# Competitive Data-Structure Dynamization

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(an 11-minute talk summarizing the conference paper)



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compaction policies for LSM (log-structured merge) systems

through the lens of competitive analysis

## **MOTIVATION**

**B-TREES VS. MOORE'S LAW** 

LSM-SYSTEM COMPACTION VIA DATA-STRUCTURE DYNAMIZATION

## **DEFINITIONS**

PROBLEM 1 — MIN-SUM DYNAMIZATION

PROBLEM 2 — K-COMPONENT DYNAMIZATION

**COMPETITIVE ANALYSIS** 

### **RESULTS**

PROBLEM 1 ALGORITHM,  $\Theta(\log^* n)$ -COMPETITIVE PROBLEM 2 LOWER BOUND PROBLEM 2 ALGORITHMS, K-COMPETITIVE

#### external-memory ordered dictionaries: Better than B-trees?



**Figure 18.3** A B-tree of height 2 containing over one billion keys. Shown inside each node x is x.n, the number of keys in x. Each internal node and leaf contains 1000 keys. This B-tree has 1001 nodes at depth 1 and over one million leaves at depth 2.

As suggested in Figure 18.3 from Introduction to Algorithms by CLRS



But THIS way achieves about 1 disk access per insert or query.

- 1. B-tree node degree  $\approx$  number of keys that can be fetched from disk in the twice the disk-access time
- 2. in 2020  $\rightarrow$  can fetch *thousands* of keys in twice the disk access time  $\rightarrow$  node degree should be over 1000
- 3. in  $2020 \rightarrow$  non-leaf nodes take up < 0.1% of the total space
- 4. Database servers are typically configured so that RAM size is 1–3% of disk size [31, p. 227] !
- 5. Can easily hold all non-leaf nodes in (10% of) RAM, and replace them with in-RAM dictionary.
- 6. Doing this achieves about 1 disk access per insertion or query.
- 7. Is it possible to get *less* than one disk access per insertion or query?

**MOTIVATION** 

**MOORE'S LAW** 

**B-TREES VS.** 



### external-memory dictionaries via LSM = "log-structured merge" [O'Neil et al 1996, and others]

- 1. INSERTs are cached in RAM, require no disk access
- 2. periodically flush RAM cache to disk in a single batch
- 3. maintain on-disk items in *immutable* sorted files called *components*
- 4. each QUERY checks the cache, then if necessary each on-disk component (one disk access per)
- 5. periodically compact destroy some components and build new ones from scratch
  - use data-structure dynamization algorithm to choose which components to destroy and build
  - build cost vs query cost tradeoff

#### notes:

- a. component builds use high-throughput sequential disk access, not slow random access
- b. LSM systems are used today by most companies that need high-throughput big-data storage
- c. most academic work assumes uniform batch sizes and uniform INSERT/QUERY rates, but these assumptions don't hold in production systems, e.g. Google Bigtable

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we call the sets in each cover "components"



Prok inpu <sup>-</sup> outp	PROBLEM 1 EXAMPLE 2					
MINIMIZE COST: $\sum_{t=1}^{n} \sum_{S \in \mathscr{C} \setminus \mathscr{C}_{t-1}} \operatorname{wt}(S) + \sum_{t=1}^{n}  \mathscr{C}_{t}   \text{(build cost + query cost)}$						
					on uniform ir	put (wt( $I_t$ ) = 1)
TRIVIAL ALCORITUM 1. incomt batch as component pays qu					build cost $\Theta(n)$	
time	input batch	cover	query cost	build cost		
1	$\{a,b\}$	$\{a, b\}$	1	wt(a) + wt(b)		
2	{ <i>c</i> }	$\{a, b\}, \{c\}$	2	wt( <i>c</i> )		
3	$\{d, e\}$	$\{a, b\}, \{c\}, \{d, e\}$	3	wt(d) + wt(e)		
		total c	cost: 6 + v	$\operatorname{wt}(a) + \operatorname{wt}(b) + \operatorname{wt}(c) +$	$\operatorname{wt}(d) + \operatorname{wt}(e)$	

