

CS 265

Stratos Idreos

BIG DATA SYSTEMS

NoSQL | Neural Networks | Image AI | LLMs | Data Science

HOW TO JUDGE A DESIGN?

HOW TO JUDGE A DESIGN?

1

**COMPLEXITY
ANALYSIS**

HOW TO JUDGE A DESIGN?

1

**COMPLEXITY
ANALYSIS**

2

**IMPLEMENTATION
& TESTING**

HOW TO JUDGE A DESIGN?

1

**COMPLEXITY
ANALYSIS**

2

**IMPLEMENTATION
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3

**GENERALIZED
MODELS**

HOW TO JUDGE A DESIGN?

1

**COMPLEXITY
ANALYSIS**

2

**IMPLEMENTATION
& TESTING**

3

**GENERALIZED
MODELS**

**This sounds ideal:
is it possible?**

ACCESS PATH SELECTION in ANALYTICAL SYSTEMS

scan vs secondary index selection

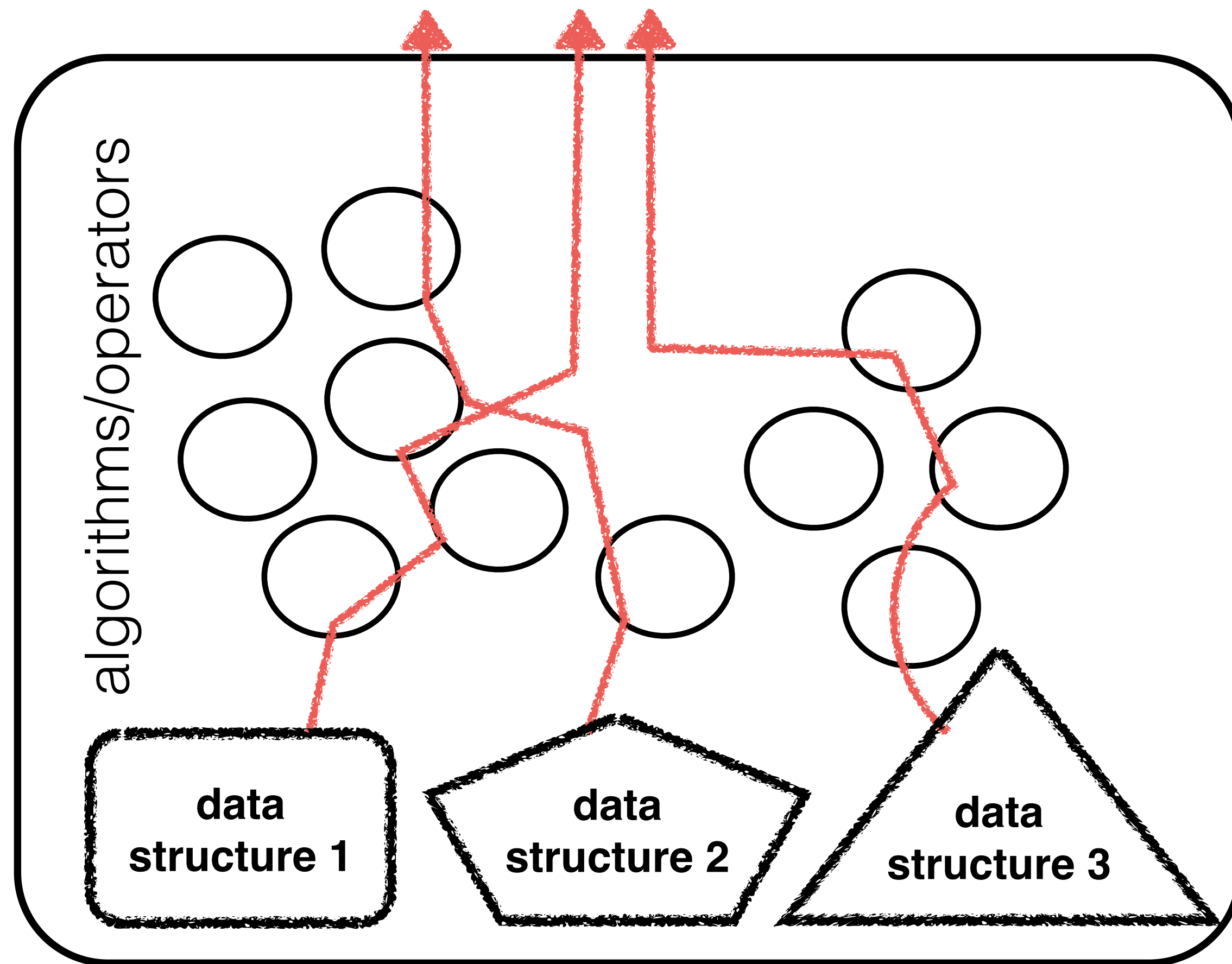
@SIGMOD 2017

data* system

ACCESS PATH SELECTION in ANALYTICAL SYSTEMS

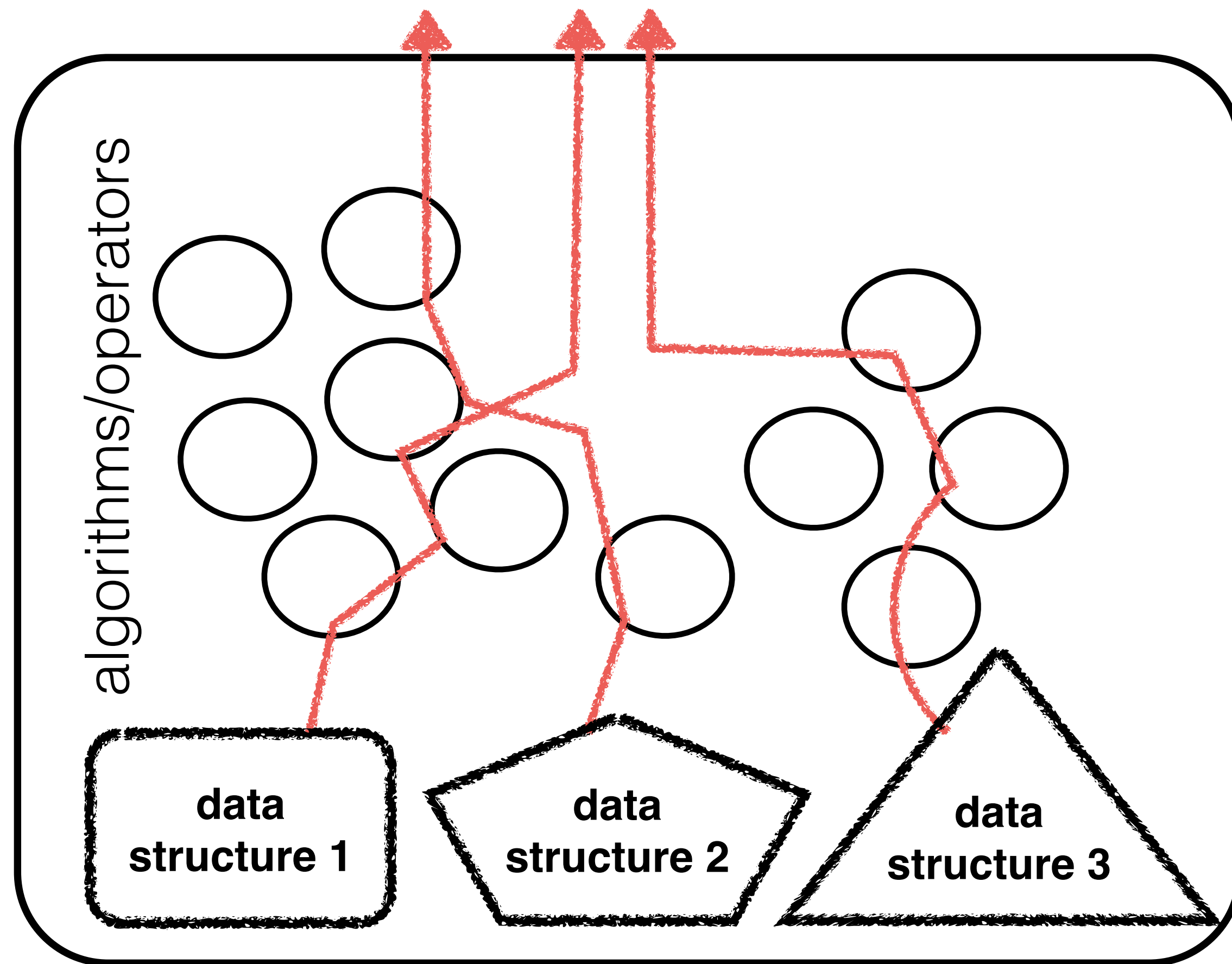
scan vs secondary index selection

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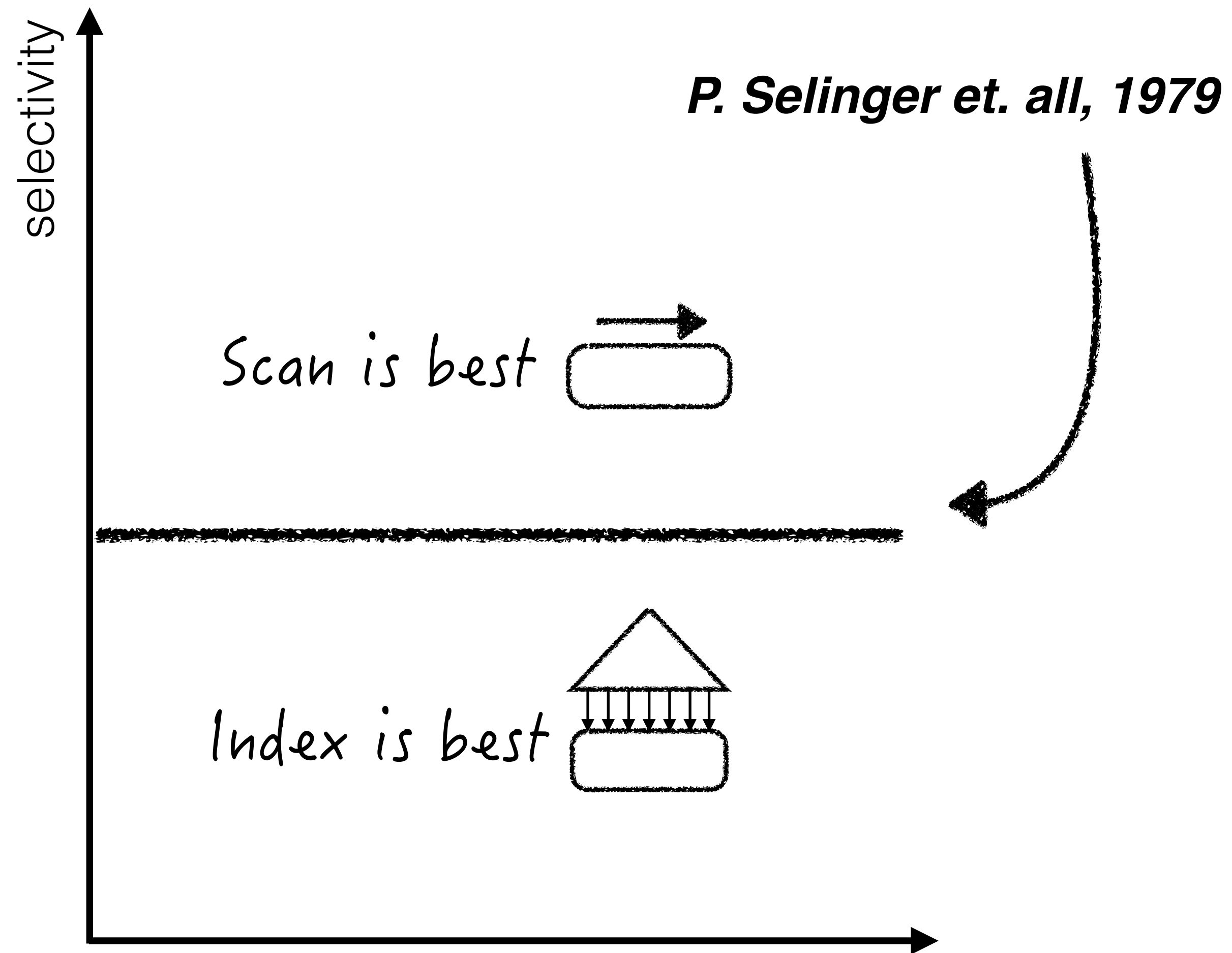
ACCESS PATH SELECTION

