SuRF: PRACTICAL RANGE FILTERING WITH FAST SUCCINCT TRIES

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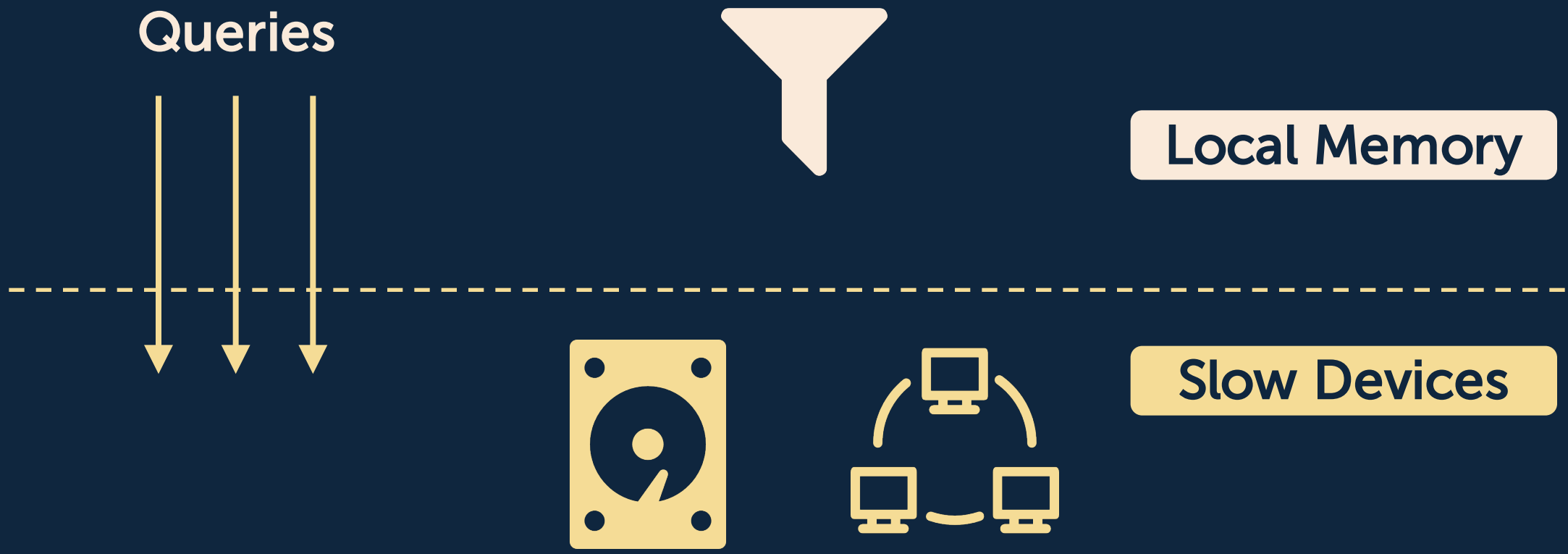
Filters pre-reject most negative queries



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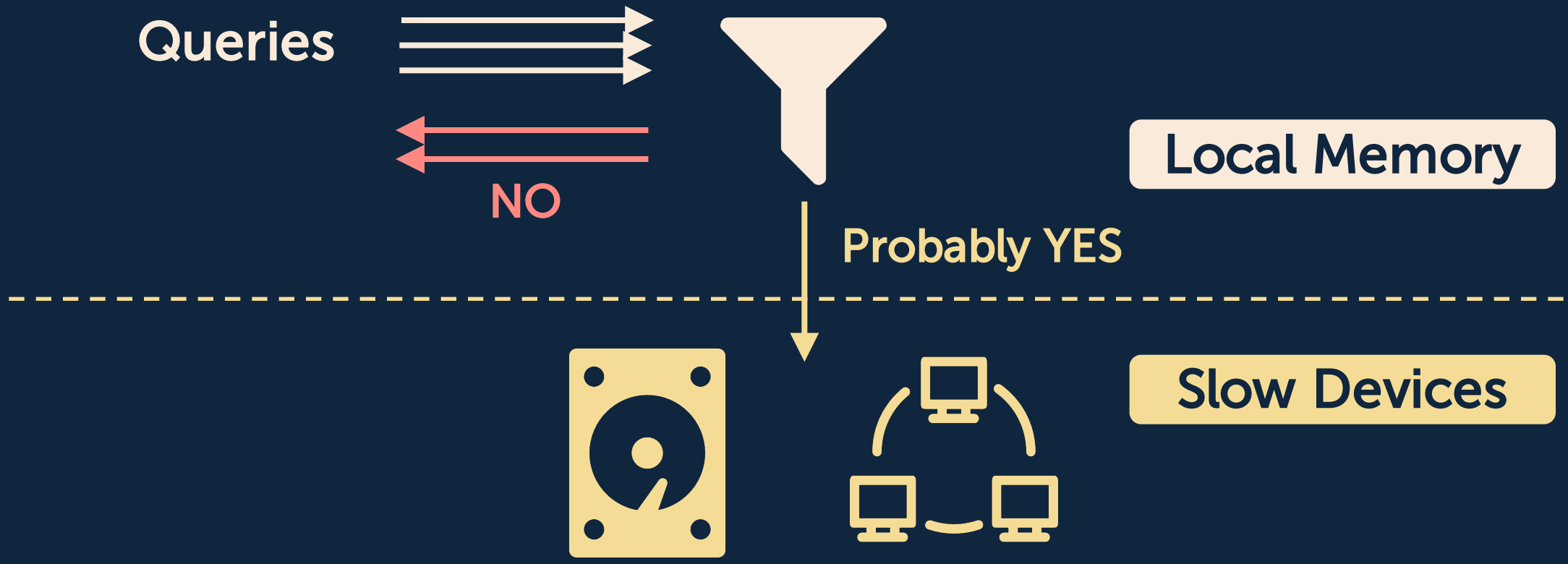

Existing filters only support point filtering

Point Filtering

SELECT * FROM Billionaires
WHERE LastName = ‘Pavlo’

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

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SELECT * FROM Billionaires
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SELECT * FROM Billionaires
WHERE LastName LIKE 'Pav%'