Prob INPUT: OUTPU t	INTRO PROBLEM 1 EXAMPLE 3					
TRI	VIAL A	$t=1 S \in \mathscr{C}_t \setminus \mathscr{C}_{t-1}$	t=1 use just o	ne component	on uniform in pays o pays b	put (wt( $I_t$ ) = 1) query cost $\Theta(n)$ build cost $\Theta(n^2)$
time	input batch	cover	query cost	build cost		
1	$\{a, b\}$	$\{a, b\}$	1	wt(a)+wt(b)		
2	{ <i>C</i> }	$\{a, b, c\}$	1	wt(a)+wt(b)+wt(c)		
3	$\{d, e\}$	$\{a, b, c, d, e\}$	1	wt(a)+wt(b)+wt(c	wt(d)+wt(e)	
			1 4 4 . 4			(())

total cost: 4 + 4wt(a)+4wt(b)+3wt(c)+2wt(d)+2wt(e)+wt(f)

time	in binary	input batch	cover	similar to classical Binomial Heap:
1	0001	$I_1$	$I_1$	At each time <i>t</i> , there is one component
2	0010	$I_2$	$I_1 \cup I_2$	for each 1 in the binary representation of $t$ .
3	0011	I3	$I_1 \cup I_2, I_3$	Each step emulates an increment in binary.
4	0100	I4	$I_1 \cup I_2 \cup I_3 \cup I_4$	$\longrightarrow$ on uniform input:
5	0101	I5	$I_1 \cup I_2 \cup I_3 \cup I_4,  I_5$	pays build cost $\Theta(n \log n)$
6	0110	$I_6$	$I_1 \cup I_2 \cup I_3 \cup I_4,  I_5 \cup I_6$	pays query cost $\Theta(n \log n)$
7	0111	<i>I</i> 7	$I_1 \cup I_2 \cup I_3 \cup I_4,  I_5 \cup I_6,$	total cost $\Theta(n \log n)$
8	0100	$I_8$	$I_1 \cup I_2 \cup I_3 \cup I_4 \cup I_5 \cup I_6 \cup$	$I_7 \cup I_8$
9	0101	I9	$I_1 \cup I_2 \cup I_3 \cup I_4 \cup I_5 \cup I_6 \cup$	$I_7 \cup I_{8,}$ $I_9$ optimal for uniform input
10	0110	I10	$I_1 \cup I_2 \cup I_3 \cup I_4 \cup I_5 \cup I_6 \cup$	$I_7 \cup I_{8}$ , $I_9 \cup I_{10}$
•		:	:	

### BINARY TRANSFORM [Bentley, 1979] achieves cost $O(n \log n)$ on uniform inputs

Problem 2: K-COMPONENT DYNAMIZATIONINTRO<br/>PROBLEM 2INPUT:  $I_1, I_2, \dots, I_n$  — a sequence of batches (sets of weighted items)DEFN<br/>K-BIN. TRANSFORMOUTPUT:  $\mathscr{C}_1, \mathscr{C}_2, \dots, \mathscr{C}_n$  — a sequence of set covers such that<br/>the sets in  $\mathscr{C}_t$  cover all items inserted up to time  $t \left( \bigcup_{S \in \mathscr{C}_t} S = \bigcup_{i=1}^t I_i \right)$ Same as beforeCONSTRAINT:  $|\mathscr{C}_t| \leq k$  — at each time t, cover size is at most kMINIMIZE BUILD COST: $\sum_{t=1}^n \sum_{S \in \mathscr{C}_t \setminus \mathscr{C}_{t-1}} \operatorname{wt}(S)$ 

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K-BINOMIAL TRANSFORM [Bentley & Saxe, 1980] achieves  $cost \Theta(kn^{1+1/k})$  on uniform inputs optimal for uniform input

At each time *t*:

- 1. Let  $i_1, \ldots, i_k$  be the k integers such that  $0 \le i_1 < i_2 < i_3 < \cdots < i_k$  and  $\sum_{j=1}^k \binom{i_j}{j} = t$ .
- 2. Use the cover consisting of k sets, where
  - the first set contains the first  $\binom{i_k}{k}$  batches,
  - the second set contains the next  $\binom{i_{k-1}}{k-1}$  batches,
  - and so on.

