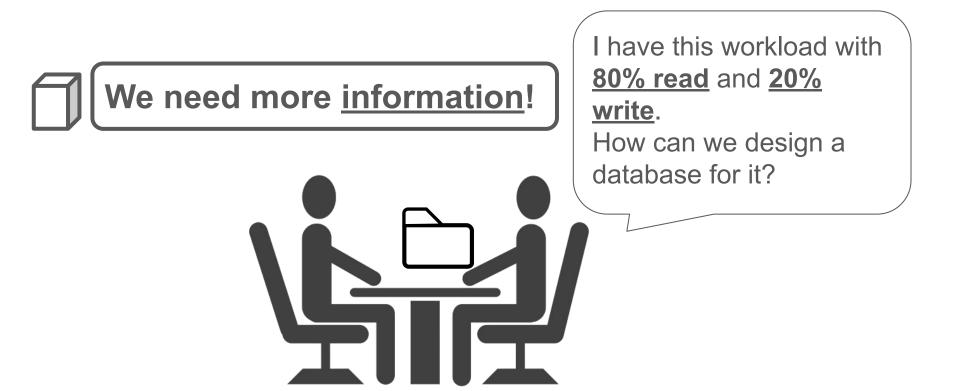
The Data Calculator

Authors: Stratos Idreos, Kostas Zoumpatianos, Brian Hentschel, Michael S. Kester, Demi Guo

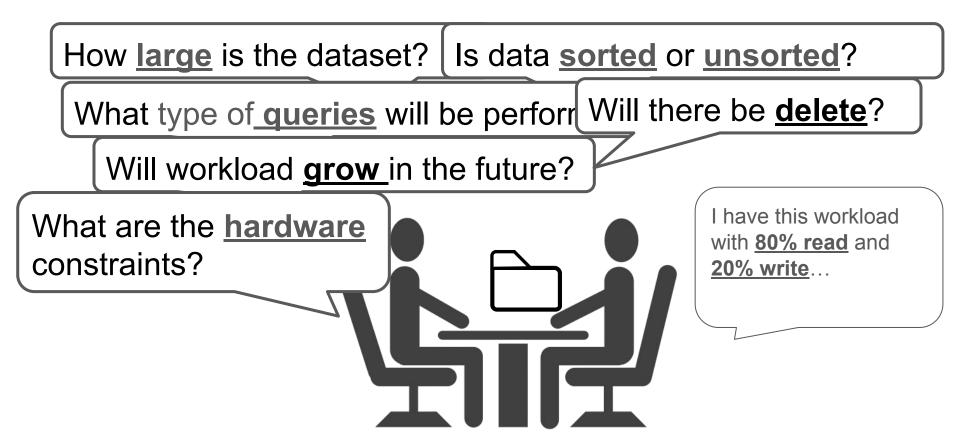
Presented by: Minjie Tang, Alec Gallardo, Ge Gao

Once Upon A Time...

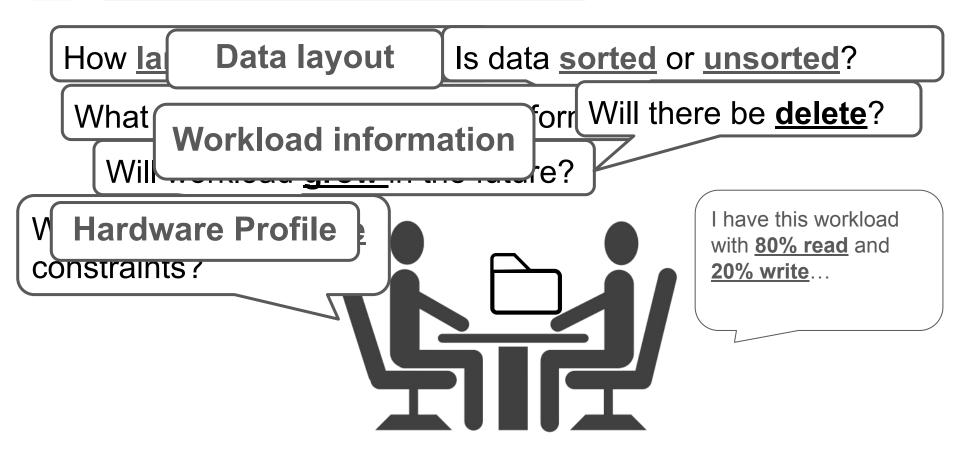
(?) What would be the <u>best data structure</u> to store this data?











Design Questions



Can we build upon a simple data structure?



Can we tune it based on our needs



Or build a new one from scratch?

 $\bigoplus_{a}^{\textcircled{B}}$ How can we take advantage of the hardware?

What if we add a Bloom filter? What if the workload shifts? What if...

Design Questions



Can we build upon a simple data structure?



Can we tune it based on our needs



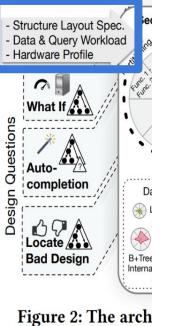
Or build a new one from scratch?



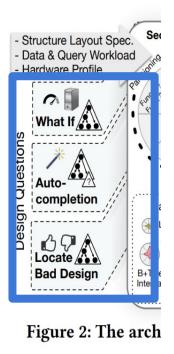
• What if we add a Bloom filter? What if the workload shifts? What if...

We wouldn't be able to implement them all!





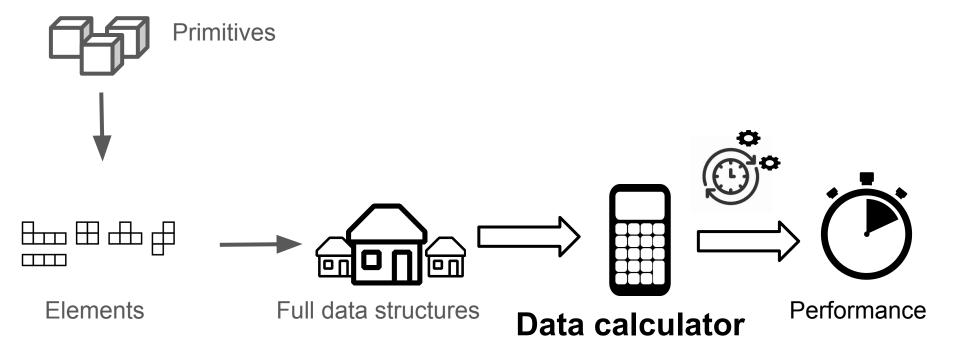
We know these



Now we want to answer these







Using Data Calculator

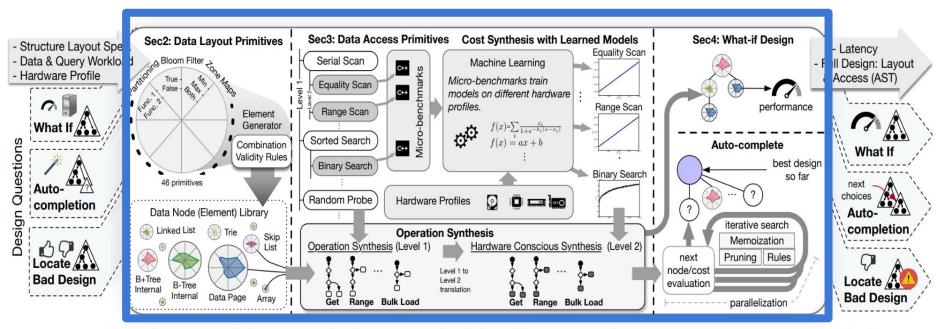
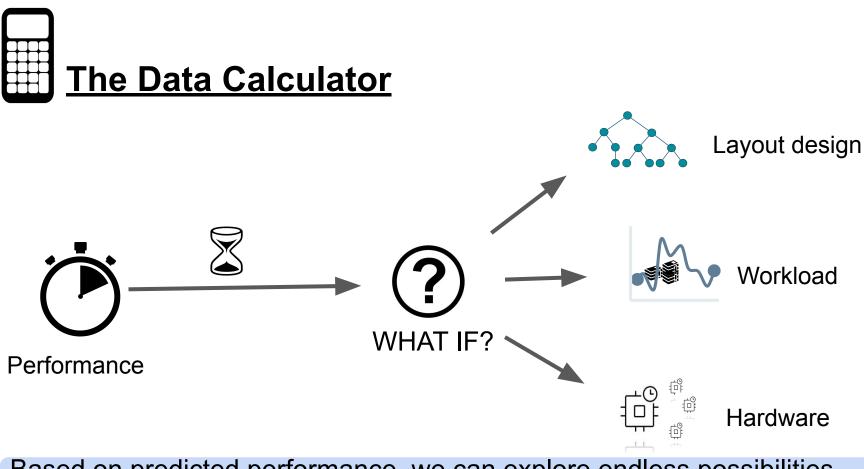


Figure 2: The architecture of the Data Calculator: From high-level layout specifications to performance cost calculation.



