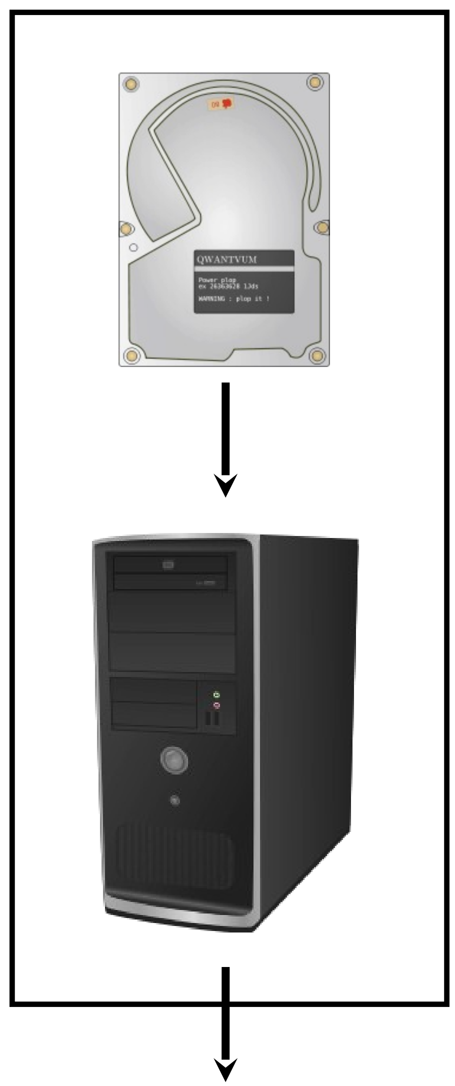
Parallel DBs

Why Scale?

Scan of 1 PB at 300MB/s (SATA r2 Limit)

Why Scale Up?

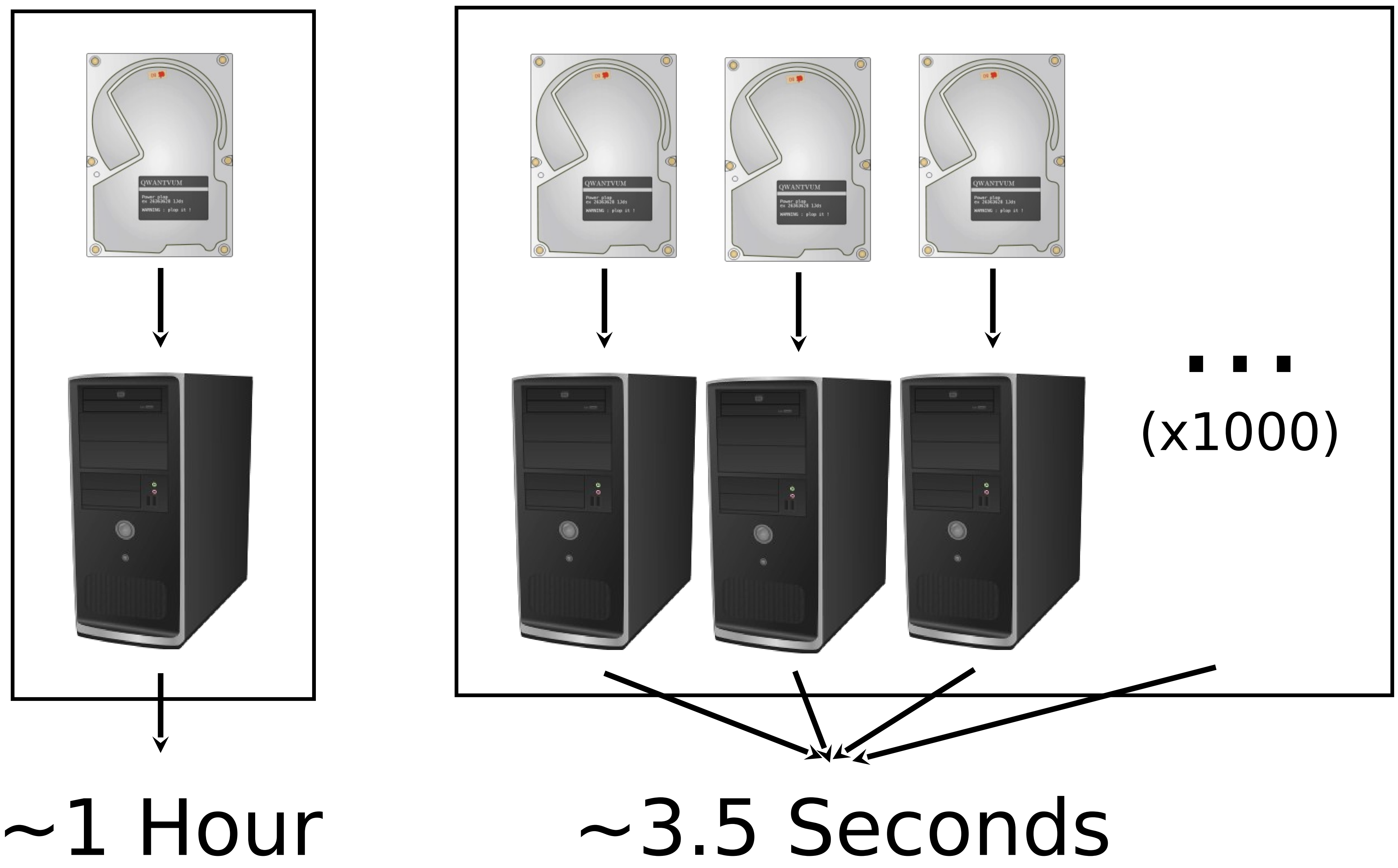
Scan of 1 PB at 300MB/s (SATA r2 Limit)



~1 Hour

Why Scale Up?

Scan of 1 PB at 300MB/s (SATA r2 Limit)



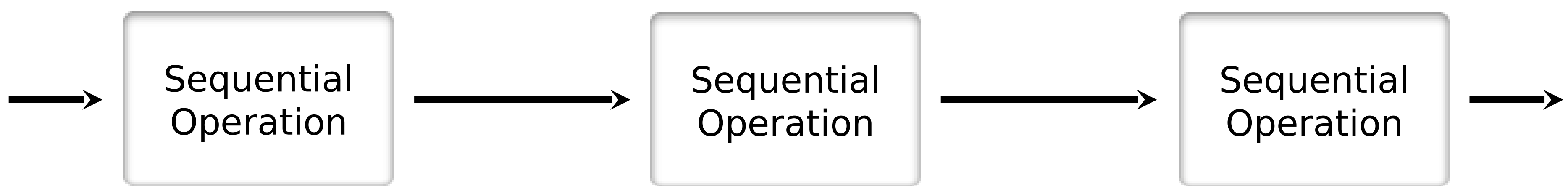
Data Parallelism

Replication

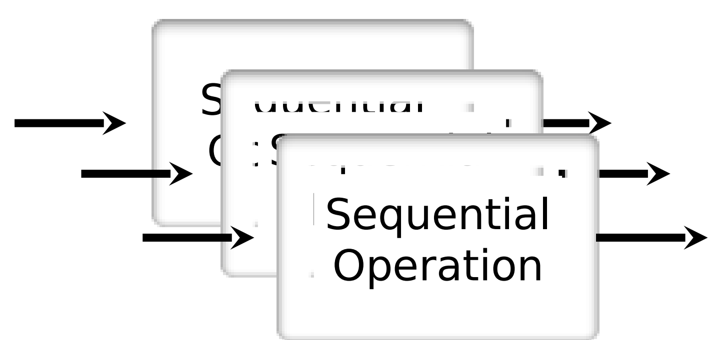
Partitioning

Operator Parallelism

- Pipeline Parallelism: A task breaks down into stages; each machine processes one stage.



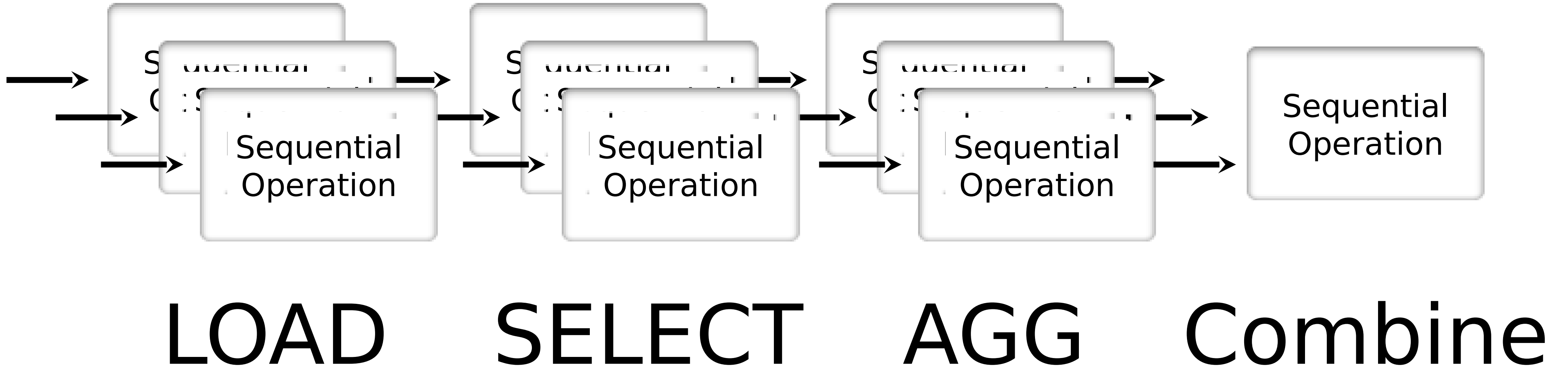
- Partition Parallelism: Many machines doing the same thing to different pieces of data.



Types of Parallelism

- Both types of parallelism are natural in a database management system.

`SELECT SUM(…) FROM Table WHERE …`

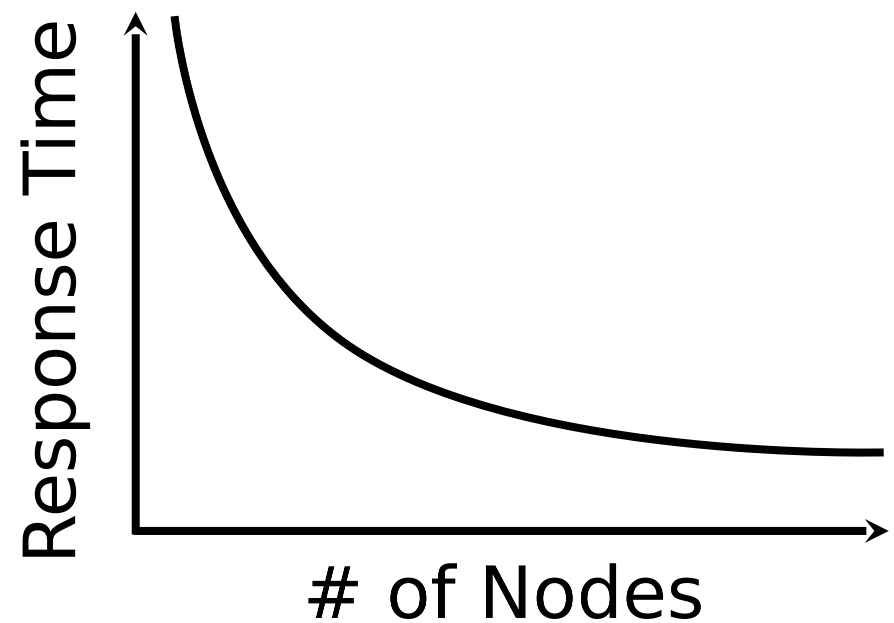


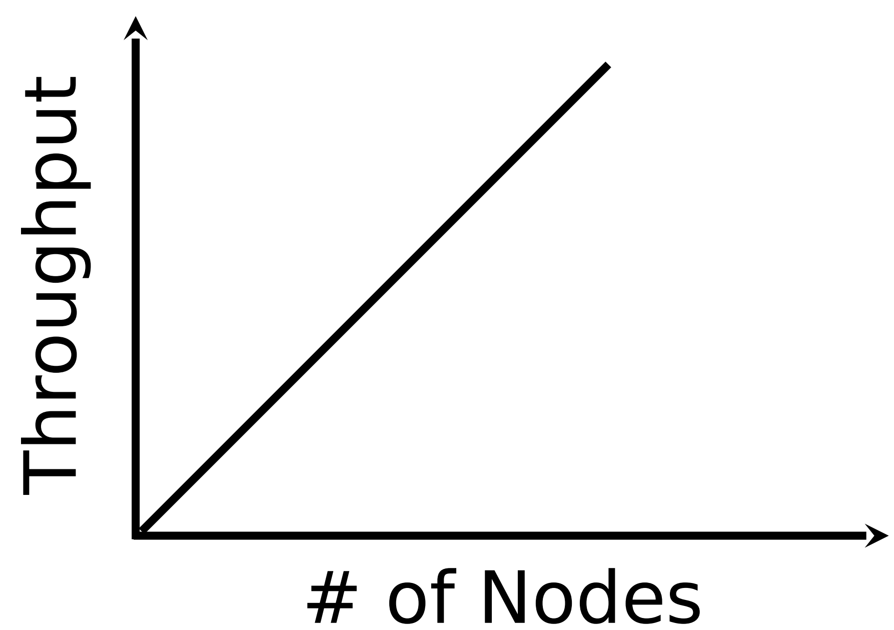
DBMSes: The First || Success Story

- Every major DBMS vendor has a || version.
- Reasons for success:
  - Bulk Processing (Partition ||-ism).
  - Natural Pipelining in RA plan.
  - <u>Users don’t need to think in ||</u>.

Types of Speedup

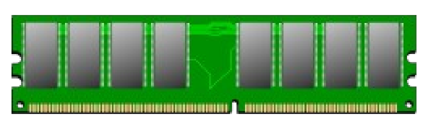
- Speed-up ||-ism
  - More resources = proportionally less time spent.
- Scale-up ||-ism
  - More resources = proportionally more data processed.



