The design of learning-based compressed data structures

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Outline

- Two classical problems in data structure & DBMS design:
  - Data indexing
  - Data compression & access
- Reframe them as a problem of approximating the distribution of the input data
- Show solutions that learn the input data regularities ***and*** guarantee efficient space-time complexity bounds

Problem 1

Data indexing

The predecessor search problem

- Given n sorted input keys, implement:

  $predecessor(x) =$ "largest key $\leq x$"

- Range queries in DBs, conjunctive queries in search engines, IP routing...
- Traditionally solved by tree- or trie-based data structures

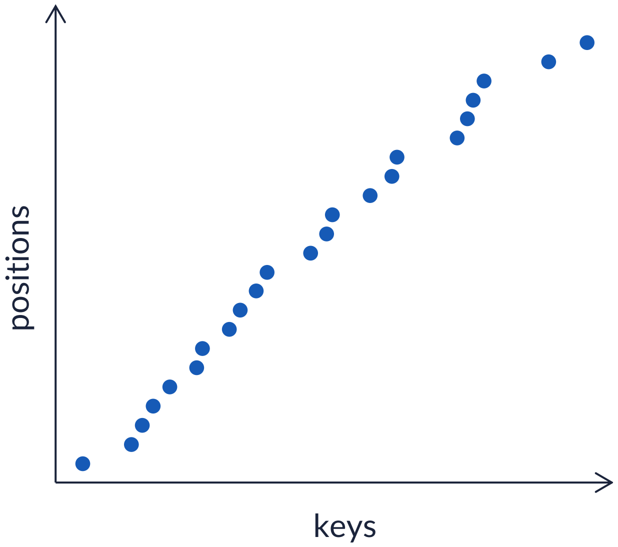
$predecessor(36) = 36$

2	11	13	15	18	23	24	29	31	34	36	44	47	48	55	59	60	71	73	74	76	88	95

1 n

$predecessor(50) = 48$

The idea: input data as pairs $(key, position)$

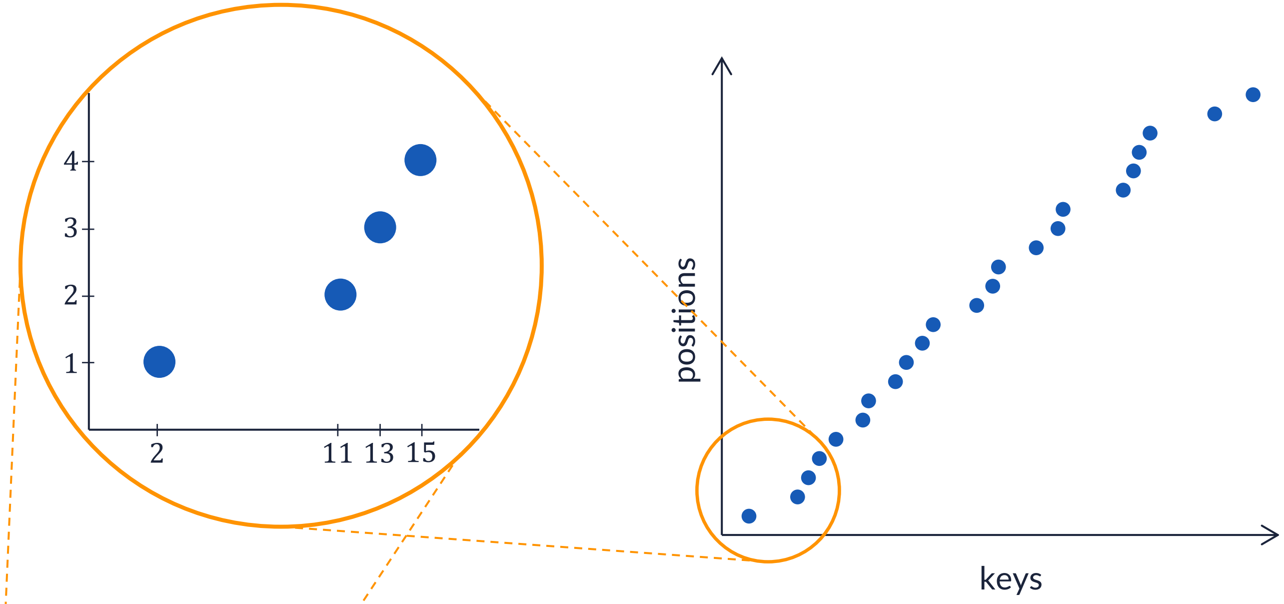


2	11	13	15	18	23	24	29	31	34	36	44	47	48	55	59	60	71	73	74	76	88	95

1 $\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad$ n

Ao et al. [VLDB 2011]

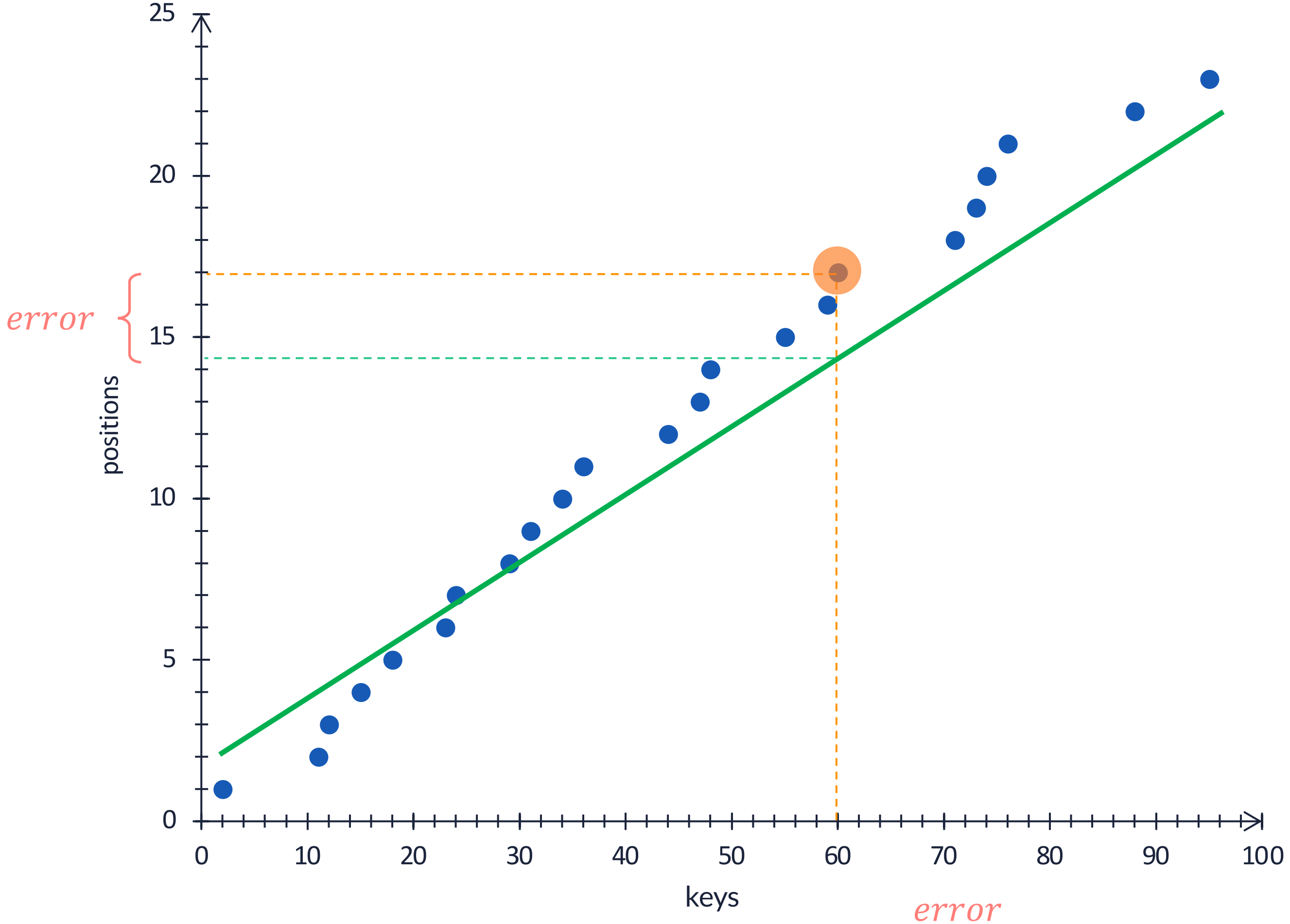
The idea: input data as pairs $(key, position)$



2	11	13	15	18	23	24	29	31	34	36	44	47	48	55	59	60	71	73	74	76	88	95
1	2	3	4																			n

Ao et al. [VLDB 2011]

The idea: learning a mapping *keys* → *positions*



error

2	11	13	15	18	23	24	29	31	34	36	44	47	48	55	59	60	71	73	74	76	88	95
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23

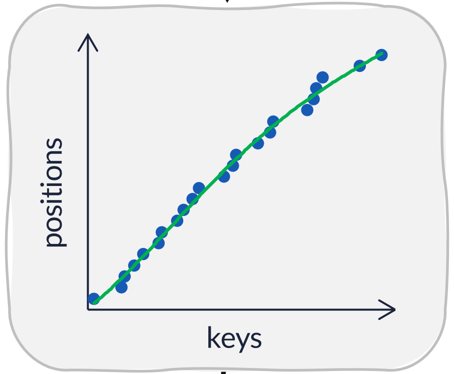
Learned indexes

Query latency = time to output a position
+ time to “fix the error” via binary search

How to strike a good balance between the model complexity and the query latency?

