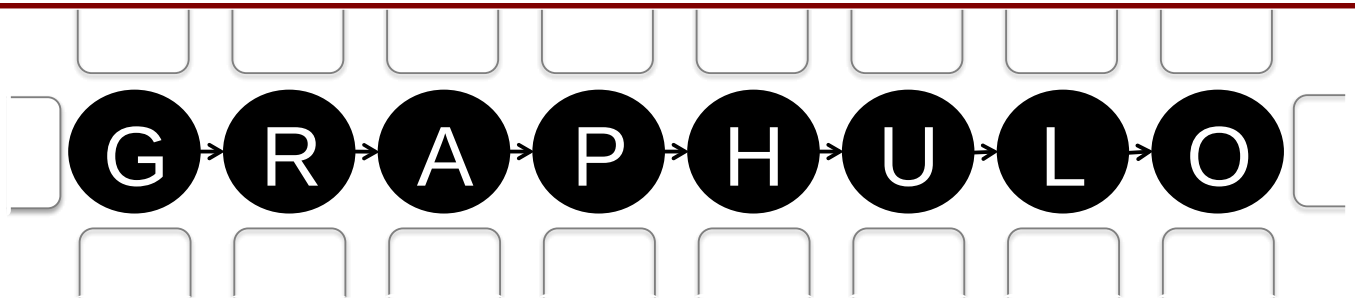

Server-side Sparse Matrix Multiply in the Accumulo Database

Dylan Hutchison[12]* Vijay Gadepally[1]* Jeremy Kepner[1]* Adam Fuchs[3]

[1]MIT Lincoln Laboratory [2]University of Washington [3]Sqrrl Inc.

2015 August

Massachusetts Institute of Technology

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This work is NOT

Creating the best system

for a particular task (matrix multiply)

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Creating the best system for a particular task (matrix multiply)

This work IS

Adding graph analytic capabilities (matrix multiply) to an all-around good system used in practice today (Accumulo)

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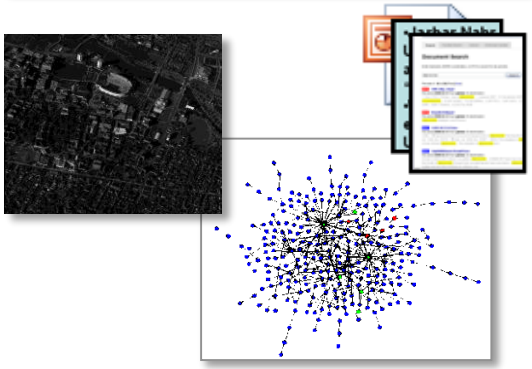
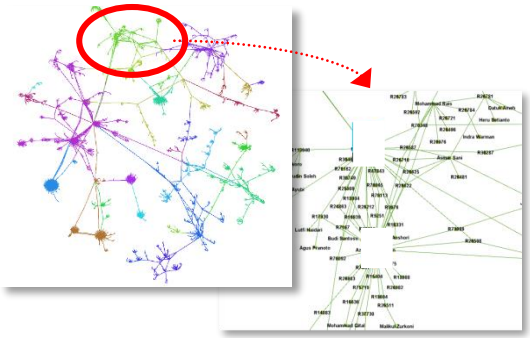
Real Graph Analytics used in Accumulo

ISR



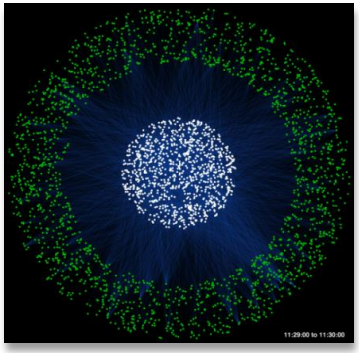
- Graphs represent entities and relationships detected through multi-INT sources
- 1,000s – 1,000,000s tracks and locations
- GOAL: Identify anomalous patterns of life

Social



- Graphs represent relationships between individuals or documents
- 10,000s – 10,000,000s individual and interactions
- GOAL: Identify hidden social networks

Cyber

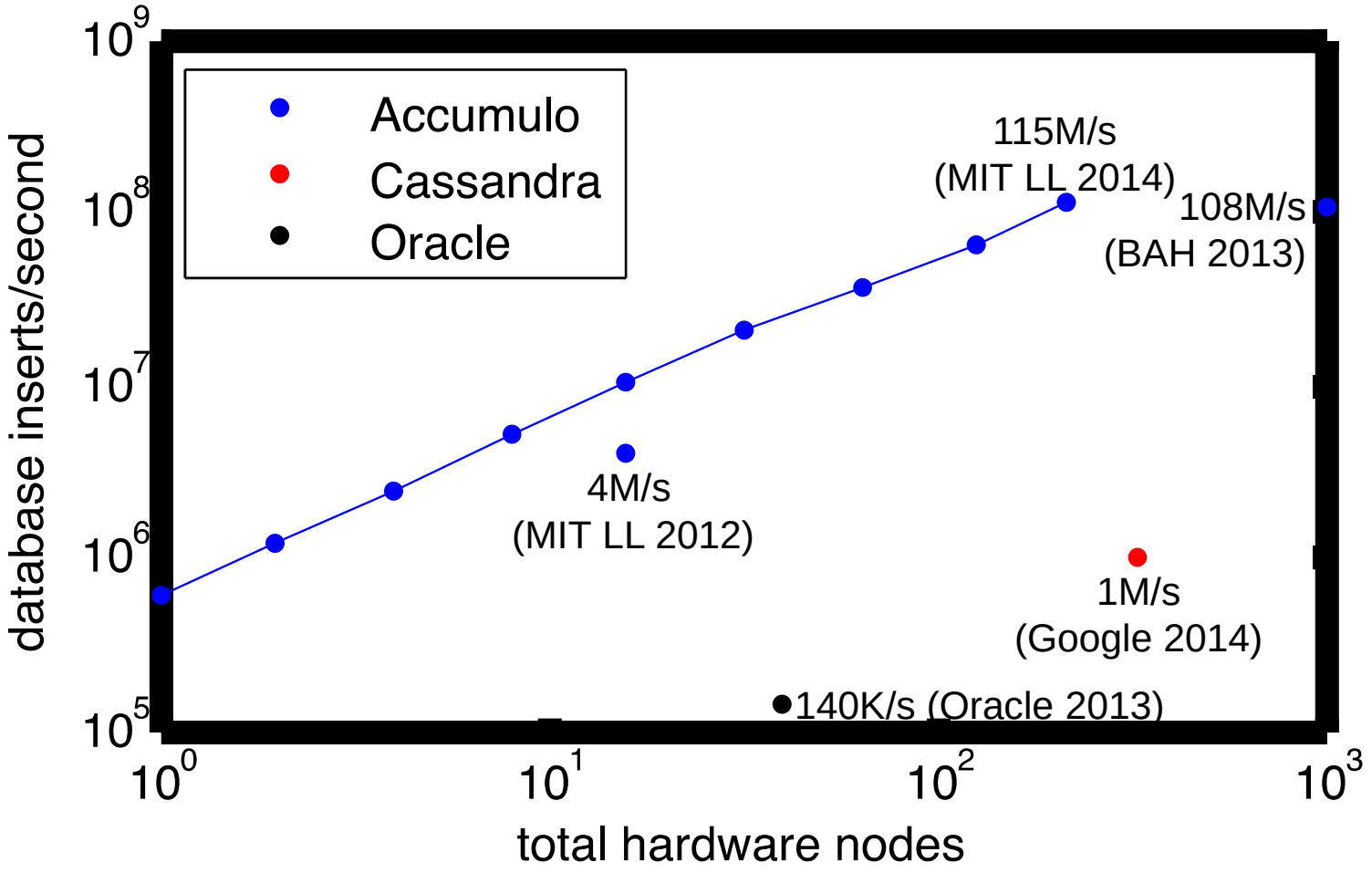


- Graphs represent communication patterns of computers on a network
- 1,000,000s – 1,000,000,000s network events
- GOAL: Detect cyber attacks or malicious software

Many groups store graph data in Accumulo

➔ Need tools for graph analysis in Accumulo

Why Accumulo?



Accumulo ingest performance is 100x greater than competing technologies

Graphulo Overview

- **Primary Goal**
  - **Open source Apache Accumulo Java library that enables many graph algorithms in Accumulo**
- **Core primitives: GraphBLAS**
- **3 Graph Schemas**
  - **Adjacency, Incidence, Single-Table**
- **4 Demonstration Graph Algorithms**
  - **Degree-filtered Breadth First Search, Jaccard coefficients, k-Truss subgraph, Non-negative Matrix Factorization**
- **Focus on Interactive Computing**
  - **"Queued" / Localized analytics within a neighborhood, as opposed to whole table analytics**
  - **Low latency more important than high throughput**
  - **Progress monitoring for user sanity**
    - ***Is the library working or stuck?***

GraphBLAS initial function list

Function	Parameters	Returns	Math Notation
SpGEMM	- sparse matrices **A** and **B** - unary functors (op)	sparse matrix	**C** = op(**A**) * op(**B**)
SpM{Sp}V **(Sp: sparse)**	- sparse matrix **A** - sparse/dense vector **x**	sparse/dense vector	**y** = **A** * **x**
SpEWiseX	- sparse matrices or vectors - binary functor and predicate	in place or sparse matrix/vector	**C** = **A** .* **B**
Reduce	- sparse matrix **A** and functors	dense vector	**y** = sum(**A**, op)
SpRef	- sparse matrix **A** - index vectors **p** and **q**	sparse matrix	**B** = **A**(**p**,**q**)
SpAsgn	- sparse matrices **A** and **B** - index vectors **p** and **q**	none	**A**(**p**,**q**) = **B**
Scale	- sparse matrix **A** - dense matrix or vector **X**	none	check manual
Apply	- any matrix or vector **X** - unary functor (op)	none	op(**X**)

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Matrix Multiply on Big Data

Traditional Matrix Multiply: $AB = C$

$$\begin{bmatrix} 6 & 5 & 0 & 2 \\ 0 & 4 & 0 & 0 \end{bmatrix} \begin{bmatrix} 0 & 0 \\ 0 & 3 \\ 5 & 0 \\ 3 & 4 \end{bmatrix} = \begin{bmatrix} 6 & 23 \\ 0 & 12 \end{bmatrix}$$

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- **Row & Column Labels**

Database Table Multiply

	tod|0500	tod|0800	tod|0900	tod|1400
word|coffee	6	5	0	2
word|desert	0	4	0	0

	word|dew	word|hot
tod|0500	0	0
tod|0800	0	3
tod|0900	5	0
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- **Sparse**

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➔ **Associative Array Mathematics[1]**