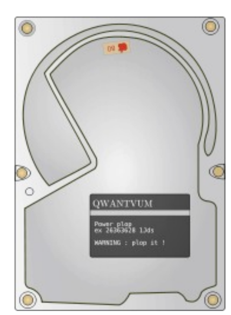


Parallelism Models

CPU

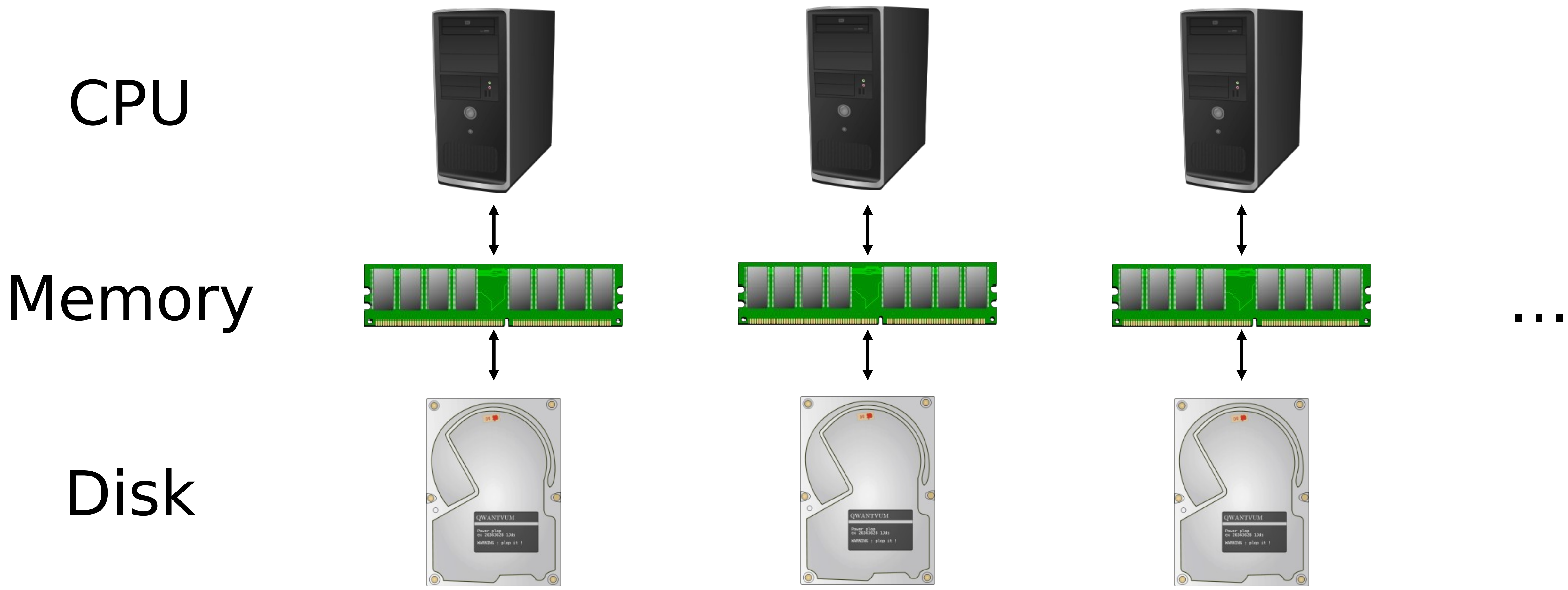


Memory



Disk

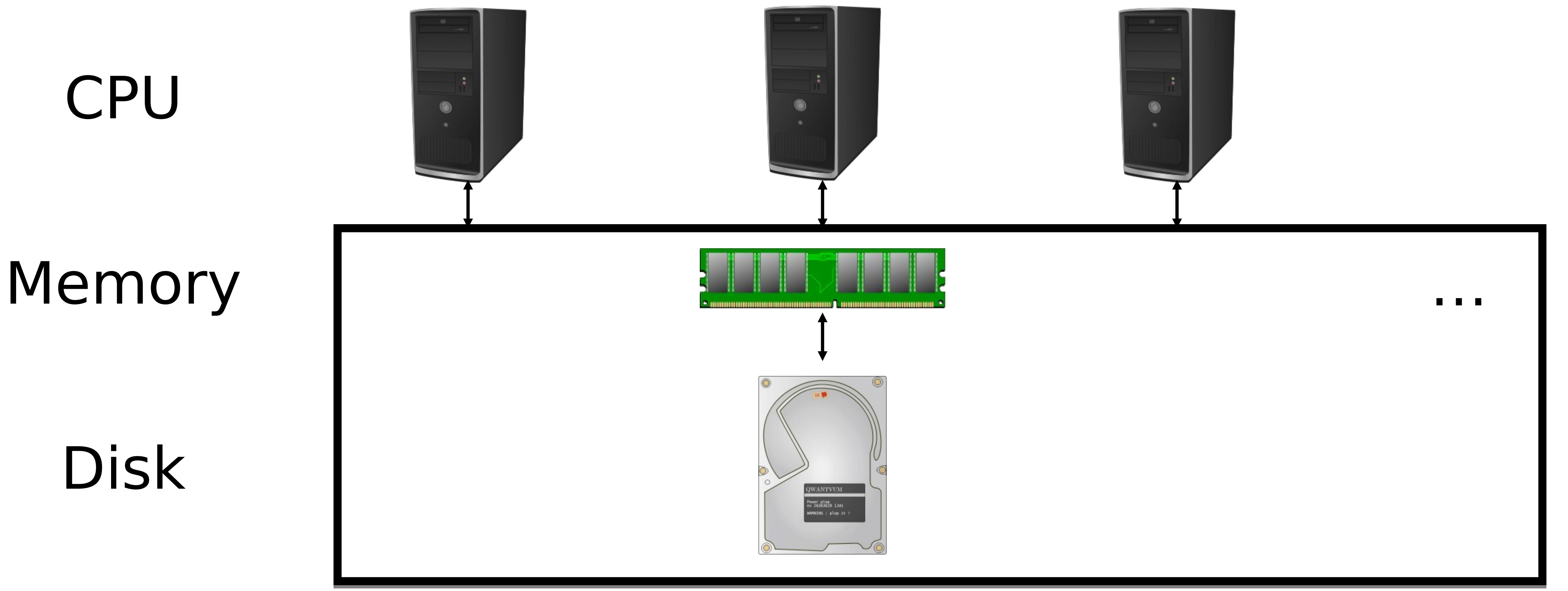
Parallelism Models



How do the nodes communicate?

Parallelism Models

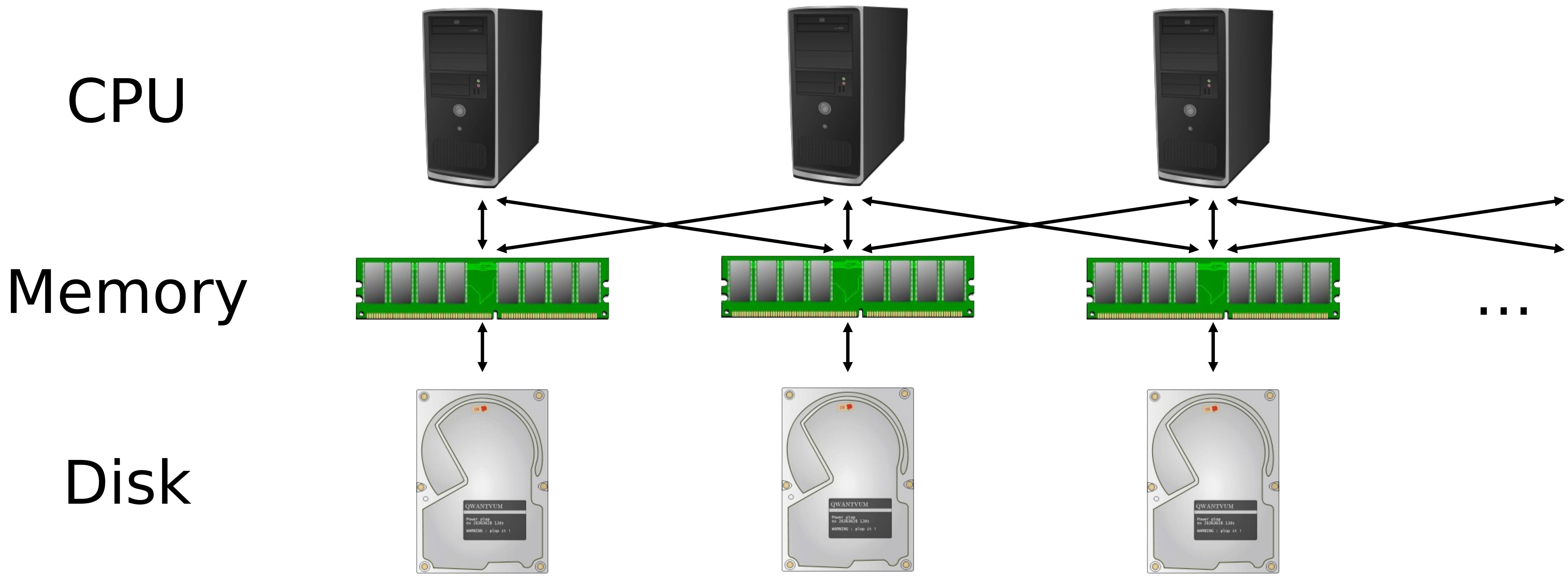
Option 1: “Shared Memory” available to all CPUs



e.g., a Multi-Core/Multi-CPU System

Parallelism Models

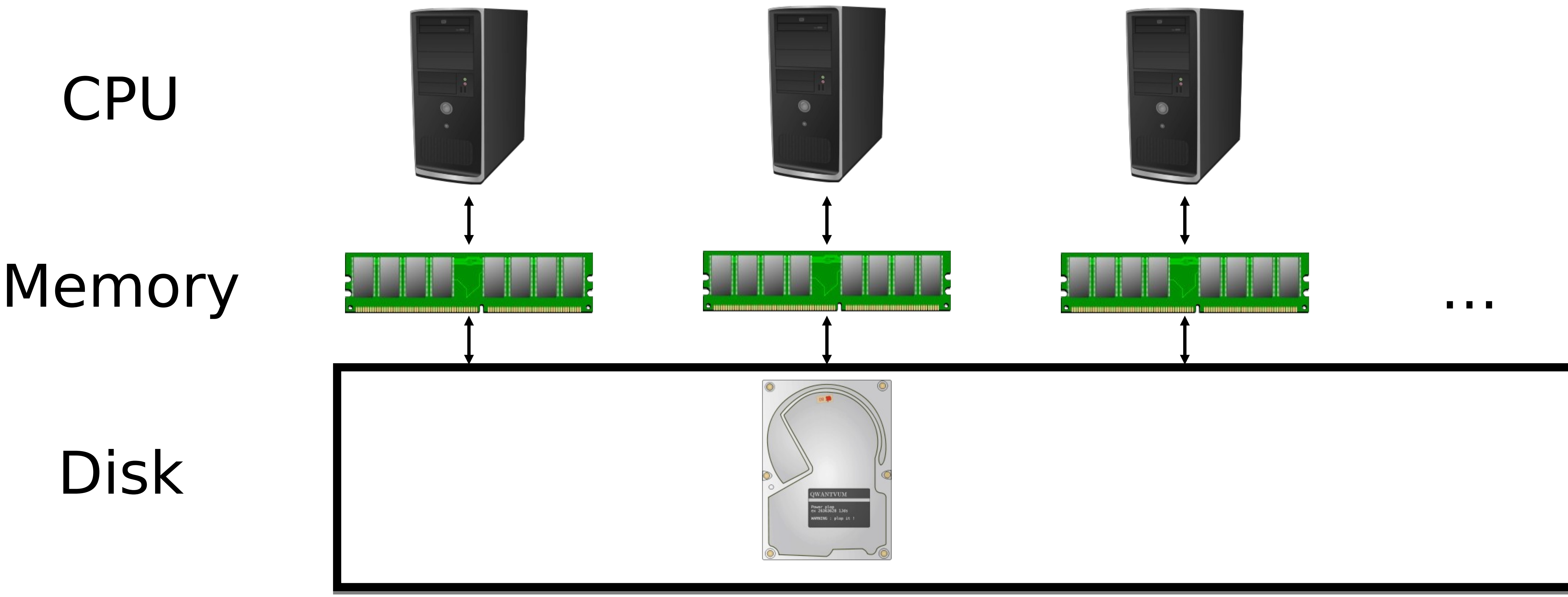
Option 2: Non-Uniform Memory Access.



Used by most AMD servers

Parallelism Models

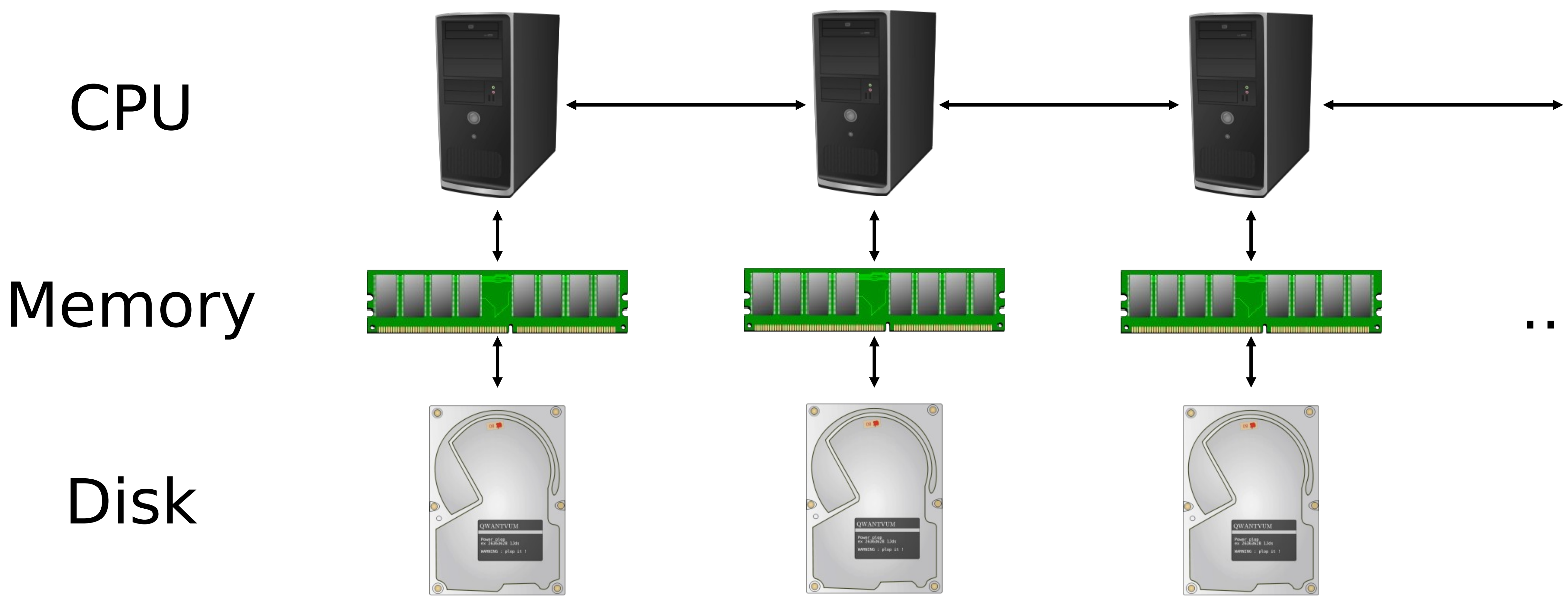
Option 3: “Shared Disk” available to all CPUs



Each node interacts with a “disk” on the network.

Parallelism Models

Option 4: “Shared Nothing” in which all communication is explicit.



Examples include MPP, Map/Reduce. Often used as basis for other abstractions.