Based on predicted performance, we can explore endless possibilities —without implementing them!

Using Data Calculator

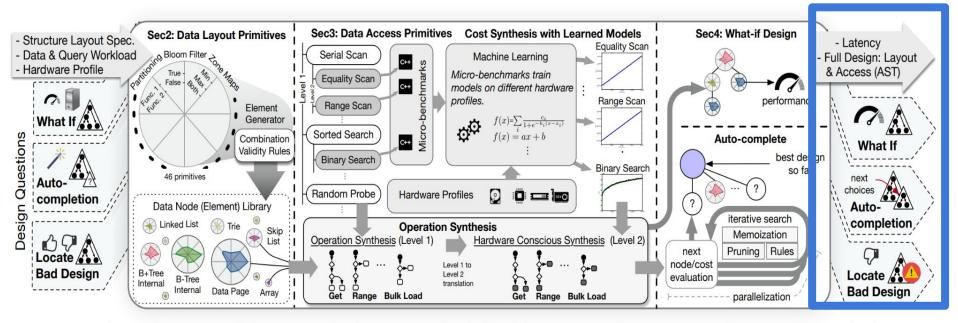
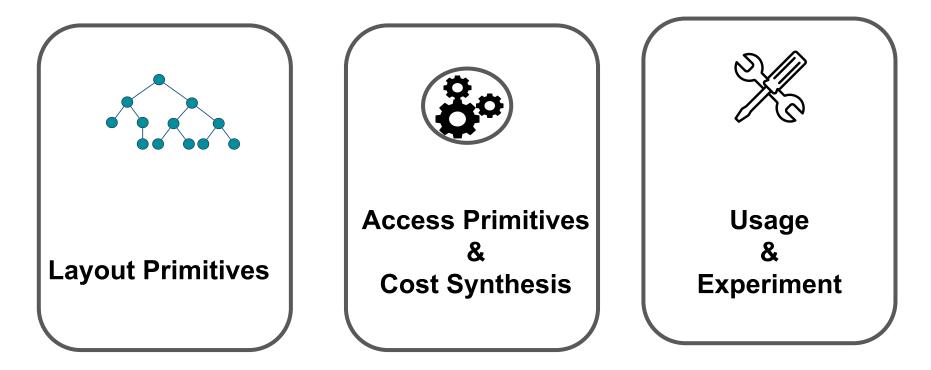
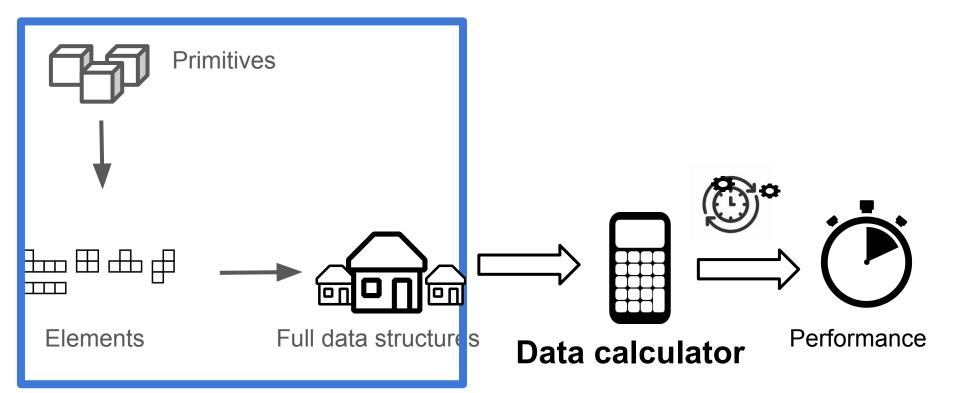


Figure 2: The architecture of the Data Calculator: From high-level layout specifications to performance cost calculation.

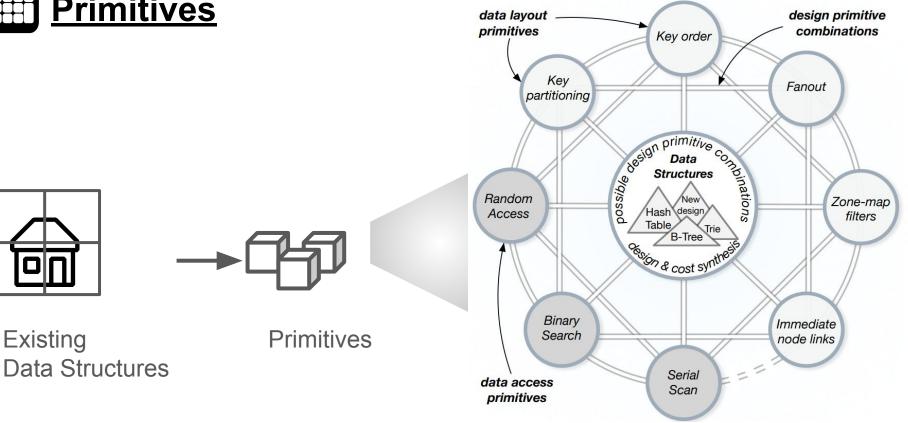




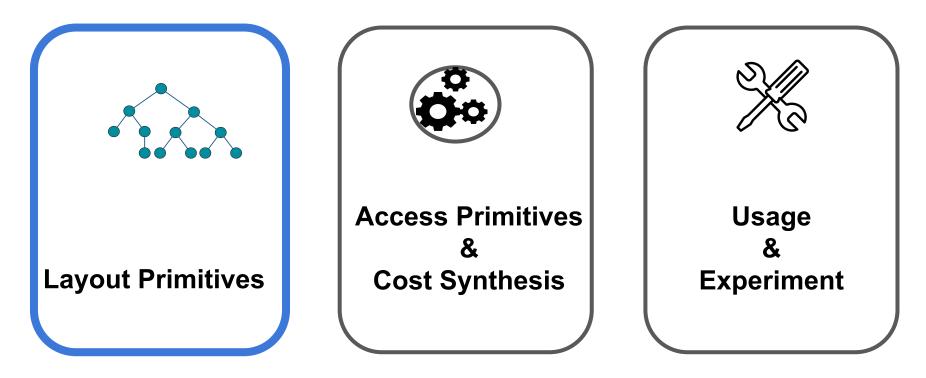


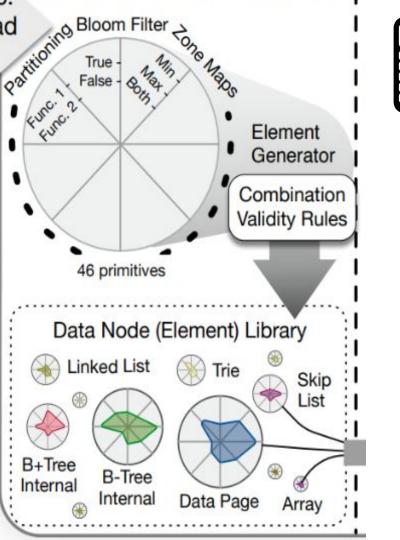












Data Layout Primitives

• defines aspects of a data structure's layout



node organization



partitioning



physical placement



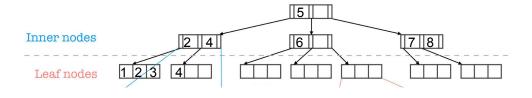


Key order: Sorted

↔ Sub-block physical layout: BFS



Yes(Leaf nodes)





Key order: Sorted

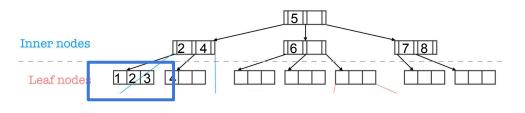
↔ Sub-block physical layout: BFS



Yes(Leaf nodes)

Memory layout:



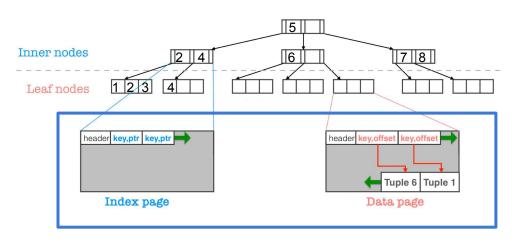




Key order: Sorted

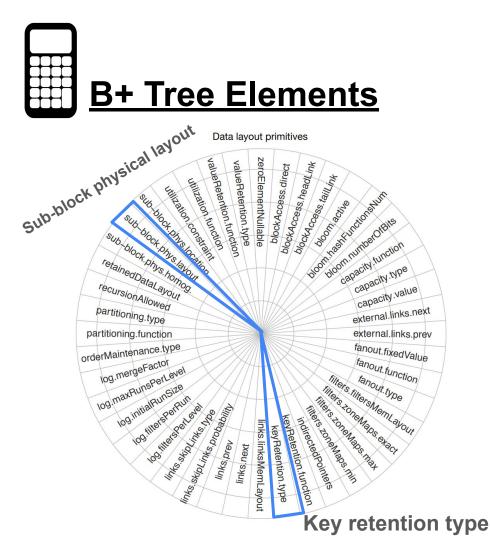
- ↔ Sub-block physical layout: BFS
 - Key retention: None (Inner nodes),

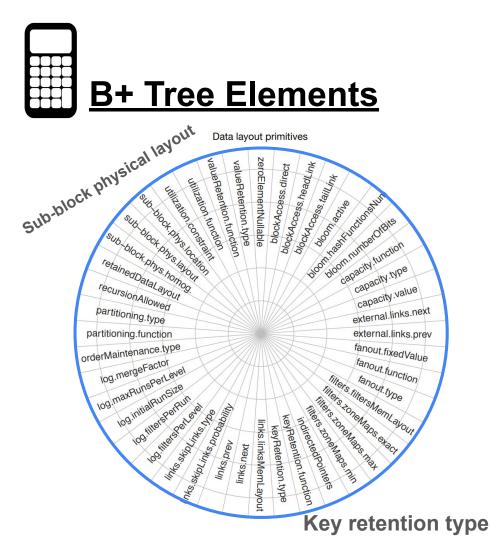
Yes(Leaf nodes)



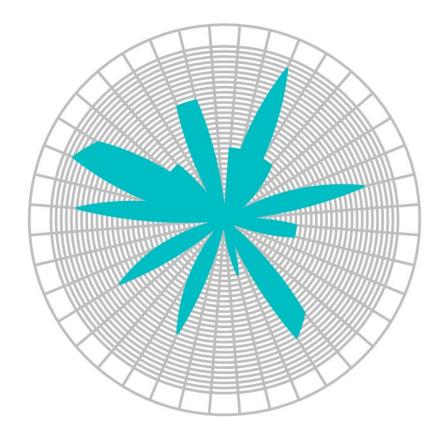
Memory layout:



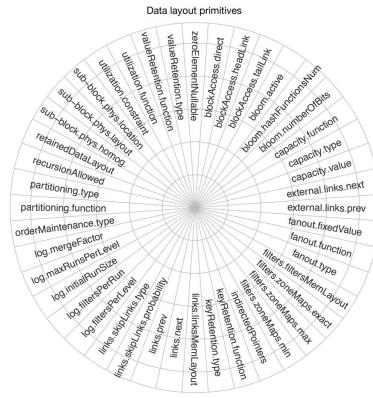


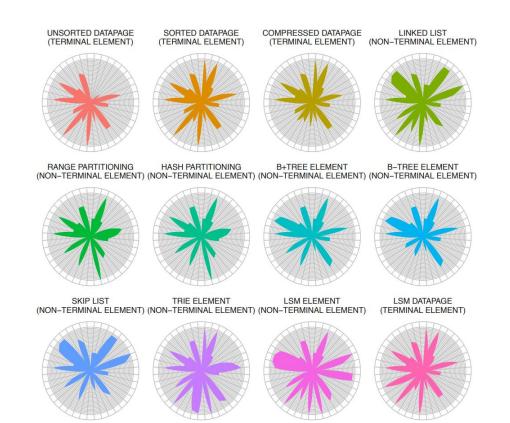


B+TREE ELEMENT (NON-TERMINAL ELEMENT)



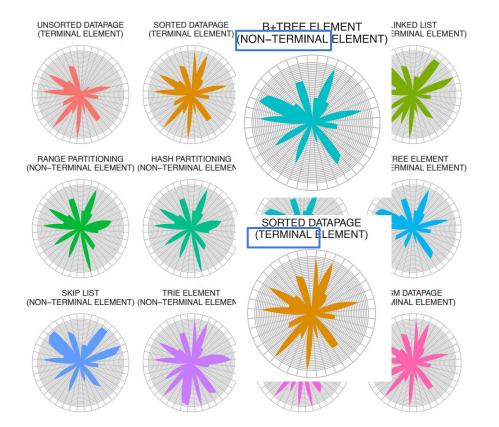






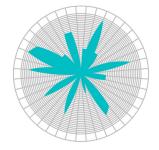


٦	Element: defining how data is stored
	and accessed in that node.



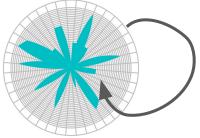


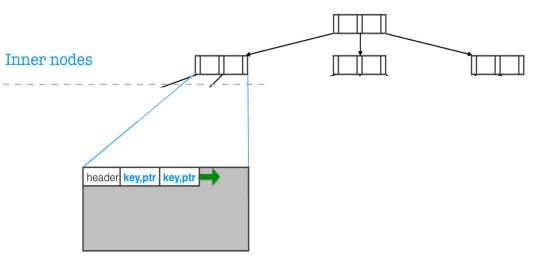
B+TREE ELEMENT (NON-TERMINAL ELEMENT)





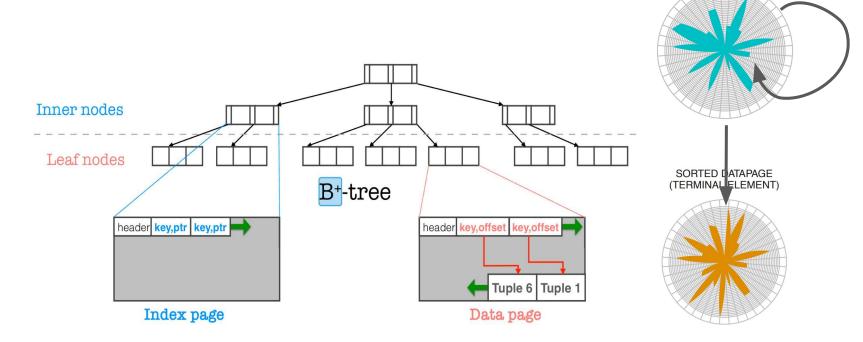




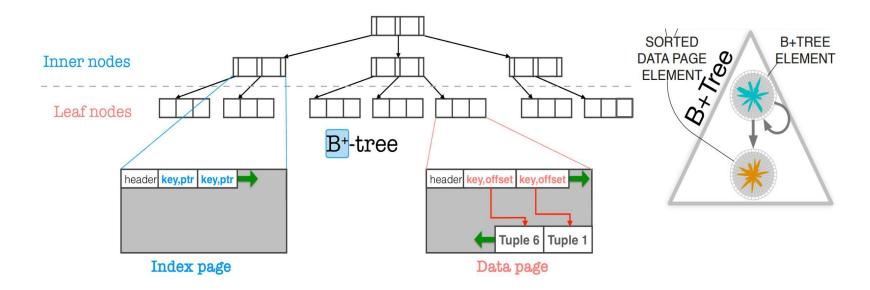


Index page







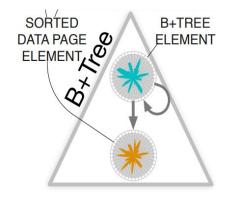


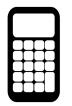


Non-terminal element: act as internal nodes that point to other elements (e.g., internal nodes in a tree).

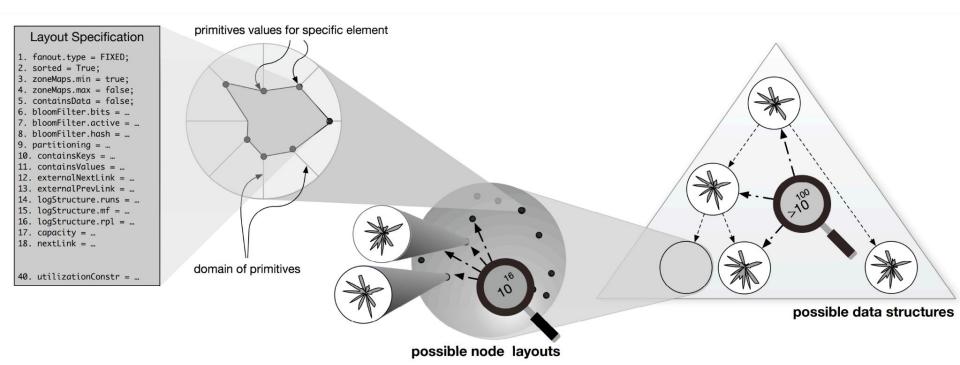


Terminal element: contain the actual data (e.g., leaves in a B+Tree).



