SuRF: PRACTICAL RANGE FILTERING WITH FAST SUCCINCT TRIES

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Michael Kaminsky, Kimberly Keeton, Andrew Pavlo

Filters answer approximate membership queries

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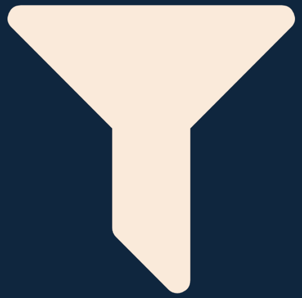
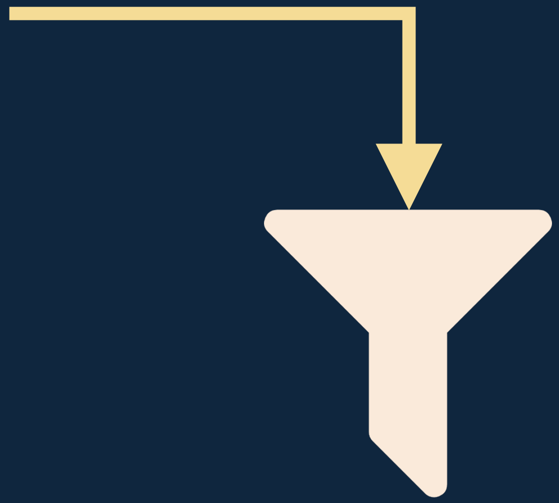


Billionaire ?

Filters answer approximate membership queries



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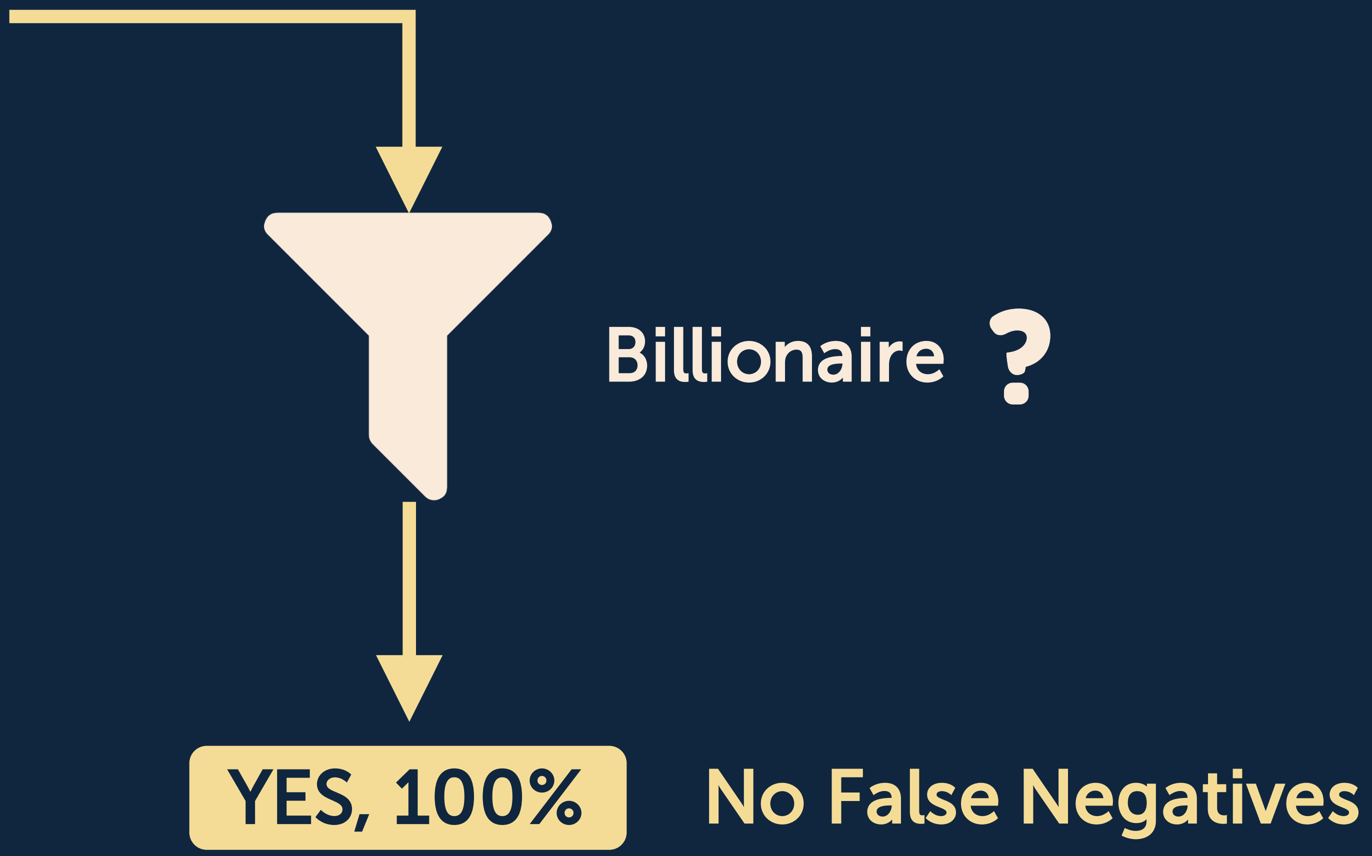

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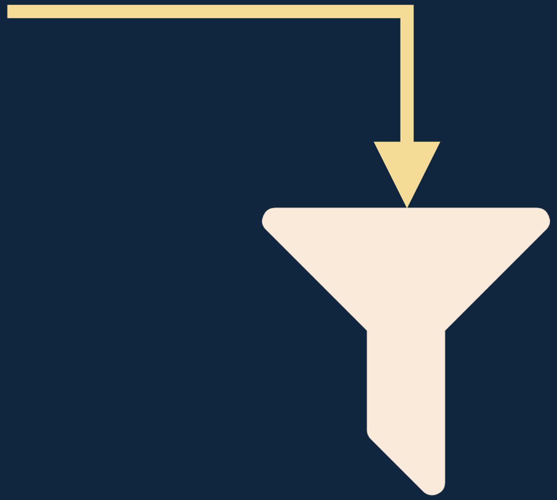

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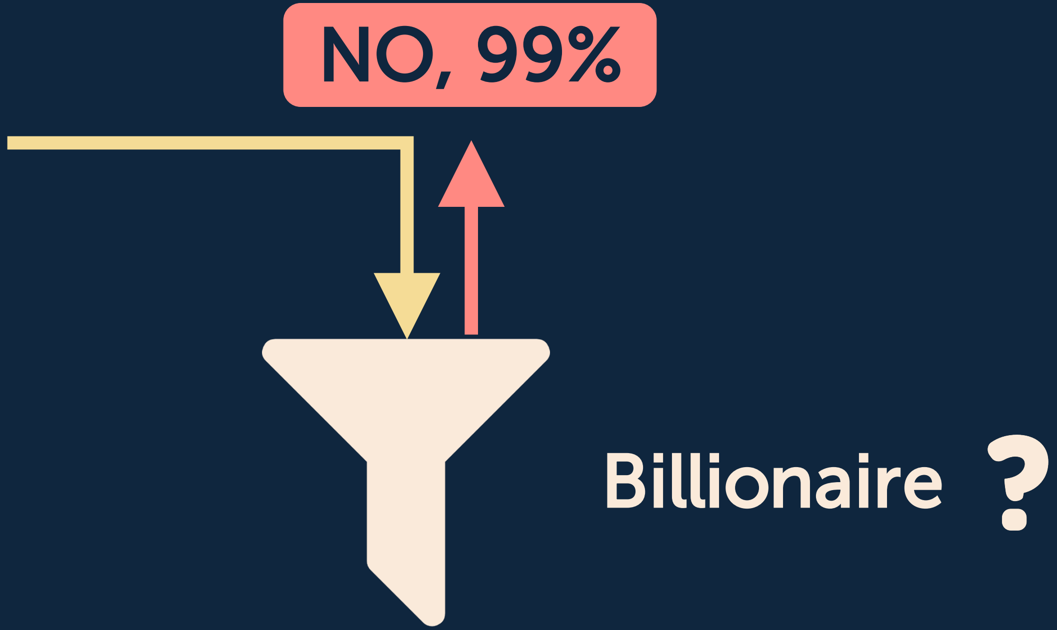

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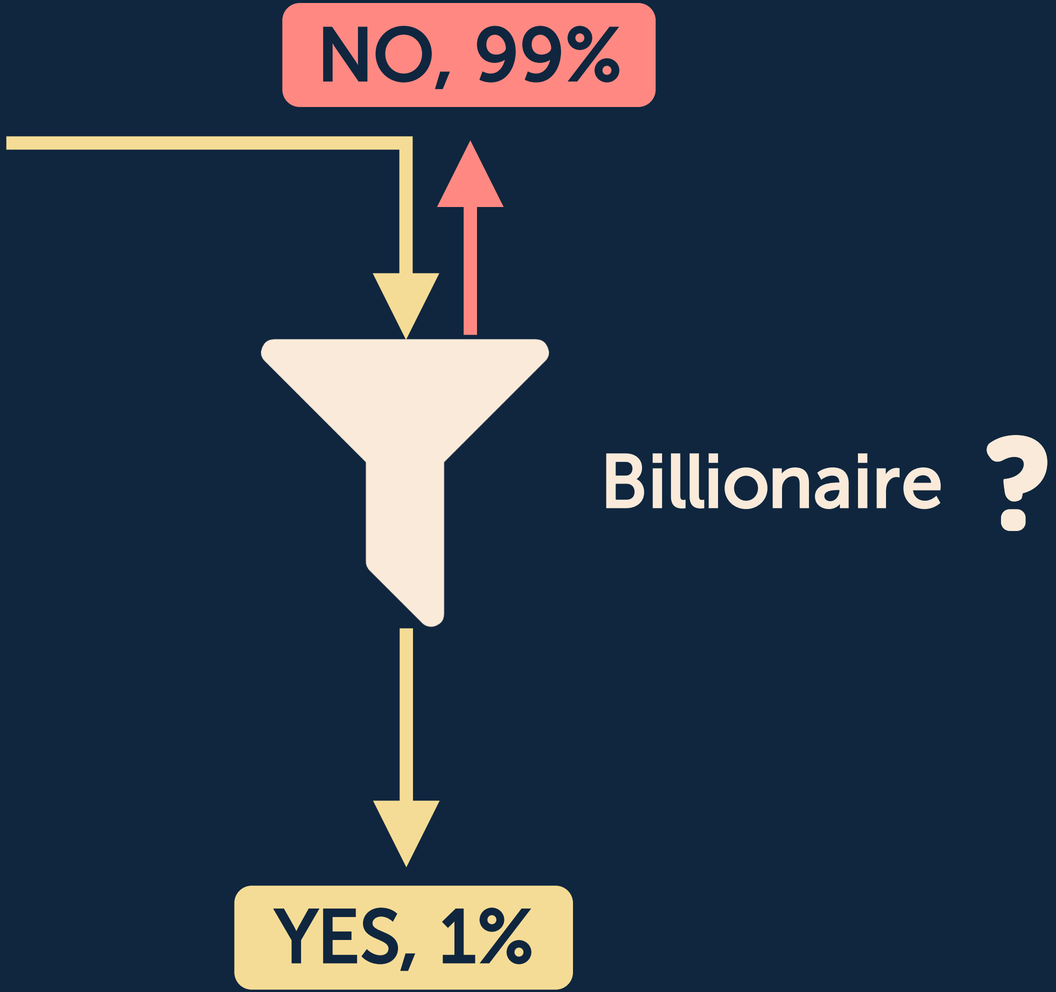

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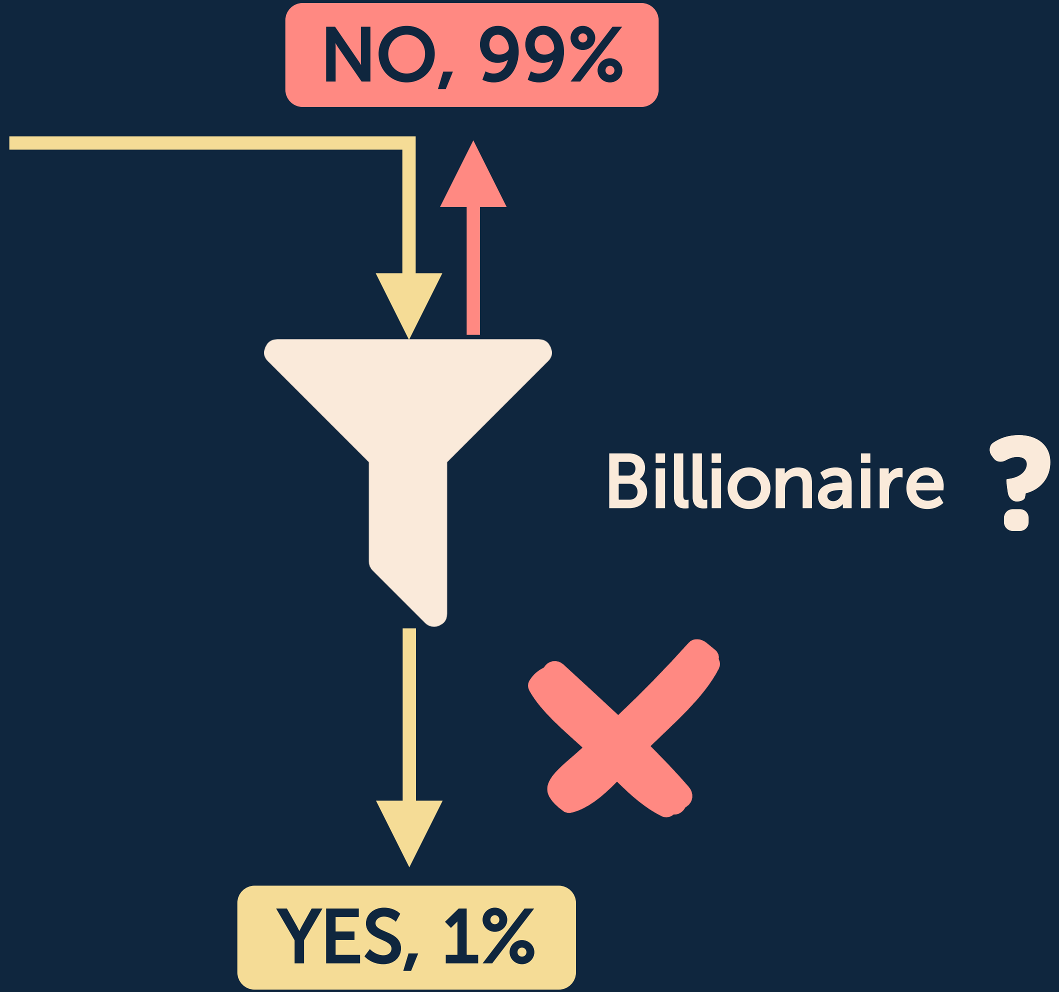

