

# Filter Representation in Vectorized Query Execution (DAMON'21) — Super Simple Explanation

Paper: “Filter Representation in Vectorized Query Execution” (Ngom et al., 2021).

This is the “explain it like I’m new” version.

You’ll learn:

- what **vectorized execution** is (batch processing)
  - why DBs need a **filter representation** inside a batch
  - what **Selection Vectors (SV)** and **Bitmaps (BM)** are
  - why **SV wins sometimes** and **BM wins sometimes**
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## 1) Vectorized execution: the 10-second definition

Instead of processing **1 row at a time**, the DB processes a **small batch** (often 1–2k rows) at a time.

Why this helps:

- **Less overhead**: fewer “next() / iterator” calls
- **Better cache use**: the CPU likes sequential work
- **SIMD opportunity**: the CPU can do the same operation on multiple values at once

(You don’t need to be a CPU expert. Just remember: **batch work is easier for the CPU to do fast.**)

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## 2) The core problem: “some rows survive, some rows don’t”

Inside one batch, you apply steps like:

- WHERE filters
- joins

- computed columns

After each step, you must remember:

which positions (rows) in this batch are still valid

That “memory” is the **filter representation**.

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### 3) Our tiny running example (we'll reuse it)

Batch positions: 0 1 2 3 4 5 6 7

Suppose a filter keeps only positions: **0, 3, 4, 7**

There are two common ways to store this.

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### 4) Two filter representations (SV vs BM)

#### A) Selection Vector (SV)

A **selection vector** is a list of the surviving indexes:

- $SV = [0, 3, 4, 7]$

Analogy: **VIP guest list**.

How you read data with SV (idea):

- for each `idx` in the list, read `col[idx]`

Good part:

- if only a few rows survive, the list is short → you do less work

Not-so-good part:

- you have an extra “jump”: read `idx` first, then read `col[idx]` (indirection)

#### B) Bitmap (BM)

A **bitmap** is 1 bit per position:

- $BM = 1 \ 0 \ 0 \ 1 \ 1 \ 0 \ 0 \ 1$

Analogy: **light switches**. 1 = ON (keep), 0 = OFF (drop).

Good part:

- it aligns perfectly with positions 0..N → very nice for simple scans and SIMD

Not-so-good part:

- iterating “only the 1s” can require extra bit-scanning logic

### **Diagram: same filter, two representations**

Same filter, two representations (tiny batch example)

Row index	0	1	2	3	4	5	6	7
Bitmap:	1	0	0	1	1	0	0	1

Selection vector: **[0, 3, 4, 7]**

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## **5) Two types of work operators do: Update vs Map**

### **Update (changes who survives)**

Example: WHERE amount > 100

- some rows fail the predicate
- the filter representation changes (SV list or BM bits change)

### **Map (does NOT change who survives)**

Example: compute amount\_with\_tax = amount \* 1.2

- you compute a new vector
  - survivors are the same as before
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## 6) Two compute strategies: Selective vs Full (this is the big “why”)

Even after you have SV/BM, you can compute in two ways.

### Strategy 1: Selective compute

Compute only for surviving rows.

In our example, survivors are [0, 3, 4, 7], so you compute 4 times.

This is usually great when selectivity is low (few survivors).

### Strategy 2: Full compute

Compute for **every** position in the batch (0..7), then ignore results for invalid rows.

This can sound wasteful, but it can be faster because:

- the loop is simple and predictable
- it can be SIMD vectorized

### Diagram: selective vs full

Two ways to compute on a filtered batch

#### Selective compute (SV style):

```
for idx in [0,3,4,7]: compute(col[idx])
```

#### Full compute (BM/SIMD style):

```
for i in 0..7: compute(col[i]) # maybe SIMD  
then keep results only where bitmap[i] = 1
```

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## 7) Selectivity: the knob that changes everything

