = \text{LOSSLESS}$ $\rightsquigarrow \Sigma_S = \{E, L, O, S\}$

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\rightsquigarrow *Huffman tree* (code trie for Huffman code)

LOSSLESS \rightarrow 01001110100011

compression ratio: $\frac{14}{8 \cdot \log 4} = \frac{14}{16} \approx 88\%$

Huffman tree – tie breaking

- ▶ The above procedure is ambiguous:
 - ▶ which characters to choose when weights are equal?
 - ▶ which subtree goes left, which goes right?

- ▶ For CS566: always use the following rule:

1. To break ties when selecting the two characters, first use the smallest letter according to the alphabetical order, or the tree containing the smallest alphabetical letter.
2. When combining two trees of different values, place the lower-valued tree on the left (corresponding to a 0-bit).
3. When combining trees of equal value, place the one containing the smallest letter to the left.


~> practice in tutorials

Encoding with Huffman code

- ▶ The overall encoding procedure is as follows:
 - ▶ **Pass 1:** Count character frequencies in S
 - ▶ Construct Huffman code E (as above)
 - ▶ Store the Huffman code in C (details omitted)
 - ▶ **Pass 2:** Encode each character in S using E and append result to C
- ▶ Decoding works as follows:
 - ▶ Decode the Huffman code E from C . (details omitted)
 - ▶ Decode S character by character from C using the code trie.
- ▶ Note: Decoding is much simpler/faster!

Huffman code – Optimality

Theorem 7.1 (Optimality of Huffman's Algorithm)

Given Σ and $w : \Sigma \rightarrow \mathbb{R}_{\geq 0}$, Huffman's Algorithm computes codewords $E : \Sigma \rightarrow \{0, 1\}^*$ with minimal expected codeword length $\ell(E) = \sum_{c \in \Sigma} w(c) \cdot |E(c)|$ among all prefix-free codes for Σ . 

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Proof sketch: by induction over $\sigma = |\Sigma|$

$$\text{IB} : \sigma = 2 \quad \checkmark$$

IH : $\forall \sigma' < \sigma$ Huffman's algorithm computes optimal PF code


► Given any optimal prefix-free code E^* (as its code trie).

► code trie $\rightsquigarrow \exists$ two sibling leaves x, y at largest depth D



Huffman code – Optimality

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 - ▶ code trie $\rightsquigarrow \exists$ two sibling leaves x, y at largest depth D
 - ▶ swap characters in leaves to have two lowest-weight characters a, b in x, y (that can only make ℓ smaller, so still optimal)
 - ▶ any optimal code for $\Sigma' = \Sigma \setminus \{a, b\} \cup \{\overline{ab}\}$ yields optimal code for Σ by replacing leaf \overline{ab} by internal node with children a and b .
- \rightsquigarrow recursive call yields optimal code for Σ' by inductive hypothesis, so Huffman's algorithm finds optimal code for Σ .



7.4 Entropy

Entropy

Definition 7.2 (Entropy)

Given probabilities p_1, \dots, p_n (for outcomes $1, \dots, n$ of a random variable), the *entropy* of the distribution is defined as

$$\mathcal{H}(p_1, \dots, p_n) = - \sum_{i=1}^n p_i \lg p_i = \underbrace{\sum_{i=1}^n p_i \lg \left(\frac{1}{p_i} \right)}_{\text{Handwritten underline}} \quad \blacktriangleleft$$

$$0 \leq \mathcal{H}(p_1, \dots, p_n) \leq \lg n = \mathcal{H}\left(\frac{1}{n}, \dots, \frac{1}{n}\right)$$

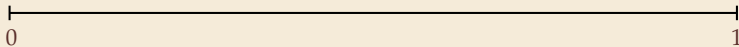
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- ▶ entropy is a **measure of information** content of a distribution
 - ▶ “20 Questions on $[0, 1]$ ”: Land inside my interval by halving.



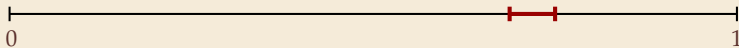
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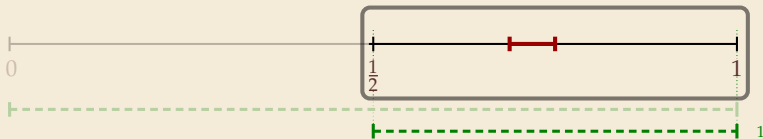
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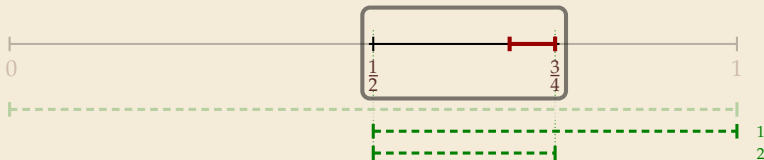
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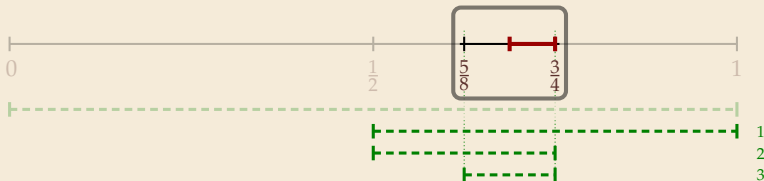
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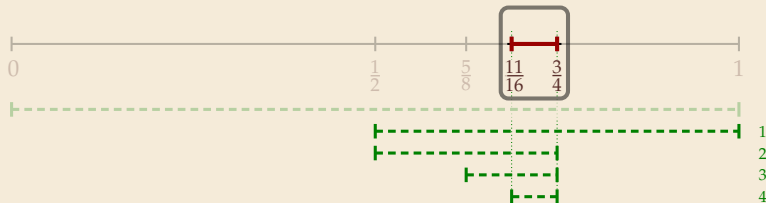
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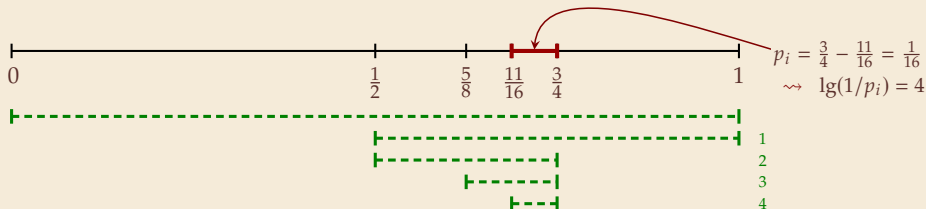
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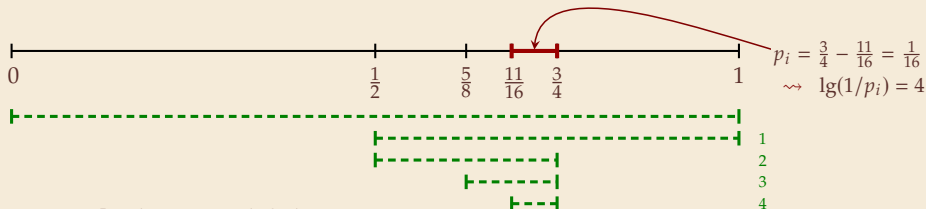
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► entropy is a **measure** of **information** content of a distribution