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

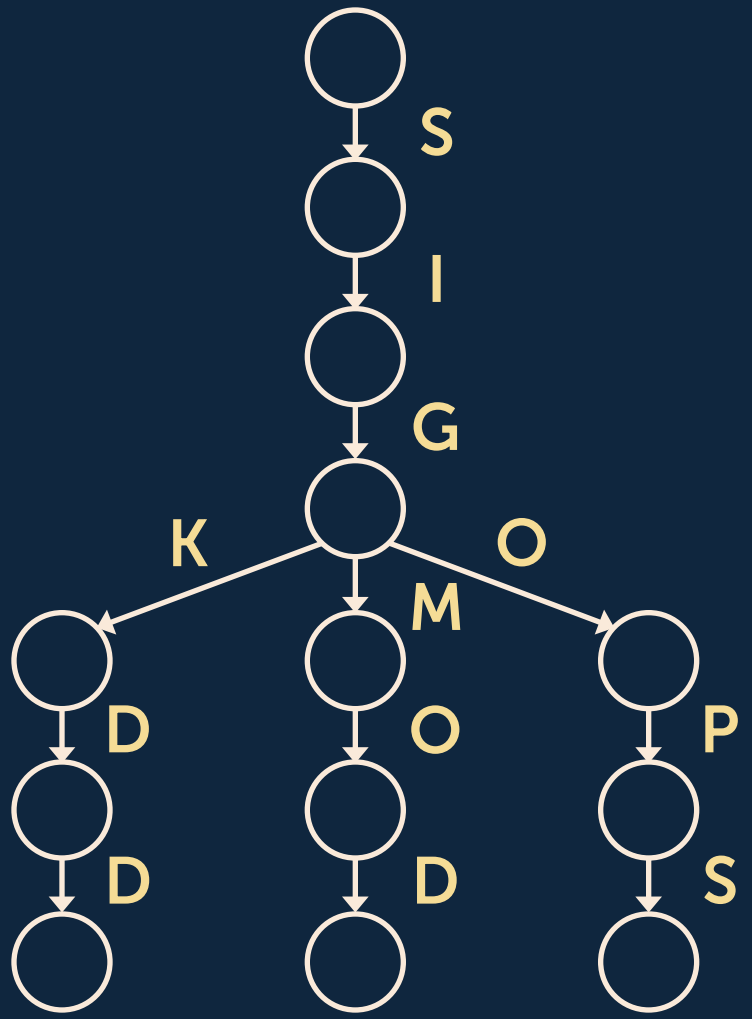
FAST: comparable to fastest trees

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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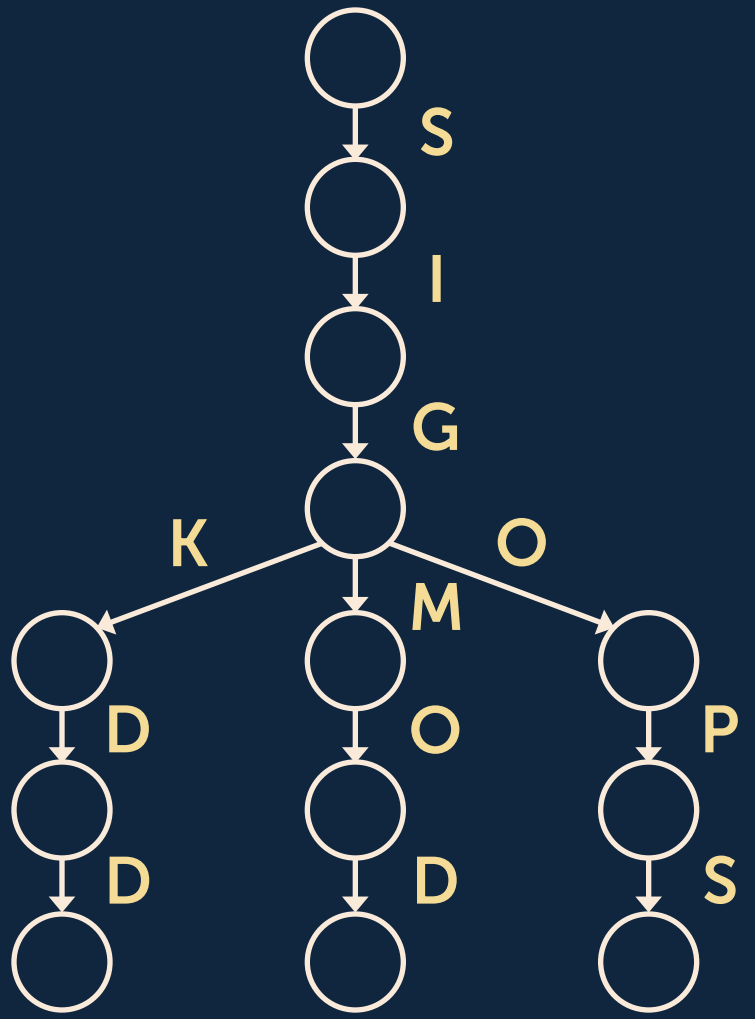
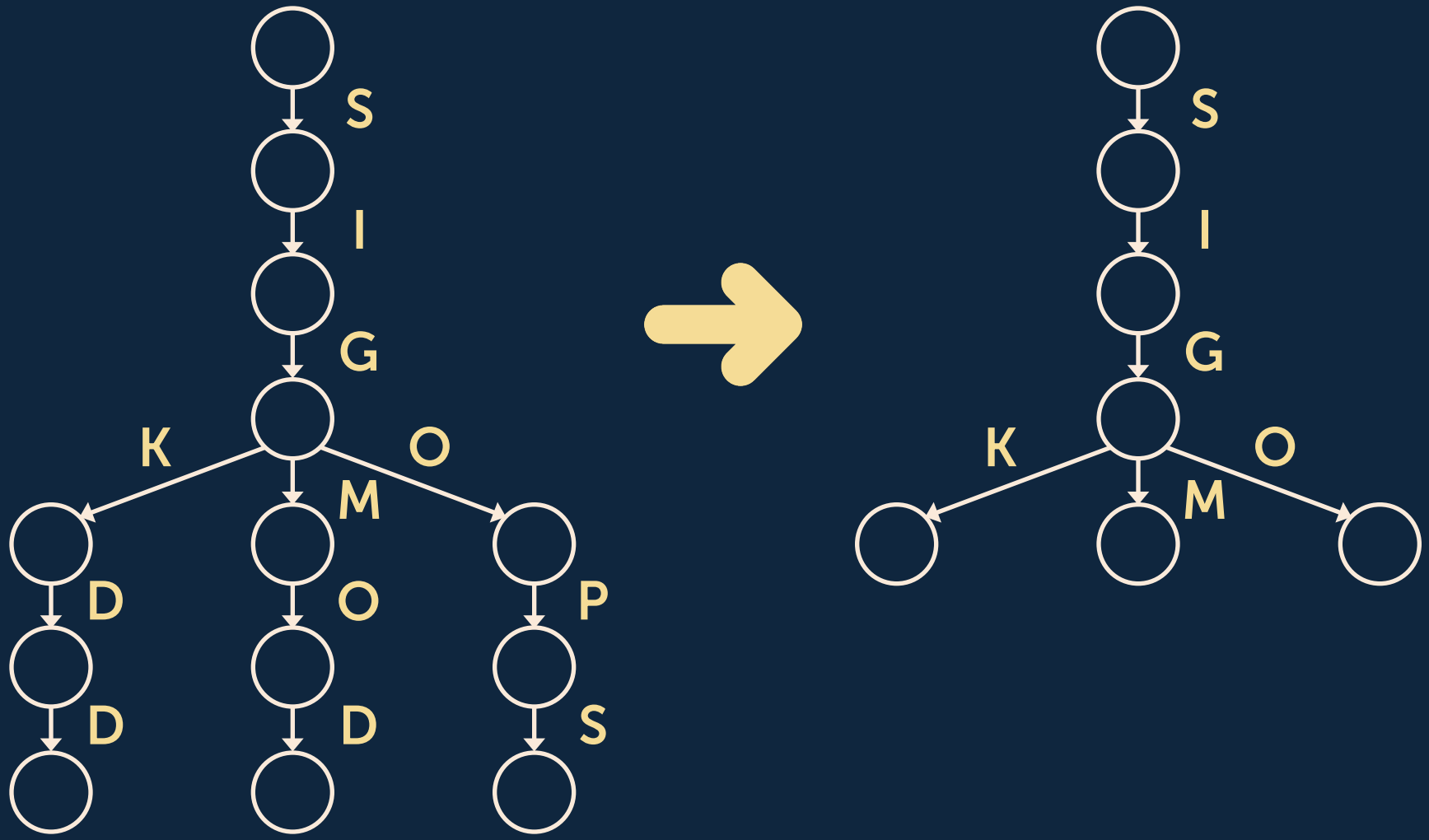


TOO BIG ✗

Make it smaller: a truncated trie



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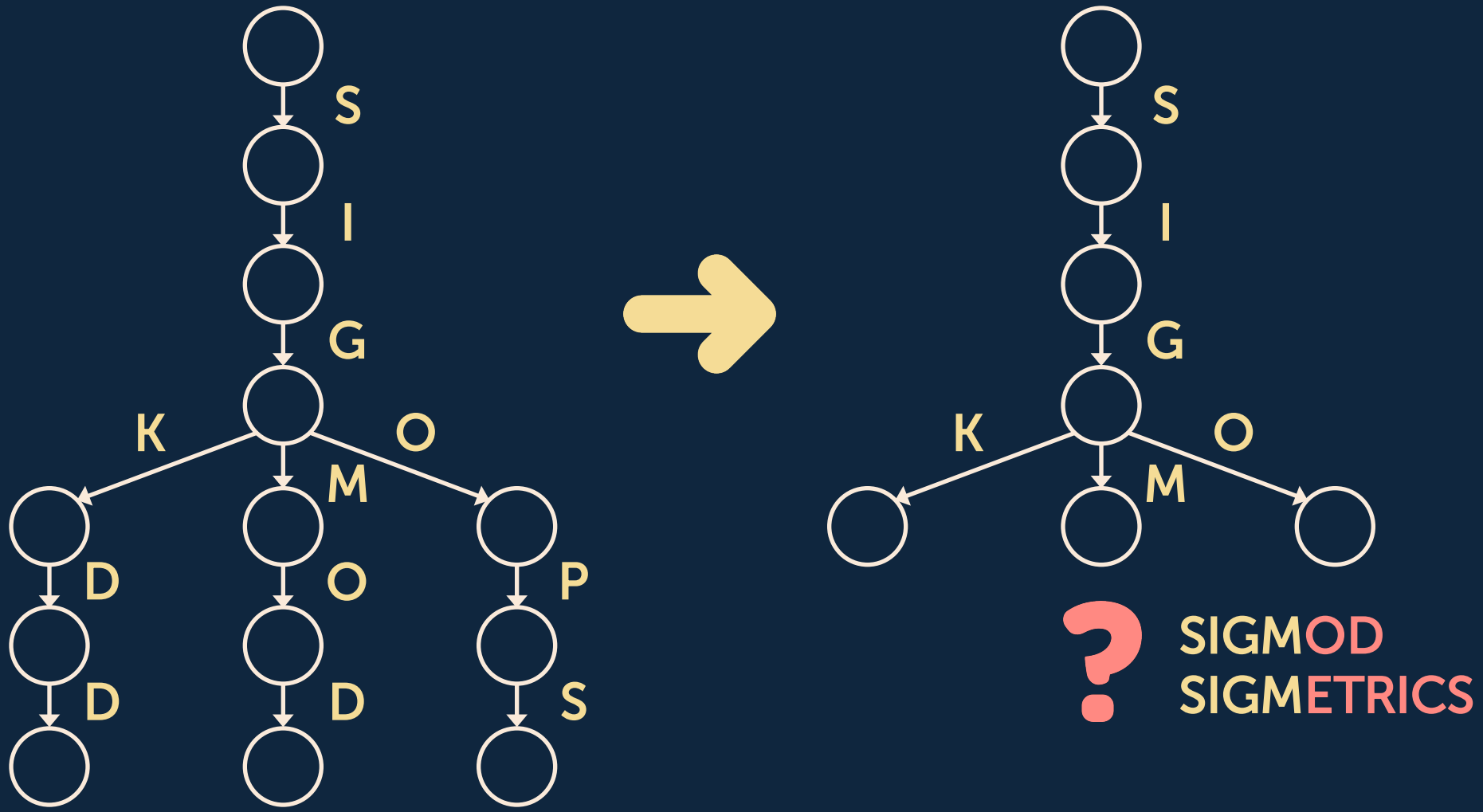
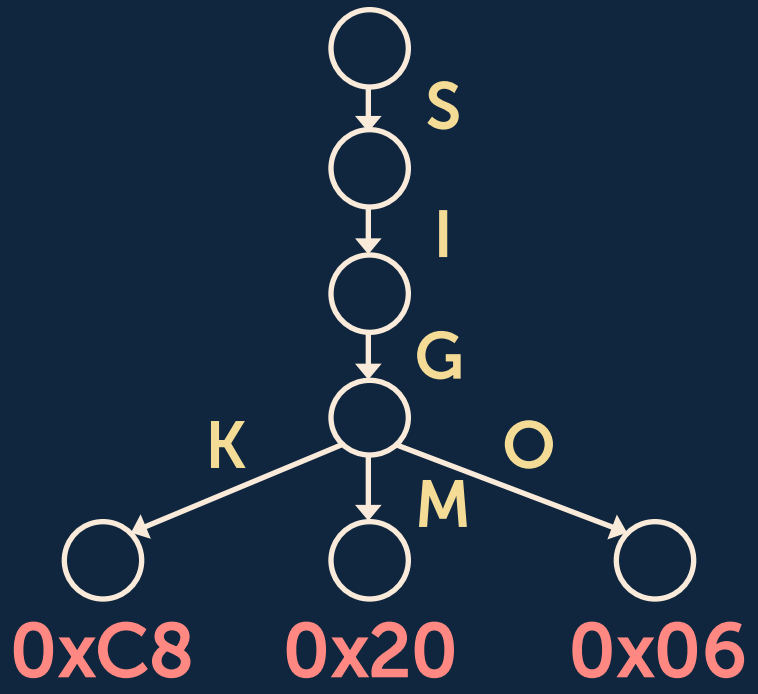
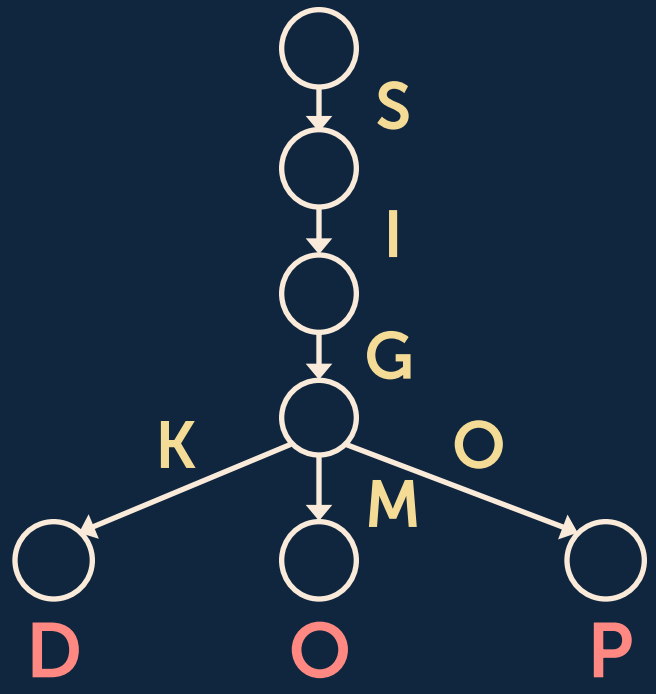