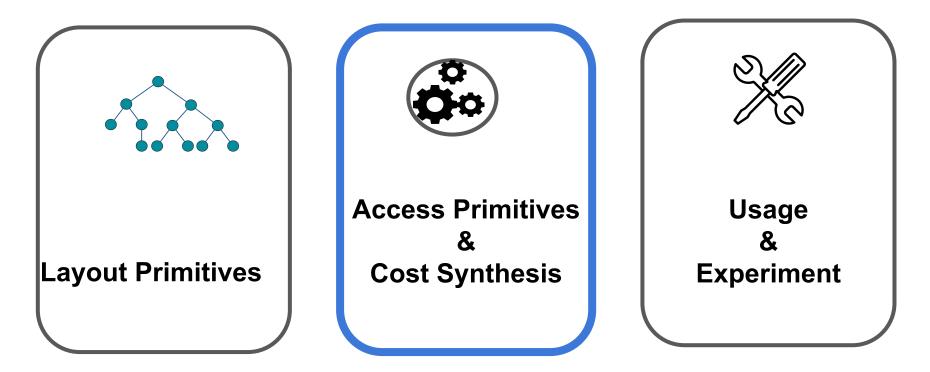


Size of Design space



https://stratos.seas.harvard.edu/files/stratos/files/periodictabledatastructures.pdf







Data Access Primitives

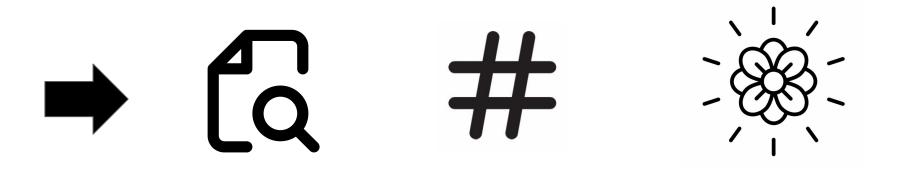


Cost Synthesis

What are access primitives?

Definition: Each access primitive characterizes one aspect of how data is accessed.

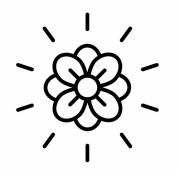




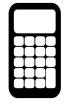
Scan Sorted Search Hash Probe

Bloom Filter Probe





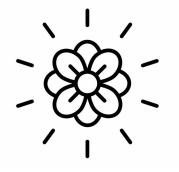
Bloom Filter Probe



Examples of Data Access Primitives

Advantages:

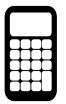
- Reduced I/O's
- Fast
- Space Efficient



Disadvantages:

• False Positives

Bloom Filter Probe



Advantages of Different Data Access Primitives



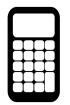
- Good for non-selective queries
- No Index
 Required



- Good for point queries
- Efficient Memory Usage

Scan

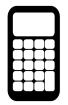
Hash Probe



Examples of Data Access Primitives

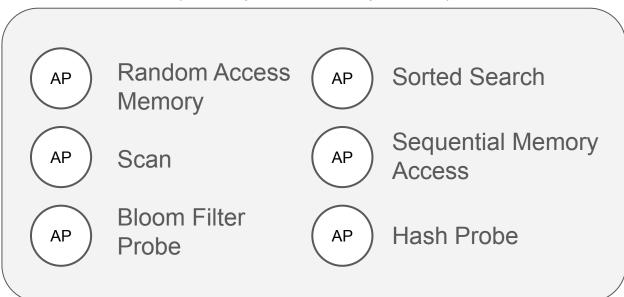
Different Access Primitives Have Different Advantages

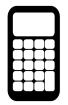
Data Access Primitives and Fitted Models				
	Data Access Primitives Level 1 (required parameters ; optional parameters)	Model Parameters	Data Access Primitives Layer 2	Fitted Models
1	Scan	Data Size	Scalar Scan (RowStore, Equal)	Linear Model (1)
2	(Element Size, Comparison,		Scalar Scan (RowStore, Range)	Linear Model (1)
3	Data Layout; None)		Scalar Scan (ColumnStore, Equal)	Linear Model (1)
4			Scalar Scan (ColumnStore, Range)	Linear Model (1)
5			SIMD-AVX Scan (ColumnStore, Equal)	Linear Model (1)
6			SIMD-AVX Scan (ColumnStore, Range)	Linear Model (1)
7	Sorted Search	Data Size	Binary Search (RowStore)	Log-Linear Model (2)
8	(Element Size, Data Layout;)		Binary Search (ColumnStore)	Log-Linear Model (2)
9			Interpolation Search (RowStore)	Log + LogLog Model (3)
10			Interpolation Search (ColumnStore)	Log + LogLog Model (3)
	Hash Probe (; Hash Family)	Structure Size	Linear Probing (Multiply-shift [29])	Sum of Sigmoids (5), Weighted Nearest Neighbors (7)
12			Linear Probing (k-wise independent, k=2,3,4,5)	Sum of Sigmoids (5), Weighted Nearest Neighbors (7)
13	Bloom Filter Probe (; Hash Family)	Structure Size, Number of Hash Functions	Bloom Filter Probe (Multiply-shift [29])	Sum of Sum of Sigmoids (6), Weighted Nearest Neighbors (7)
14			Bloom Filter Probe (k-wise independent, k=2,3,4,5)	Sum of Sum of Sigmoids (6), Weighted Nearest Neighbors (7)
15	Sort	Data Size	QuickSort	NLogN Model (4)
16	(Element Size; Algorithm)		MergeSort	NLogN Model (4)
17			ExternalMergeSort	NLogN Model (4)
18	Random Memory Access	Region Size	Random Memory Access	Sum of Sigmoids (5), Weighted Nearest Neighbors (7)
19	Batched Random Memory Access	Region Size	Batched Random Memory Access	Sum of Sigmoids (5), Weighted Nearest Neighbors (7)
20	Unordered Batch Write	Write Data Size	Contiguous Write (RowStore)	Linear Model (1)
21	(Layout;)		Contiguous Write (ColumnStore)	Linear Model (1)
22	Ordered Batch Write	Write Data Size,	Batch Ordered Write (RowStore)	Linear Model (1)
23	(Layout;)	Data Size	Batch Ordered Write (ColumnStore)	Linear Model (1)
24	Scattered Batch Write	Number of Elements,	ScatteredBatchWrite	Sum of Sum of Sigmoids
		Region Size		(6), Weighted Nearest
		-		Neighbors (7)



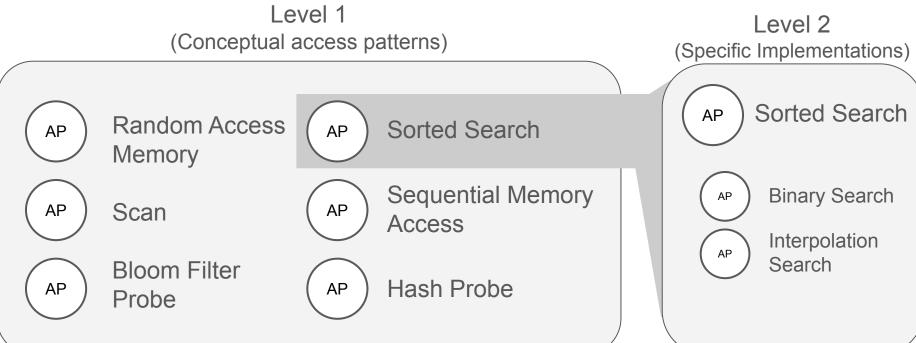
Levels of Data Access Primitives

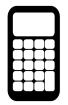
Level 1 (Conceptual access patterns)



