7 Compression

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Sebastian Wild

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Outline

7 Compression

7.1 Context

Overview

- Unit 4–6: How to *work* with strings
  - finding substrings
  - finding approximate matches
  - finding repeated parts
  - ...

- Unit 7–8: How to *store* strings
  - computer memory: must be binary
  - how to compress strings (save space)
  - how to robustly transmit over noisy channels $\rightsquigarrow$ Unit 8

Terminology

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

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

- 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*: $\dfrac{|C| \cdot \lg|\Sigma_C|}{|S| \cdot \lg|\Sigma_S|} \overset{\Sigma_C=\{0,1\}}{=} \dfrac{|C|}{|S| \cdot \lg|\Sigma_S|}$

  < 1 means successful compression
  $= 1$ means no compression
  > 1 means "compression" made it bigger!? (yes, that happens ...)

Types of Data Compression

- **Logical vs. Physical**
  - **Logical Compression** uses meaning of data
    $\rightsquigarrow$ only applies to a certain domain, e. g., sound recordings
  - **Physical Compression** only knows the (physical) **bits** in the data, not the meaning behind them

- **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 *physical, lossless* compression algorithms.
  These techniques can be used for any application.

What makes data compressible?

- Physical, lossless compression methods mainly exploit two types of redundancies in source texts:

  1. **uneven character frequencies**
     some characters occur more often than others $\rightarrow$ Part I
  2. **repetitive texts**
     different parts in the text are (almost) identical $\rightarrow$ Part II

There is no such thing as a free lunch!

Not *everything* is compressible ($\rightarrow$ tutorials)

$\rightsquigarrow$ 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

$\rightsquigarrow$ encoding function $E : \Sigma_S \to \Sigma_C^\star$

  - 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 $c \in \Sigma_C$
- 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

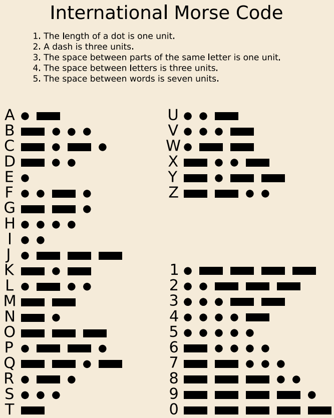
- 👍 Encoding & Decoding as fast as it gets

- 👎 Unless all characters equally likely, it wastes a lot of space
- 👎 inflexible (how to support adding a new character?)

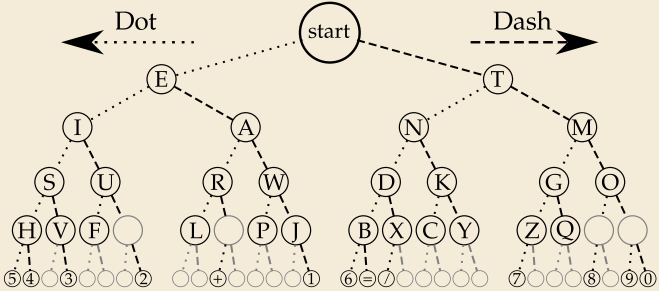
Variable-length codes

- to gain more flexibility, have to allow different lengths for codewords

- actually an old idea: **Morse Code**



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



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

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 (137 994 as of May 2019, 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 `1`s 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 = banana with the coded text $C = \underbrace{110}_{\texttt{b}}\underbrace{0}_{\texttt{a}}\underbrace{10}_{\texttt{n}}\underbrace{0}_{\texttt{a}}\underbrace{10}_{\texttt{n}}\underbrace{0}_{\texttt{a}}$

ϟ C = 1100100100 decodes **both** to banana and to bass: $\underbrace{110}_{\texttt{b}}\underbrace{0}_{\texttt{a}}\underbrace{100}_{\texttt{s}}\underbrace{100}_{\texttt{s}}$

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

but how should we have known?