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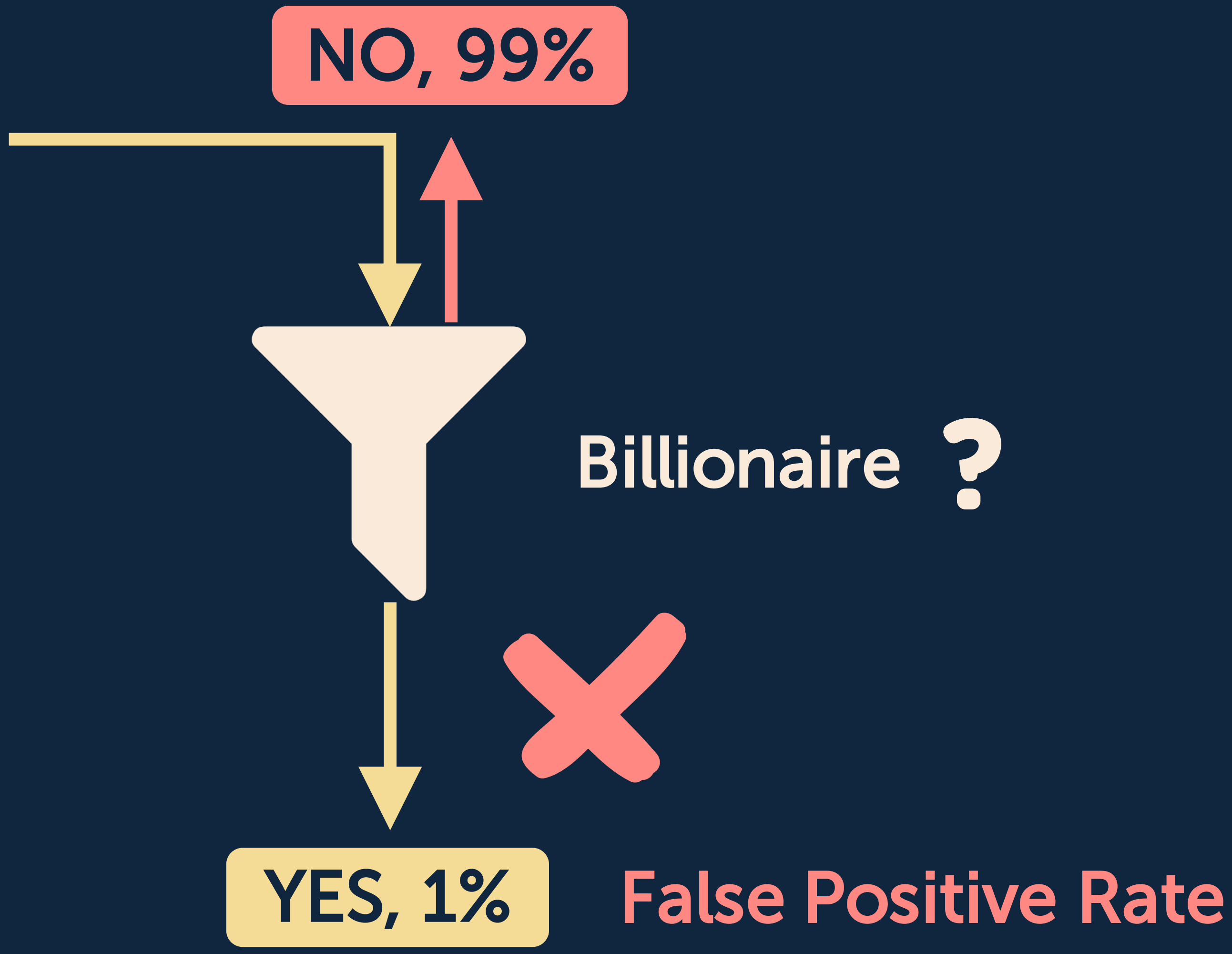
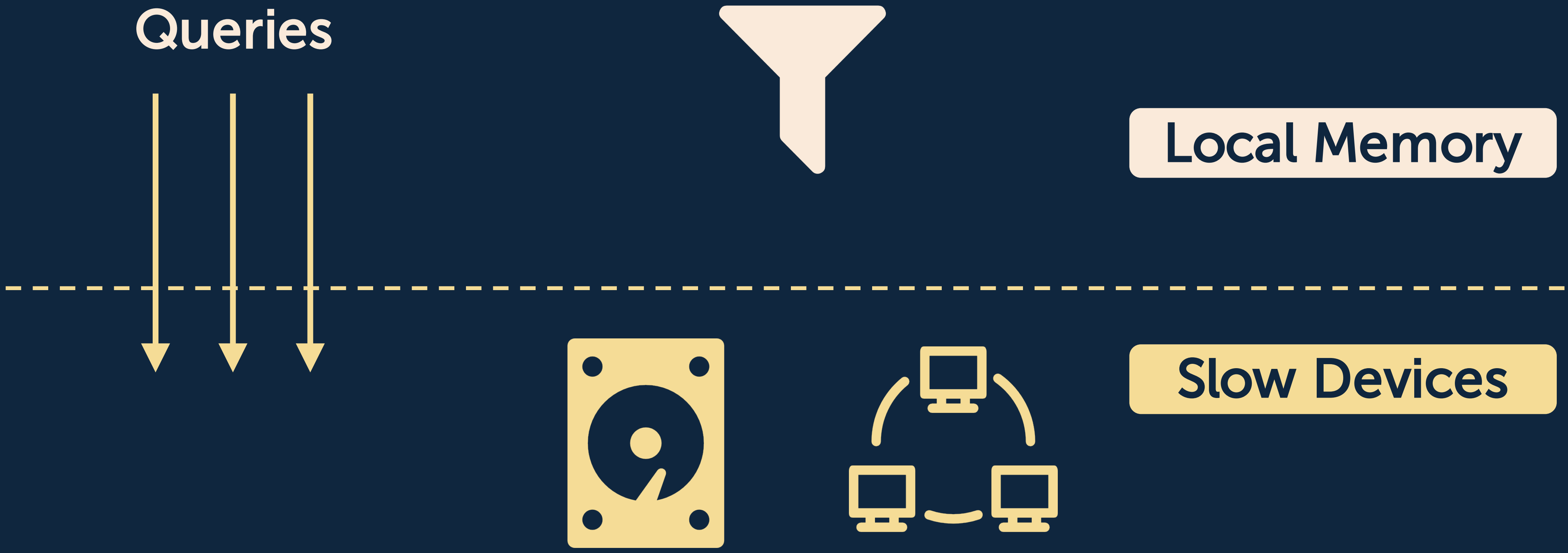


Filters pre-reject most negative queries



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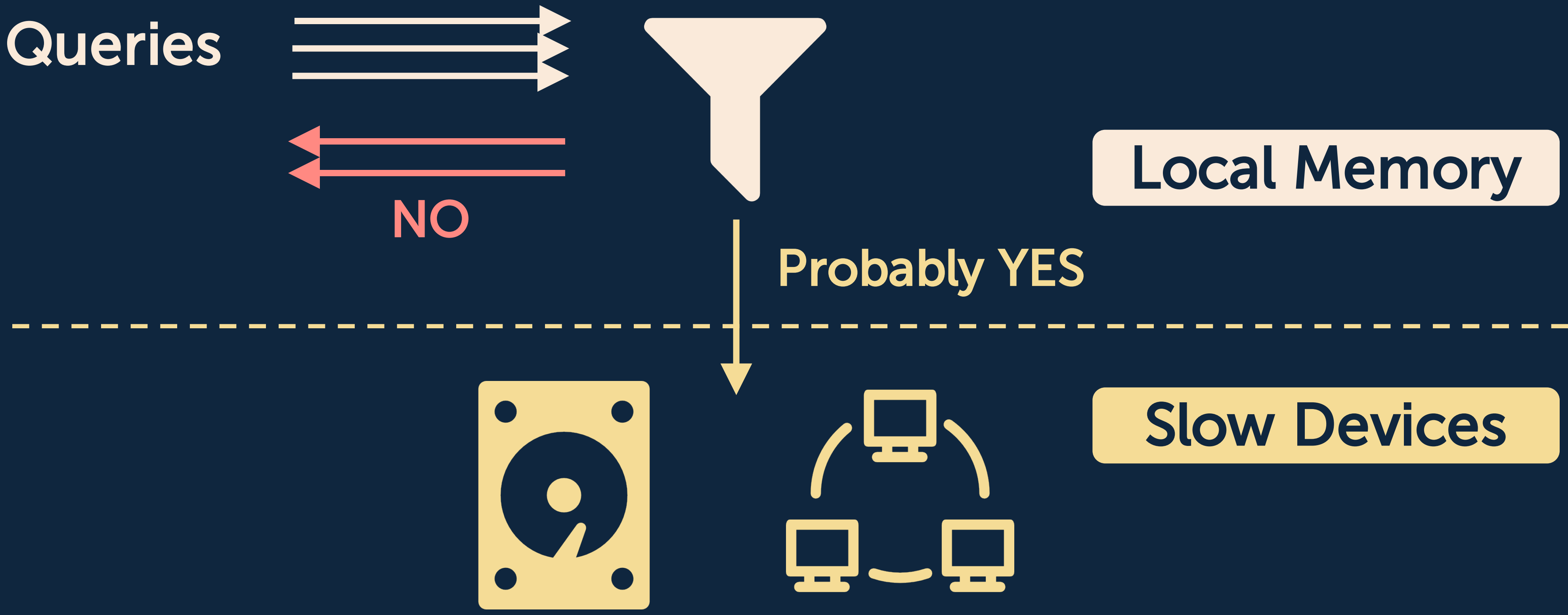

Existing filters only support point filtering

Point Filtering

SELECT * FROM Billionaires
WHERE LastName = 'Pavlo'

Bloom Filter (1970)
Quotient Filter (2012)
Cuckoo Filter (2014)

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Point Filtering	Range Filtering
SELECT * FROM Billionaires WHERE LastName = ‘Pavlo’	SELECT * FROM Billionaires WHERE LastName LIKE ‘Pav%’

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Our solution: Succinct Range Filters (SuRF)