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⇒ Need to cut $[0, 1)$ in half $\lg(1/p_i)$ times

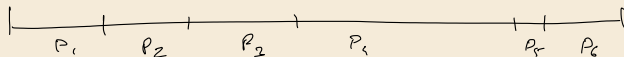
► more precisely: the expected number of bits (Yes/No questions) required to nail down the random value

Entropy and Huffman codes

- would ideally encode value i using $\lg(1/p_i)$ bits

not always possible; cannot use codeword of 1.5 bits ...

not as length of single codeword that is;
but can be possible *on average*!



positive example:

$$\text{all } p_i = 2^{-k_i}$$

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Theorem 7.3 (Entropy bounds for Huffman codes)

For any probabilities p_1, \dots, p_σ for $\Sigma = \{a_1, \dots, a_\sigma\}$, the Huffman code E for Σ with weights $p(a_i) = p_i$ satisfies $\mathcal{H} \leq \ell(E) \leq \mathcal{H} + 1$ where $\mathcal{H} = \mathcal{H}(p_1, \dots, p_\sigma)$. ◀

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Proof sketch:

- ▶ $\ell(E) \geq \mathcal{H}$

Any prefix-free code E induces weights $q_i = 2^{-|E(a_i)|}$.

By *Kraft's Inequality*, we have $q_1 + \dots + q_\sigma \leq 1$.

so $\frac{1}{2}$

in general $p_i \neq q_i$

$\sigma = 2$

$$p_1 = \varepsilon$$

$$p_2 = 1 - \varepsilon$$

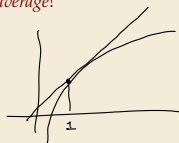
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$$\ln(x) \leq x - 1 \quad \triangleleft x \geq 0$$

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Hence we can apply *Gibb's Inequality* to get

$$\mathcal{H} = \underbrace{\sum_{i=1}^{\sigma} p_i \lg\left(\frac{1}{p_i}\right)}_{\sum p_i = 1} \leq \underbrace{\sum_{i=1}^{\sigma} p_i \lg\left(\frac{1}{q_i}\right)}_{\sum q_i \leq 1} = \ell(E).$$

$$\begin{aligned} 0 &\geq \sum p_i \ln\left(\frac{1}{p_i}\right) - \sum p_i \ln\left(\frac{1}{q_i}\right) \\ &= \sum p_i \ln\left(\frac{q_i}{p_i}\right) \\ &\leq \sum p_i (q_i/p_i - 1) \\ &= \underbrace{\sum q_i}_{\leq 1} - \underbrace{\sum p_i}_1 \leq 0 \end{aligned}$$

Entropy and Huffman codes [2]

Proof sketch (continued):

► $\ell(E) \leq \mathcal{H} + 1$

Set $q_i = 2^{-\lceil \lg(1/p_i) \rceil}$. We have $\sum_{i=1}^{\sigma} p_i \lg\left(\frac{1}{q_i}\right) = \sum_{i=1}^{\sigma} p_i \lceil \lg(1/p_i) \rceil \leq \mathcal{H} + 1$.

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We construct a code E' for Σ with $\underline{|E'(a_i)| \leq \lg(1/q_i)}$ as follows;
w.l.o.g. assume $q_1 \leq q_2 \leq \dots \leq q_{\sigma}$

- If $\sigma = 2$, E' uses a single bit each.

Here, $q_i \leq 1/2$, so $\lg(1/q_i) \geq 1 = |E'(a_i)|$ ✓

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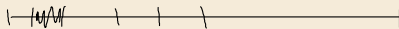
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If $q_1 = q_2$, this is like Huffman; otherwise, q_1 is a unique smallest value and $q_1 + q_2 + \dots + q_\sigma \leq 1$.



Entropy and Huffman codes [2]

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By the inductive hypothesis, we have $|E'(\boxed{a_1 a_2})| \leq \lg\left(\frac{1}{2q_2}\right) = \lg\left(\frac{1}{q_2}\right) - 1$.

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By construction, $|E'(a_1)| = |E'(a_2)| = |E'(\boxed{a_1 a_2})| + 1$, so $|E'(a_1)| \leq \lg(\frac{1}{q_1})$ and $|E'(a_2)| \leq \lg(\frac{1}{q_2})$.