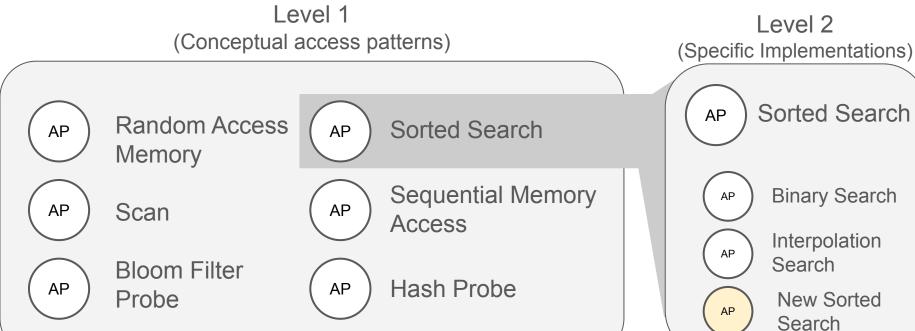


Levels of Data Access Primitives



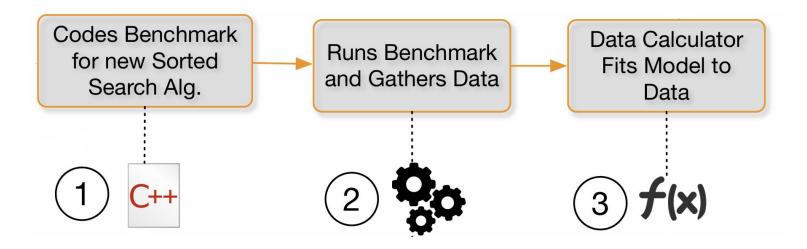


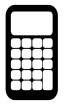
Levels of Data Access Primitives



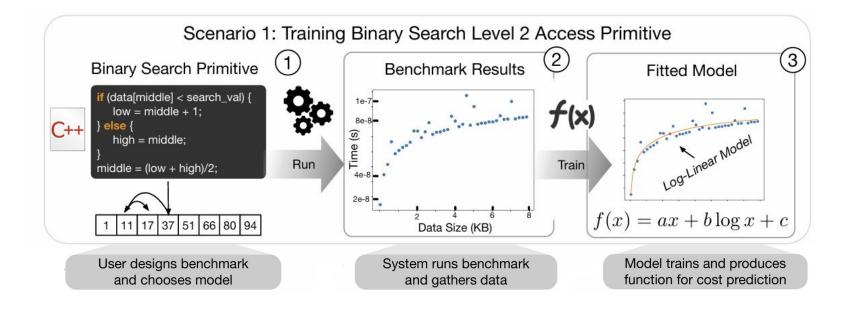


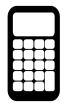
Learned Cost Models





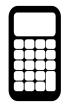
Learned Cost Model Examples





Learned Cost Models (examples)

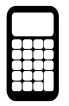
Models used for fitting data access primitives			
	Model	Description	
1	Linear	Fits a simple line through data	
2	Log-Linear	Fits a linear model with a basis composed of the identity and logarithmic functions plus a bias	
3	Log+LogLog	Fits a model with log, log-log, and linear components	
4	NLogN	Fits a model with primarily an NlogN and linear component	
5	Sum of Sigmoids	Fits a model which has two cost components, both of which have <i>k</i> approximate steps occurring at the same locations.	
6	Sum of Sum of Sigmoids	Fits a model which has two cost components, both of which have <i>k</i> approximate steps occurring at the same locations.	
7	Weighted Nearest Neighbors	Takes the k nearest neighbors under the I_2 norm and computes a weighted average of their outputs. The input x is allowed to be a vector of any size.	



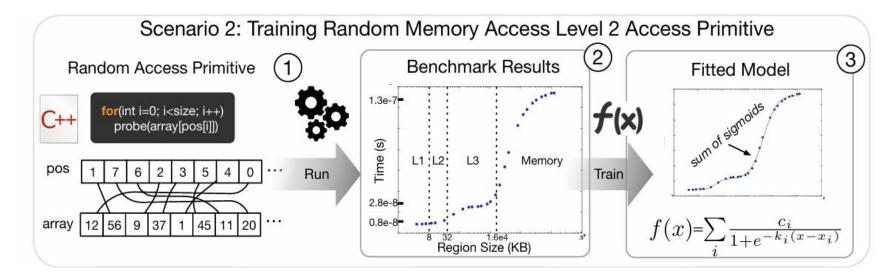
Learned Cost Models (examples)

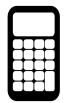


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Learned Cost Model Examples





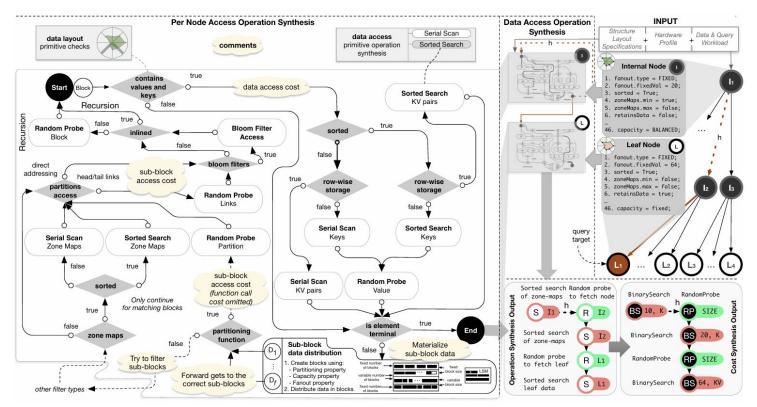
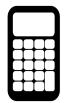


Figure 5: Synthesizing the operation and cost for dictionary operation Get, given a data structure specification.



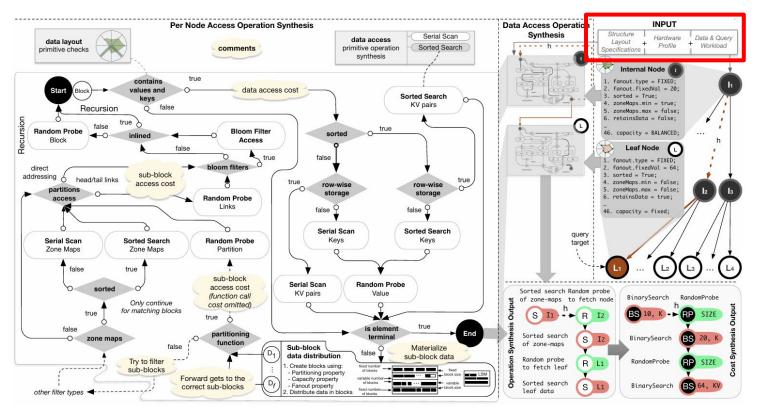
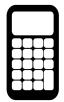


Figure 5: Synthesizing the operation and cost for dictionary operation Get, given a data structure specification.



INPUT

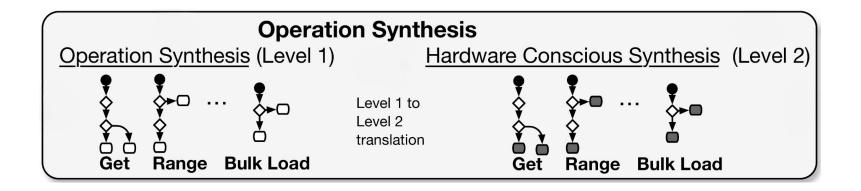
.

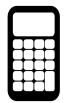


	INPUT	,
Structure Layout <mark>-</mark> Specifications	Hardware Profile	Data & Query + Workload



	INPUT	·
Structure Layout Specifications	Hardware Profile	Data & Query Workload





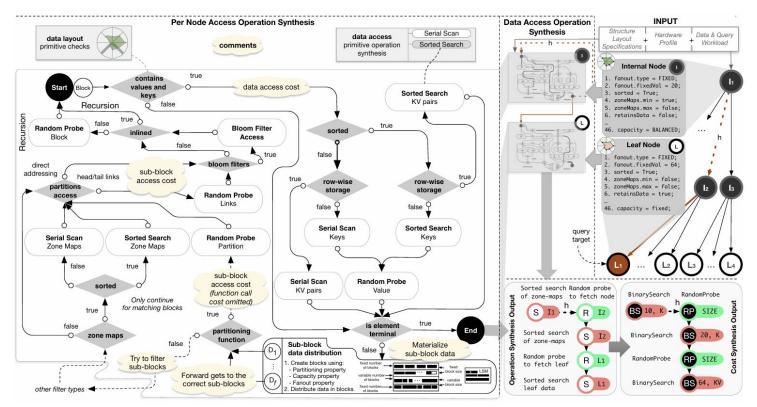
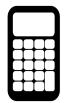


Figure 5: Synthesizing the operation and cost for dictionary operation Get, given a data structure specification.