First practical, general-purpose range filter

SMALL: close to theoretic minimum

64-bit integer keys, 1% false positive rate: ≈ 12 bits per key

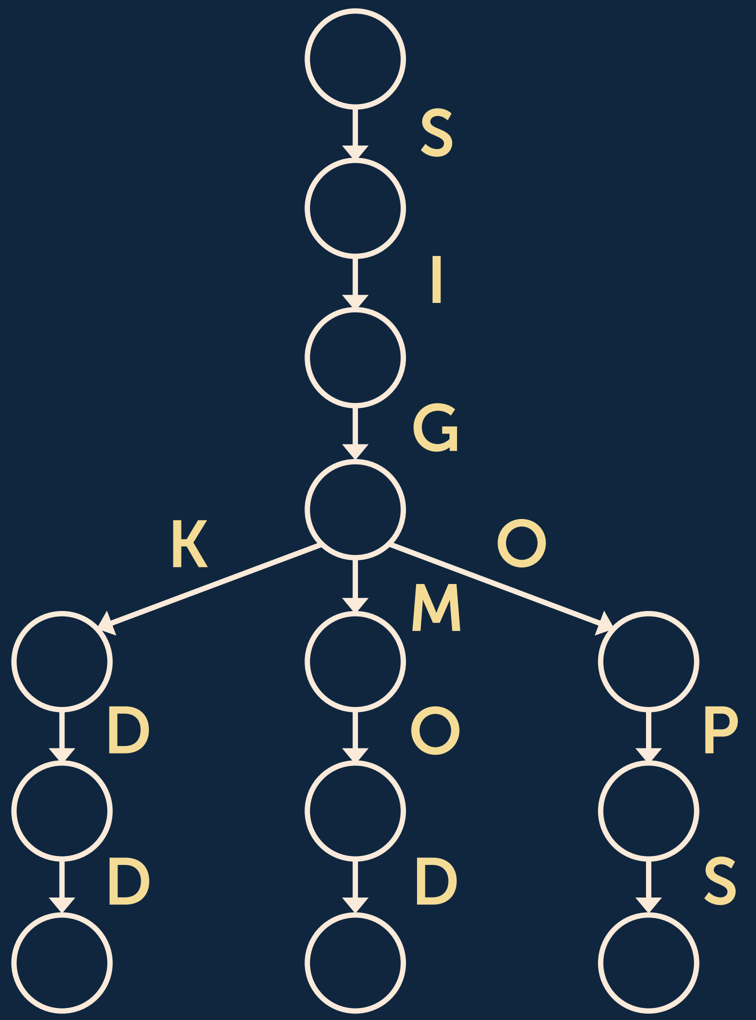
FAST: comparable to fastest trees

10 million 64-bit integer keys: ≈ 200 ns per query

USEFUL: evaluated in RocksDB

speed up range queries by up to 5x

Starting point: a complete trie



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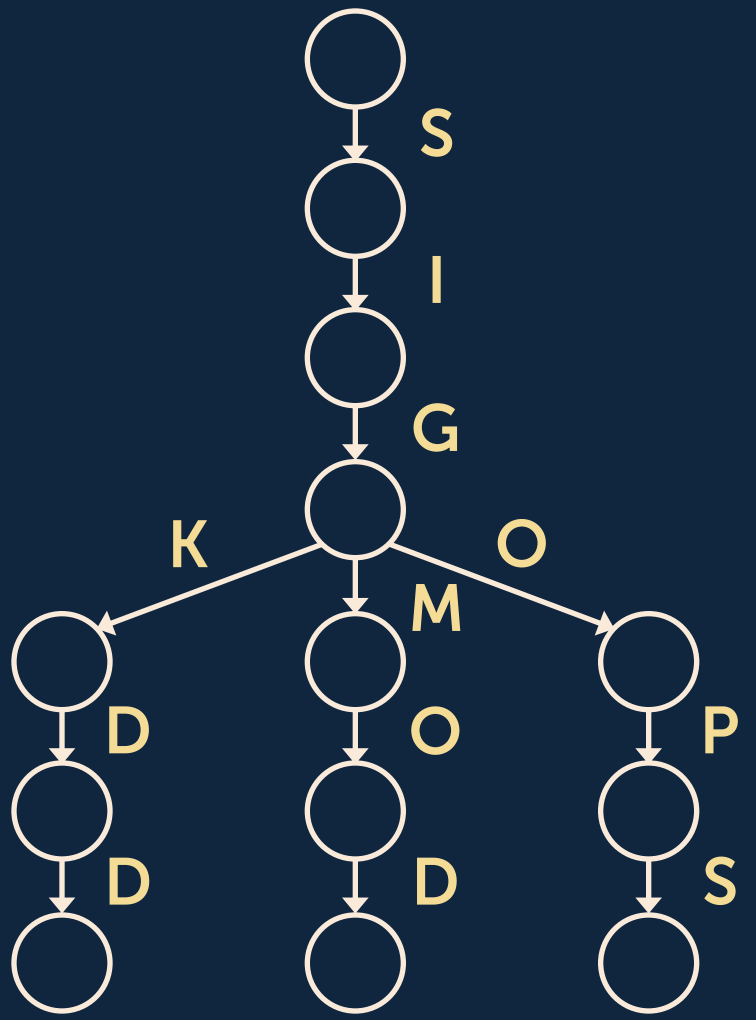
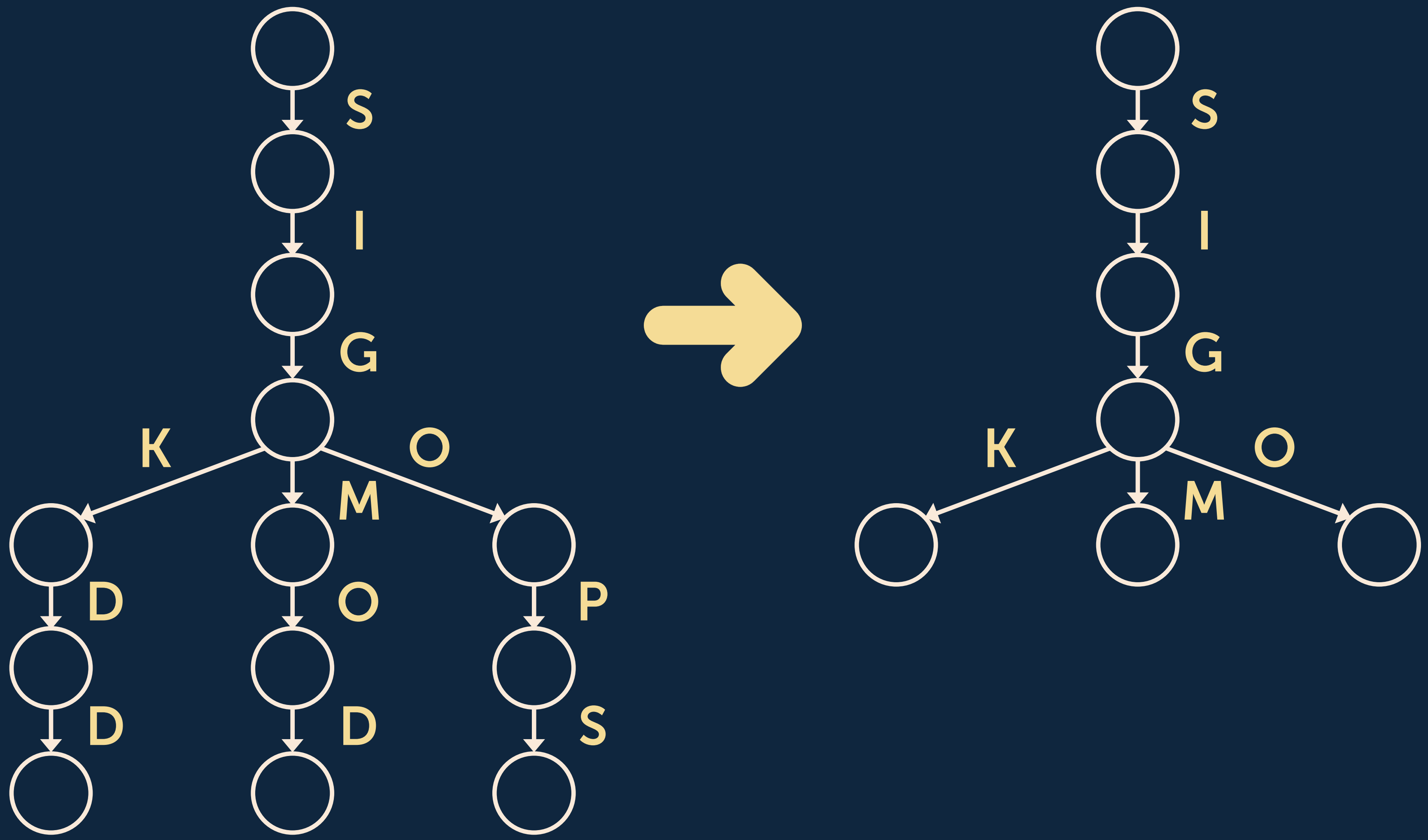


TOO BIG ✗

Make it smaller: a truncated trie



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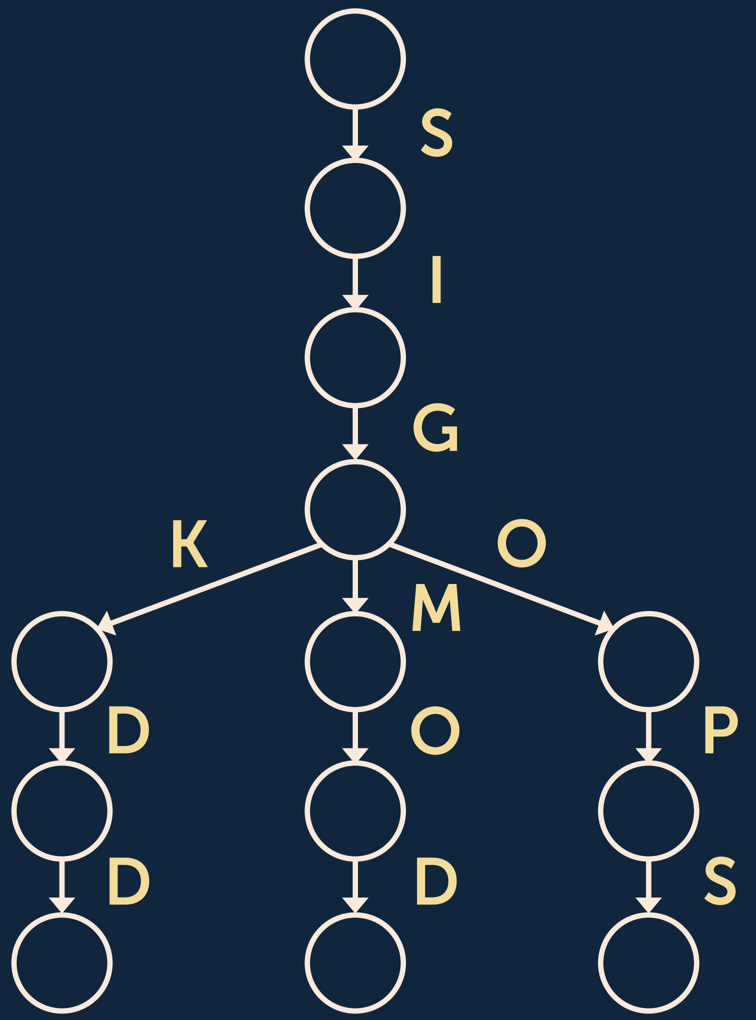
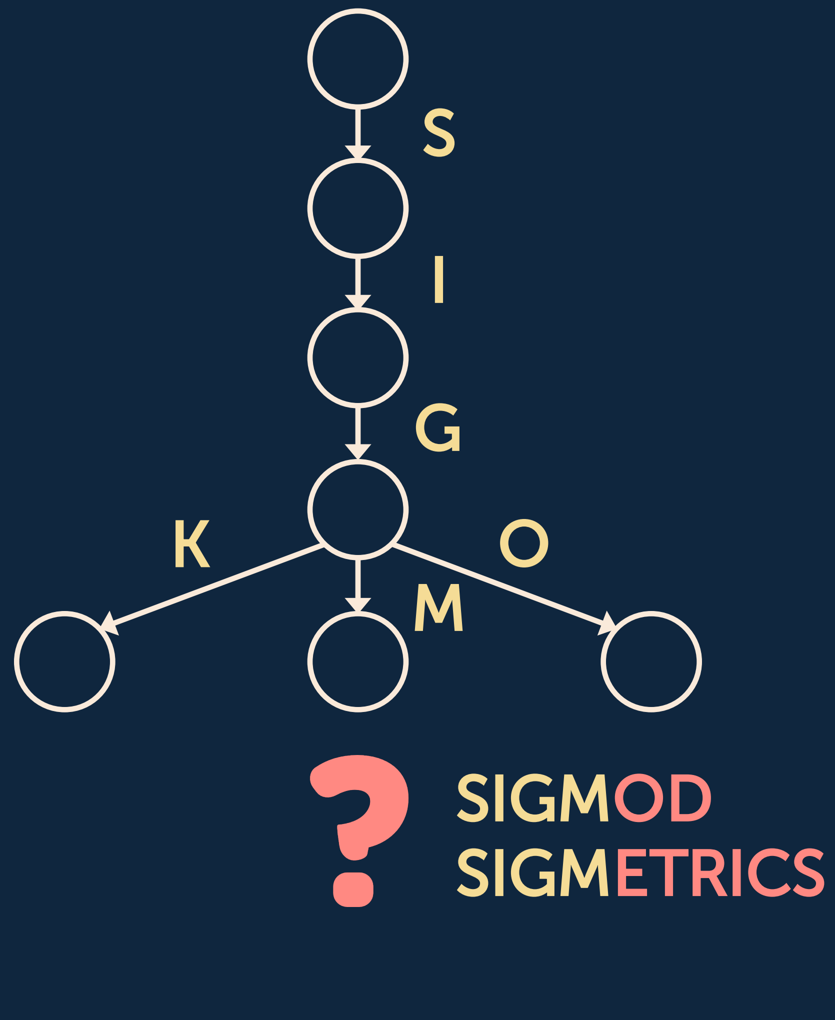
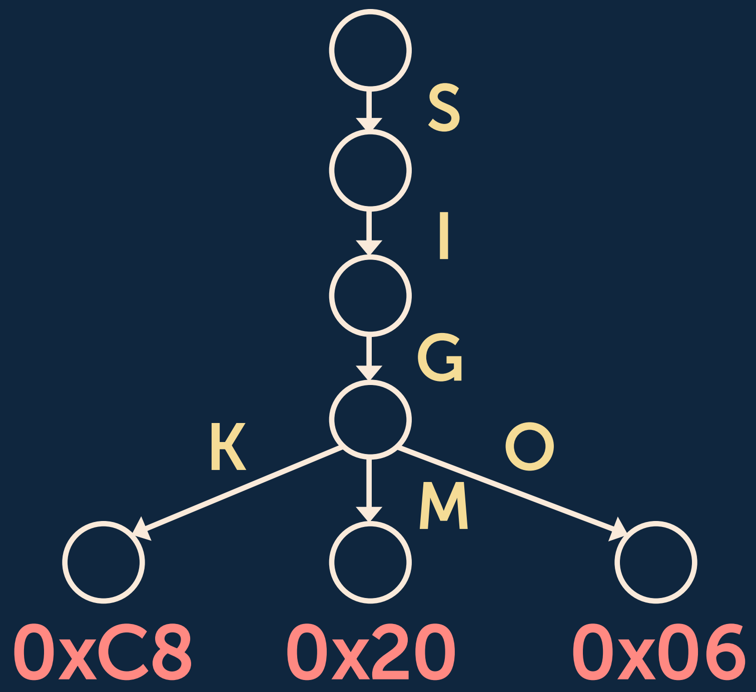