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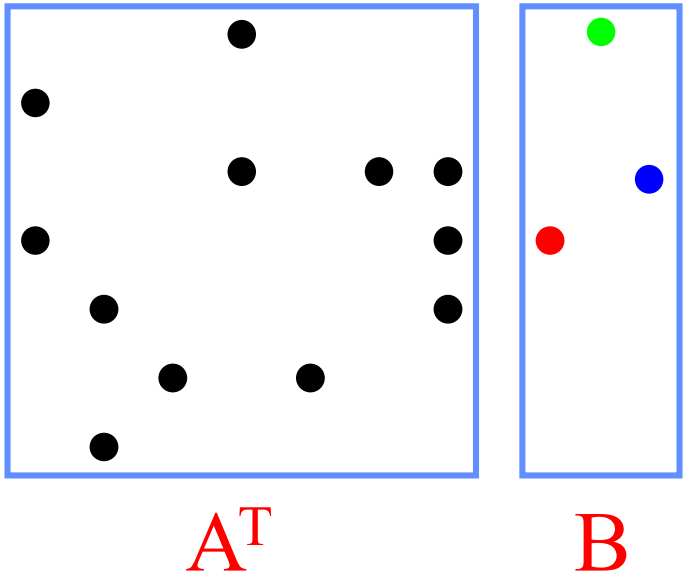
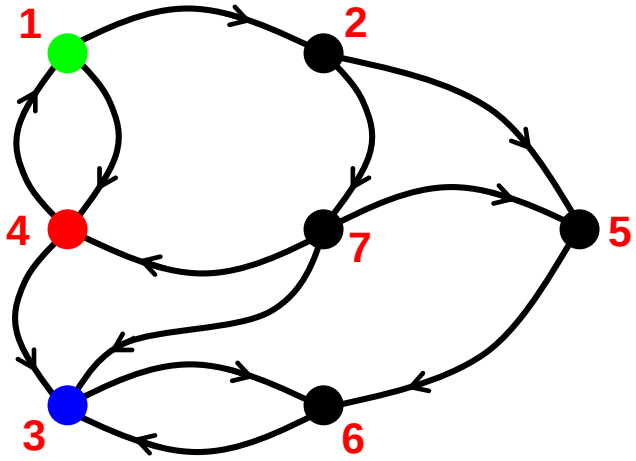
[1]J. Kepner and V. Gadepally. "*Adjacency matrices, incidence matrices, database schemas, and associative arrays*" in International Parallel & Distributed Processing Symposium Workshops (IPDPSW). IEEE, 2014

Application: Multi-Source Breadth-First Search





- Sparse array representation => space efficient
- Sparse matrix-matrix multiplication => work efficient
- Three possible levels of parallelism: searches, vertices, edges
- Basis for a wide range of graph algorithms

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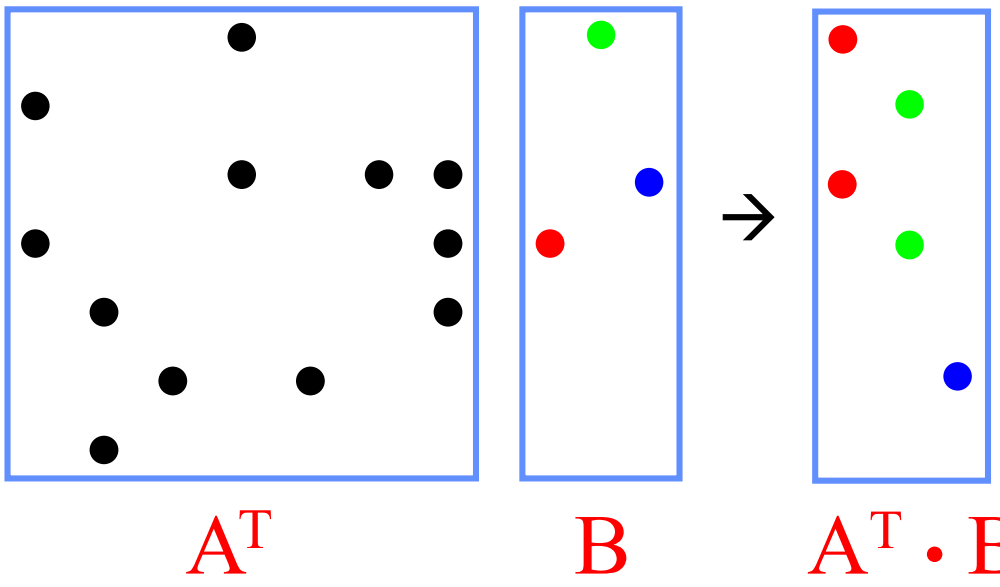

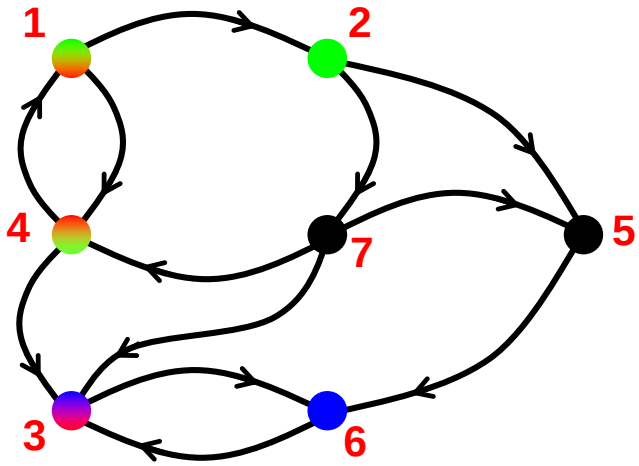

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Background on Accumulo

Key					Value
Row ID	Column			Timestamp	
	Family	Qualifier	Visibility		

Best for:

- Large, de-normalized tables (NoSQL)
- Hadoop HDFS / Java ecosystem
- Huge data volume – TBs to PBs
- Cell-level visibility
- Robust horizontal scaling

Use Transpose Tables
see D4M Schema[1]

- Row store by default
  - Scan over rows for O(log n) lookup & sorted order
  - Log-structured Merge Tree design
- Iterator processing framework

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[1] *D4M 2.0 Schema: A General Purpose High Performance Schema for the Accumulo Database* Kepner et al, IEEE HPEC 2013

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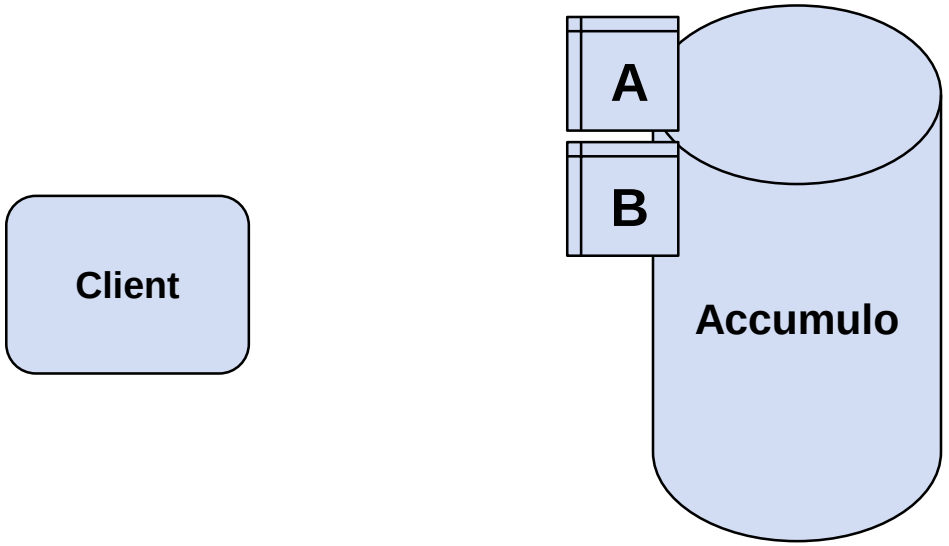
Table Multiply Before Graphulo



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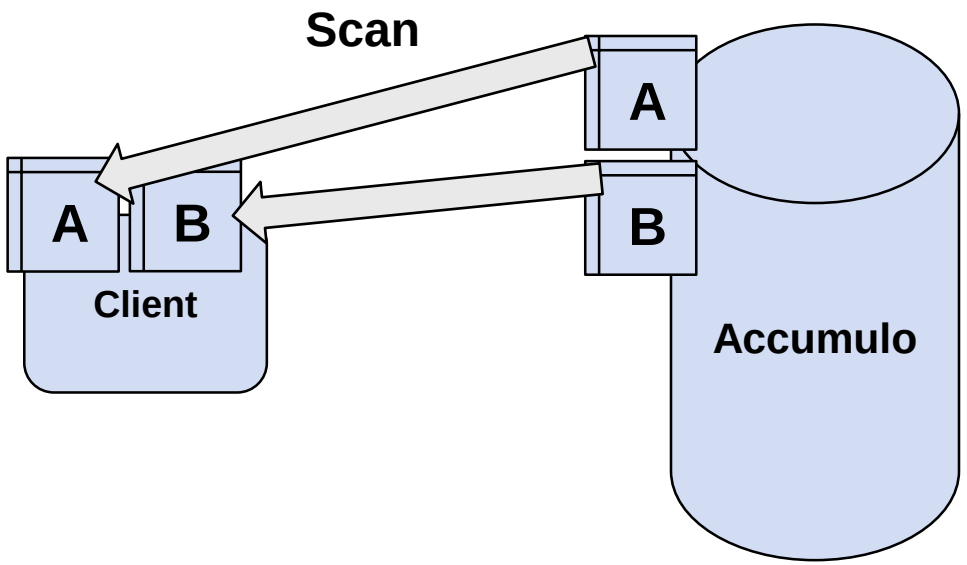
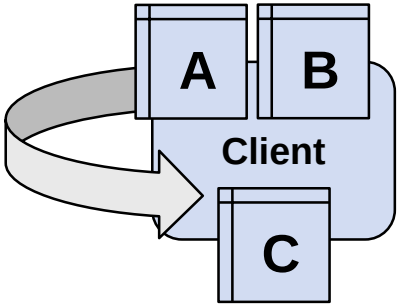
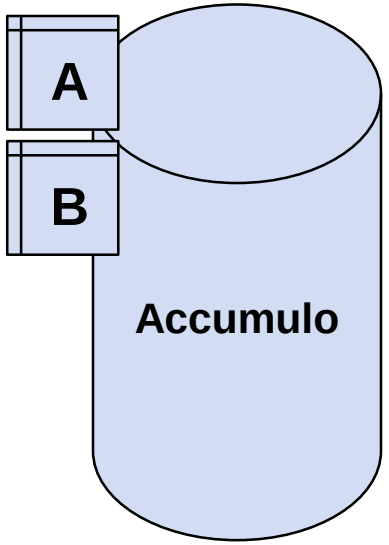