Often we need more complex models than linear ones

key



$position$ (approximate)

2	11	13	15	18	23	24	29	31	34	36	44	47	48	55	59	60	71	73	74	76	88	95

1 … n

Binary search in
$[position - error, position + error]$

Ao et al. [VLDB 2011], Kraska et al. [SIGMOD 2018]

Introducing the PGM-index

Piecewise linear ε-approx.
Fast to construct and space-optimal
(number of segments is minimised)

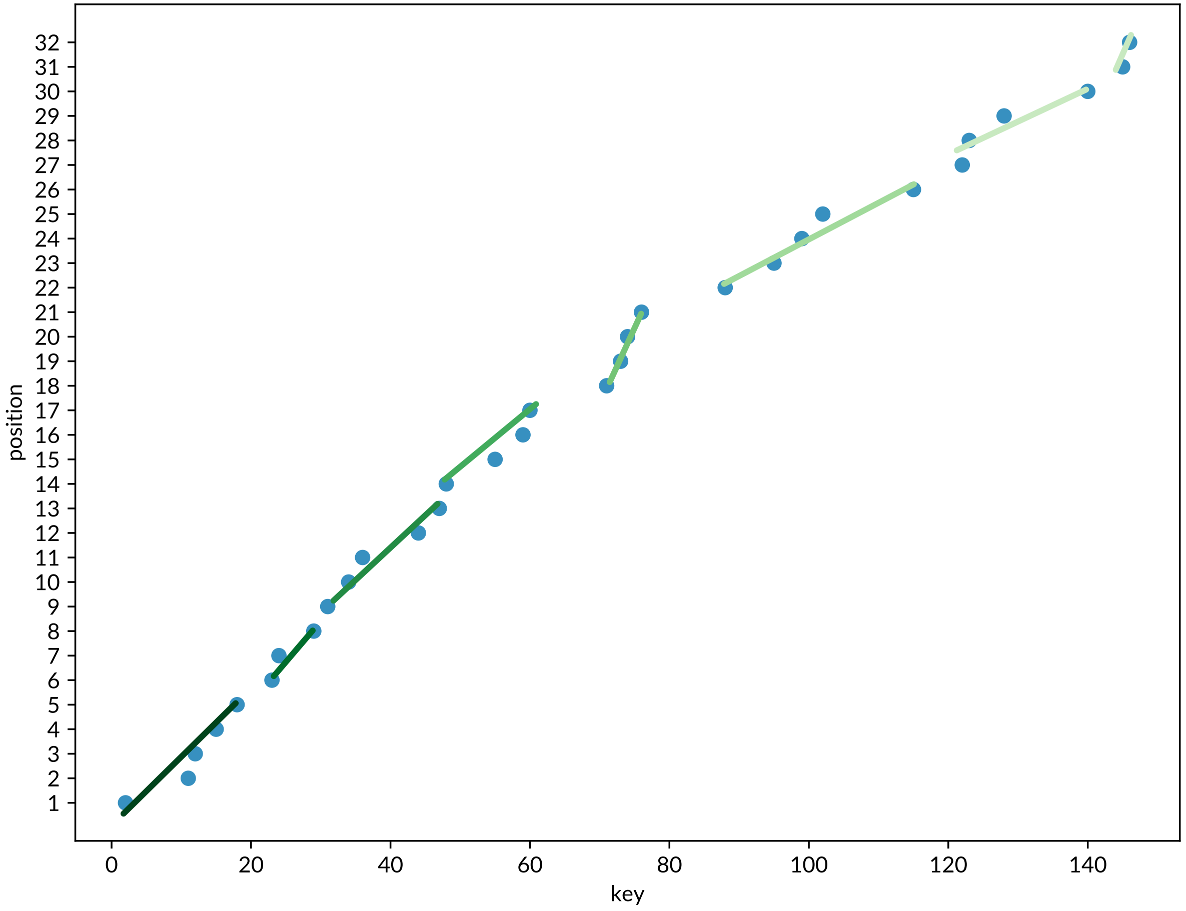
Fixed model “error” ε
Control the size of the search range
(like the page size in a B-tree)

Recursive design
Adapt to the memory hierarchy
and enable query-time guarantees

Ferragina and Vinciguerra [VLDB 2020]

PGM-index construction

Step 1. Compute the optimal piecewise linear ε-approximation in $\mathcal{O}(n)$ time



2	11	12	15	18	23	24	29	31	34	36	44	47	48	55	59	60	71	73	74	76	88	95	99	102	115	122	123	128	140	145	146

1 n

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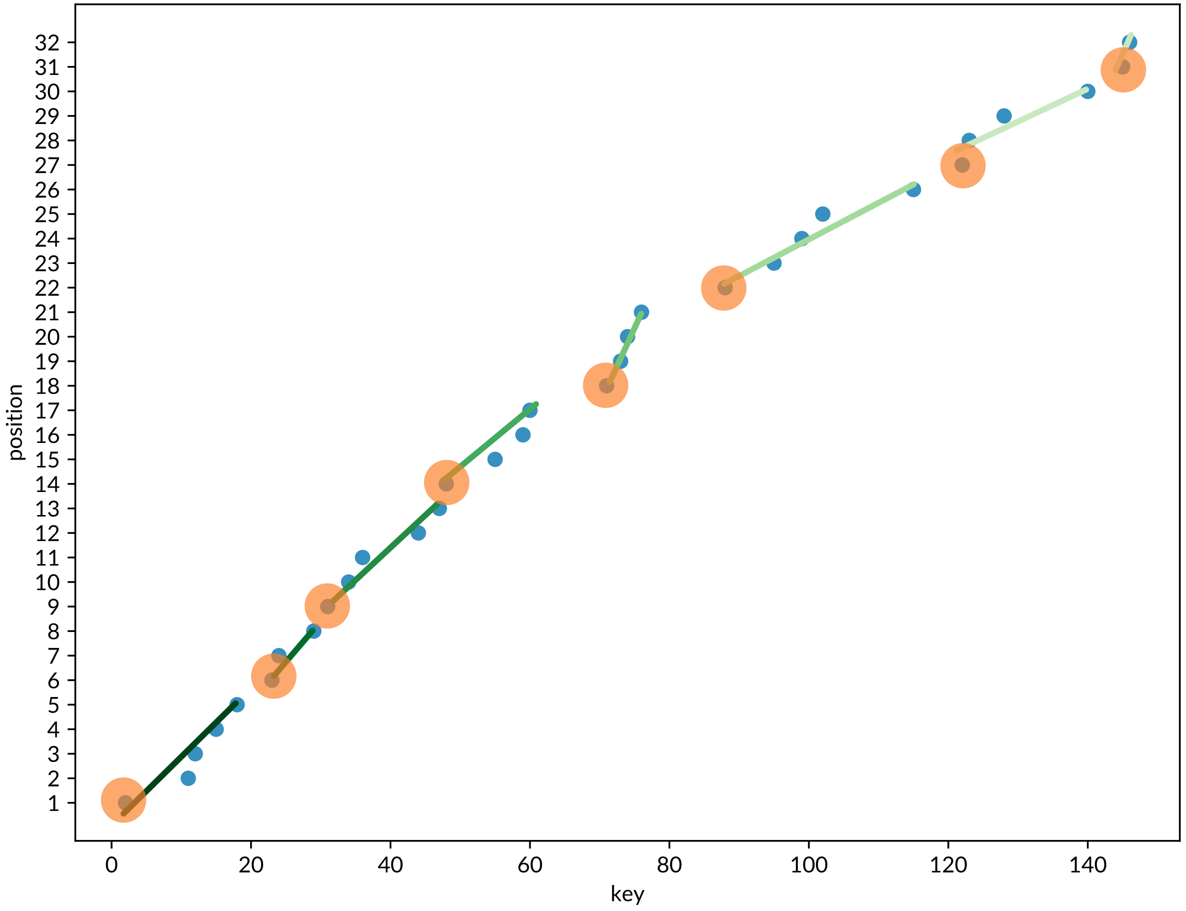