MIN-SUM DYNAMIZATION, K-COMPONENT DYNAMIZATION INPUT:  $I_1, I_2, ..., I_n$  — a sequence of batches (sets of weighted items) OUTPUT:  $\mathscr{C}_1, \mathscr{C}_2, ..., \mathscr{C}_n$  — a sequence of set covers such that the sets in  $\mathscr{C}_t$  cover all items inserted up to time  $t \left( \bigcup_{S \in \mathscr{C}_t} S = \bigcup_{i=1}^t I_i \right)$ ... INTRO MODEL

Prior results for uniform input, but production LSM-system inputs are online and non-uniform.

Non-uniform inputs can be easier (less costly) than uniform inputs.

### **COMPETITIVE ANALYSIS**

**DEFN:** An algorithm is *online* if its cover at each time t is independent of  $I_{t+1}, I_{t+2}, ..., I_n$ .

**DEFN:** An algorithm is *c*-competitive if, for every input, its solution costs at most *c* times the optimum **Standard** for that input. The competitive ratio of the algorithm is the minimum such *c*.

**GOAL:** online algorithms with smallest possible competitive ratios...

#### PREVIOUS RESULTS

- For Min-Sum Dynamization, Bentley's Binary Transform yields competitive ratio  $\Theta(\log n)$ .
- For k-Component Dynamization, the k-Binomial Transform yields competitive ratio  $\Theta(kn^{1/k})$ .

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#### MIN-SUM DYNAMIZATION, K-COMPONENT DYNAMIZATION

**INPUT:**  $I_1, I_2, ..., I_n$  — a sequence of batches (sets of weighted items)

**OUTPUT**:  $\mathscr{C}_1, \mathscr{C}_2, \dots, \mathscr{C}_n$  — a sequence of set covers such that the sets in  $\mathscr{C}_t$  cover all items inserted up to time  $t \left( \bigcup_{S \in \mathscr{C}_t} S = \bigcup_{i=1}^t I_i \right)$ 

#### **PREVIOUS RESULTS**

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- For Min-Sum Dynamization, Bentley's Binary Transform yields competitive ratio  $\Theta(\log n)$ .
- For k-Component Dynamization, the k-Binomial Transform yields competitive ratio  $\Theta(kn^{1/k})$ .

### **MAIN RESULTS**

- THM 2.1. Min-Sum Dynamization has an online algorithm with competitive ratio  $\Theta(\log^* n)$ .
- **THMS 3.1—3.4.** For k-Component Dynamization, there are deterministic online algorithms with competitive ratio k, and this is best possible for deterministic algorithms.
- **EXTENSIONS**: the *k*-Component Dynamization results extend to allow *lazy deletions*, *updates, item expiration* as they occur in LSM systems such as Bigtable (see the paper).

#### MIN-SUM DYNAMIZATION, K-COMPONENT DYNAMIZATION

**INPUT**:  $I_1, I_2, ..., I_n$  — a sequence of batches (sets of weighted items)

**OUTPUT**:  $\mathscr{C}_1, \mathscr{C}_2, \dots, \mathscr{C}_n$  — a sequence of set covers such that the sets in  $\mathscr{C}_t$  cover all items inserted up to time  $t \left( \bigcup_{S \in \mathscr{C}_t} S = \bigcup_{i=1}^t I_i \right)$ 

#### **PREVIOUS RESULTS**

• • •

- For Min-Sum Dynamization, Bentley's Binary Transform yields competitive ratio  $\Theta(\log n)$ .
- For k-Component Dynamization, the k-Binomial Transform yields competitive ratio  $\Theta(kn^{1/k})$ .