Use suffix bits to reduce false positive rate

Hashed Suffix Bits



Real Suffix Bits



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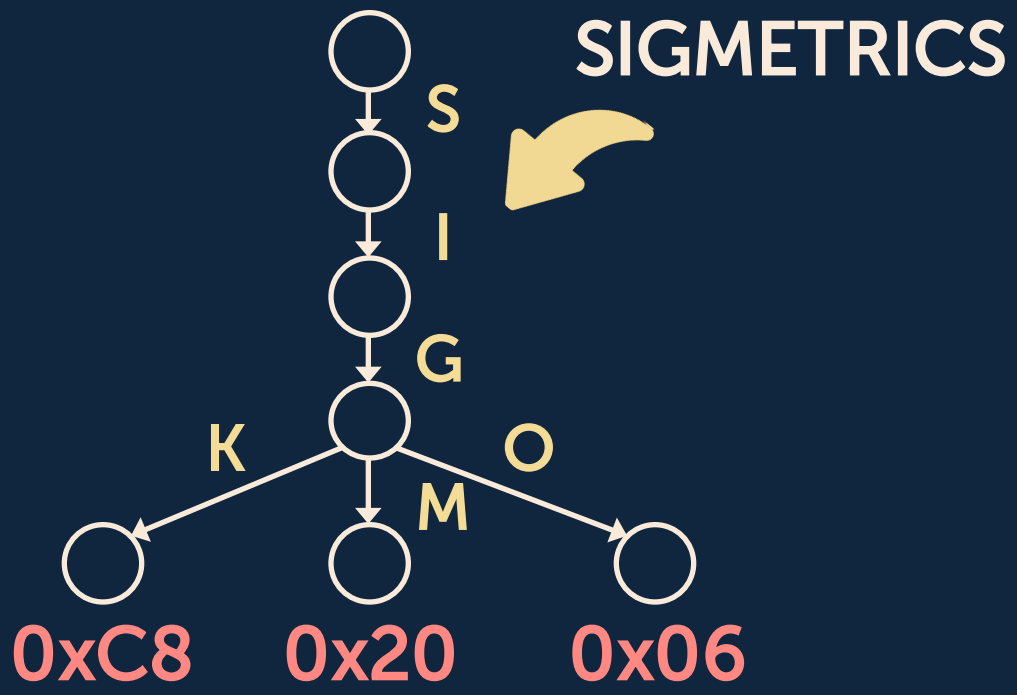

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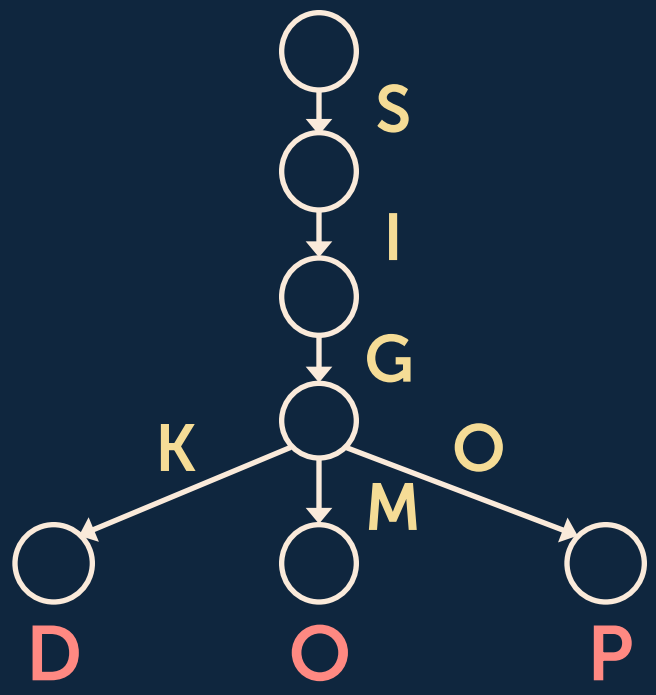

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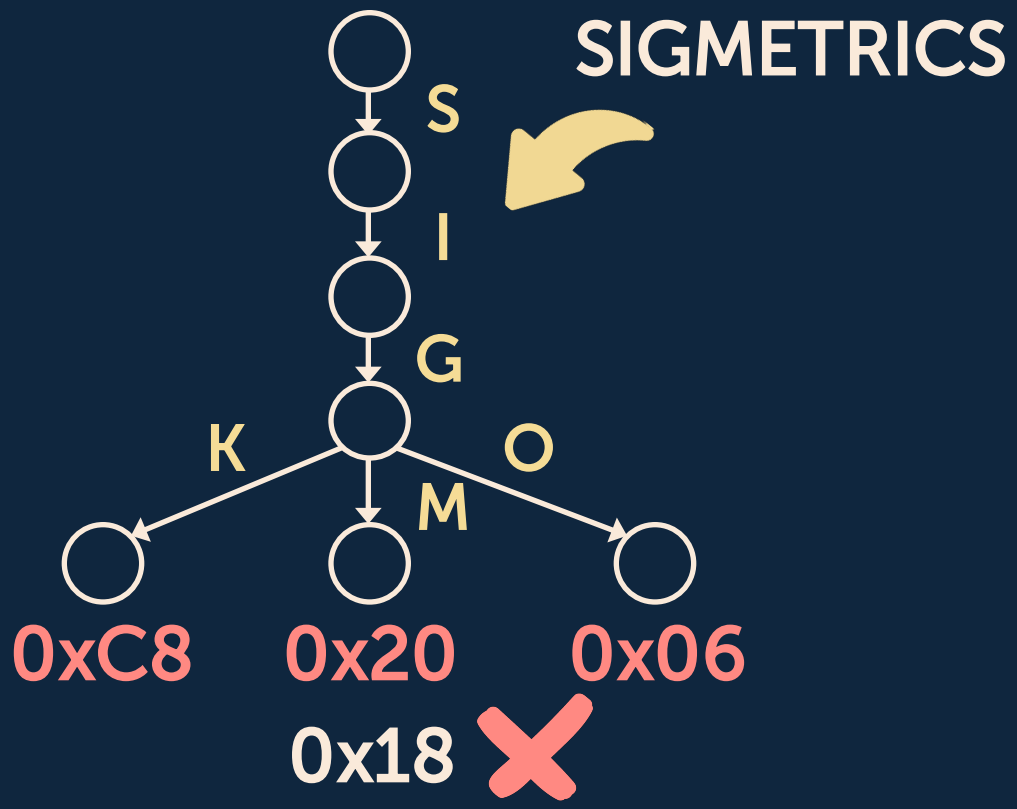