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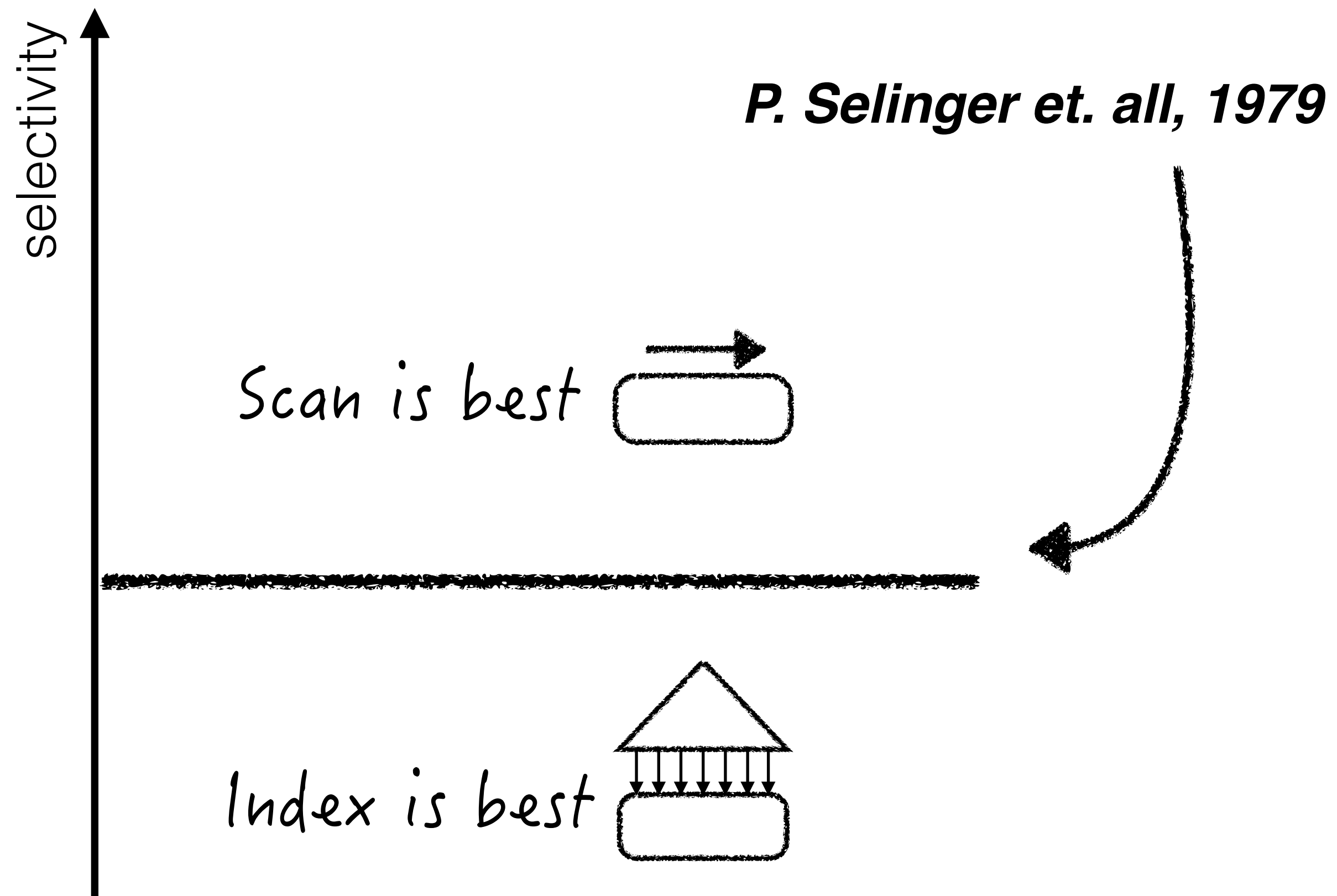
ACCESS PATH SELECTION

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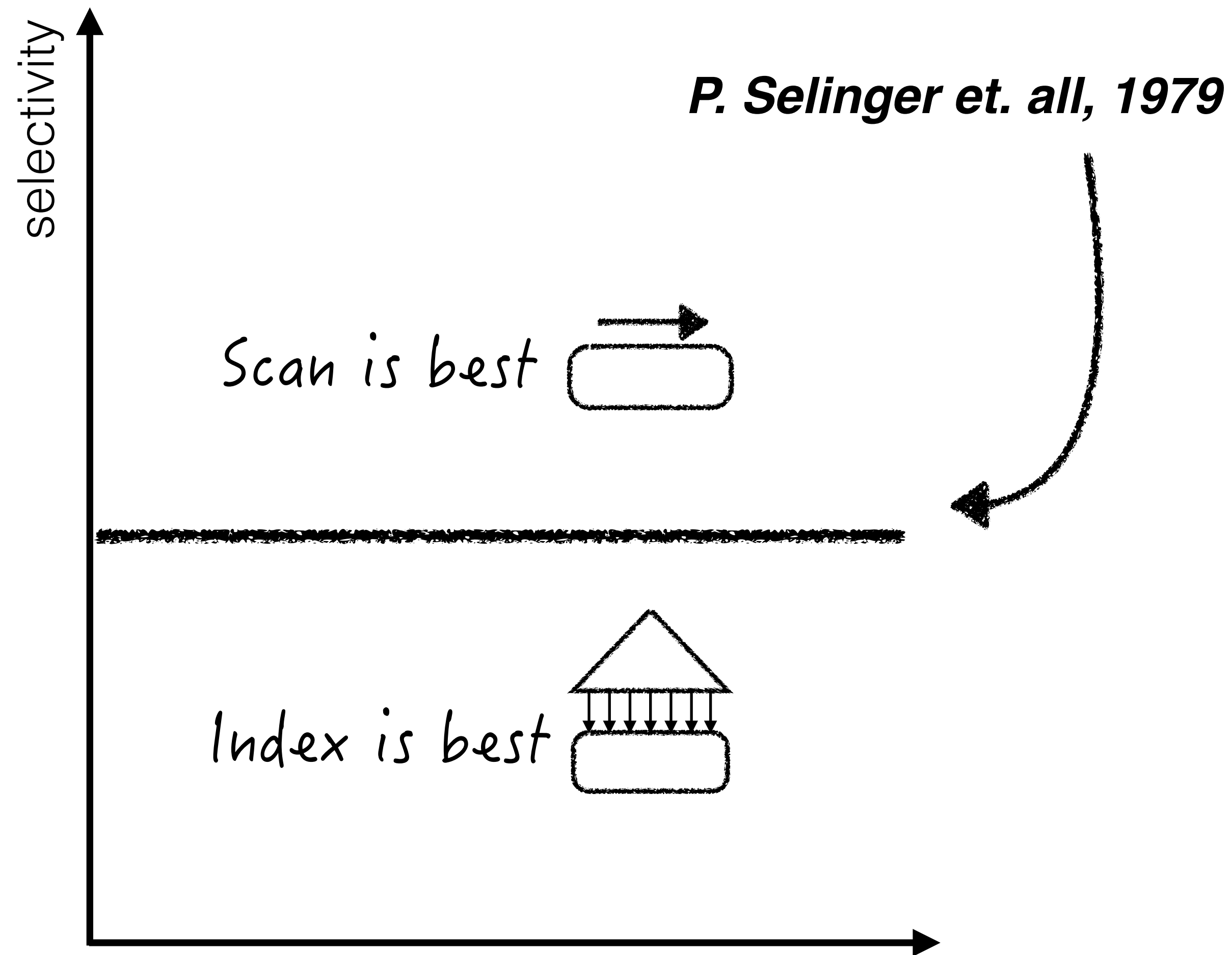


DO WE STILL NEED INDEXING? (AND IF YES HOW DO WE CHOOSE)