$E(\texttt{n}) = \texttt{10}$ is a (proper) **prefix** of $E(\texttt{s}) = \texttt{100}$

⇝ Leaves decoding wondering whether to stop after reading 10 or continue

⇝ Require a ***prefix-free*** code: $\boxed{\text{No codeword is a prefix of another.}}$

prefix-free $\implies$ instantaneously decodable

Code tries

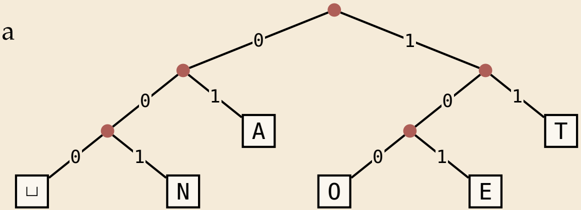
- From now on only consider prefix-free codes E:
  $E(c)$ is not a prefix of $E(c')$ for any $c, c' \in \Sigma_S$.

- **Example:**

c	A	E	N	O	T	␣
$E(c)$	01	101	001	100	11	000

Any prefix-free code corresponds to a *(code) trie* (trie of codewords) with characters of Σ_S at **leaves**.

no need for end-of-string symbols $ here (already prefix-free!)



- Encode `AN␣ANT` $\longrightarrow$ `010010000100111`
- Decode `111000001010111` $\longrightarrow$ `TO␣EAT`

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 $\rightarrow$ next)
  - **adaptive coding:** code depends on message and changes during encoding; implicitly stored withing the message (e. g., LZW $\rightarrow$ 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%		

$\rightsquigarrow$ Want shorter codes for more frequent characters!

Huffman coding

e. g. frequencies / probabilities

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

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

- If we use $w(c)$ = #occurrences of c in S,
  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.

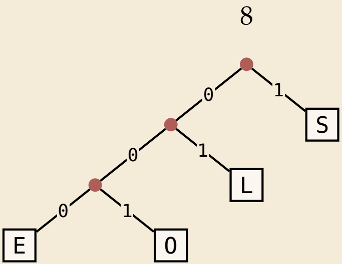
Huffman's algorithm:

1. Find two characters $\mathtt{a}$, $\mathtt{b}$ with lowest weights.
   - We will encode them with the same prefix, plus one distinguishing bit, i. e., $E(\mathtt{a}) = u\mathtt{0}$ and $E(\mathtt{b}) = u\mathtt{1}$ for a bitstring $u \in \{0,1\}^\star$ (u to be determined)
2. (Conceptually) replace $\mathtt{a}$ and $\mathtt{b}$ by a single character "$\boxed{\mathtt{ab}}$" with $w(\boxed{\mathtt{ab}}) = w(\mathtt{a}) + w(\mathtt{b})$.
3. Recursively apply Huffman's algorithm on the smaller alphabet. This in particular determines $u = E(\boxed{\mathtt{ab}})$.

- 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: $S = \texttt{LOSSLESS}$ $\rightsquigarrow$ $\Sigma_S = \{\texttt{E}, \texttt{L}, \texttt{O}, \texttt{S}\}$
- Character frequencies: $\texttt{E} : 1$, $\texttt{L} : 2$, $\texttt{O} : 1$, $\texttt{S} : 4$



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

$\texttt{LOSSLESS} \to \texttt{01001110100011}$ 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 COMP 526: 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.

Huffman code – Optimality

Theorem 7.1 (Optimality of Huffman's Algorithm)

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

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

- Given any optimal prefix-free code E^* (as its code trie).
- code trie $\rightsquigarrow$ $\exists$ two sibling leaves x, y at largest depth D
- swap characters in leaves to have two lowest-weight characters $\mathtt{a}$, $\mathtt{b}$ in x, y (that can only make ℓ smaller, so still optimal)
- any optimal code for $\Sigma' = \Sigma \setminus \{\mathtt{a}, \mathtt{b}\} \cup \{\boxed{\mathtt{ab}}\}$ yields optimal code for Σ by replacing leaf $\boxed{\mathtt{ab}}$ by internal node with children $\mathtt{a}$ and $\mathtt{b}$.