Table Multiply Before Graphulo

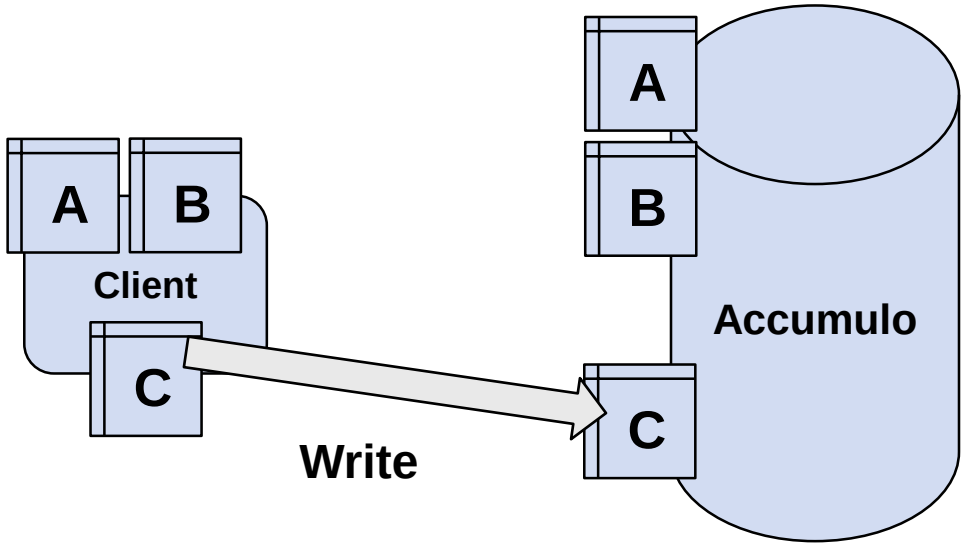
Multiply in-memory*





***Blocked algorithms exist for large tables at reduced efficiency**

Table Multiply Before Graphulo



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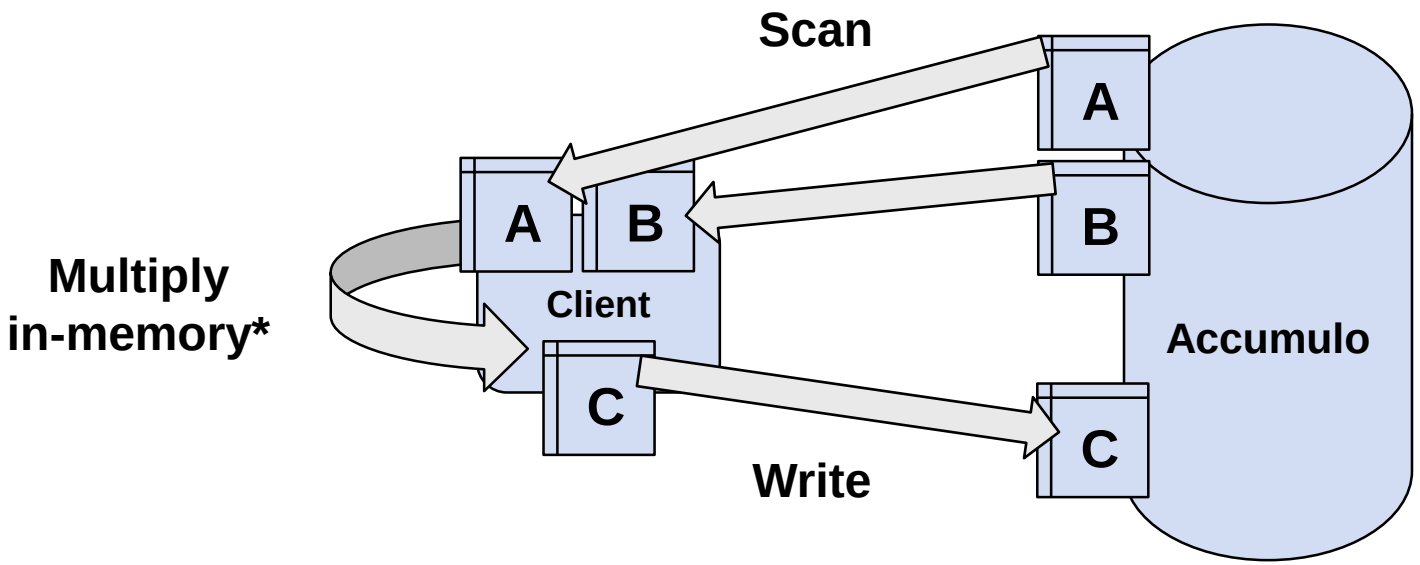

Old: DB = Indexed Storage

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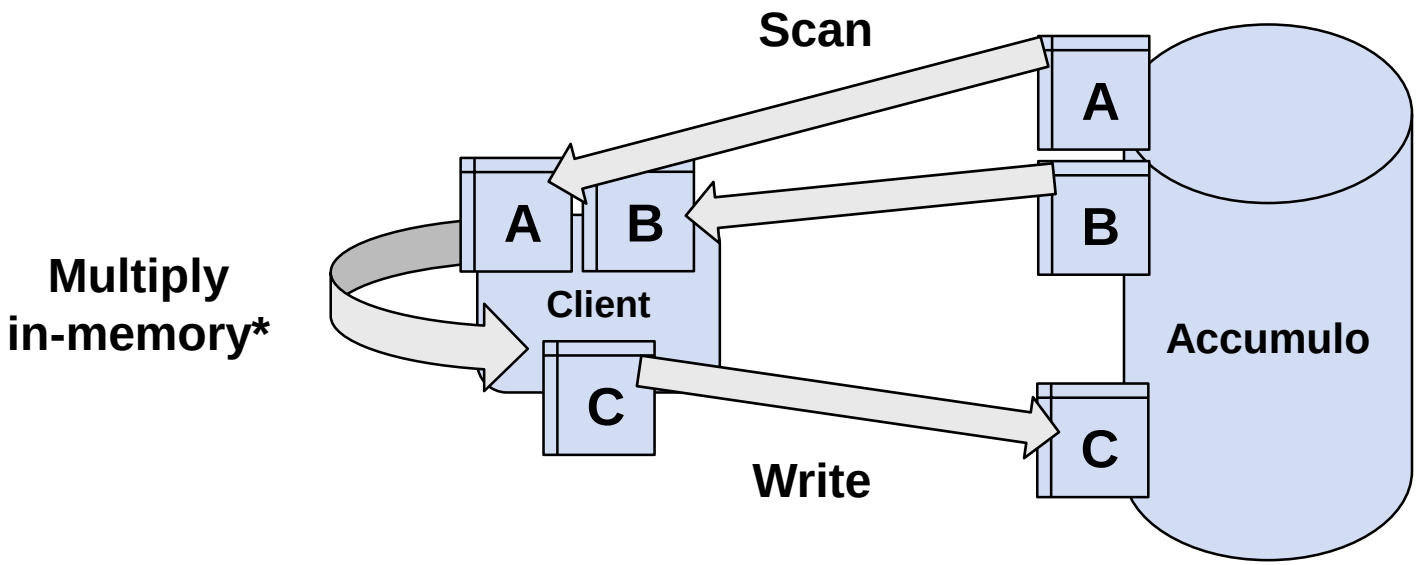

Old: DB = Indexed Storage

New: DB = Indexed Storage + Computation Engine

***Blocked algorithms exist for large tables at reduced efficiency**

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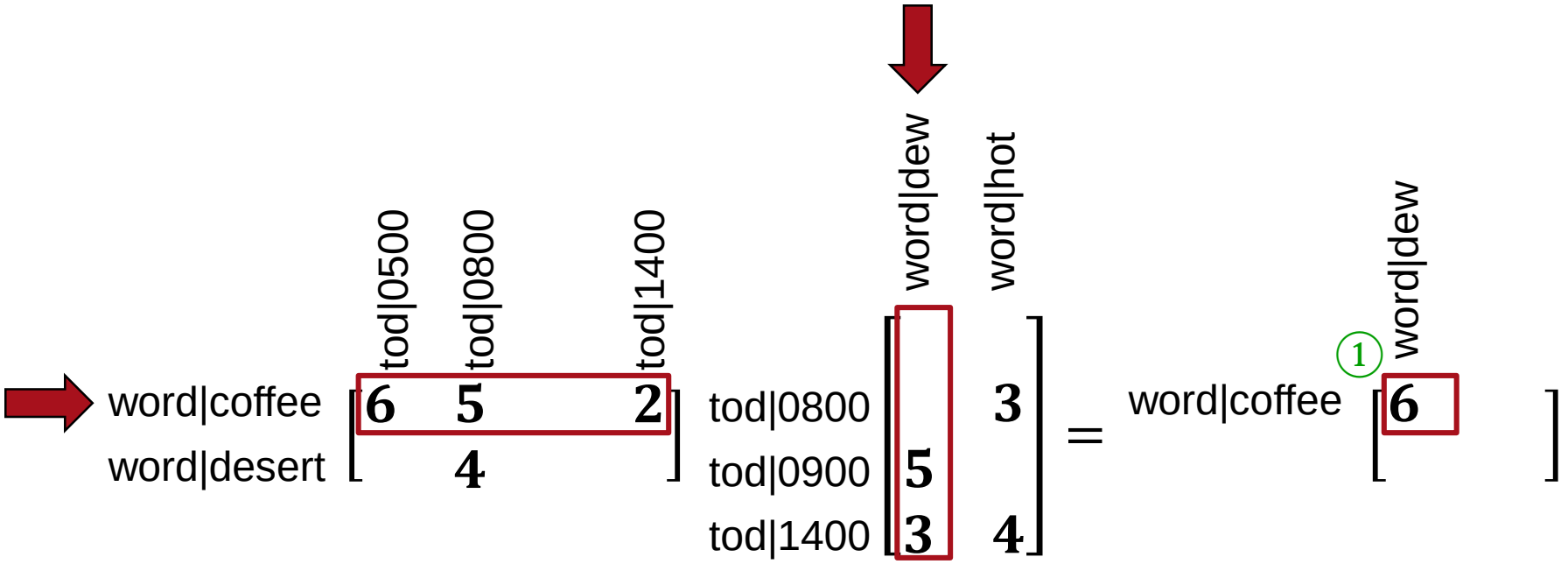
Inner Product



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  for $j = 1 : L$ = 2
    for $k = 1 : M$ = 4
      $\mathbf{C}(i,j) \oplus\!= \mathbf{A}(i,k) \otimes \mathbf{B}(k,j)$

$$\mathbf{C}(i,j) = \bigoplus_{k=1}^{M} \mathbf{A}(i,k) \otimes \mathbf{B}(k,j)$$

