

A Fully On-disk Updatable Learned Index

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FACT 1

Learned indexes in **main memory** show promising performance in **throughput** and **index size**. FACT 2

Widely used database systems are still **on disk** due to the large dataset size, index size and so on.



The Case for Learned Index Structures SIGMOD 2020



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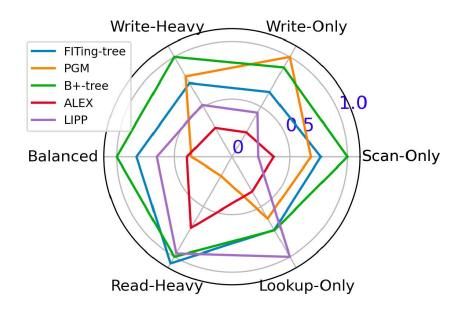
Can we apply learned indexes on the disk setting?



The Case for Learned Index Structures SIGMOD 2020



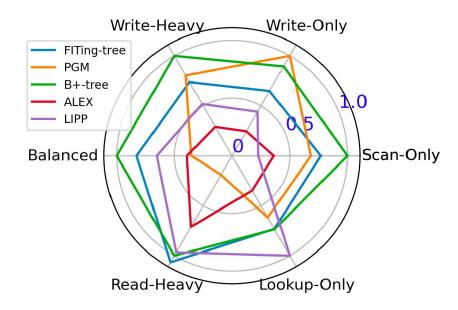
Normalized throughputs on the FB dataset





Updatable Learned Indexes Meet Disk-Resident DBMS - From Evaluations to Design Choices SIGMOD 2023

Normalized throughputs on the FB dataset



Overall, **B+-tree** is the (second-)best.

LIPP outperforms other indexes on Lookup-Only workload.

PGM outperforms other indexes on **Write-Only** workload.



Updatable Learned Indexes Meet Disk-Resident DBMS - From Evaluations to Design Choices SIGMOD 2023

#blocks/nodes fetched in Read-Only workload

_						- Lookup
				# Total Block <mark>s</mark> (L)		← Scan
	FITing-tree	5	3	4.2	5	
	PGM	6	3.9	5.2	5.6	
-	ALEX	7.7	6.5	8.1	10.6	
	LIPP	1.8 (18.8)	-	3	24	
	B+-tree	4	3	4	4.5	

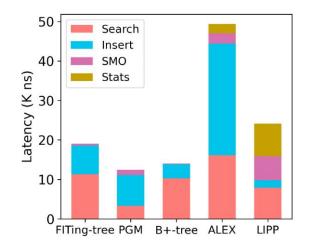
Challenge 1. A learned index cannot guarantee to reduce **I/O costs** when searching data on disk.

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Latency breakdown in Write-Only workload



Challenge 2. Most learned indexes suffer from large **insertion overheads**.

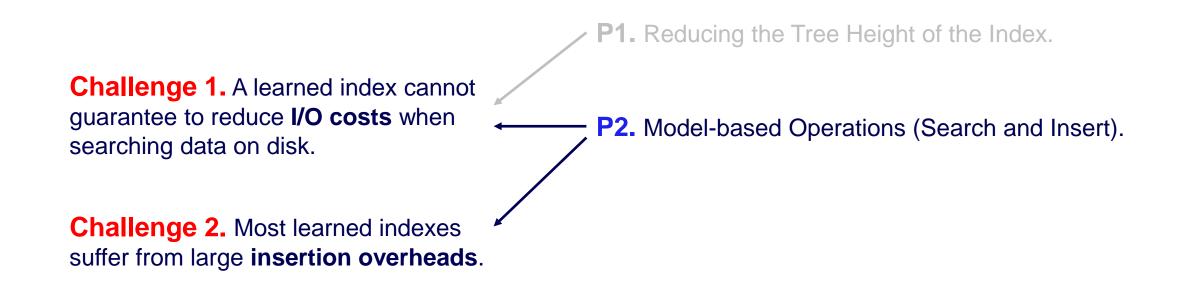
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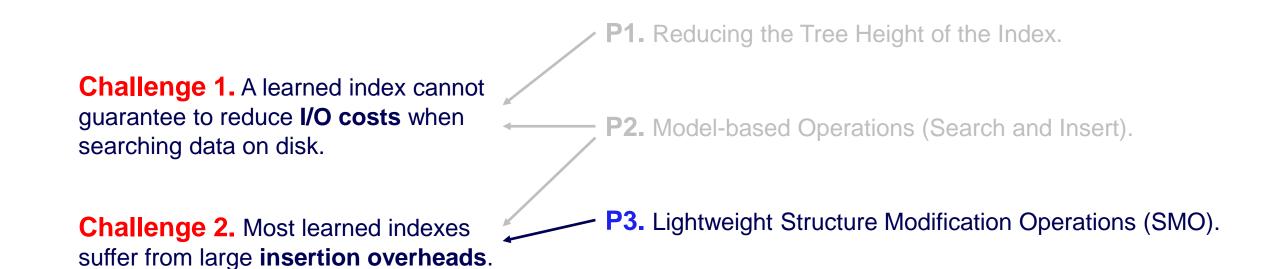
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P1. Reducing the Tree Height of the Index.