By optimality of E , we have $\ell(E) \leq \ell(E') \leq \sum_{i=1}^{\sigma} p_i \lg\left(\frac{1}{q_i}\right) \leq \mathcal{H} + 1$.

Clicker Question



When does Huffman coding yield more efficient compression than a fixed-length character encoding?

- ☐ A always
- ☐ B when $\mathcal{H} \approx \lg(\sigma)$
- ☐ C when $\mathcal{H} < \lg(\sigma)$
- ☐ D when $\mathcal{H} < \lg(\sigma) - 1$
- ☐ E when $\mathcal{H} \approx 1$



→ sli.do/cs566

Clicker Question



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- ☐ E ~~when $\mathcal{H} \approx 1$~~



→ sli.do/cs566

Empirical Entropy

- ▶ Theorem 7.3 works for *any* character *probabilities* p_1, \dots, p_σ
... but we only have a string S ! (nothing random about it!)

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use relative frequencies: $p_i = \frac{|S|_{a_i}}{|S|} = \frac{\text{\#occurences of } a_i \text{ in string } S}{\text{length of } S}$

- ▶ Recall: For $S[0..n)$ over $\Sigma = \{a_1, \dots, a_\sigma\}$,
length of Huffman-coded text is

$$|C| = \sum_{i=1}^{\sigma} |S|_{a_i} \cdot |E(a_i)| = n \sum_{i=1}^{\sigma} \overset{=p_i}{\frac{|S|_{a_i}}{n}} \cdot |E(a_i)| = \underline{n\ell(E)}$$

↪ Theorem 7.3 tells us rather precisely how well Huffman compresses:

$$\mathcal{H}_0(S) \cdot n \leq |C| \leq (\mathcal{H}_0(S) + 1)n$$

- ▶ $\mathcal{H}_0(S) = \mathcal{H}\left(\frac{|S|_{a_1}}{n}, \dots, \frac{|S|_{a_\sigma}}{n}\right) = \sum_{i=1}^{\sigma} \frac{n}{|S|_{a_i}} \log_2\left(\frac{|S|_{a_i}}{n}\right)$ is called the *empirical entropy* of S ↖ zero-th order empirical entropy

Huffman coding – Discussion

- ▶ running time complexity: $O(\sigma \log \sigma)$ to construct code
 - ▶ build PQ + $\sigma \cdot (2 \text{ deleteMins and } 1 \text{ insert})$
 - ▶ can do $\Theta(\sigma)$ time when characters already sorted by weight
 - ▶ time for encoding text (after Huffman code done): $O(n + |C|)$
- ▶ many variations in use (tie-breaking rules, estimated frequencies, adaptive encoding, ...)

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optimal prefix-free character encoding



very fast decoding



needs 2 passes over source text for encoding

- ▶ one-pass variants possible, but more complicated



have to store code alongside with coded text

Part II

Compressing repetitive texts

7.5 Run-Length Encoding

Run-Length encoding

- ▶ simplest form of repetition: *runs* of characters

[illegible]

same character repeated

- ▶ here: only consider $\Sigma_S = \{0, 1\}$ (work on a binary representation)
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use runs as phrases: $S = \underbrace{00000}_{\text{phrase 1}} \underbrace{111}_{\text{phrase 2}} \underbrace{0000}_{\text{phrase 3}}$

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use runs as phrases: $S = \underbrace{00000}_{\text{run 1}} \underbrace{111}_{\text{run 2}} \underbrace{0000}_{\text{run 3}}$

↪ We have to store

- ▶ the first bit of S (either 0 or 1)
 - ▶ the length of each subsequent run
 - ▶ Note: don't have to store bit for later runs since they must alternate.
- ▶ Example becomes: 0, 5, 3, 4

Run-Length encoding

- ▶ simplest form of repetition: *runs* of characters

[illegible]

same character repeated

- ▶ here: only consider $\Sigma_S = \{0, 1\}$ (work on a binary representation)
 - ▶ can be extended for larger alphabets

→ run-length encoding (RLE):

use runs as phrases: $S = \underbrace{00000}_{\text{run 1}} \underbrace{111}_{\text{run 2}} \underbrace{0000}_{\text{run 3}}$

⇒ We have to store

- ▶ the first bit of S (either 0 or 1)
 - ▶ the length of each subsequent run
 - ▶ Note: don't have to store bit for later runs since they must alternate.
- ▶ Example becomes: 0, 5, 3, 4
- ▶ **Question:** (How to encode a run length k in binary?) (k can be arbitrarily large!)

Clicker Question



How would you encode a string that can be arbitrarily long?



→ *sli.do/cs566*

Elias codes

- ▶ Need a *prefix-free encoding* for $\mathbb{N} = \{1, 2, 3, \dots, \}$
 - ▶ must allow arbitrarily large integers
 - ▶ must know when to stop reading

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- But that's simple! Just use *unary* encoding!


$7 \mapsto 00000001$ $3 \mapsto 0001$ $0 \mapsto 1$ $30 \mapsto 00000000000000000000000000000001$

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 Much too long

- (wasn't the whole point of RLE to get rid of long runs??)

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- (wasn't the whole point of RLE to get rid of long runs??)

- Refinement: *Elias gamma code*

- Store the **length** ℓ of the binary representation in **unary**
- Followed by the binary digits themselves

Elias codes

$\mathbb{N}_{\geq 1}$

- ▶ Need a *prefix-free encoding* for $\mathbb{N} = \{1, 2, 3, \dots\}$

- ▶ must allow arbitrarily large integers
- ▶ must know when to stop reading

- ▶ But that's simple! Just use **unary encoding**!

$7 \mapsto 00000001$ $3 \mapsto 0001$ $0 \mapsto 1$ $30 \mapsto 00000000000000000000000000000001$



Much too long

- ▶ (wasn't the whole point of RLE to get rid of long runs??)