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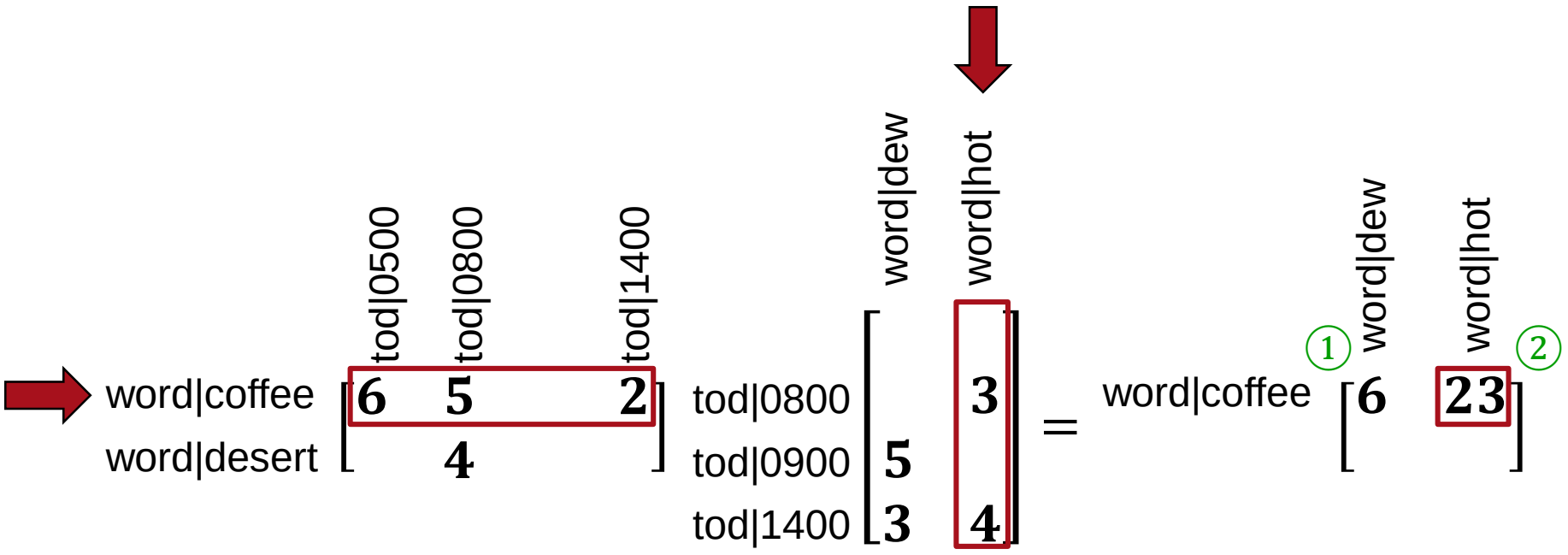

1st Scan

$$\textbf{for } i = 1 : N = 2$$
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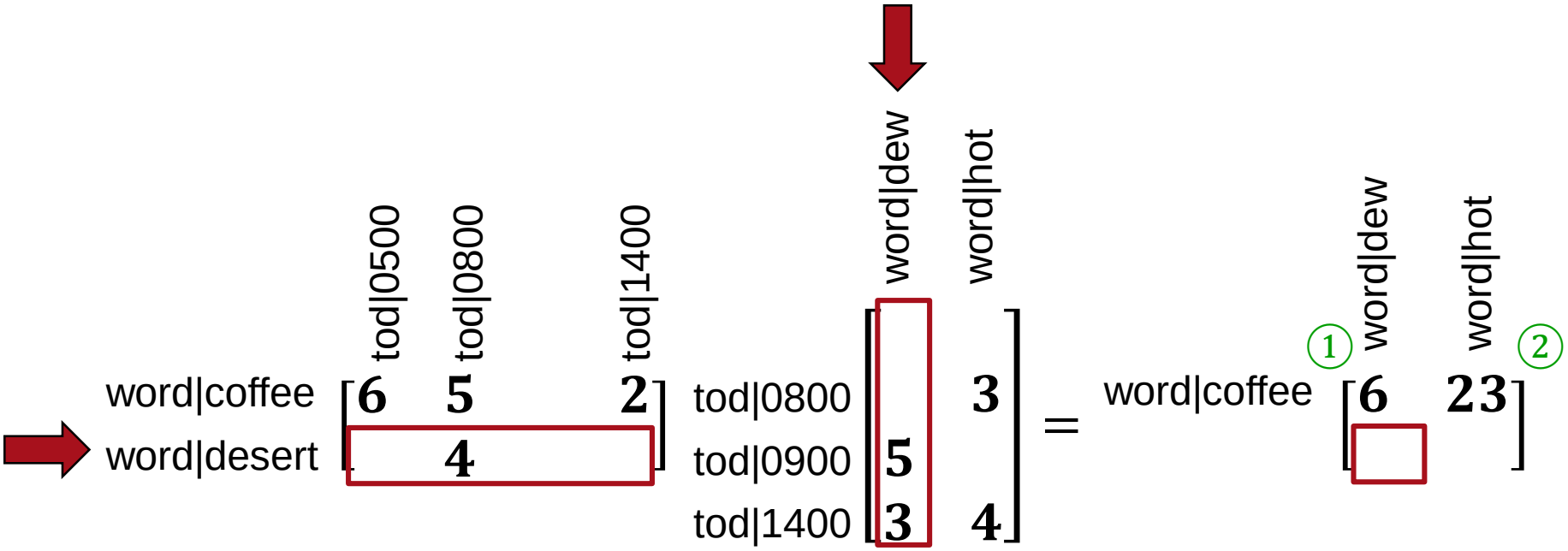

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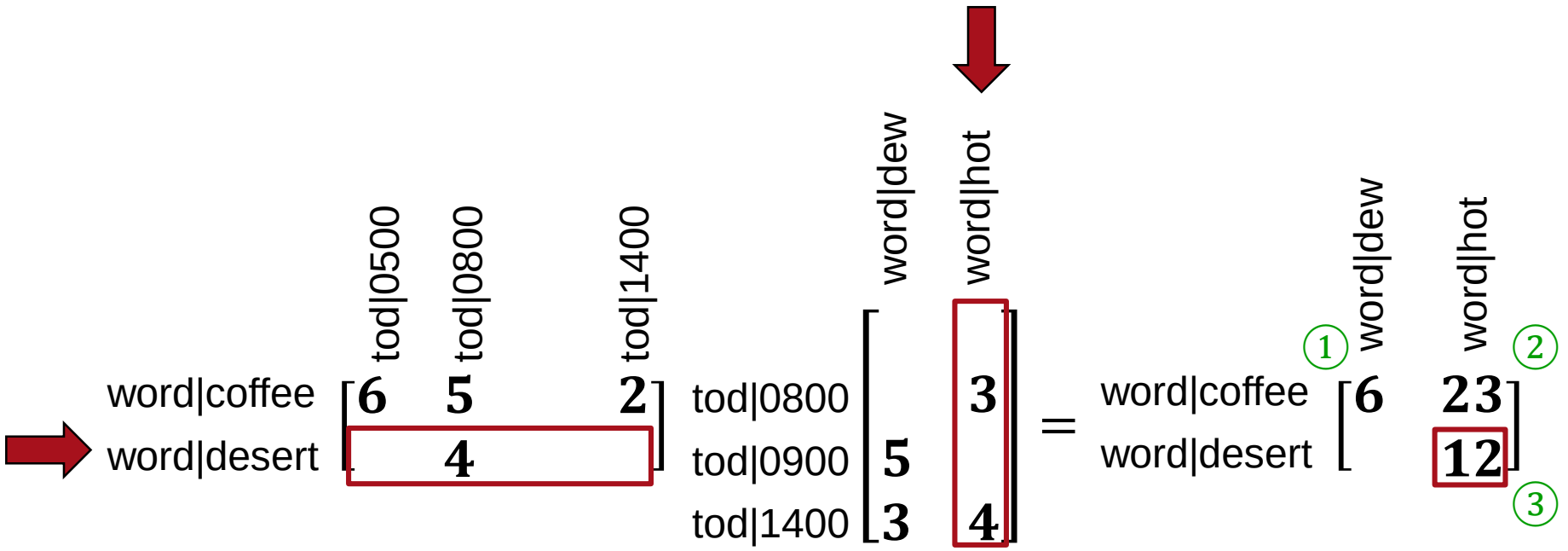

2nd Scan

for $i = 1 : N$ = 2
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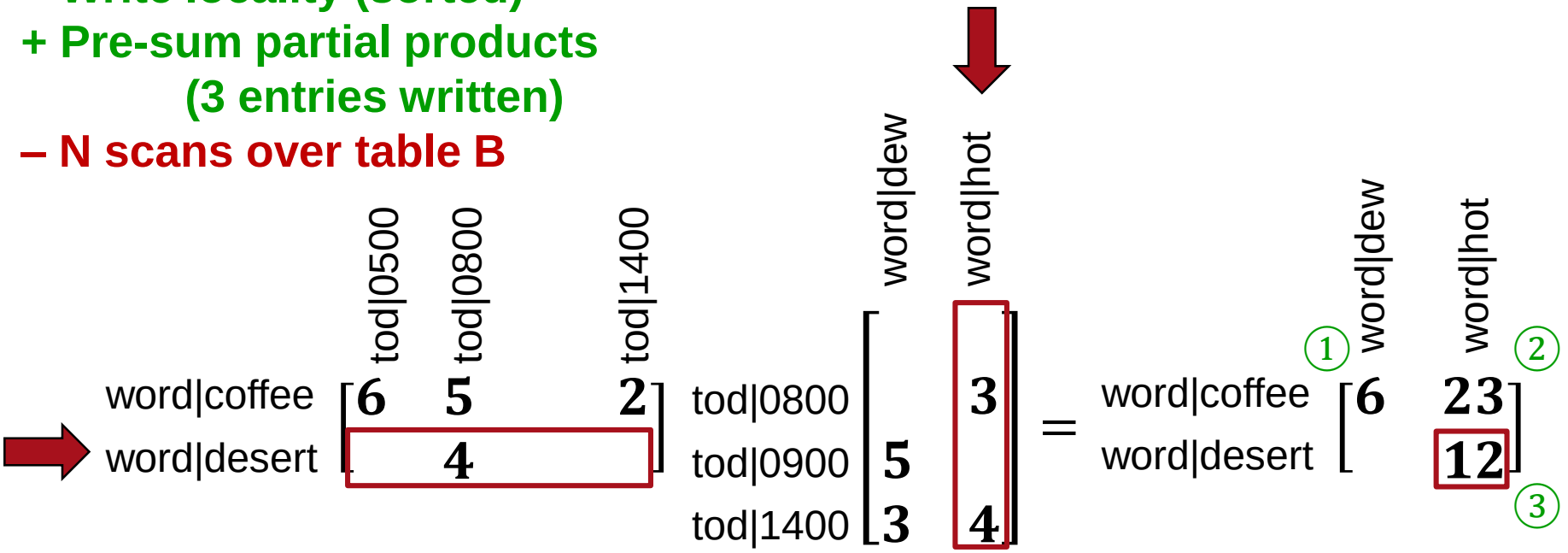
Inner Product

+ Write locality (sorted)
+ Pre-sum partial products
(3 entries written)
– N scans over table B



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Outer Product

Now explicitly showing A^T

	word|coffee	word|desert
tod|0500	**6**	
tod|0800	**5**	**4**
tod|1400	**2**	

	word|dew	word|hot
tod|0800		**3**
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$=$ $\begin{bmatrix} & \\ & \end{bmatrix}$