$\rightsquigarrow$ recursive call yields optimal code for Σ' by inductive hypothesis, so Huffman's algorithm finds optimal code for Σ.

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

$$\mathcal{H}(p_1, \dots, p_n) \;=\; -\sum_{i=1}^{n} p_i \lg p_i \;=\; \sum_{i=1}^{n} p_i \lg\left(\frac{1}{p_i}\right)$$

◀

- entropy is a **measure** of **information** content of a distribution
  - more precisely: the expected number of bits (Yes/No questions) required to nail down the random value

$\rightsquigarrow$ would ideally encode value i using $\lg(1/p_i)$ bits
that is not always possible; cannot use 1.5 bits . . . but:

Theorem 7.3 (Entropy bounds for Huffman codes)

For any $\Sigma = \{a_1, \dots, a_\sigma\}$ and $w : \Sigma \to \mathbb{R}_{\ge 0}$ and its Huffman code E, we have

$$\mathcal{H}\left(\frac{w(a_1)}{W}, \dots, \frac{w(a_\sigma)}{W}\right) \;\le\; \ell(E) \;\le\; \mathcal{H}\left(\frac{w(a_1)}{W}, \dots, \frac{w(a_\sigma)}{W}\right) + 1$$

where $W = w(a_1) + \cdots + w(a_\sigma)$.

◀

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 coding – Discussion

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

👍 optimal prefix-free character encoding

👍 very fast decoding

👍 robust encoding local errors only affect 1–2 symbols

👎 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

Beyond Character Encoding

- Many "natural" texts show repetitive redundancy

```
All work and no play makes Jack a dull boy.  All work and no play makes Jack a dull
boy.  All work and no play makes Jack a dull boy.  All work and no play makes Jack
a dull boy.  All work and no play makes Jack a dull boy.  All work and no play makes
Jack a dull boy.  All work and no play makes Jack a dull boy.  All work and no play
makes Jack a dull boy.  All work and no play makes Jack a dull boy.  All work and no
play makes Jack a dull boy.  All work and no play makes Jack a dull boy.  All work and
no play makes Jack a dull boy.  All work and no play makes Jack a dull boy.  All work
and no play makes Jack a dull boy.  All work and no play makes Jack a dull boy.  All
work and no play makes Jack a dull boy.  All work and no play makes Jack a dull boy.
```

- character-by-character encoding will **not** capture such repetitions
  - ⇝ Huffman won't compression this very much

⇝ Have to encode whole *phrases* of S by a codeword

7.4 Run-Length Encoding

Run-Length encoding

- simplest form of repetition: *runs* of characters

same character repeated

```
0000000000000000000000000000000000000000
0000000000000000000000000000000000000000
0000000000000000000000000000000000000000
0001011001000001111110000000000011111000
0011111111100011111111100000001111111000
0011110110100011100011110000111000000000
0011000000000000000000011100011100000000
0011000000000000000000011001110000000000
0011000000000000000000011001110000000000
0011011000000000000000111001100111110000
0011111111100000000000111001111111111000
0011101111110000000000111000111110011100
0000000001110000000011100001110000001110
0000000001110000000011000001110000001100
0000000000110000000110000000110000001110
0000000000110000011100000001110000001100
0000000001110001110000000000110000001110
0000000001100001110000000000111000011100
0011011111110001111011101000011111111000
0111111111100011111111111110000111110000
0001011000000001010011001000000100100000
0000000000000000000000000000000000000000
0000000000000000000000000000000000000000
```

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

$\rightsquigarrow$ **run-length encoding (RLE):**
use runs as phrases: $S = \underbrace{\texttt{00000}}\ \underbrace{\texttt{111}}\ \underbrace{\texttt{0000}}$

$\rightsquigarrow$ We have to store
- the first bit of S (either `0` or `1`)
- the length each each 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!)