ACCESS PATH SELECTION in ANALYTICAL SYSTEMS

scan vs secondary index selection

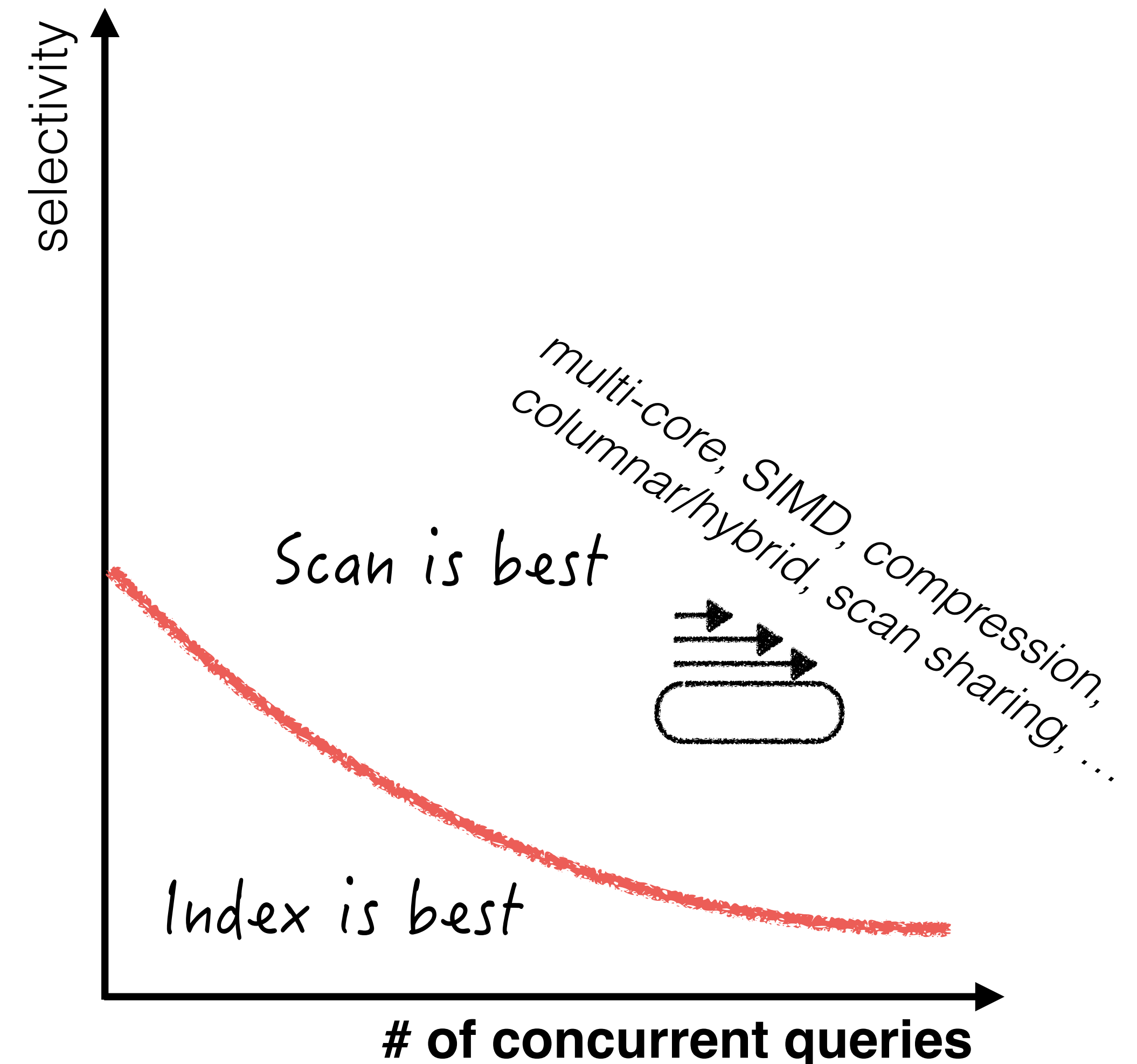
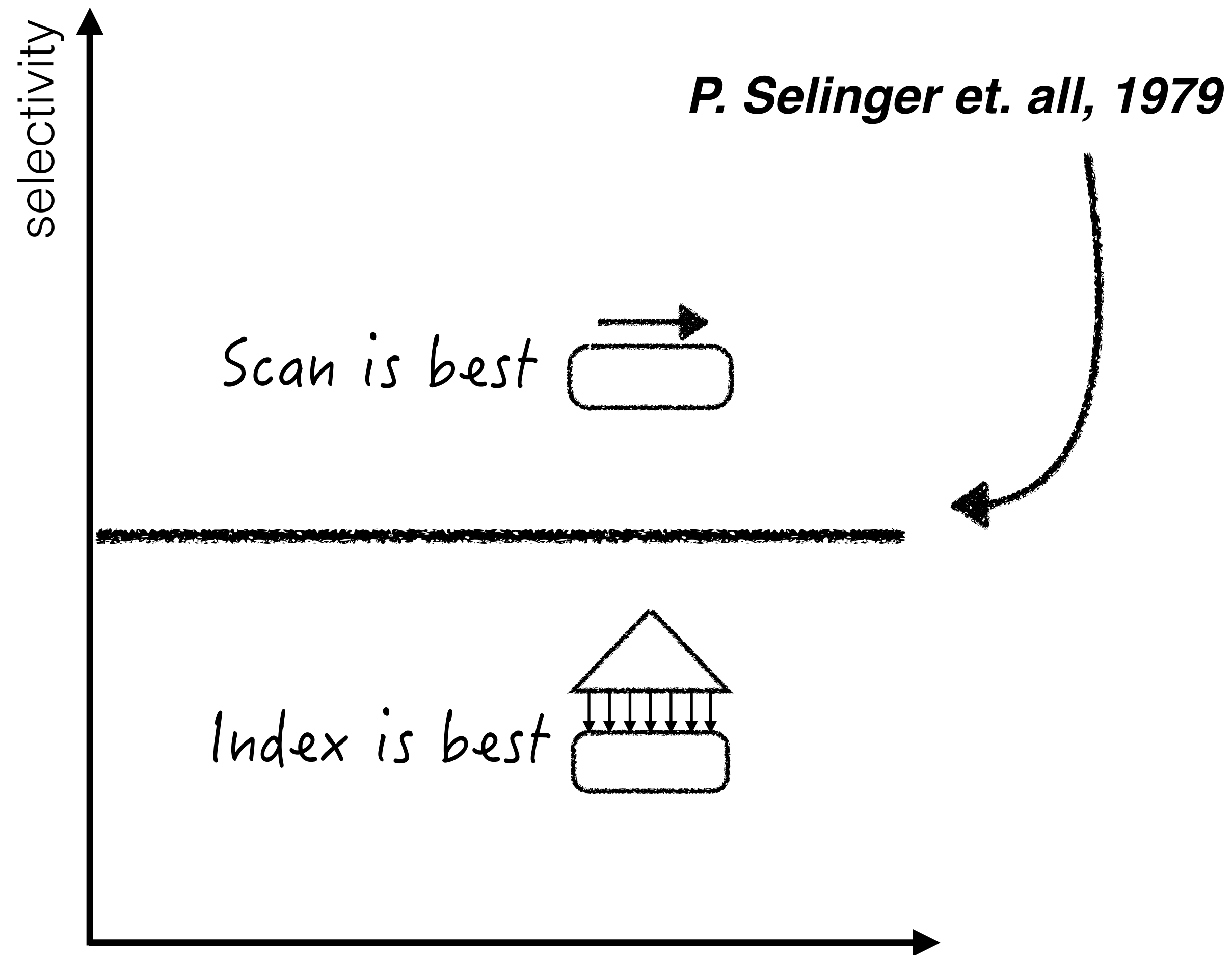
@SIGMOD 2017



ACCESS PATH SELECTION in ANALYTICAL SYSTEMS

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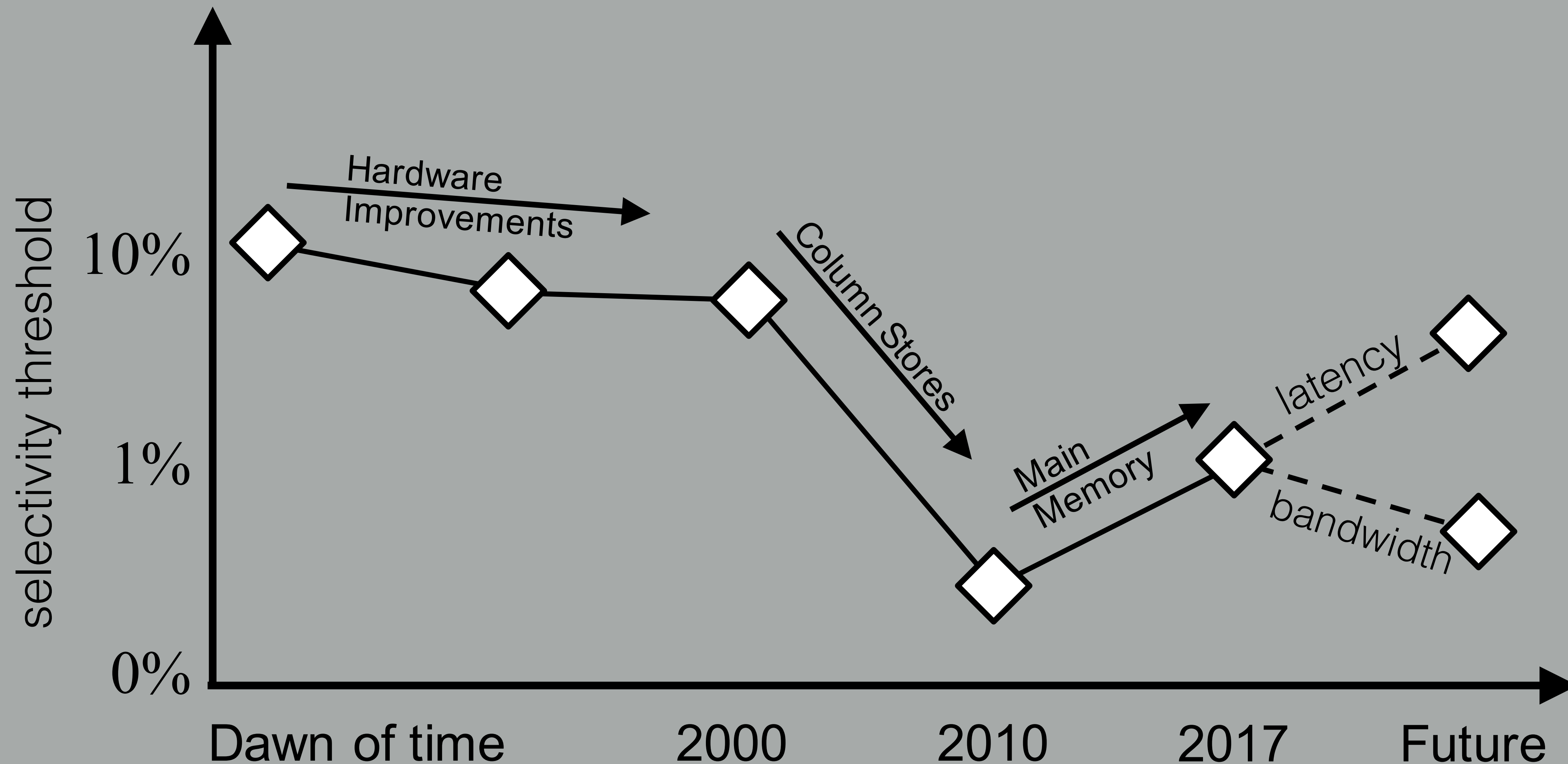
@SIGMOD 2017