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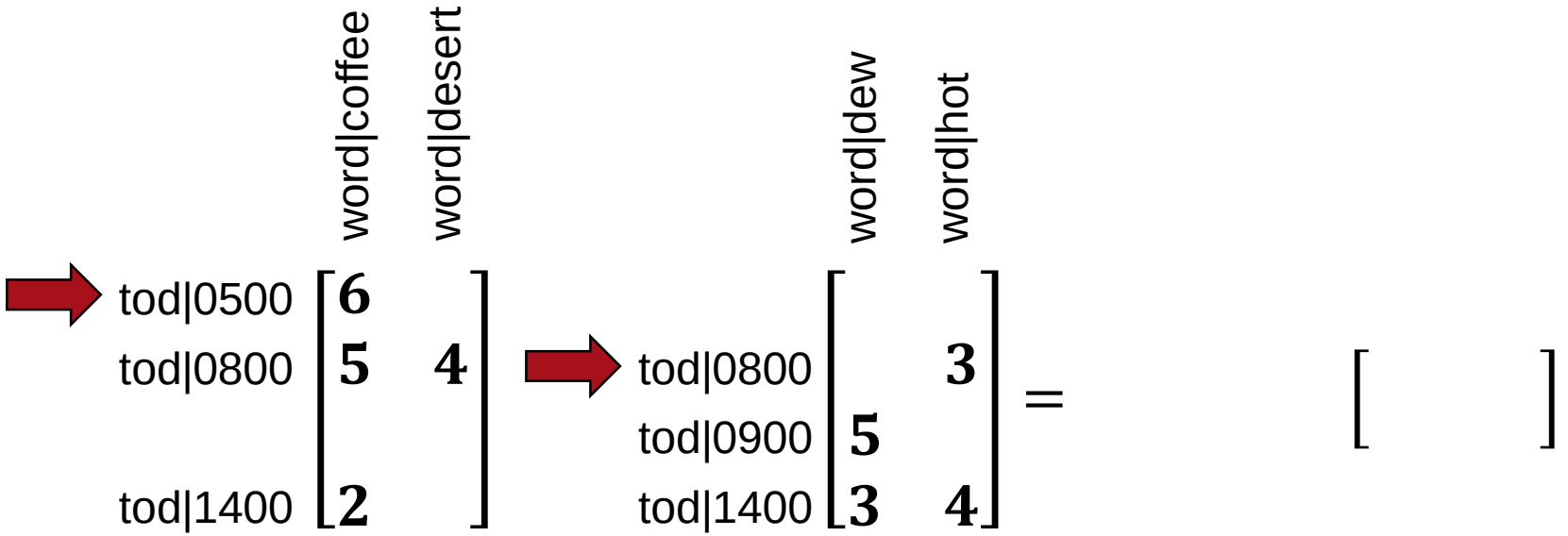
Outer Product

1. Align Rows



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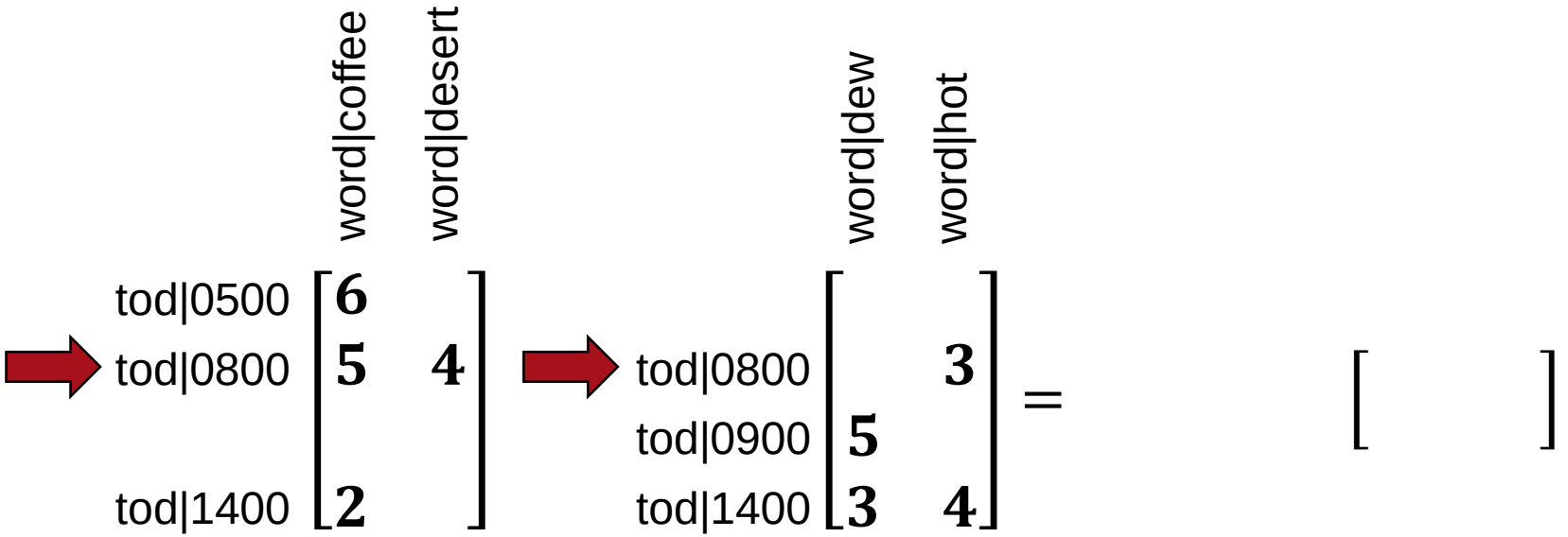

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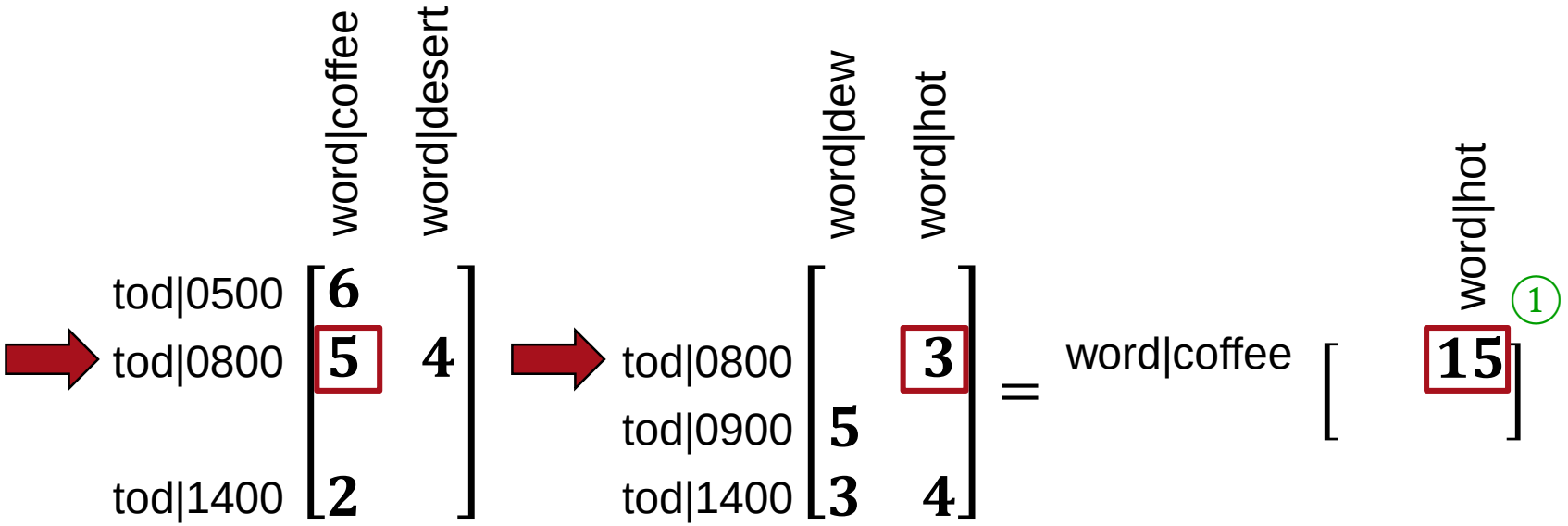
2. Cartesian Product



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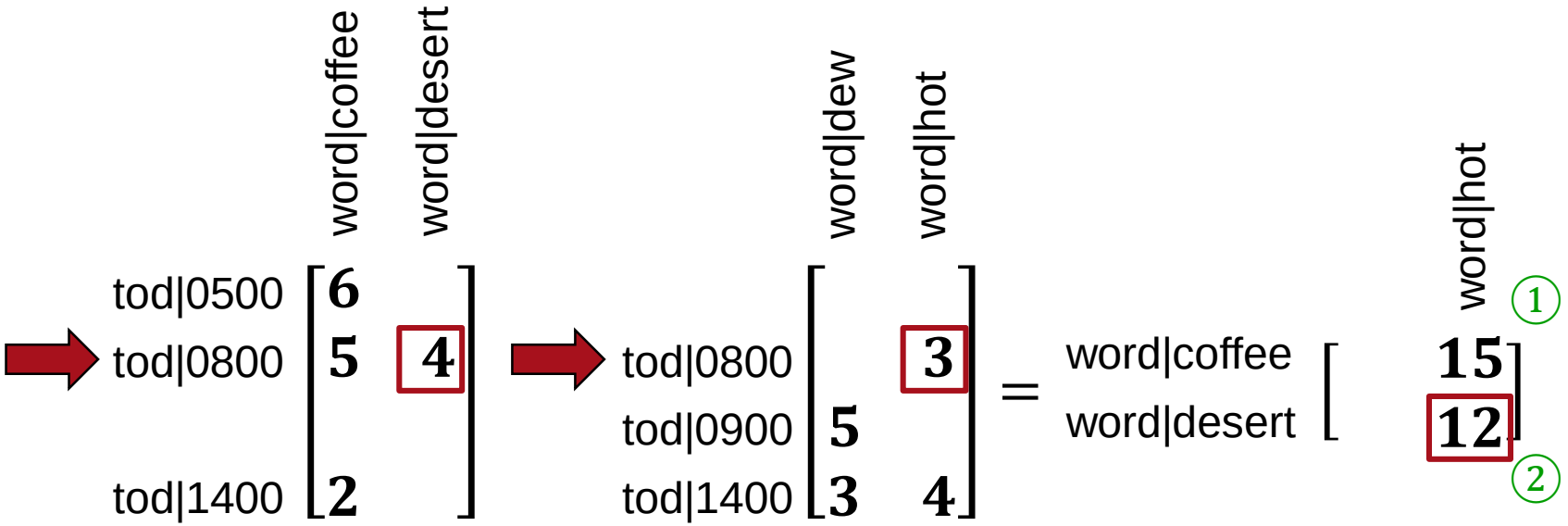

