Lower bounds for succinct data structures

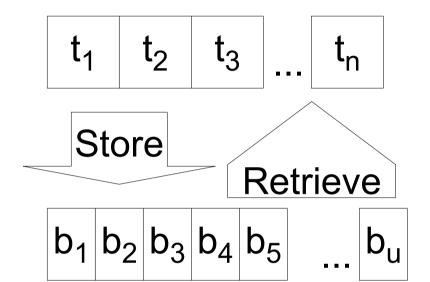
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Bits vs. trits

• Store n "trits" $t_1, t_2, ..., t_n \in \{0, 1, 2\}$



In u bits $b_1, b_2, ..., b_u \in \{0,1\}$

Want:

Small space u (optimal = $\lceil n \lg_2 3 \rceil$)

Fast retrieval: Get t by probing few bits (optimal = 2)

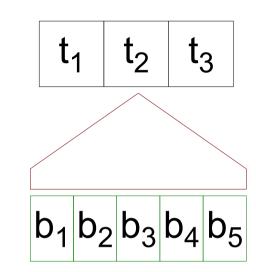
Two solutions

Arithmetic coding:

Store bits of
$$(t_1, ..., t_n) \in \{0, 1, ..., 3^n - 1\}$$

Optimal space: $\lceil n \lg_2 3 \rceil \approx n \cdot 1.584$

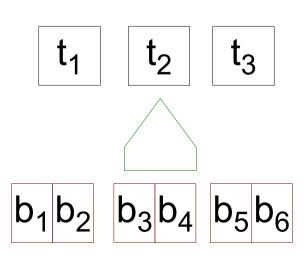
Bad retrieval: To get t_i probe all > n bits



Two bits per trit

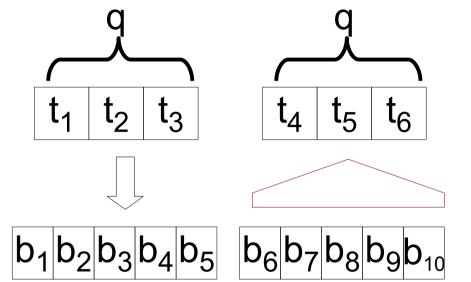
Bad space n 2

Optimal retrieval: Probe 2 bits



Polynomial tradeoff

• Divide n trits $t_1, ..., t_n \in \{0,1,2\}$ in blocks of q



Arithmetic-code each block

Space:
$$[q lg_2 3] n/q < (q lg_2 3 + 1) n/q$$

= $n lg_2 3 + n/q$

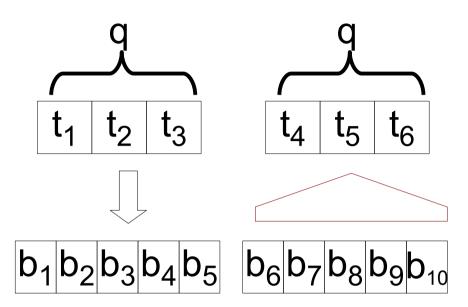
Retrieval: Probe O(q) bits

polynomial tradeoff between redundancy, probes

Polynomial tradeoff

• Divide n trits $t_1, ..., t_n \in \{0,1,2\}$ in blocks of q

Arithmetic-code each block



Space:
$$[q lg_2 3] n/q = (q lg_2 3 + 1/q^{\Theta(1)}) n/q$$

= $n lg_2 3 + n/q^{\Theta(1)}$

Retrieval: Probe O(q) bits

polynomial tradeoff between redundancy, probes

Logarithmic forms

Exponential tradeoff

Breakthrough [Pătraşcu '08, later + Thorup]

Space: n $\lg_2 3 + n/2^{\Omega(q)}$

Retrieval: Probe q bits

exponential tradeoff between redundancy, probes

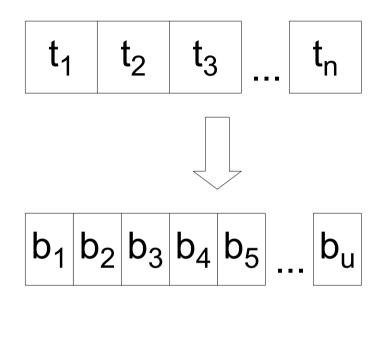
• E.g., optimal space [n lg₂ 3], probe O(lg n)

Our results

Theorem[V.]:

Store n trits $t_1, ..., t_n \in \{0,1,2\}$ in u bits $b_1, ..., b_u \in \{0,1\}$.