Elias codes

- Need a prefix-free encoding for $\mathbb{N} = \{1, 2, 3, \ldots, \}$
  - 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` $30 \mapsto$ `0000000000000000000000000000001`

  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 $\ell \geq 1$, 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`

Run-length encoding – Examples

- Encoding:
  $S =$ `11111110010000000000000000000011111111111`

  $C =$ `10011101010000101000001011`

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

- Decoding:
  $C =$ `00001101001001010`
  $b =$
  $\ell =$
  $k =$
  $S =$ `00000000000001111011`

Run-length encoding – Discussion

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

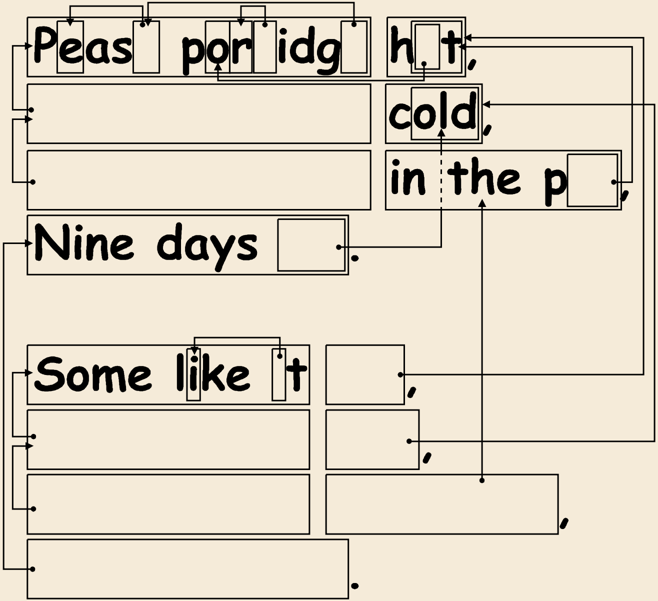
👍 fairly simple and fast

👍 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** when run lengths $k = 2$ or 6

7.5 Lempel-Ziv-Welch

Warmup



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

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

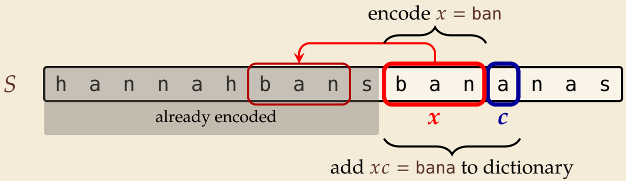
Lempel-Ziv Compression

- 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`", "`<br/>`"
- **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 already seen).
  - Variants of Lempel-Ziv compression
    - "LZ77" Original version ("sliding window")
      Derivatives: LZSS, LZFG, LZRW, LZP, DEFLATE, ...
      DEFLATE used in (pk)`zip`, `gzip`, `PNG`
    - "LZ78" Second (slightly improved) version
      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!
- 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: `YO!␣YOU!␣YOUR␣YOYO!` $\qquad\qquad \Sigma_S$ = ASCII character set (0–127)

	`Y`	`O`	`!`	`␣`	`YO`	`U`	`!␣`	`YOU`	`R`	`␣Y`	`O`	`YO`	`!`
C =	89	79	33	32	128	85	130	132	82	131	79	128	33

D =

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

Code	String
128	`YO`
129	`O!`
130	`!␣`
131	`␣Y`
132	`YOU`
133	`U!`
134	`!␣Y`
135	`YOUR`
136	`R␣`
137	`␣YO`
138	`OY`
139	`YO!`