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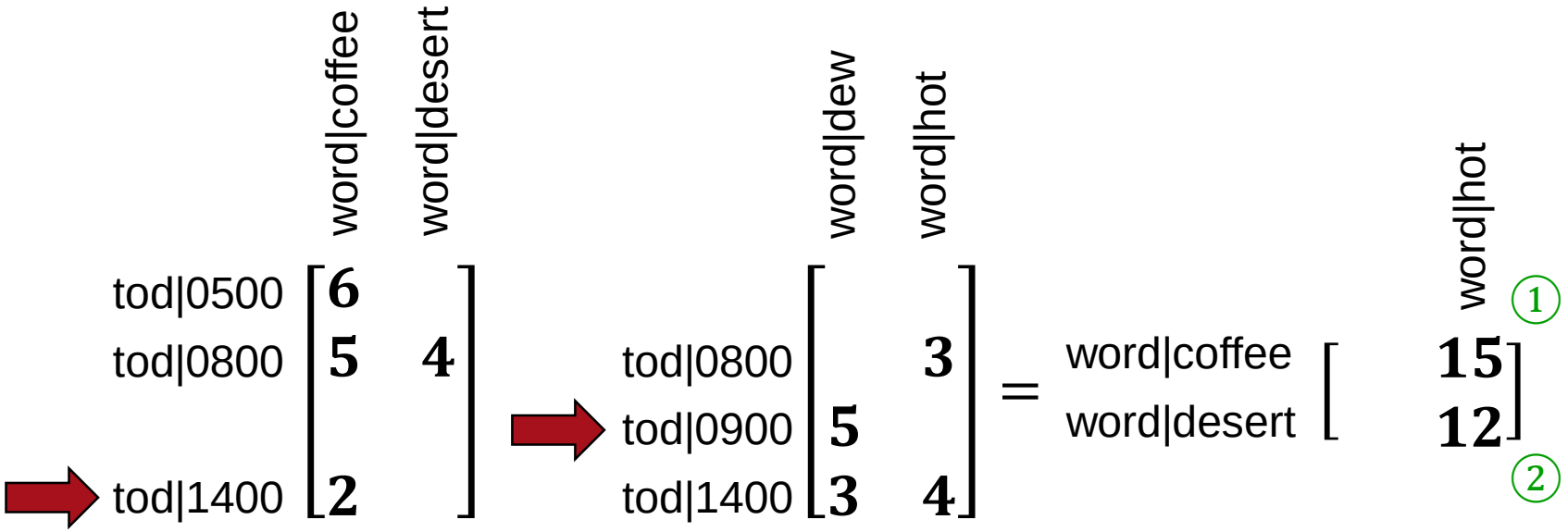

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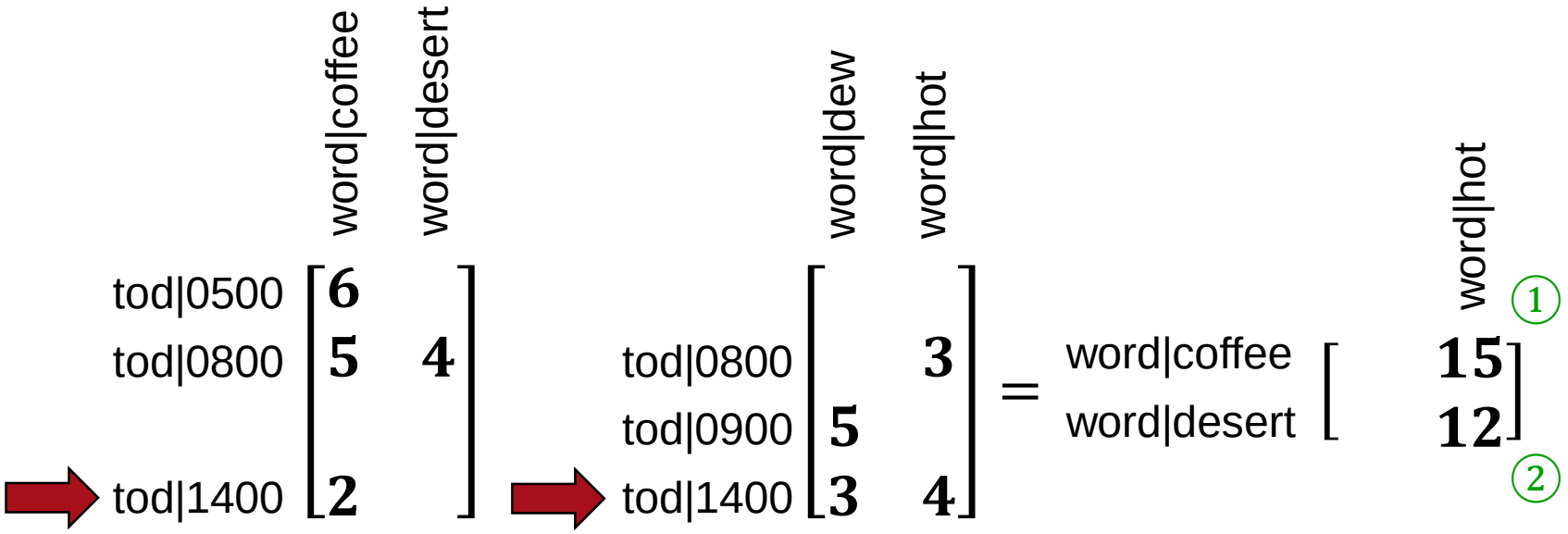

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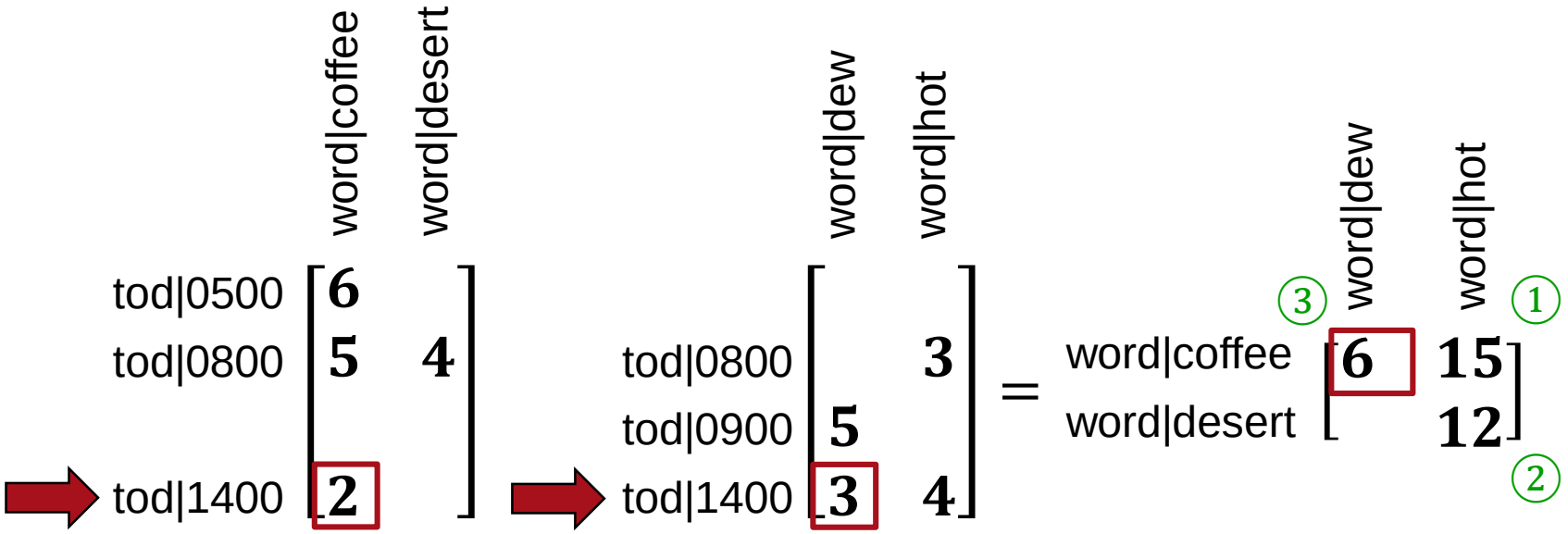

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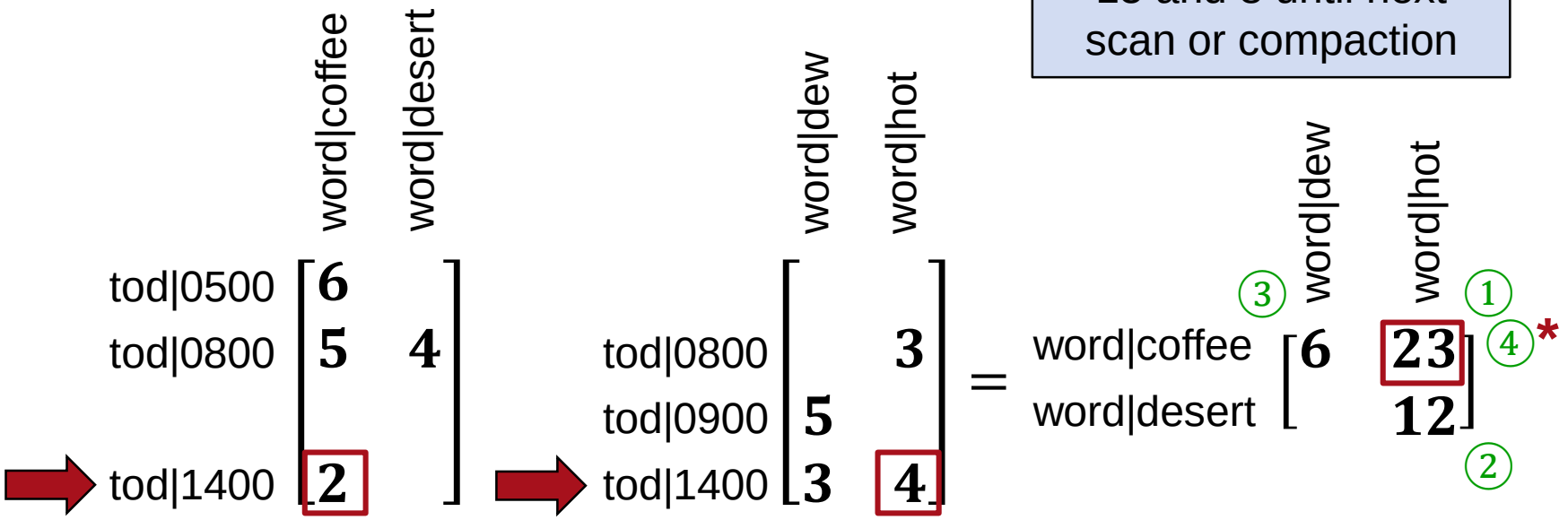
$$\quad\quad \textbf{for } j = 1 : L \text{ = 2}$$
$$\quad\quad\quad \mathbf{C}(i,j) \oplus\!= \mathbf{A}(i,k) \otimes \mathbf{B}(k,j)$$

$$\mathbf{C} = \bigoplus_{k=1}^{M} \mathbf{A}(:,k)\mathbf{B}(k,:)$$

Outer Product

2. Cartesian Product

***Lazy ⊕**: Accumulo stores both 15 and 8 until next scan or compaction



$$\textbf{for } k = 1 : M \text{ = 4}$$
$$\quad \textbf{for } i = 1 : N \text{ = 2}$$
$$\quad\quad \textbf{for } j = 1 : L \text{ = 2}$$
$$\quad\quad\quad \mathbf{C}(i,j) \oplus\!= \mathbf{A}(i,k) \otimes \mathbf{B}(k,j)$$