If get t_i by probing q bits then space $u > n \lg_2 3 + n/2^{O(q)}$.



• Matches [Pătraşcu Thorup]: space < n $\lg_2 3 + n/2^{\Omega(q)}$

Outline

• Bits vs. trits

• Proof bits vs. trits

• Bits vs. sets

• Cells vs. prefix sums

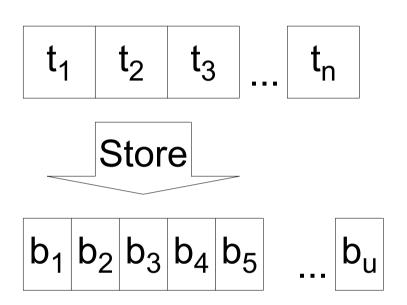
Recall our results

Theorem:

Store n trits
$$t_1, ..., t_n \in \{0,1,2\}$$

in u bits $b_1, ..., b_u \in \{0,1\}$.

If get t_i by probing q bits then space $u > n \lg_2 3 + n/2^{O(q)}$.



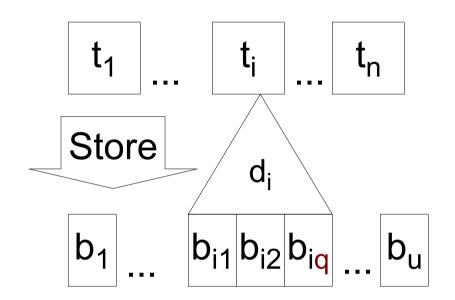
• For now, assume non-adaptive probes:

$$t_i = d_i (b_{i1}, b_{i2}, ..., b_{iq})$$

Proof idea

•
$$t_i = d_i (b_{i1}, b_{i2}, ..., b_{iq})$$

• Uniform $(t_1, ..., t_n) \in \{0,1,2\}^n$ Let $(b_1, ..., b_u) := Store(t_1, ..., t_n)$



• Space $u \approx \text{optimal} \Rightarrow (b_1, ..., b_u) \in \{0,1\}^u \approx \text{uniform} \Rightarrow$

$$1/3 = Pr[t_i = 2] = Pr[d_i(b_{i1}, ..., b_{iq}) = 2] \approx A/2q \neq 1/3$$

Contradiction, so space u >> optimal

Q.e.d.

Information-theory lemma

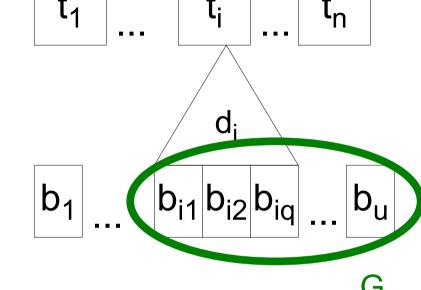
[Edmonds Rudich Impagliazzo Sgall, Raz, Shaltiel V.]