**Selectivity** = fraction of rows that survive.

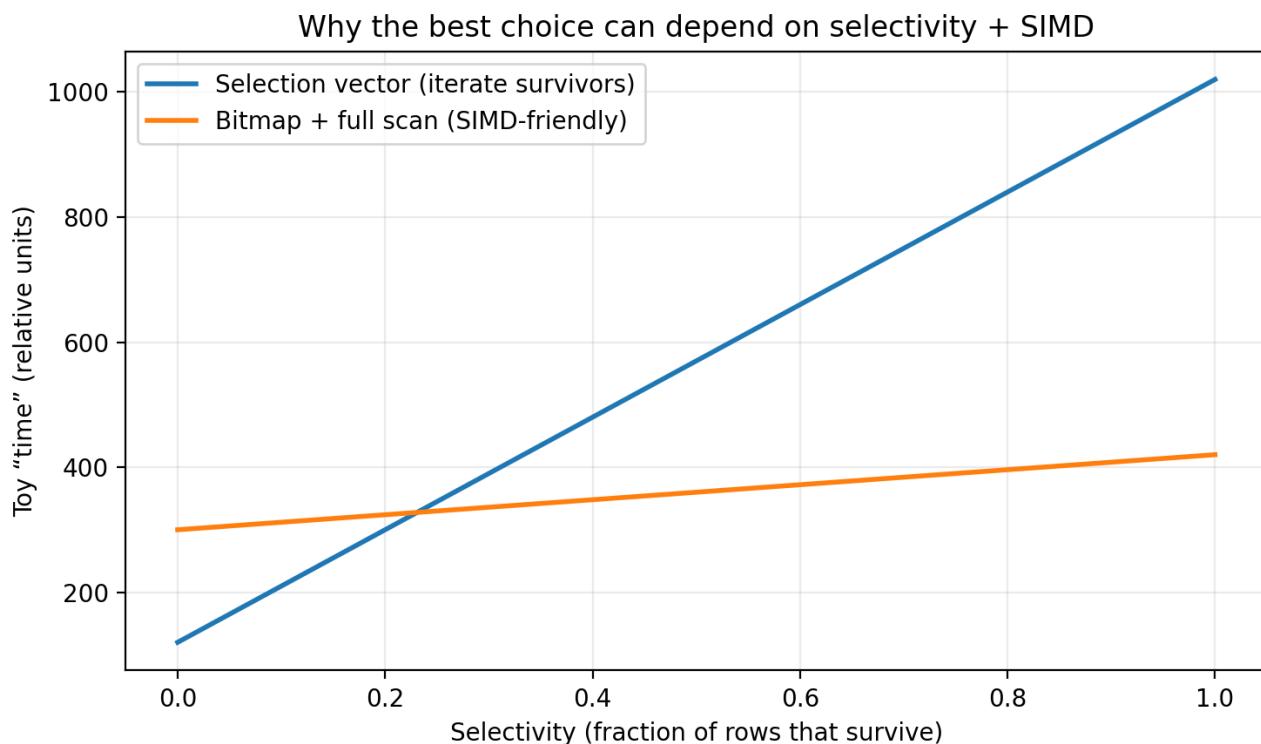
- 10% selectivity → 10% survive → most rows die
- 90% selectivity → 90% survive → most rows live

Intuition (real life):

- If only **3 people** passed security, you only guide those 3 to the room (selective)
- If **almost everyone** passed, you just open the door and let the whole crowd flow (full scan)

### Diagram: why “best choice” can flip

This chart is a **toy intuition** picture (not exact paper numbers), but it shows the idea:



## 8) The paper’s main result (in simple words)

Their experiments show:

- **Bitmaps (BM) are strong** when the operation can be done with **SIMD** (vectorized CPU instructions).
- **Selection vectors (SV) are strong** for many other operations because “iterate survivors” can be cheaper than bitmap scanning.

So it’s not “BM always wins” or “SV always wins”.

It depends on:

- **selectivity** (how many survive)
  - **iteration cost** (how expensive is it to loop?)
  - **operation cost** (how expensive is the actual computation?)
  - **SIMD-friendliness** (can we do it in a vectorized way?)
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## 9) Concrete examples (the stuff you can picture)

### Example A: simple numeric predicate (SIMD-friendly)

Predicate: `amount > 100`

- This is a simple comparison over numbers.
- CPUs can often do many comparisons at once (SIMD).

Here, using **BM** can be very good, especially if selectivity is moderate/high.

### Example B: string-heavy predicate (often not SIMD-friendly)

Predicate: `email LIKE '%@gmail.com'` or regex checks

- String ops have variable length, branching, and irregular memory access.

Here, **SV** often makes sense if selectivity is low, because you don't want extra bitmap scanning overhead.

### Example C: expensive UDF

Predicate: `is_fraud(transaction)` where `is_fraud` is complex

- The operation itself is expensive.
- If you can avoid calling it for rows that will be filtered out, that's huge.

This pushes you toward **SV + selective compute** (if selectivity is low).

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## 10) Cheat-sheet (quick decision guide)

This is a practical starter rule (not perfect, but useful):

- **Few survivors (low selectivity)** → prefer **SV + selective compute**
- **Many survivors (high selectivity)** AND computation is **SIMD-friendly** → prefer **BM + full compute**

Simple table:

Situation   Likely better   Why   --- --- ---	Filter keeps <b>very few</b> rows   SV   You only touch survivors	Filter keeps <b>most</b> rows + work is SIMD-friendly   BM   Full scans + SIMD are efficient	Work is branchy/irregular (strings, complex UDFs)   SV   Bitmap scanning overhead often won't pay	Not sure   Benchmark   Paper's big message: it's workload + hardware dependent
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## 11) Glossary (tiny)

- **Tuple**: row
- **Vector / batch**: small chunk of rows (often 1–2k)
- **Selectivity**: fraction that survives
- **SIMD**: do the same operation on multiple values in one instruction
- **Selection vector (SV)**: list of surviving indexes
- **Bitmap (BM)**: 1 bit per position (1 = survive)

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## 12) 30-second recap

- Vectorized engines process **batches** to reduce overhead.
- Inside each batch, we need to track **which rows are valid**.
- Two main choices: **SV** (list of survivors) and **BM** (bits).
- **SV often wins** when few survive or work is irregular.
- **BM often wins** when work is SIMD-friendly and many survive.