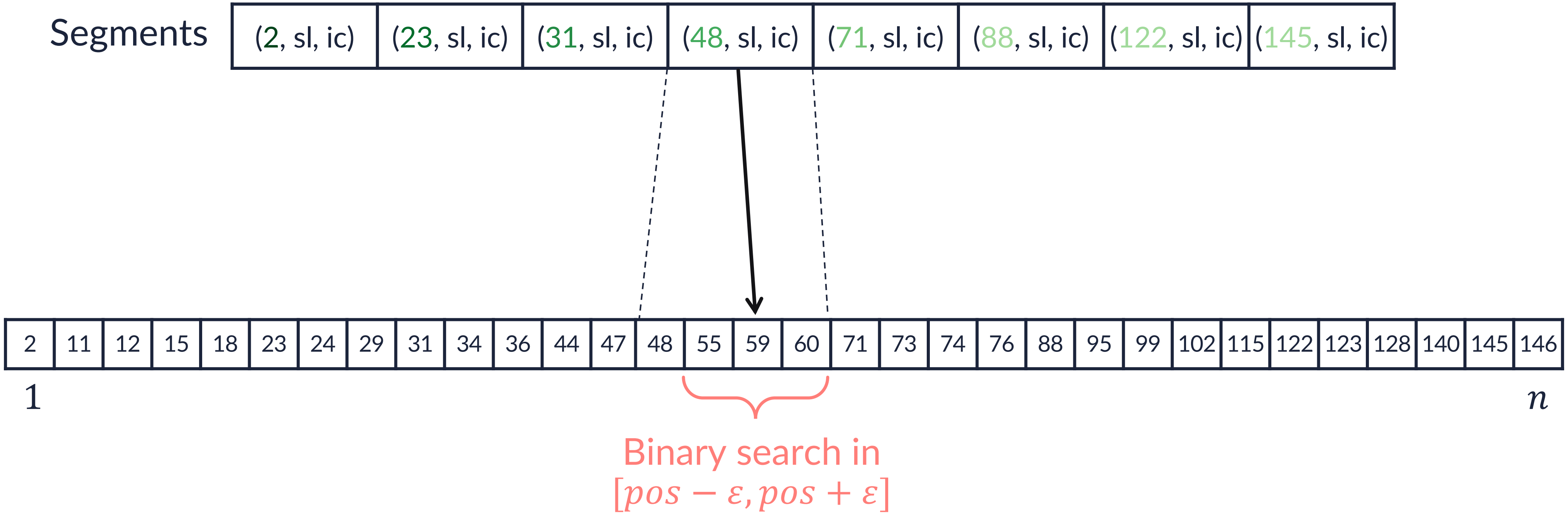
Step 2. Store the segments as triples $s_i = (key, slope, intercept)$

2	11	12	15	18	23	24	29	31	34	36	44	47	48	55	59	60	71	73	74	76	88	95	99	102	115	122	123	128	140	145	146

1 n

Partial memory layout of the PGM-index

Each segment indexes a variable and potentially large sequence of keys while guaranteeing a search range size of $2\varepsilon + 1$

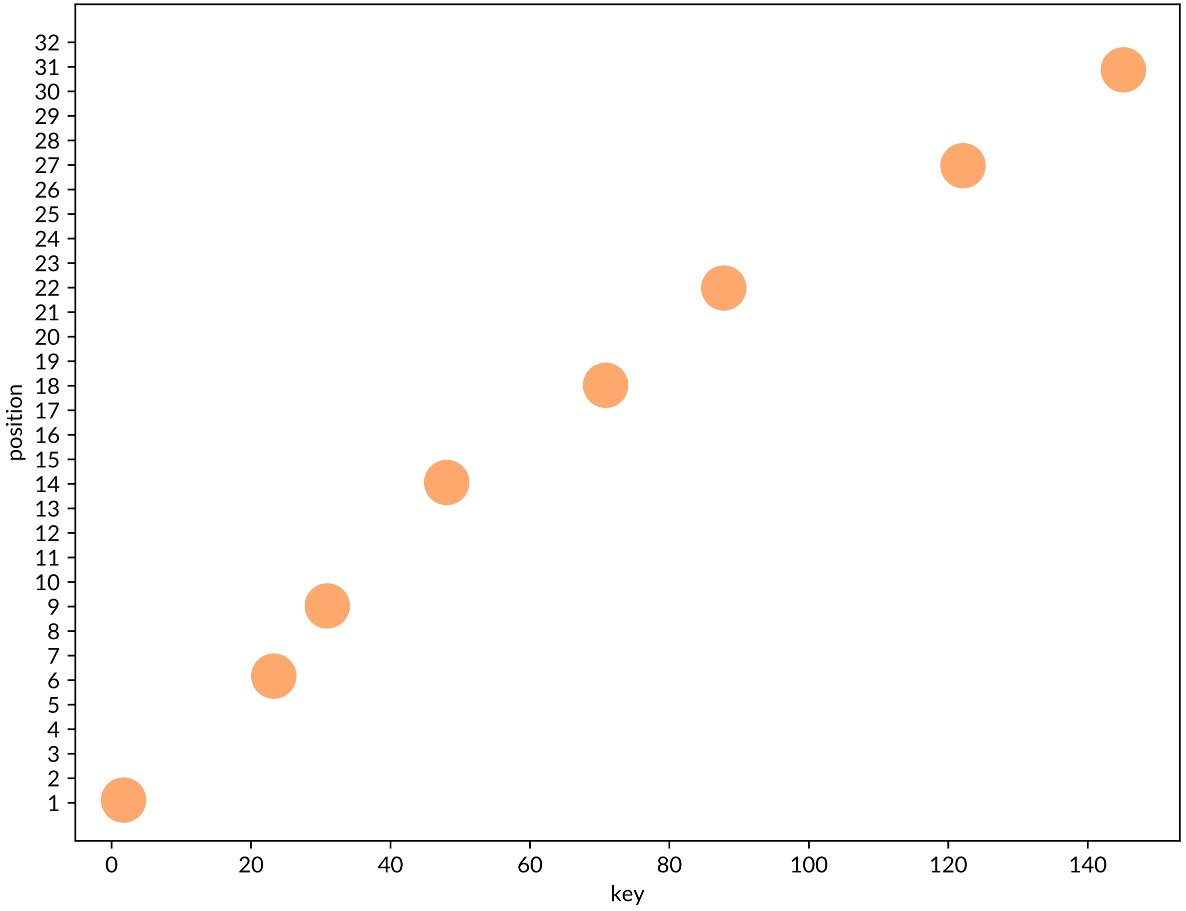


PGM-index construction

Step 1. Compute the optimal piecewise linear ε-approximation in $\mathcal{O}(n)$ time

Step 2. Store the segments as triples $s_i = (key, slope, intercept)$

Step 3. Keep only $s_i.key$



2	11	12	15	18	23	24	29	31	34	36	44	47	48	55	59	60	71	73	74	76	88	95	99	102	115	122	123	128	140	145	146