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 P1. Reducing the Tree Height of the Index.
 P2. Model-based Operations (Search and Insert).
 P3. Lightweight Structure Modification Operations (SMO).

P4. Better Scan Performance.

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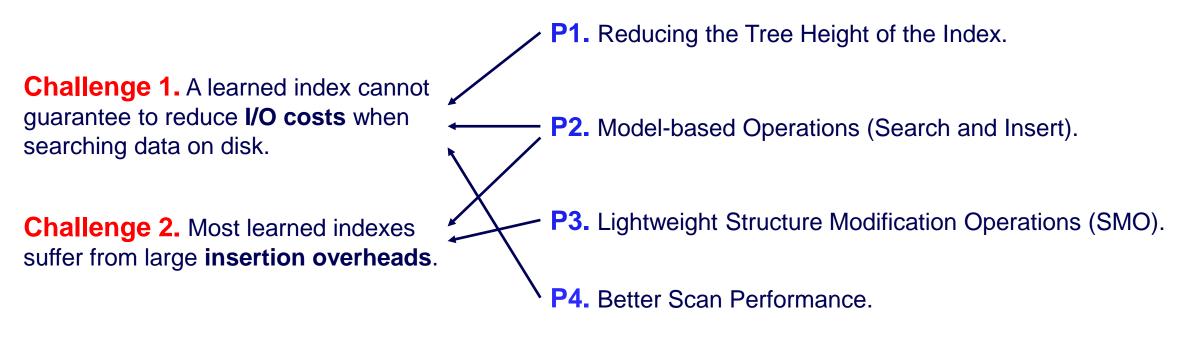
P1. Reducing the Tree Height of the Index.

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P4. Better Scan Performance.

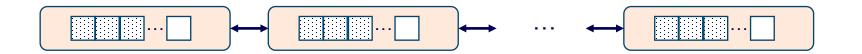
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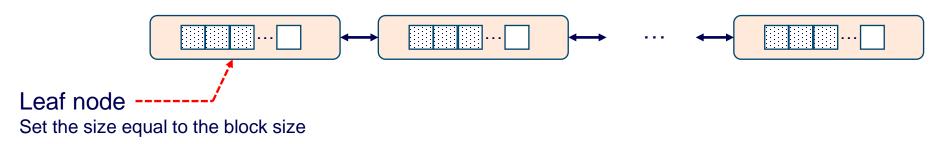
P5. Support Duplicate Index Keys.

AULID, <u>an updatable</u> <u>learned</u> <u>index on</u> <u>d</u>isk <u>Simple Yet Effective</u>