ACCESS PATH SELECTION in ANALYTICAL SYSTEMS

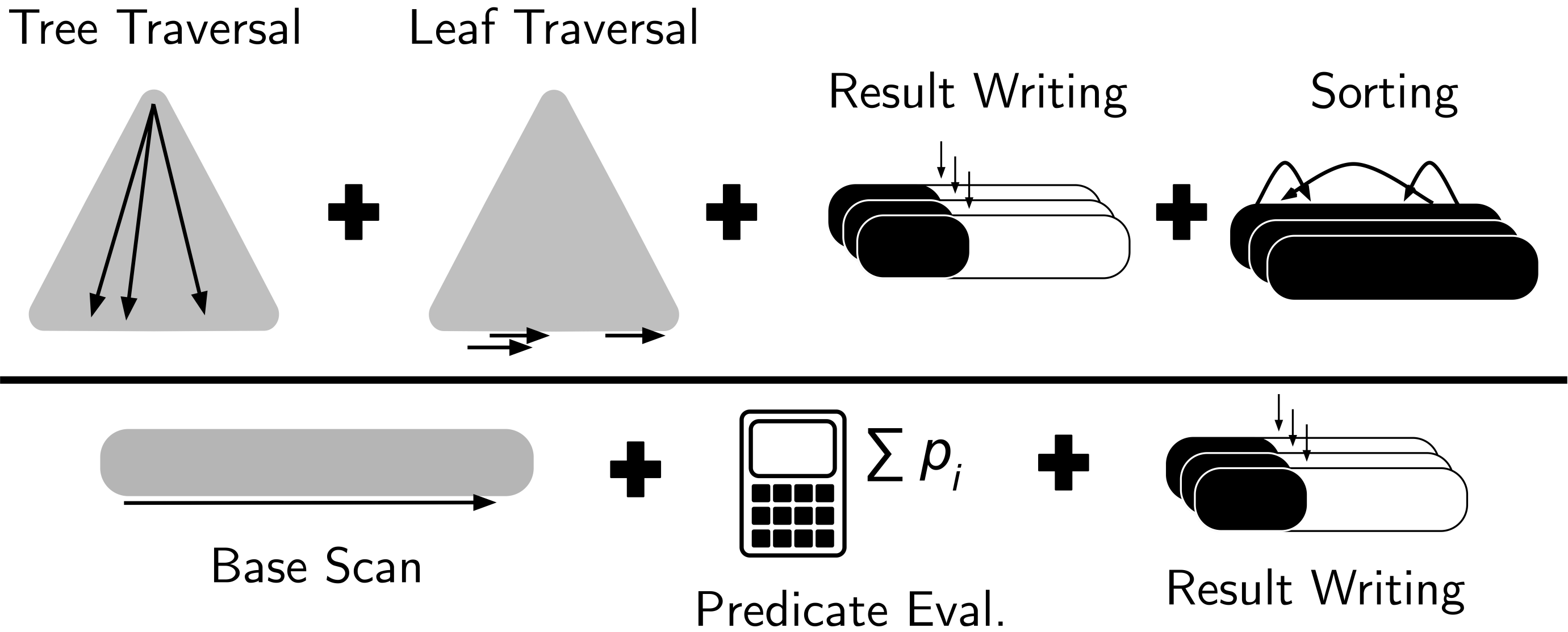
scan vs secondary index selection

@SIGMOD 2017



$$APS(q, S_{tot}) = \frac{q \cdot \frac{1 + \lceil \log_b(N) \rceil}{N} \cdot \left(BW_S \cdot C_M + \frac{b \cdot BW_S \cdot C_A}{2} + \frac{b \cdot BW_S \cdot f_p \cdot p}{2} \right)}{\max(ts, 2 \cdot f_p \cdot p \cdot q \cdot BW_S) + S_{tot} \cdot rw \cdot \frac{BW_S}{BW_R}} \\ + \frac{S_{tot} \left(\frac{BW_S \cdot C_M}{b} + (aw + ow) \cdot \frac{BW_S}{BW_I} + rw \cdot \frac{BW_S}{BW_R} \right)}{\max(ts, 2 \cdot f_p \cdot p \cdot q \cdot BW_S) + S_{tot} \cdot rw \cdot \frac{BW_S}{BW_R}} \\ + \frac{S_{tot} \cdot \log_2(S_{tot} \cdot N) \cdot BW_S \cdot C_A}{\max(ts, 2 \cdot f_p \cdot p \cdot q \cdot BW_S) + S_{tot} \cdot rw \cdot \frac{BW_S}{BW_R}}$$

scan vs secondary index selection @SIGMOD 2017

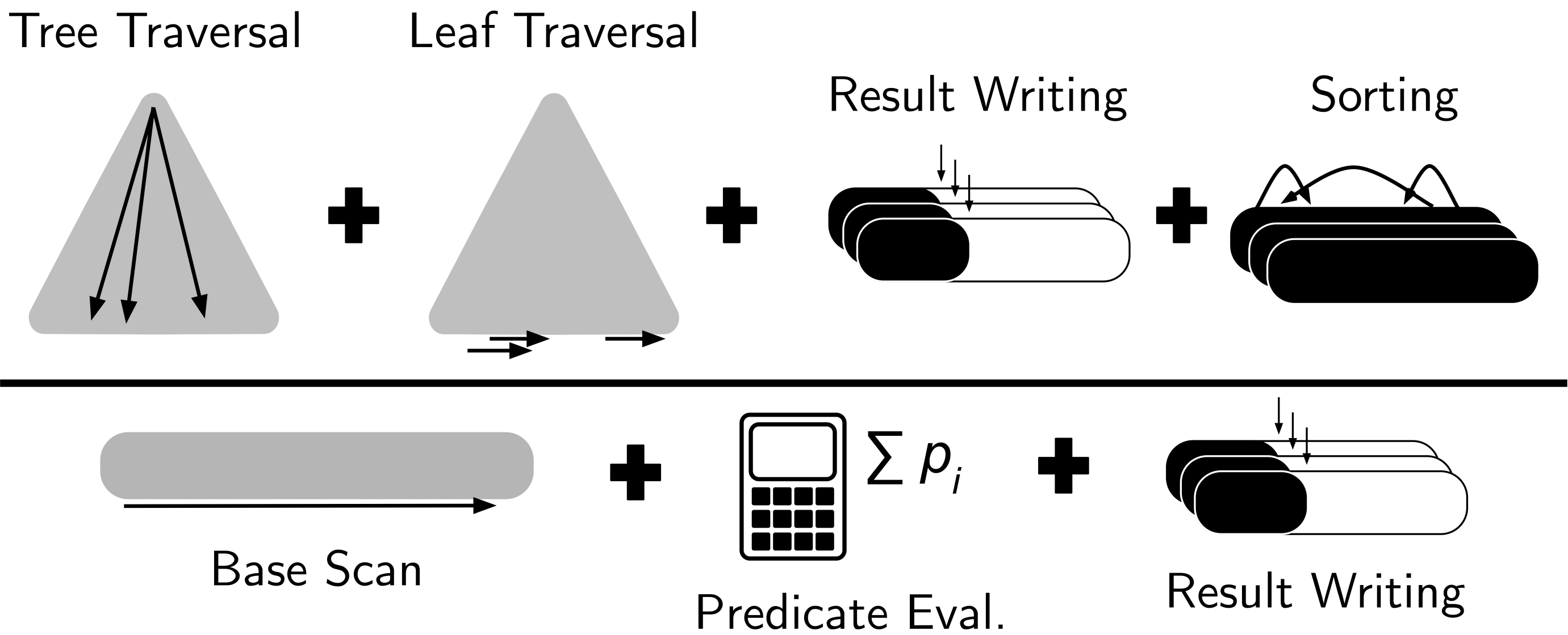


Workload	q s_i S_{tot}	number of queries selectivity of query i total selectivity of the workload
Dataset	N ts	data size (tuples per column) tuple size (bytes per tuple)
Hardware	C_A C_M BW_S BW_R BW_I p f_p	L1 cache access (sec) LLC miss: memory access (sec) scanning bandwidth (GB/s) result writing bandwidth (GB/s) leaf traversal bandwidth (GB/s) The inverse of CPU frequency Factor accounting for pipelining
Scan & Index	rw b aw ow	result width (bytes per output tuple) tree fanout attribute width (bytes of the indexed column) offset width (bytes of the index column offset)

HARD & SLOW

$$APS(q, S_{tot}) = \frac{q \cdot \frac{1 + \lceil \log_b(N) \rceil}{N} \cdot \left(BW_S \cdot C_M + \frac{b \cdot BW_S \cdot C_A}{2} + \frac{b \cdot BW_S \cdot f_p \cdot p}{2} \right)}{\max(ts, 2 \cdot f_p \cdot p \cdot q \cdot BW_S) + S_{tot} \cdot rw \cdot \frac{BW_S}{BW_R}} \\ + \frac{S_{tot} \left(\frac{BW_S \cdot C_M}{b} + (aw + ow) \cdot \frac{BW_S}{BW_I} + rw \cdot \frac{BW_S}{BW_R} \right)}{\max(ts, 2 \cdot f_p \cdot p \cdot q \cdot BW_S) + S_{tot} \cdot rw \cdot \frac{BW_S}{BW_R}} \\ + \frac{S_{tot} \cdot \log_2(S_{tot} \cdot N) \cdot BW_S \cdot C_A}{\max(ts, 2 \cdot f_p \cdot p \cdot q \cdot BW_S) + S_{tot} \cdot rw \cdot \frac{BW_S}{BW_R}}$$

scan vs secondary index selection @SIGMOD 2017



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Access Path Selection in Main-Memory Optimized Data Systems: Should I Scan or Should I Probe? Michael Kester, Manos Athanassoulis, Stratos Idreos. In Proceedings of the ACM SIGMOD International Conference on Management of Data, 2017