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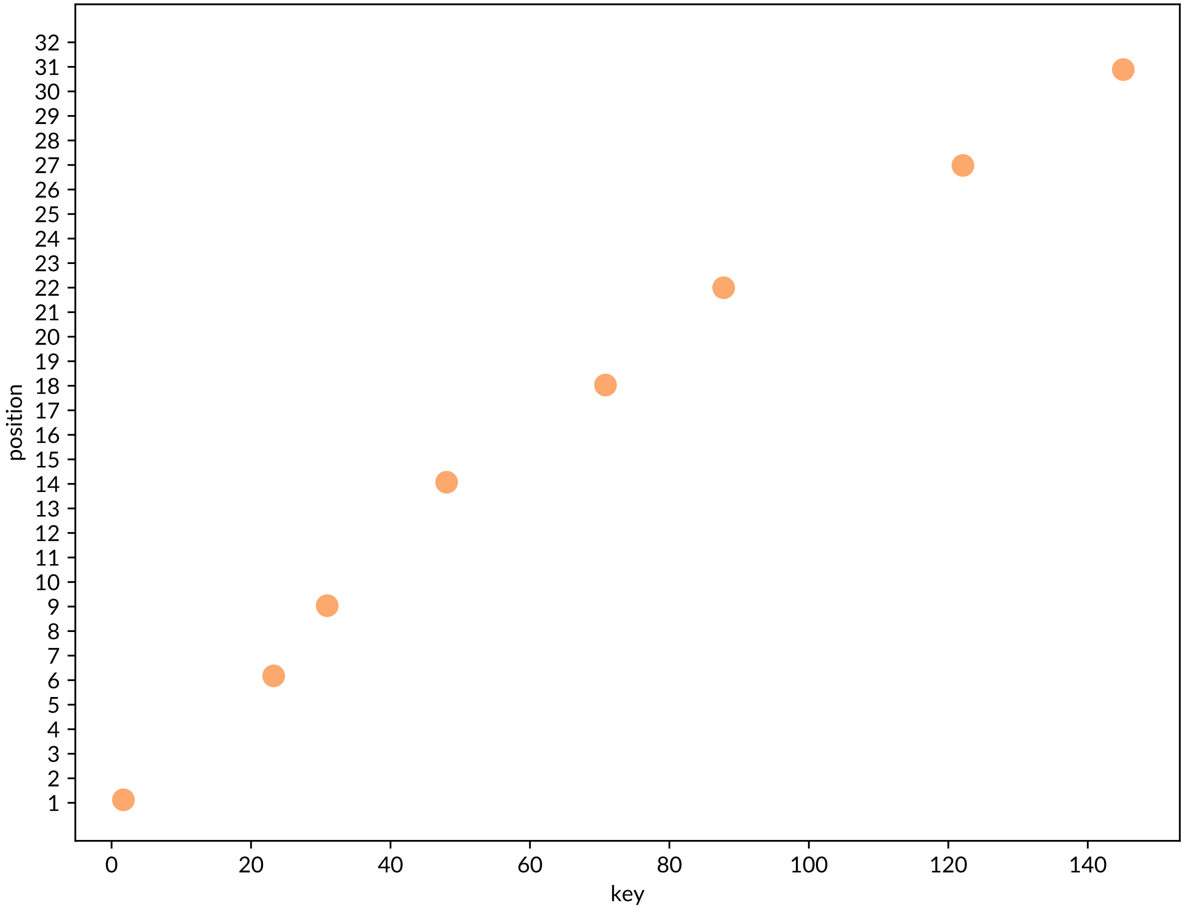

2	23	31	48	71	88	122	145

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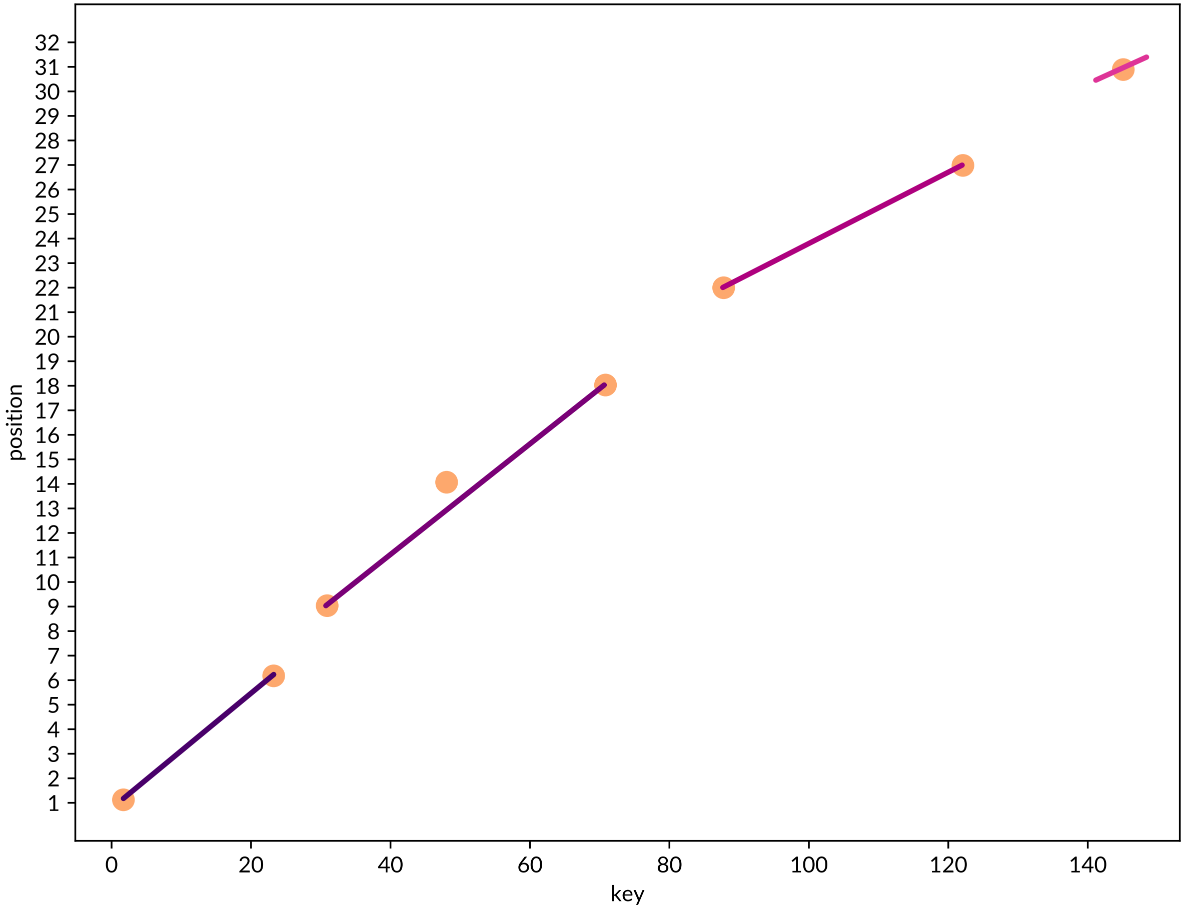


2	23	31	48	71	88	122	145

Step 3. Keep only $s_i.key$

Step 4. Repeat recursively

Memory layout of the PGM-index

(2, sl, ic)

(2, sl, ic)	(31, sl, ic)	(88, sl, ic)	(145, sl, ic)

(2, sl, ic)	(23, sl, ic)	(31, sl, ic)	(48, sl, ic)	(71, sl, ic)	(88, sl, ic)	(122, sl, ic)	(145, sl, ic)