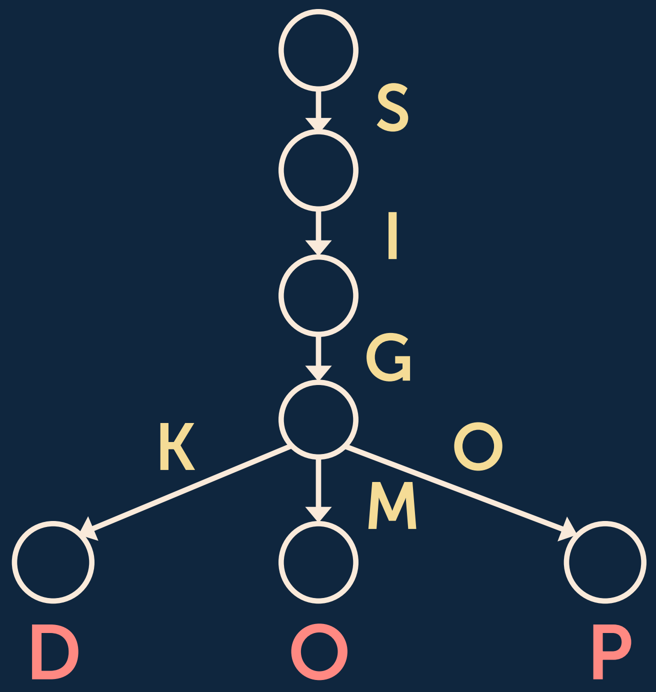


Use suffix bits to reduce false positive rate

Hashed Suffix Bits



Real Suffix Bits



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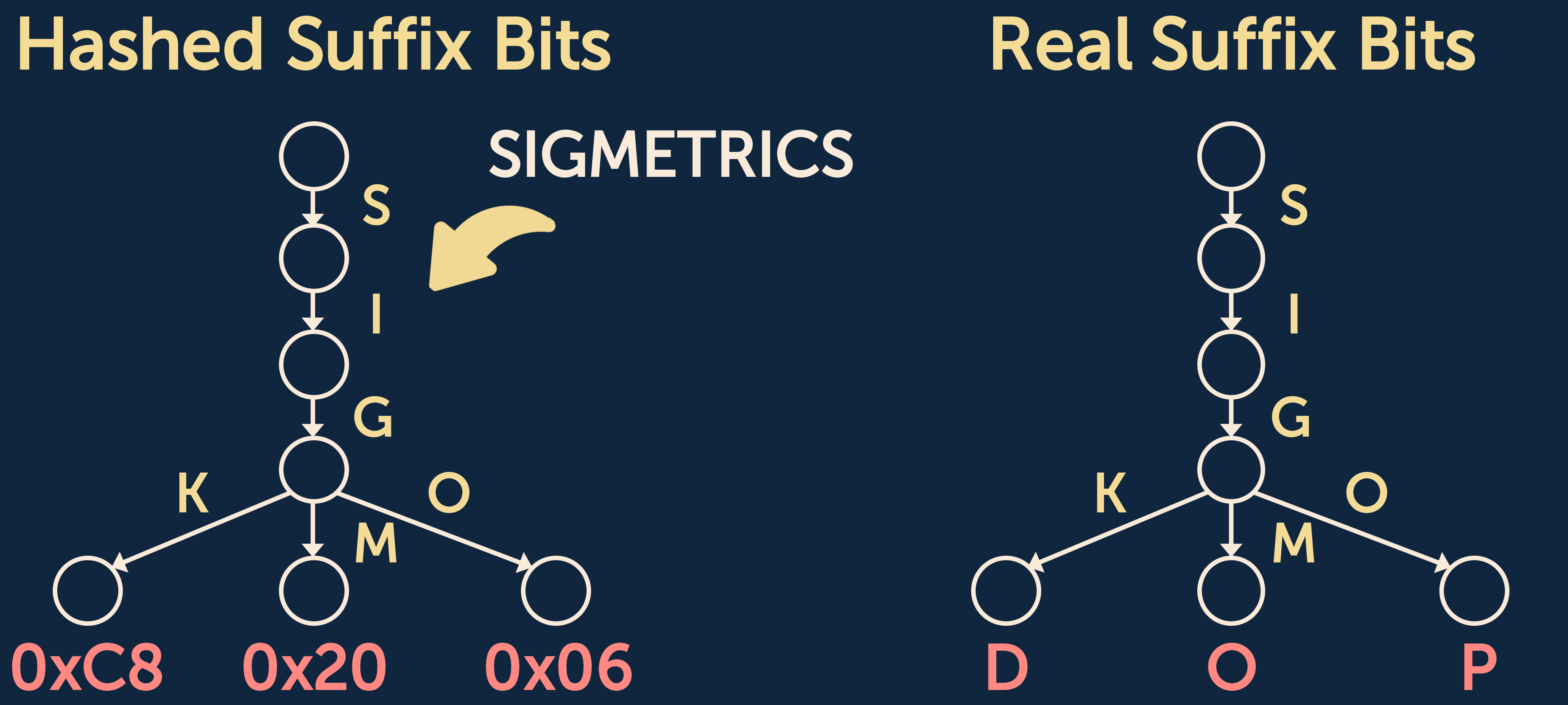

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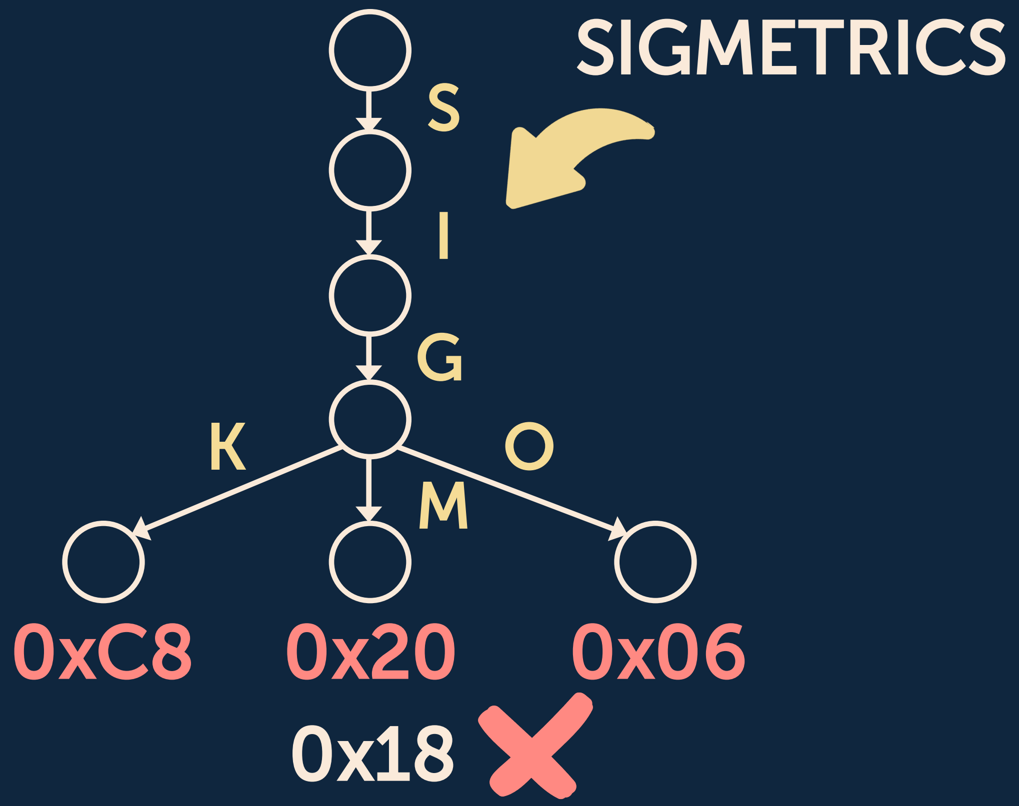

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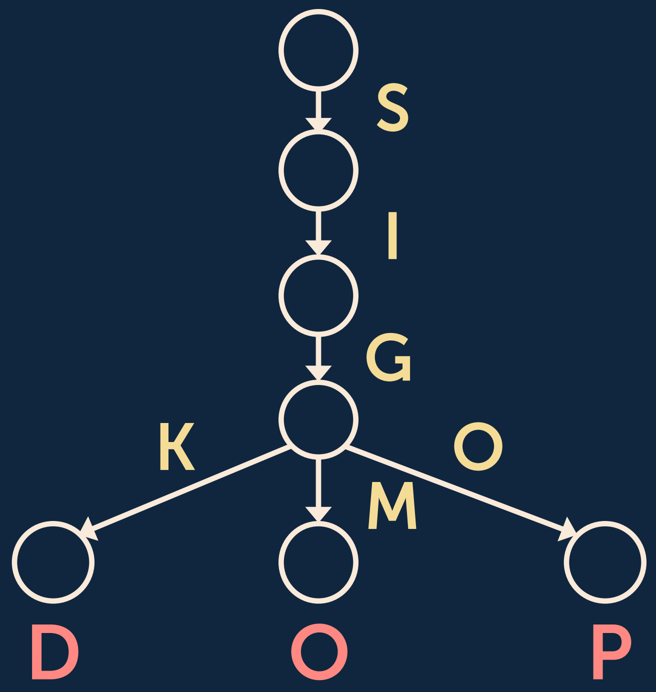

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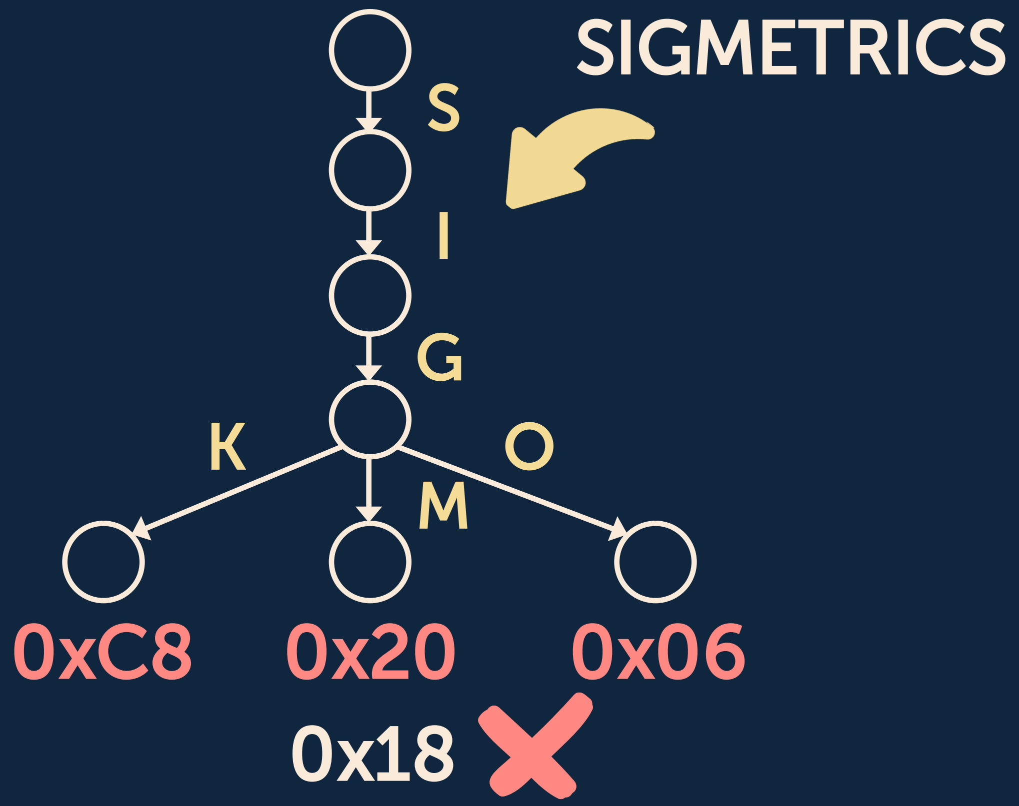