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Lemma: Random (b_1, ..., b_n) uniform in B \subseteq \{0,1\}^n
             |B| \approx 2^{u} \Rightarrow there is large set G \subseteq [u]:
             for every i_1, ..., i_q \in G : (b_{i_1}, ..., b_{i_q}) \approx uniform in {0,1}^q
Proof: |B| \approx 2^{u} \Rightarrow H(b_{1}, ..., b_{n}) large
    \Rightarrow H(b<sub>i</sub> | b<sub>1</sub>, ..., b<sub>i-1</sub>) large for many i (\in G)
  Closeness[ (b_{i_1}, ..., b_{i_n}), uniform ] \geq H(b_{i_1}, ..., b_{i_n})
```

$$\geq$$
 H(b_{iq} | b₁, ..., b_{iq-1}) +...+ H(b_{i1} | b₁, ..., b_{i1-1}), large Q.e.d.

Proof

- Argument OK if probes in G
- $t_i = d_i (b_{i1}, b_{i2}, ..., b_{iq})$
- Uniform $(t_1, ..., t_n) \in \{0,1,2\}^n$ $\downarrow \downarrow$



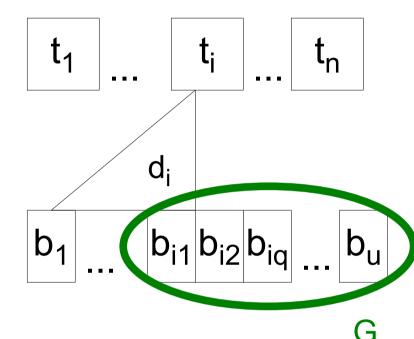
uniform $(b_1, ..., b_u) \in B := \{Store(t) \mid t \in \{0,1,2\}^n \}$

$$|B| = 3^n \approx 2^u \Rightarrow (Lemma) \Rightarrow (b_{i1}, ..., b_{iq}) \approx uniform \Rightarrow$$

$$1/3 = Pr[t_i = 2] = Pr[d_i(b_{i1}, ..., b_{iq}) = 2] \approx A/2q \neq 1/3$$

Probes not in G

If every t_i probes bits not in G



- Argue as in [Shaltiel V.]:
- Condition on heavy bits := probed by many t_i
- Can find t_i ≈ uniform in {0,1,2}, all probes in G

Handling adaptivity

• So far $t_i = d_i (b_{i1}, b_{i2}, ..., b_{iq})$

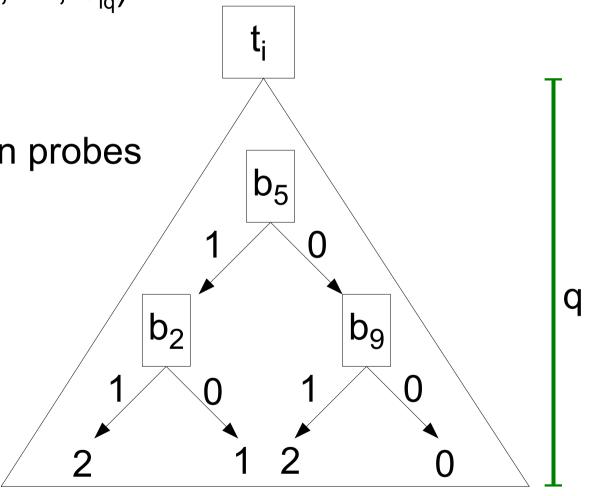
In general,

q adaptively chosen probes

= decision tree

2q bits

depth q



$$1/3 = Pr[t_i = 2] = Pr[d_i(b_{i1}, ..., b_{i2q}) = 2] \approx A/2q \neq 1/3$$

Outline

• Bits vs. trits

Proof bits vs. trits

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Bits vs. sets

• Store $S \subseteq \{1, 2, ..., n\}$ of size |S| = k

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In u bits $b_1, ..., b_n \in \{0,1\}$

$$\begin{vmatrix} b_1 & b_2 & b_3 & b_4 & b_5 \end{vmatrix}$$
 ... $\begin{vmatrix} b_u & b_1 & b_2 & b_4 & b_5 \end{vmatrix}$

Want:

Small space u (optimal = $\lceil \lg_2 (n \text{ choose k}) \rceil$)

Answer " $i \in S$?" by probing few bits (optimal = 1)

Previous results

- Store S ⊆ {1, 2, ..., n}, |S| = k in bits, answer "i ∈ S?"
 - [Minsky Papert '69] Average-case study
 - [Buhrman Miltersen Radhakrishnan Venkatesh; Pagh '00]

Space O(optimal), probe O(lg(n/k))

Lower bounds for $k < n^{1-\epsilon}$

• No lower bound was known for $k = \Omega(n)$

Our results

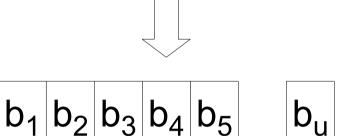
Theorem[V.]:

Store
$$S \subseteq \{1, 2, ..., n\}, |S| = n/3$$

in u bits $b_1, ..., b_u \in \{0, 1\}$

If answer " $i \in S$?" probing q bits then space u > optimal + $n/2^{O(q)}$.

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• First lower bound for $|S| = \Omega(n)$

Outline

• Bits vs. trits

Proof bits vs. trits

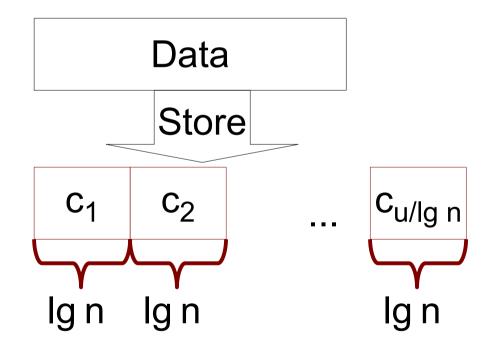
• Bits vs. sets

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Cell-probe model

So far: q = number of bit probes

Cell model: q = number of probes in cells of lg(n) bits



Relationship: q bit ⊆ q cell ⊆ q lg(n) bit

Results in cell-probe model

Cells vs. trits:

Cells vs. sets:

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q probes, space = optimal + n / lg^{\Omega(q)}n [Pagh, Pătraşcu] Lower bounds?
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Outline

• Bits vs. trits

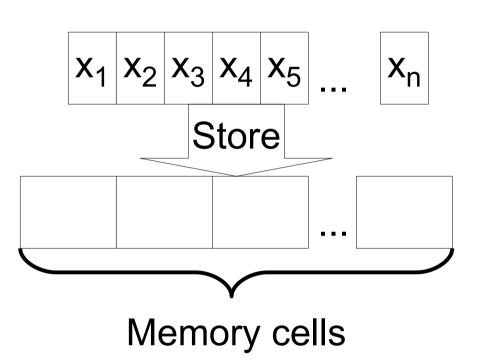
Proof bits vs. trits

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Prefix sums

Store n bits x₁, x₂, ..., xₙ ∈ {0,1}
 in memory cells



Want:

Small space

Fast answer prefix sum (a.k.a. Rank) queries:

Sum(i) :=
$$\sum_{k \le i} x_k \in \{0, 1, 2, ..., n\}$$

History

• Fundamental problem: succinct trees, sets, ...

Trivial

• [Jacobson '89]

Space =
$$n + O(n / lg n)$$

Time = $O(1)$ cell probes

• [Pătraşcu '08]

Space =
$$n + n / lg^q n$$

Time = $O(q)$ cell probes

Our results

Theorem[Pătraşcu V.]:
 Store n bits in memory

If answer Sum(i) := $\sum_{k \le i} x_k$ queries by probing q cells then space > n+ n/lg^{O(q)} n.

• Matches [Pătraşcu]: space < n + n / $lg^{\Omega(q)}$ n

Proof idea

Efficient data structure ⇒ Break queries' correlations

• For $i < j, A \subseteq \{0,1\}^n$