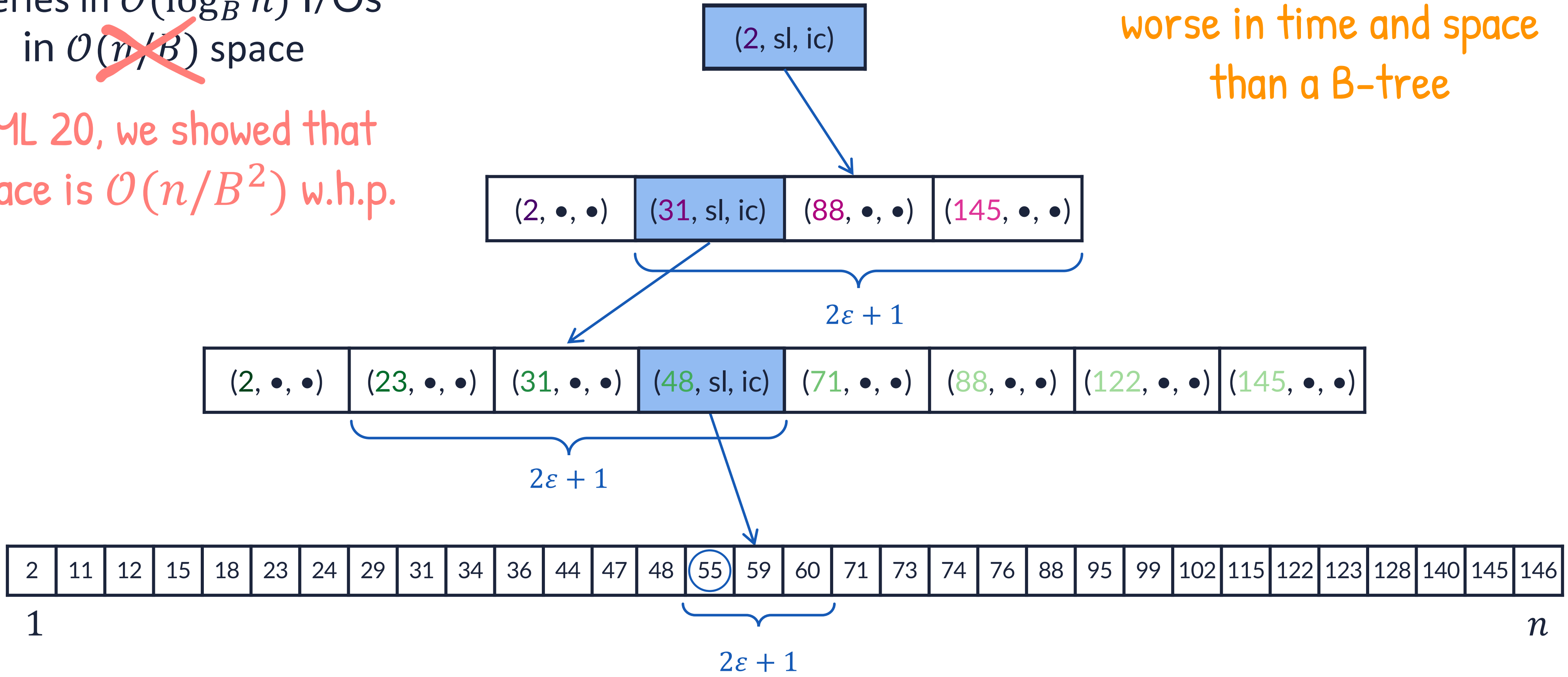
2	11	12	15	18	23	24	29	31	34	36	44	47	48	55	59	60	71	73	74	76	88	95	99	102	115	122	123	128	140	145	146

1 n

Predecessor search with a PGM-index

If B = disk page-size,
set $\varepsilon = \Theta(B)$ for
queries in $\mathcal{O}(\log_B n)$ I/Os
in $\mathcal{O}(\cancel{n/B})$ space

In ICML 20, we showed that
the space is $\mathcal{O}(n/B^2)$ w.h.p.



The PGM-index is <u>never</u>
worse in time and space
than a B-tree

Experiments

Static-scenario: experimental settings

- The majority of papers test learned indexes on positive lookups

= locate the predecessor of a key

- An index must answer *correctly* and *efficiently* also when the query keys are not in the input (training) data

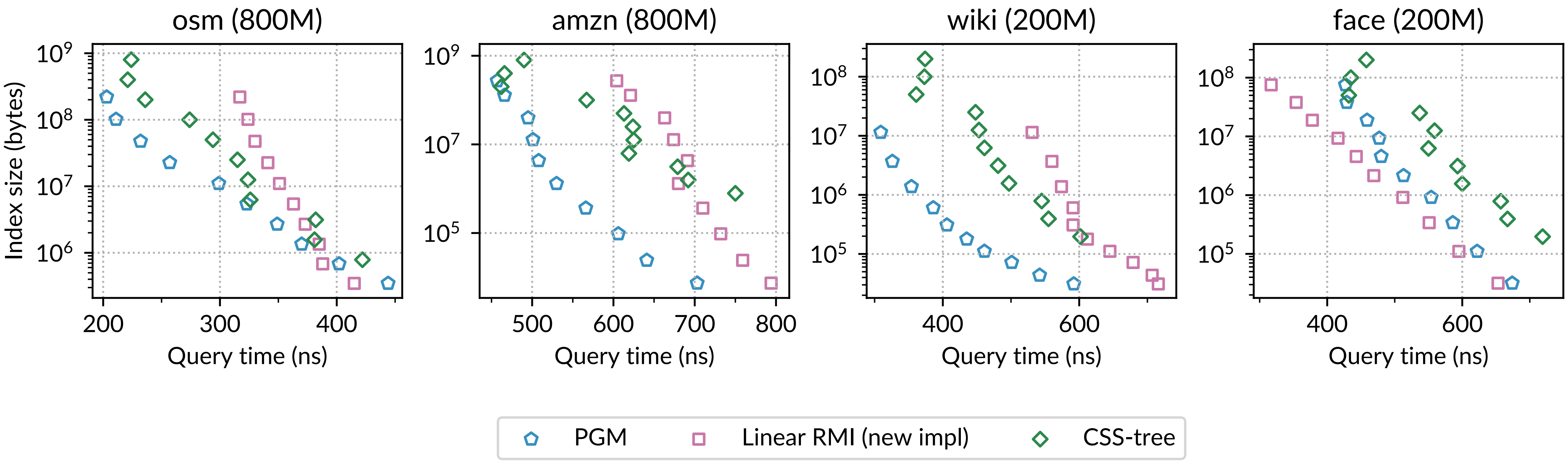
- Here we test each index on 10M random predecessor queries

- In-memory data with 8-byte keys, 8-byte payload

Static-scenario: experiments

Linear RMI and PGM have the same size

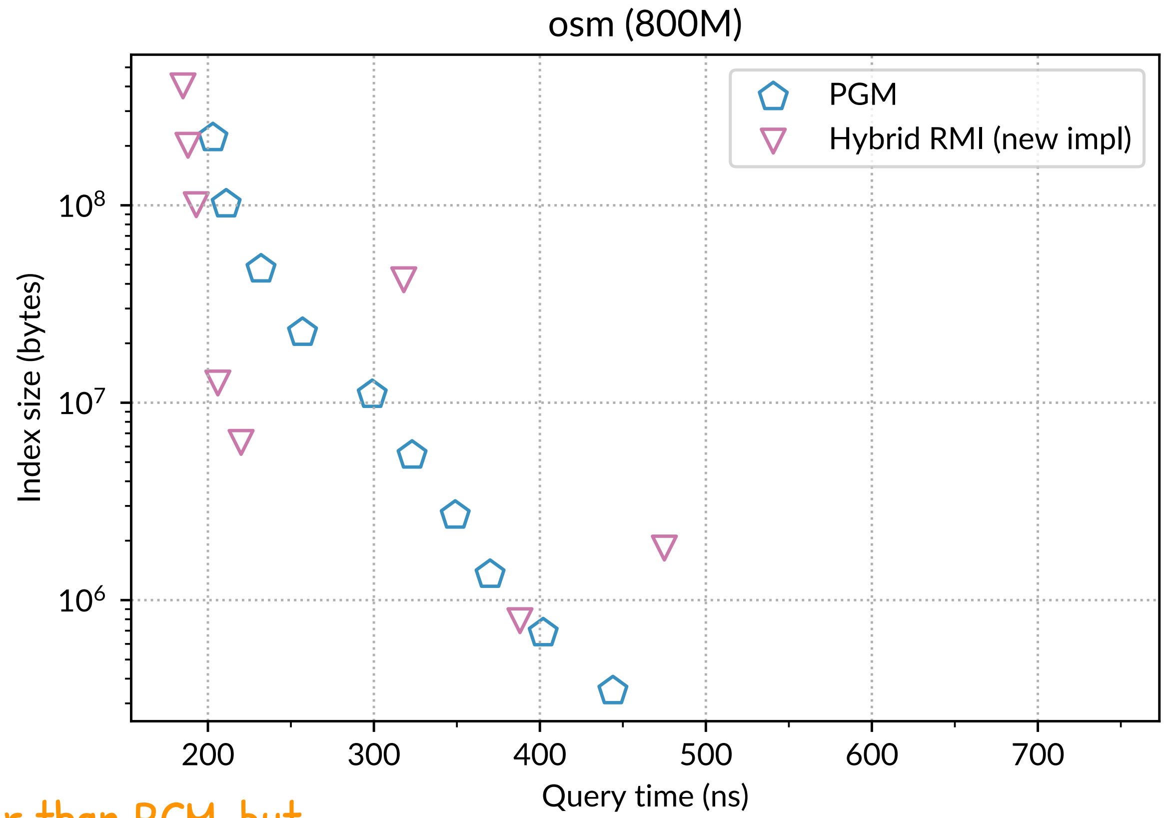
PGM is often better than Linear RMI and CSS-tree



Linear RMI implementation and datasets from Marcus et al. [VLDB 2021]

Static-scenario: experiments with Hybrid RMI

(RMI with non-linear models, tuned via grid search)