- ▶ Refinement: Elias gamma code

- ▶ Store the **length** ℓ of the binary representation in **unary**
- ▶ Followed by the binary digits themselves
- ▶ little tricks:
 - ▶ always have $\ell \geq 1$, so store $\ell - 1$ instead
 - ▶ binary representation always starts with 1 \rightsquigarrow don't need terminating 1 in unary

\rightsquigarrow Elias gamma code = $\ell - 1$ zeros, followed by binary representation

Examples: $1 \mapsto 1$, $3 \mapsto 011$, $5 \mapsto 00101$, $30 \mapsto 000011110$

Clicker Question



Decode the **first** number in Elias gamma code (at the beginning) of the following bitstream:

000110111011100110.
13



→ *sli.do/cs566*

Run-length encoding – Examples

► Encoding:

$S = 111111100100000000000000000000001111111111$

 $k = 7$

$C = 100111$

► Decoding:

$C = 00001101001001010$

$$S =$$

Run-length encoding – Examples

► Encoding:

$S = 1111111\mathbf{00}100000000000000000000000001111111111$

 $k = 2$

$C = 100111010$

► Decoding:

$C = 00001101001001010$

$$S =$$

Run-length encoding – Examples

► Encoding:

$S = 111111100$ **1** $0000000000000000000000001111111111$

 $k = 1$

$C = 1001110101$

► Decoding:

$C = 00001101001001010$

$$S =$$

Run-length encoding – Examples

► Encoding:

$$S = 1111111001000000000000000000001111111111$$
 $k = 20$

$C = 1001110101000010100$

► Decoding:

$C = 00001101001001010$

$$S =$$

Run-length encoding – Examples

► Encoding:

$$S = 111111100100000000000000000000000011111111111$$
 $k = 11$

$C = 10011101010000101000001011$

► Decoding:

$C = 00001101001001010$

$$S =$$

Run-length encoding – Examples

► Encoding:

$S = 11111111001000000000000000000000000011111111111$

$C = 10011101010000101000001011$

Compression ratio: $26/41 \approx 63\%$

► Decoding:

$C = 00001101001001010$

$S =$

Run-length encoding – Examples

► Encoding:

$S = 11111111001000000000000000000000000011111111111$

$C = 10011101010000101000001011$

Compression ratio: $26/41 \approx 63\%$

► Decoding:

$C = 00001101001001010$

$S =$

Run-length encoding – Examples

► Encoding:

$S = 11111111001000000000000000000000000011111111111$

$C = 10011101010000101000001011$

Compression ratio: $26/41 \approx 63\%$

► Decoding:

$C = \textcolor{red}{0}0001101001001010$

$b = 0$

$S =$

Run-length encoding – Examples

► Encoding:

$$S = 111111100100000000000000000000001111111111$$

$C = 10011101010000101000001011$

Compression ratio: $26/41 \approx 63\%$

► Decoding:

$C = 0001101001001010$

$$b = 0$$
$$\ell = 3 + 1$$
$$S =$$

Run-length encoding – Examples

► Encoding:

$S = 111111100100000000000000000000001111111111$

$C = 10011101010000101000001011$

Compression ratio: $26/41 \approx 63\%$

► Decoding:

$C = 00001101001001010$

$b = 0$

$\ell = 3 + 1$

$k = 13$

$S = 00000000000000$

Run-length encoding – Examples

► Encoding:

$S = 11111111001000000000000000000000000011111111111$

$C = 10011101010000101000001011$

Compression ratio: $26/41 \approx 63\%$

► Decoding:

$C = 00001101001001010$

$b = 1$

$\ell = 2 + 1$

$k =$

$S = 00000000000000$

Run-length encoding – Examples

► Encoding:

$S = 11111110010000000000000000000000000011111111111$

$C = 10011101010000101000001011$

Compression ratio: $26/41 \approx 63\%$

► Decoding:

$C = 00001101001001010$

$b = 0$

$\ell = 0 + 1$

$k =$

$S = 0000000000000001111$

Run-length encoding – Examples

► Encoding:

$S = 111111100100000000000000000000001111111111$

$C = 10011101010000101000001011$

Compression ratio: $26/41 \approx 63\%$

► Decoding:

$C = 00001101001001010$

$b = 0$

$\ell = 0 + 1$

$k = 1$

$S = 0000000000000011110$

Run-length encoding – Examples

► Encoding:

$$S = 111111100100000000000000000000001111111111$$

$C = 10011101010000101000001011$

Compression ratio: $26/41 \approx 63\%$

► Decoding:

$C = 00001101001001010$

$$b = 1$$
$$\ell = 1 + 1$$
 $k =$
$$S = 000000000000000011110$$

Run-length encoding – Examples

► Encoding:

$S = 111111100100000000000000000000001111111111$

$C = 10011101010000101000001011$

Compression ratio: $26/41 \approx 63\%$

► Decoding:

$C = 000011010010010\mathbf{10}$

$b = 1$

$\ell = 1 + 1$

$k = 2$


$S = 0000000000000011110\mathbf{11}$


Run-length encoding – Discussion


- ▶ extensions to larger alphabets possible (must store next character then)
- ▶ used in some image formats (e. g. TIFF)

Run-length encoding – Discussion

- ▶ extensions to larger alphabets possible (must store next character then)
- ▶ used in some image formats (e. g. TIFF)

 fairly simple and fast

 can compress n bits to $\Theta(\log n)!$
for extreme case of constant number of runs

 negligible compression for many common types of data

- ▶ No compression until run lengths $k \geq 6$
 - ▶ **expansion** for run length $k = 2$ or 6
-

7.6 Lempel-Ziv-Welch

Warmup

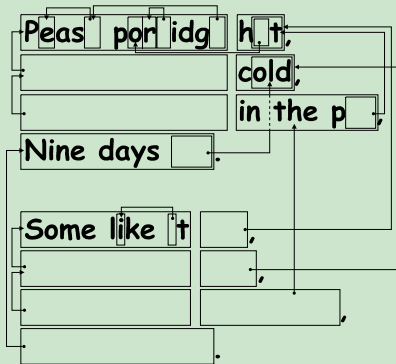
Peas	por	idg	h t,
			cold,
			in the p ,
Nine days			
Some like t			

<https://classic.csunplugged.org/text-compression/>



<https://www.flickr.com/photos/quintanaroo/2742726346>

Clicker Question



What is the **second-to-last line** of the poem to the left?



