

# Succinct Data Structures

## Part One

# Motivation

- Some data sets are downright gigantic.
  - The human genome uses 3 billion base pairs.
  - Google gets billions of search queries a day.
  - Census data for some countries runs to billions of entries.
- Simply loading the data sets into memory – let alone storing them in fancy data structures – pushes up on system limits.
- **Goal:** Store our data using as few bits as possible while still being able to answer interesting questions about that data.

# Outline for Today

- ***The Binary Rank Problem***
  - Prefix sums on bitvectors.
- ***Solving Binary Rank***
  - And learning about how to save bits along the way.
- ***Jacobson's Succinct Rank Structure***
  - A surprisingly space-efficient data structure for binary ranking.

# Binary Ranking

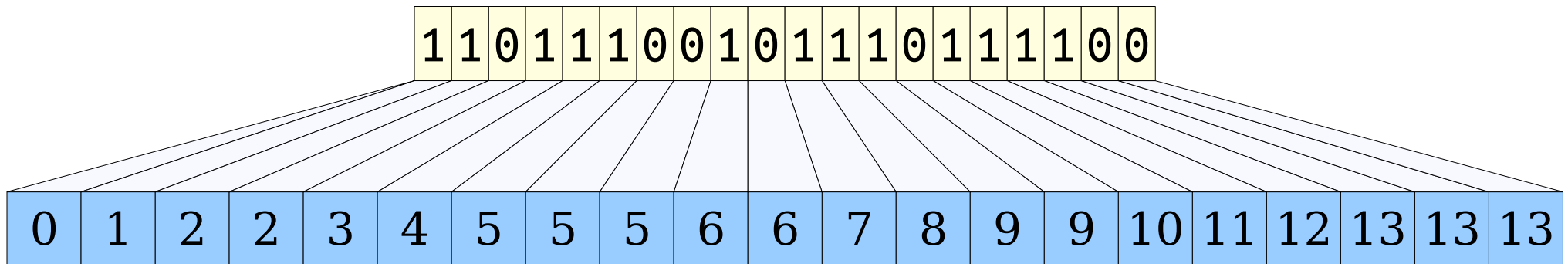
# Binary Ranking

- The *binary ranking problem* is the following:  
*Given a list of  $n$  bits and an index  $i$ , return the sum of all the bits up to position  $i$  in the list.*
- It's basically the problem of computing prefix sums in bitvectors.

1	1	0	1	1	1	0	0	1	0	1	1	1	0	1	1	1	1	0	0
---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---	---

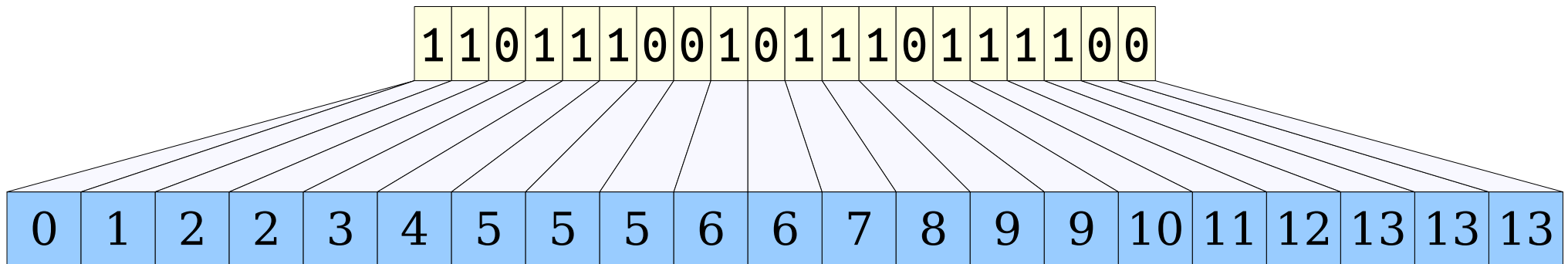
# Binary Ranking

- Let's imagine we want to be able to answer rank queries in time  $O(1)$ .
- We could do this by writing down the prefix sums for all positions in an array, then just looking up the answer in a table.
- **Question:** How much space does this use?



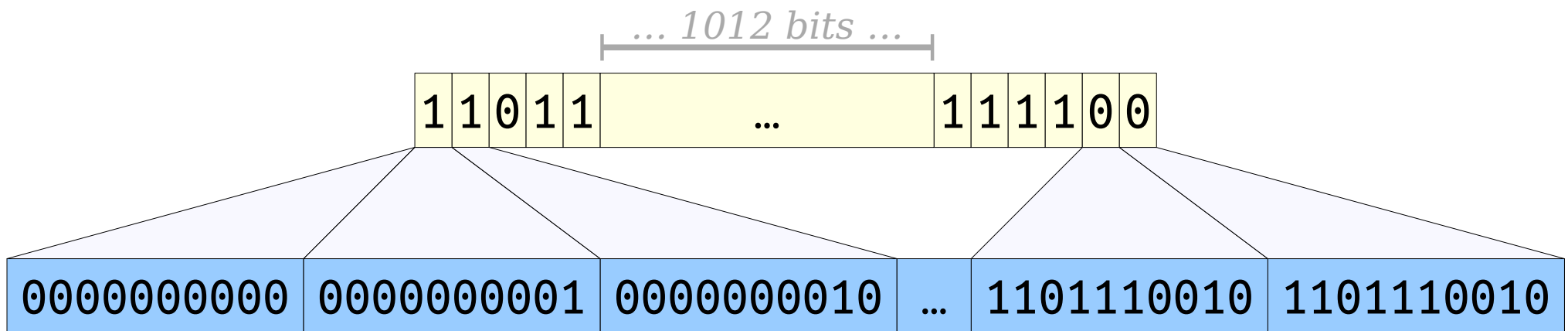
# Binary Ranking

- It sure looks like this uses  $\Theta(n)$  space.
- But what do we mean by “space” here?
  - Integers usually are represented by machine words.
  - We assume each machine word has  $w$  bits in it (e.g.  $w = 32$ ,  $w = 64$ , etc.), for a constant  $w$  known to us.
- Space:  $\Theta(nw)$  bits. This leaves a lot to be desired.
  - On a 64-bit machine, this is a 64x blowup in memory!
- Can we do better?