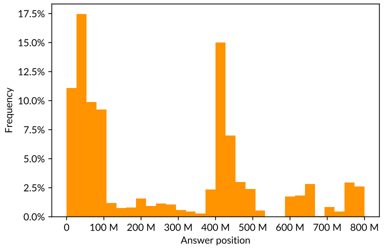


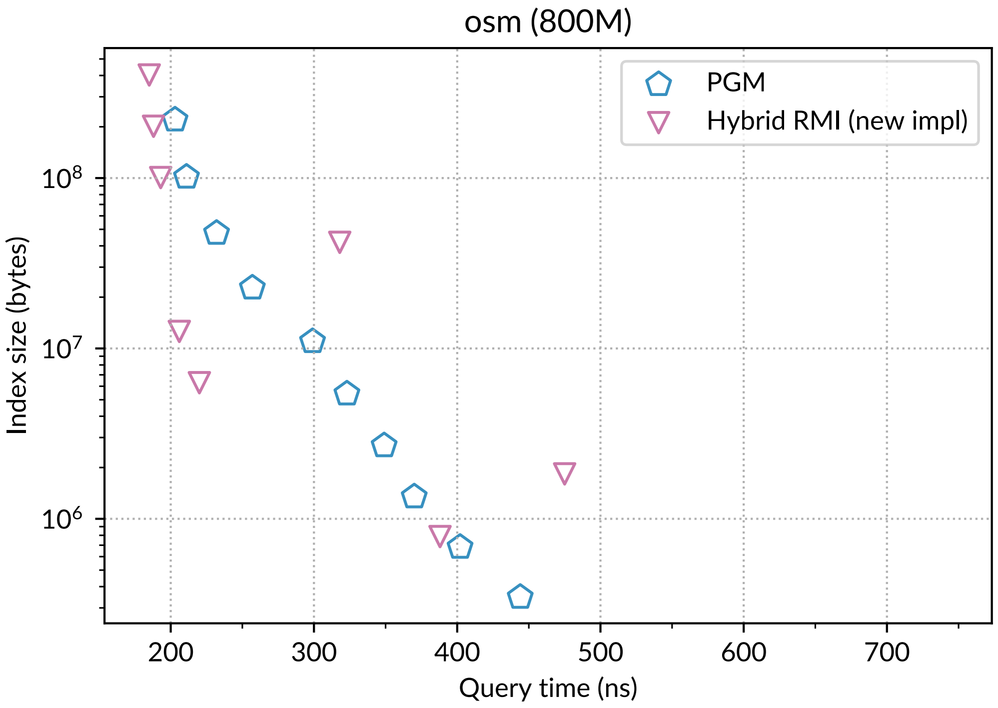
Hybrid RMI is often better than PGM, but...

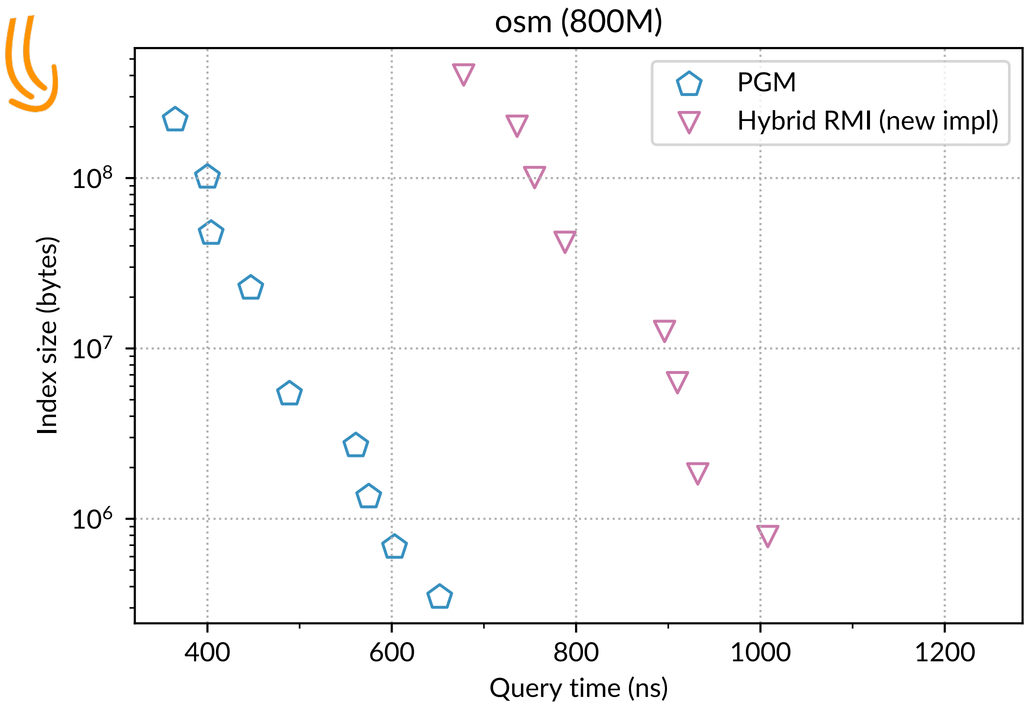
Tuned Hybrid RMI implementation and datasets from Marcus et al. [VLDB 2021]

Why worst-case bounds are important?

Adversarial query workload







Tuned Hybrid RMI implementation and datasets from Marcus et al. [VLDB 2021]

Dynamic-scenario: experimental settings

- Many papers show only the index/model size and disregard other design choices, e.g. half-empty nodes

  Here we show the overall data structure size

- We test PGM, B-tree, B+tree, Y-fast trie, ALEX, ART

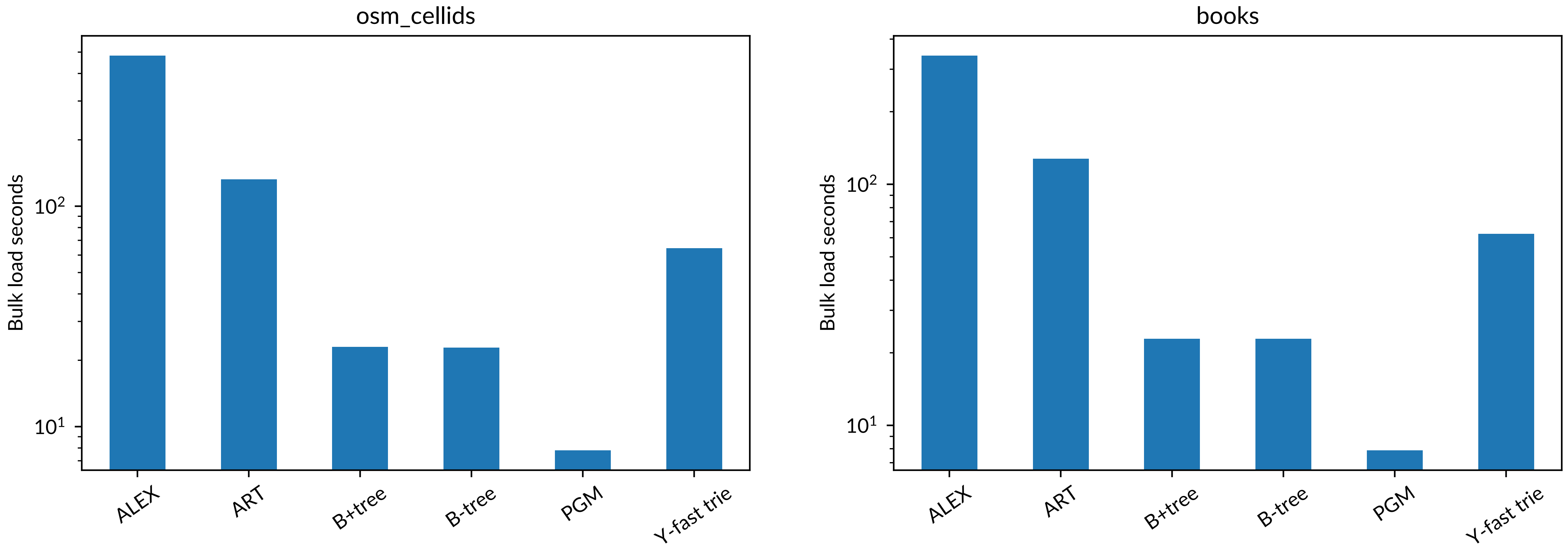
  For the first four, we vary the page-size and show the fastest configuration