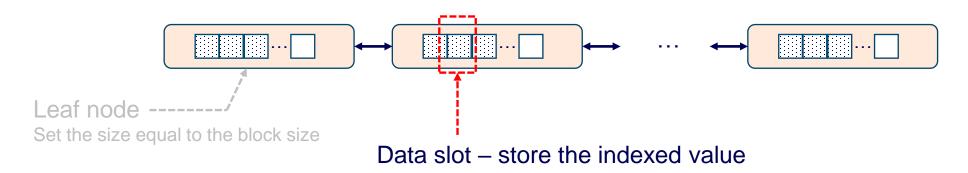
Leaf Node Layer

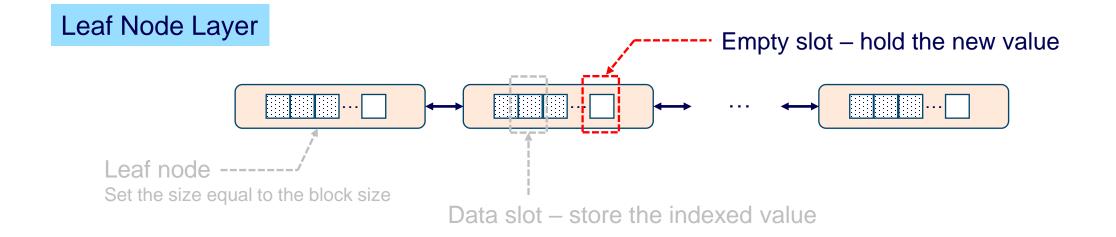


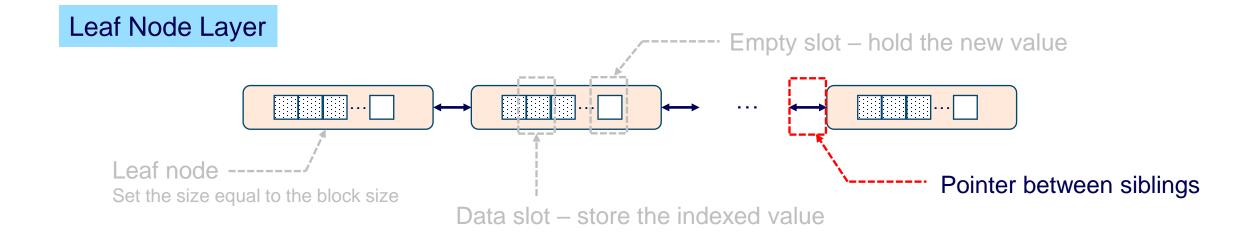
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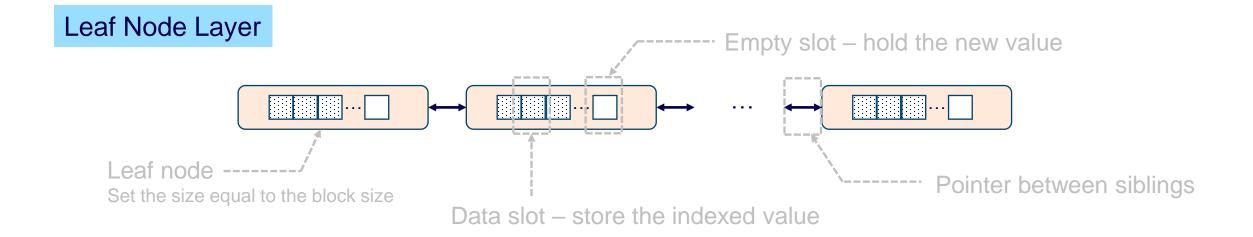


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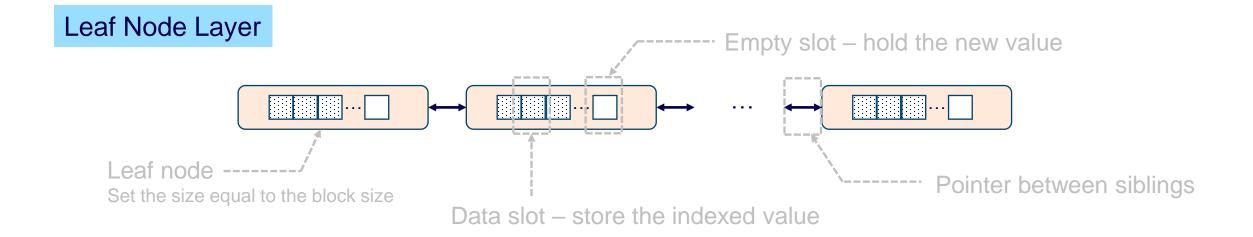






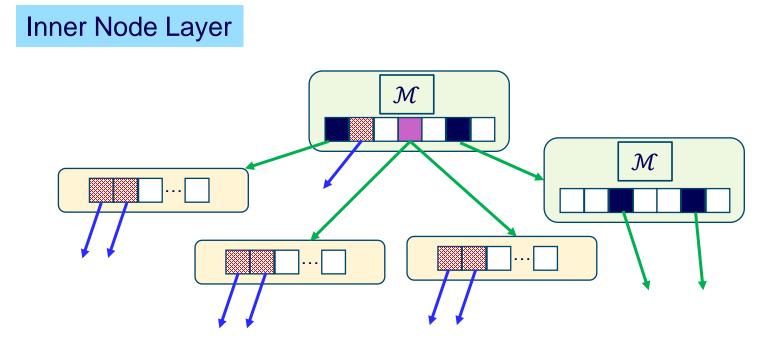
Benefits

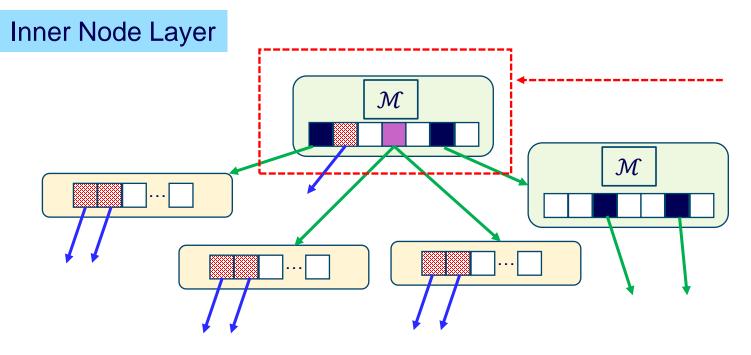
- Low overhead for scan operations in fetching the *next* item (P4).