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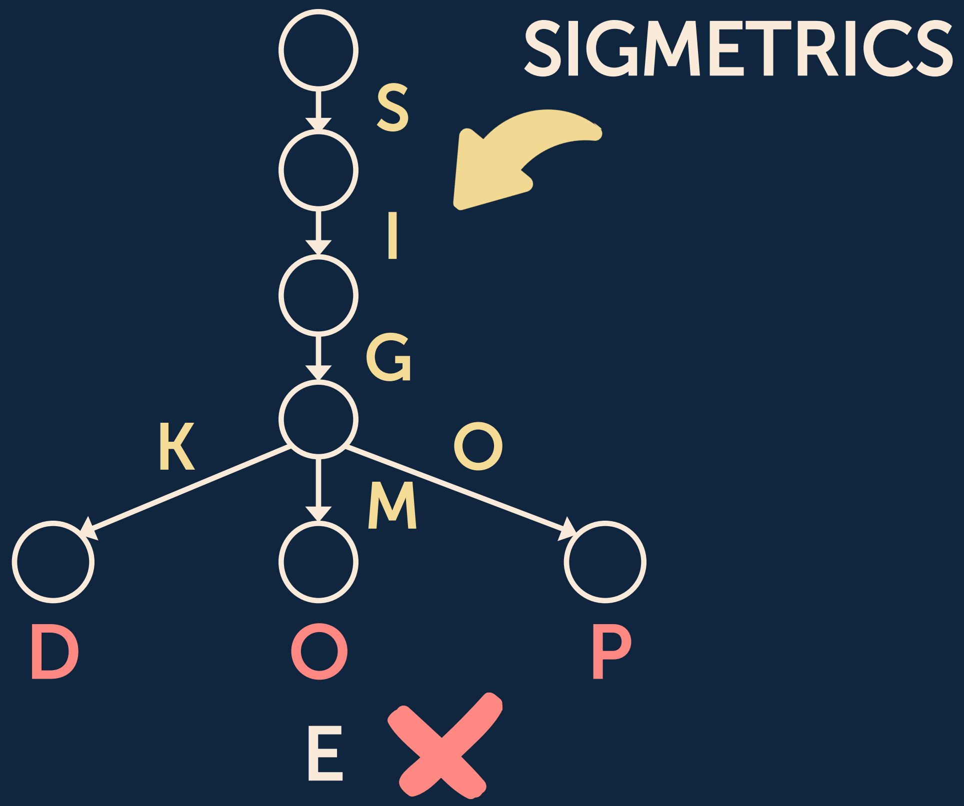

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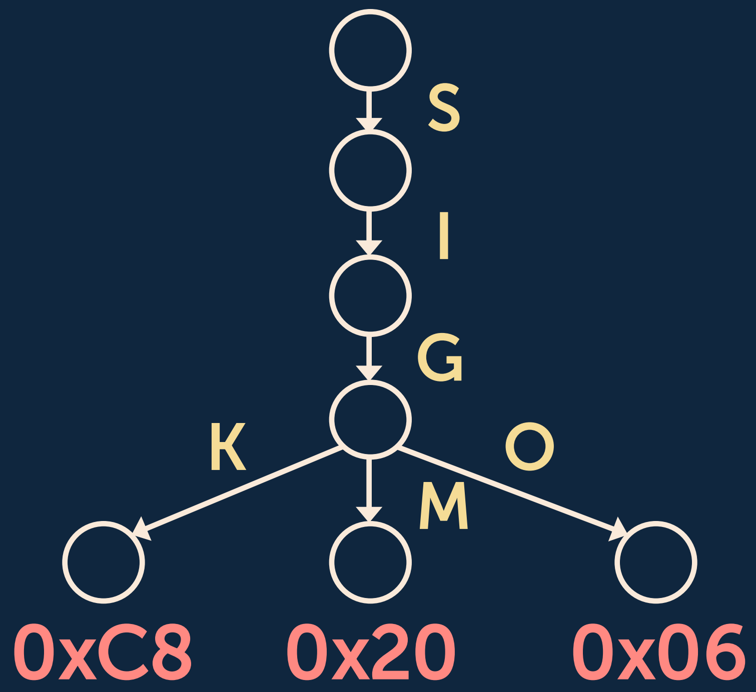

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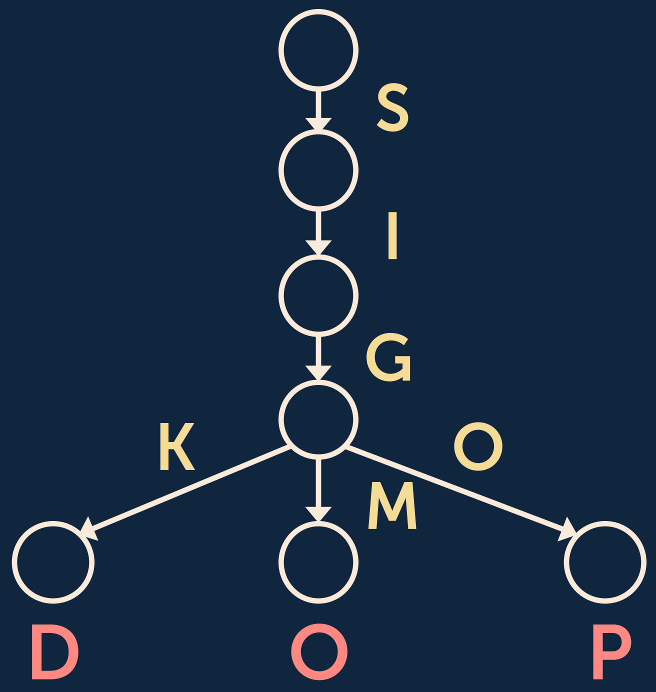

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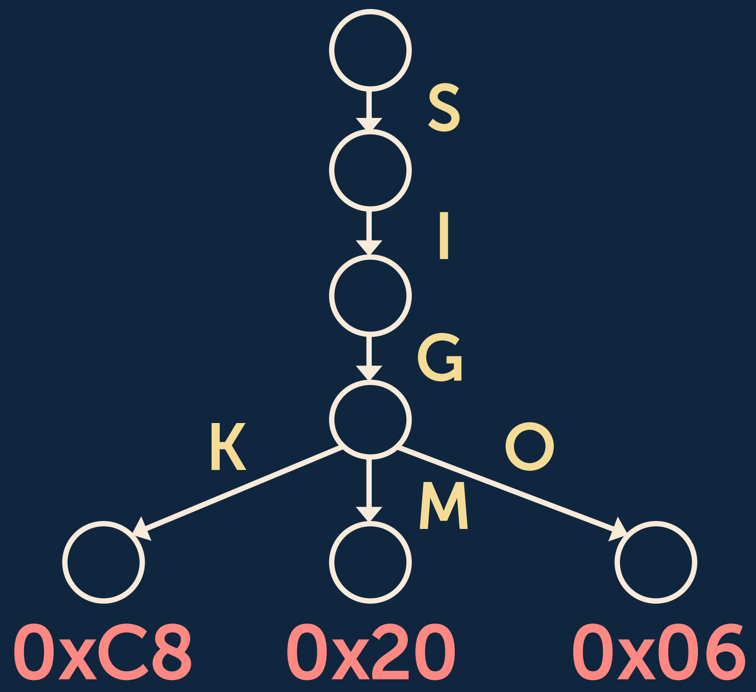

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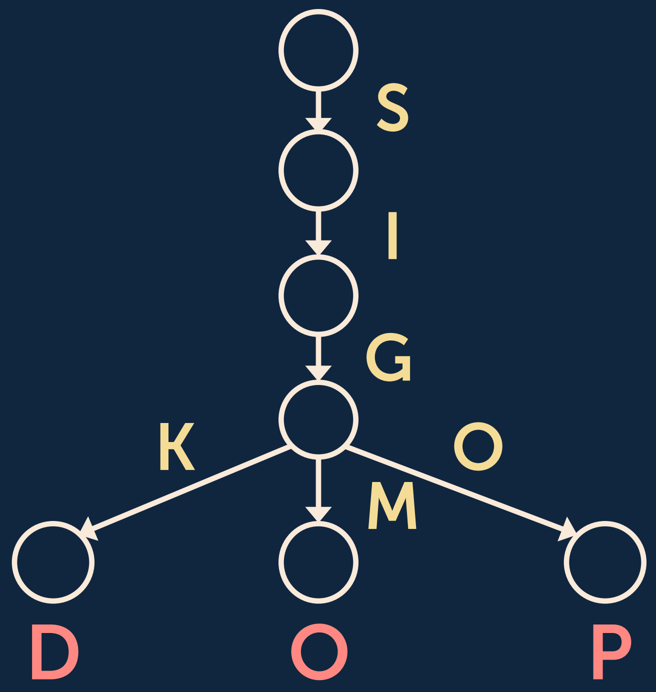

+ Each bit reduces FPR by half

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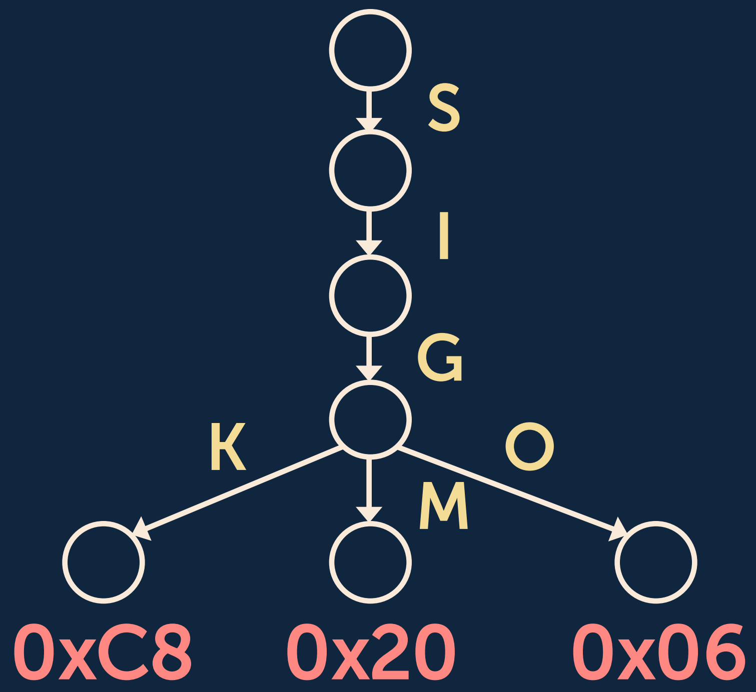

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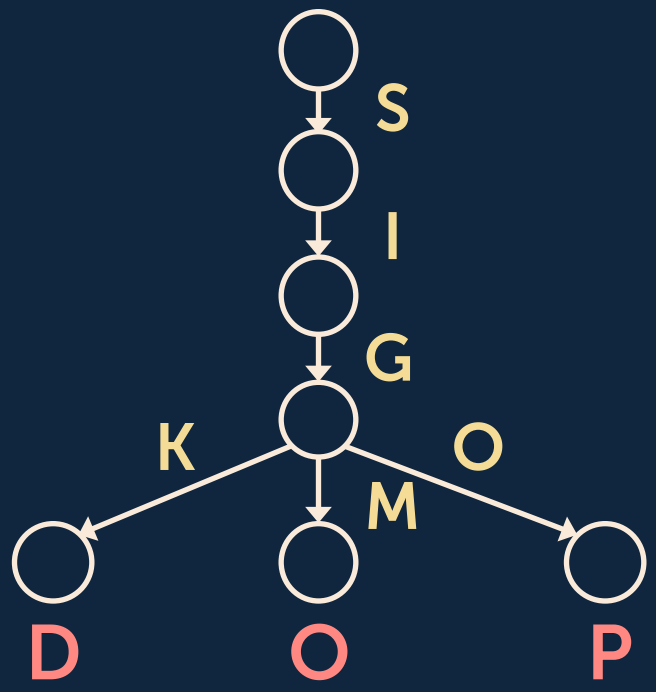

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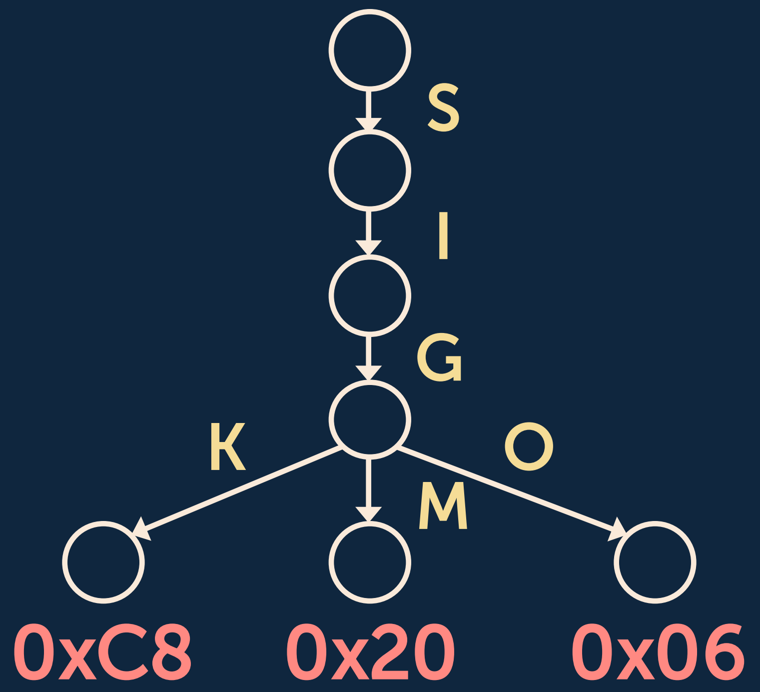

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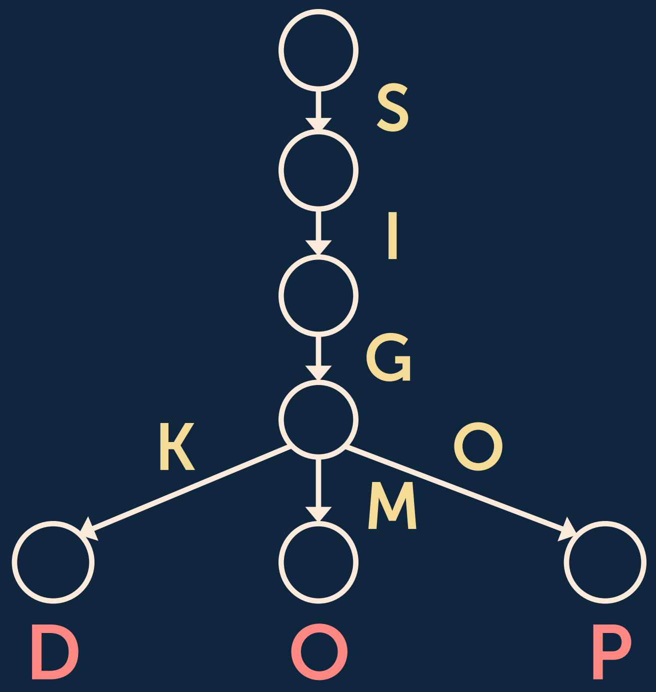