# Counting Bits

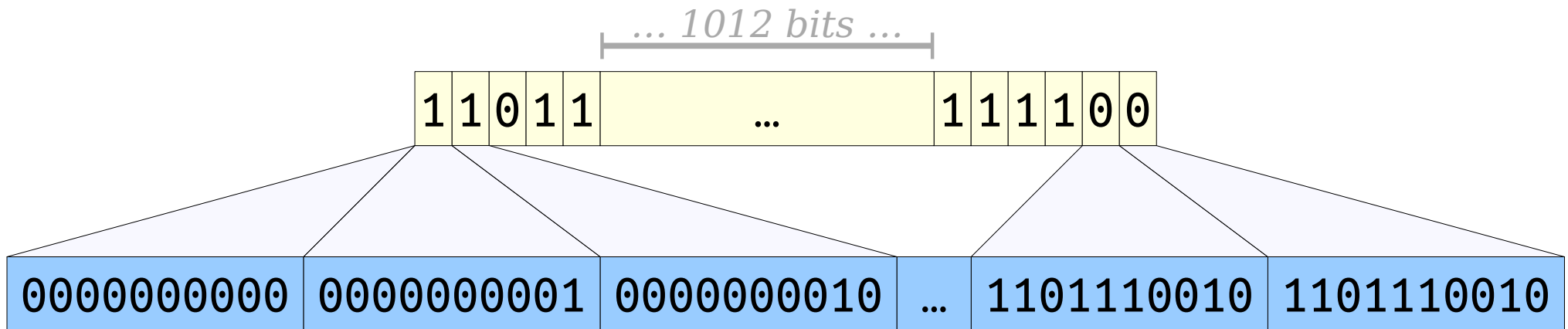
- Let's suppose we have an array of  $1023 = 2^{10} - 1$  bits.
- The prefix sum at each point would be an integer between 0 and 1023, inclusive.
- We only need 10 bits to represent such a prefix sum.
- **Idea:** Allocate an array of  $10n$  bits, interpreted as an array of  $n$  10-bit numbers.
- This reduces our space usage down to  $10n$ . It's better than before, but still  $10\times$  bigger than the original array.





# Counting Bits

- If we maintain an array of prefix sums for an array of  $n$  bits, each individual prefix sum is a value between 0 and  $n$ , inclusive.
- There are  $n+1$  possibilities for what those numbers can be, so each integer requires  $\lg(n+1)$  bits.
  - We could use fewer bits by using shorter integers for earlier values, but that won't necessarily asymptotically improve space usage.
- Our solution therefore uses  $O(n \log n)$  bits, but allows for rank queries in time  $O(1)$ .
- Can we do better?



# Counting Bits

- We'll say that a solution to binary ranking is a  $\langle s(n), q(n) \rangle$  solution if
  - its space usage is  $s(n)$ , and
  - queries take time  $q(n)$ .
- We currently have a  $\langle O(n \log n), O(1) \rangle$  solution to binary ranking.
- **Question:** Can we do better?

	Bits Needed	Query Time
Prefix Sum Array	$O(n \log n)$	$O(1)$

# Counting Bits

- We are currently using  $O(n \log n)$  bits of storage space:  $O(n)$  numbers, each of which is  $O(\log n)$  bits long.
- To improve on this, we could either
  - reduce how many numbers we're storing, or
  - reduce how many bits each number uses.
- **Question:** What might that look like?

	Bits Needed	Query Time
Prefix Sum Array	$O(n \log n)$	$O(1)$

# Improving Space Usage

- Split the input array of bits into blocks of  $b$  bits each. Then, only store prefix sums at the start of each block.
- To compute the prefix sum at index  $k$ :
  - Compute  $i = \lfloor k/b \rfloor$ , the index of the block containing  $k$ .
  - Write down the precomputed prefix sum for block  $i$ .
  - Run a linear scan to compute the sum of the first  $k \bmod b$  bits of block  $i$ .
  - Add these numbers together.

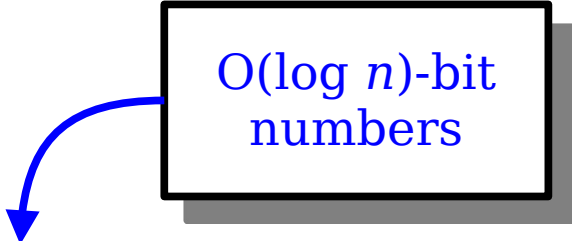
$$\text{rank}(36) = 22$$

(block 4)

0	5	11	14	19	24
11011100	10111011	11000100	11010101	11100110	11110100

# Improving Space Usage

- Total space usage:  $O((n \log n) / b)$ .
  - We're storing  $\Theta(n / b)$  numbers.
  - Each number needs  $O(\log n)$  bits.
- Query time:  $O(b)$ .
  - We may have to scan  $\Theta(b)$  bits.
- There is no “optimal” choice of  $b$  here.
  - Increasing  $b$  decreases memory usage but increases query time.
  - Decreasing  $b$  decreases query time but increases memory usage.
- We'll therefore leave  $b$  as a free parameter that whoever is using our data structure can tune.