Benefits

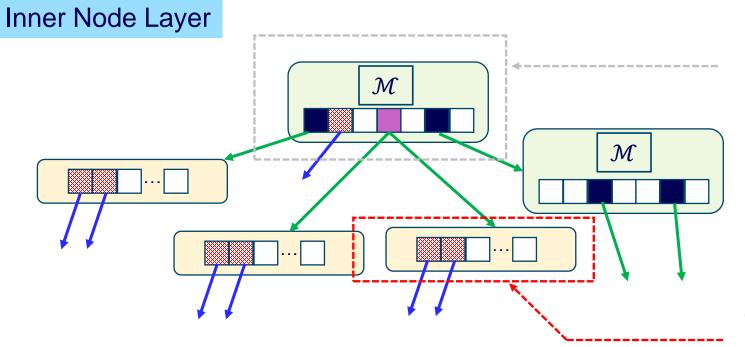
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- Low insertion overhead and SMO overhead (P3).





Mixed inner node

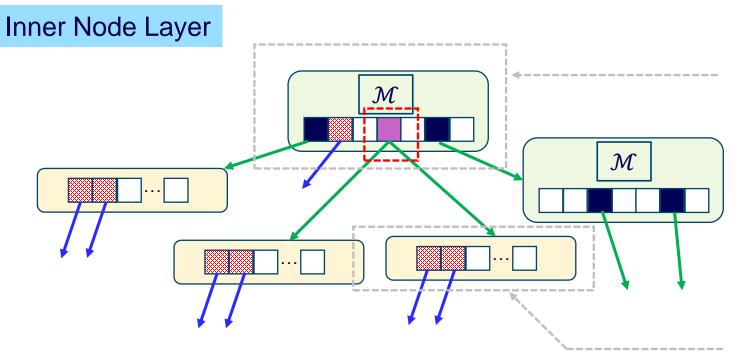
- Can hold different **slot** types
- Use a **model** to determine which slot to be accessed next



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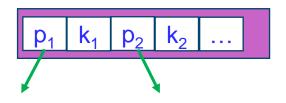
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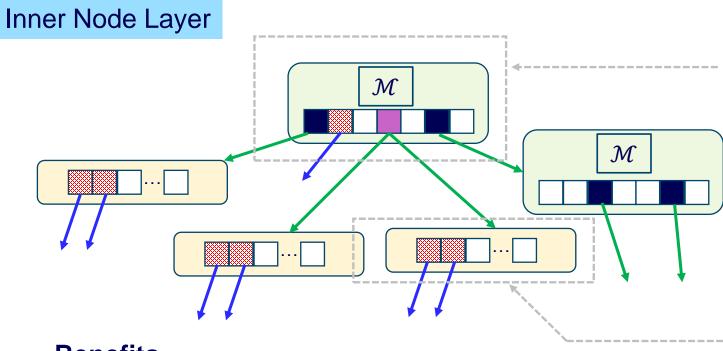