Parallelizing

OLAP - Parallel Queries

OLTP - Parallel Updates

Parallelizing

OLAP - Parallel Queries

OLTP - Parallel Updates

Parallelism & Distribution

- *Distribute* the Data
  - Redundancy
  - Faster access
- *Parallelize* the Computation
  - Scale up (compute faster)
  - Scale out (bigger data)

Operator Parallelism

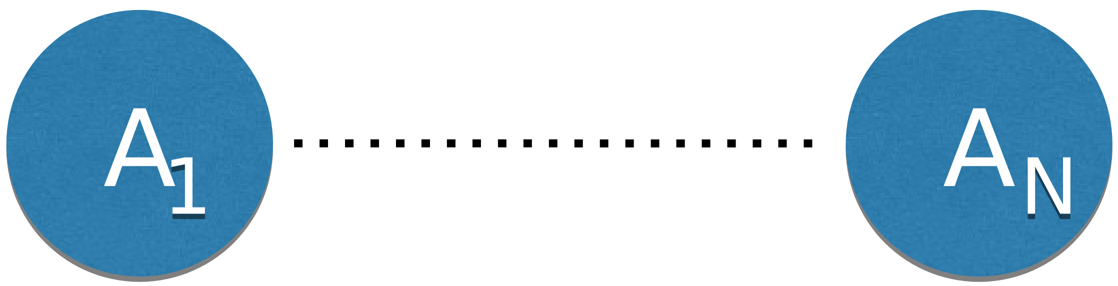
- **General Concept**: Break task into individual units of computation.
- **Challenge**: How much data does each unit of computation need?
- **Challenge**: How much data *transfer* is needed to allow the unit of computation?

Same challenges arise in Multicore, CUDA programming.

Parallel Data Flow

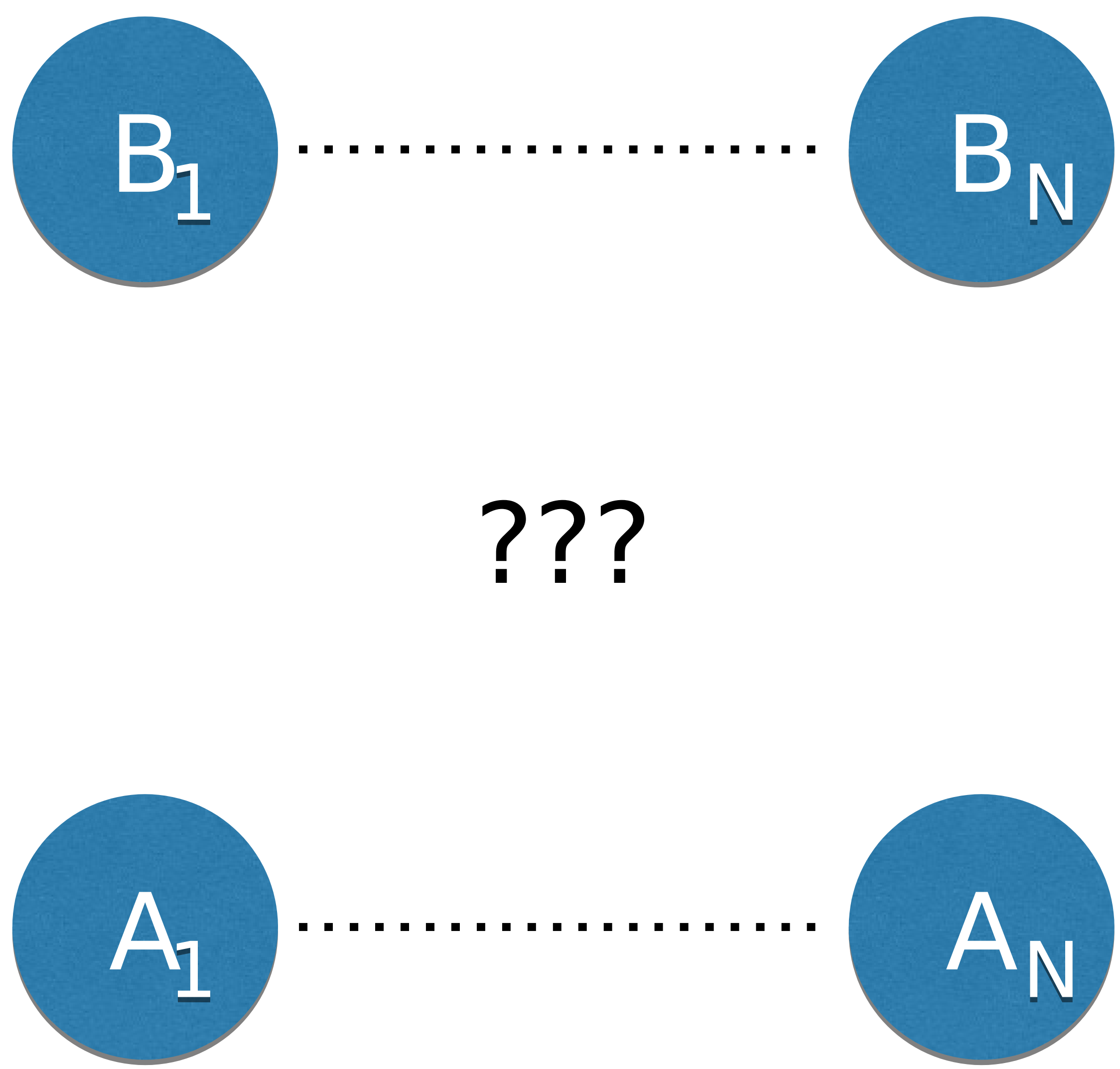
No Parallelism

Parallel Data Flow



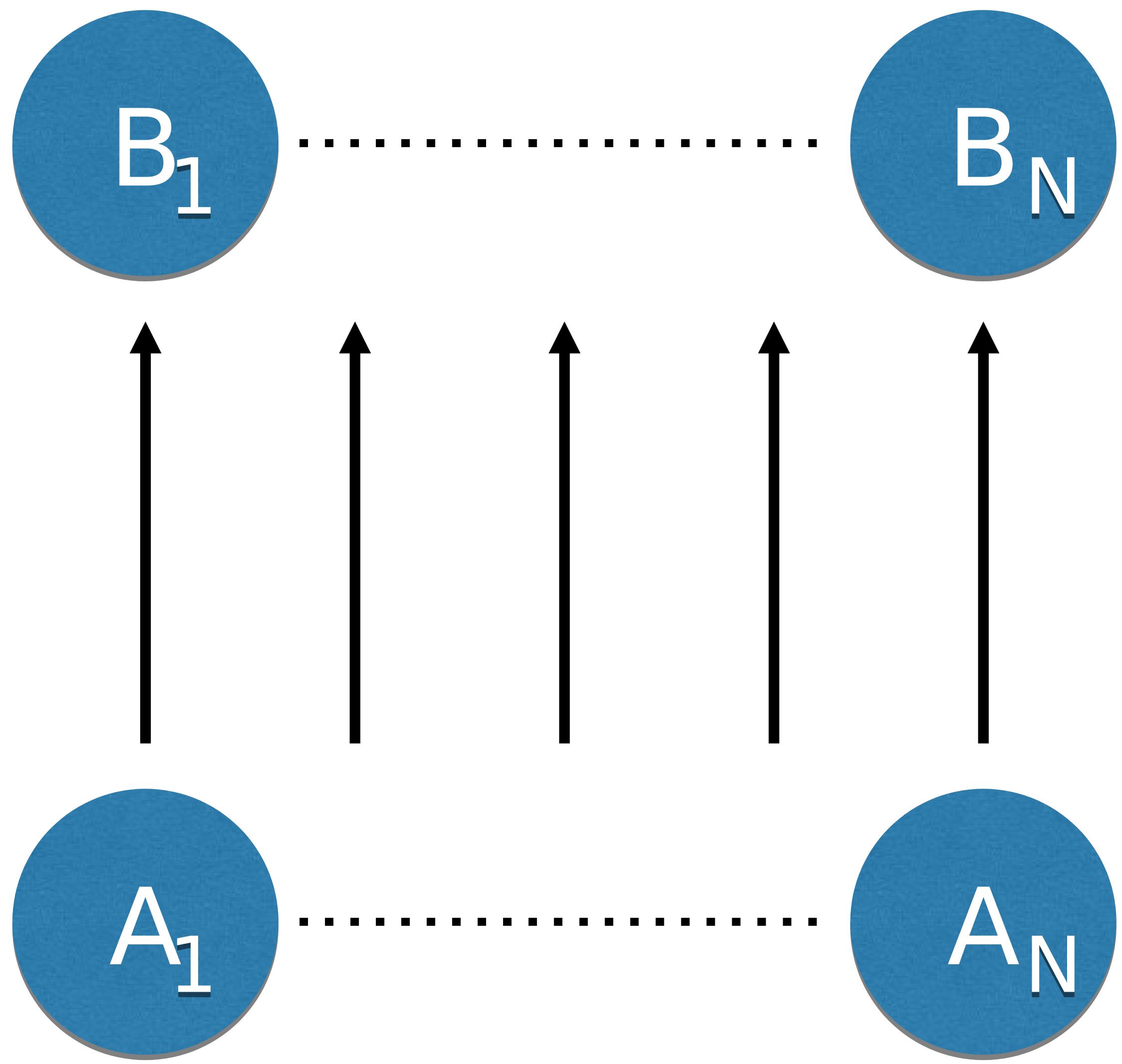
N-Way Parallelism

Parallel Data Flow



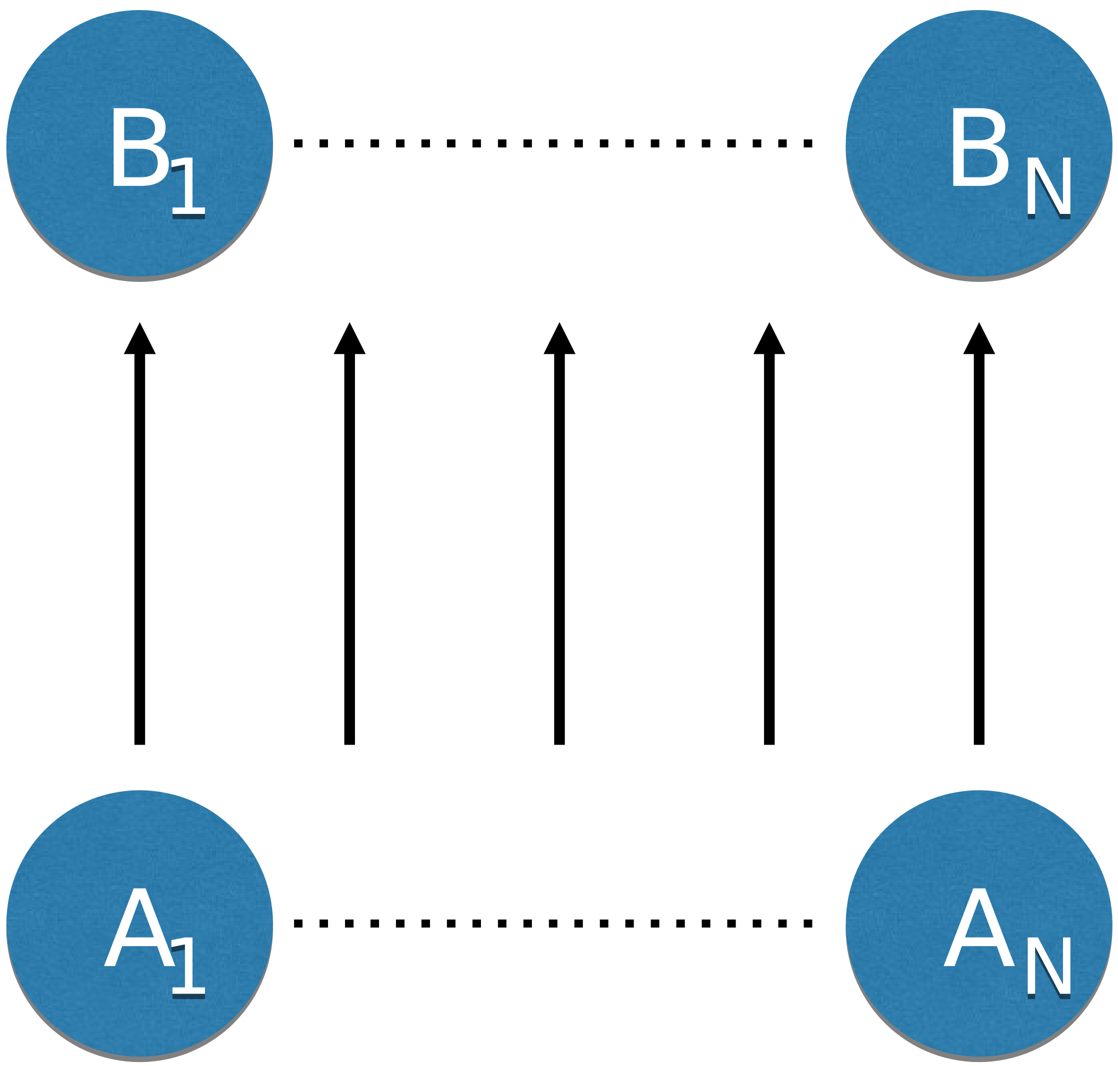
Chaining Parallel Operators

Parallel Data Flow



One-to-One Data Flow (“Map”)