#### MAIN RESULTS

- THM 2.1. Min-Sum Dynamization has an online algorithm with competitive ratio Θ(log\* n).
   OPEN: constant competitive ratio for Min-Sum Dynamization?
- THMS 3.1—3.4. For k-Component Dynamization, there are deterministic online algorithms with competitive ratio k, and this is best possible for deterministic algorithms.
   OPEN: randomized algorithms for k-Component Dynamization?
- EXTENSIONS: the results on k-Component Dynamization extend to allow lazy deletions, updates, item expiration as they occur in big-data storage systems (see the paper).
   OPEN: same extensions for Min-Sum Dynamization?

See the paper for many more open problems.

### RESULTS OPEN PROBLEMS



**THM 2.1.** The online algorithm below has competitive ratio  $\Theta(\log^* n)$ .

at each time  $t \leftarrow 1, 2, ..., n$  do:

1. add current batch  $I_t$  to the current cover as a single new set

- 2. let  $2^{j}$  be the largest power of 2 such that t is an integer multiple of  $2^{j}$
- 3. merge all sets S in the cover such that  $wt(S) \leq 2^{j}$  into one new set



**PROBLEM 1** 

ALGORITHM

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### Problem 2: K-COMPONENT DYNAMIZATION

 $t=1 S \in \mathcal{C}_t \setminus \mathcal{C}_{t-1}$ 

MINIMIZE BUILD COST:  $\sum \sum$ 

INPUT:  $I_1, I_2, ..., I_n$  — a sequence of batches (sets of weighted items) OUTPUT:  $\mathscr{C}_1, \mathscr{C}_2, ..., \mathscr{C}_n$  — a sequence of set covers such that the sets in  $\mathscr{C}_t$  cover all items inserted up to time  $t \left( \bigcup_{S \in \mathscr{C}_t} S = \bigcup_{i=1}^t I_i \right)$ CONSTRAINT:  $|\mathscr{C}_t| \leq k$  — at each time t, cover size is at most k

wt(S)

PROBLEM 2 LOWER BOUND

**THM 3.1**. Any deterministic online algorithm has competitive ratio at least k.

Here we give the idea for k=2.

input alg cover time weight alg cost **OPT cost?** {1} 1  $\{1\}, \{\varepsilon\}$  $1 + \varepsilon$ 2  $\mathcal{E}$  $\{1\}, \{\varepsilon, 0\}$ 0 0 3 Е Е  $\{1\}, \{\varepsilon, 0, 0\}$ 0 0 4 : : :  $\{1\}, \{\varepsilon, 0, 0, ..., 0\}$ 0 0 *m*-1 Е Е  $\{1, \varepsilon, 0, 0, ..., 0, 0\}$ 0  $1 + \varepsilon$ 0 Е m total:  $2 + (m-1)\varepsilon$  $\min(2+\varepsilon, 1+(m-1)\varepsilon)$ Alg chooses  $m \approx 1/\epsilon$ , so If there were no "setup cost"  $\frac{\text{alg cost}}{\text{oPt cost}} \approx \frac{2+1}{2} = 3/2$ of 1 at time 1, ratio would be  $\frac{\text{alg cost}}{\text{OPT cost}} \approx \frac{1+1}{1} = 2$ 

### Problem 2: K-COMPONENT DYNAMIZATION

 $I_1, I_2, ..., I_n$  — a sequence of batches (sets of weighted items) INPUT: **OUTPUT**:  $\mathscr{C}_1, \mathscr{C}_2, \dots, \mathscr{C}_n$  — a sequence of set covers such that the sets in  $\mathscr{C}_t$  cover all items inserted up to time  $t\left(\bigcup_{S\in\mathscr{C}_t}S=\bigcup_{i=1}^t I_i\right)$ 

**CONSTRAINT**:  $|\mathscr{C}_t| \leq k$  — at each time *t*, cover size is at most *k* 

MINIMIZE BUILD COST:  $\sum \quad \sum \quad wt(S)$  $t=1 S \in \mathscr{C}_t \setminus \mathscr{C}_{t-1}$ 

**PROBLEM 2** LOWER BOUND

THM 3.1. Any deterministic online algorithm has competitive ratio at least k.