```
0 = Pr_{x \in A} [Sum(i) > t AND Sum(j) < t]
\approx Pr_{x \in A} [Sum(i) > t] Pr_{x \in A} [Sum(j) < t]
> (1/10) (1/10) >> 0
```

Contradiction, so data structure cannot be efficient

Proof idea

$$0 = Pr_{x \in A} [Sum(i) > t AND Sum(j) < t]$$

$$\approx Pr_{x \in A} [Sum(i) > t] Pr_{x \in A} [Sum(j) < t]$$

$$> (1/10) (1/10)$$
(2)

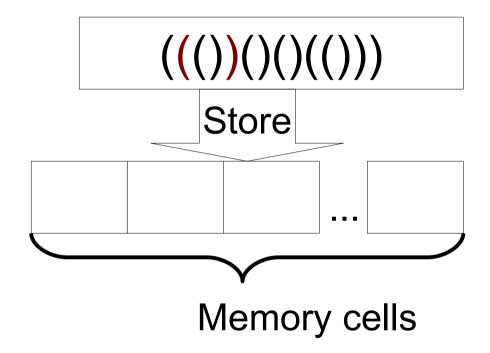
Reasoning:

Fix heavy cells. Then ∃ i, j s.t. Sum(i) and Sum(j):

- (1) depend on disjoint, nearly uniform cells \Rightarrow independent
- (2) have high entropy

Balanced brackets

- Store n balanced brackets
 - Want: Small space Fast answer match queries:



- Theorem[V.]: space > optimal + n/lg² n. for non-adaptive q probes
- [Pătraşcu]: space < optimal + n / $lg^{\Omega(q)}$ n non-adaptive

Summary

New lower bounds for basic data structures:

Representing trits, sets, prefix sums, balanced brackets using space = optimal + redundancy

- Sometimes matching [Pătraşcu]
- Open problems: storing sets:
 - 2 cell probes and optimal space?

Bit-probe lower bounds for set-size n/4 ? (have n/3)

Future directions

Lower bounds for generating distributions

- Example: f: {0,1} ^r → {0,1} ⁿ
 each bit f_i depends on ≤ q input bits
 prove f(uniform) far from uniform on sets of size n/4
 - Known[V.]: distance ≥ 1/2^{O(q)}
 - Open: distance ≥ 1 o(1)
 - ⇒ Lower bound for storing sets of size n/4

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