Parallel Data Flow



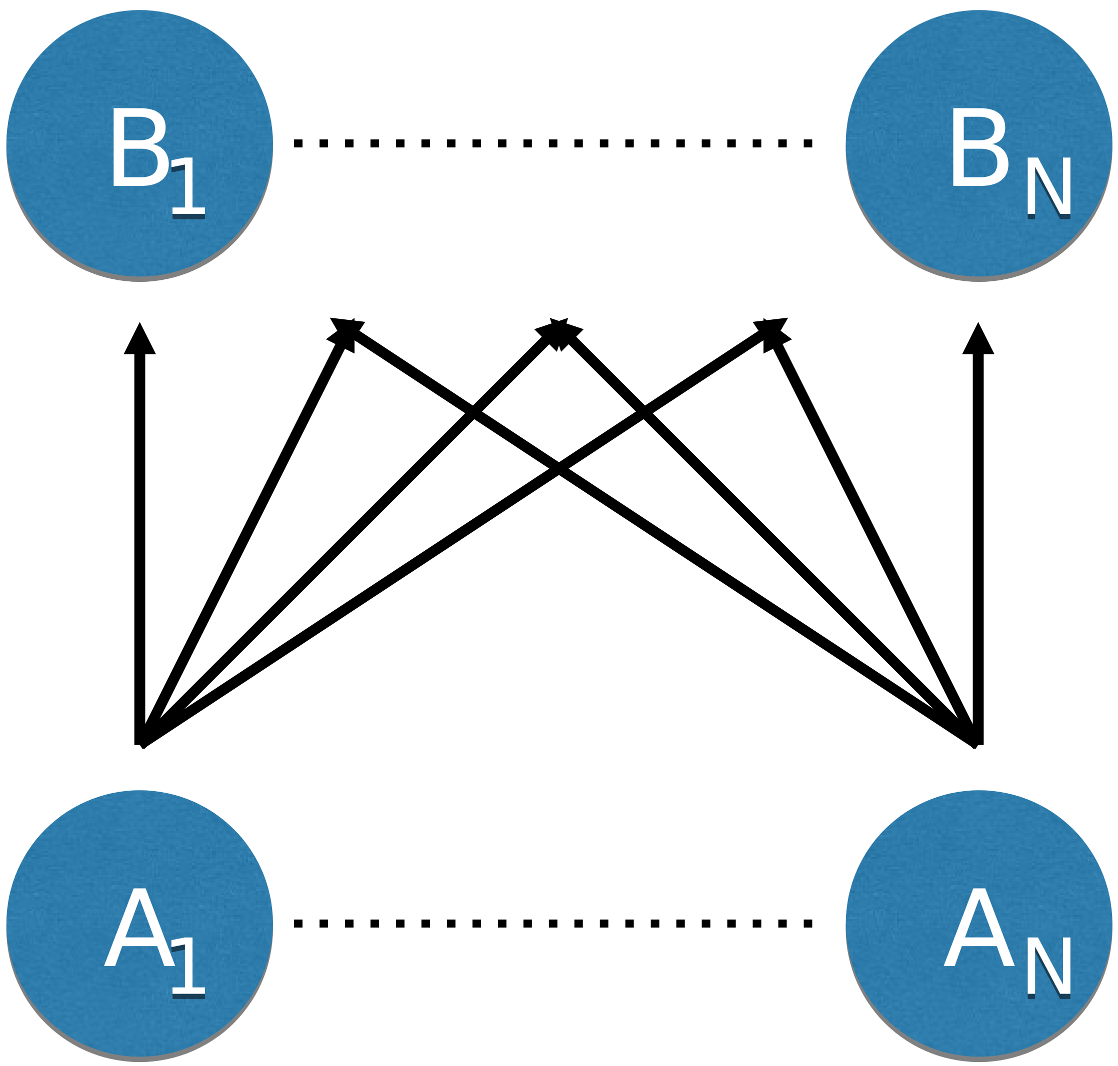
One-to-One Data Flow

Parallel Data Flow

<u>Extreme 1</u>

All-to-All

All nodes send all records to all downstream nodes



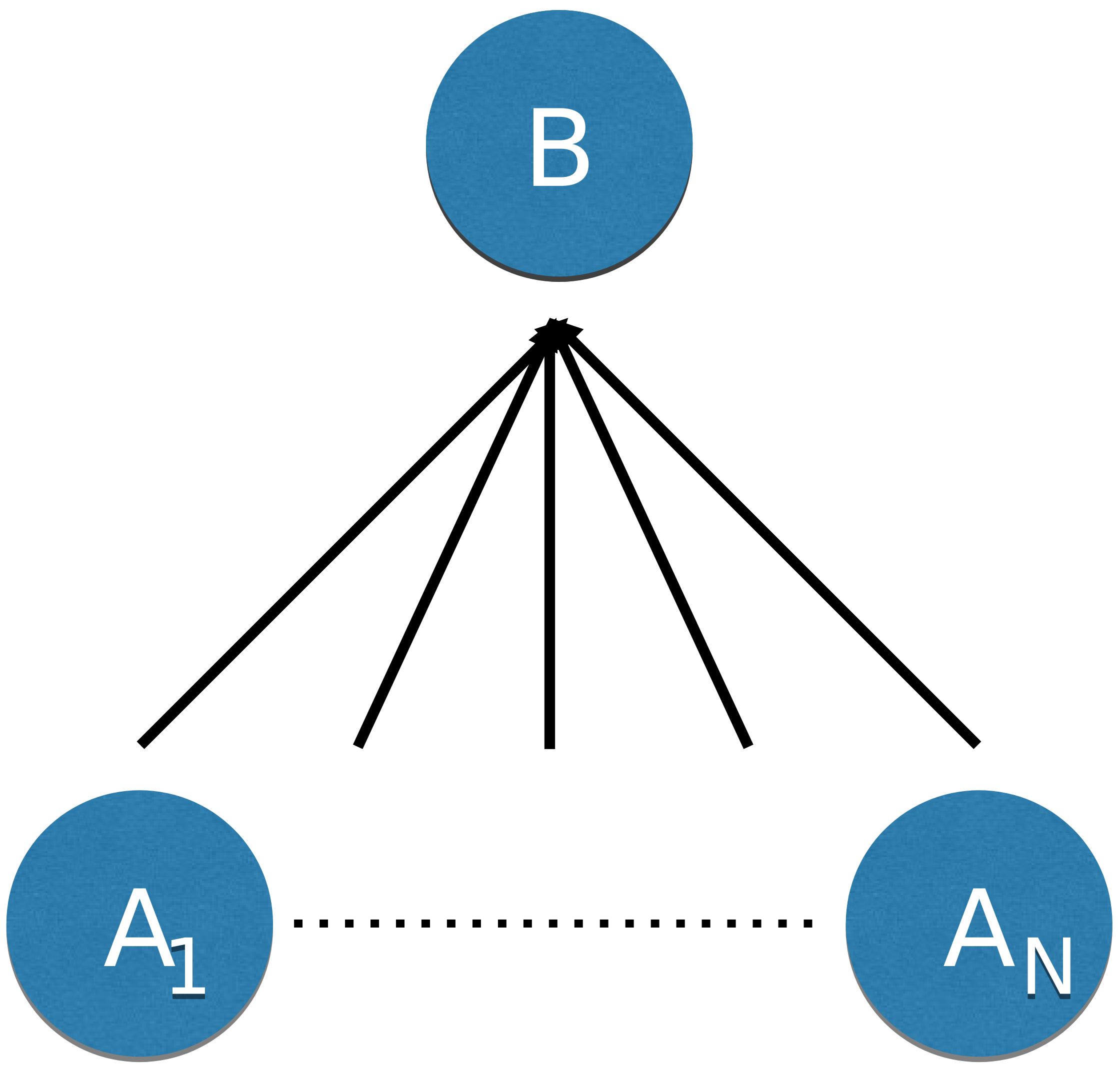
<u>Extreme 2</u>

Partition

Each record goes to exactly one downstream node

Many-to-Many Data Flow

Parallel Data Flow



Many-to-One Data Flow (“Reduce/Fold”)

Parallel Operators

Select **Project** **Union (bag)**

What is a logical “unit of computation”?

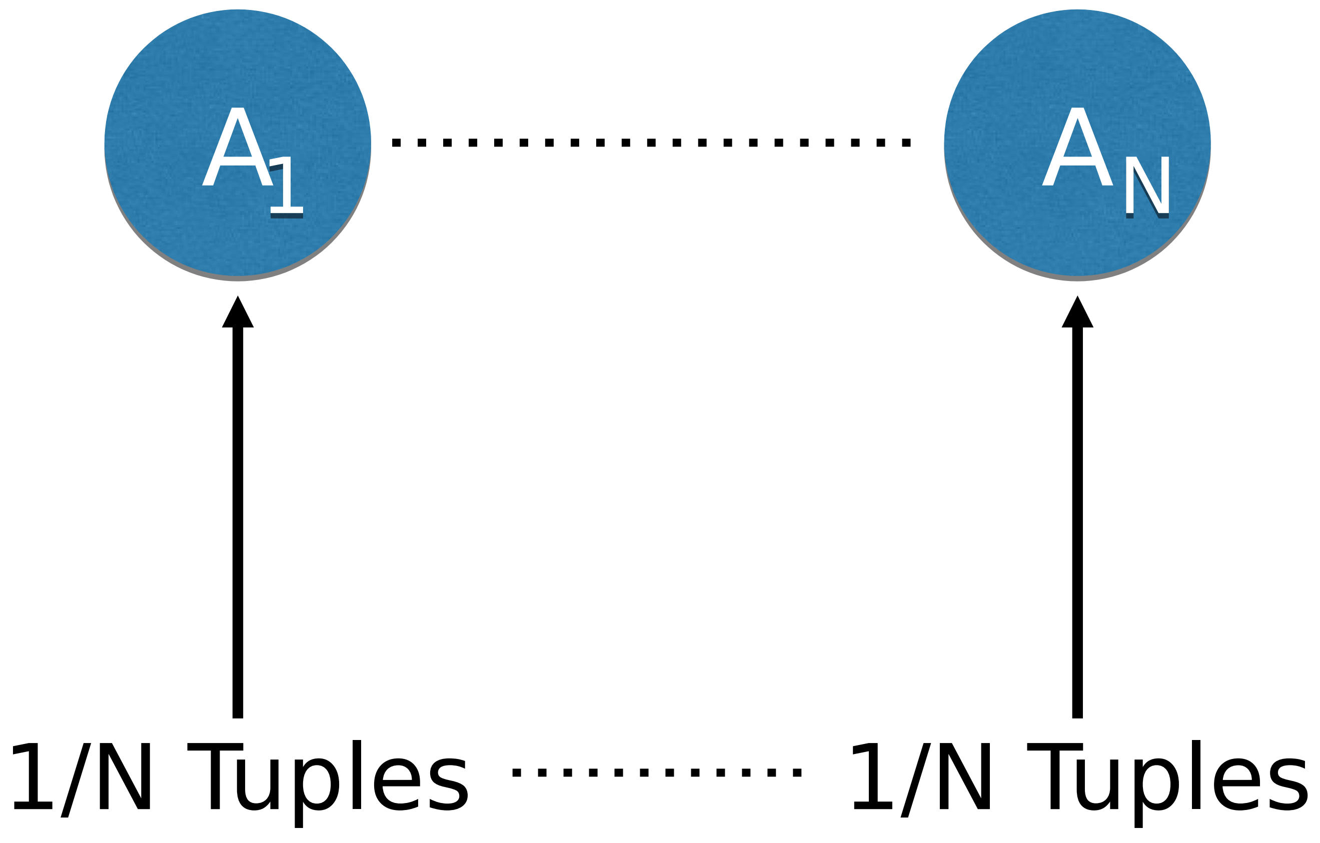
(1 tuple)

Is there a data dependency between units?

(no)

Parallel Operators

Select **Project** **Union (bag)**

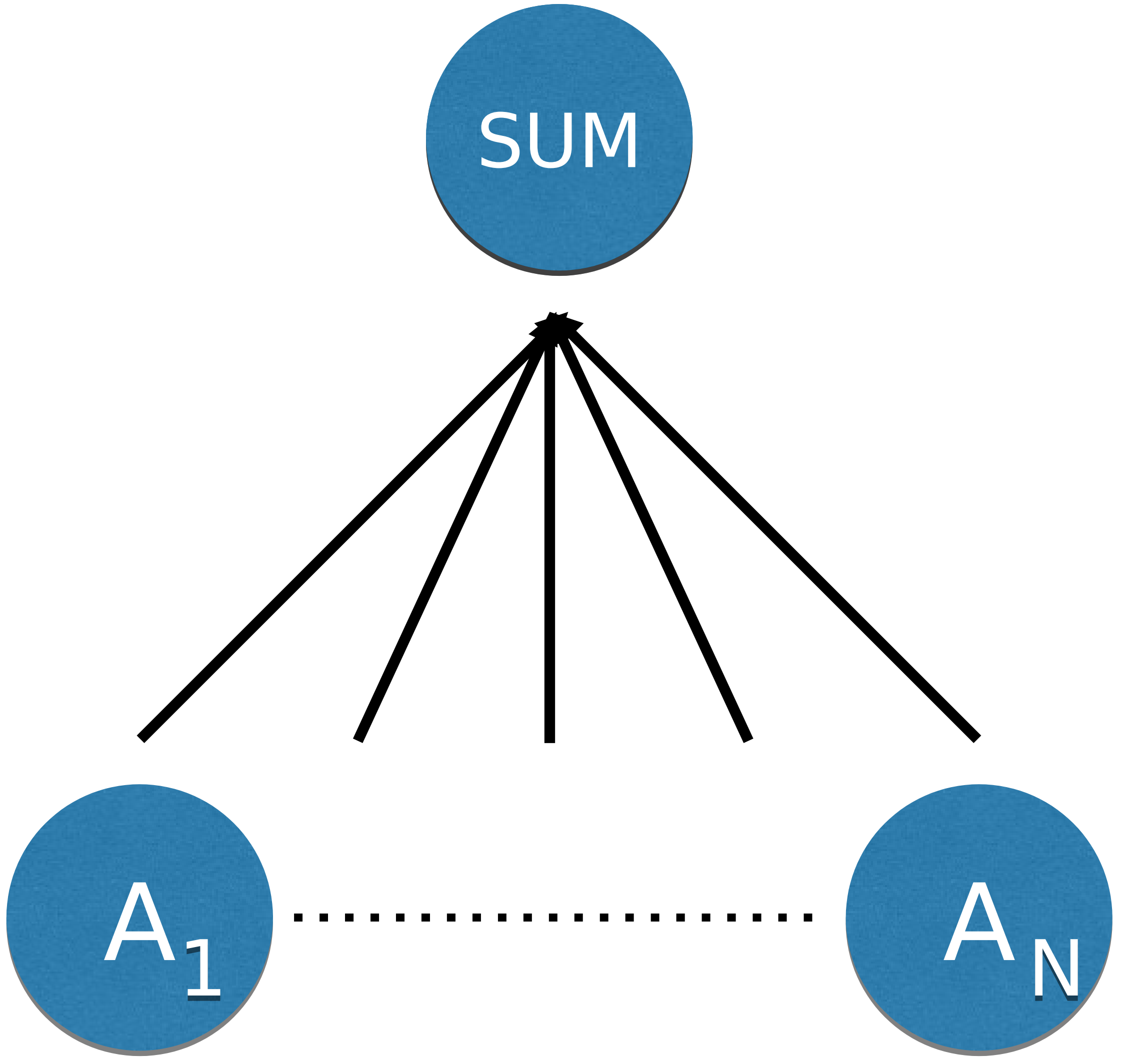


Parallel Aggregates

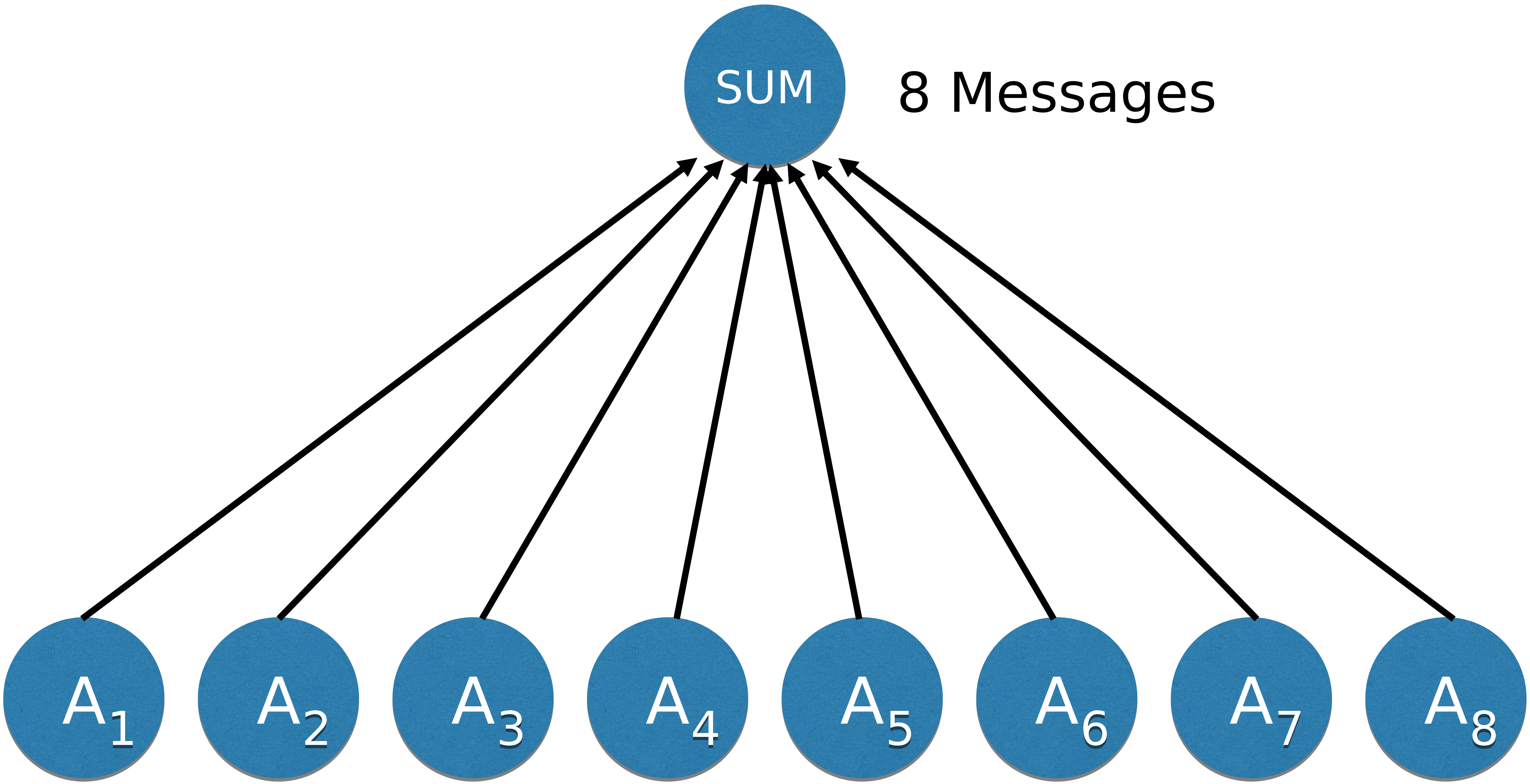
Algebraic: Bounded-size intermediate state
(Sum, Count, Avg, Min, Max)