- Extract batch of 100M query+insert ops from dataset with 800M keys

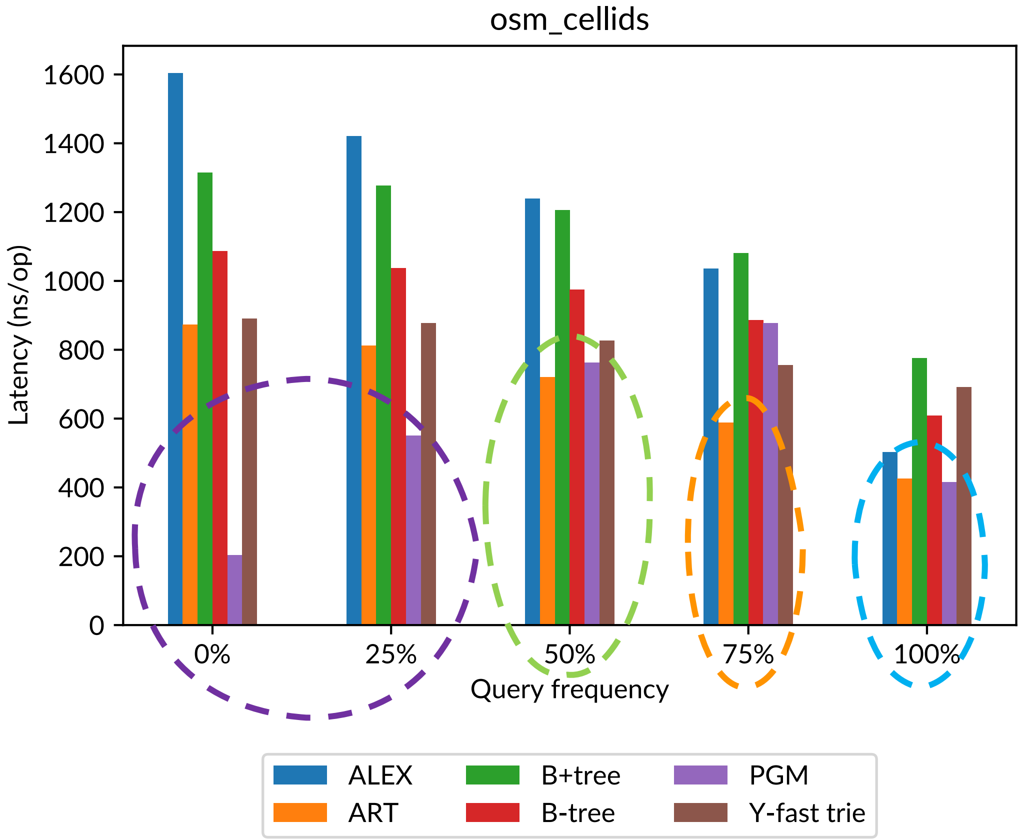
- Use the remaining keys to bulk load each structure

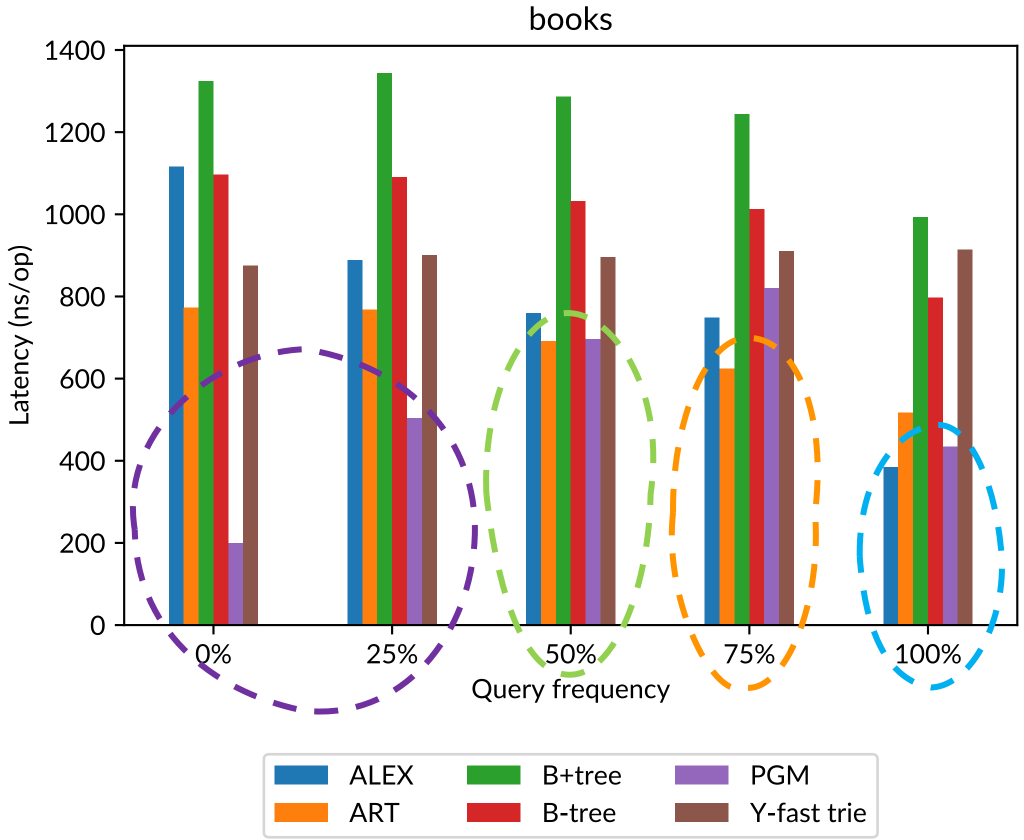
  8-byte keys, 8-byte payload

Bulk loading +700M records



Dynamic-scenario: latency over 100M ops





- PGM is faster for write-heavy workloads (0% to 25%)
- PGM and ART are faster for balanced workloads (50%)
- ART is faster for read-heavy workloads (75%)
- PGM, ART and ALEX are faster for read-only workloads (100%)

Dynamic-scenario: overall memory usage

- PGM is the most memory-efficient (12.9 GB)
- B-tree is the second-best (16.5 GB)
- ART is the most memory-hungry (34.6 GB)
- Some learned indexes can be larger than traditional ones (ALEX is +15% than B-tree, +47% than PGM)

Dynamic-scenario: range queries

- Small range sizes (10 results)
  - All data structures take from 2 to 4 µs
  - ALEX is the fastest

- Medium range sizes (1K results)
  - Y-fast trie is the fastest, 7 µs
  - PGM is the second-fastest, +51%
  - ALEX is the third-fastest, +7× wrt Y-fast trie

- Large range sizes (100K results)
  - Y-fast trie is still the fastest, 605 µs
  - PGM is still the second-fastest, +1% wrt Y-fast trie
  - ALEX is still the third-fastest, +7× wrt Y-fast trie

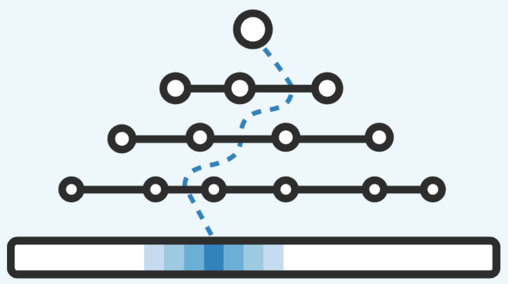
More structures in the PGM library

Variants of the PGM

- CompressedPGM
- EliasFanoPGM
- BucketingPGM

MultidimensionalPGM

- Orthogonal range queries
- k-NN queries (thanks DBlab @ Nagoya Univ.)