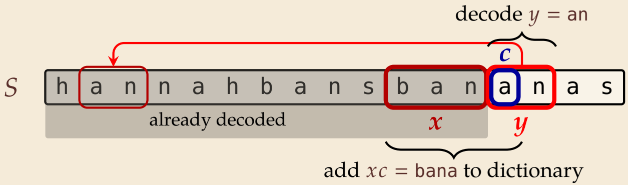
LZW encoding – Code

```
procedure LZWencode(S[0..n))
    x := ε // previous phrase, initially empty
    C := ε // output, initially empty
    D := dictionary, initialized with codes for c ∈ Σ_S // stored as trie
    k := |Σ_S| // next free codeword
    for i := 0, . . . , n − 1 do
        c := S[i]
        if D.containsKey(xc) then
            x := xc
        else
            C := C · D.get(x) // append codeword for x
            D.put(xc,k) // add xc to D, assigning next free codeword
            k := k + 1;\; x := c
    end for
    C := C · D.codeFor(x)
    return C
```

LZW decoding

- Decoder has to replay the process of growing the dictionary!

⇝ **Decoding:**
after decoding a substring y of S, add xc to D,
where x is previously encoded/decoded substring of S,
and $c = y[0]$ (first character of y)



⇝ Note: only start adding to D after *second* substring of S is decoded

LZW decoding – Example

- Same idea: build dictionary while reading string.
- Example: 67 65 78 32 66 129 133

$D =$

Code #	String
...	
32	␣
...	
...	
65	A
66	B
67	C
...	
78	N
...	
83	S
...	

input	decodes to	Code #	String (human)	String (computer)
67	C			
65	A	128	CA	67, A
78	N	129	AN	65, N
32	␣	130	N␣	78, ␣
66	B	131	␣B	32, B
129	AN	132	BA	66, A
133	???	133		

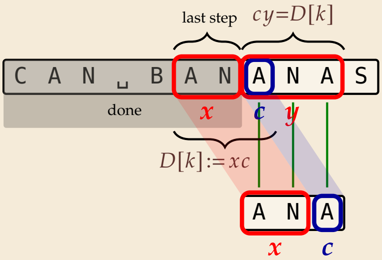
LZW decoding – Bootstrapping

- example: Want to decode 133, but not yet in dictionary!

⚠ decoder is "one step behind" in creating dictionary

⇝ problem occurs if *we want to use a code* that we are *just about to build*.

- But then we actually know what is going on:
  - Situation: decode using k in the step that will define k.
  - decoder know last phrase x, needs phrase $y = D[k] = xc$



1. en/decode x.

2. store $D[k] := xc$

3. next phrase y equals $D[k]$

⇝ $D[k] = xc = x \cdot x[0]$ (all known)

LZW decoding – Code

```
procedure LZWdecode(C[0..m))
    D := dictionary [0..2^d) → Σ_S^+, initialized with codes for c ∈ Σ_S // stored as array
    k := |Σ_S| // next unused codeword
    q := C[0] // first codeword
    y := D[q] // lookup meaning of q in D
    S := y // output, initially first phrase
    for j := 1, . . . , m − 1 do
        x := y // remember last decoded phrase
        q := C[j] // next codeword
        if q == k then
            y := x · x[0] // bootstrap case
        else
            y := D[q]
        S := S · y // append decoded phrase
        D[k] := x · y[0] // store new phrase
        k := k + 1
    end for
    return S
```

LZW decoding – Example continued

- Example: 67 65 78 32 66 129 133 83

$D =$

Code #	String
...	
32	␣
...	
...	
65	A
66	B
67	C
...	
78	N
...	
83	S
...	

input	decodes to	Code #	String (human)	String (computer)
67	C			
65	A	128	CA	67, A
78	N	129	AN	65, N
32	␣	130	N␣	78, ␣
66	B	131	␣B	32, B
129	AN	132	BA	66, A
133	ANA	133	ANA	129, A
83	S	134	ANAS	133, S

LZW – Discussion

- As presented, LZW uses coded alphabet $\Sigma_C = [0..2^d)$.
  - $\leadsto$ use another encoding for code numbers $\mapsto$ binary, e. g., Huffman
- need a rule when dictionary is full; different options:
  - increment d $\leadsto$ longer codewords
  - "flush" dictionary and start from scratch $\leadsto$ limits extra space usage
  - often: reserve a codeword to trigger flush at any time
- encoding and decoding both run in linear time (assuming $|\Sigma_S|$ constant)