0	5	11	14	19	24
11011100	10111011	11000100	11010101	11100110	11110100

# The Story So Far

- Earlier, we said there were two strategies we could use to reduce space:
  - Store fewer numbers.
  - Use fewer bits per number.
- Our blocking approach hits this first point. What about the second?

	Bits Needed	Query Time
Prefix Sum Array	$O(n \log n)$	$O(1)$
Partial Prefix Sum Array	$O\left(\frac{n \log n}{b}\right)$	$O(b)$

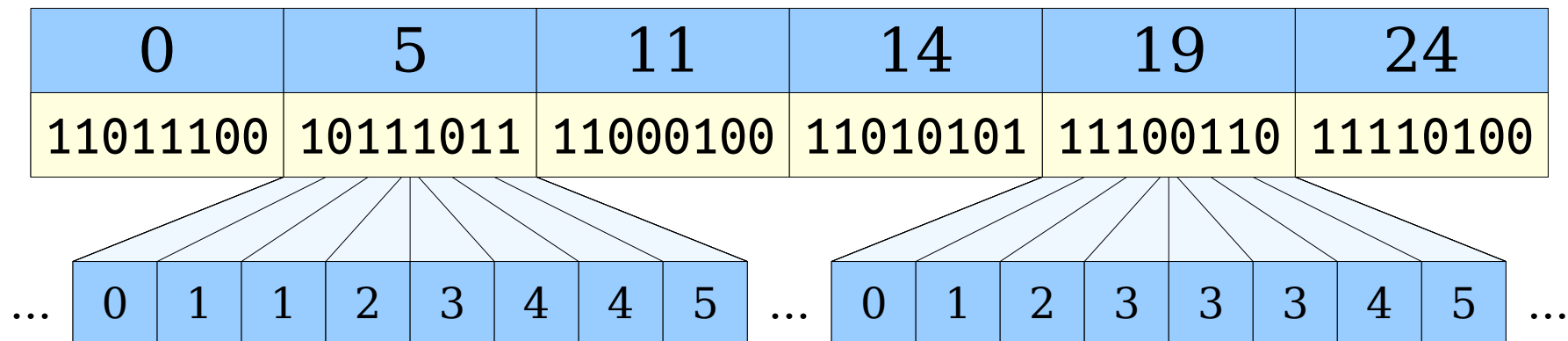
# Combining Things Together

- The “slow” step in our query is the linear scan across the bits of a block. Can we speed things up?
- That linear scan is essentially a rank query on an array of  $b$  bits.
- **Idea:** Rather than use a linear scan there, use our existing  $\langle \Theta(n \log n), O(1) \rangle$  solution at a per-block level.

0	5	11	14	19	24
11011100	10111011	11000100	11010101	11100110	11110100

# Combining Things Together

- Instead of one single top-level array, maintain two parallel arrays.
  - The top-level array stores the bit sum up until the start of each block.
  - The second-level array can be thought of as an “array of arrays,” with one array per block, holding answers to rank queries purely within the block.
- There isn't room in the slides to draw out the full second array; hopefully you can infer from the picture what the remaining entries would be.



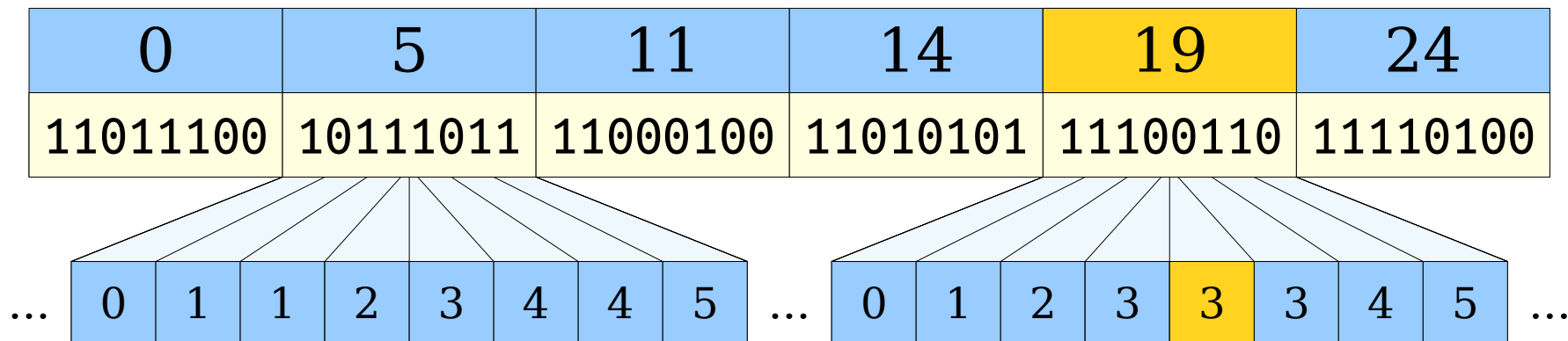


# Combining Things Together

- To answer a rank query at index  $k$ :
  - Compute  $i = \lfloor k/b \rfloor$ , the index of the block where the query ends.
  - Look up the  $i$ th entry of the top-level table.
  - Look up the  $(k \bmod b)$ th entry of the second-level table's section for block  $i$ .
  - Return the sum of those numbers.
- Query cost:  **$O(1)$** .

