

ADVANCED

overall tree
= binary tree of mini trees

mini trees

micro trees

actual nodes

$\frac{1}{7} \lg n$ nodes

$\lg n$ nodes

n nodes



DATA STRUCTURES

6

Succinct Data Structures

Advanced Data Structures · Summer 2026

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6 Succinct Data Structures

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6.1 A Motivating Example

Computing over compressed data

- ▶ traditionally:
 - ▶ compression for **archiving** data, minimize size of representation
 - ▶ computation/analysis: minimize time; use extra data structures
 - ↪ always decompress data first!
 - ▶ reaches limits of fast memory for large datasets

- ▶ Approach in space-efficient data structures:
 - ▶ Represent data in compressed form
 - ▶ Augment with **small** index data structures to enable fast queries **directly on compressed representation**
 - ▶ *succinct* = $(1 + o(1)) \cdot$ information-theoretic lower bound

Computing over compressed data

$T[0..n) =$

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
a	b	a	n	a	n	a	a	n	d	a	n	a	p	p	l	e

$C[0..m) =$ 0111100010010001011110101001101101111111110

Huffman Code

a	↦	0
b	↦	11100
d	↦	11101
e	↦	11110
l	↦	11111
n	↦	10
p	↦	110

- ▶ Can decode from beginning \rightsquigarrow fine for storage / transmission



But how to read $T[9]$ without full decoding? How to know where its codeword starts?

- ▶ We don't. But we can store it!
 - ▶ Naive way: Store starting index for each char
- $\rightsquigarrow n$ numbers in $[n]$ $\rightsquigarrow n \lg n$ bits.

Much more than the (compressed) text!



entropy-compressed bitvector
Clever **succinct index** supports random access in constant time with $o(n)$ extra bits!

Dynamic Bitvectors

Recall: Dynamic rank/select lower bounds (Fredman-Saks)

Note: Can use bitvector to represent n numbers from universe $[0..u)$

↪ Cannot have dynamic bitvectors **and** fast rank/select queries, $\Omega\left(\frac{\lg n}{\lg \lg n}\right)$.

↪ *Focus here on static bitvectors.*

6.2 Bitvectors

Bitvector Representation in C++

- ▶ `std::vector<char/int>, bool[]`
 - ▶ easy to access
 - ▶ fastest read and write access
 - ▶ ≥ 1 **byte** per bit
 - ▶ `std::vector<byte>`
 - ▶ special overload
 - ▶ *may* use only 1 bit each
 - ▶ (with my GNU g++ it used same space as `vector<char>`)
 - ▶ `std::vector<uint64_t>`
 - ▶ store 64 bits in one 8 byte integer
 - ▶ use bit tricks to access and write individual bits
- ↪ in practice: `sdsl::bit_vector` (based on packing bits to words)
- ▶ from external library SDSL Lite
 - ▶ <https://github.com/simongog/sdsl-lite>

Rank & Select on Bitvectors

- ▶ $B[0..n]$ static array of n bits (Boolean array).
 - ▶ easy to store using n bits of space
- ▶ $B.\text{rank}(i) = \# \text{ 1s in } B[0..i]$ (first $i \in [0..n]$ positions) (=prefix sum)
- ▶ $B.\text{select}_1(r) = \min\{j : B.\text{rank}(j+1) \geq r\} \cup \{n\}$
= index of r th 1 in B , ($r = 1, 2, \dots$)

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 26 27 28 29 30 31
0 1 0 1 0 0 0 0 0 0 1 1 0 1 1 0 1 1 1 1 1 1 0 1 1 1 1 1 1 0 0 0

- ▶ $\text{rank}(12) = \text{rank}(13) = 4$
- ▶ $\text{select}_1(3) = 10$
- ▶ $\text{select}_1(4) = 11$

$\rightsquigarrow B[i] = B.\text{rank}(i+1) - B.\text{rank}(i)$ (no need to discuss access separately)

Goal: Support rank and select on bitvector using $n + o(n)$ bits of space.