Holistic: Unbounded-size intermediate state
(Median, Mode/Top-K Count, Count-Distinct;
Not Distribution-Friendly)

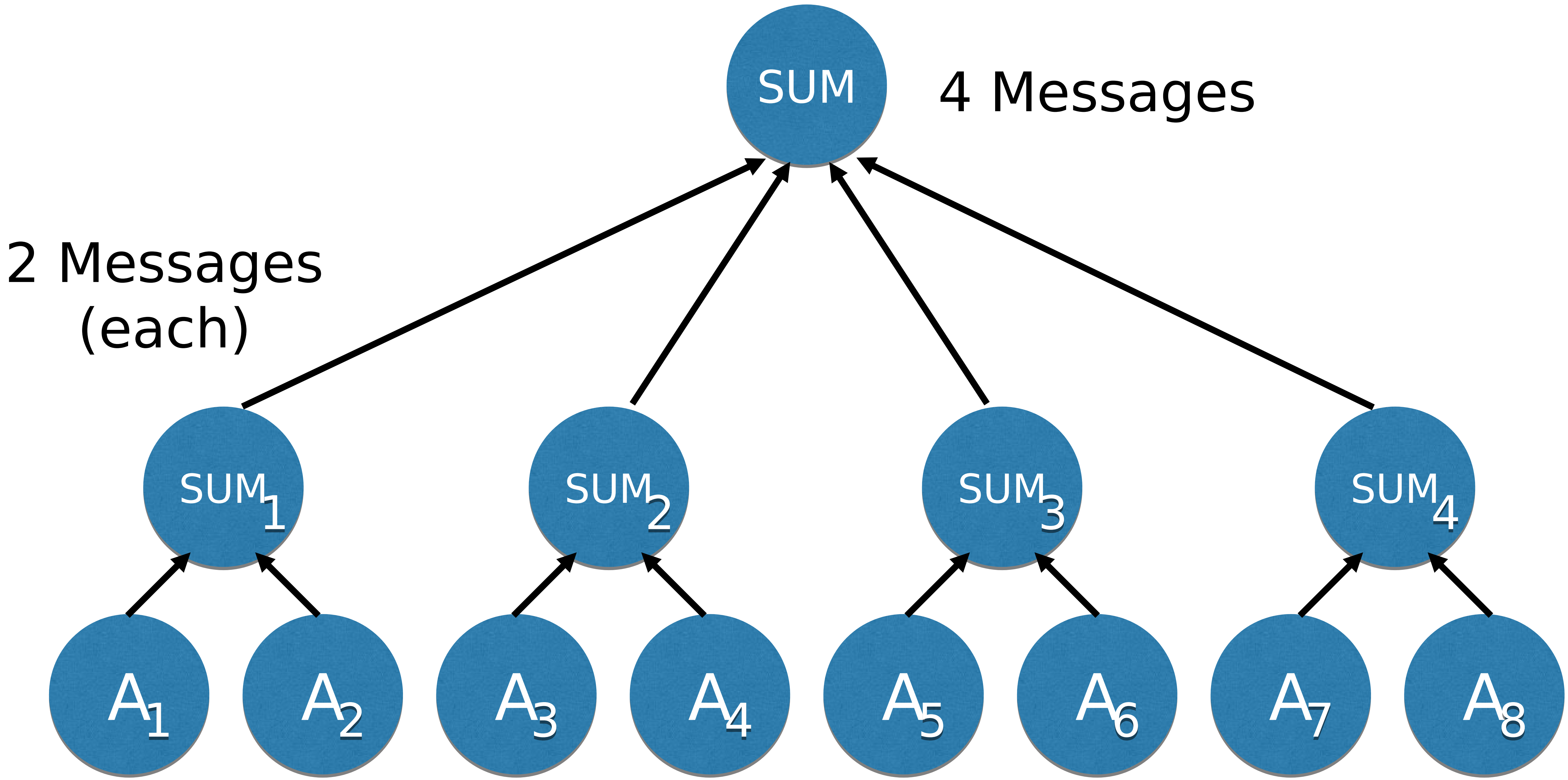
Fan-In Aggregation



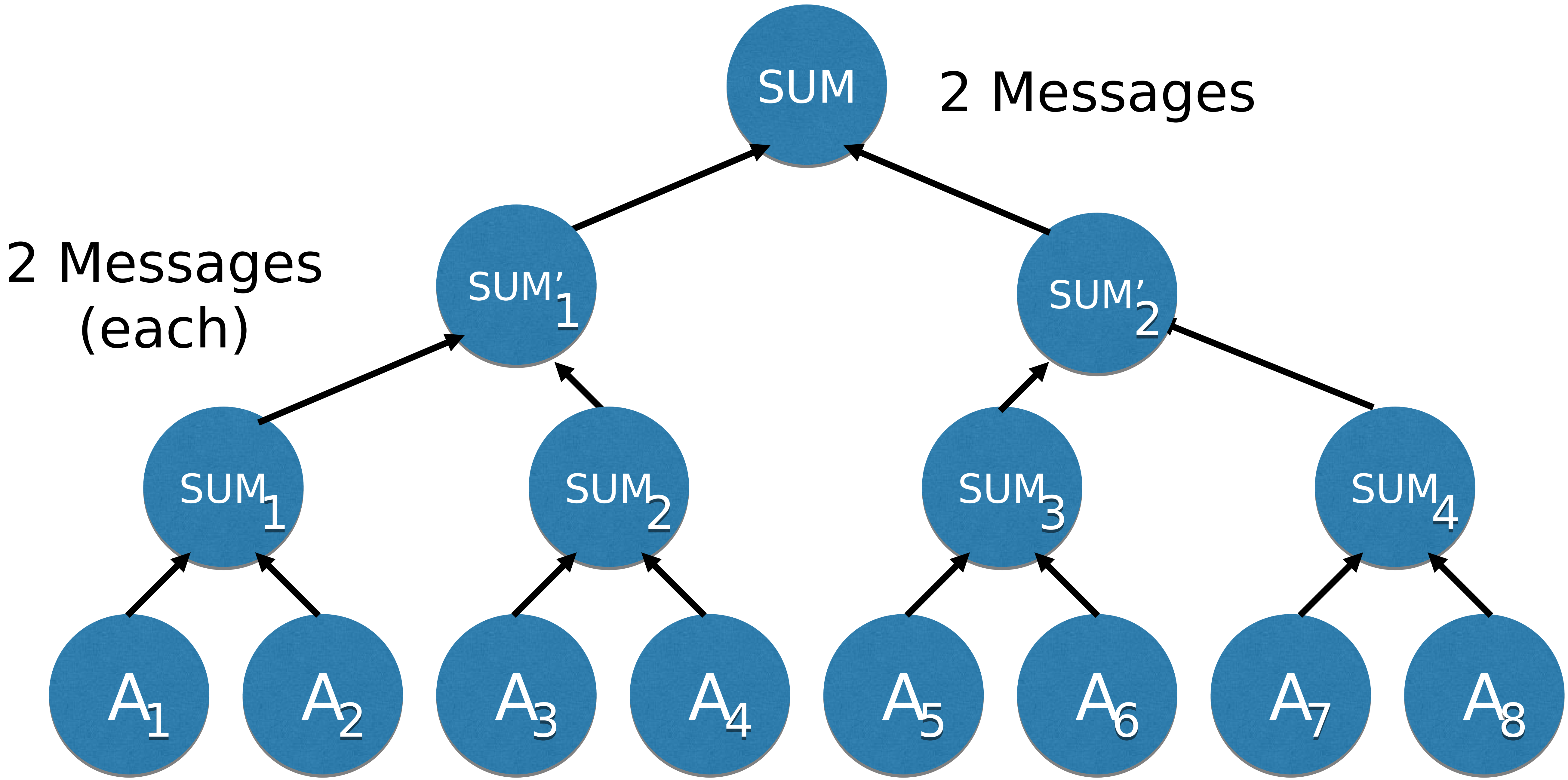
Fan-In Aggregation



Fan-In Aggregation



Fan-In Aggregation



Fan-In Aggregation

If Each Node Performs K Units of Work…
(K Messages)
How Many Rounds of Computation Are Needed?

$Log_K(N)$

Fan-In Aggregation Components

Combine(Intermediate_1, …, Intermediate_N) = Intermediate

$$\langle \mathrm{SUM}_1, \mathrm{COUNT}_1 \rangle \otimes \ldots \otimes \langle \mathrm{SUM}_N, \mathrm{COUNT}_N \rangle$$

$$= \langle \mathrm{SUM}_1 + \ldots + \mathrm{SUM}_N, \mathrm{COUNT}_1 + \ldots + \mathrm{COUNT}_N \rangle$$

Compute(Intermediate) = Aggregate

$$\mathrm{Compute}(\langle \mathrm{SUM}, \mathrm{COUNT} \rangle) = \mathrm{SUM} / \mathrm{COUNT}$$

Parallel Joins

FOR i IN 1 to N

FOR j IN 1 to K

JOIN(~~Block~~ Partition i of R,

~~Block~~ Partition j of S)

One Unit of Computation

Parallel Joins

K Partitions of S

N Partitions of R

Block 1 of R
$\bowtie$
Block 1 of S

K

Block 1 of R
$\bowtie$
Block K of S

N

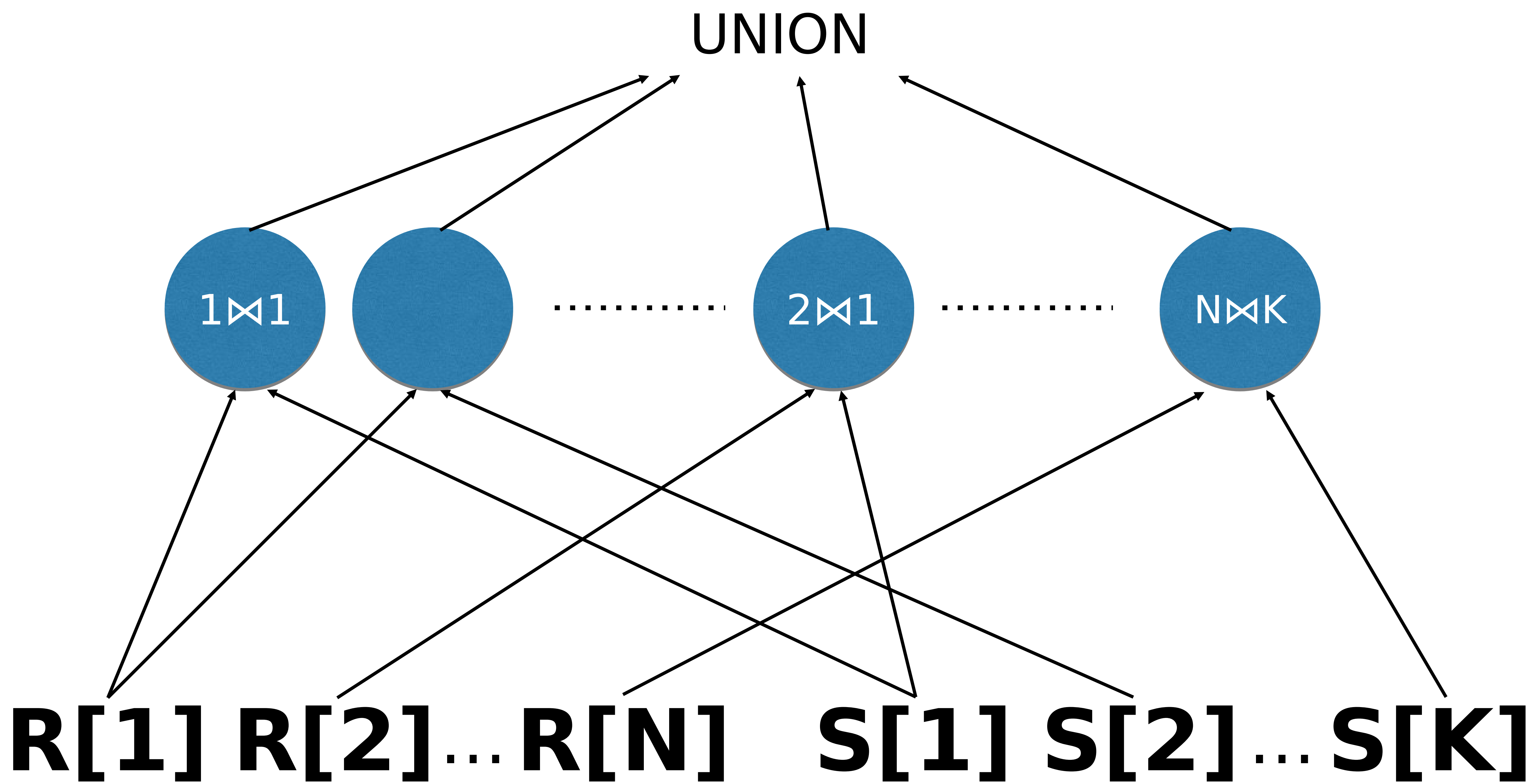
N

Block N of R
$\bowtie$
Block 1 of S

K

Block N of R
$\bowtie$
Block K of S

Parallel Joins



Parallel Joins

How much data needs to be transferred?