→ sli.do/cs566

Lempel-Ziv Compression

- ▶ Huffman and RLE mostly take advantage of frequent or repeated *single characters*.
- ▶ **Observation:** Certain *substrings* are much more frequent than others.
 - ▶ in English text: the, be, to, of, and, a, in, that, have, I
 - ▶ in HTML: "<a href", "<img src", "
"

Lempel-Ziv Compression

- ▶ Huffman and RLE mostly take advantage of frequent or repeated *single characters*.
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 - ▶ in English text: the, be, to, of, and, a, in, that, have, I
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"
- ▶ **Lempel-Ziv** stands for family of *adaptive* compression algorithms.
 - ▶ **Idea:** store repeated parts by reference!
 - ~> each codeword refers to
 - ▶ either a single character in Σ_S ,
 - ▶ or a *substring* of S (that both encoder and decoder have seen before).

Lempel-Ziv Compression

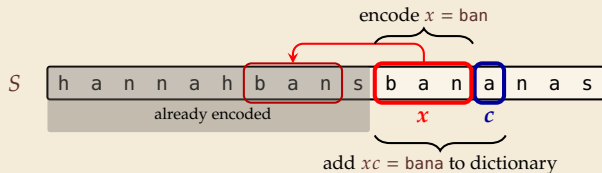
- ▶ Huffman and RLE mostly take advantage of frequent or repeated *single characters*.
- ▶ **Observation:** Certain *substrings* are much more frequent than others.
 - ▶ in English text: the, be, to, of, and, a, in, that, have, I
 - ▶ in HTML: "<a href", "<img src", "
"
- ▶ **Lempel-Ziv** stands for family of *adaptive* compression algorithms.
 - ▶ **Idea:** store repeated parts by reference!
 - ~> each codeword refers to
 - ▶ either a single character in Σ_S ,
 - ▶ or a *substring* of S (that both encoder and decoder have seen before).
 - ▶ Variants of Lempel-Ziv compression
 - ▶ **"LZ77"** Original version (sliding window, overlapping phrases)
Derivatives: LZSS, LZFG, LZRW, LZW, DEFLATE, ...
DEFLATE used in (pk)zip, gzip, PNG
 - ▶ **"LZ78"** Second version (whole-phrase references)
Derivatives: LZW, LZMW, LZAP, LZY, ...
LZW used in compress, GIF

Lempel-Ziv-Welch

- ▶ here: *Lempel-Ziv-Welch (LZW)* (arguably the “cleanest” variant of Lempel-Ziv)
- ▶ *variable-to-fixed encoding*
 - ▶ all codewords have k bits (typical: $k = 12$) \rightsquigarrow fixed-length
 - ▶ but they represent a variable portion of the source text!

Lempel-Ziv-Welch

- ▶ here: *Lempel-Ziv-Welch (LZW)* (arguably the “cleanest” variant of Lempel-Ziv)
- ▶ *variable-to-fixed encoding*
 - ▶ all codewords have k bits (typical: $k = 12$) \rightsquigarrow fixed-length
 - ▶ but they represent a variable portion of the source text!
- ▶ maintain a **dictionary** D with 2^k entries \rightsquigarrow codewords = indices in dictionary
 - ▶ initially, first $|\Sigma_S|$ entries encode single characters (rest is empty)
 - ▶ **add** a new entry to D **after each step**:
 - ▶ **Encoding**: after encoding a substring x of S , add xc to D where c is the character that follows x in S .



\rightsquigarrow new codeword in D

- ▶ D actually stores codewords for x and c , not the expanded string

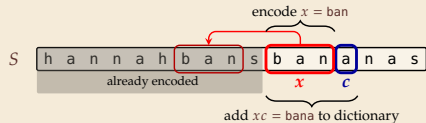
LZW encoding – Example

Input: Y0!_YOU!_YOUR_Y0Y0!

Σ_S = ASCII character set (0–127)

$C =$

$D =$



Code	String
...	
32	_
33	!
...	
79	0
...	
82	R
...	
85	U
...	
89	Y
...	

Code	String
128	
129	
130	
131	
132	
133	
134	
135	
136	
137	
138	
139	

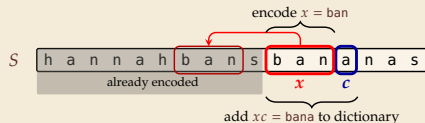
LZW encoding – Example

Input: **Y**0!_YOU!_YOUR_Y0Y0!

Σ_S = ASCII character set (0–127)

Y
C = 89

D =



Code	String
...	
32	_
33	!
...	
79	0
...	
82	R
...	
85	U
...	
89	Y
...	

Code	String
128	
129	
130	
131	
132	
133	
134	
135	
136	
137	
138	
139	

LZW encoding – Example

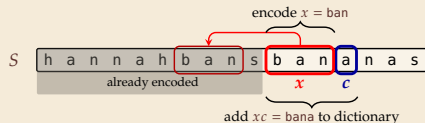
Input: Y0!_YOU!_YOUR_YOYO!

Σ_S = ASCII character set (0–127)

Y

C = 89

D =



Code	String
...	
32	_
33	!
...	
79	0
...	
82	R
...	
85	U
...	
89	Y
...	