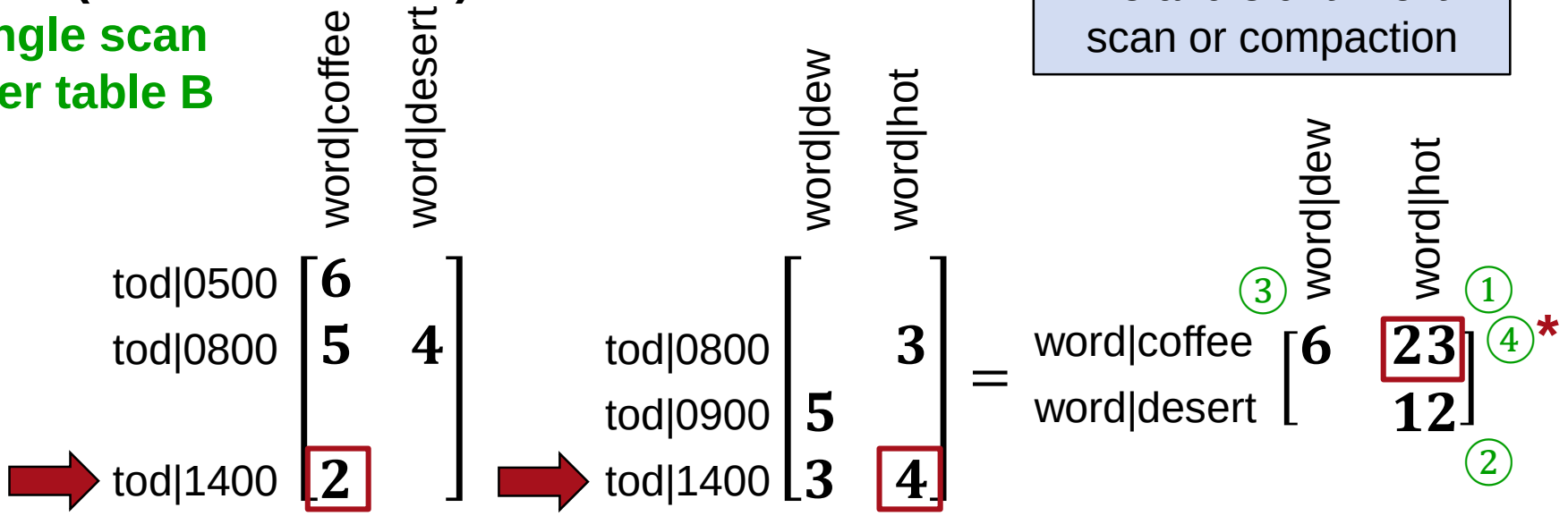
$$\mathbf{C} = \bigoplus_{k=1}^{M} \mathbf{A}(:,k)\mathbf{B}(k,:)$$

Outer Product

- **No write locality; unsorted writes**
- **Hard to pre-sum partial products (4 entries written)**

+ Single scan over table B

***Lazy ⊕:** Accumulo stores both 15 and 8 until next scan or compaction



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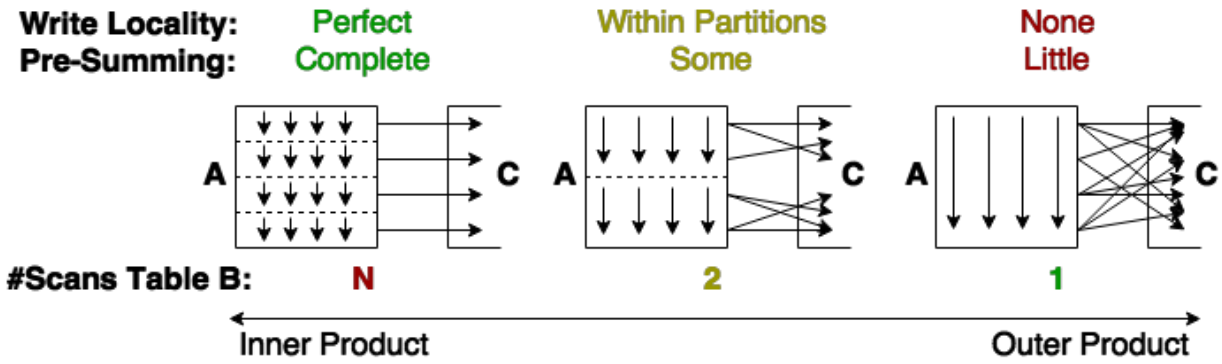
$$\mathbf{C} = \bigoplus_{k=1}^{M} \mathbf{A}(:,k)\mathbf{B}(k,:)$$

Inner vs. Outer Product

- **Outer product best for Accumulo**
  - **Single pass over table B = single disk read**
  - **BatchWriter ingest handles unsorted writes**
  - **Combiners handle $\oplus$**
  - **Less extra partial products written for sparse data**

- **Inner product still has merit**
  - **Better for dense data**
  - **Hybrid 2D-like algorithm possible**



Outline

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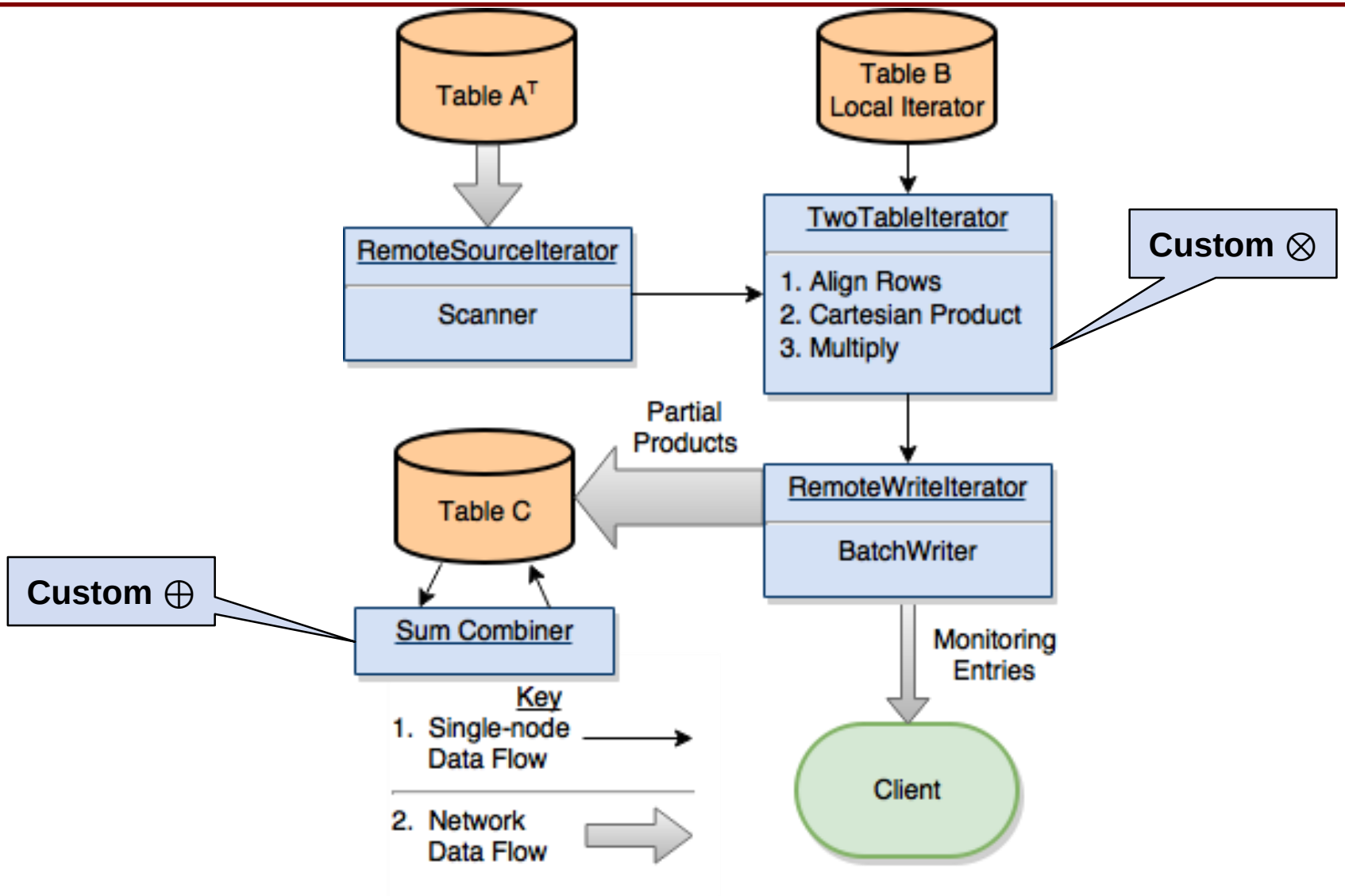
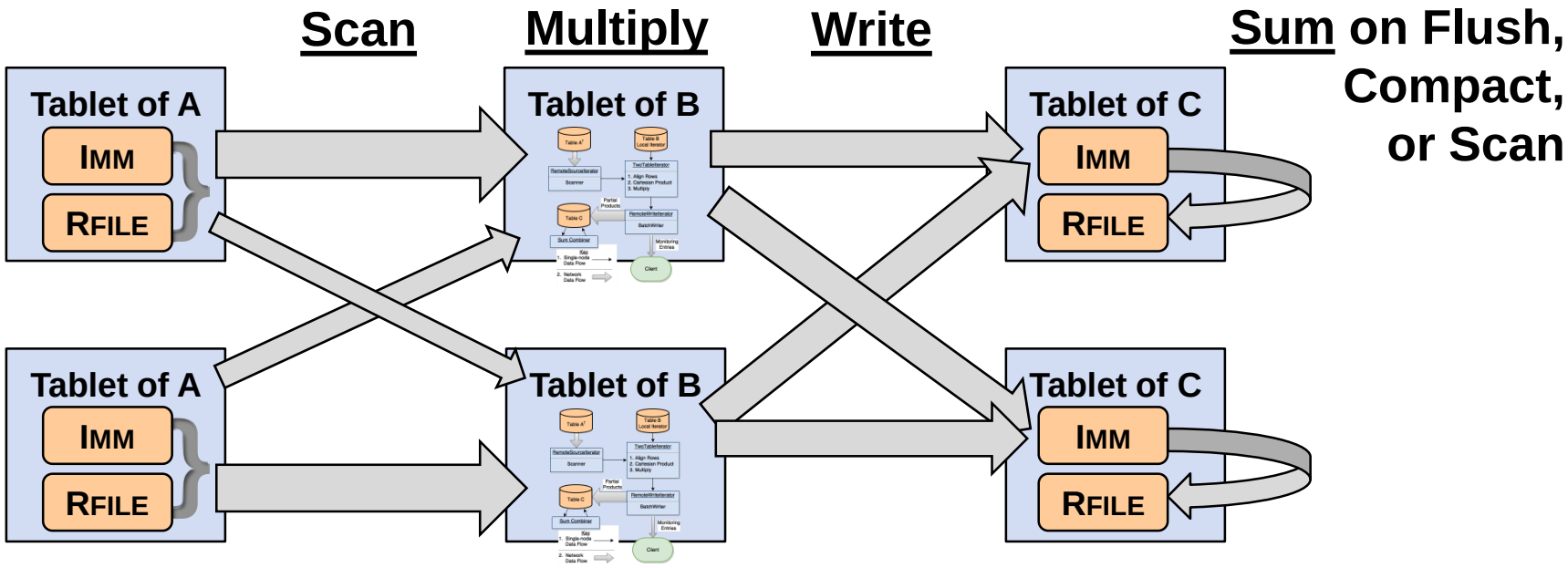
Outer Product in Graphulo Iterators