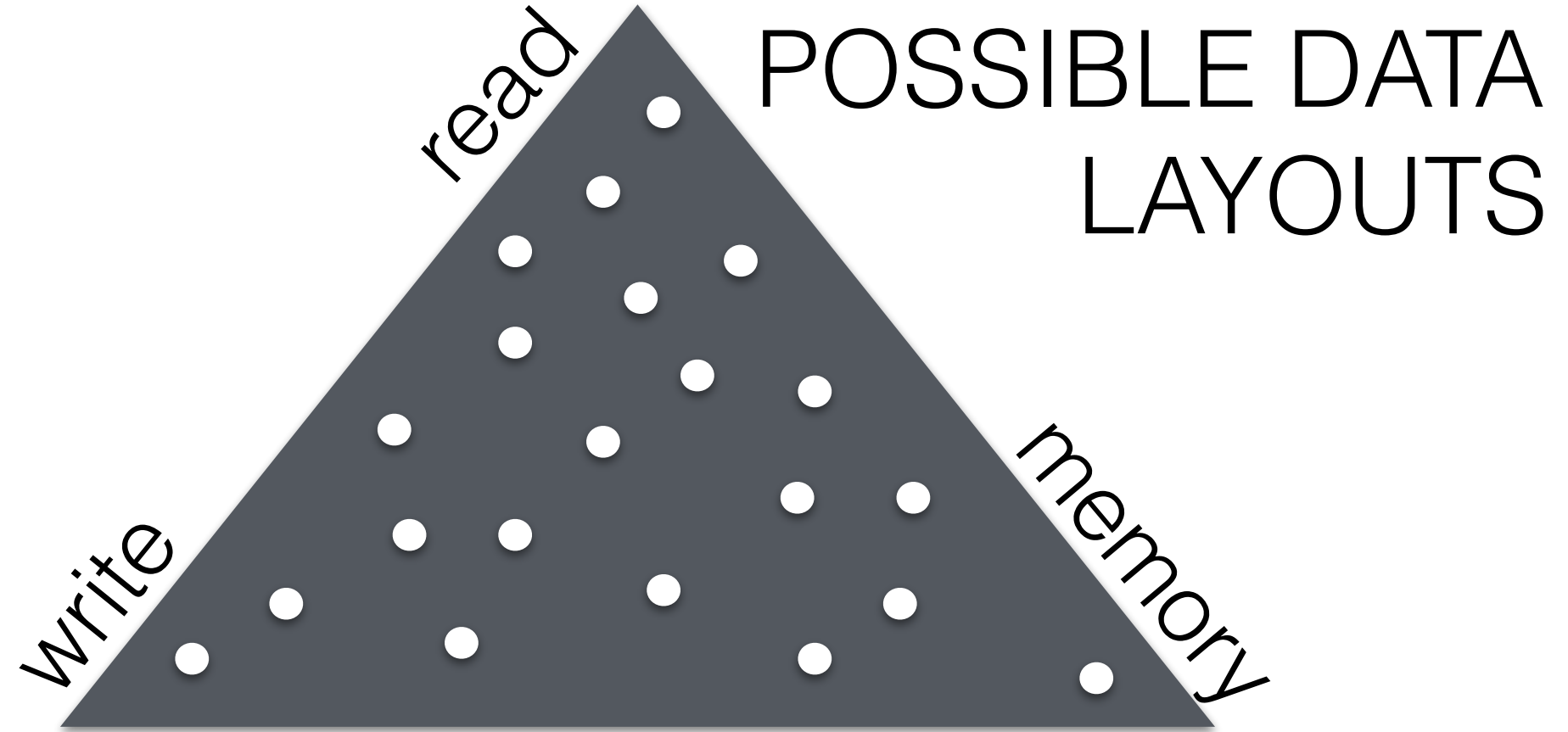


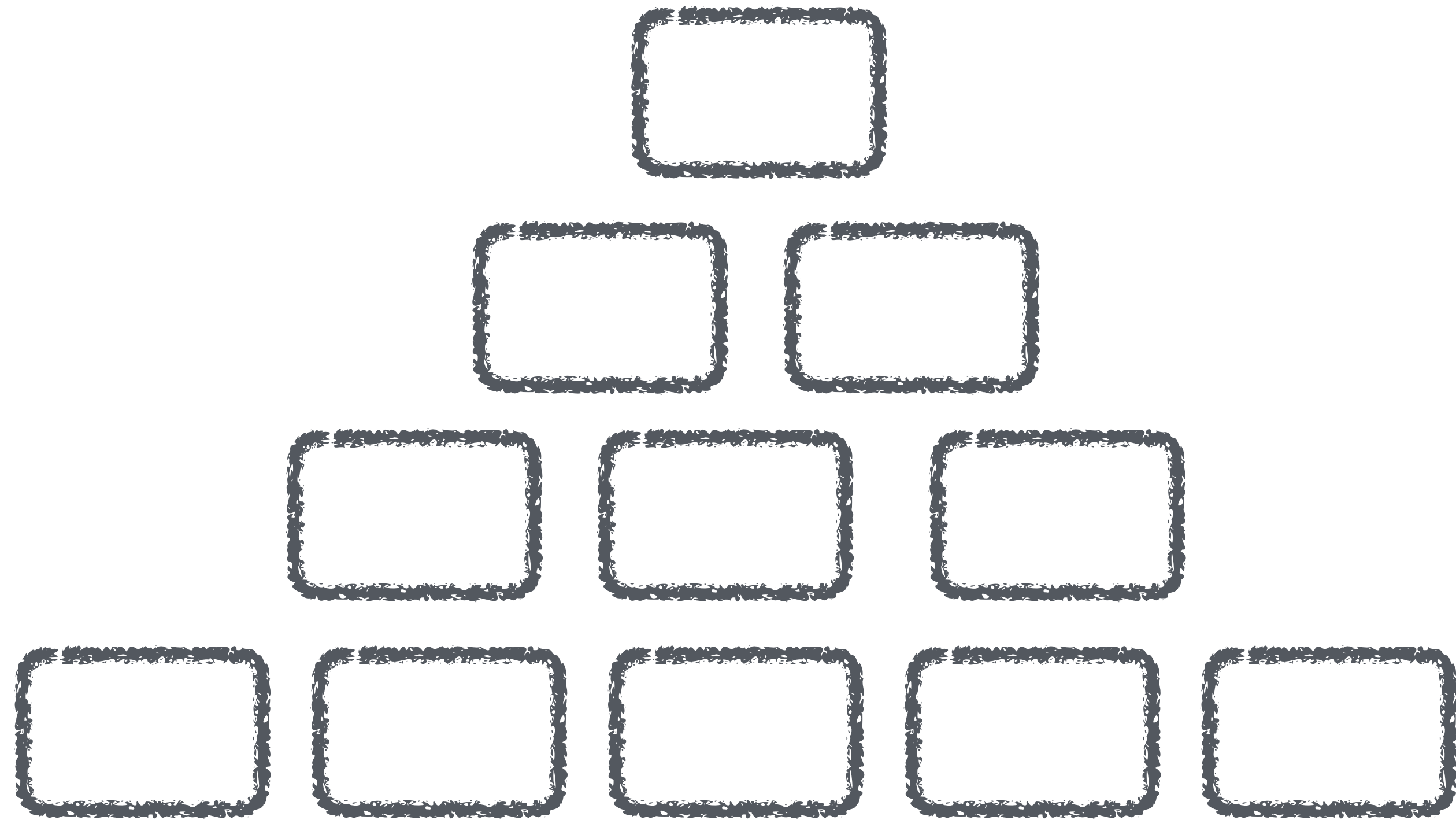
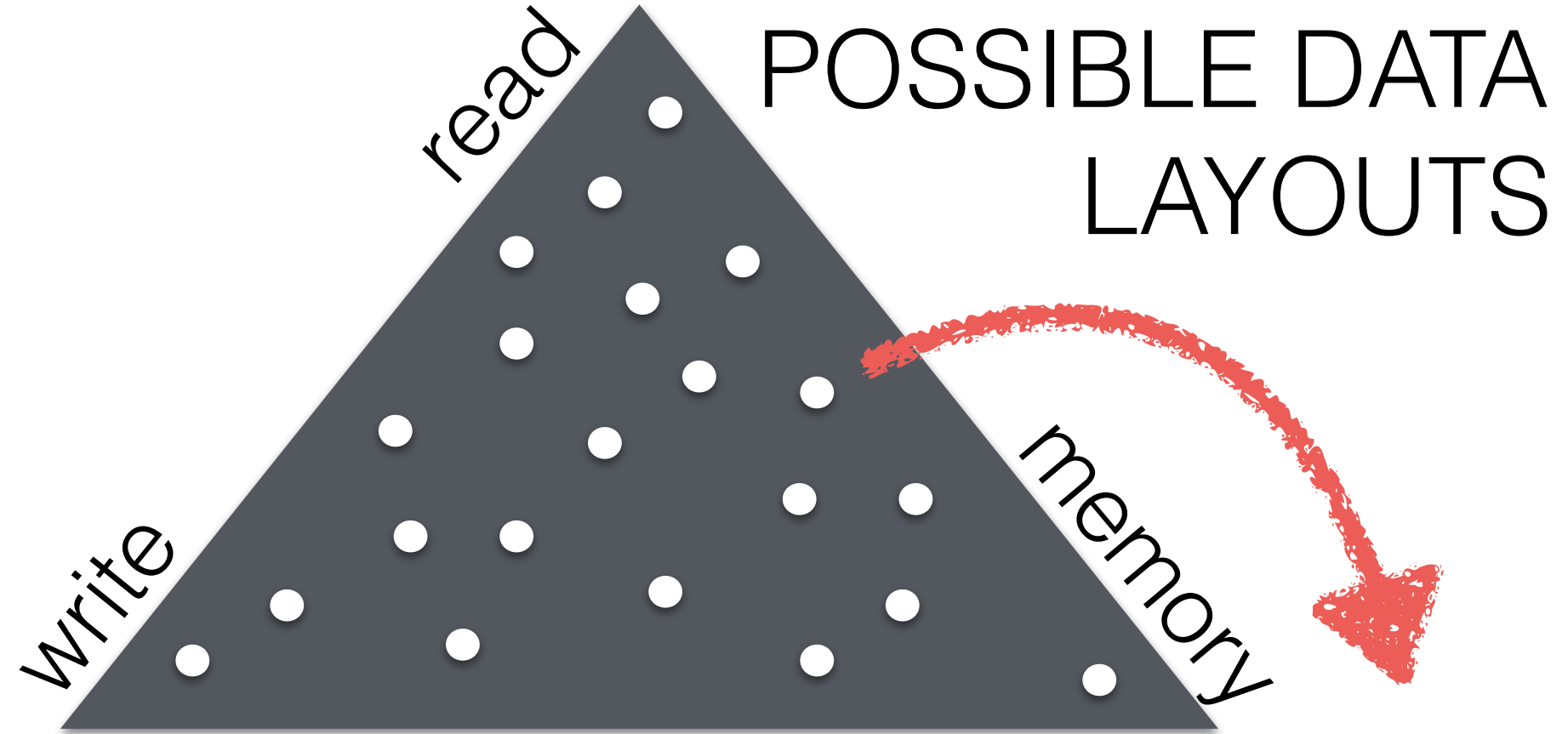
S. BING YAO
models/advisors