👍 fast encoding & decoding

👍 works in streaming model (no random access, no backtrack on input needed)

👍 significant compression for many types of data

👎 captures only local repetitions (with bounded dictionary)

Compression summary

Huffman codes	Run-length encoding	Lempel-Ziv-Welch
fixed-to-variable	variable-to-variable	variable-to-fixed
2-pass	1-pass	1-pass
must send dictionary	can be worse than ASCII	can be worse than ASCII
60% compression on English text	bad on text	45% compression on English text
optimal binary character encopding	good on long runs (e.g., pictures)	good on English text
rarely used directly	rarely used directly	frequently used
part of pkzip, JPEG, MP3	fax machines, old picture-formats	GIF, part of PDF, Unix compress

Part III

Text Transforms

Text transformations

- compression is effective is we have one the following:
  - long runs $\leadsto$ RLE
  - frequently used characters $\leadsto$ Huffman
  - many (local) repeated substrings $\leadsto$ LZW
- but methods can be frustratingly "blind" to other "obvious" redundancies
  - LZW: repetition too distant ϟ dictionary already flushed
  - Huffman: changing probabilities (local clusters) ϟ averaged out globally
  - RLE: run of alternating pairs of characters ϟ not a run
- Enter: **text transformations**
  - invertible functions of text
  - do not by themselves reduce the space usage
  - but help compressors "see" redundancy

  $\leadsto$ use as pre-/postprocessing in compression pipeline

7.6 Move-to-Front Transformation

Move to Front

- *Move to Front (MTF)* is a heuristic for *self-adjusting linked lists*
  - unsorted linked list of objects
  - whenever an element is accessed, it is moved to the front of the list (leaving the relative order of other elements unchanged)
  - $\leadsto$ list "learns" probabilities of access to objects makes access to frequently requested ones cheaper

- Here: use such a list for storing source alphabet Σ_S
  - to encode c, access it in list an
  - encode c using it (old) position in list (then apply MTF).
  - $\leadsto$ codewords are integers, i. e., $\Sigma_C = [0..\sigma)$

$\leadsto$ clusters of few characters $\leadsto$ many small numbers

MTF – Code

- **Transform (encode):**

```
procedure MTF−encode(S[0..n))
    L := list containing Σ_C (sorted order)
    C := ε
    for i := 0, . . . , n − 1 do
        c := S[i]
        p := position of c in L
        C := C · p
        Move c to front of L
    end for
    return C
```

- **Inverse transform (decode):**

```
procedure MTF−encode(C[0..m))
    L := list containing Σ_C (sorted order)
    S := ε
    for j := 0, . . . , m − 1 do
        p := C[j]
        c := character at position p in L
        S := S · c
        Move c to front of L
    end for
    return S
```

- Important: encoding and decoding produce same accesses to list

MTF – Example

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
S	E	I	C	N	F	A	B	D	G	H	J	K	L	M	O	P	Q	R	T	U	V	W	X	Y	Z

S = `INEFFICIENCIES`

C = 8 13 6 7 0 3 6 1 3 4 3 3 3 18

- What does a run in S encode to in C?
- What does a run in C mean about the source S?

MTF – Discussion

- MTF itself does not compress text (if we store codewords with fixed length)

$\rightsquigarrow$ prime use as part of longer pipeline

- two simple ideas for encoding codewords:
  - Elias gamma code $\rightsquigarrow$ smaller numbers gets shorter codewords
    works well for text with small "local effective" alphabet
  - Huffman code (better compression, but need 2 passes)
- but: most effective after BWT ($\rightarrow$ next)

7.7 Burrows-Wheeler Transform

Burrows-Wheeler Transform

- Burrows-Wheeler Transform (BWT) is a sophisticated text-transformation technique.
  - coded text has same letters as source, just in a different order
  - But: The coded text (typically) more compressible with MTF(!)