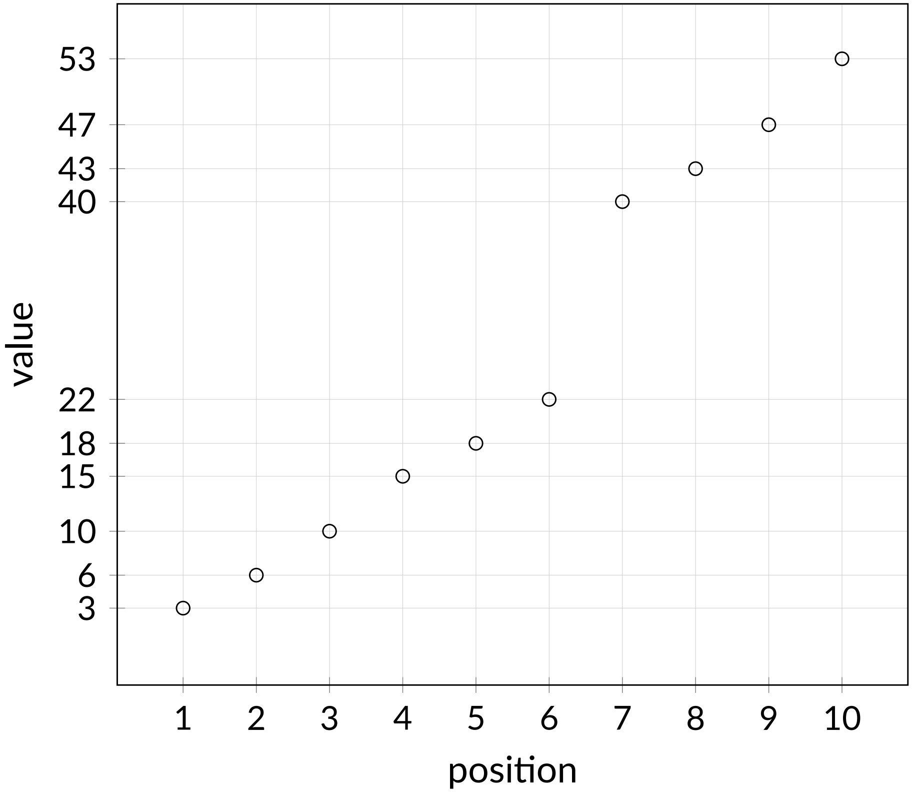


pgm.di.unipi.it

Problem 2

Data compression & access

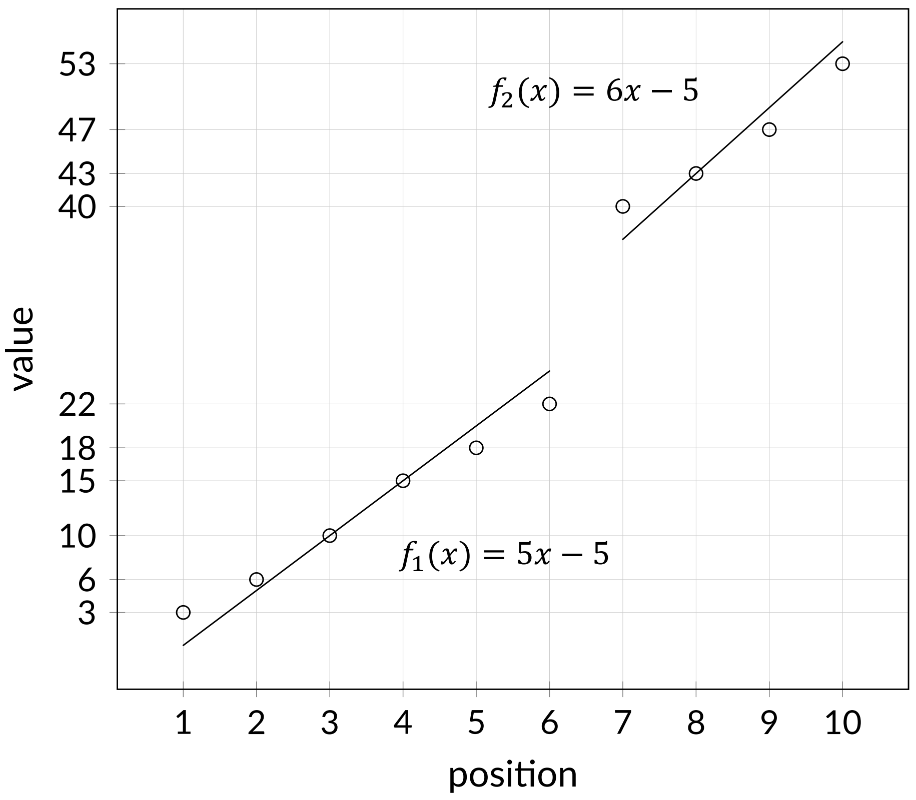
The idea



3	6	10	15	18	22	40	43	47	53
1	2	3	4	5	6	7	8	9	10

The idea: data = segments

Represent integers with
an information loss of ε

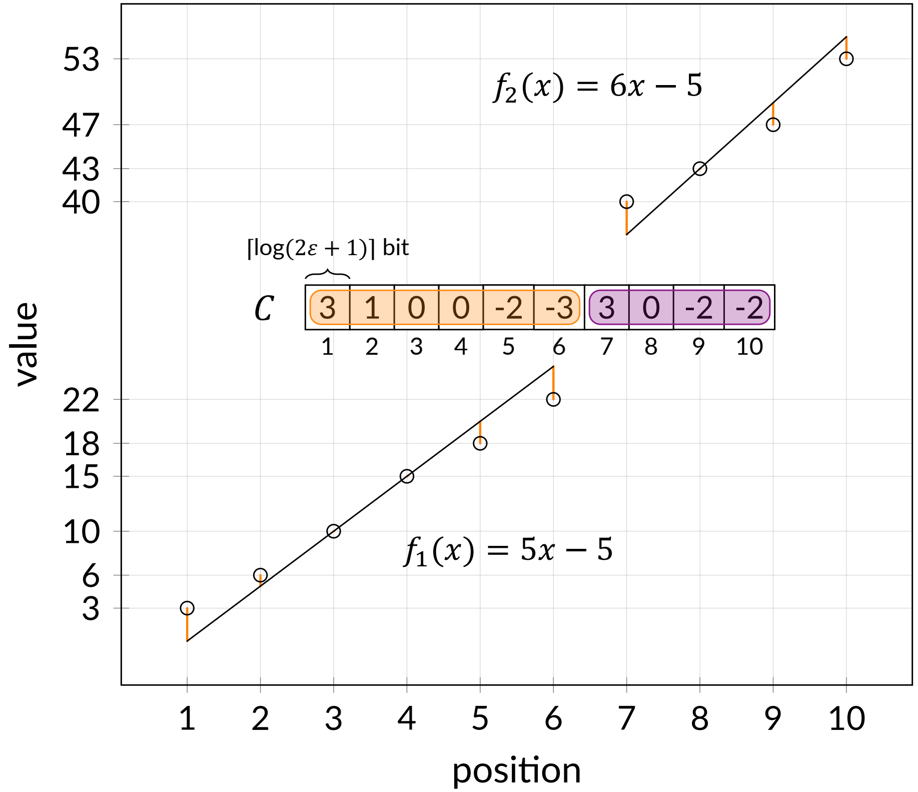


3	6	10	15	18	22	40	43	47	53
1	2	3	4	5	6	7	8	9	10

The idea: data = segments + corrections

Represent integers with an information loss of ε

Complement the approximations to recover the original set



LA-vector: a compressed array supporting efficient random access and other query operations

$x_i = f(i) + C[i]$

3	6	10	15	18	22	40	43	47	53
1	2	3	4	5	6	7	8	9	10

Experiments on LA-vector, in brief

- Tested on DNA, 5Gram, URLs, and inverted lists
- Fast random access and competitive queries wrt well-engineered compressed data structures
- Space occupancy close to the most compressed (but less query-efficient) approaches

SIAM 2021 Symposium on Algorithm Engineering and Experiments

Boffa, Ferragina, Vinciguerra: *A "learned" approach to quicken and compress rank/select dictionaries.*

Code available at github.com/gvinciguerra/la_vector

Conclusions

Wrap up

exploit new compression opportunities

- Introduced data structures that learn the input data regularities, without giving up worst-case bounds:
  - The *PGM-index* for data indexing
  - The *LA-vector* for compressing and indexing data

robust; resistant to adversarial queries

- Practical performance on par with or orders of magnitude better than traditional data structures

- Libraries are open-source, we invite users and contributors

  We are extending the PGM to big integers (up to 256 bytes)

Open questions

1. Can we further improve the performance of Dynamic PGM over read-heavy workloads?

2. Can we learn ε-approximate nonlinear models efficiently?

3. Do these models improve the $\mathcal{O}(n/\varepsilon^2)$ space bound of the piecewise-linear model adopted by PGM?

References

- P. Ferragina and G. Vinciguerra. *The PGM-index: a fully-dynamic compressed learned index with provable worst-case bounds*. PVLDB, 13(8): 1162-1175, 2020.
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- P. Ferragina, F. Lillo, and G. Vinciguerra. *On the performance of learned data structures*. Theoretical Computer Science, 871: 107-120, 2021.
- A. Boffa, P. Ferragina, and G. Vinciguerra. *A "learned" approach to quicken and compress rank/select dictionaries*. In: Proc. 23rd SIAM Symposium on Algorithm Engineering and Experiments (ALENEX 2021).