Code	String
128	Y0
129	
130	
131	
132	
133	
134	
135	
136	
137	
138	
139	

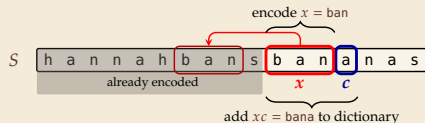
LZW encoding – Example

Input: Y0!_YOU!_YOUR_YOYO!

Σ_S = ASCII character set (0–127)

Y 0
C = 89 79

$D =$



Code	String
...	
32	_
33	!
...	
79	0
...	
82	R
...	
85	U
...	
89	Y
...	

Code	String
128	Y0
129	
130	
131	
132	
133	
134	
135	
136	
137	
138	
139	

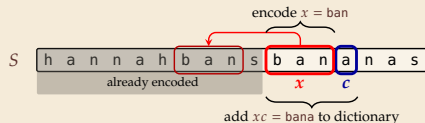
LZW encoding – Example

Input: Y0!_YOU!_YOUR_YOYO!

Σ_S = ASCII character set (0–127)

Y 0
C = 89 79

$D =$



Code	String
...	
32	_
33	!
...	
79	0
...	
82	R
...	
85	U
...	
89	Y
...	

Code	String
128	Y0
129	0!
130	
131	
132	
133	
134	
135	
136	
137	
138	
139	

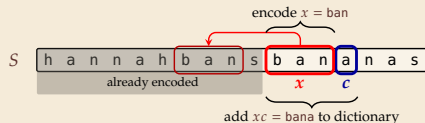
LZW encoding – Example

Input: Y0!_YOU!_YOUR_YOYO!

Σ_S = ASCII character set (0–127)

Y 0 !
C = 89 79 33

$D =$



Code	String
...	
32	_
33	!
...	
79	0
...	
82	R
...	
85	U
...	
89	Y
...	

Code	String
128	Y0
129	0!
130	
131	
132	
133	
134	
135	
136	
137	
138	
139	

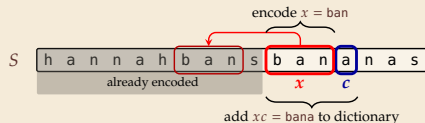
LZW encoding – Example

Input: Y0!_YOU!_YOUR_YOYO!

Σ_S = ASCII character set (0–127)

Y 0 !
C = 89 79 33

$D =$



Code	String
...	
32	_
33	!
...	
79	0
...	
82	R
...	
85	U
...	
89	Y
...	

Code	String
128	Y0
129	0!
130	!_
131	
132	
133	
134	
135	
136	
137	
138	
139	

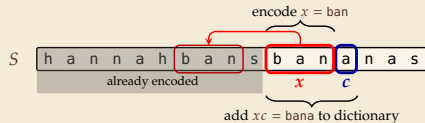
LZW encoding – Example

Input: Y0!_YOU!_YOUR_YOYO!

Σ_S = ASCII character set (0–127)

Y 0 ! _
C = 89 79 33 32

$D =$



Code	String
...	
32	_
33	!
...	
79	0
...	
82	R
...	
85	U
...	
89	Y
...	

Code	String
128	Y0
129	0!
130	!_
131	
132	
133	
134	
135	
136	
137	
138	
139	

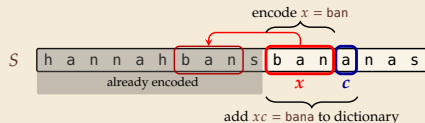
LZW encoding – Example

Input: Y0! ␣YOU! ␣YOUR ␣Y0Y0!

Σ_S = ASCII character set (0–127)

Y 0 ! ␣
C = 89 79 33 32

D =



Code	String
...	
32	␣
33	!
...	
79	0
...	
82	R
...	
85	U
...	
89	Y
...	

Code	String
128	Y0
129	0!
130	! ␣
131	␣ Y
132	
133	
134	
135	
136	
137	
138	
139	

LZW encoding – Example

Input: Y0!_YOU!_YOUR_YOYO!

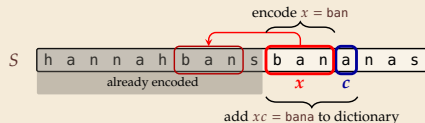
Σ_S = ASCII character set (0–127)

Y 0 ! _ Y0
C = 89 79 33 32 128

$D =$

Code	String
...	
32	_
33	!
...	
79	0
...	
82	R
...	
85	U
...	
89	Y
...	

Code	String
128	Y0
129	0!
130	!_
131	_Y
132	
133	
134	
135	
136	
137	
138	
139	



LZW encoding – Example

Input: Y0!_YOU!_YOUR_YOYO!

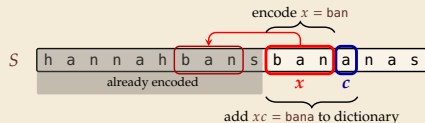
Σ_S = ASCII character set (0–127)

Y 0 ! _ Y0
C = 89 79 33 32 128

$D =$

Code	String
...	
32	_
33	!
...	
79	0
...	
82	R
...	
85	U
...	
89	Y
...	

Code	String
128	Y0
129	0!
130	!_
131	_Y
132	YOU
133	
134	
135	
136	
137	
138	
139	



LZW encoding – Example

Input: Y0!_Y0U!_YOUR_Y0Y0!

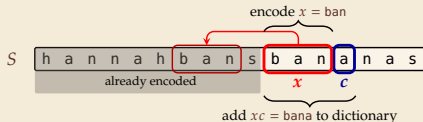
Σ_S = ASCII character set (0–127)

Y 0 ! _ Y0 U
C = 89 79 33 32 128 85

$D =$

Code	String
...	
32	_
33	!
...	
79	0
...	
82	R
...	
85	U
...	
89	Y
...	