Versatile Bitvectors

► Set of integers

► $S \subset [0..u) \rightsquigarrow B[0..u)$ with $B[x] = 1 \iff x \in S$

$\rightsquigarrow B.\text{select}(B.\text{rank}(x + 1)) = S.\text{predecessor}(x)$

\rightsquigarrow efficient intersection, union, etc. via bitwise logical operations

► used, e. g., for “**Roaring Bitmaps**”: one bitvector / integer set per attribute

► Unary encoded integers

► integers $x_1, \dots, x_k \in \mathbb{N}_{\geq 0} \rightsquigarrow B = 1^{x_1}0 1^{x_2}0 \dots 1^{x_k}0$

► $x_1 + \dots + x_j = B.\text{rank}(B.\text{select}_0(j))$

► x_j as difference of prefix sums

► Sparse array index

► suppose $A[0..n)$ is mostly 0, but with some k indices having non-zero values

\rightsquigarrow Store in $V[0..k)$ all non-zero values compactly, in $B[0..n)$ store $B[i] = 1 \iff A[i] \neq 0$

\rightsquigarrow Simulate $A[x] = \begin{cases} 0 & \text{if } B[x] = 0 \\ V[B.\text{rank}[x]] & \text{else} \end{cases}$

► **Note:** In all these cases, rather natural to expect skewed frequencies of 1s and 0s.

6.3 Supporting Rank

Rank Index for Bitvector

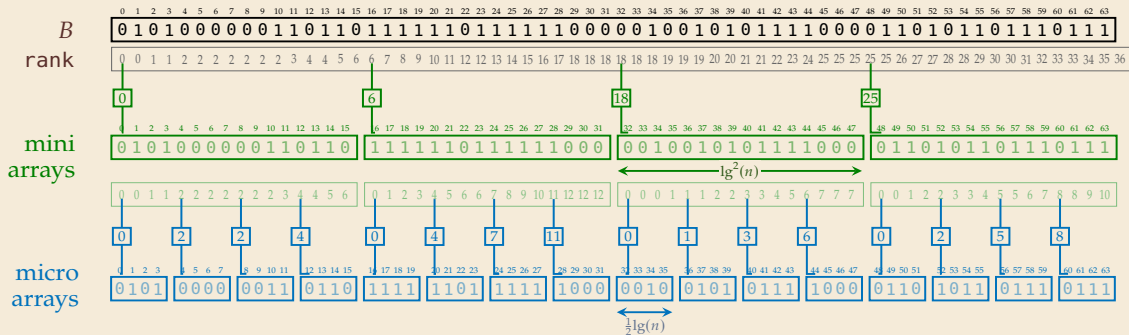
► Apart from B , we store:

1. Rank of first pos. of each **mini array** of $L = \lg^2(n)$ bits $\rightsquigarrow \frac{n}{L} \cdot \lg(n) = \frac{n}{\lg n} = o(n)$ bits

2. Rank of first pos. in **micro array** of $\ell = \frac{1}{2} \lg(n)$ bits *relative to its mini array*

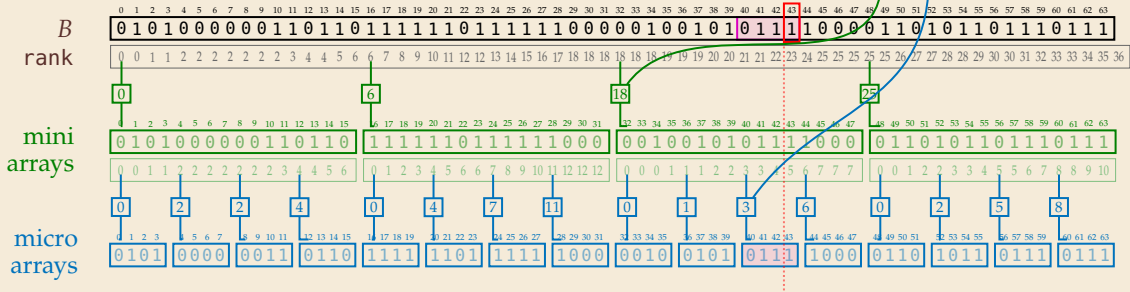
\rightsquigarrow ranks are numbers in $[0..L]$ $\rightsquigarrow \lg L = 2 \lg \lg n$ bits suffice for each

$\rightsquigarrow \frac{n}{\ell} \lg L = \frac{n}{\frac{1}{2} \lg n} \cdot 2 \lg \lg n = \frac{4n \lg \lg n}{\lg n} = o(n)$ bits



How to find rank

$$B.\text{rank}(43) = 18 + 3 + 2 = 23$$



► How to compute $B.\text{rank}(i)$?