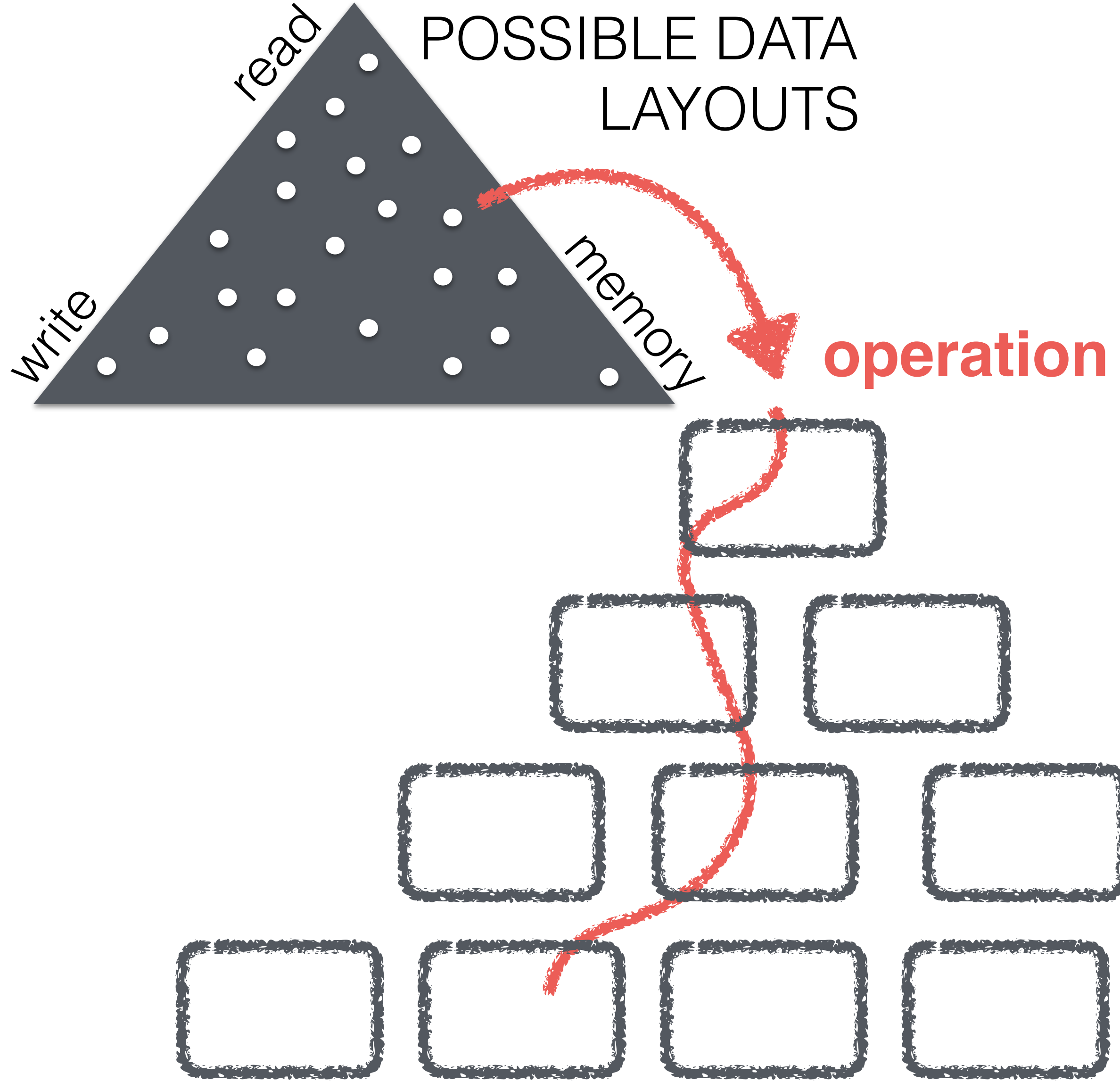


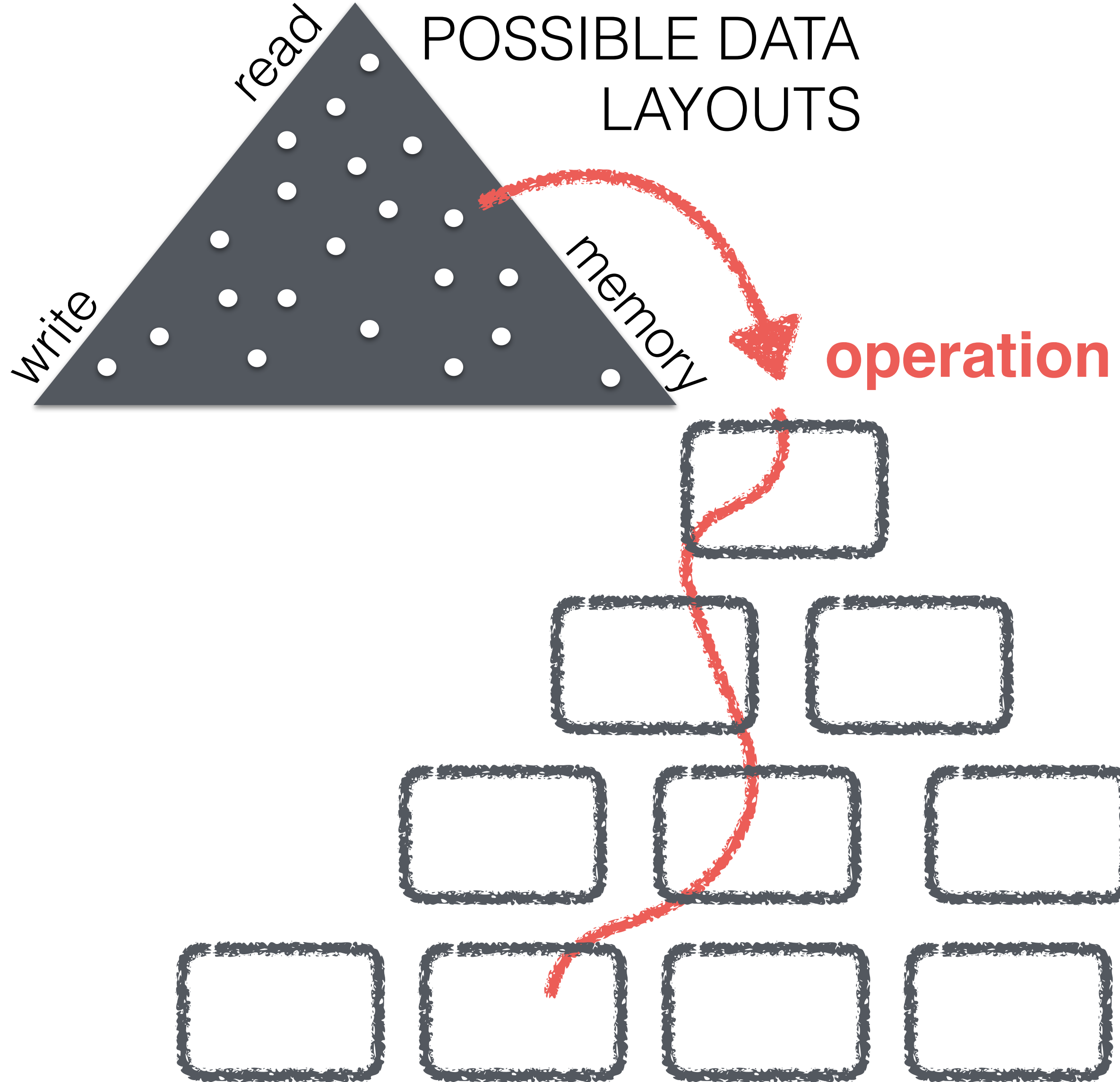
STEFAN MANEGOLD
model synthesis

We need something else: Something more scalable & robust!

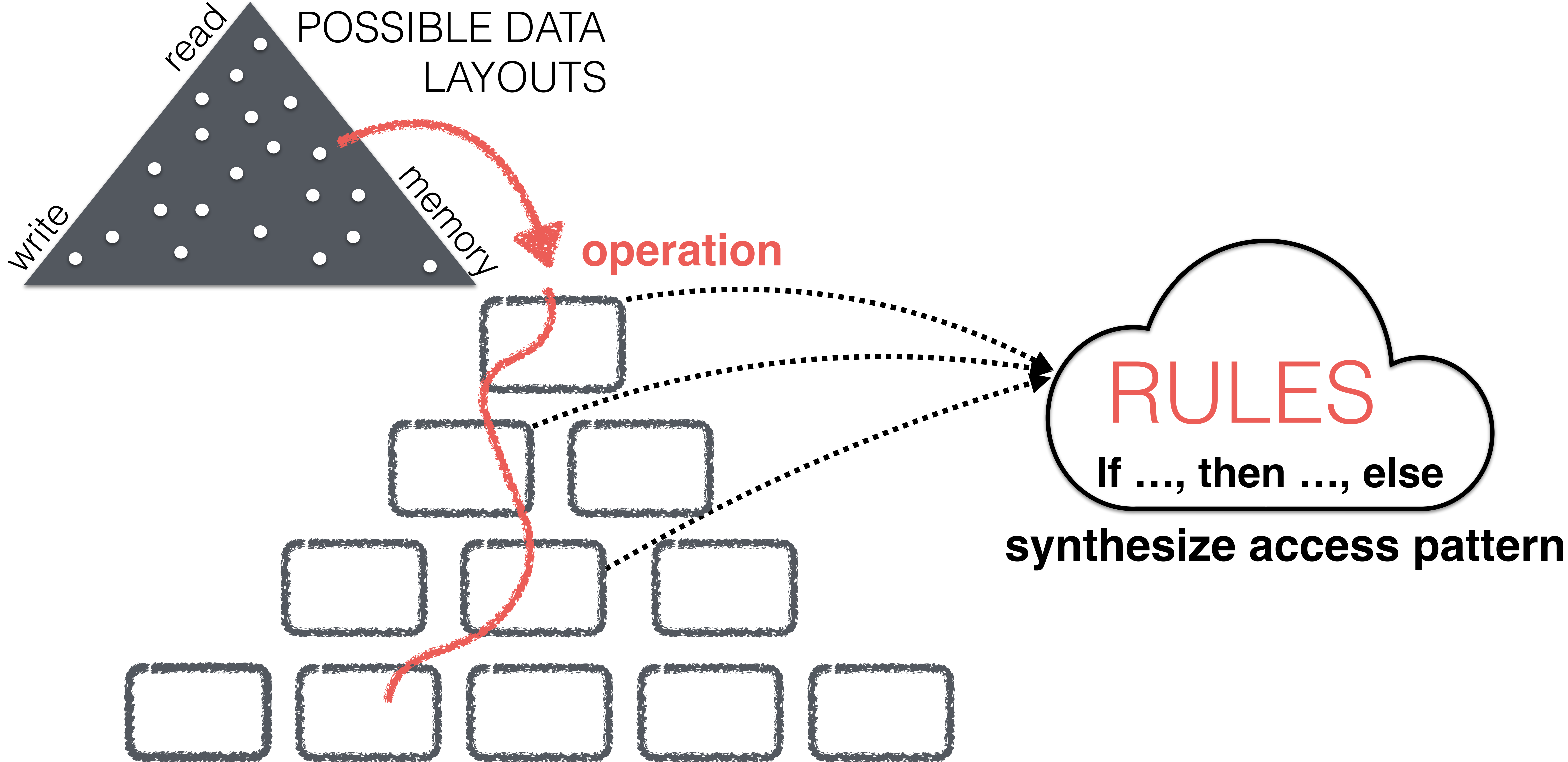








ALGORITHM & COST SYNTHESIS



sorted keys
columnar layout

**sorted keys
columnar layout**

RULES →

**sorted
search**

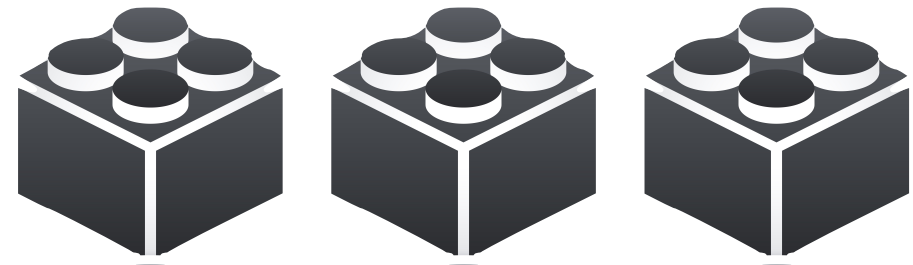
DEPENDS ON **HARDWARE ENGINEERING**

sorted keys
columnar layout

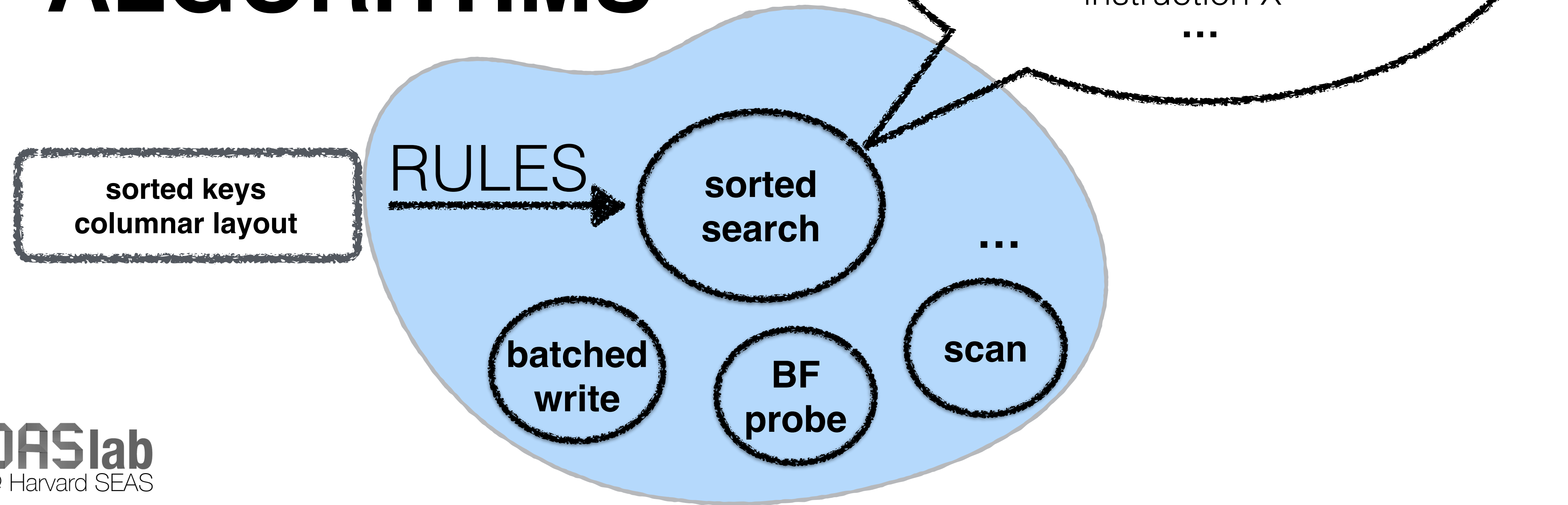
RULES →

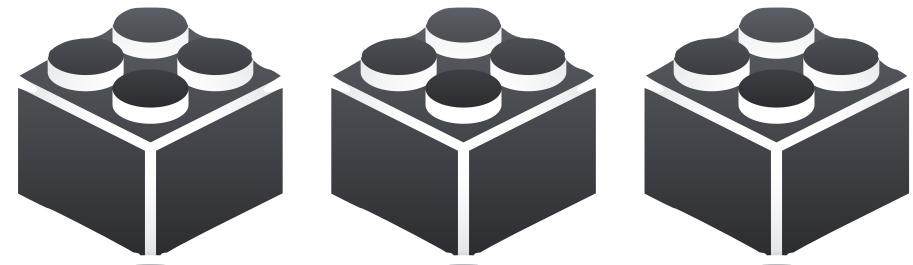
sorted
search

binary search1
binary search2
interpolation search1
interpolation search2
using new SIMD
instruction X
...