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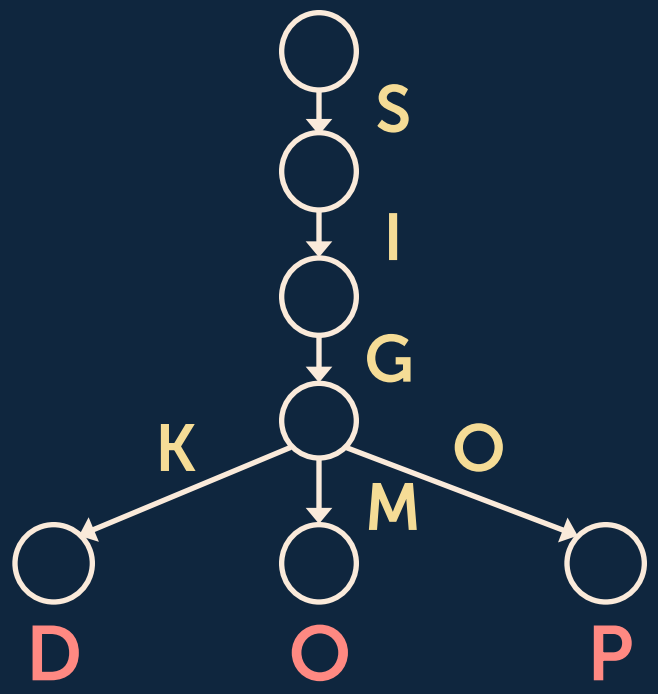

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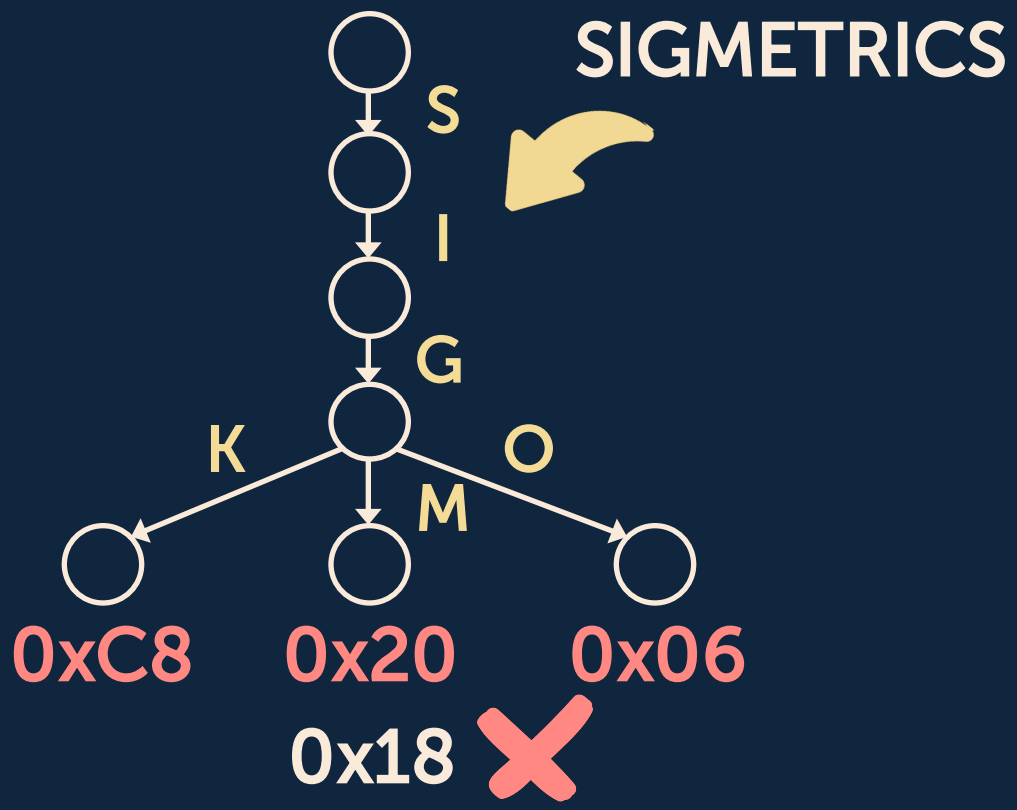

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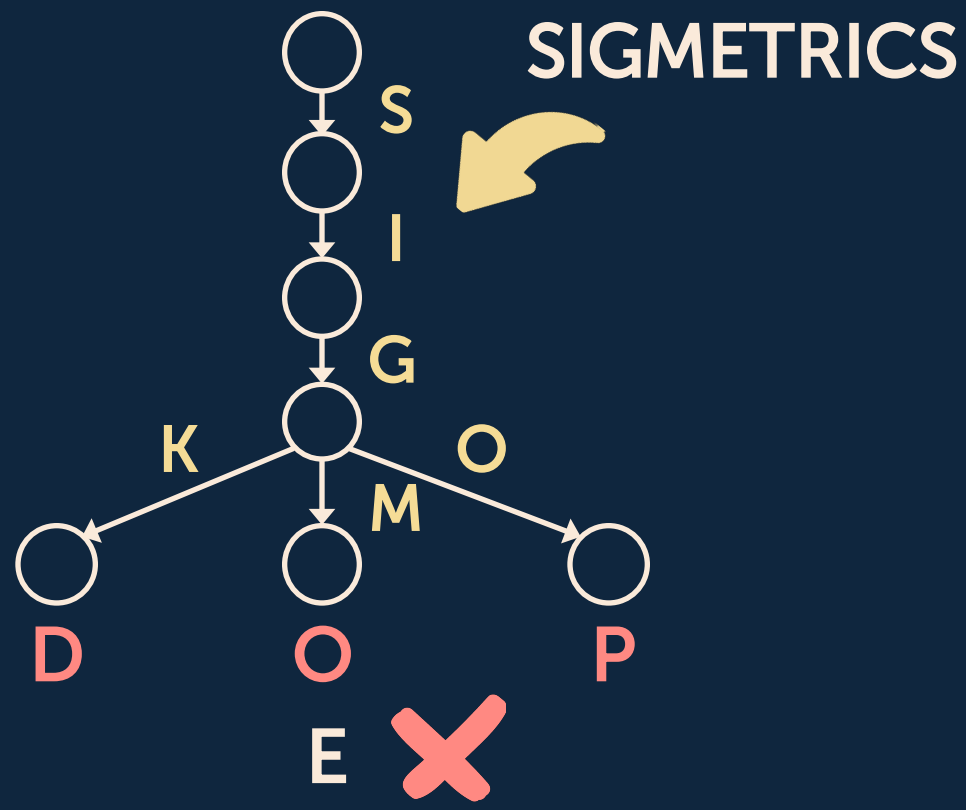

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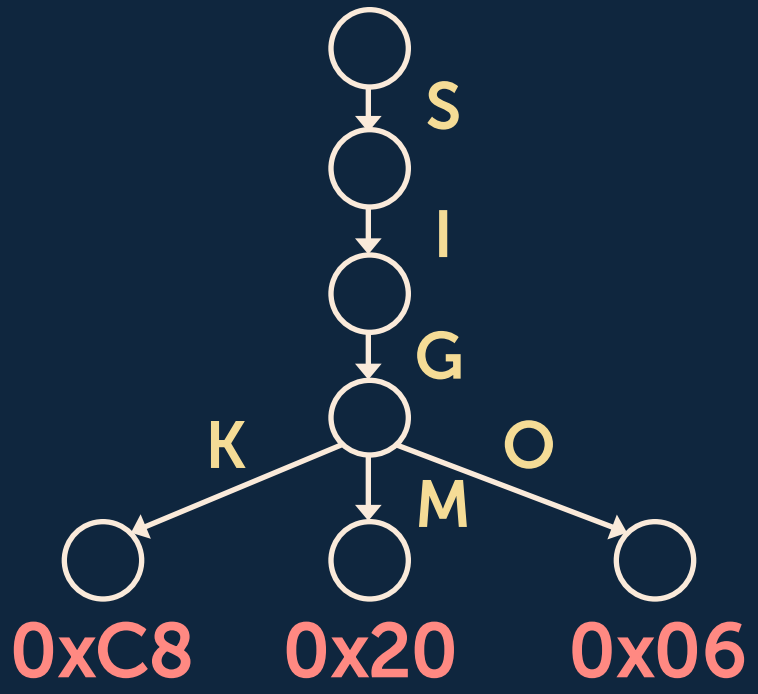

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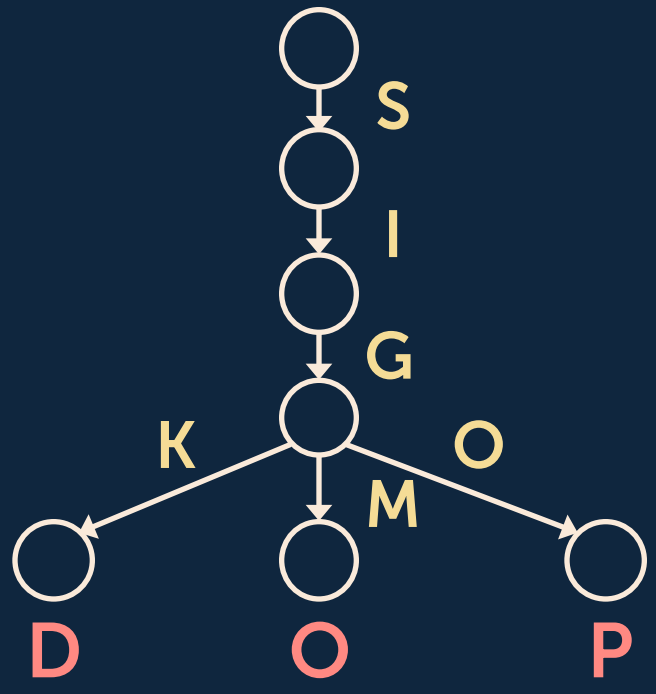