*rank*(36) = 22

(block 4)

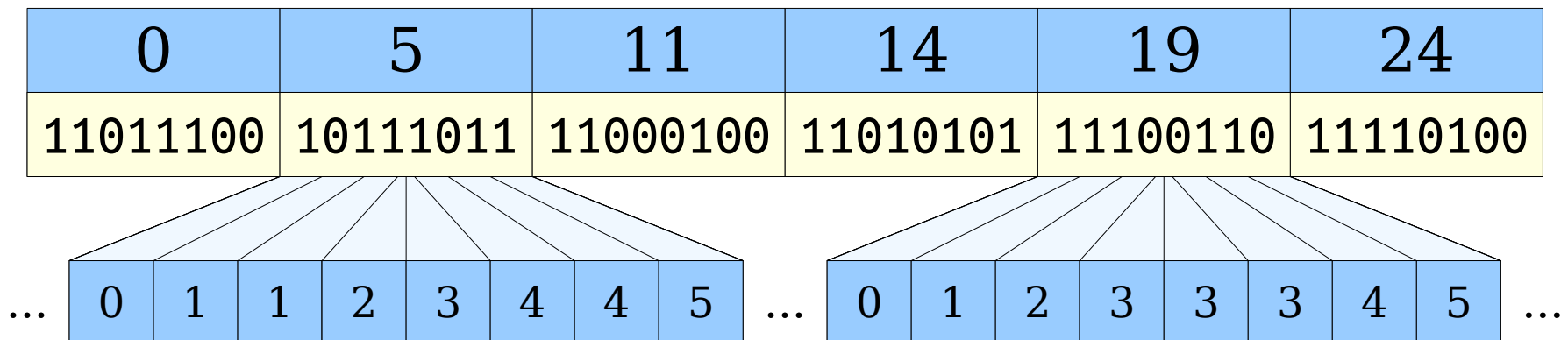


# Combining Things Together

- How much memory does this use?

Answer at

<https://cs166.stanford.edu/pollev>



# Intuiting $O\left(\frac{n \log n}{b} + n \log b\right)$

- As  $b$  increases:
  - We use less space *storing partial prefix sums* at the start of each block, since there are fewer blocks.
  - Each block has more bits, so the *sums within each block* require more bits.
- As  $b$  decreases:
  - We use more space *storing partial prefix sums* at the start of each block, since there are more blocks.
  - Each block has fewer bits, so the *sums within each block* requires fewer bits.
- **Question:** What choice of  $b$  minimizes the above quantity?

# Optimizing $O\left(\frac{n \log n}{b} + n \log b\right)$

- Start by taking the derivative:

$$\frac{d}{db} \left( \frac{n \log n}{b} + n \log b \right) = \frac{-n \log n}{b^2} + \frac{n}{b}$$

- Setting equal to zero and solving:

$$\frac{-n \log n}{b^2} + \frac{n}{b} = 0$$

$$-\log n + b = 0$$

$$b = \log n$$

- Asymptotically optimal choice is  **$b = \Theta(\log n)$** , giving space usage  **$O(n \log \log n)$** .

# The Story So Far

- Our new approach is more space-efficient than our original approach, and works nicely in practice.
  - $\lg \lg 2^{64} = 6$ .
- **Question:** Can we do better?

	Bits Needed	Query Time
Prefix Sum Array	$O(n \log n)$	$O(1)$
Partial Prefix Sum Array	$O\left(\frac{n \log n}{b}\right)$	$O(b)$
Two-Level Prefix Sums	$O(n \log \log n)$	$O(1)$

# Feedback Loops

- Think back to how we arrived at our  $\Theta(n \log \log n)$ -space solution.
  - We split our array apart into blocks of size  $b$ .
  - We stored the prefix sums at the start of each block.
  - We used our  $\Theta(n \log n)$ -space solution for each block.
- More generally, for that last step, we could have used *any* rank structure we wanted.

0	5	11	14	19	24
11011100	10111011	11000100	11010101	11100110	11110100
Block-Level Rank	Block-Level Rank	Block-Level Rank	Block-Level Rank	Block-Level Rank	Block-Level Rank

# Feedback Loops

- Last time, we used our  $\langle O(n \log n), O(1) \rangle$  structure per block. It was the best approach we had available.
- But we now have a  $\langle O(n \log \log n), O(1) \rangle$  structure available, which uses asymptotically fewer bits!
- What happens if we use that one within each block?

[illegible]

# Feedback Loops

- Split the input apart into blocks of size  $b$ .
- Store the prefix sum at the start of each block.
- Use our  $\langle O(n \log \log n), O(1) \rangle$  solution within each block.
- Compute the overall rank of an index  $k$  by combining these answers together.

[illegible]



# Feedback Loops

- The actual data structure consists of three arrays:
  - A top-level array of prefix sums before each  $b$ -bit block.
  - A second-level array of prefix sums before each  $(\log b)$ -bit “miniblock.”
  - A third-level array with prefix sums before each bit of each “miniblock.”
- We group these tables into three arrays, one per level, to avoid storing pointers.

0		5		11		14		19		24	
11011100		10111011		11000100		11010101		11100110		11110100	
0		3		...		0		3		...	
1101		1100		...		1100		0100		...	
0	1	2	2	0	1	2	2	0	1	2	2
...		...		...		...		...		...	
0		3		...		0		3		...	
1101		1100		...		1100		0100		...	
0	1	2	2	0	1	1	1	0	1	1	1
...		...		...		...		...		...	
0		4		...		0		4		...	
1111		0100		...		1111		0100		...	
0	1	2	3	0	1	1	1	0	1	1	1

# Feedback Loops

- How much memory does this structure use, and what's the query cost?