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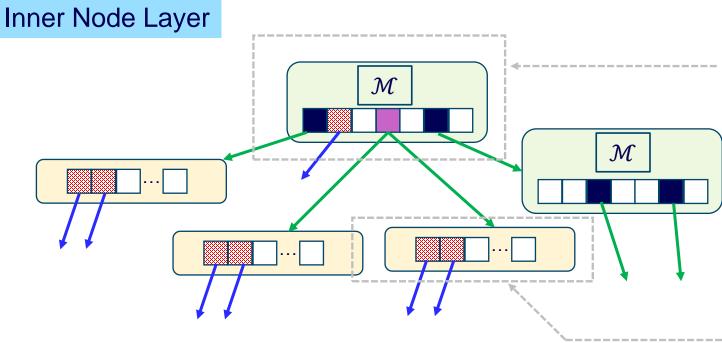
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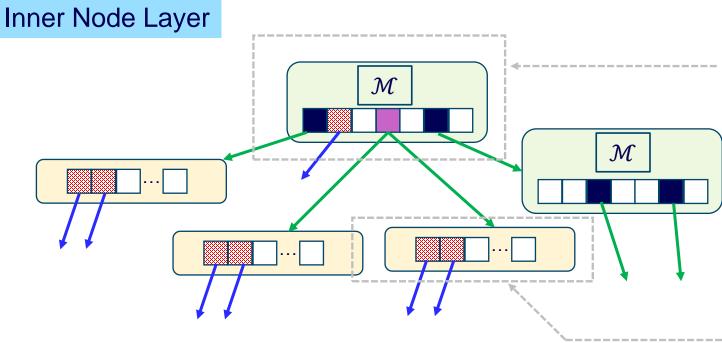
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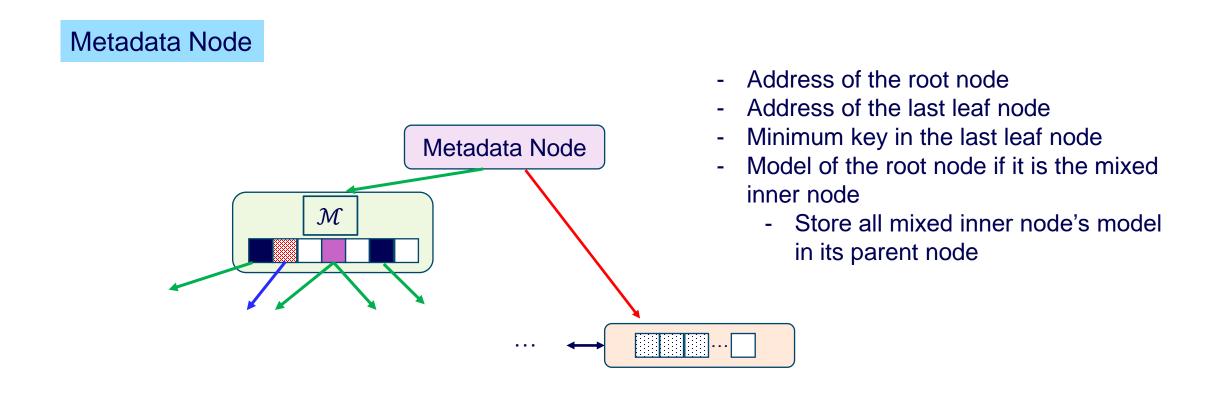
Benefits

- Reducing the **tree height** of the index (P1).
- Model-based operations (search and insert) (P2).
- Low **SMO** overhead in inner nodes (**P3**).

Mixed inner node

- Can hold different **slot** types
- Use a **model** to determine which slot to be accessed next

Packed inner node



Bulkload

Step 1: Construct the leaf nodes and collect the maximum key and address of each leaf node.

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Step 2: Call **FMCD**-based algorithm to construct the inner nodes.

Fastest Minimum Conflict Degree (FMCD)



Updatable Learned Index with Precise Positions VLDB 2021

Bulkload

Step 1: Construct the leaf nodes and collect the maximum key and address of each leaf node.

Step 2: Call **FMCD**-based algorithm to construct the inner nodes.

Packed inner nodes to hold the keys when #keys mapped to the same slot is not greater than **64**.

A special routing slot to hold the keys when #keys mapped to the same slot is greater than 64 while not larger than 1024.

When #keys mapped to the same slot is greater than **1024**, we build another **mixed node**.



Bulkload

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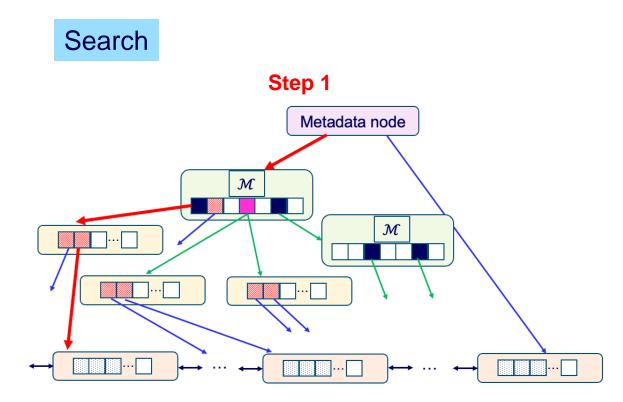
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Step 3: Build the metadata node.