- Encoding algorithm needs **all** of S (no streaming possible).

  ⇝ BWT is a *block compression method*.

- BWT followed by MTF, RLE, and Huffman is the algorithm used by the `bzip2` program.

  achieves best compression on English text of any algorithm we have seen:

```
4047392 bible.txt
1191071 bible.txt.gz
 888604 bible.txt.7z
 845635 bible.txt.bz2
```

BWT transform

$T =$ `time␣flies␣quickly␣` `flies␣quickly␣time␣`

- *cyclic shift* of a string:

$\rightsquigarrow$ cyclic shift

- add *end-of-word character* $\$$ to S (as in Unit 6)

- The Burrows-Wheeler Transform proceeds in three steps:
  1. Place *all cyclic shifts* of S in a list L
  2. Sort the strings in L lexicographically
  3. B is the *list of trailing characters* (last column, top-down) of each string in L

BWT transform – Example

$S =$ `alf␣eats␣alfalfa$`

1. Write all cyclic shifts
2. Sort cyclic shifts
3. Extract last column

$B =$ `asff$f␣e␣lllaaata`

```
alf␣eats␣alfalfa$
lf␣eats␣alfalfa$a
f␣eats␣alfalfa$al
␣eats␣alfalfa$alf
eats␣alfalfa$alf␣
ats␣alfalfa$alf␣e
ts␣alfalfa$alf␣ea
s␣alfalfa$alf␣eat
␣alfalfa$alf␣eats
alfalfa$alf␣eats␣
lfalfa$alf␣eats␣a
falfa$alf␣eats␣al
alfa$alf␣eats␣alf
lfa$alf␣eats␣alfa
fa$alf␣eats␣alfal
a$alf␣eats␣alfalf
$alf␣eats␣alfalfa
```

sort

BWT

```
$alf␣eats␣alfalfa
␣alfalfa$alf␣eats
␣eats␣alfalfa$alf
a$alf␣eats␣alfalf
alf␣eats␣alfalfa$
alfa$alf␣eats␣alf
alfalfa$alf␣eats␣
ats␣alfalfa$alf␣e
eats␣alfalfa$alf␣
f␣eats␣alfalfa$al
fa$alf␣eats␣alfal
falfa$alf␣eats␣al
lf␣eats␣alfalfa$a
lfa$alf␣eats␣alfa
lfalfa$alf␣eats␣a
s␣alfalfa$alf␣eat
ts␣alfalfa$alf␣ea
```

BWT – Implementation & Properties

Compute BWT efficiently:

- cyclic shifts S $\widehat{=}$ suffixes of S
- BWT is essentially suffix sorting!
  - $B[i] = S[L[i] - 1]$ (L = suffix array!)
    (if $L[i] = 0$, $B[i] = \$$)
  - $\rightsquigarrow$ Can compute B in $O(n)$ time

	r		$\downarrow$ $L[r]$
`alf␣eats␣alfalfa$`	0	`$alf␣eats␣alfalfa`	16
`lf␣eats␣alfalfa$a`	1	`␣alfalfa$alf␣eats`	8
`f␣eats␣alfalfa$al`	2	`␣eats␣alfalfa$alf`	3
`␣eats␣alfalfa$alf`	3	`a$alf␣eats␣alfalf`	15
`eats␣alfalfa$alf␣`	4	`alf␣eats␣alfalfa$`	0
`ats␣alfalfa$alf␣e`	5	`alfa$alf␣eats␣alf`	12
`ts␣alfalfa$alf␣ea`	6	`alfalfa$alf␣eats␣`	9
`s␣alfalfa$alf␣eat`	7	`ats␣alfalfa$alf␣e`	5
`␣alfalfa$alf␣eats`	8	`eats␣alfalfa$alf␣`	4
`alfalfa$alf␣eats␣`	9	`f␣eats␣alfalfa$al`	2
`lfalfa$alf␣eats␣a`	10	`fa$alf␣eats␣alfal`	14
`falfa$alf␣eats␣al`	11	`falfa$alf␣eats␣al`	11
`alfa$alf␣eats␣alf`	12	`lf␣eats␣alfalfa$a`	1
`lfa$alf␣eats␣alfa`	13	`lfa$alf␣eats␣alfa`	13
`fa$alf␣eats␣alfal`	14	`lfalfa$alf␣eats␣a`	10
`a$alf␣eats␣alfalf`	15	`s␣alfalfa$alf␣eat`	7
`$alf␣eats␣alfalfa`	16	`ts␣alfalfa$alf␣ea`	6