Answer at

<https://cs166.stanford.edu/pollev>

0		5		11		14		19		24	
11011100		10111011		11000100		11010101		11100110		11110100	
0		3		...		0		3		...	
1101		1100		...		1100		0100		...	
01220122		...		01220111		...		01230111		...	
0		3		...		0		3		...	
1101		1100		...		1100		0100		...	
01220122		...		01220111		...		01230111		...	

# Feedback Loops

- **Claim:** The choice of  $b$  that asymptotically minimizes  $\Theta((n \log n) / b + n \log \log b)$  is given by  $b = \Theta(\log n)$ .
- We now have an  $\langle O(n \log \log \log n), O(1) \rangle$  solution for ranking!

0		5		11		14		19		24	
11011100		10111011		11000100		11010101		11100110		11110100	
0		3		...		0		3		...	
1101		1100		...		1100		0100		...	
01220122		...		01220111		...		01230111		...	
0		3		...		0		4		...	
1101		1100		...		1100		0100		...	
01220122		...		01220111		...		01230111		...	

# Feedback Loops

- As you might expect, we can feed this solution back into itself to come up with a  $\langle \Theta(n \log \log \log \log n), O(1) \rangle$  solution to ranking.
- More generally, let  $\log^{(k)} n$  denote the logarithm function iterated  $k$  times.
- **Question:** Does this solution allow us to get a  $\langle \Theta(n \log^{(k)} n), O(1) \rangle$  solution for all choices of  $k$ ?

Answer at  
<https://cs166.stanford.edu/pollevent>

$O(\log n)$ -bit  
numbers

[illegible]

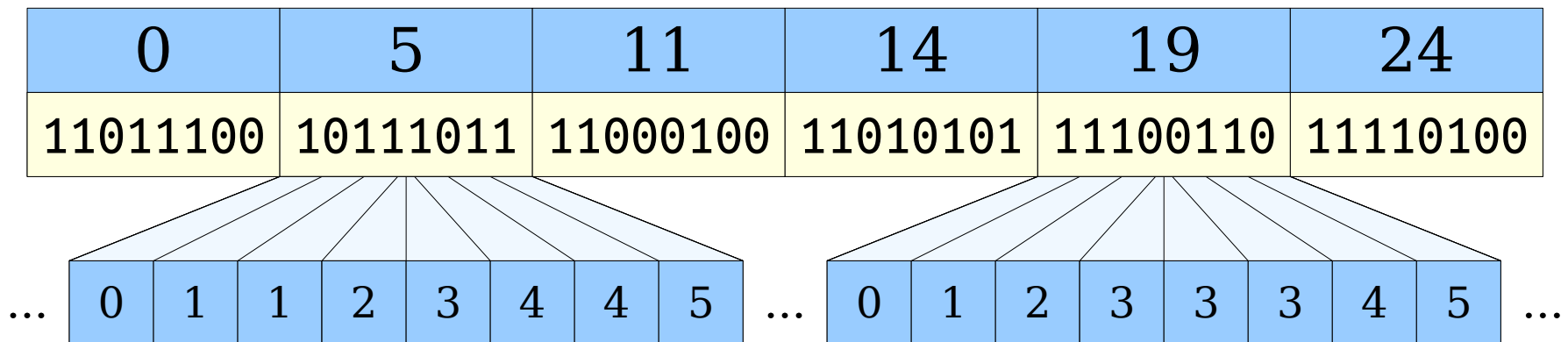
# Counting Layers

- Our  $\langle O(n \log^{(1)} n), O(1) \rangle$  solution to ranking uses a single array of integers to store prefix sums.

0	1	2	2	3	4	5	...				25	26	27	28	29	29	29
1101110010111011110001001101010111100110111101111100																	