How many “units of computation” do we create?

Parallel Joins

What if we partitioned “intelligently”?

Parallel Joins

Hash(R.B)%4 \ Hash(S.B)%4	0	1	2	3
0	√	X	X	X
1		√		
2			√	
3				√

R $\bowtie_B$ **S**: Which Partitions of S Join w/ Bucket 0 of R?

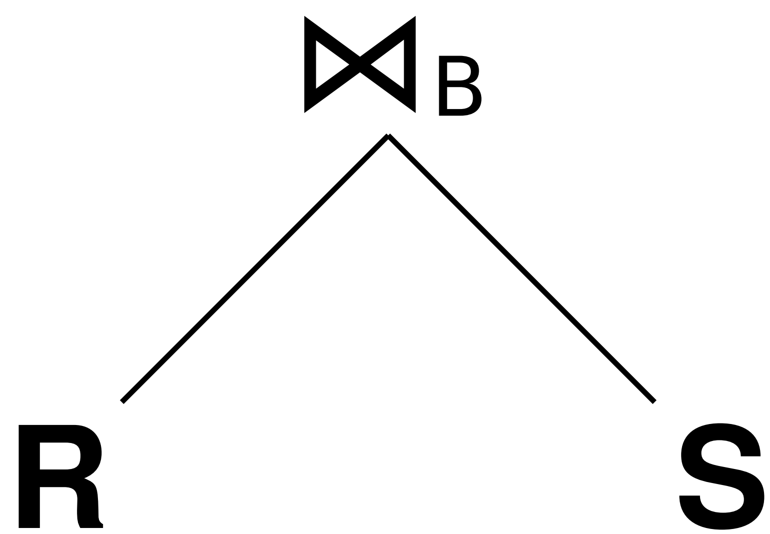
Parallel Joins

R.B \ S.B	B<25	25≤B<50	50≤B<75	75≤B
B<25	√	√	√	√
25≤B<50	X	√	√	√
50≤B<75	X	X	√	√
75≤B	X	X	X	√

R $\bowtie_{R.B < S.B}$ **S**: Which Partitions of S Can Produce Output?

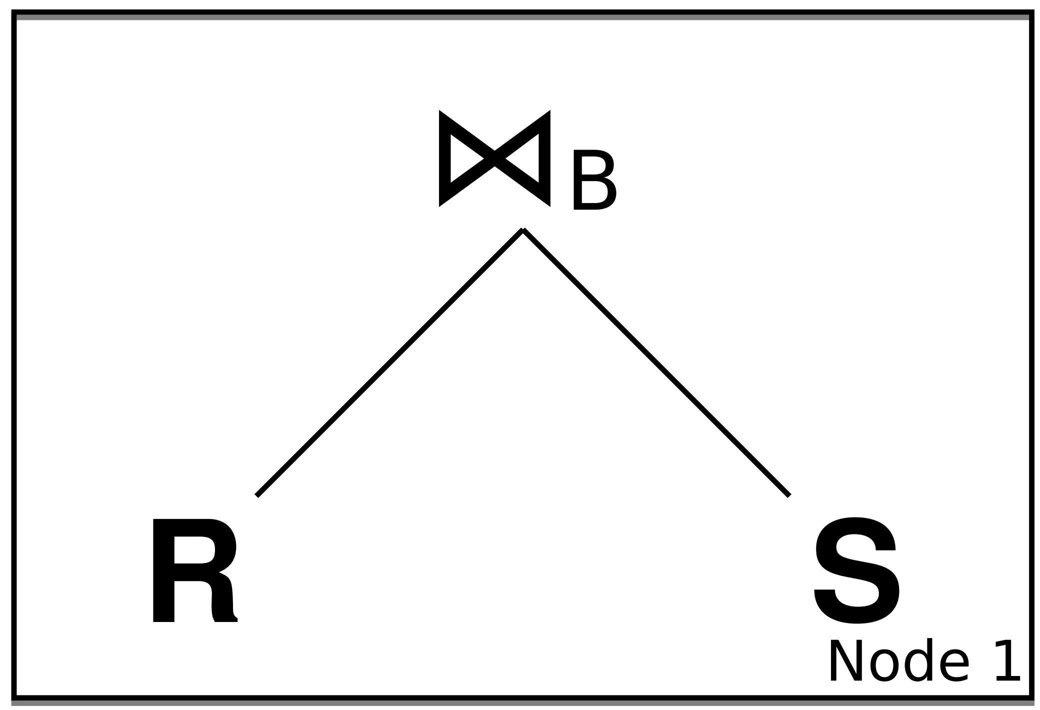
Distributing the Work

Let's start simple… what can we do with no partitions?



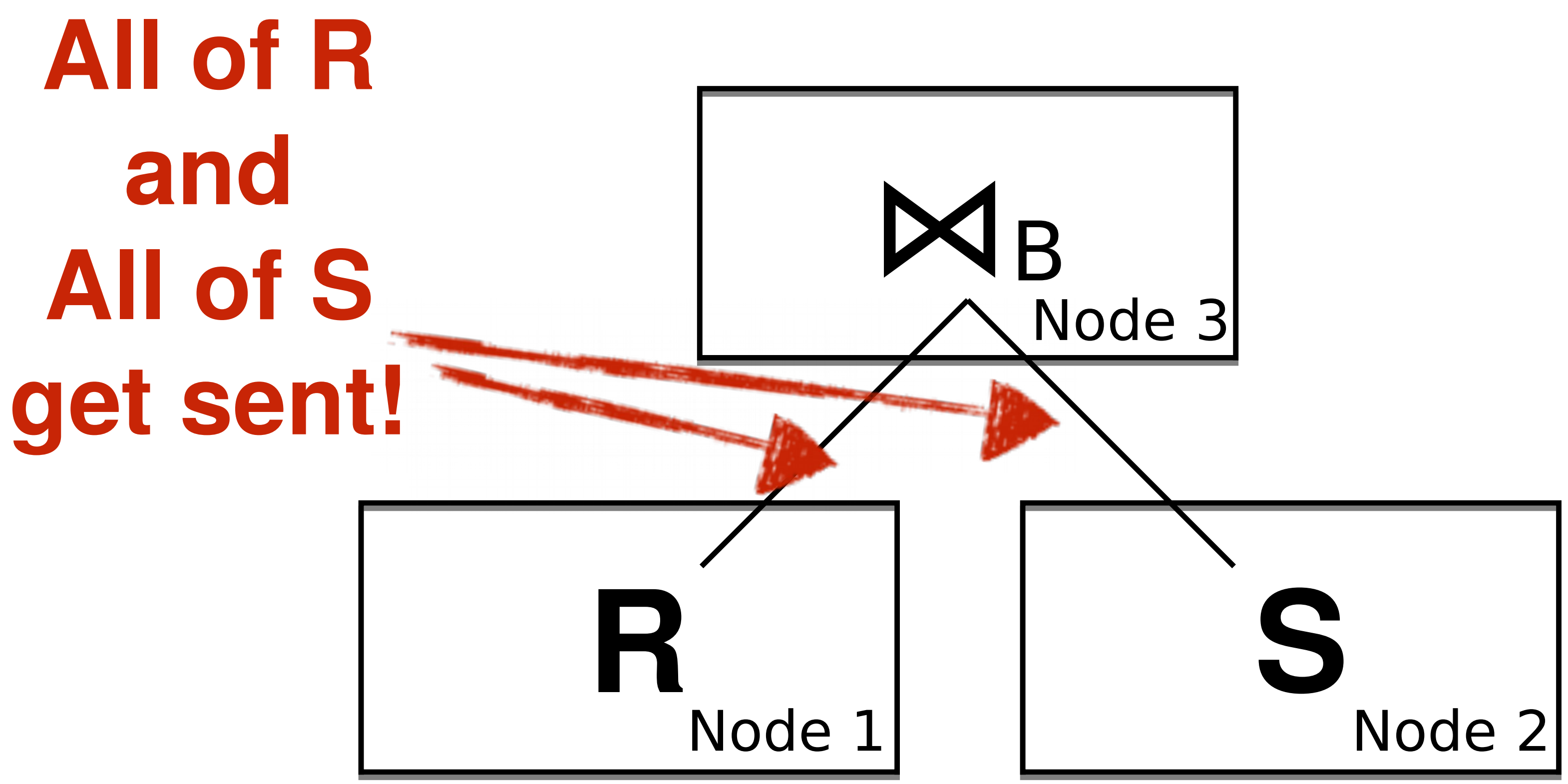
R and S may be any RA expression…

Distributing the Work



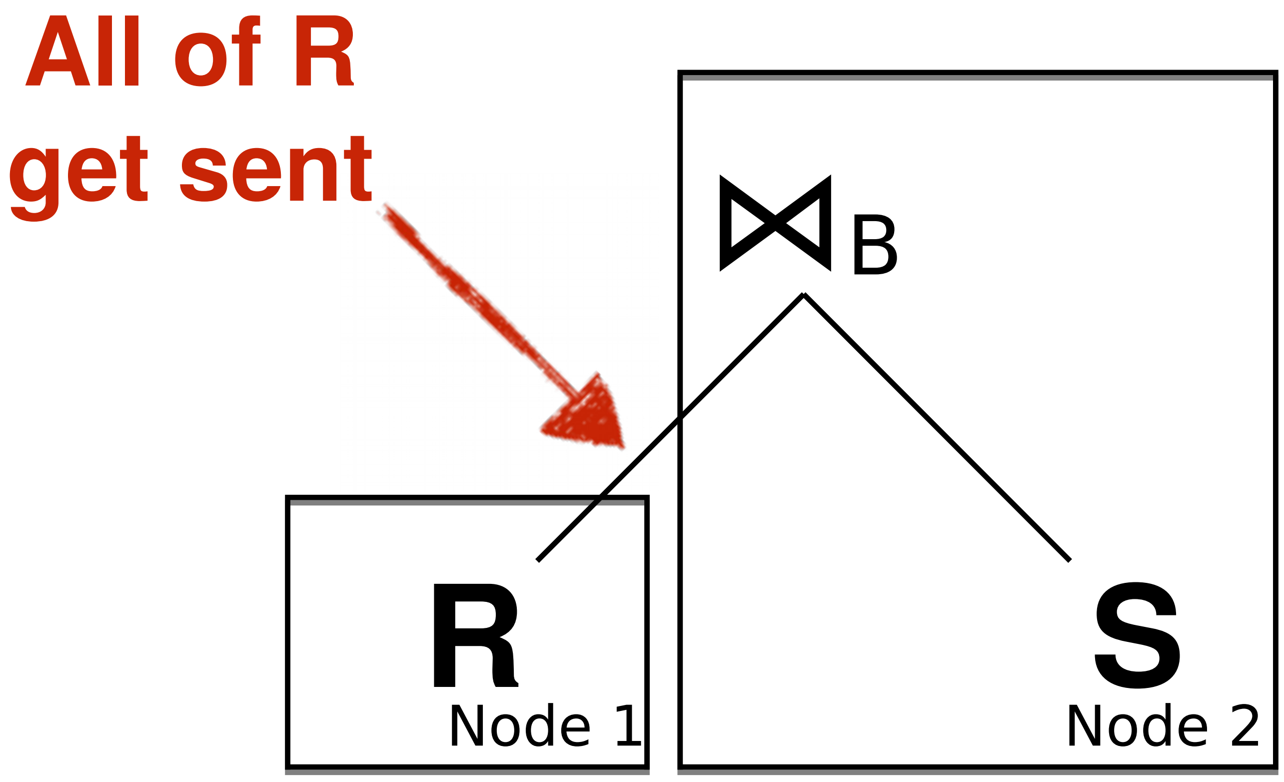
No Parallelism!

Distributing the Work



Lots of Data Transfer!

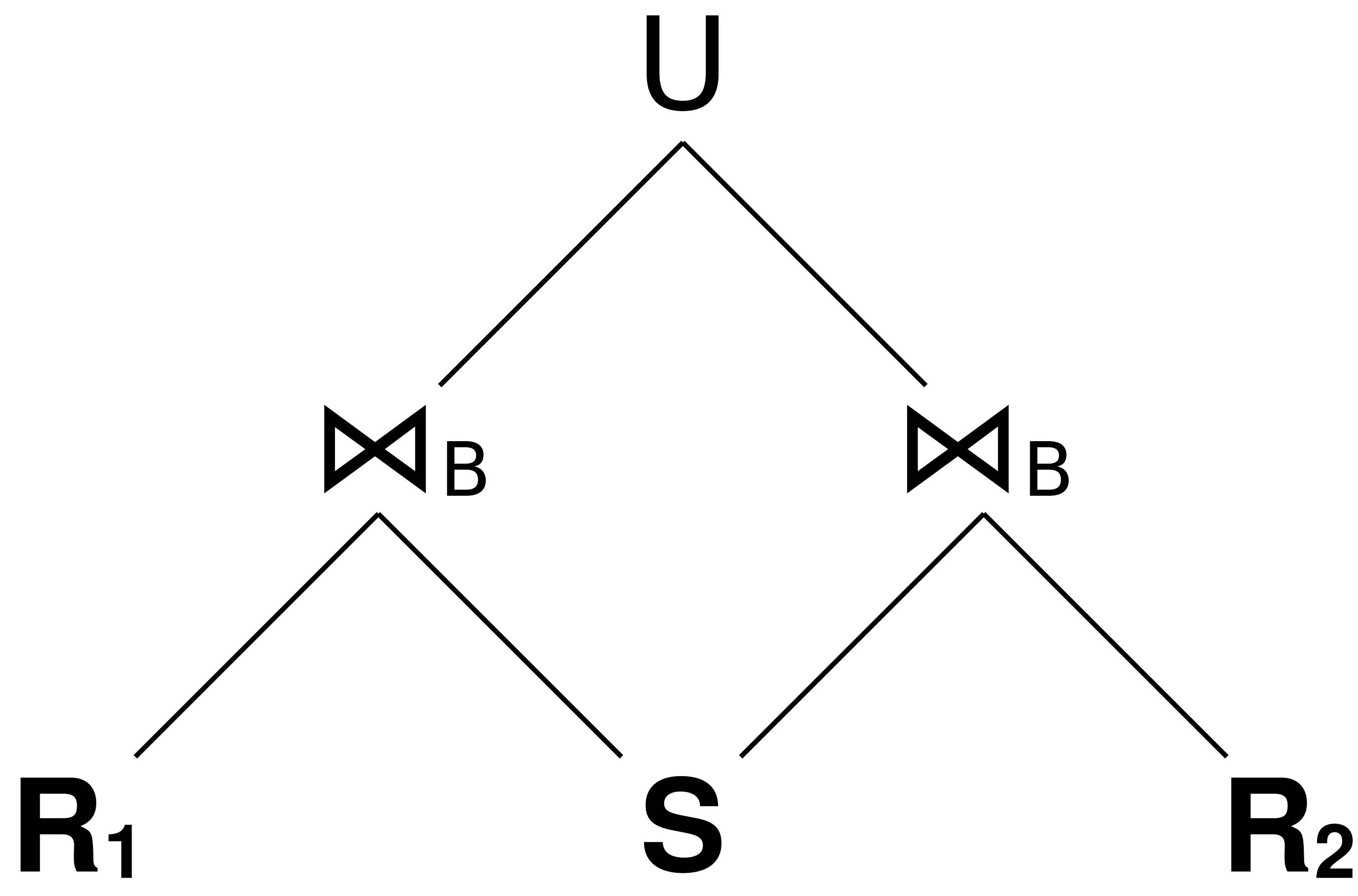
Distributing the Work



Better! We can guess whether R or S is smaller.