COMPONENTS OF KEY-VALUE ALGORITHMS





COMPONENTS OF KEY-VALUE ALGORITHMS

sorted keys
columnar layout

RULES →

sorted
search

batched
write

BF
probe

scan

...

binary search1
binary search2

code,
model

code,
model

interpolation search1
interpolation search2

using new SIMD
instruction X

code,
model

...

LEARNING

SYNTHESIS FROM LEARNED MODELS

coding, modeling, generalized models, and a touch of ML

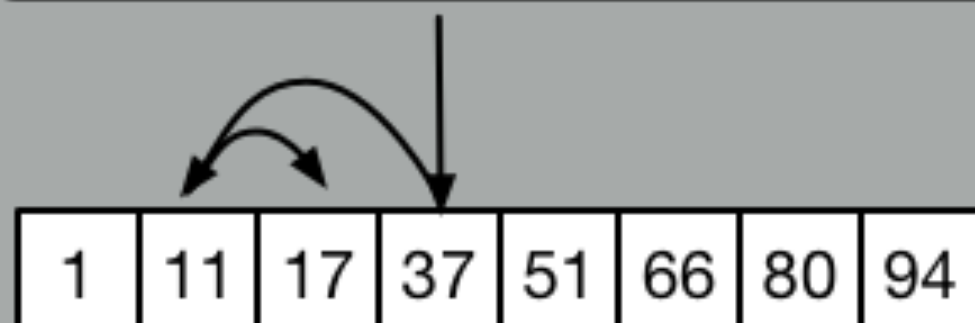


1. MINIMAL CODE

e.g., binary search

```
if (data[middle] < search_val) {  
    low = middle + 1;  
} else {  
    high = middle;  
}  
middle = (low + high)/2;
```