Code	String
128	Y0
129	0!
130	!_
131	_Y
132	YOU
133	
134	
135	
136	
137	
138	
139	



LZW encoding – Example

Input: Y0!_Y0U!_YOUR_Y0Y0!

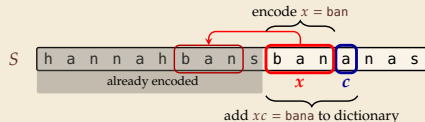
Σ_S = ASCII character set (0–127)

	Y	0	!	_	Y0	U
C =	89	79	33	32	128	85

D =

Code	String
...	
32	_
33	!
...	
79	0
...	
82	R
...	
85	U
...	
89	Y
...	

Code	String
128	Y0
129	0!
130	!_
131	_Y
132	YOU
133	U!
134	
135	
136	
137	
138	
139	



LZW encoding – Example

Input: Y0!_YOU!_YOUR_YOYO!

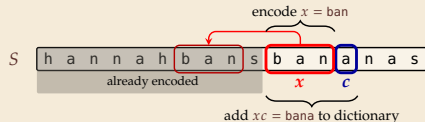
Σ_S = ASCII character set (0–127)

Y 0 ! _ Y0 U !_
C = 89 79 33 32 128 85 130

D =

Code	String
...	
32	_
33	!
...	
79	0
...	
82	R
...	
85	U
...	
89	Y
...	

Code	String
128	Y0
129	0!
130	!_
131	_Y
132	YOU
133	U!
134	
135	
136	
137	
138	
139	



LZW encoding – Example

Input: Y0!_YOU!_YOUR_YOYO!

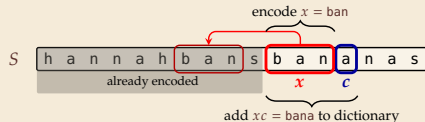
Σ_S = ASCII character set (0–127)

Y 0 ! _ Y0 U !_
C = 89 79 33 32 128 85 130

D =

Code	String
...	
32	_
33	!
...	
79	0
...	
82	R
...	
85	U
...	
89	Y
...	

Code	String
128	Y0
129	0!
130	!_
131	_Y
132	YOU
133	U!
134	!_Y
135	
136	
137	
138	
139	



LZW encoding – Example

Input: Y0!_YOU!_YOU_R_YOYO!

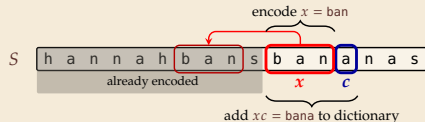
Σ_S = ASCII character set (0–127)

Y	0	!	_	Y0	U	!_	YOU
C = 89	79	33	32	128	85	130	132

$D =$

Code	String
...	
32	_
33	!
...	
79	0
...	
82	R
...	
85	U
...	
89	Y
...	

Code	String
128	Y0
129	0!
130	!_
131	_Y
132	YOU
133	U!
134	!_Y
135	
136	
137	
138	
139	



LZW encoding – Example

Input: Y0!_YOU!_YOUR_Y0Y0!

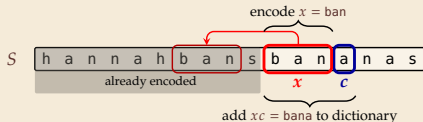
Σ_S = ASCII character set (0–127)

Y 0 ! _ Y0 U !_ YOU
C = 89 79 33 32 128 85 130 132

D =

Code	String
...	
32	_
33	!
...	
79	0
...	
82	R
...	
85	U
...	
89	Y
...	

Code	String
128	Y0
129	0!
130	!_
131	_Y
132	YOU
133	U!
134	!_Y
135	YOUR
136	
137	
138	
139	



LZW encoding – Example

Input: Y0!_YOU!_YOUR_Y0Y0!

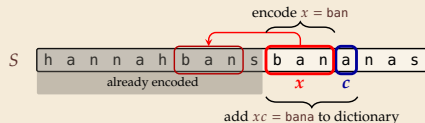
Σ_S = ASCII character set (0–127)

Y 0 ! _ Y0 U !_ YOU R
C = 89 79 33 32 128 85 130 132 82

D =

Code	String
...	
32	_
33	!
...	
79	0
...	
82	R
...	
85	U
...	
89	Y
...	

Code	String
128	Y0
129	0!
130	!_
131	_Y
132	YOU
133	U!
134	!_Y
135	YOUR
136	
137	
138	
139	



LZW encoding – Example

Input: Y0!_YOU!_YOUR_Y0Y0!

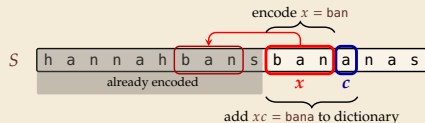
Σ_S = ASCII character set (0–127)

Y 0 ! _ Y0 U !_ YOU R
C = 89 79 33 32 128 85 130 132 82

D =

Code	String
...	
32	_
33	!
...	
79	0
...	
82	R
...	
85	U
...	
89	Y
...	

Code	String
128	Y0
129	0!
130	!_
131	_Y
132	YOU
133	U!
134	!_Y
135	YOUR
136	R_
137	
138	
139	



LZW encoding – Example

Input: Y0!_YOU!_YOUR_Y0Y0!

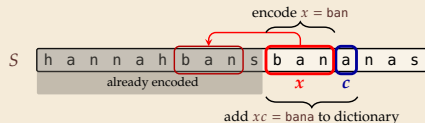
Σ_S = ASCII character set (0–127)

Y	0	!	_	Y0	U	!_	YOU	R	_Y
C = 89	79	33	32	128	85	130	132	82	131

$D =$

Code	String
...	
32	_
33	!
...	
79	0
...	
82	R
...	
85	U
...	
89	Y
...	

