# Learning-based compressed data structures Paolo Ferragina, Giorgio Vinciguerra



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- The deluge of data has made the use of compressed data structures indispensable
- These structures build on two sources of compressibility: statistical properties and repetitiveness of the data
  But there is a new promising kind of regularity to be studied: approximate linearity

## The predecessor search problem

Given *n* sorted keys implement mrad(x) ="largest keys x"





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

Why do we care? Range queries and joins in DBs, conjunctive queries in search engines, IP routing, ...



Features

#### **Experimental results**

• As fast as static B-tree, 83× more compressed

key

- Optimal time and space complexity guarantees
- Never worse than traditional indexes such as B-trees
- Resistant to adversarial inputs and queries
- Supports multidimensional data and queries
- Auto-tunable to the desired memory usage or query time
- Up to 3× faster than a dynamic B-tree and 1000× more compressed on 10<sup>9</sup> integers
- About 3 seconds to construct on 10<sup>9</sup> integers

# **Rank/Select dictionaries**

Store an integer set S in compressed form, support rank(x) ="# elements  $\leq x$  in S" select(i) = "ith smallest element in S"

Why do we care? Building block of compressed data structures for texts, genomes, graphs, ...

### *Idea*: data = segments + corrections



#### **The LA-vector**

Orchestrate piecewise linear  $\varepsilon$ -approximations, corrections and indexing. Faster *select* and competitive *rank* wrt well-engineered solutions

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