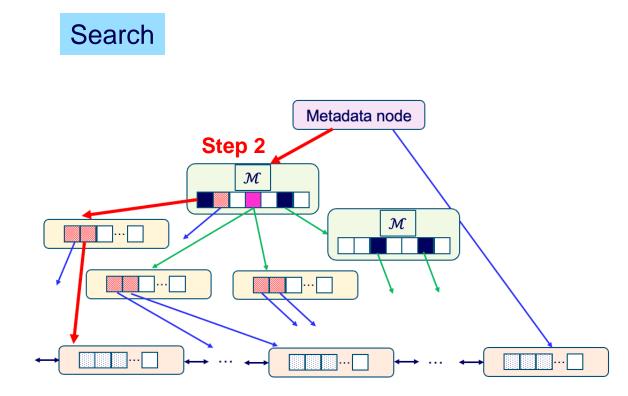
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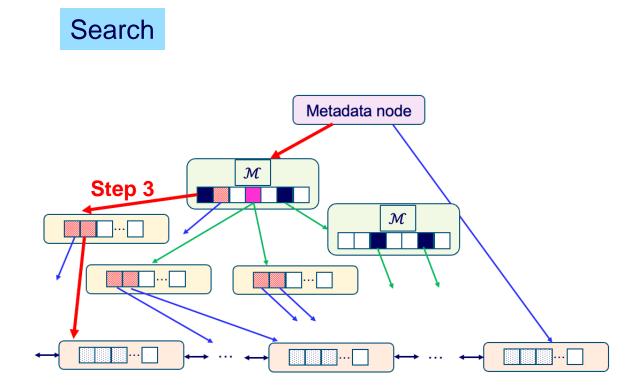
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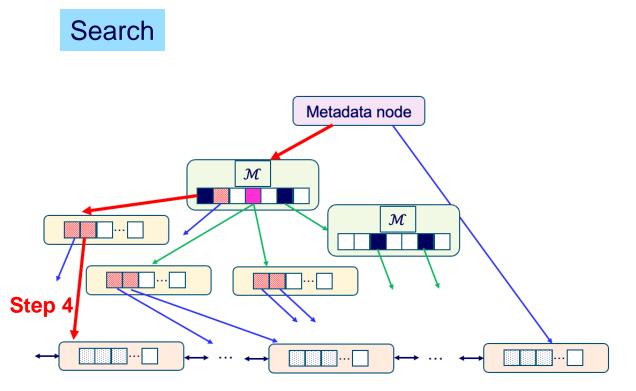


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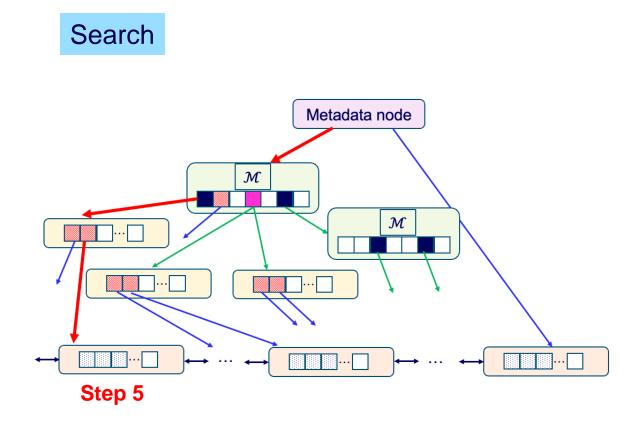
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Step 5: Do a binary search on the leaf node.

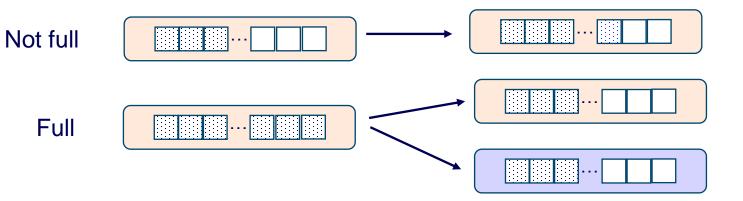
Insert

Step 1: Insert into leaf node



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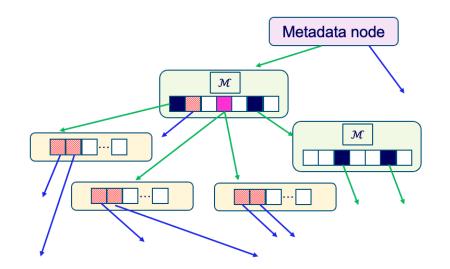


Store the large half values in the **original** block.

Collect address and key_{max} of the new leaf node.

Insert

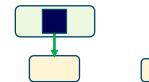
Step 2: Insert (key_{max}, addr) into the inner nodes.