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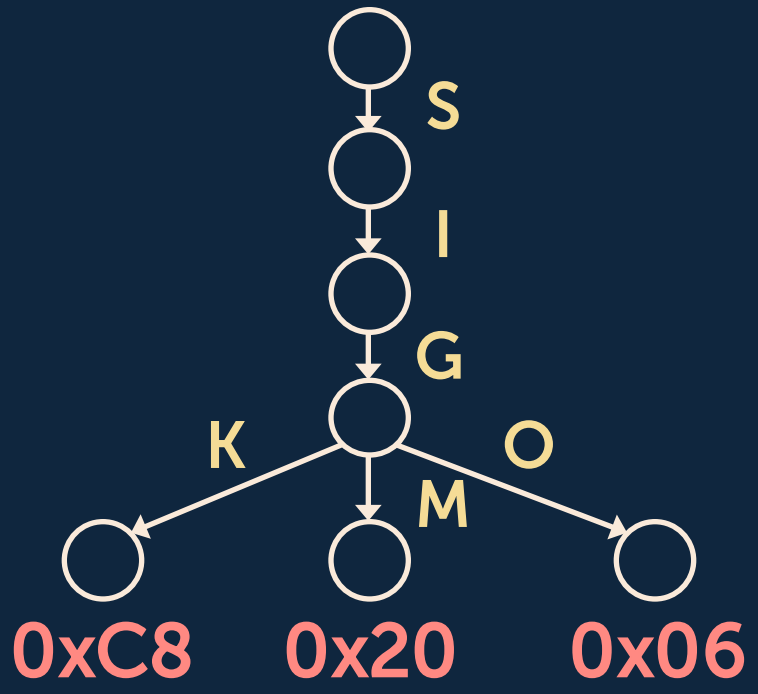

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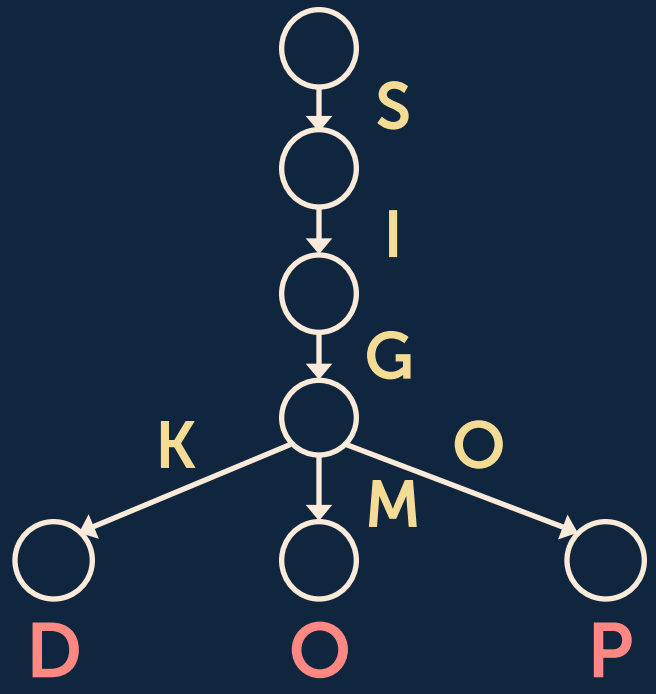

✚ Each bit reduces FPR by half

Use suffix bits to reduce false positive rate

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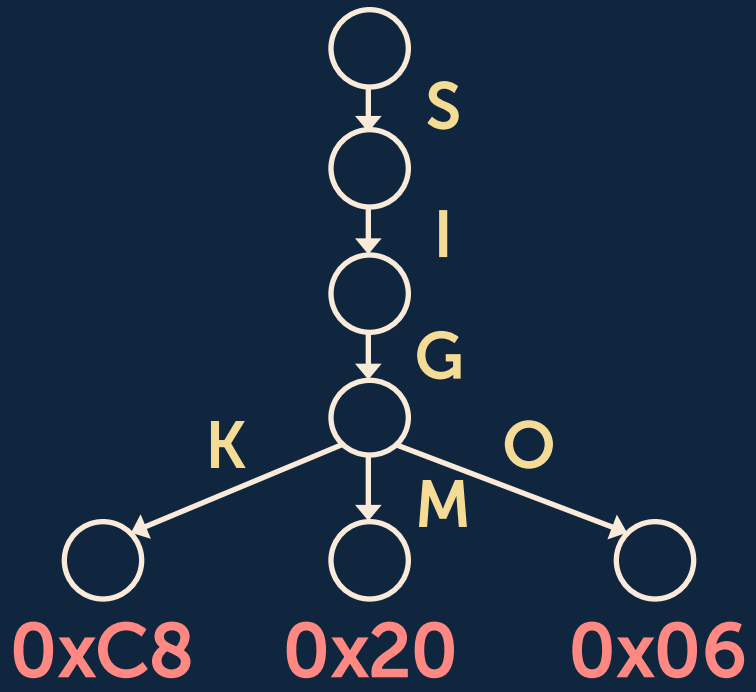

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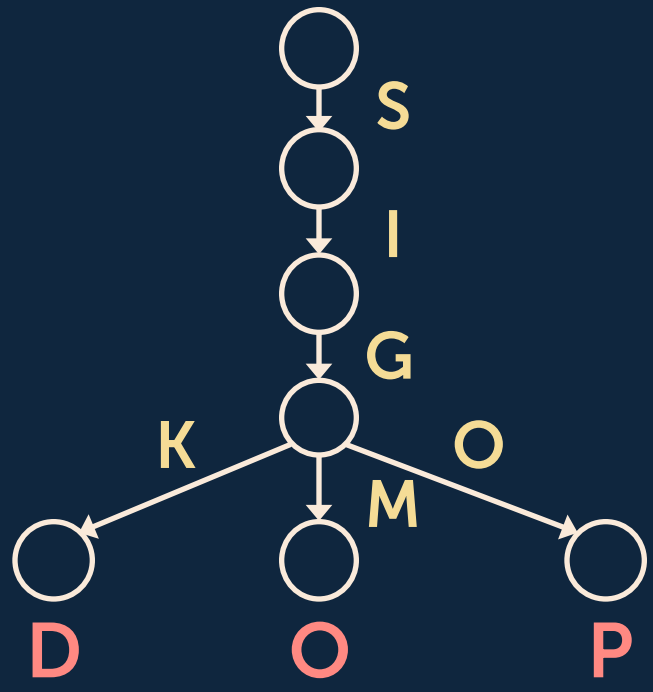

➕ Each bit reduces FPR by half

➖ Cannot help range queries

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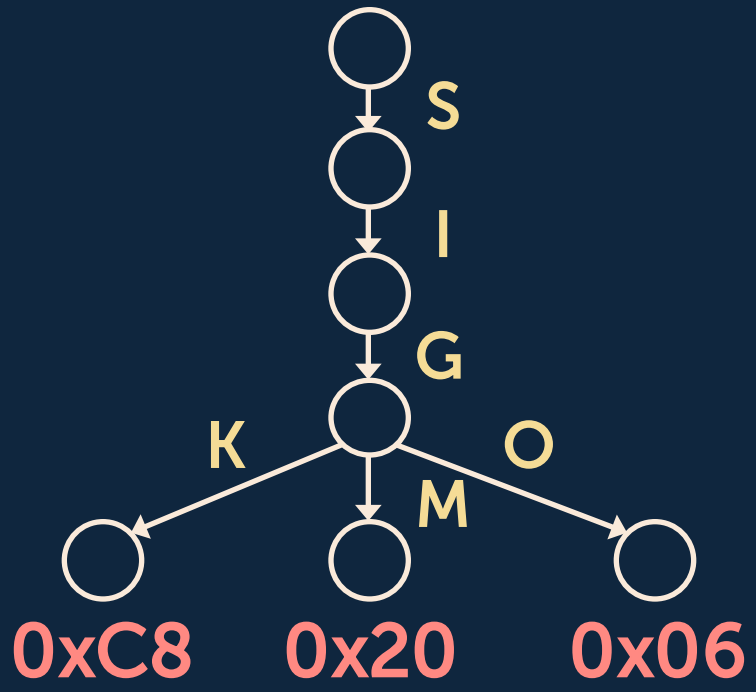

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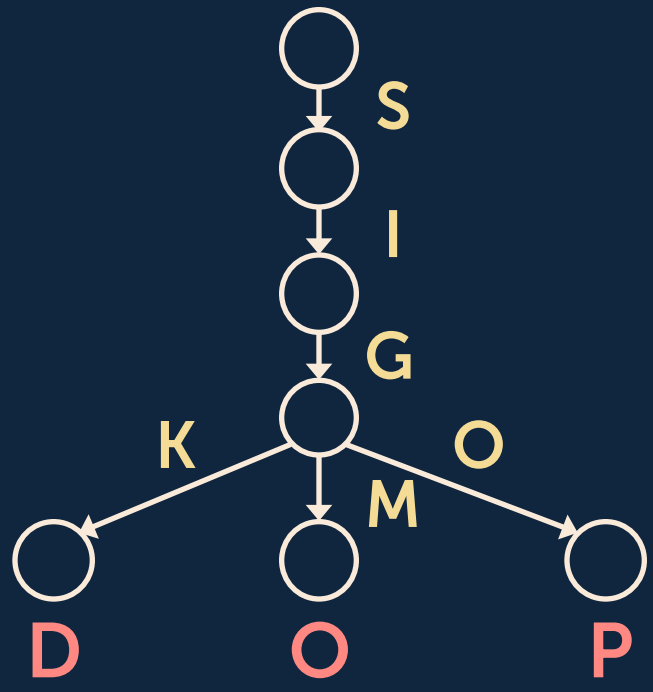