Code	String
128	Y0
129	0!
130	!_
131	_Y
132	YOU
133	U!
134	!_Y
135	YOUR
136	R_
137	
138	
139	



LZW encoding – Example

Input: Y0!_YOU!_YOUR_Y0Y0!

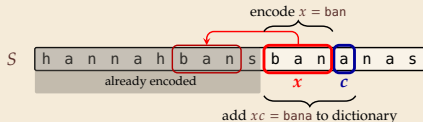
Σ_S = ASCII character set (0–127)

Y	0	!	_	Y0	U	!_	YOU	R	_Y
C = 89	79	33	32	128	85	130	132	82	131

$D =$

Code	String
...	
32	_
33	!
...	
79	0
...	
82	R
...	
85	U
...	
89	Y
...	

Code	String
128	Y0
129	0!
130	!_
131	_Y
132	YOU
133	U!
134	!_Y
135	YOUR
136	R_
137	_Y0
138	
139	



LZW encoding – Example

Input: Y0!_YOU!_YOUR_YOYO!

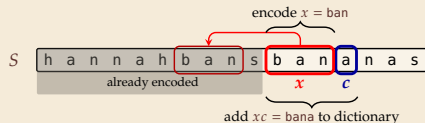
Σ_S = ASCII character set (0–127)

Y	0	!	_	Y0	U	!_	YOU	R	_Y	0
C = 89	79	33	32	128	85	130	132	82	131	79

$D =$

Code	String
...	
32	_
33	!
...	
79	0
...	
82	R
...	
85	U
...	
89	Y
...	

Code	String
128	Y0
129	0!
130	!_
131	_Y
132	YOU
133	U!
134	!_Y
135	YOUR
136	R_
137	_Y0
138	
139	



LZW encoding – Example

Input: Y0!_YOU!_YOUR_YOYO!

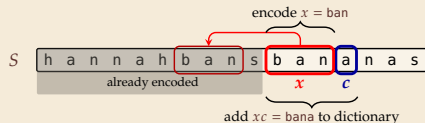
Σ_S = ASCII character set (0–127)

Y 0 ! _ Y0 U !_ YOU R _Y 0
 $C =$ 89 79 33 32 128 85 130 132 82 131 79

$D =$

Code	String
...	
32	_
33	!
...	
79	0
...	
82	R
...	
85	U
...	
89	Y
...	

Code	String
128	Y0
129	0!
130	!_
131	_Y
132	YOU
133	U!
134	!_Y
135	YOUR
136	R_
137	_Y0
138	YOY
139	



LZW encoding – Example

Input: Y0!_YOU!_YOUR_Y0Y0!

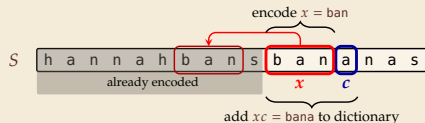
Σ_S = ASCII character set (0–127)

Y	0	!	_	Y0	U	!_	YOU	R	_Y	0	Y0
C = 89	79	33	32	128	85	130	132	82	131	79	128

$D =$

Code	String
...	
32	_
33	!
...	
79	0
...	
82	R
...	
85	U
...	
89	Y
...	

Code	String
128	Y0
129	0!
130	!_
131	_Y
132	YOU
133	U!
134	!_Y
135	YOUR
136	R_
137	_Y0
138	0Y
139	



LZW encoding – Example

Input: Y0!_YOU!_YOUR_Y0Y0!

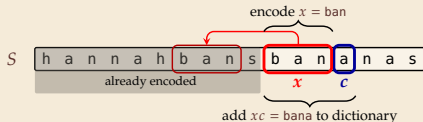
Σ_S = ASCII character set (0–127)

Y 0 ! _ Y0 U !_ YOU R _Y 0 Y0
 $C =$ 89 79 33 32 128 85 130 132 82 131 79 128

$D =$

Code	String
...	
32	_
33	!
...	
79	0
...	
82	R
...	
85	U
...	
89	Y
...	

Code	String
128	Y0
129	0!
130	!_
131	_Y
132	YOU
133	U!
134	!_Y
135	YOUR
136	R_
137	_Y0
138	0Y
139	Y0!



LZW encoding – Example

Input: Y0!_YOU!_YOUR_Y0Y0!

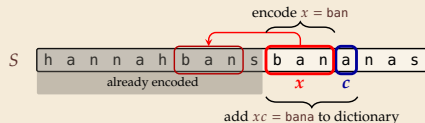
Σ_S = ASCII character set (0–127)

Y 0 ! _ Y0 U !_ YOU R _Y 0 Y0 !
 $C =$ 89 79 33 32 128 85 130 132 82 131 79 128 33

$D =$

Code	String
...	
32	_
33	!
...	
79	0
...	
82	R
...	
85	U
...	
89	Y
...	

Code	String
128	Y0
129	0!
130	!_
131	_Y
132	YOU
133	U!
134	!_Y
135	YOUR
136	R_
137	_Y0
138	0Y
139	Y0!



LZW encoding – Code

```
1 procedure LZWencode( $S[0..n]$ )
2    $x := \varepsilon$  // previous phrase, initially empty
3    $C := \varepsilon$  // output, initially empty
4    $D :=$  dictionary, initialized with codes for  $c \in \Sigma_S$  // stored as trie ( $\rightsquigarrow$  Unit 8)
5    $k := |\Sigma_S|$  // next free codeword
6   for  $i := 0, \dots, n - 1$  do
7      $c := S[i]$ 
8     if  $D.\text{containsKey}(xc)$  then
9        $x := xc$ 
10    else
11       $C := C \cdot D.\text{get}(x)$  // append codeword for  $x$ 
12       $D.\text{put}(xc, k)$  // add  $xc$  to  $D$ , assigning next free codeword
13       $k := k + 1$ ;  $x := c$ 
14  end for
15   $C := C \cdot D.\text{get}(x)$ 
16  return  $C$ 
```