Why does BWT help?

- sorting groups characters *by what follows*
  - Example: `lf` always preceded by `a`

$\rightsquigarrow$ B has local clusters of characters

  - that makes MTF effective

- repeated substring in S $\rightsquigarrow$ *runs* of character in B
  - picked up by RLE

Inverse BWT

- Great, can compute BWT efficiently and it helps compression. *But how can we decode it?*

not even obvious that it is at all invertible!

- **"Magic" solution:**
  1. Create array $D[0..n]$ of pairs: $D[r] = (B[r], r)$.
  2. Sort D *stably* with respect to *first entry*.
  3. Use D as linked list with $(\text{char}, \text{next entry})$

Example:

$B =$ `ard$rcaaaabb`

$S =$ `abracadabra$`

	D	sorted D (char, next)
0	(a, 0)	($, 3)
1	(r, 1)	(a, 0)
2	(d, 2)	(a, 6)
3	($, 3)	(a, 7)
4	(r, 4)	(a, 8)
5	(c, 5)	(a, 9)
6	(a, 6)	(b, 10)
7	(a, 7)	(b, 11)
8	(a, 8)	(c, 5)
9	(a, 9)	(d, 2)
10	(b, 10)	(r, 1)
11	(b, 11)	(r, 4)

Inverse BWT – The magic revealed

- Inverse BWT very easy to compute:
  - only sort individual characters in B (not suffixes)
  - $\rightsquigarrow$ $O(n)$ with counting sort
- *but why does this work!?*
- decode char by char
  - can find unique \$ $\rightsquigarrow$ starting row
- to get next char, we need
  - (i) char in *first* column of *current row*
  - (ii) find row with that char's copy in BWT
  - $\rightsquigarrow$ then we can walk through and decode
- for (i): first column = characters of B in sorted order ✓
- for (ii): relative order of same character same!
  - ith `a` in BWT $\rightarrow$ ith `a` in first column
  - $\rightsquigarrow$ stably sorting $(B[r], r)$ by first entry enough ✓

r	$L[r]$	$T_{L[r]}$	$B[r]$
0	9	`$bananaba`	**n**
1	5	`aban$bana`	**n**
2	7	`an$banana`	**b**
3	3	`anaban$ba`	**n**
4	1	`ananaban$`	**b**
5	6	`ban$banan`	**a**
6	0	`bananaban`	**$**
7	8	`n$bananab`	**a**
8	4	`naban$ban`	**a**
9	2	`nanaban$b`	**a**

BWT – Discussion

- Running time: $\Theta(n)$
  - **encoding** uses suffix sorting
  - decoding only needs counting sort
  - $\leadsto$ decoding much simpler & faster (but same Θ-class)

- typically slower than other methods
- need access to entire text (or apply to blocks independently)
- BWT-MTF-RLE-Huffman pipeline tends to have best compression

Summary of Compression Methods

Huffman	Variable-width, single-character (optimal in this case)
RLE	Variable-width, multiple-character encoding
LZW	Adaptive, fixed-width, multiple-character encoding Augments dictionary with repeated substrings
MTF	Adaptive, transforms to smaller integers should be followed by variable-width integer encoding
BWT	Block compression method, should be followed by MTF