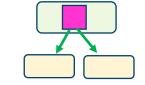


1. Empty slot





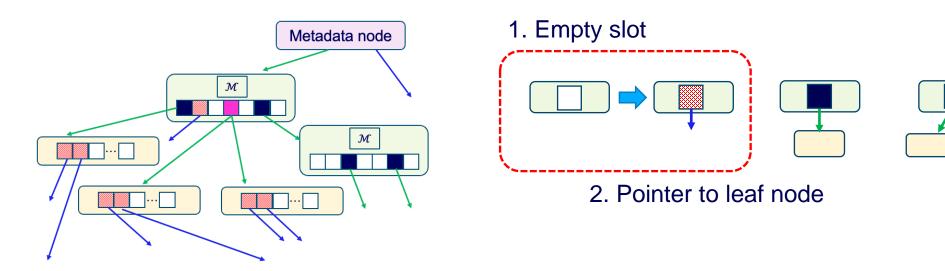




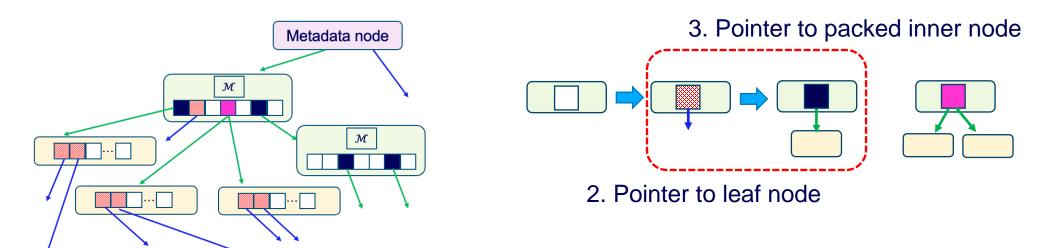
2. Pointer to leaf node

4. Special routing slot

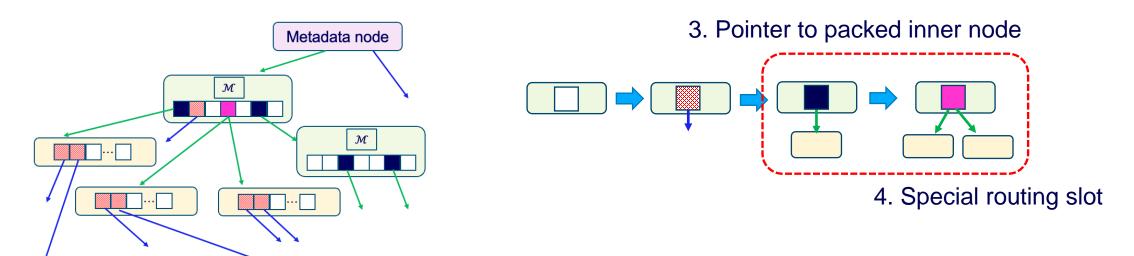
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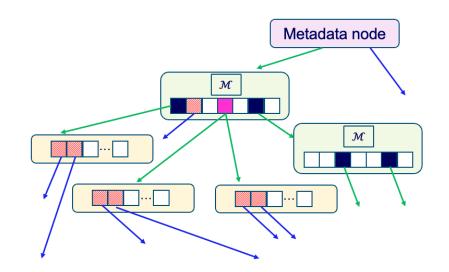
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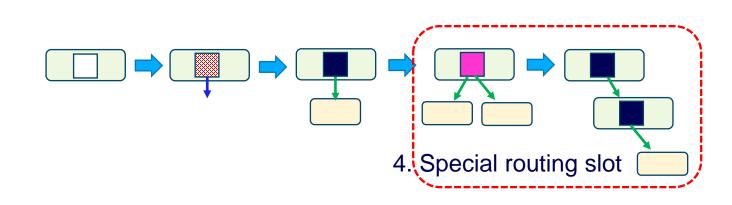


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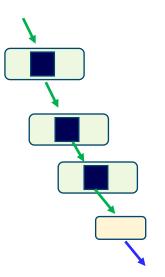
Insert





Tree Adjustment

Why – with more data inserted, some parts of the index may have a large height.

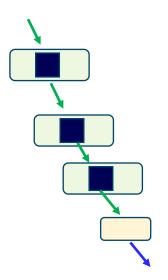


Tree Adjustment

Why – with more data inserted, some parts of the index may have a large height.

When – two criteria met at the same time:

- Percentage of the items in a subtree rooted at node n in the third layer or a deeper layer is larger than α .
- Number of current items rooted at node n is larger than β times of the initial size.



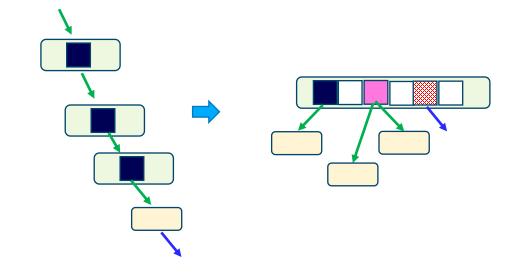
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How – reload the inner node items rooted at node n and call our revised FMCD algorithm.



Experiment – Goal

Q1: How good is AULID as compared to other learned indexes and a B+-tree when disk-resident?

Q2: How well does AULID scale to large datasets?

Q3: Do the proposed index structure design and structural modification operation help improve the performance?

Q4: What are the impacts of different parameter settings on AULID performance?