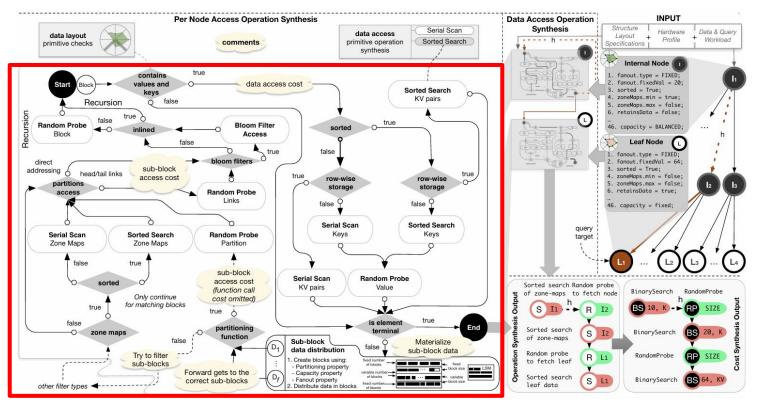
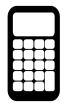
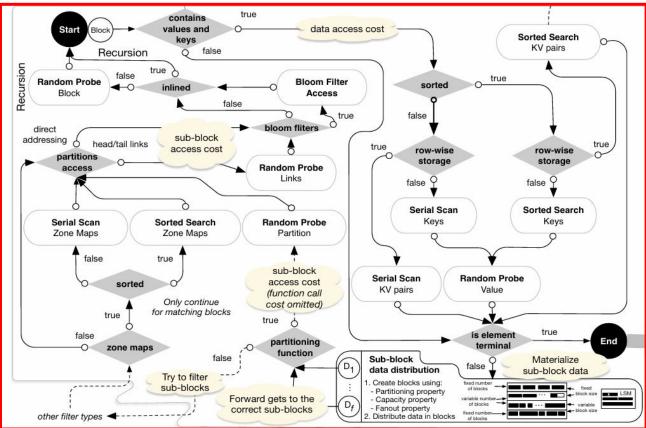
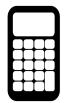


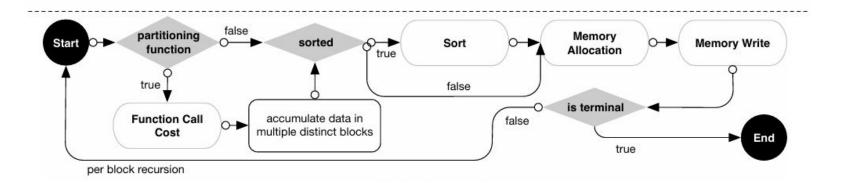
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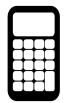






Cost Synthesis (Bulk Loading Example)





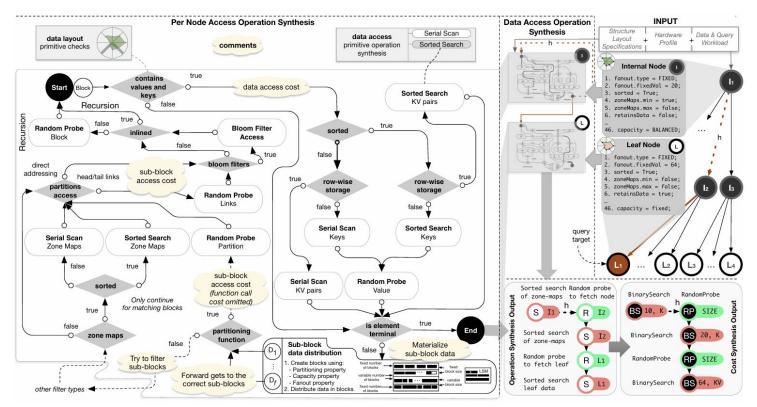
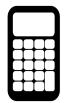


Figure 5: Synthesizing the operation and cost for dictionary operation Get, given a data structure specification.



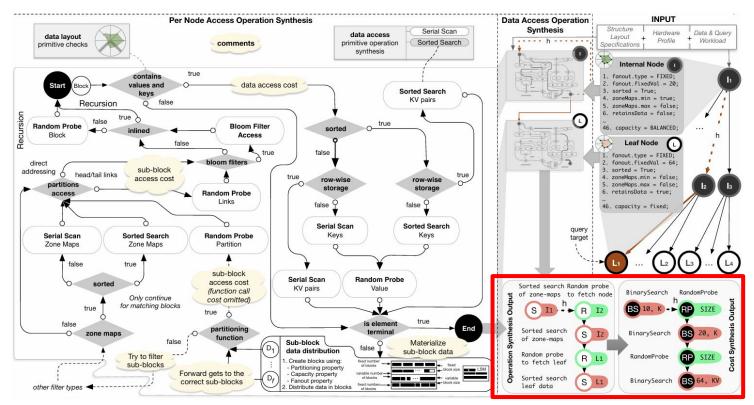
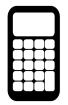
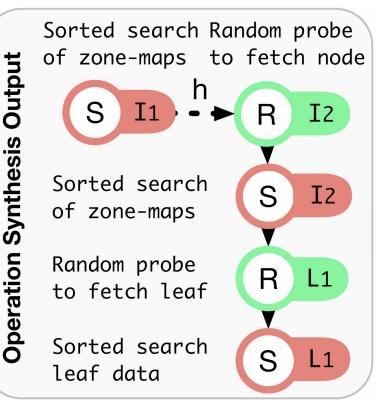
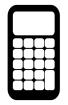


Figure 5: Synthesizing the operation and cost for dictionary operation Get, given a data structure specification.

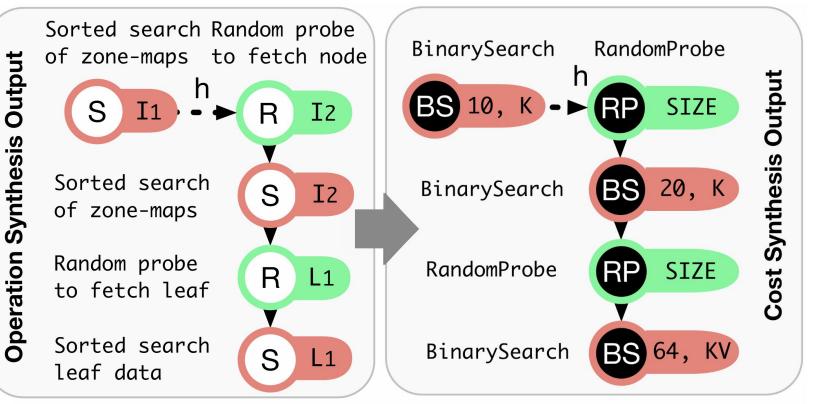


Operation Synthesis to Cost Synthesis

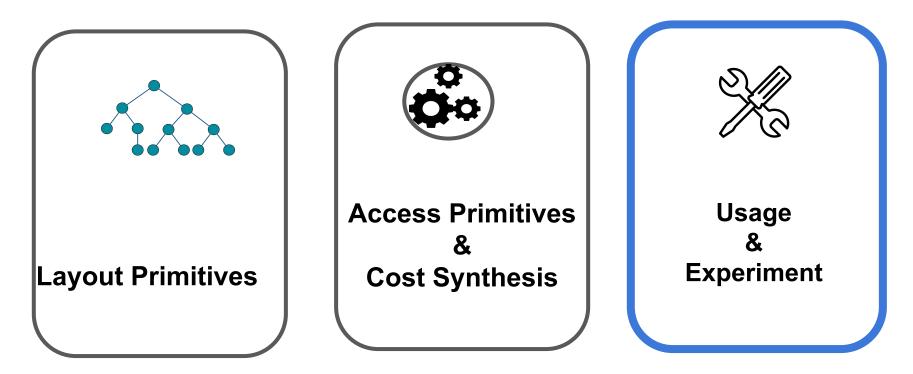




Operation Synthesis to Cost Synthesis







What Can We Do With Data Calculator?

There are too many WHAT-IF questions for designing database!

WHAT IF I want to bring bloom filter to my B-Tree?

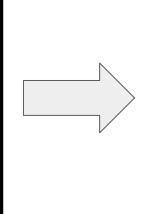
WHAT IF I am given a different workload?

WHAT IF I have to use a different hardware?

WHAT IF I need to adjust for a different cache?

Without Data Calculator

DAYS OR EVEN WEEKS OF ACTUAL IMPLEMENTATION



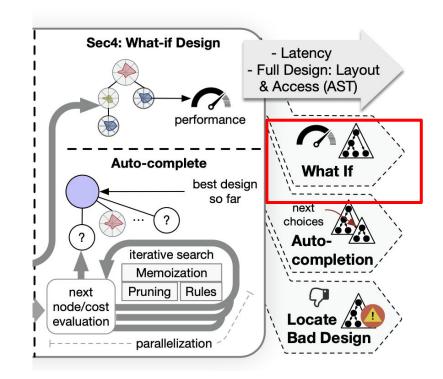
With Data Calculator

HOURS OR EVEN
MINUTES
OF COST
SYNTHESIS



Complete Design Benchmarking Adjusting **Benchmarking Again Compare & Decide**

EVERY STEP WITHIN A MINUTE!