C++



SYNTHESIS FROM LEARNED MODELS

coding, modeling, generalized models, and a touch of ML



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e.g., binary search

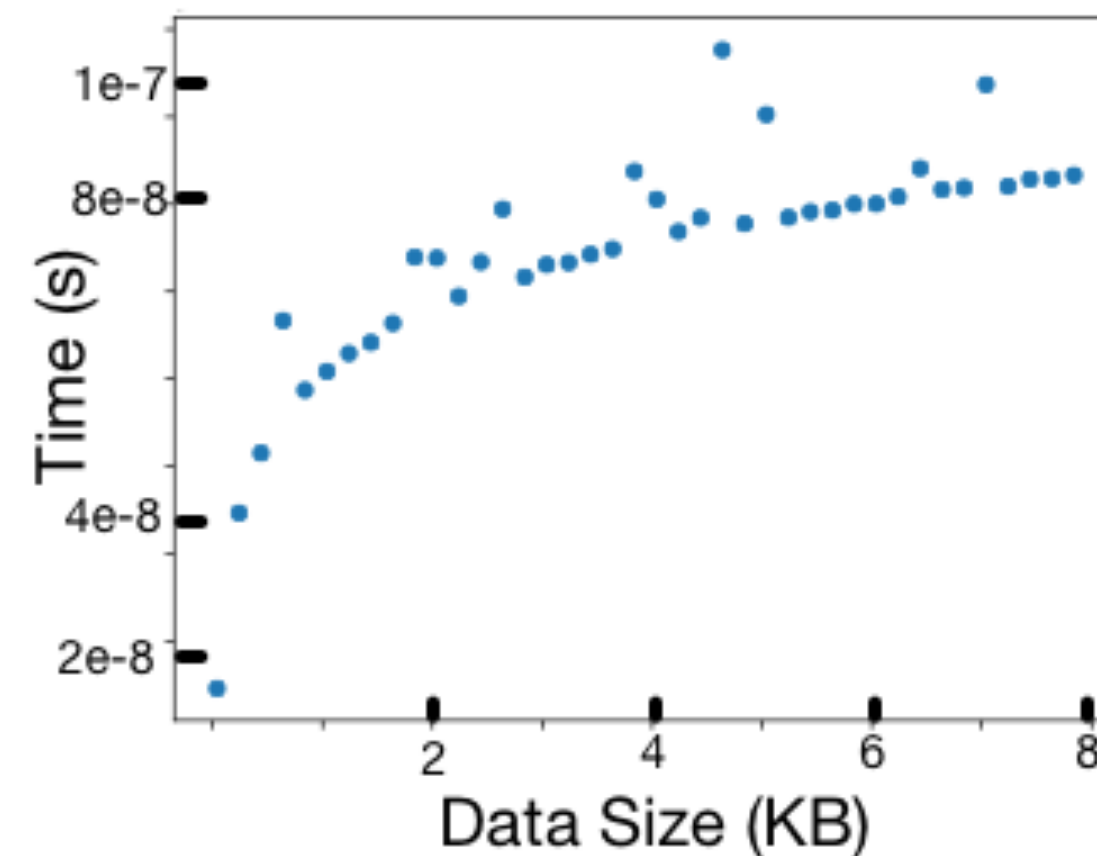
```
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```



Run

1	11	17	37	51	66	80	94
---	----	----	----	----	----	----	----

2. BENCHMARK



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coding, modeling, generalized models, and a touch of ML



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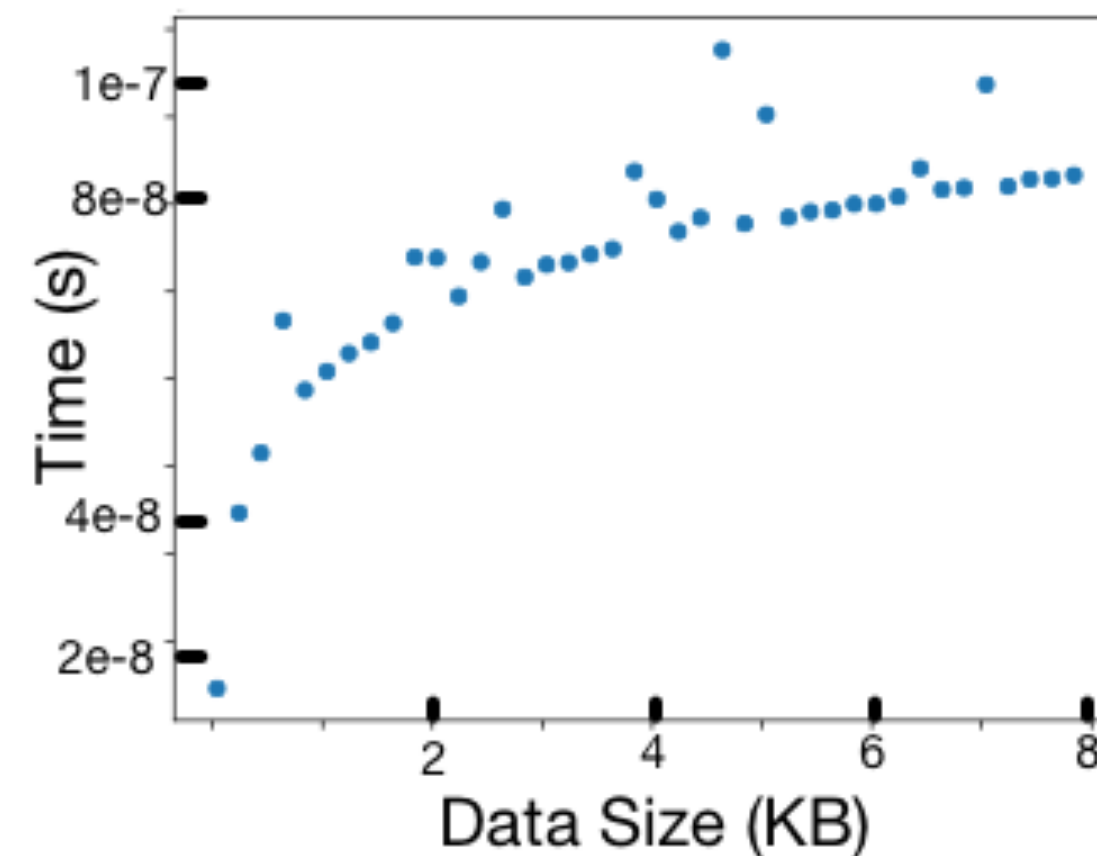
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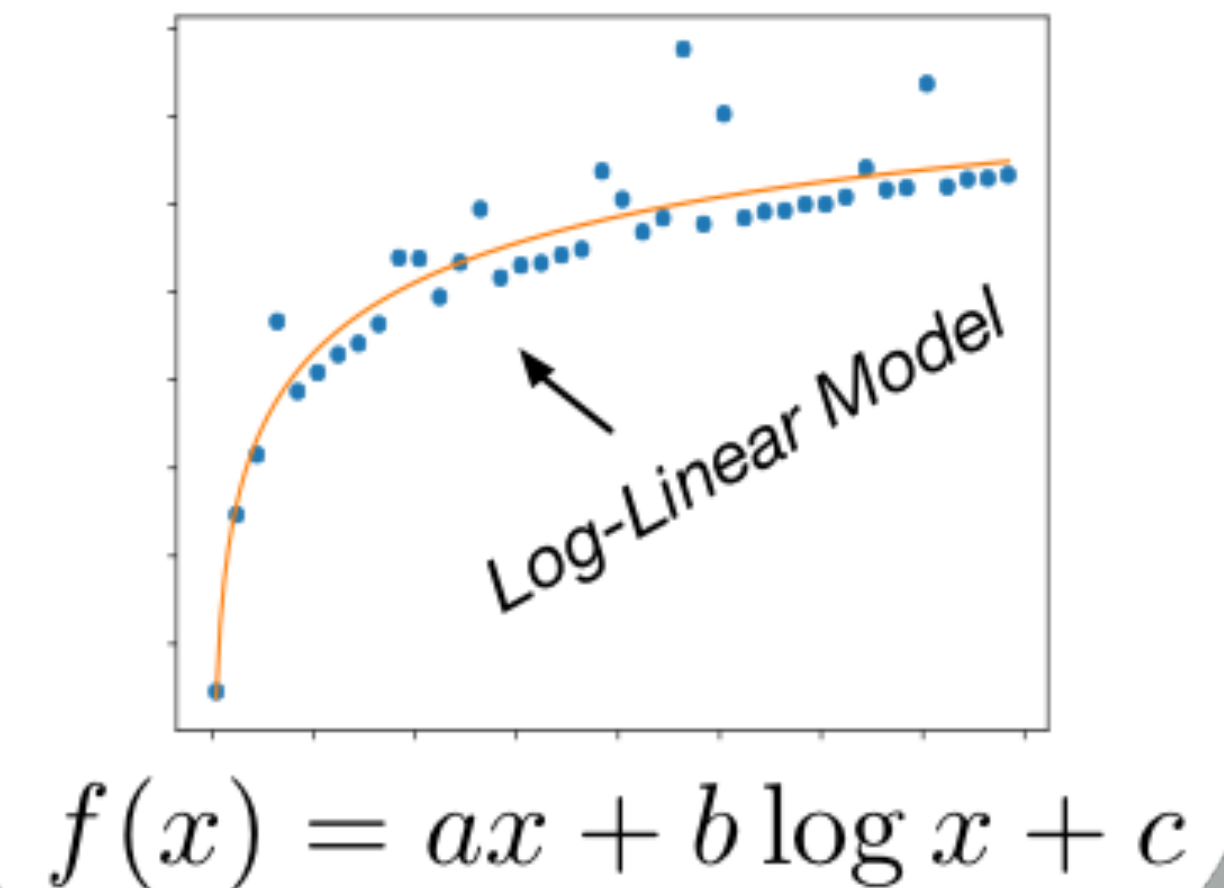
2. BENCHMARK



$f(x)$

Train

3. FIT MODEL



SYNTHESIS FROM LEARNED MODELS

coding, modeling, generalized models, and a touch of ML



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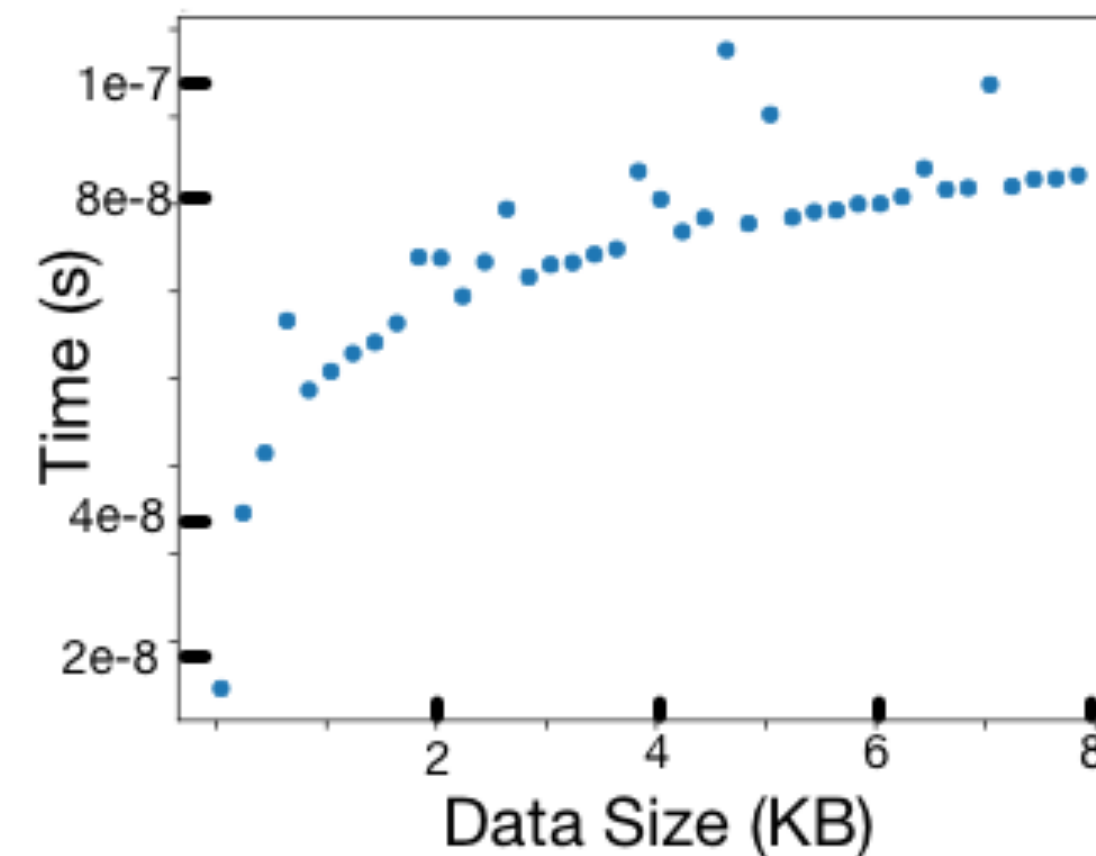
C++

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Run

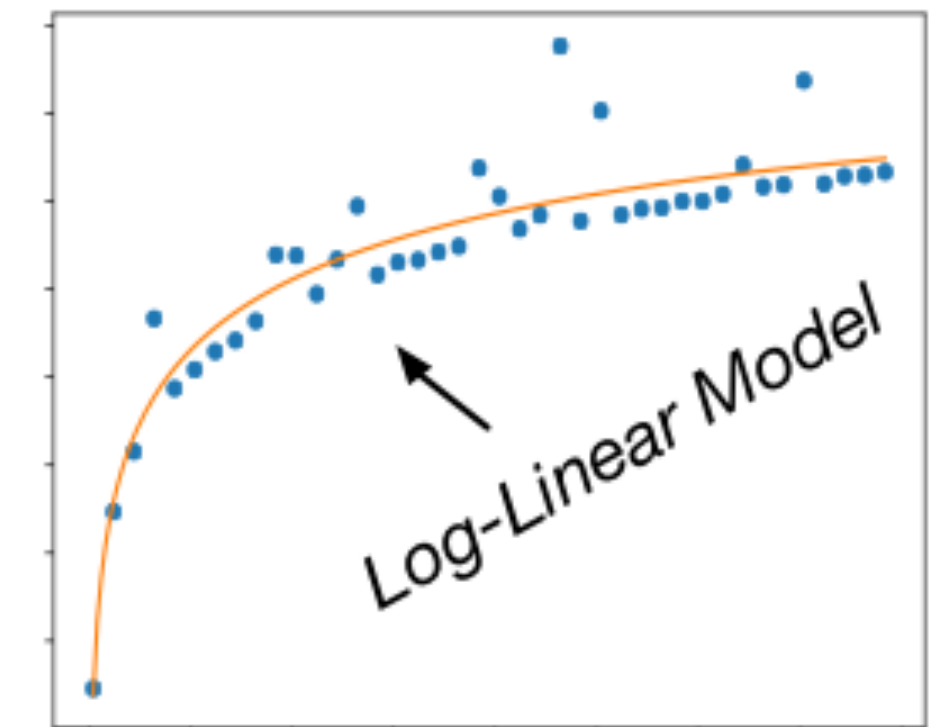
2. BENCHMARK



$f(x)$

Train

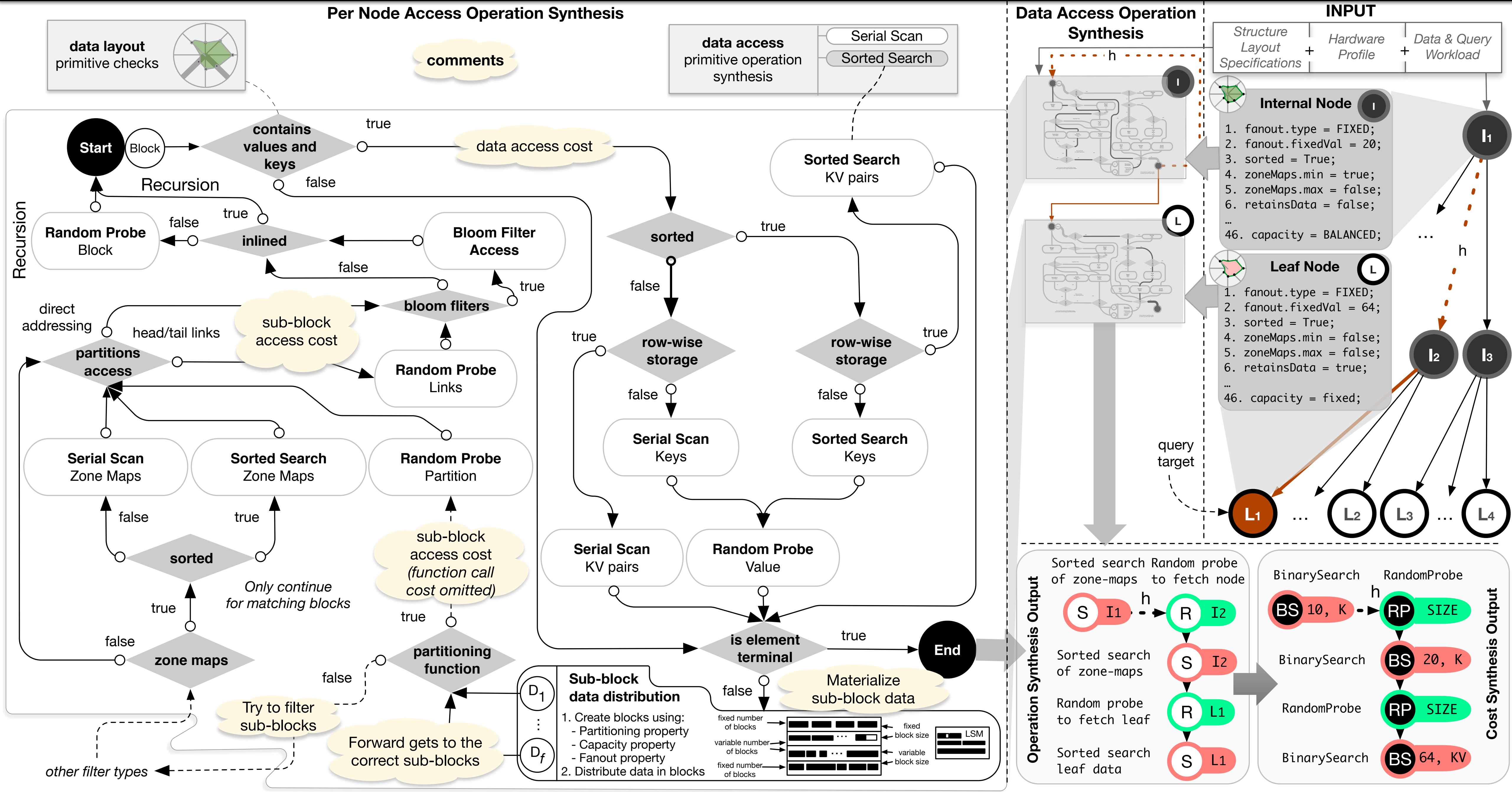
3. FIT MODEL



$$f(x) = ax + b \log x + c$$

FOLDING ALGORITHMIC, ENGINEERING, AND H/W, PROPERTIES INTO THE COEFFICIENTS

RULE/MODEL BASED SYSTEM SYNTHESIZES ALGORITHM AND COST



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