Accumulo Distributes Graphulo Iterators



- Tablets can be hosted on any tablet server
  - Accumulo load balances tablet allocation
- Matrix multiply iterators run on B's tablets in parallel
  - Scan from A's tablets in parallel
  - BatchWrite to C's tablets in parallel

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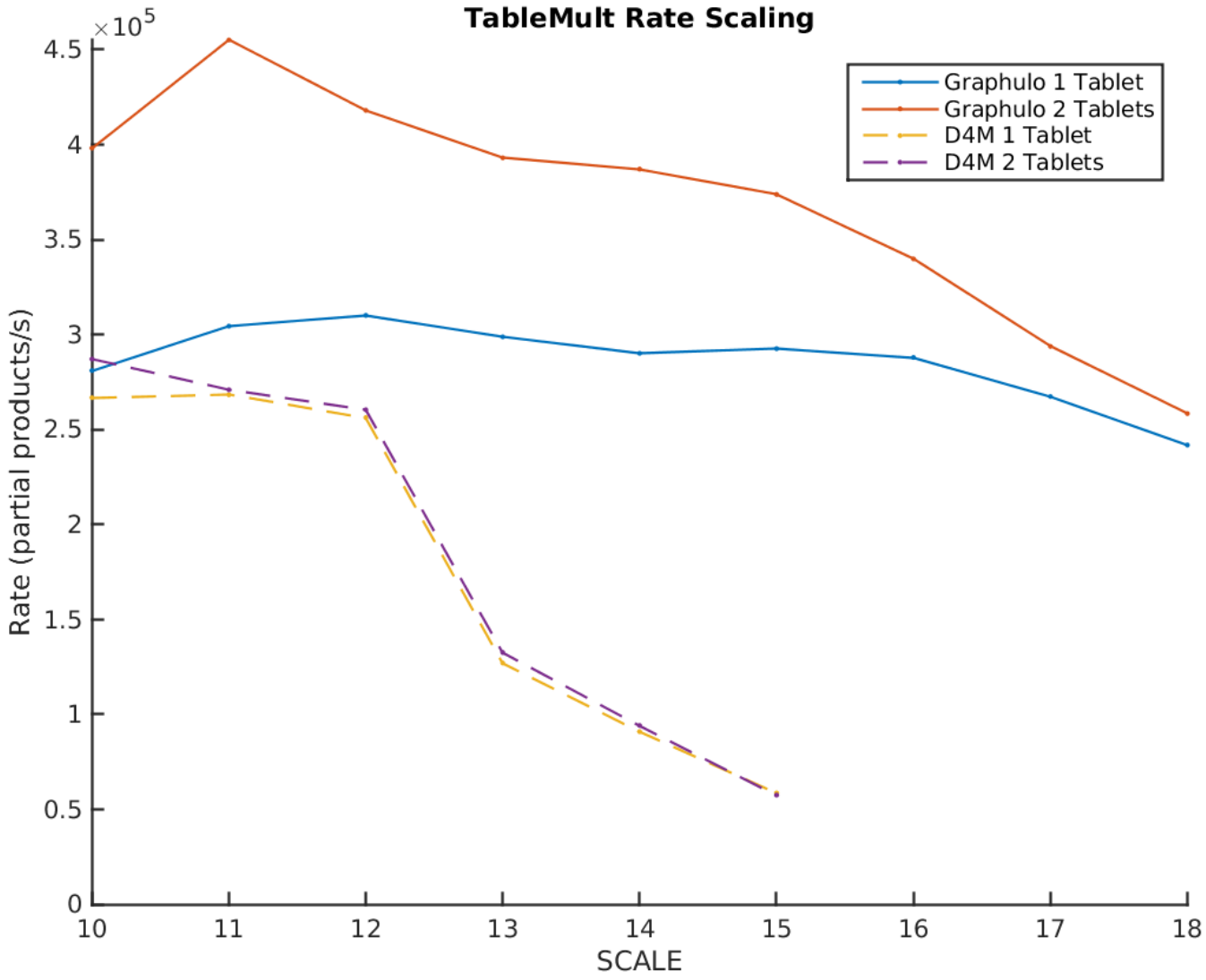
Performance Experiment

- **Compare to pre-Graphulo alternative:**
  - **D4M Matlab client as Middleman**
- **Scaled / Weak scaling study:**
  - **How multiply rate varies with increasing problem size at fixed resources**
  - **Ideal: constant multiply rate**
- **Fixed / Strong scaling study:**
  - **How multiply rate varies with increasing resources at fixed problem size**
  - **Ideal: multiply rate scales linearly with increasing resources**

- **Environment:**
  - **Laptop, 16GB RAM, 2 Dual-core i7 processors, Accumulo 1.6.1**
- **Vary problem size between SCALE 10 and 18**
  - **Unpermuted Power law graph generator**
  - **# of nodes in each input table is 2^{SCALE}. Used 16 edges/node**
- **Vary resources with # Accumulo Tablets (Varies # Threads)**

Performance Experiment



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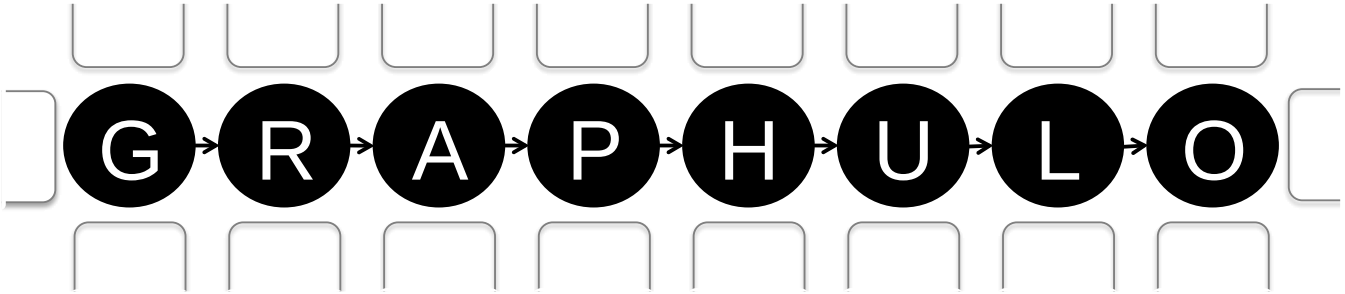
Conclusion

- **Promising performance**
  - **Write rates near 400k / sec, near highest single-node recorded rates**
  - **Experiments on a larger cluster will confirm weak & strong scaling**
- **Outer product better suited to Accumulo**
  - **Hybrid inner-outer product algorithms worth studying**
- **Current Graphulo research is**
  - **implementing remaining GraphBLAS**
  - **developing graph algorithms**



Backup

TABLE I: Output Table **C** Sizes and Experiment Timings

SCALE	Entries in Table **C**		Graphulo 1 Tablet		D4M 1 Tablet		Graphulo 2 Tablets		D4M 2 Tablets	
	PartialProducts	AfterSum	Time (s)	Rate (pp/s)	Time (s)	Rate (pp/s)	Time (s)	Rate (pp/s)	Time (s)	Rate (pp/s)
10	8.05×10^5	2.69×10^5	2.87	2.81×10^5	3.02	2.67×10^5	2.02	3.98×10^5	2.80	2.87×10^5
11	2.36×10^6	8.15×10^5	7.76	3.04×10^5	8.80	2.68×10^5	5.19	4.55×10^5	8.72	2.71×10^5
12	6.82×10^6	2.43×10^6	2.20×10^1	3.10×10^5	2.66×10^1	2.56×10^5	1.63×10^1	4.18×10^5	2.62×10^1	2.60×10^5
13	1.91×10^7	7.04×10^6	6.40×10^1	2.99×10^5	1.50×10^2	1.27×10^5	4.86×10^1	3.93×10^5	1.44×10^2	1.33×10^5
14	5.27×10^7	2.00×10^7	1.82×10^2	2.90×10^5	5.79×10^2	9.09×10^4	1.36×10^2	3.87×10^5	5.59×10^2	9.42×10^4
15	1.47×10^8	5.83×10^7	5.03×10^2	2.93×10^5	2.51×10^3	5.86×10^4	3.94×10^2	3.74×10^5	2.56×10^3	5.75×10^4
16	4.00×10^8	1.63×10^8	1.39×10^3	2.88×10^5			1.18×10^3	3.40×10^5		
17	1.09×10^9	4.59×10^8	4.06×10^3	2.67×10^5			3.70×10^3	2.94×10^5		
18	2.94×10^9	1.28×10^9	1.21×10^4	2.42×10^5			1.14×10^4	2.58×10^5		

Inner-Outer Hybrid Algorithm

$$
\begin{array}{l}
\textbf{for } p = 1 : P \\
\quad \textbf{for } k = 1 : M \\
\quad\quad \textbf{for } i = \left(\left\lfloor \frac{(p-1)N}{P} \right\rfloor + 1 \right) : \left\lfloor \frac{pN}{P} \right\rfloor \\
\quad\quad\quad \textbf{for } j = 1 : L \\
\quad\quad\quad\quad \mathbf{C}(i,j) \oplus\!= \mathbf{A}(i,k) \otimes \mathbf{B}(k,j)
\end{array}
$$

P = N – Inner Product

P = 1 – Outer Product

D4M Schema for Sparse Arrays in Key/Value Databases (Accumulo)

Input Data

Time	Col1	Col2	Col3
2001-01-01	a		a
2001-01-02	b	b	
2001-01-03		c	c

Accumulo Table: Ttranspose

	01-01-2001	02-01-2001	03-01-2001
Col1|a	1		
Col1|b		1	
Col2|b		1	
Col2|c			1
Col3|a	1		
Col3|c			1

Accumulo Table: T

	Col1|a	Col1|b	Col2|b	Col2|c	Col3|a	Col3|c
01-01-2001	1				1	
02-01-2001		1	1			
03-01-2001				1		1

- **Tabular data expanded to create many type/value columns**
- **Transpose pairs allows quick look up of either row or column**

[1] *D4M 2.0 Schema: A General Purpose High Performance Schema for the Accumulo Database* Kepner et al, IEEE HPEC 2013