- ✚ Benefit point & range queries

Use suffix bits to reduce false positive rate

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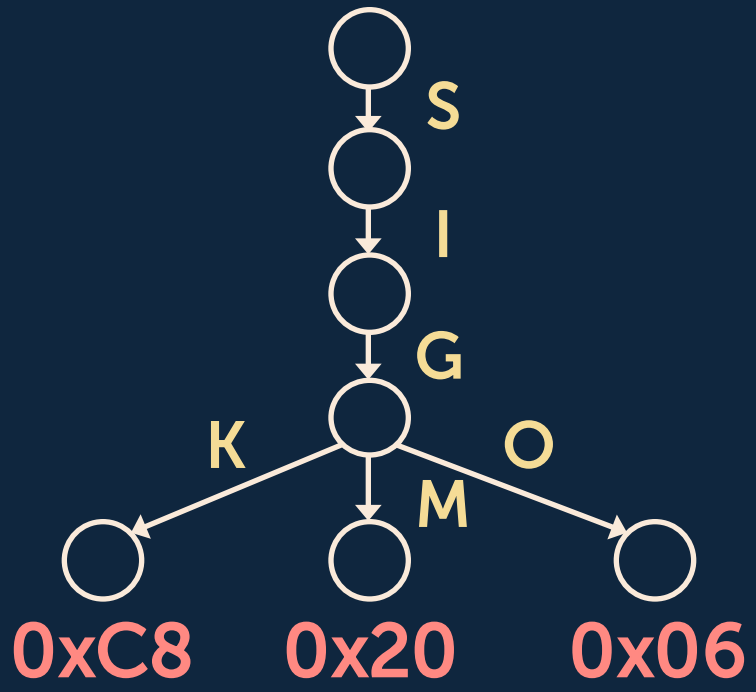

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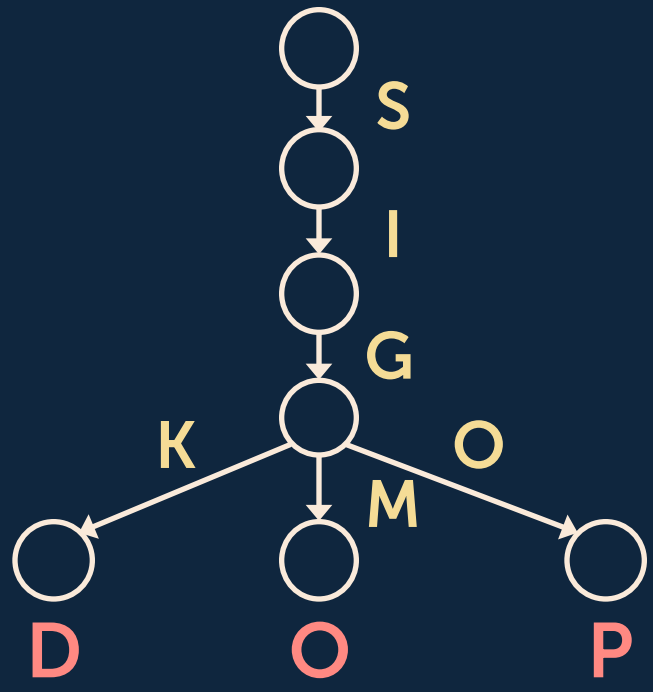
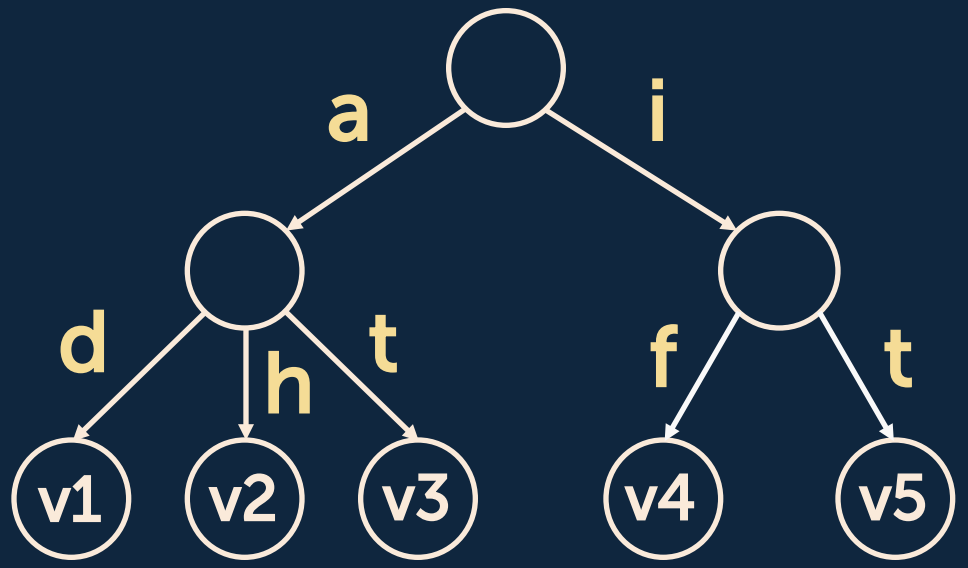


- ✚ Benefit point & range queries
- ▬ Weaker distinguishability

Succinct Data Structure

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

LOUDS-Sparse encoding example



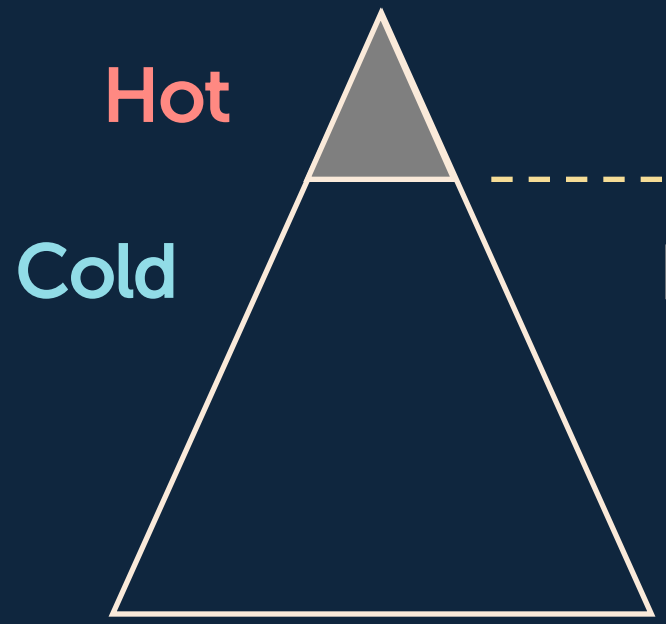
LOUDS-Sparse

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



LOUDS-Dense

LOUDS-Sparse

< 1% space overhead

3x speed-up

SuRF's encoding is small and fast

① Small

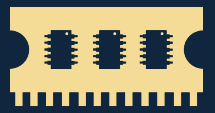
≈10 + suffix bits per key for 64-bit integers

≈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



Cached Filters

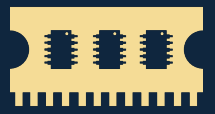
B, B, B, ...

L_{N-2} • • • ..., 6, 20, ... B SSTable

L_{N-1} • • • ..., 12, 21, ... B

L_N • • • ..., 11, 19, ... B

Bloom filters speed up point queries in RocksDB



Cached Filters

B, B, B, ...

GET(16)

L_{N-2} • • • ..., 6, 20, ... B

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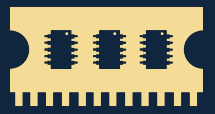
L_N • • • ..., 11, 19, ... B

Bloom filters speed up point queries in RocksDB



Cached Filters
B, B, B, ...

NO

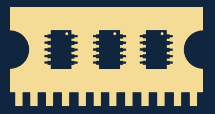
GET(16)

L_{N-2} • • • ..., 6, 20, ... B

L_{N-1} • • • ..., 12, 21, ... B

L_N • • • ..., 11, 19, ... B

Bloom filters can't help range queries in RocksDB



Cached Filters
B, B, B, ...