Here we sketch a proof for k=2.

time	input weight	alg cover	alg cost	OPT cost?	
1	1	{1}	1	1	1
2	Е	$\{1\}, \{\varepsilon\}$	Е	$1 + \varepsilon$	Е
3	0	$\{1\}, \{\varepsilon, 0\}$	Е	0	Е
4	0	$\{1\}, \{\varepsilon, 0, 0\}$	Е	0	Е
0 0 0	•	0 0 0	0 0 0	•	0 0 0
<i>m</i> -1	0	$\{1\}, \{\varepsilon, 0, 0,, 0\}$	Е	0	Е
т	0	$\{1, \varepsilon, 0, 0,, 0, 0\}$	1 <b>+</b> ε	0	Е
<i>m</i> +1	$\sqrt{\epsilon}$	$\{1, \varepsilon, 0,, 0\}, \{\sqrt{\epsilon}\}$	$\sqrt{\epsilon}$	$1 + \sqrt{\epsilon} + \epsilon$	$\sqrt{\epsilon} + \epsilon$
<i>m</i> +2	0	$\{1, \varepsilon, 0,, 0\}, \{\sqrt{\epsilon}, 0\}$	$\sqrt{\epsilon}$	0	$\sqrt{\epsilon} + \epsilon$
:	:	:	:	:	:
	0	$\{1, \varepsilon, 0,, 0\}, \{\sqrt{\epsilon}, 0,, 0\}$	$\sqrt{\epsilon}$	0	$\sqrt{\epsilon} + \epsilon$
	0	$\{1, \varepsilon, 0,, 0, \sqrt{\epsilon}, 0,, 0\}$	$1 + \sqrt{\epsilon} + \epsilon$	0	$\sqrt{\epsilon} + \epsilon$

r this second und the ratio is  $2 - O(\sqrt{\epsilon})$ . peating drives e total ratio bitrarily near 2.



The paper also gives a second "recursive rent-or-buy" algorithm with a very different analysis.

PROBLEM 2 ALGORITHM 1

for Problem 2, k-Component Dynamization:

**THM 3.2.** The online algorithm below has competitive ratio k.

at each time  $t \leftarrow 1, 2, ..., n$ , in response to batch  $I_t$  do:

- 1. if there are k sets in the cover:
  - a. increase all sets' credits continuously until a set S has credit[S]  $\geq$  wt(S)
  - b. let  $S_t$  be the oldest such set
  - c. merge  $I_t$ ,  $S_t$ , and all sets newer than  $S_t$  into one new set with credit 0
- 2. else: add  $I_t$  as a new set, with credit 0

### **PROOF OUTLINE:**

- 1. let  $\delta_t$  be the decrease in credit in iteration t
- 2. total credit given to sets is  $k \sum_{t} \delta_{t}$
- 3. sets  $S_t$  contribute at most  $k \sum_t \delta_t$  to algorithm's cost (as credit $[S_t] \ge wt(S_t)$  when merged)
- 4. remaining sets contribute at most  $k \sum_{t} wt(I_t)$  to algorithm's cost (as items decrease in "rank")
- 5. so algorithm's cost is at most  $k \sum_{t} \operatorname{wt}(I_t) + \delta_t$
- 6. charge credit to OPT (via implicit LP-dual soln) to show OPT cost is at least  $\sum_{t} wt(I_t) + \delta_t$

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# QUESTIONS, IF TIME PERMITS