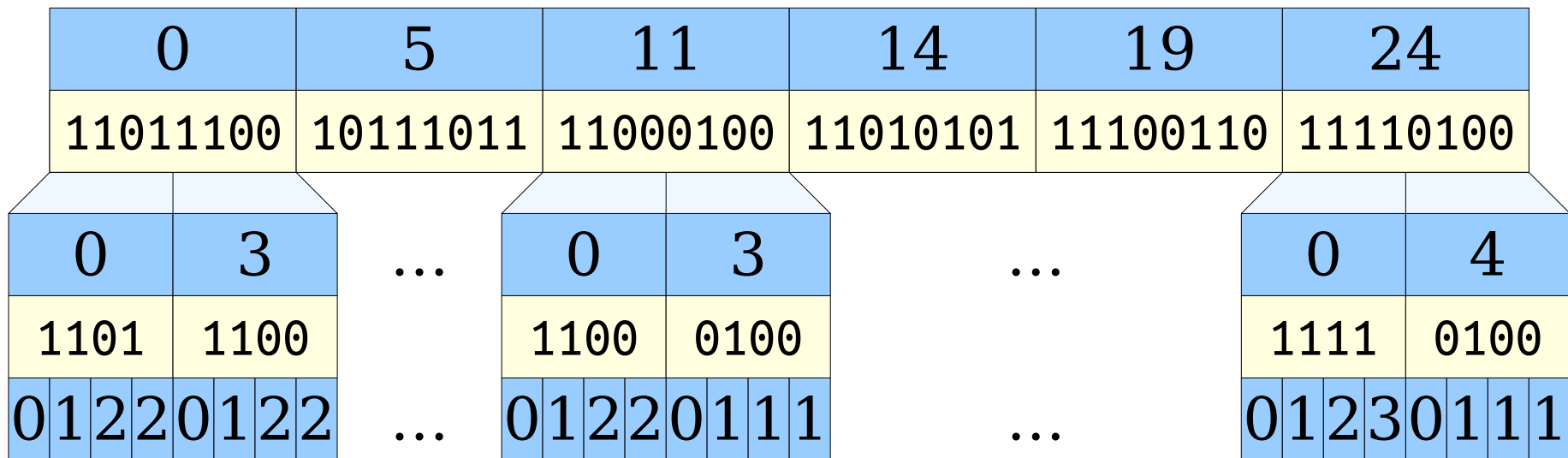
# Counting Layers

- Our  $\langle O(n \log^{(2)} n), O(1) \rangle$  solution to ranking uses two prefix arrays, one at the top level and one for the blocks.



# Counting Layers

- Our  $\langle O(n \log^{(3)} n), O(1) \rangle$  solution to ranking uses three prefix arrays: one at the top level, one at the block level, and one for “miniblocks.”



# Counting Layers

- More generally, if we have  $k$  layers of arrays, we use  $O(nk + n \log^{(k)} n)$  bits.
  - Each of the first  $k - 1$  layers requires  $O(n)$  bits. (*Why?*)
  - The last layer uses  $O(n \log^{(k)} n)$  bits. (*Why?*)
- Our query time is  $O(k)$ , since we have  $k$  layers to navigate.

0		5		11		14		19		24	
11011100		10111011		11000100		11010101		11100110		11110100	
0		3		...		0		3		...	
1101		1100		...		1100		0100		...	
0	1	2	2	0	1	2	2	0	1	2	2
...		...		...		...		...		...	
0		3		...		0		3		...	
1101		1100		...		1100		0100		...	
0	1	2	2	0	1	1	1	0	1	2	3
...		...		...		...		...		...	
0		4		...		0		4		...	
1111		0100		...		1111		0100		...	
0	1	2	3	0	1	1	1	0	1	2	3



# Counting Layers

- We now have a  $\langle O(nk + n \log^{(k)} n), O(k) \rangle$  solution for ranking.
- If  $k$  is a fixed constant, this is a  $\langle O(n \log^{(k)} n), O(1) \rangle$  solution to ranking.
- **Question:** What if we pick  $k$  in terms of  $n$ ?

0				5				11				14				19				24			
11011100				10111011				11000100				11010101				11100110				11110100			

0		3		...	0		3		...	0		4													
1101		1100			1100		0100			1111		0100													
0	1	2	2	0	1	2	2	...	0	1	2	2	0	1	1	1	...	0	1	2	3	0	1	1	1

# Intuiting $O(nk + n \log^{(k)} n)$

- What's the impact of tuning  $k$ ?
  - If  $k$  is too large, then we have *too many layers of recursion* and the recursive prefix sums use too much space.
  - If  $k$  is too small, then we have *too few layers of recursion* and the final array of numbers will be too big.
- There should be an optimal choice of  $k$  that balances these constraints. What is it?

# Iterated Logarithms

- **Intuition:** The log function is incredibly effective at shrinking down large quantities.
  - Number of protons in the known universe:  $\approx 2^{240}$ .
  - $\log^{(0)} 2^{240} = 1,766,847, [\dots 57 \text{ digits } \dots], 292,619,776$
  - $\log^{(1)} 2^{240} = 240$
  - $\log^{(2)} 2^{240} \approx 7.91$
  - $\log^{(3)} 2^{240} \approx 2.98$
  - $\log^{(4)} 2^{240} \approx 1.58$
- More generally, for any natural number  $n$ , there is some minimum  $k$  for which  $\log^{(k)} n \leq 2$ .
- The **iterated logarithm of  $n$** , denoted  **$\log^* n$** , is the smallest choice of  $k$  that makes  $\log^{(k)} n \leq 2$ .
- Question to ponder: what's the smallest  $n$  where  $\log^* n = 10$ ?

# Iterated Logarithms

- For any choice of  $k$ , we have a

$$\langle O(nk + n \log^{(k)} n), O(k) \rangle$$

solution to ranking.

- Pick  **$k = \log^* n$** . This gives us a

$$\langle \mathbf{O(n \log^* n)}, \mathbf{O(\log^* n)} \rangle$$

solution to binary ranking.

- In practice, this is *essentially* a  $\langle O(n), O(1) \rangle$  solution to ranking.
  - (If  $n \leq 2^{64}$ , then  $\log^* n = 4$ . So four layers of structure would always suffice.)

# The Story So Far

- We have an (almost) linear-space solution to ranking.
- There's still more room for improvement.
  - Practically, we're still using  $\approx 5n$  total bits.
  - Theoretically, we'd like to remove the  $\log^* n$  factor.
- Can we do better?

	Bits Needed	Query Time
Prefix Sum Array	$O(n \log n)$	$O(1)$
Two-Level Prefix Sums	$O(n \log \log n)$	$O(1)$
Multilevel Prefix Sums	$O(n \log^* n)$	$O(\log^* n)$

Time-Out for Announcements!

# Problem Set 1

- Problem Set 0 (Concept Refresher) was due today at 1:00PM.
  - Need more time? You can use up to two late days to extend the deadline by 24 or 48 hours.
- Problem Set 1 (**RMQ**) goes out today. It's due next Tuesday at 1:00PM.
  - You may work with a partner on this assignment if you'd like.
  - Play around with the RMQ structures from last week, and see what it's like to code them up!
- As always, ping us on EdStem or stop by office hours if you have questions!