- Benefit point & range queries

Use suffix bits to reduce false positive rate

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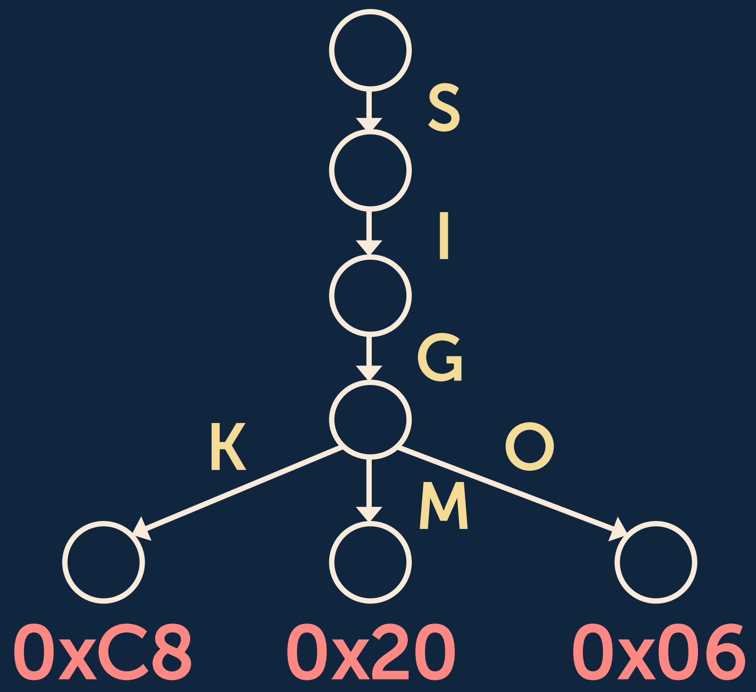

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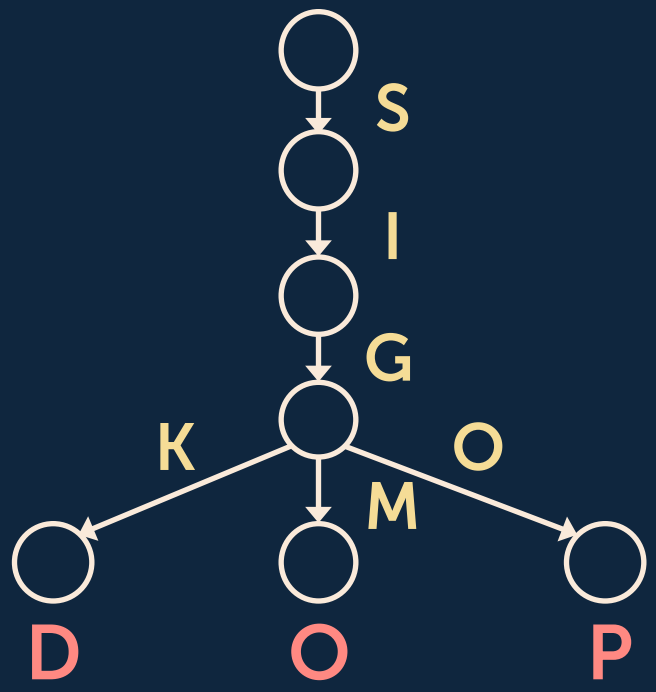


- ➕ Benefit point & range queries
- ➖ Weaker distinguishability

Succinct Data Structure

… uses an amount of space that is “close” to the information-theoretic lower bound, but still allows efficient query operations. [wikipedia]

SuRF's encoding is small and fast

① Small

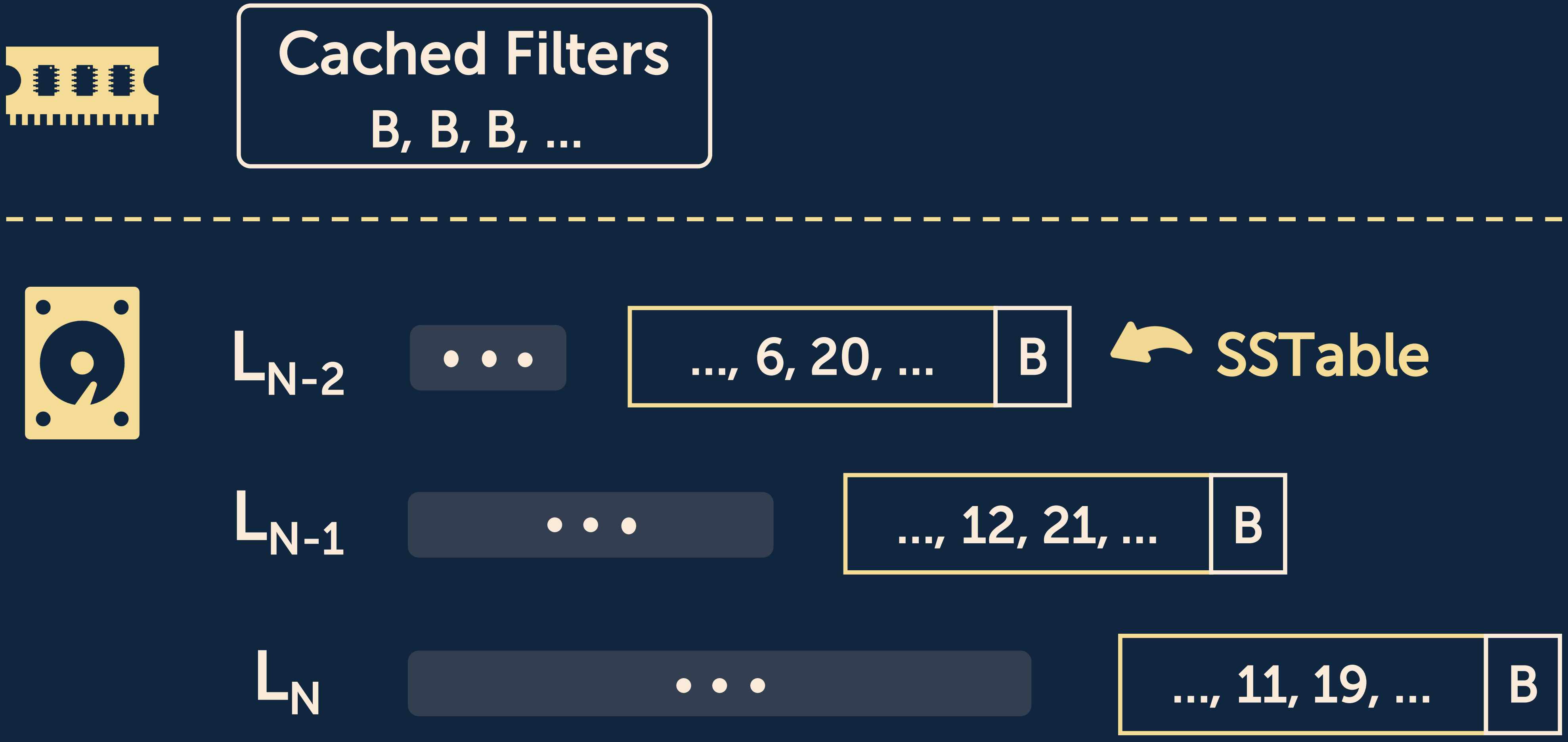
≈10 + suffix bits per key for 64-bit integers

≈14 + suffix bits per key for emails

② Fast

Matches state-of-the-art pointer-based trees

Bloom filters speed up point queries in RocksDB



Bloom filters speed up point queries in RocksDB

Cached Filters

B, B, B, …

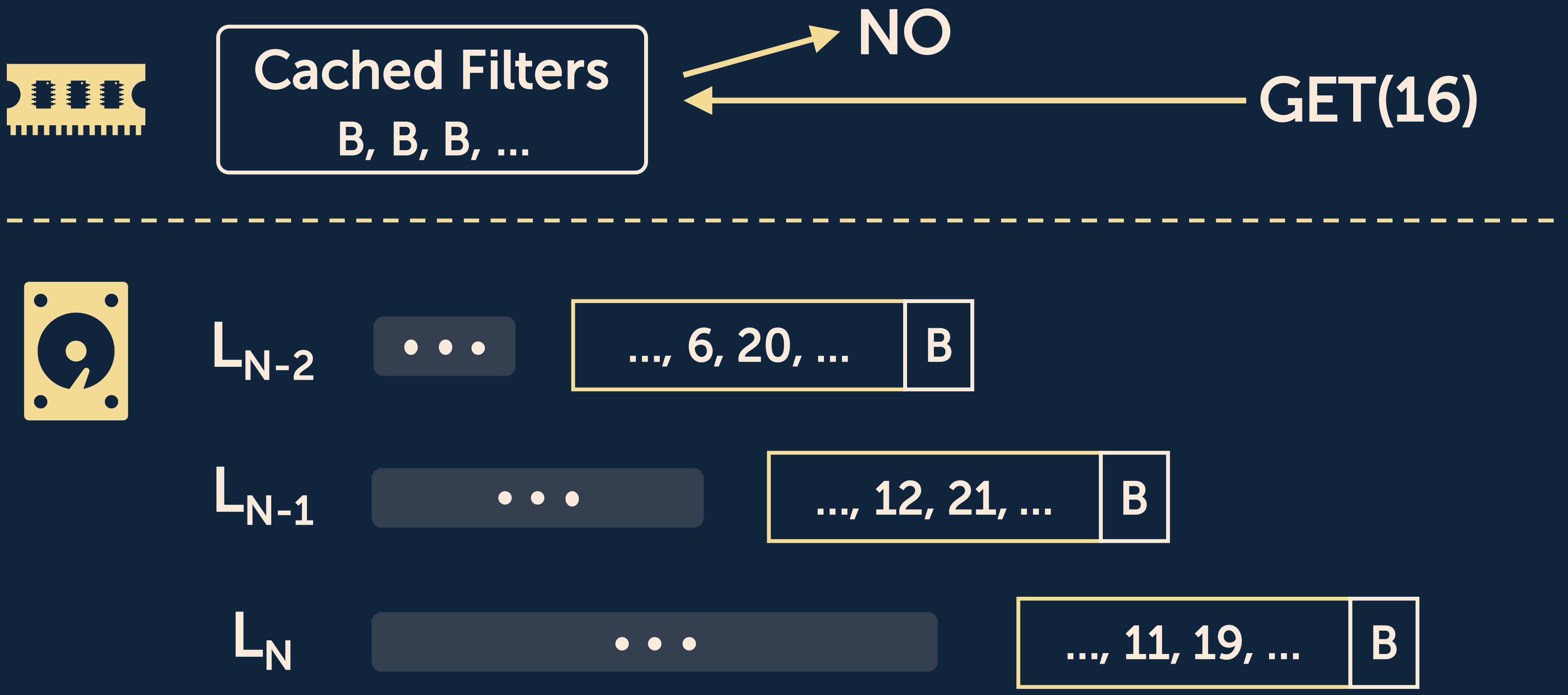
GET(16)