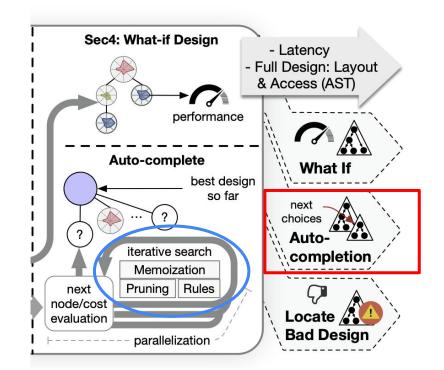


But What If I Don't Even Have a Complete Design?

Data Calculator can auto-complete for you!

?How?

Dynamic Programming!

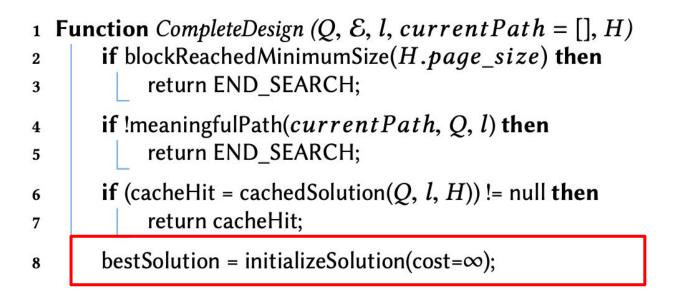


¹ Function CompleteDesign (Q, \mathcal{E} , l, currentPath = [], H)				
2	if blockReachedMinimumSize(H.page_size) then			
3	return END_SEARCH;			
4	if !meaningfulPath(currentPath, Q, l) then			
5	return END_SEARCH;			
6	if (cacheHit = cachedSolution(Q, l, H)) != null then			
7	return cacheHit;			
8	bestSolution = initializeSolution(cost= ∞);			
	$\mathbf{Q} \rightarrow \mathbf{workload}$			
	$\epsilon \rightarrow design space$			
	$I \rightarrow current hierarchy$			
	currentPath \rightarrow specification to be done			
	$H \rightarrow hardware profile$			

1 F	Function CompleteDesign ($Q, \mathcal{E}, l, currentPath = [], H$)
2	<pre>if blockReachedMinimumSize(H.page_size) then</pre>
3	return END_SEARCH;
4	if !meaningfulPath(currentPath, Q, l) then
5	return END_SEARCH;
6	<pre>if (cacheHit = cachedSolution(Q, l, H)) != null then</pre>
7	return cacheHit;
8	bestSolution = initializeSolution(cost= ∞);

 $\text{bestSolution} = \text{initializeSolution}(\text{cost}=\infty);$

Terminate when 1. Size exceeds capacity 2. Further Design not meaningful 3. Design already in cache

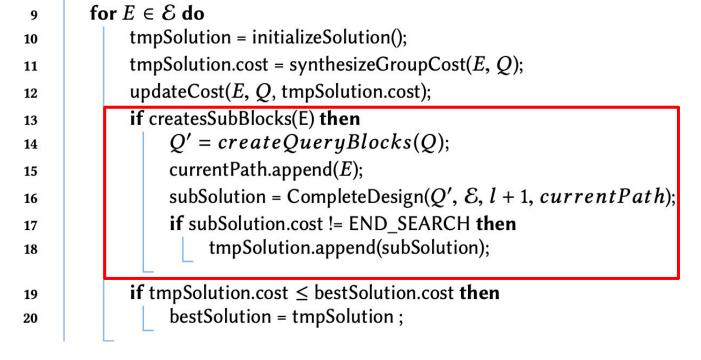


Initialize the solution assuming no limit on cost

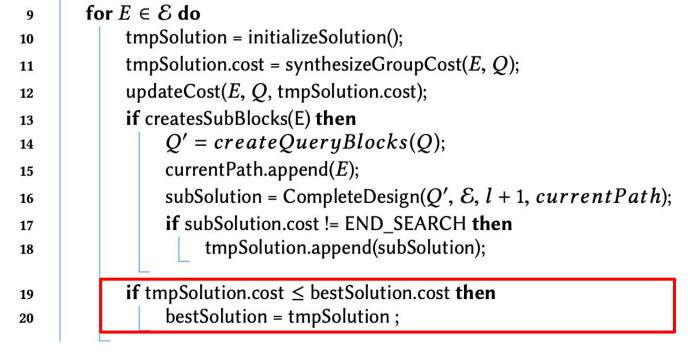
9	for $E \in \mathcal{E}$ do		
10	<pre>tmpSolution = initializeSolution();</pre>		
11	<pre>tmpSolution.cost = synthesizeGroupCost(E, Q);</pre>		
12	updateCost(<i>E</i> , <i>Q</i> , tmpSolution.cost);	updateCost(<i>E</i> , <i>Q</i> , tmpSolution.cost);	
13	if createsSubBlocks(E) then		
14	Q' = createQueryBlocks(Q);		
15	currentPath.append(E);		
16	subSolution = CompleteDesign($Q', \mathcal{E}, l + 1, current$	ntPath);	
17	if subSolution.cost != END_SEARCH then		
18	tmpSolution.append(subSolution);		
19	if tmpSolution.cost ≤ bestSolution.cost then		
20	bestSolution = tmpSolution ;		

For each candidate element:

- 1. Initialize solution and calculate its cost with element E
- 2. Update current solution with the cost



If there exists element under E: Recursively update cost with subelement as a new level of hierarchy



Update current best solution if the new solution costs less

cacheSolution(Q, l, bestSolution); return bestSolution;

Store the current best solution in the cache and return it



System implementation: C++

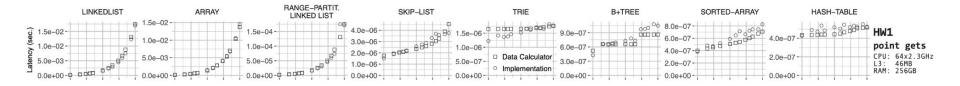
Benchmark analysis & Learning: Python

Idea: Compare cost with actual implementation and cost synthesis

Operation type: Point Get, Range Get, Update, Bulk Load

HW1 CPU: 64 x 2.3 GHz L3: 46MB RAM: 256GB HW2 CPU: 4 x 2.3 GHz L3: 46MB RAM: 16GB HW3 CPU: 64 x 2 GHz L3: 16MB RAM: 1TB





Number of entries (log scale)

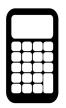


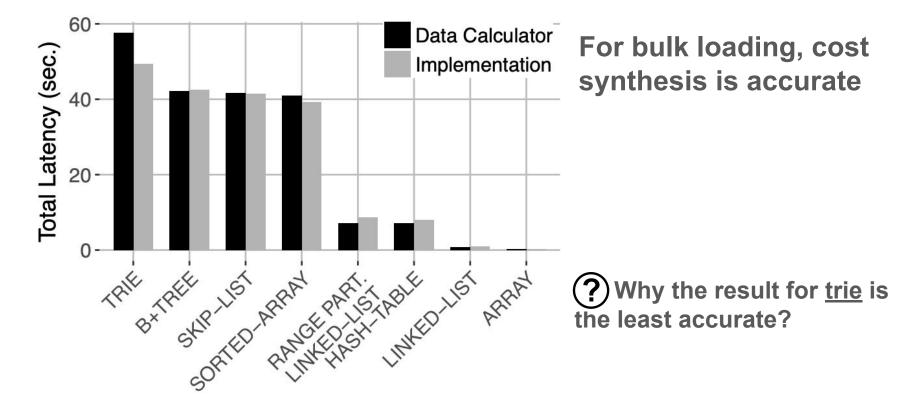
Cost Synthesis is sufficiently accurate!

Cost synthesis is accurate for all experimented data structures!