Back to CS166!



# An Alternative Approach

# An Alternative Approach

- Our best approach so far involves the following idea:
  - Split the input array into smaller blocks.
  - Recursively build fast ranking structures per block.
- The recursion in that second step is where we get the  $O(\log^* n)$  query time from.
- **Question:** Can we avoid having to run the recursion in the last step?

# An Alternative Approach

- When we set out to split our input apart into blocks, we left the choice of block size  $b$  unspecified.
- Later, we found that  $b = \Theta(\log n)$  was the optimal choice.
  - This means that our blocks are *tiny* compared to the size of our input array.
- **Key Intuition:** These blocks are so small that there can't be “too many” distinct blocks.
- **Question:** Where have you seen this idea before?

# The Four Russians Strategy

- As an example, imagine that we pick our block size as  $b = 3$ .

- There are only eight possible blocks:

000 001 010 011 100 101 110 111

- We could therefore build a table keyed on a combination of a block and an index in into the block:

	000	001	010	011	100	101	110	111
Index 0	0	0	0	0	0	0	0	0
Index 1	0	0	0	0	1	1	1	1
Index 2	0	0	1	1	1	1	2	2

# The Four Russians Strategy

- There are only  $2^b$  possible blocks.
- There are  $O(b)$  positions within a block.
- Each prefix sum within a block requires  $O(\log b)$  bits to write out.
- Total space:  $O(2^b \cdot b \cdot \log b)$ .

	000	001	010	011	100	101	110	111
Index 0	0	0	0	0	0	0	0	0
Index 1	0	0	0	0	1	1	1	1
Index 2	0	0	1	1	1	1	2	2

# The Four Russians Strategy

- Total space:  $O(2^b \cdot b \cdot \log b)$ .
- Plugging in  $b = \frac{1}{2} \lg n$  gives a space usage of
  - $= O(2^{\frac{1}{2} \lg n} \cdot \log n \cdot \log \log n)$
  - $= O(n^{\frac{1}{2}} \log n \log \log n)$
  - $= o(n^{\frac{2}{3}})$ .
- This is *sublinear* space for sufficiently large  $n$ .

	000	001	010	011	100	101	110	111
Index 0	0	0	0	0	0	0	0	0
Index 1	0	0	0	0	1	1	1	1
Index 2	0	0	1	1	1	1	2	2

# The Four Russians Strategy

- Split the input apart into blocks of size  $\frac{1}{2} \lg n$ .
- Compute the prefix sum to the start of each block.
  - This uses  $O((n \log n) / \log n) = O(n)$  bits.
- Build a table of all possible rank queries on all possible blocks. This uses  $o(n^{2/3})$  bits.
- Total space:  **$O(n)$** .

0	2	5	6	8	10	13	13	14	16	18	20
110	111	001	011	101	111	000	100	110	101	101	110

	000	001	010	011	100	101	110	111
Index 0	0	0	0	0	0	0	0	0
Index 1	0	0	0	0	1	1	1	1
Index 2	0	0	1	1	1	1	2	2

# The Four Russians Strategy

- To perform a query for the rank sum up to index  $k$ :
  - Compute  $i = \lfloor k/b \rfloor$ , the index block  $k$  falls in.
  - Use the bits of block  $i$  as an index into the secondary table, then look up row  $k \bmod b$ .
  - Add the Four Russians table number to the  $i$ th entry of the top-level array.
- Query time:  **$O(1)$** .

*rank*(17) = 12

(block 5)

0	2	5	6	8	10	13	13	14	16	18	20
110	111	001	011	101	111	000	100	110	101	101	110

	000	001	010	011	100	101	110	111
Index 0	0	0	0	0	0	0	0	0
Index 1	0	0	0	0	1	1	1	1
Index 2	0	0	1	1	1	1	2	2



# The Story So Far

- This new approach uses  $O(n)$  bits and can support queries in time  $O(1)$ .
- It seems like there's no more room for improvement here – are we done?

	Bits Needed	Query Time
Prefix Sum Array	$O(n \log n)$	$O(1)$
Multilevel Prefix Sums	$O(n \log^* n)$	$O(\log^* n)$
Four Russians	$O(n)$	$O(1)$

# The Story So Far

- Our Four Russians approach uses  $\Theta(n)$  extra bits beyond the bits in the original array. The actual number is actually

$$2n + o(n)$$

because we need to store

- $n / (\frac{1}{2} \lg n) = 2n / \lg n$  indices in the top-level table,
- each index is  $\lg(n + 1)$  bits long, and
- we need  $o(n)$  bits for the precomputed tables.
- This is a marked improvement over our original approach, but it still means we need at least twice as many bits as in the original array.
- **Goal:** Reduce the space usage *even further*.

# The Story So Far

- The two space-efficient solutions we've developed so far are based on different ideas.
  - Multilevel Prefix Sums: subdivide the array into blocks, then recursively subdivide those blocks even further.
  - Four Russians: Once we reach blocks of size  $\frac{1}{2} \lg n$  or smaller, precompute all possible answers to all possible queries.
- What happens if we combine these strategies together?

	Bits Needed	Query Time
Multilevel Prefix Sums	$O(n \log^* n)$	$O(\log^* n)$
Four Russians	$O(n)$	$O(1)$

# The Combined Approach

- We begin with an array of  $n$  bits. We ultimately need to reduce the array size to  $\frac{1}{2} \lg n$  to use the Four Russians approach.
- If we immediately subdivide into blocks of that size, we get our  $\langle O(n), O(1) \rangle$  solution.
- **Idea:** Introduce some intermediate level of subdivision between the original array and the blocks of size  $\frac{1}{2} \lg n$ .