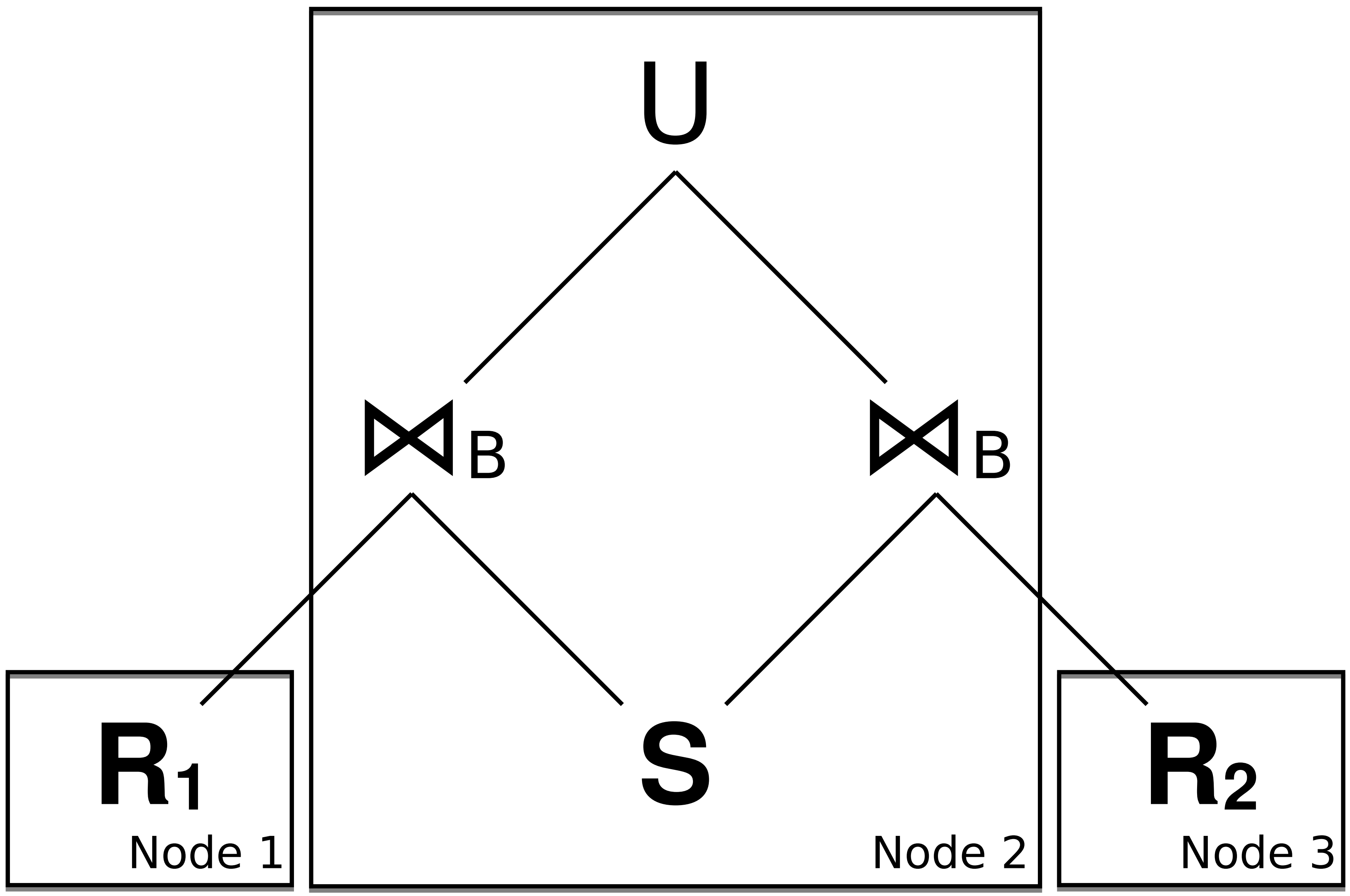
Distributing the Work

What can we do if R is partitioned?



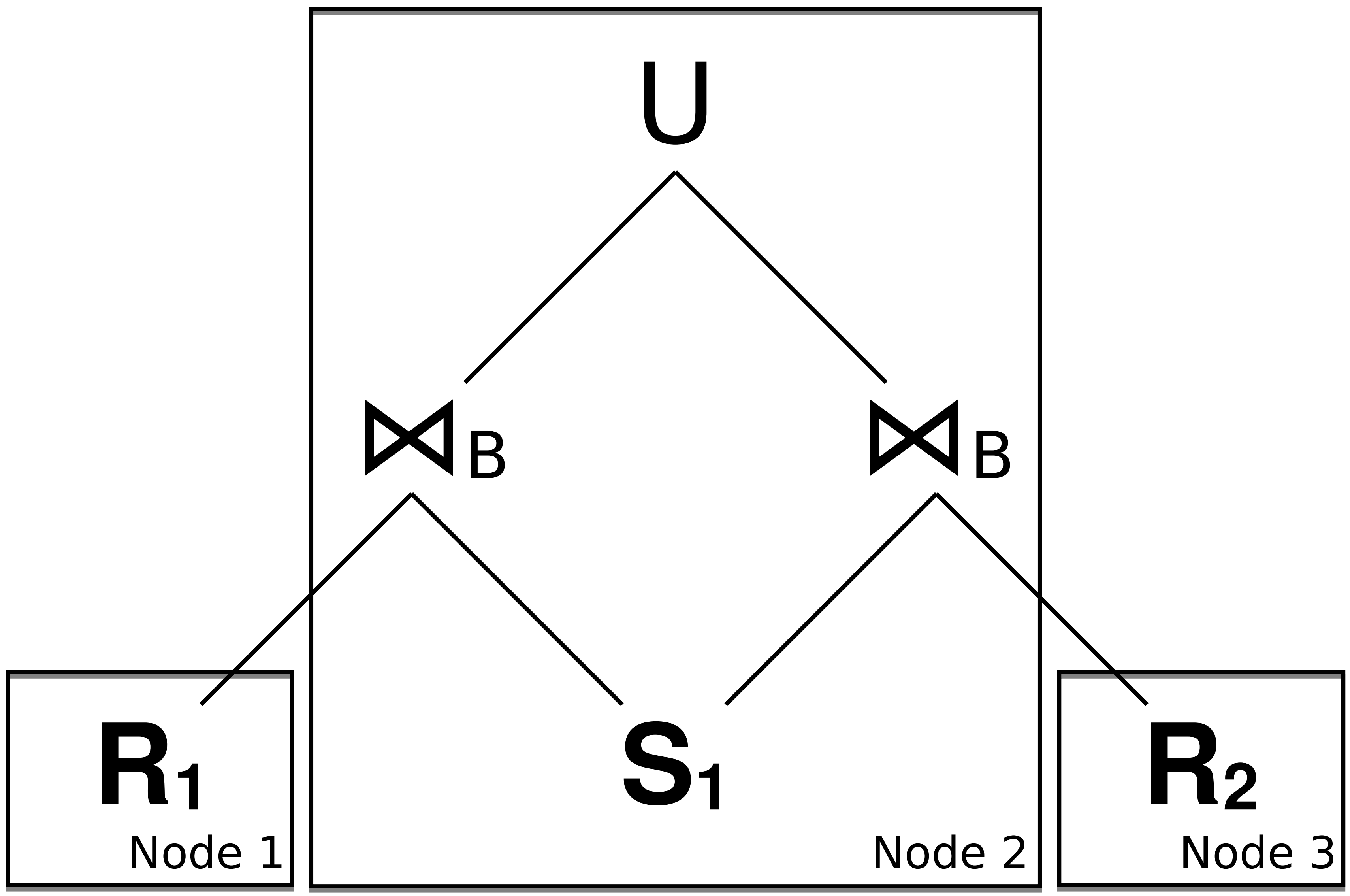
Distributing the Work

There are lots of partitioning strategies, but this one is interesting….



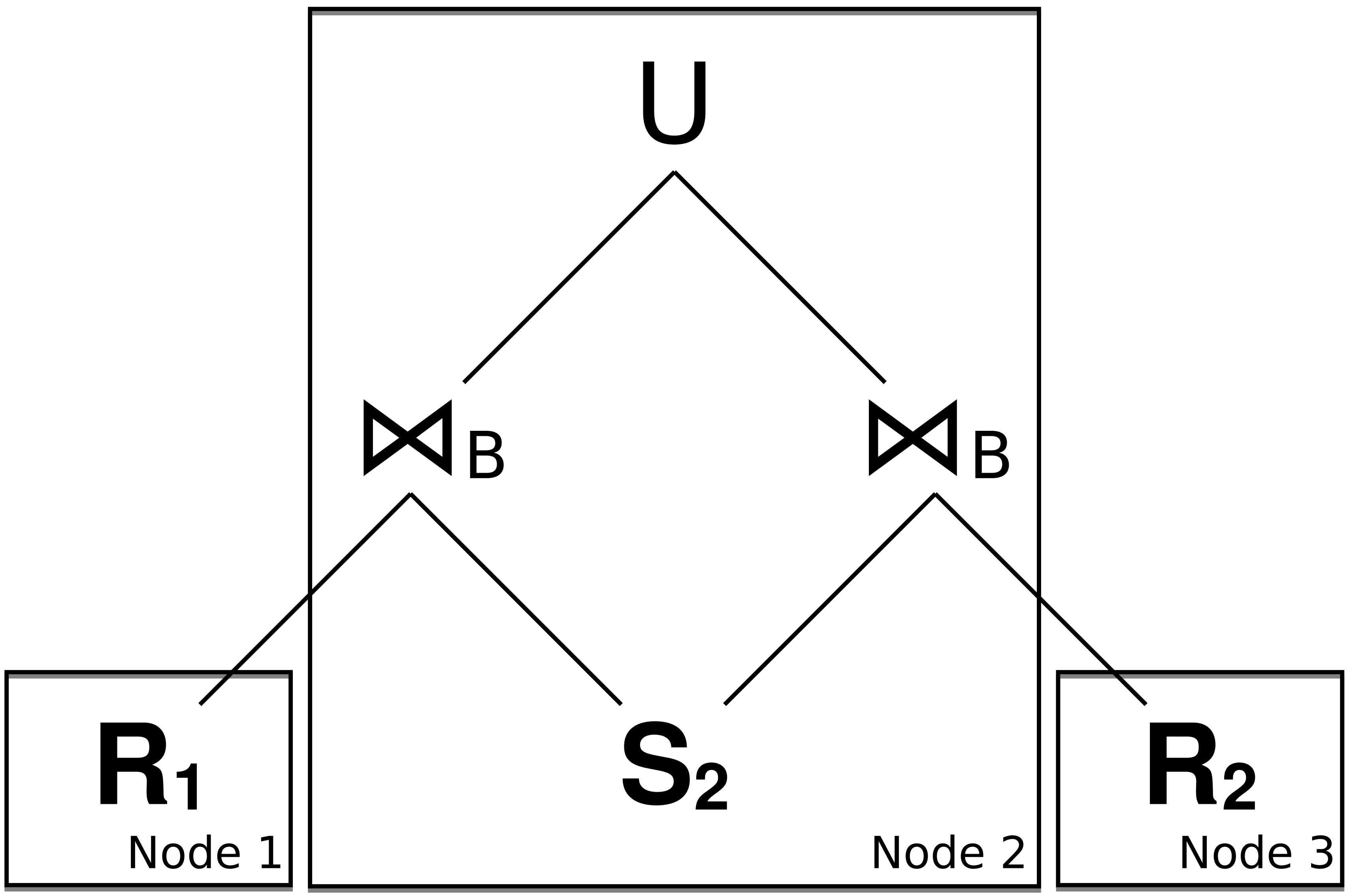
Distributing the Work

… it can be used as a model for partitioning S…



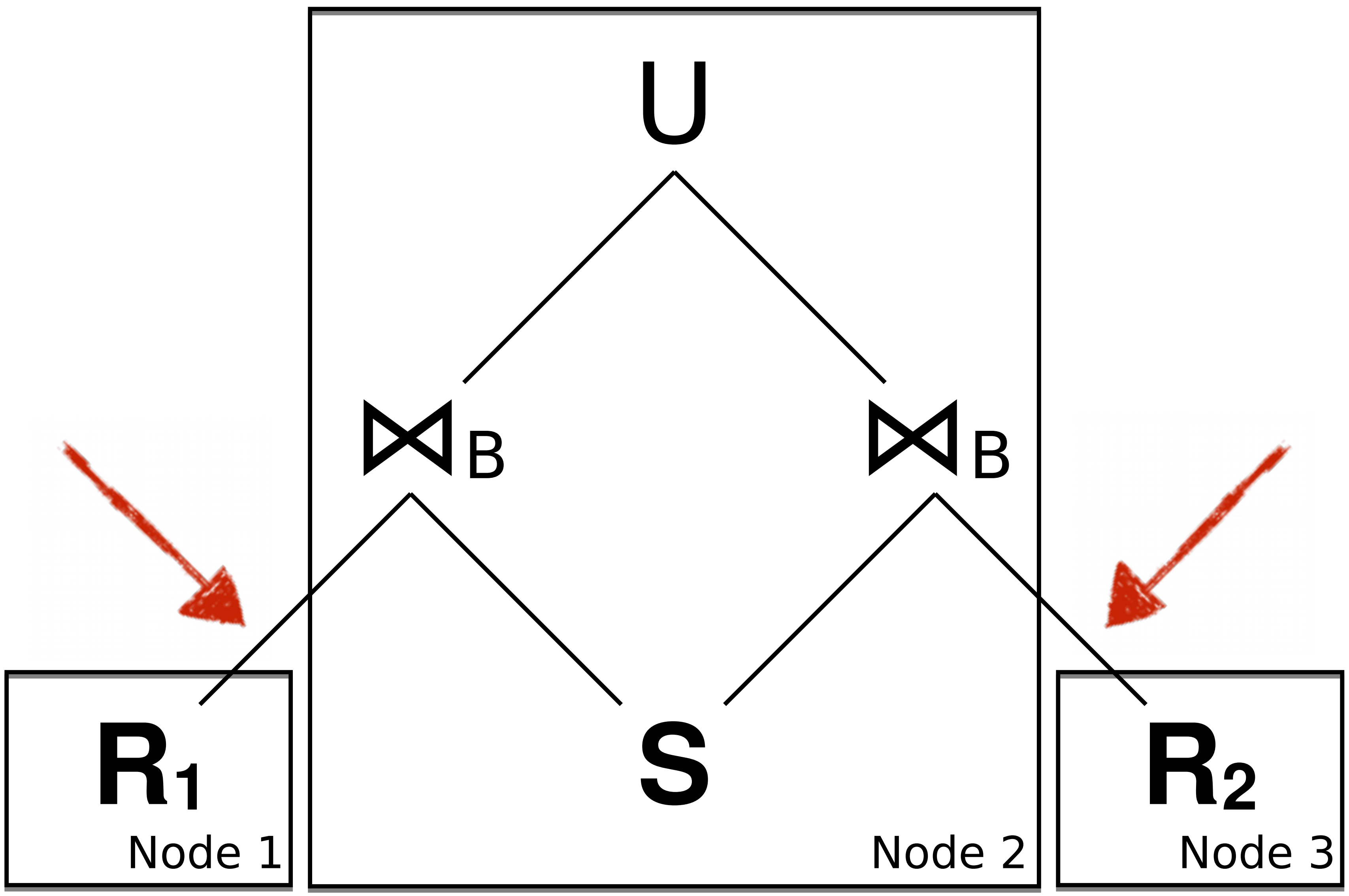
Distributing the Work

… it can be used as a model for partitioning S…



Distributing the Work

...and neatly captures the data transfer issue.