SEEK(14, 18)

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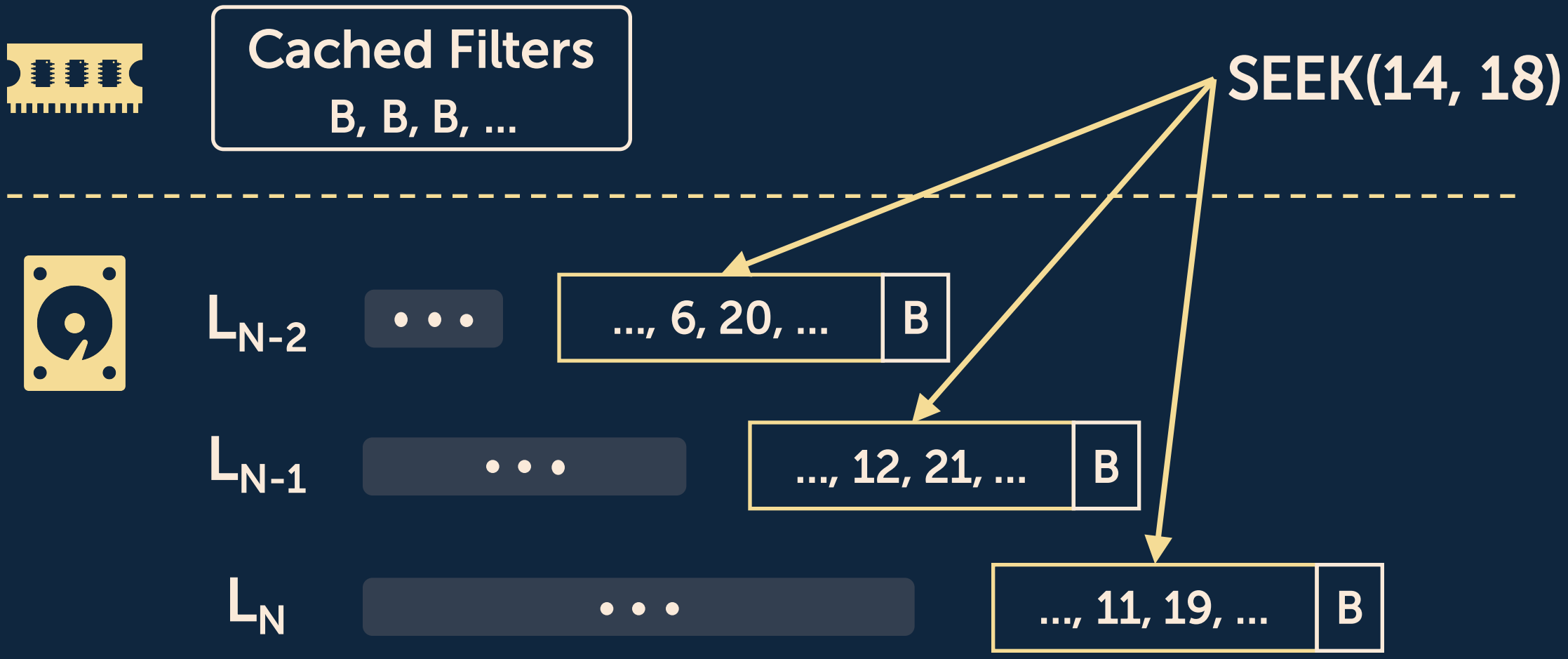
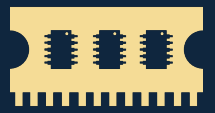


SuRFs can benefit both point and range queries



Cached Filters

S, S, S, ...

L_{N-2} • • • ..., 6, 20, ... S

L_{N-1} • • • ..., 12, 21, ... S

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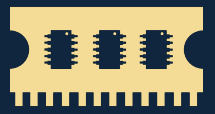
SuRFs can benefit both point and range queries



Cached Filters
S, S, S, ...

NO

GET(16)
SEEK(14, 18)

L_{N-2} • • • ..., 6, 20, ... S

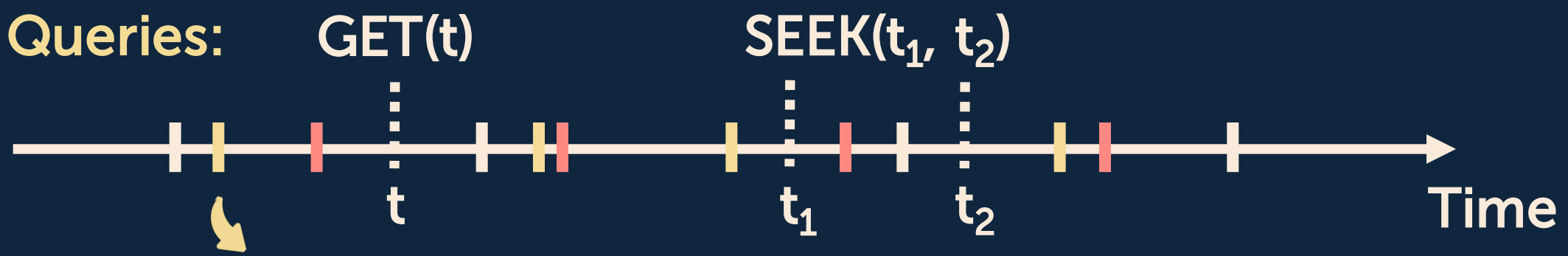
L_{N-1} • • • ..., 12, 21, ... S

L_N • • • ..., 11, 19, ... S

Evaluation setup: a time-series benchmark

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

Evaluation setup: a time-series benchmark



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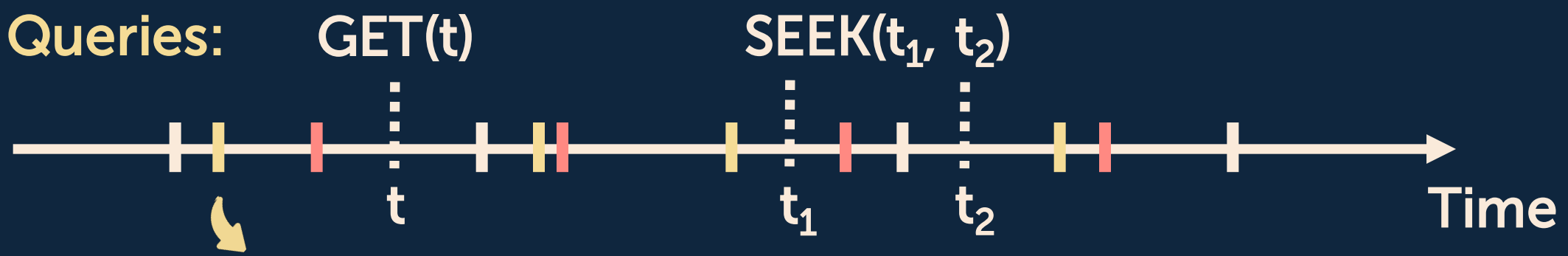

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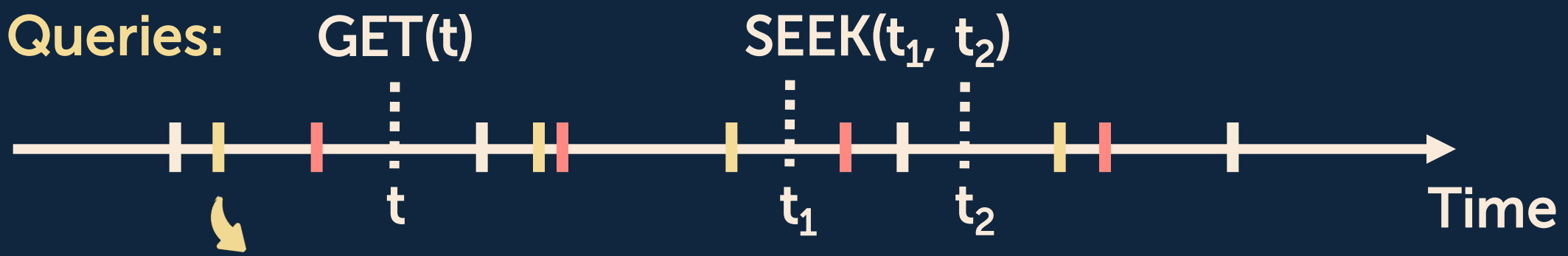
System Config