# The Combined Approach

- Subdivide the array into  $\Theta(n / b)$  blocks of size  $b$ .
- Write prefix sums of  $O(\log n)$  bits at the start of each block.
- Subdivide each block into  $\Theta(b / \log n)$  miniblocks of size  $\frac{1}{2} \lg n$ .
- Write prefix sums of  $O(\log b)$  bits at the start of each miniblock.
- Precompute a table of all rank queries on all miniblocks (not shown), using  $o(n^{2/3})$  bits.

0	5	11	14	19	24
11011100	10111011	11000100	11010101	11100110	11110100

Miniblock size:  
 $\frac{1}{2} \lg n$  bits

1101	0101
0	3

Block size:  
 $b$  bits

# The Combined Approach

- To perform a query for the prefix sum at index  $k$ :
  - Compute  $i = \lfloor k/b \rfloor$ , the index of the block containing  $k$ . Write down the prefix sum at the start of block  $i$  in the top-level array.
  - Compute  $j = \lfloor (k \bmod b) / (\frac{1}{2} \lg n) \rfloor$ , the index of the miniblock within block  $i$  containing  $k$ . Write down the prefix sum at the start of miniblock  $i$  in the second-level array.
  - Look up  $(k \bmod b) \bmod \frac{1}{2} \lg n$  in the precomputed table for the miniblock to get the prefix sum within the miniblock.
  - Add these values together.
- Total query time:  **$O(1)$** .

0	5	11	14	19	24
11011100	10111011	11000100	11010101	11100110	11110100

1101	0101
0	3

Miniblock size:  
 $\frac{1}{2} \lg n$  bits

Block size:  
 $b$  bits

# The Combined Approach

- Space for top-level array:  $O((n \log n) / b)$ .
- Space for the miniblocks:  $O((n \log b) / \log n)$ 
  - $O(n / \log n)$  total miniblocks.
  - $O(\log b)$  bits per miniblock for a prefix sum.
- Space for the Four Russians table:  $o(n^{2/3})$ .
- Total space:  **$O((n \log n) / b + (n \log b) / \log n) + o(n^{2/3})$** .
- What's the optimal choice of  $b$  here?

0	5	11	14	19	24
11011100	10111011	11000100	11010101	11100110	11110100

Miniblock size:  
 $\frac{1}{2} \lg n$  bits

1101	0101
0	3

Block size:  
 $b$  bits

# Optimizing $O\left(\frac{n \log n}{b} + \frac{n \log b}{\log n}\right)$

- Start by taking the derivative:

$$\frac{d}{db} \left( \frac{n \log n}{b} + \frac{n \log b}{\log n} \right) = \frac{-n \log n}{b^2} + \frac{n}{b \log n}$$

- Setting equal to zero and solving:

$$\frac{-n \log n}{b^2} + \frac{n}{b \log n} = 0$$

$$-\log^2 n + b = 0$$

$$b = \log^2 n$$

- Asymptotically optimal space usage is when we pick  $b = \Theta(\log^2 n)$ .
- If we do that, our space usage is

$$O\left(\frac{n \log n}{b} + \frac{n \log b}{\log n}\right)$$



# The Combined Approach

- We now have a solution that uses a *sublinear* number of auxiliary bits.
- The space usage for the original array, plus our structure, is  $n + o(n)$ . As  $n$  increases, we need proportionally fewer and fewer bits!

	Bits Needed	Query Time
Multilevel Prefix Sums	$O(n \log^* n)$	$O(\log^* n)$
Four Russians	$O(n)$	$O(1)$
Two-Level Four Russians (Jacobson's Structure)	$O\left(\frac{n \log \log n}{\log n}\right)$	$O(1)$

# Succinct Data Structures

- A data structure is called **succinct** if it uses  $B + o(B)$  bits, where  $B$  is the information-theoretic minimum number of bits needed to solve the problem.
- In the case of binary rank, we must use at least  $n$  bits of space.
  - We can recover the original bit array using rank queries, and an arbitrary  $n$ -element bit array can't be stored in fewer than  $n$  bits.
  - (Why can't we use fewer than  $n$  bits?)
- Our space usage for our rank structure is  $n + o(n)$  and is thus succinct.

# Further Work

- These ideas – plus some further refinements – work well in practice.
  - Check out the libraries `rank9`, `poppy`, etc. to see how these look in practice.
- Further work in Theoryland has produced  $\langle O(n / \log^k n), O(k) \rangle$  structures for any constant  $k$ .
  - Many of the techniques employed here come from data compression – very cool!
- There's also work done into compressing bitvectors while allowing for fast access to individual elements, allowing for even greater space reductions.
  - Assuming the bitvector has some “nice” structure to it, we can sometimes encode it in space  $o(n)$  as well!

# Summary for Today

- When you drop to the level of counting individual bits, data structure design gets a lot more complex (and interesting)!
- Recursively subdividing larger structures into smaller pieces is a great way to reduce space usage.
- The Method of Four Russians is a fantastic way to handle arrays once they get sufficiently small.
- Using a fixed number of recursive reductions, then switching to a Four Russians speedup, is a common strategy for building sublinear-space data structures.

# Next Time

- ***Succinct Select***
  - Computing the inverse of rank queries.
- ***Sparse/Dense Subdivisions***
  - Handling disparate cases nonuniformly.