- find rank up to element's mini array
- add rank up to element's micro array (mini-array local)
- add micro-array-local rank of position
 - can either do this naively by scanning $\frac{1}{2} \lg n$ bits $\rightsquigarrow O(\log n)$ time
 - or use bit marks and pop-count instructions on CPUs $\rightsquigarrow O(1)$ time
 - or use exhaustive *lookup table!* $\frac{1}{2} \lg n$ bits \rightsquigarrow only $2^{1/2 \lg n} = \sqrt{n}$ different micro arrays

Exhaustive Tabulation

Classic word-RAM technique: bootstrap on small cases with *exhaustive tabulation*

- ▶ **Idea 1:** on word-RAM, can use integers (and hence small bit sequences) as array index
 - ▶ **Idea 2:** for micro subproblems on tiny bit sequences, cannot have many *different* micro subproblems
- ↪ Precompute all micro subproblems in a lookup table, indexed by the subproblem's bitpattern
- ↪ $O(1)$ time for micro subproblem (after preprocessing)

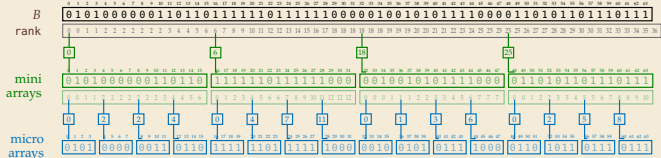
Back to Rank!

Recall: Our task is to compute the local rank in a micro array of $\ell = \frac{1}{2} \lg n$ bits.

Preprocessing: Build table for all possible queries for all *possible* micro arrays

$$\mu R[0..2^\ell][0..\ell] =$$

idx	micro array	rank(0)	rank(1)	rank(2)	rank(3)	rank(4)
0	0000	0	0	0	0	0
1	0001	0	0	0	0	1
2	0010	0	0	0	1	1
3	0011	0	0	0	1	2
4	0100	0	0	1	1	1
5	0101	0	0	1	1	2
6	0110	0	0	1	2	2
7	0111	0	0	1	2	3
8	1000	0	1	1	1	1
9	1001	0	1	1	1	2
10	1010	0	1	1	2	2
11	1011	0	1	1	2	3
12	1100	0	1	2	2	2
13	1101	0	1	2	2	3
14	1110	0	1	3	3	3
15	1111	0	1	2	3	4



- ▶ Note: $\# \text{micro arrays} = \frac{n}{\frac{1}{2} \lg n} \gg$
 $\# \text{different micro arrays} = 2^{1/2 \lg n} = \sqrt{n}$
- ▶ To access micro-array $\text{rank}(i)$
 1. Read micro array *type* (bits), here from B
 2. Treat *type* as binary number $\rightsquigarrow \text{idx } t$
 3. Return $\mu R[t][i]$

Space: $2^\ell \cdot \ell \cdot \lg \ell = \sqrt{n} \cdot \text{polylog}(n) = o(n)$

Four Russians?

The *exhaustive-tabulation technique* is often called “Four Russians trick” in the literature . . .

- ▶ The algorithmic technique was published 1970 by V. L. Arlazarov, E. A. Dinitz, M. A. Kronrod, and I. A. Faradžev



Arlazarov, Dinitz, Kronrod, Faradžev: *On economical construction of the transitive closure of a directed graph*, Dokl. Akad. Nauk SSSR 1970

inofficial translation: <https://minorfree.github.io/FourRussian/>

- ▶ all worked in Moscow at that time . . . but Soviet \neq Russian; Dinitz emigrated to Isreal (Arlazarov and Kronrod are Russian)
- ▶ American authors coined the othering term “Method of Four Russians” . . . name in widespread use

The Original Application: Boolean Matrix Multiplication

Suppose we want to multiply two $n \times n$ Boolean matrices $C = A \cdot B$.

We divide A , B , and C into $\ell \times \ell$ *micro matrices*.

↪ C consists of $\left(\frac{n}{\ell}\right)^2$ micro matrices, each of which is the sum of $\frac{n}{\ell}$ micro-matrix products.

The number of *different* possible micro matrix products is $L = 2^{\ell^2} \cdot 2^{\ell^2}$.

If we pick $\ell = \frac{1}{4}\sqrt{\lg n}$, we have only $L = 2^{2\ell^2} = \sqrt{n}$ different products.

↪ **Exhaustive Tabulation:** Can *precompute* all \sqrt{n} possible micro-matrix sums/products!