LINKEDLIST	ARRAY	RANGE-PARTIT. LINKED LIST	SKIP-LIST	TRIE	B+TREE	SORTED-ARRAY	HASH-TABLE
(v) 1.5e−02- 1.0e−02- 1.0e−02-		1.5e-04-	4.0e-06 -			8.0e-07- 6.0e-07- 4.0e-07- 6.0e - 07- 6.0e - 00- 6.0e	4.0e-07-
5.0e-03 - 5.0e-03 - 5.0e-03 -		5.0e-05-	2.0e-06-	0e-06- 0e-07- Data Calculator • Implementation	6.0e-07- 0 3.0e-07-	4.0e-07-8 48 4 2.0e-07-	L3: 46MB
0.0e+00-		0.0e+00-p pdg 0	0.0e+00-	0.0e+00	0.0e+00-	0.0e+00-	0.0e+00 - RAM: 256GB
000000000000000000000000000000000000	8		5.0e-06- 4.0e-06- 3.0e-06- 2.0e.06- B ^C B	.5e-06-0 - 0 - 0 - 0 - 0 - 0 - 0 - 0 - 0 -	9.0e-07-	8.0e-07-	4.0e-07-0 BBB 0 BB 0 B B 0 B B 0 B B B B B B B
5.0e-03 - 5.0e-03 - 5.0e-03 -		5.0e-05-	1.0e-06-	5.0e-07-	3.0e-07-	4.0e-07-	2.0e-07- L3: 46MB RAM: 16GB
0.0e+00-0.0e+00-			0.0e+00-	0.0e+00-	0.0e+00-	0.0e+00-	- 0.0e+00 - - - - - - - - - -
3.0e-02- 2.0e-02- 2.0e-02- 2.0e-02-		2.00-04	4.0e−06 - 00 00 00 00 00 00 00 00 00 00 00 00 0		1.0e-06-		
1.0e-02- 1.0e-02- 5.0e-03-	0			1.0e-06-	5.0e-07-0	7.5e-07- 5.0e-07- 2.5e-07-	5.0e-07- 2.5e-07- RAM: 1TB
0.00000 7 1 1 1 1 1 0.00000			0.0e+00-	0.0e+00-	0.0e+00-	0.0e+00-	0.0e+00-
3.0e-02- 2.0e-02- 2.0e-02-		3.0e-04 - 0 2.0e-04 - 0	4.0e-06- 2.0e-06-	2.0e-06-0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	1.5e-06 - 000 000 000 000 000 000 000 000 00	1.0e-06- 7.5e-07- 5.0e-07-	1.0e-06 7.5e-07-€ 8€€ 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
1.0e-02- 1.0e-02- 5.0e-03-	_6 ⁸	1.0e-04-	2.0e-06-	.0e-06-	5.0e-07-0	2.5e-07-	2.5e-07- CPU: 64x2GHz L3: 16MB
0.0e+00-p p p p p p p p p p p p p p p p p p p		B 60	0.0e+00-	0.0e+00-	0.0e+00-	0.0e+00-	0.0e+00-
2.0e-01- 1.5e-01-		6 0e-02-	4.0e-02		6.0e-02-	5.0e-02-	2.0e-01-
1.5e-01-		8	4.0e-02 - 2	9.0e-01 - 0	4.0e-02-	4.0e-02-	- Pango goto
5.0e-02-		2 0e-02-	2.0e-02-	6.0e-01 -	2.0e-02-	2.0e-02-	5.0e-02- E CPU: 64×2GHz
0.0e+00- 10 ⁵ 10 ^{5.5} 10 ⁶ 10 ^{6.5} 10 ⁷ 1	\mathbf{p}		0.0e+00 - 0 - 0 - 0 - 0 - 0 - 0 - 0 - 0 - 0	0.0e+00 - 10 ⁵ 10 ^{5.5} 10 ⁶ 10 ^{6.5} 10 entries (log scale)	0.0e+00 - 0 - 0 - 0 - 0 - 0 - 0 - 0 - 0 - 0	0.0e+00-0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	0.0e+00-0 0 0 RAM: 1TB 0 ⁷ 10 ⁵ 10 ^{5.5} 10 ⁶ 10 ^{6.5} 10 ⁷

? any interesting pattern?







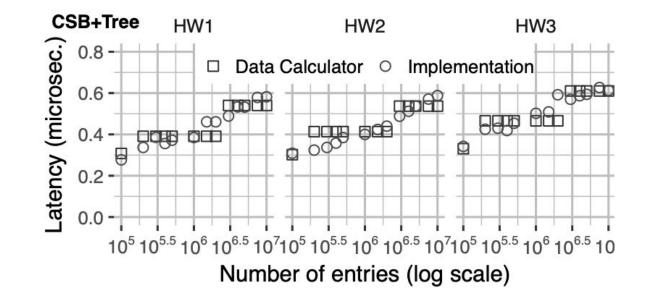
How "far" each node is placed to each other

Crucial for calculating the cost of traversing data structure

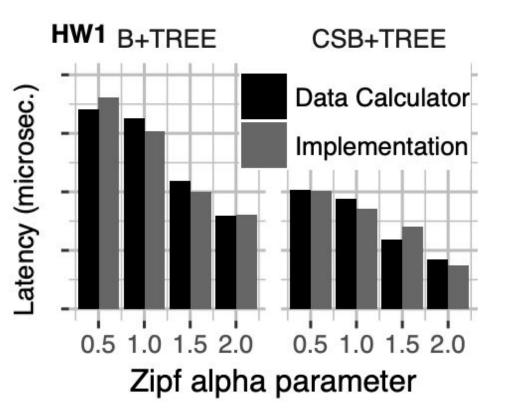
Represented as layout primitive

Cache-Sensitive B+ Tree vs. B+ Tree

						ole PL	B+Tree/CSB+Tree/FAST			
	Primitive	Domain	size	н	LL	UDP	B+	CSB+	FAST	ODP
17	Sub-block physical layout.This represents the physical layout of sub-blocks.Scatter: random placement in memory.BFS: laid out in a breadth-first layout.BFS layer list: hierarchical level nesting of BFS layouts.Rules: requires fanout/radix != terminal.	BFS BFS layer(level-grouping: int) scatter (up to 3 different values for layer- grouping are considered)	5	scatter	scatter		scatter	BFS	BFS-LL	



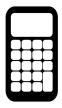
It is accurate for CSB+ tree as well!



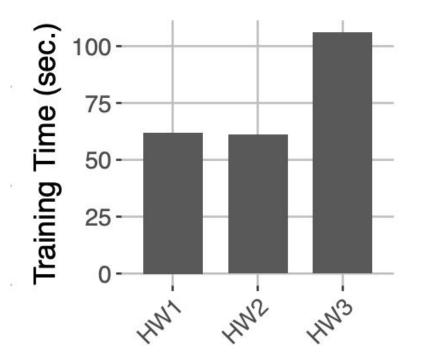
Accuracy of cost synthesis increases as skewness of workload increases.



? Why does it improve more for B+ Tree?



Experiment: Speed of Cost Synthesis



Training by seconds vs. Implementing by days

Experiment: Speed of Cost Synthesis

"What if we change our **hardware** from HW1 to HW3?"

20s

"Is there a better design for **this new hardware and workload** if we restrict search on a specific set of possible elements?"

47s

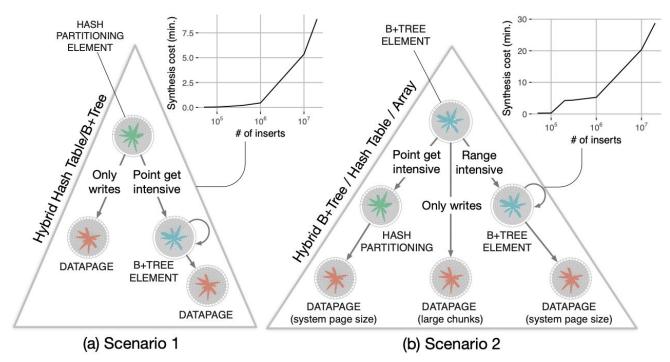
"Would it be beneficial to add a Bloom filter in all B-tree leaves?"

20s

"What if the **query workload** changes to have **skew** targeting just 0.01% of the key space?"

24s

<u>Give Me a Better Design \rightarrow in 30 Minutes!</u>



Scenario 1: mixed read&write, all read are point queries in 20% of the domain

Scenario 2: mixed read&write, half of read are point queries in 10% of the domain, the other half are range queries in another 10% of the domain



Introduction of more design elements

Support for cost synthesis of advanced operations (such as point/range delete)

Optimization for cost synthesis





Design Primitives:

Fundamental building blocks for describing data structures.

Enables the exploration of a massive design space.

Learned Cost Models:

Predict operation latencies without implementation or workload execution.

Adaptable to hardware and workload profiles.

What-If Analysis:

Answer complex questions about design, hardware, and workload trade-offs interactively. Auto-Completion:

Semi-automated synthesis of new data structures and auto-completion of partial designs.



Reflections

Ge:

The paper provides a transformative approach to data structure design by introducing a framework that combines fundamental design primitives and learned cost models to explore, synthesize, and evaluate a vast design space. The tool's ability to predict costs without implementation or workload execution is particularly impressive.

Alec:

I enjoyed working on this paper, it provided a good framework for evaluating cost of more complex structures by breaking things down into the costs of their constituent parts, and accounts for differences in hardware (without the ambiguity of big O notation for actual numbers). It also provides algorithms for optimization rather than just being a tool to view results of a hypothetical data structure which is pretty neat.

Minjie:

Even though nowadays when we design database we need to consider more factors like cloud storage, distributed environments and so on. This paper set up a nice starting point for how we can extend these ideas, combining them with new paradigms.