Dataset: ≈100 GB on SSD

DRAM: 32 GB

Evaluation setup: a time-series benchmark



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

System Config

Dataset: ≈100 GB on SSD

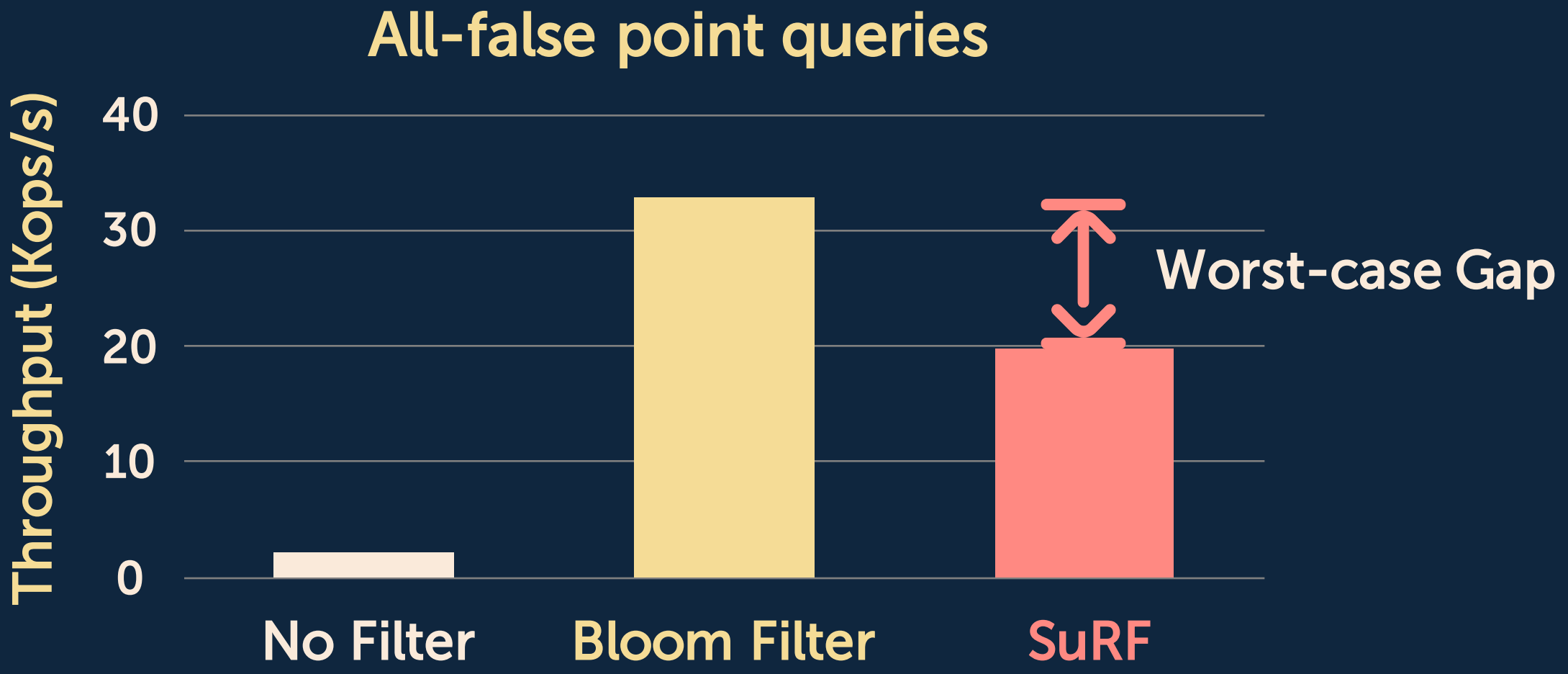
DRAM: 32 GB

Filter Config

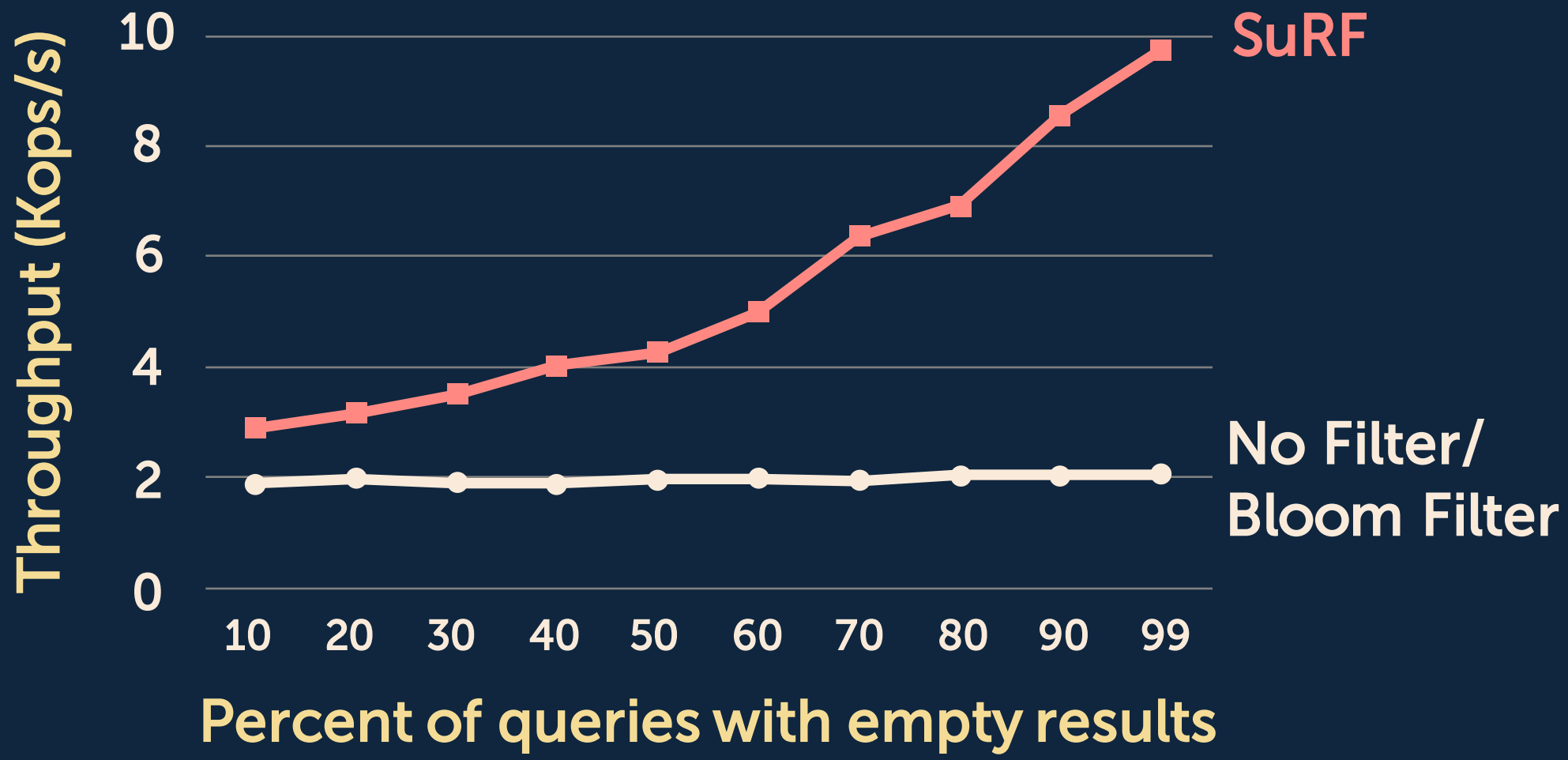
Bloom filter: 14 bits per key

SuRF: 4-bit real suffix

SuRFs still benefit point queries in RocksDB



SuRFs speed up range queries in RocksDB



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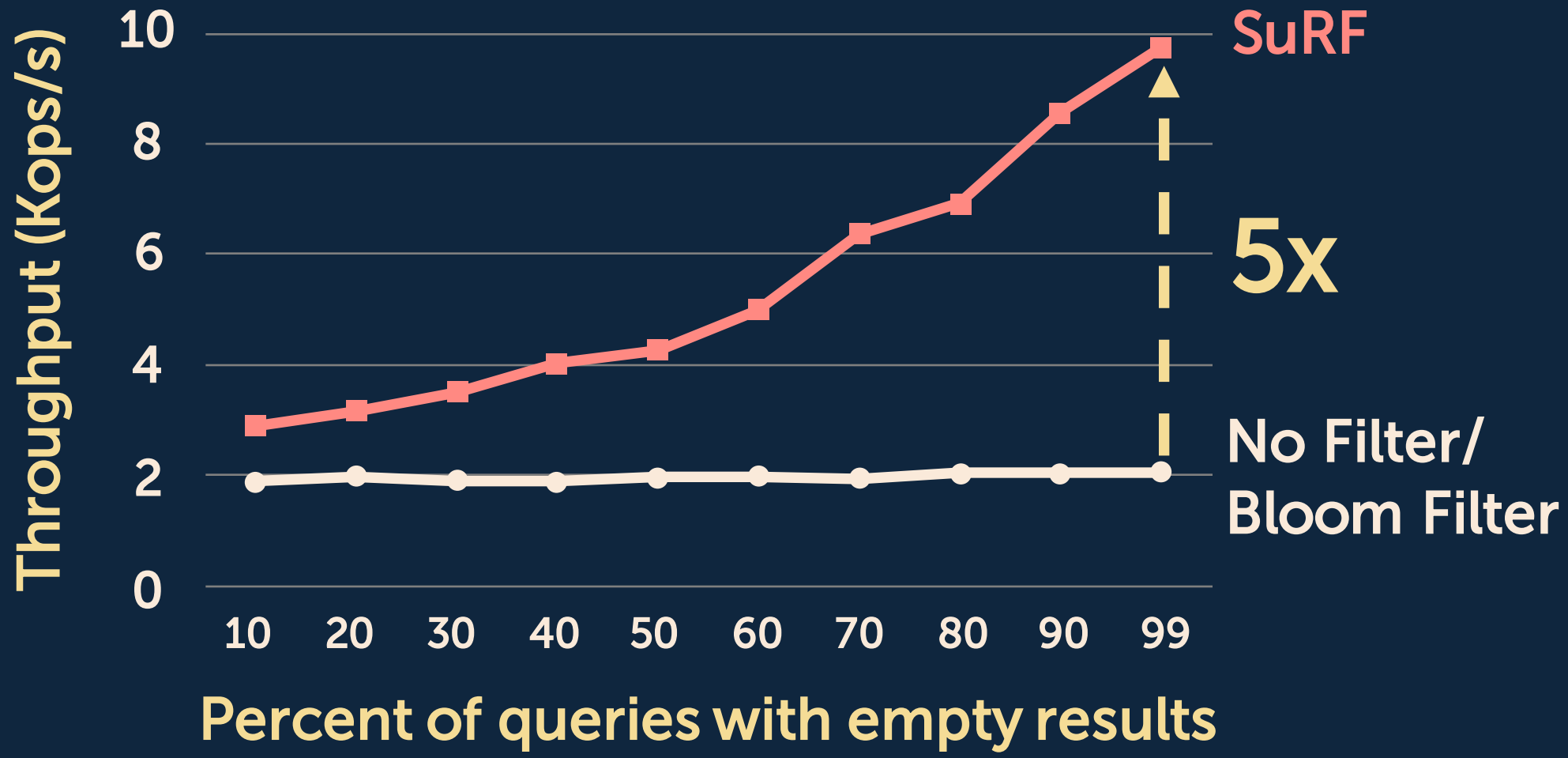

Conclusion

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

github.com/efficient/SuRF

[Demo] rangefilter.io