For two micro matrices a and b , we store $a \cdot b$ at the offset $a_{1,1} \dots a_{\ell,\ell} b_{1,1} \dots b_{\ell,\ell}$, where we interpret this bitstring as a binary number.

On a word RAM, we can use this as indirect memory access in $O(1)$ time.

↪ Any micro matrix sum/product takes $O(1)$ time after a total of $O(\sqrt{n} \cdot \log^{3/2} n)$ preprocessing.

The total time to compute one micro matrix in C is thus $O\left(\frac{n}{\ell}\right)$.

So the total time to compute C is $O(n^3/\ell^3) = O(n^3/\log^{3/2} n)$.

Note: By taking $n \times \ell$ resp. $\ell \times n$ “micro strips” instead of squares, we can choose $\ell = \Theta(\log n)$ and obtain final time $O(n^3/\log^2 n)$.

6.4 Supporting Select

6.5 Compressed Bitvectors

Applications

- ▶ variable-cell arrays
- ▶ monotone perfect hashing
- ▶ prefix sums

6.6 Sequences

Rank & Select on Sequences

Recall: Decoding only needs access to

1. i th char c of $\text{sort}(T) = \text{sort}(B)$
2. *position* of (that copy of) c in B

Both can be supported using rank/select on sequences.

- ▶ $\text{rank}_c(T[0..n], i) = |T[0..i]|_c^{\text{\#occurrences of } c}$
 $= \#c$ in first i characters of T
- ▶ $\text{select}_c(T[0..n], r)$
 $= \min\{j : |T[0..j]|_c \geq r\} \cup \{n\}$
 $= \text{index of } r\text{th } c \text{ in } T, (r = 1, 2, \dots)$

Random Access in BWT

- ▶ store offsets $O[c] = \sum_{c'=0}^{c-1} |B|_{c'}$ for $c \in \Sigma$
- ▶ i th char of $\text{sort}(B) = \text{unique } c \text{ for which } O[c] \leq i < O[c + 1]$
- ▶ position of r th c in $B = \text{select}_c(B, r)$

$T[0..9]$

0	1	2	3	4	5	6	7	8
b	a	n	a	n	a	b	a	n

$\text{rank}_a(T, i)$

0	1	2	3	4	5	6	7	8	9
0	0	1	1	2	2	3	3	4	4

$\text{rank}_b(T, i)$

0	1	2	3	4	5	6	7	8	9
0	1	1	1	1	1	1	2	2	2

$\text{rank}_n(T, i)$

0	1	2	3	4	5	6	7	8	9
0	0	0	1	1	2	2	2	2	3

$\text{select}_a(T, r)$

/	1	3	5	7	9	9	9	9	9
---	---	---	---	---	---	---	---	---	---

$\text{select}_b(T, r)$

/	0	6	9	9	9	9	9	9	9
---	---	---	---	---	---	---	---	---	---

$\text{select}_n(T, r)$

/	2	4	8	9	9	9	9	9	9
---	---	---	---	---	---	---	---	---	---

$\text{sort}(T)$

0	1	2	3	4	5	6	7	8
a	a	a	a	b	b	n	n	n

$O[0..\sigma] = [0, 4, 6, 9]$

Wavelet Trees



The **Wavelet Trees** for a $T \in [0..n)$ over $\Sigma = [0..\sigma)$

- ▶ supports access to $T[i]$ in $O(\log \sigma)$ time,
- ▶ $\text{rank}_c(T, i)$ and $\text{select}_c(T, r)$ in $O(\log \sigma)$ time, and
- ▶ occupies $\sim n \lg \sigma$ bits of space. (Further compression possible!) \rightsquigarrow *Advanced Data Structures*
- ▶ The generalized σ - $\text{rank}_c(T, i) = \text{rank}_c(T, i) + \sum_{c' < c} |T|_{c'}$ is also supported in $O(\log \sigma)$ time

Storing $B[0..n]$ as a wavelet tree \rightsquigarrow reconstruct ℓ chars from T in $O(\ell \log \sigma)$ time
if starting position known

e.g., $t = \lg n$

Storing **every t th entry** of $R[0..n]$ \rightsquigarrow may need to go back t characters for access
 $\rightsquigarrow O((\ell + t) \log \sigma)$ time for decode
using $\sim n \lg n/t$ extra bits of space

Locally decodable BWT

- ▶ no longer need to store $T[0..n)$!
- ▶ compressible (e.g., Wavelet trees with compressed bitvectors)

6.7 Trees

6.8 Graphs