L_{N-2} • • • | …, 6, 20, … | B

L_{N-1} • • • | …, 12, 21, … | B

L_N • • • | …, 11, 19, … | B

Bloom filters speed up point queries in RocksDB



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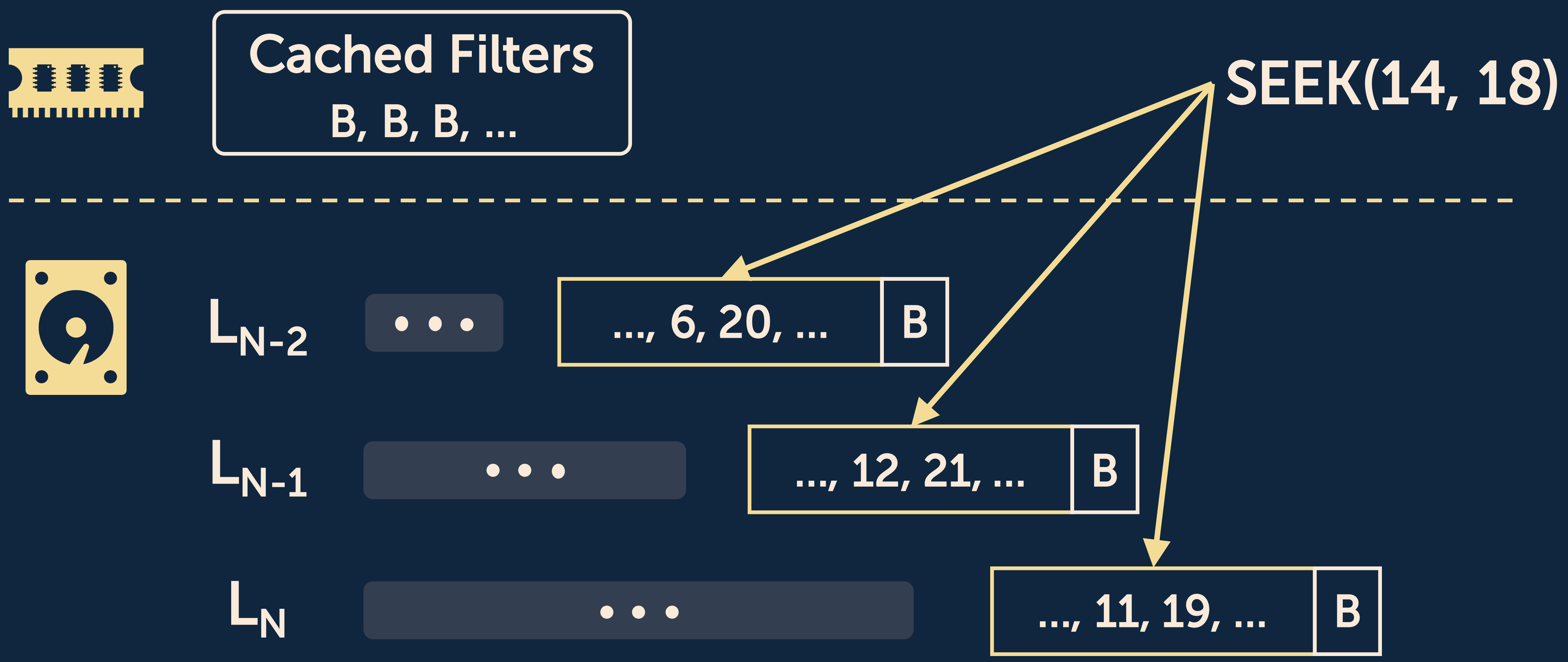
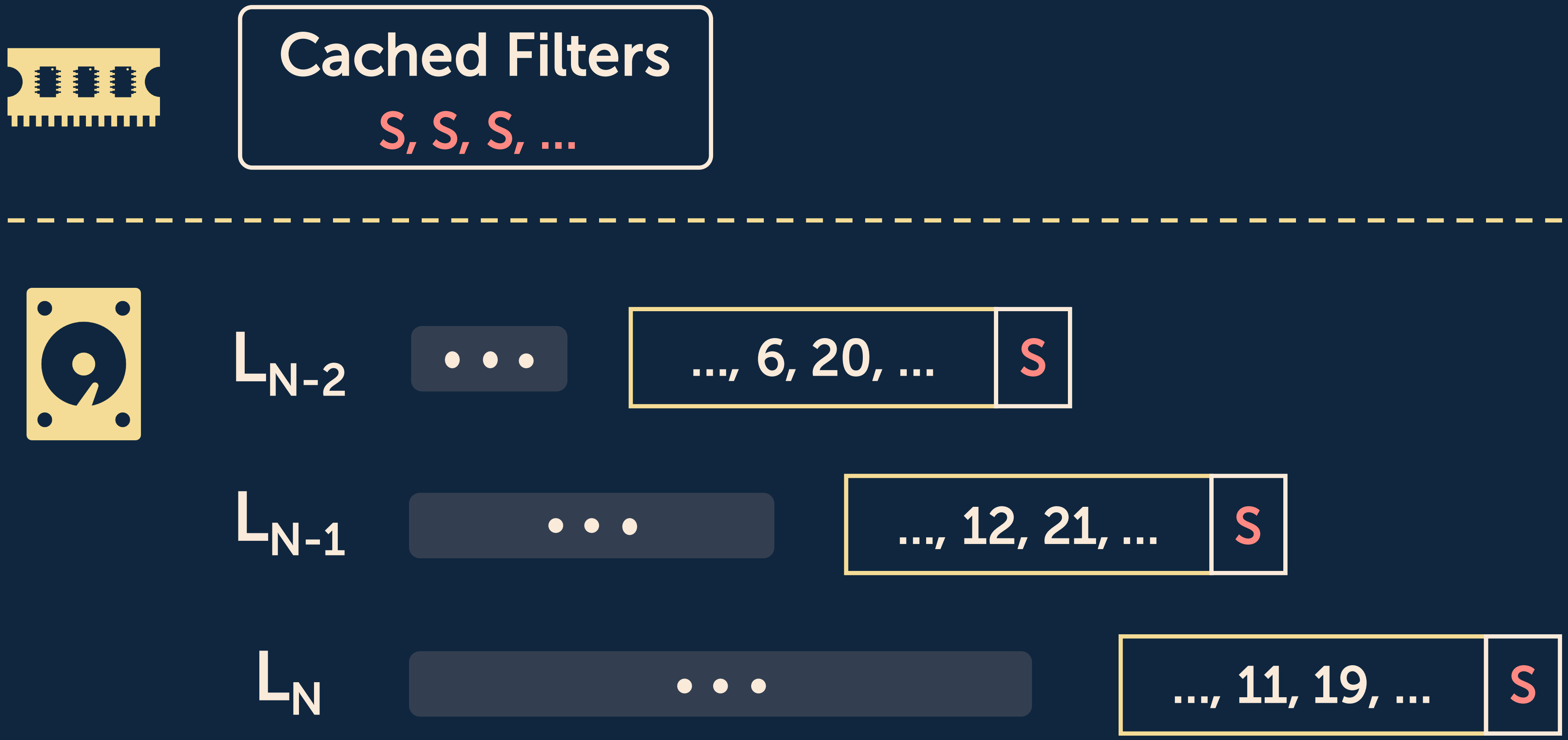


SuRFs can benefit both point and range queries



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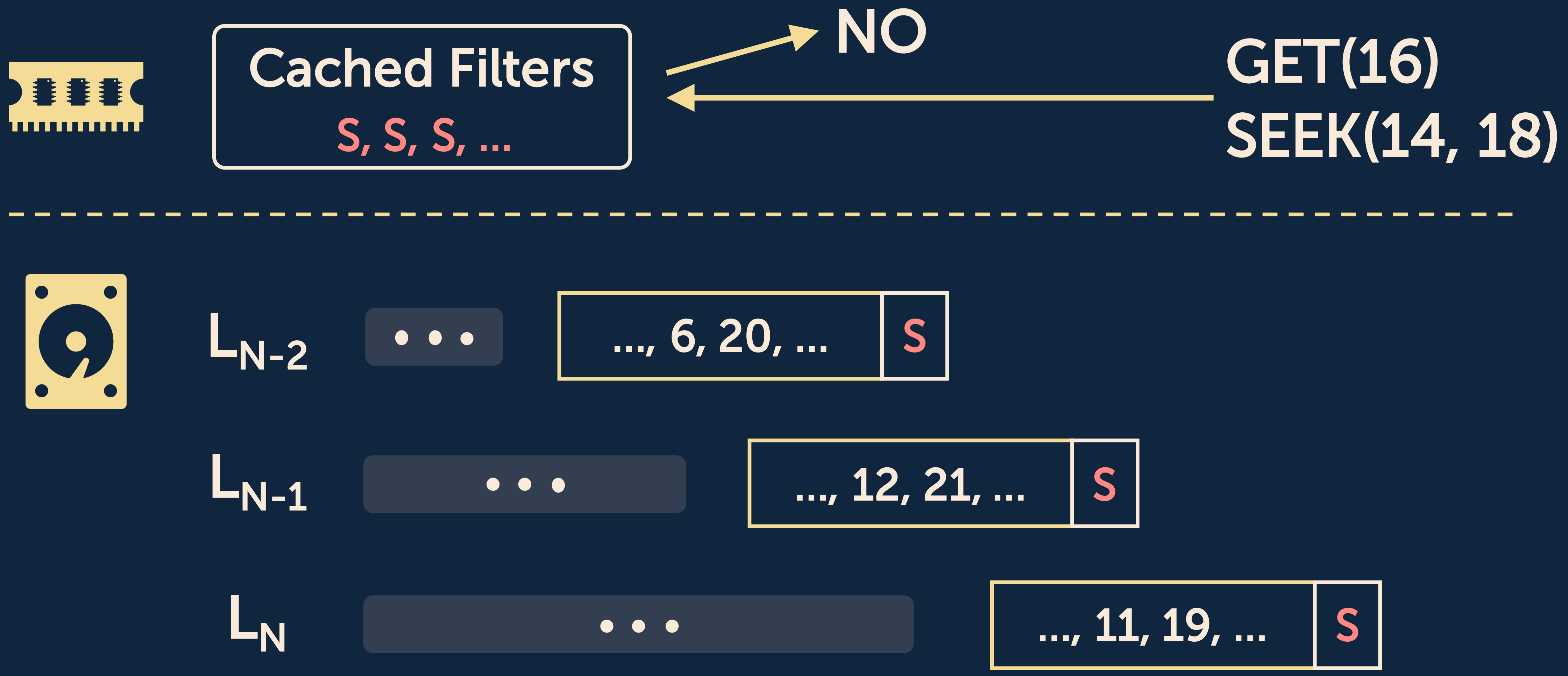

Evaluation setup: a time-series benchmark

Key: 64-bit timestamp + 64-bit sensor ID
Value: 1KB payload

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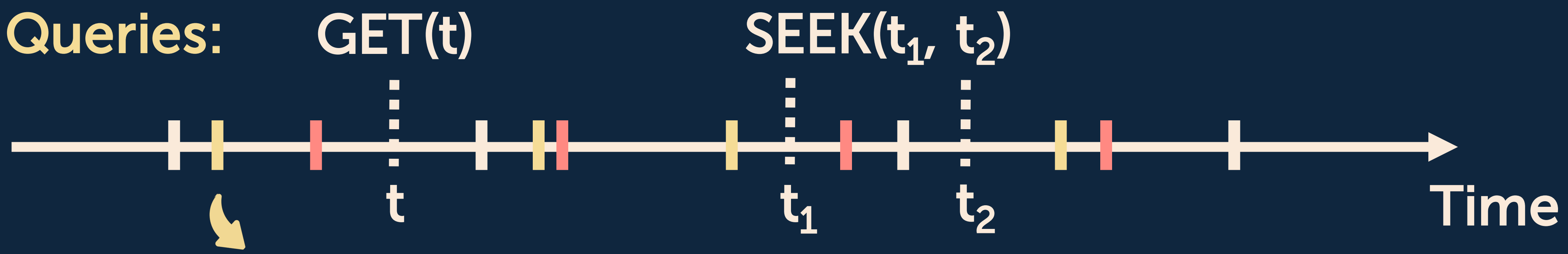

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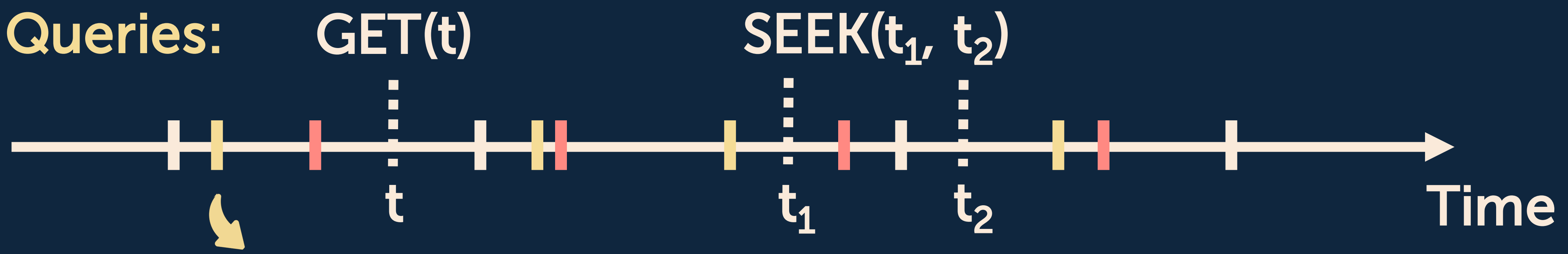

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System Config

Dataset: ≈100 GB on SSD

DRAM: 32 GB

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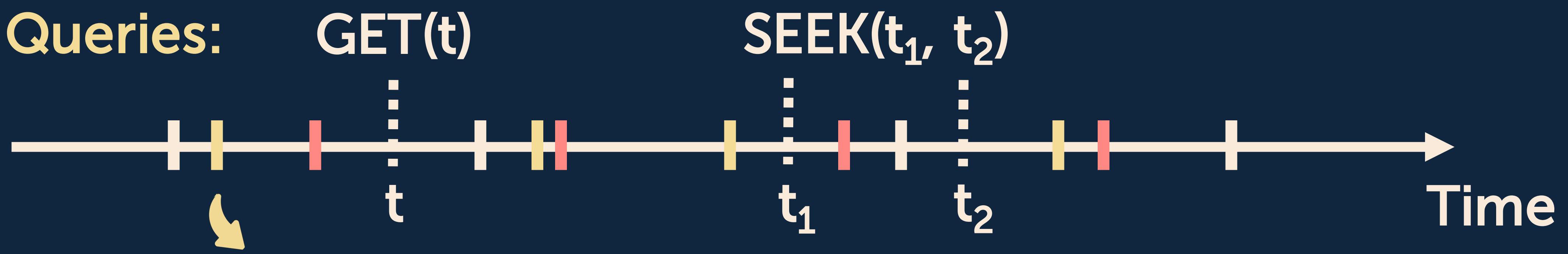