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Experiment – Setup

Datasets

Hardness		Global Hardness		
		Easy	Normal	Hard
Local Hardness	Easy	C1		
	Normal		C2	C4
	Hard		C3	

C1: COVID (200M / 800M)
C2: PLANET (200M / 800M)
C3: GENOME (200M / 800M)
C4: OSM (200M / 800M)

Baselines ALEX, PGM, FITing-tree, LIPP, B+-tree



Are Updatable Learned Indexes Ready? VLDB 2022

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Updatable Learned Indexes Meet Disk-Resident DBMS - From Evaluations to Design Choices SIGMOD 2023

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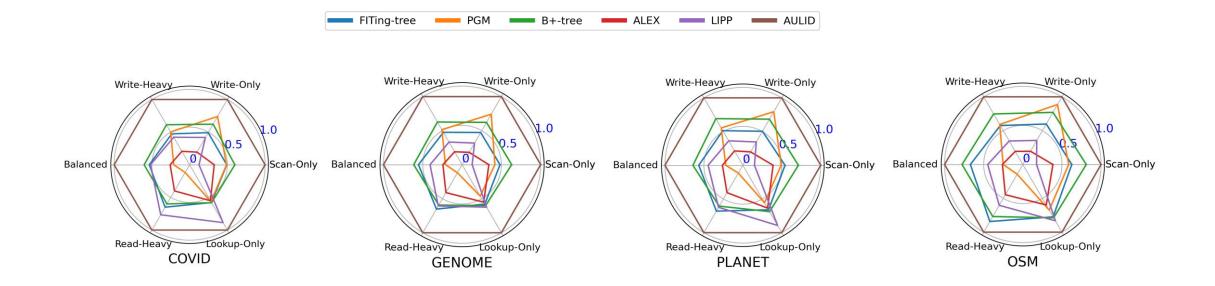
Workload

Lookup-Only	Scan-Only	Write-Only	Write-Heavy	Balanced	Read-Heavy
100% lookups	100% scans	100% inserts		50% inserts 50% lookups	10% inserts 90% lookups

Metric



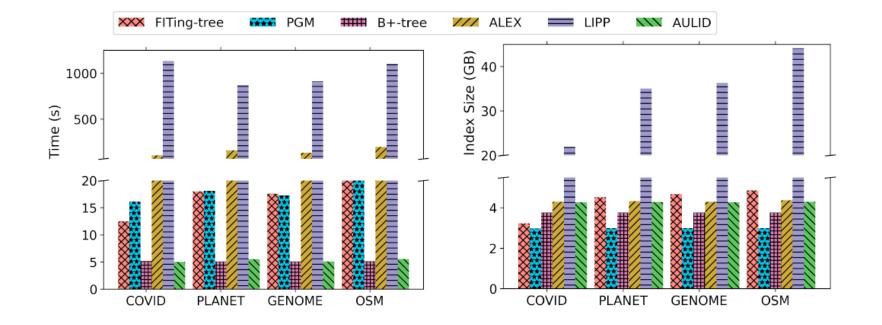
Experiment – Throughput Comparison



✓ AULID significantly beats other indexes in all datasets and workloads.

 \checkmark B+-tree is the **second best** in **most** workloads and datasets.

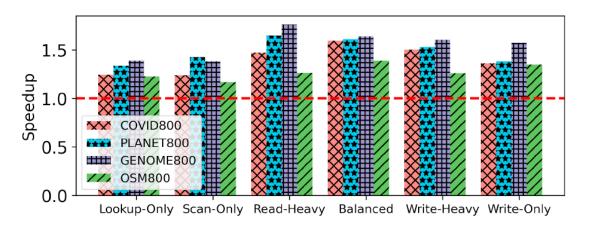
Experiment – Bulkload & Storage



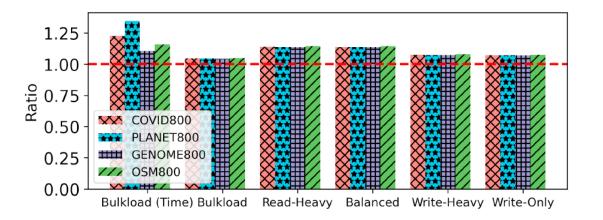
✓ AULID has **similar** bulkload time to B+-tree and is **faster** than other indexes.

✓ AULID has a **stable** index size among different dataset and is **competitive** to B+-tree.

Experiment – Large Scale Data



Throughput Speedup



Storage/time ratio

✓ The superiority of AULID also holds on large scale datasets.

Conclusion

□We reveal the **challenges** when applying the learned indexes on disk and propose our design **principles**.

□We propose AULID to meet the principles with the carefully designed index layout and operations.

□Our experiments show AULID **significantly beats** our baselines in all workloads and testing datasets.

Thanks!