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System Config

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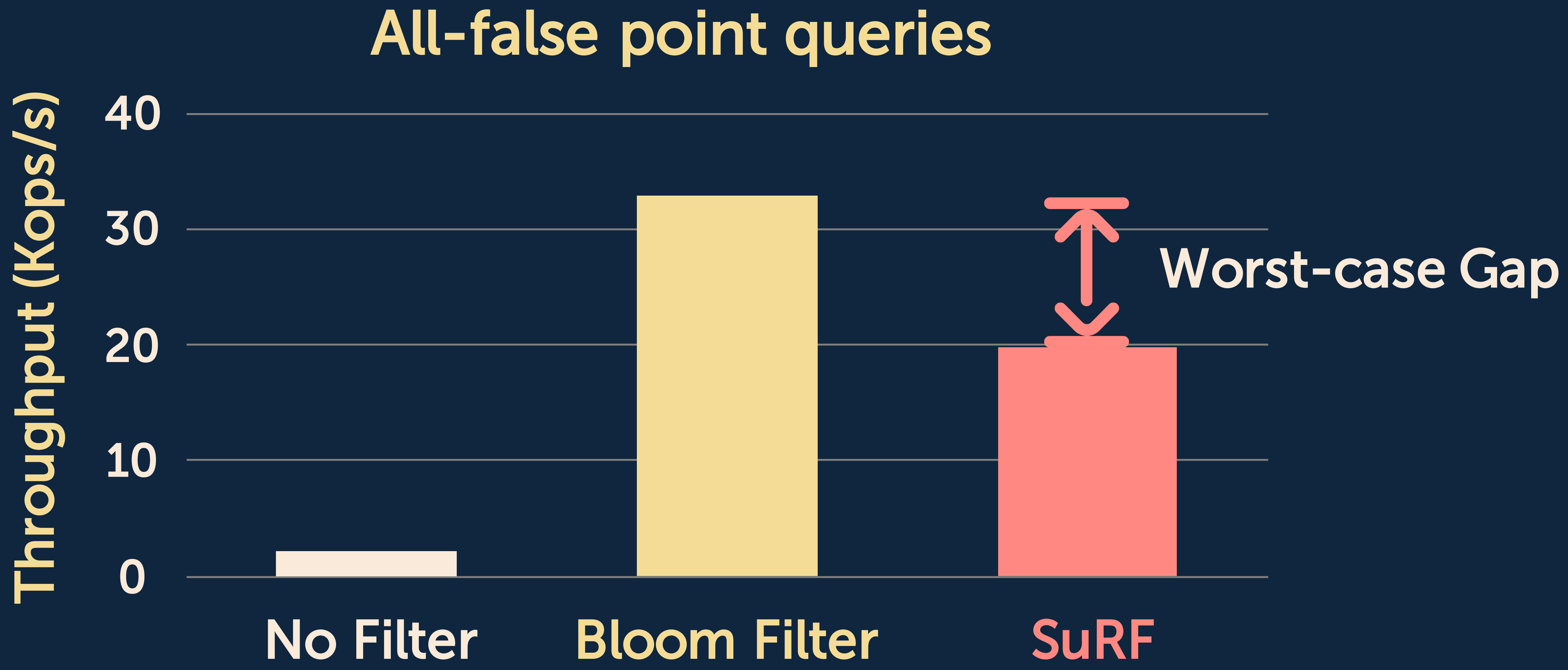
Filter Config

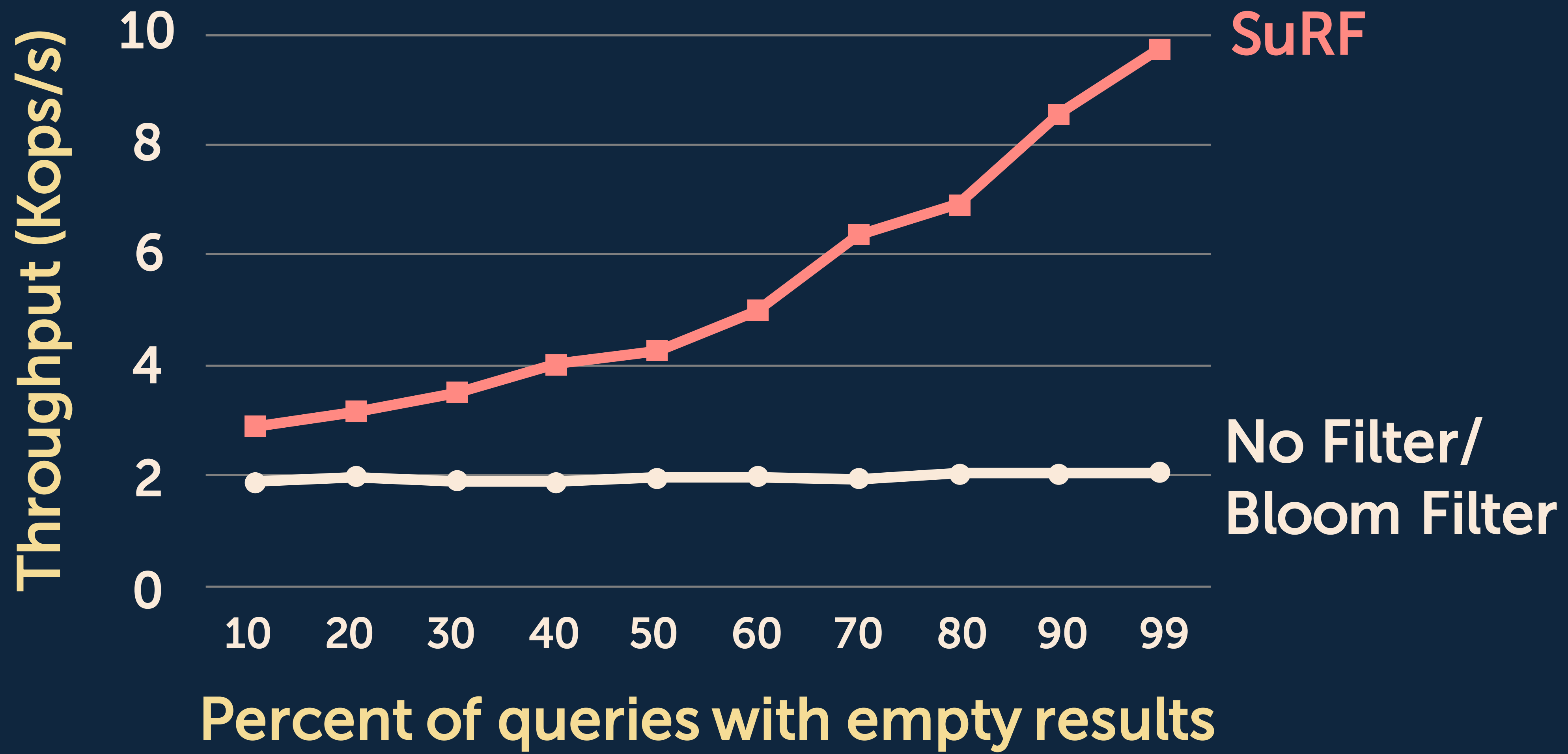
Bloom filter: 14 bits per key

SuRF: 4-bit real suffix

SuRFs still benefit point queries in RocksDB



SuRFs speed up range queries in RocksDB



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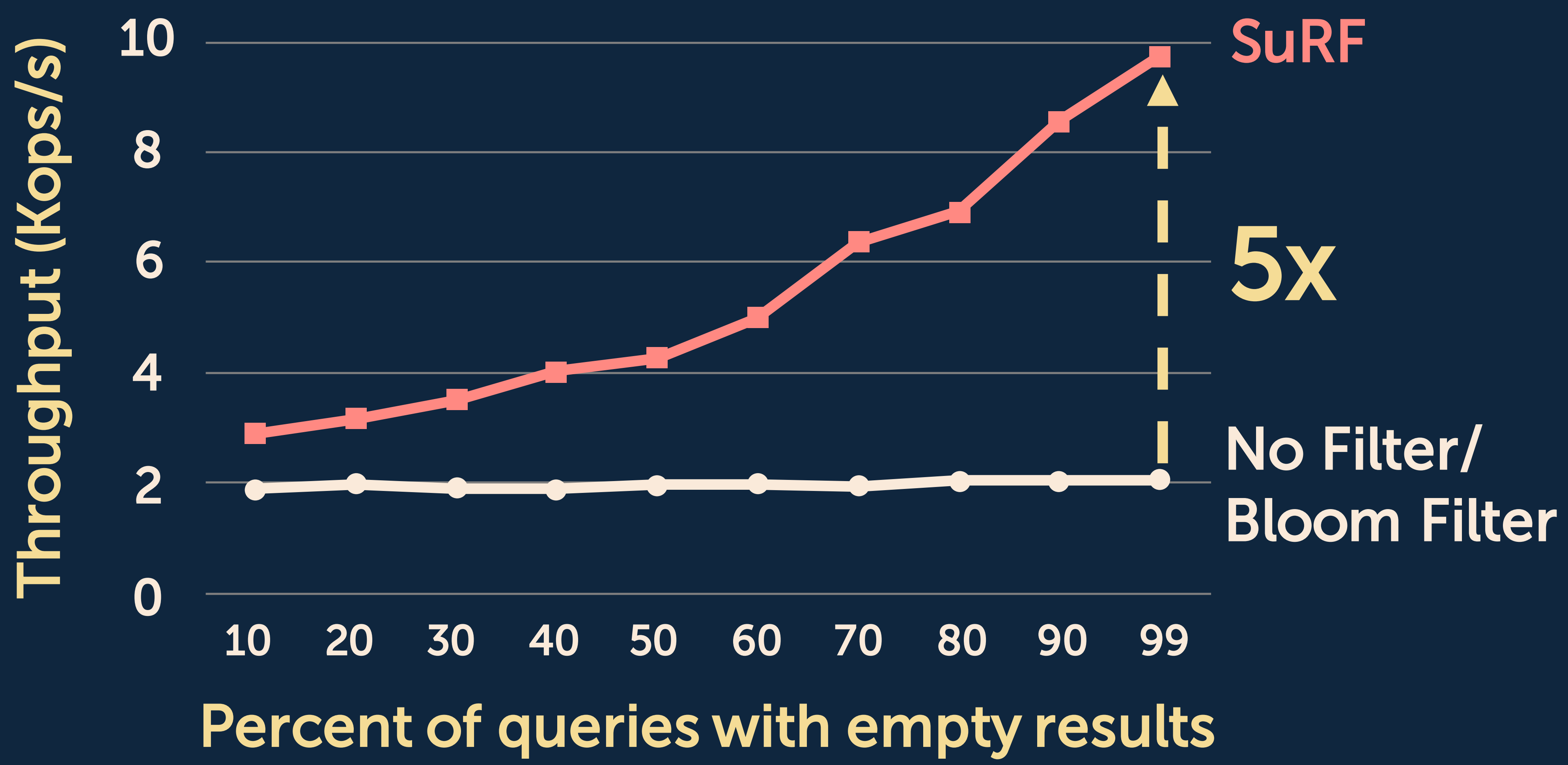


Conclusion

SuRF is a fast and compact data structure optimized for range filtering

github.com/efficient/SuRF

[Demo] rangefilter.io

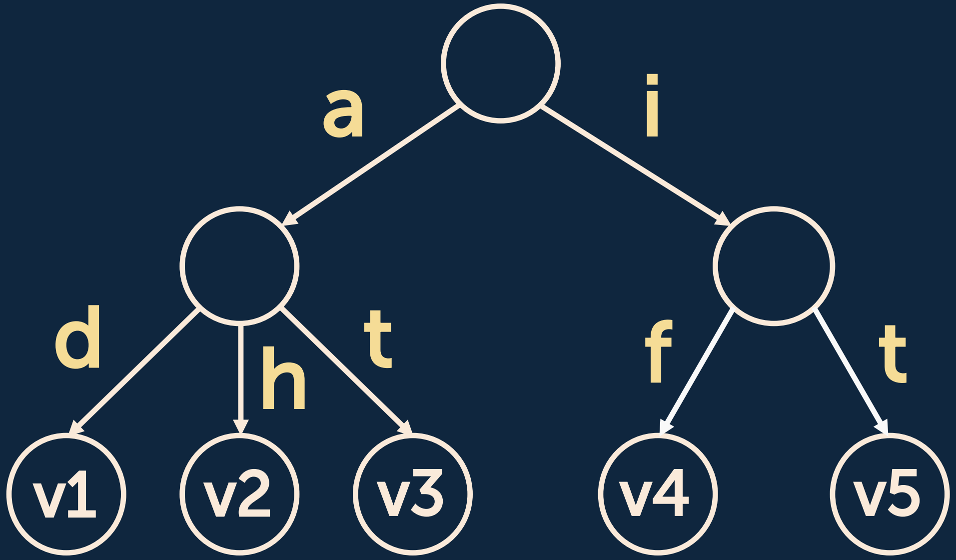
Backup Slides

Comparing ARF to SuRF

Experiment: insert 5M 64-bit integers, 10M Zipf-distributed range queries (ARF uses 2M queries for training)

	ARF	SuRF	Improvement
Bits per Key (held constant)	14	14	-
Range Query Throughput (Mops/s)	0.16	3.3	20x
False Positive Rate	25.7	2.2	12x
Build Time (s)	118	1.2	98x
Build Memory (GB)	26	0.02	1300x
Training Time (s)	117	N/A	N/A
Training Throughput (Mops/s)	0.02	N/A	N/A

LOUDS-Sparse encoding example



LOUDS-Sparse

Label:	a	i	d	h	t	f	t
Has-child:	1	1	0	0	0	0	0
Structure:	1	0	1	0	0	1	0
Value:			v1	v2	v3	v4	v5

Theoretic Limit ≈ 9.4N bits

10N bits

moveToChild (p) = select(S, rank(HC, p) + 1)

LOUDS-DS trades small space for performance

< 1% space overhead

3x speed-up

B3