Distributing the Work

So let's use it:

S_i joins with $R_1, R_2, \ldots, R_N$ <u>locally</u>.

Goal: Minimize amount of data sent from R_k to S_i

Solution 1: Use a partitioning strategy

Solution 2: "Hints" to figure out what R_k should send

Sending Hints

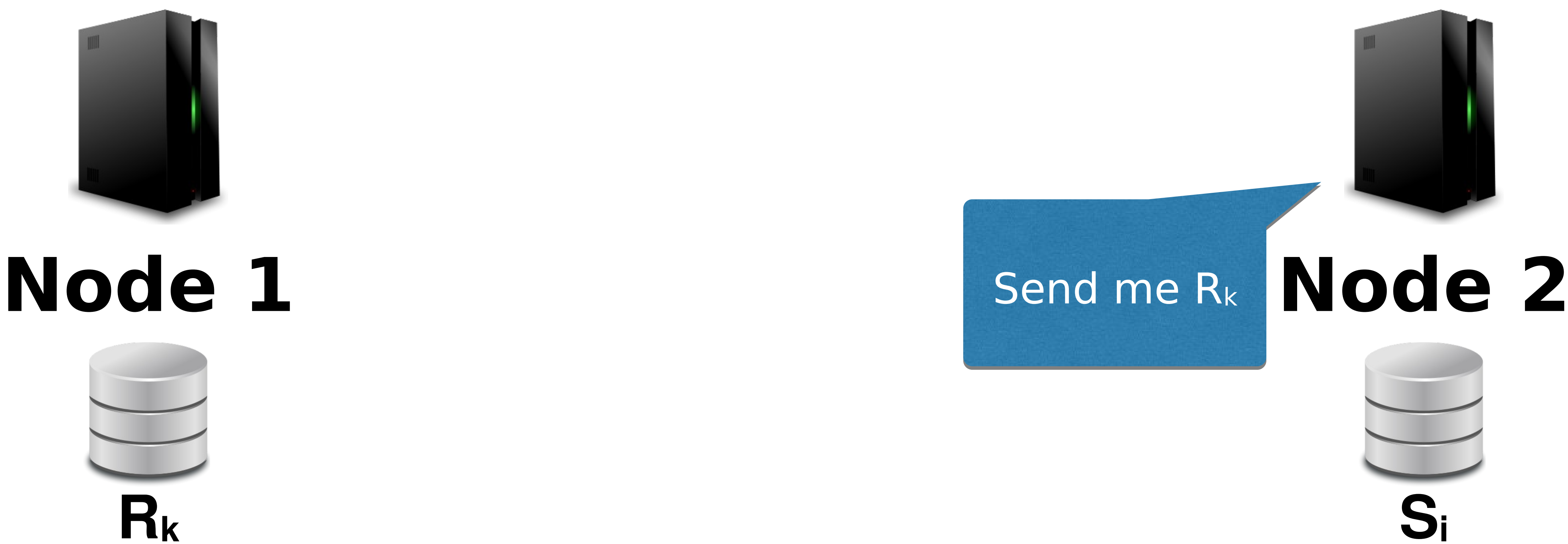
$$\mathbf{R_k} \bowtie_B \mathbf{S_i}$$

The naive approach…

Sending Hints

$$R_k \bowtie_B S_i$$

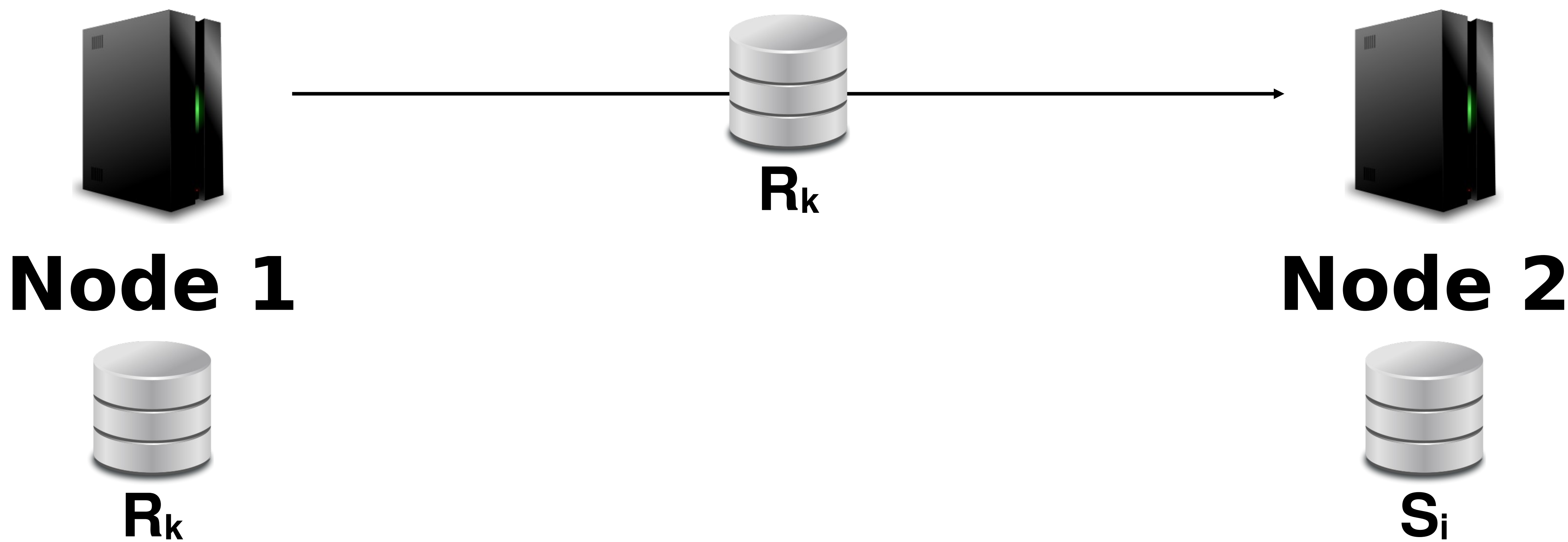
The naive approach…



Sending Hints

$$R_k \bowtie_B S_i$$

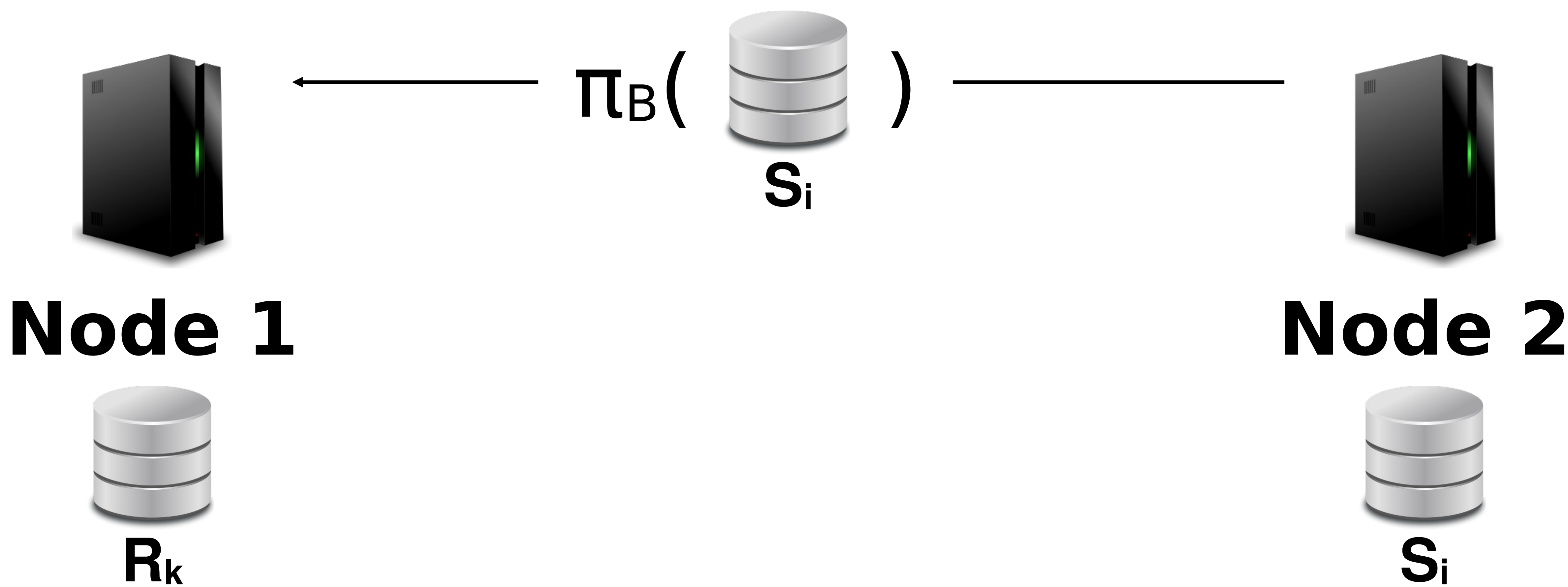
The naive approach…



Sending Hints

$$\mathbf{R_k} \bowtie_B \mathbf{S_i}$$

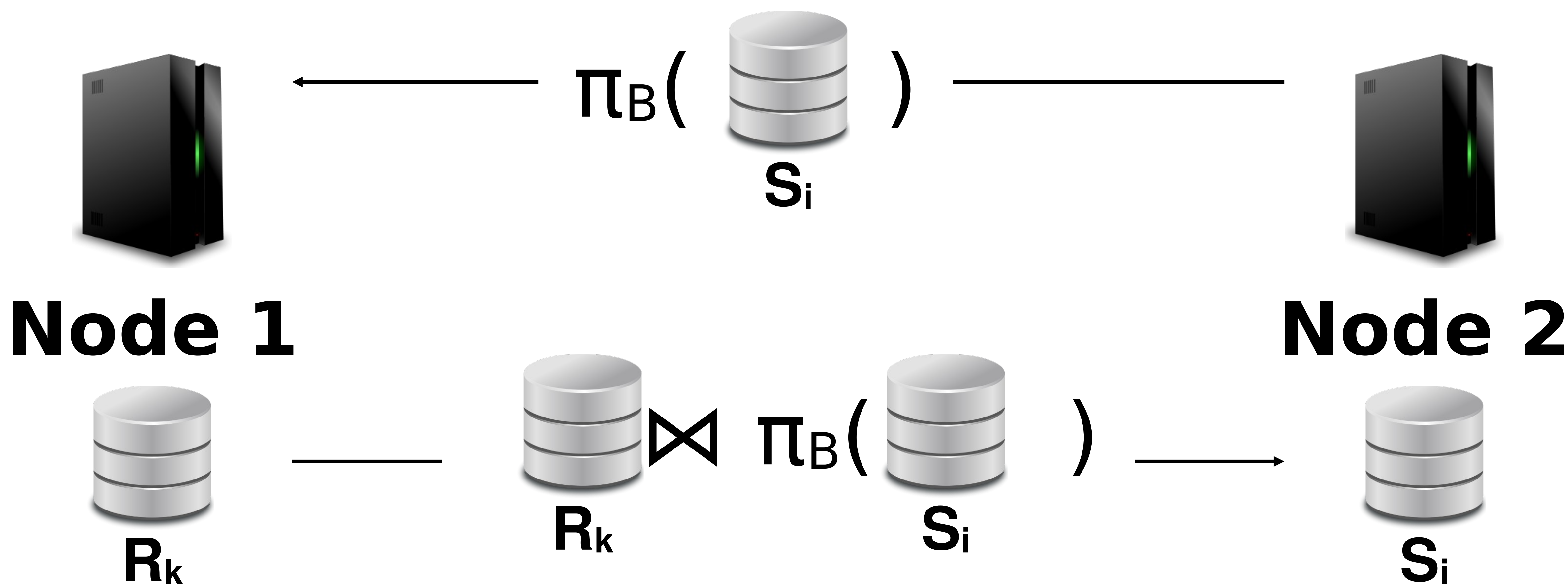
The smarter approach…



Sending Hints

$$\mathbf{R_k} \bowtie_B \mathbf{S_i}$$

The smarter approach…



Sending Hints

$$\mathbf{R}_{\mathbf{k}} \bowtie_{B} \mathbf{S}_{\mathbf{i}}$$

The smarter approach…

Node 1

<1,A>
<2,B>
<2,C>
<3,D>
<4,E>

Node 2

<2,X>
<3,Y>
<6,Y>

Sending Hints

$$\mathbf{R}_k \bowtie_B \mathbf{S}_i$$

The smarter approach…

Node 1

<1,A>
<2,B>
<2,C>
<3,D>
<4,E>

Node 2

<2,X>
<3,Y>
<6,Y>

Send me rows with a ‘B’ of 2,3, or 6

Sending Hints

$$\mathbf{R}_{\mathbf{k}} \bowtie_{B} \mathbf{S}_{\mathbf{i}}$$

The smarter approach…

Node 1

<1,A>
<2,B>
<2,C>
<3,D>
<4,E>

<2,B>
<2,C>
<3,D>

Send me rows with a ‘B’ of 2,3, or 6

Node 2

<2,X>
<3,Y>
<6,Y>

This is called a <u>semi-join</u>.

Sending Hints

Now Node 1 sends as little data as possible…

… but Node 2 needs to send a lot of data.

Can we do better?

Sending Hints

$$\mathbf{R}_{\mathbf{k}} \bowtie_{B} \mathbf{S}_{\mathbf{i}}$$

Strategy 1: Parity Bits

Node 1

<1,A>1
<2,B>0
<2,C>0
<3,D>1
<4,E>0

Node 2

0<2,X>
0<6,Y>

Sending Hints

$\mathbf{R_k} \bowtie_B \mathbf{S_i}$

Strategy 1: Parity Bits

Node 1

<1,A>1
<2,B>0
<2,C>0
<3,D>1
<4,E>0

Node 2

Send me data with a parity bit of ‘0’

0<2,X>
0<6,Y>

Sending Hints

$$R_k \bowtie_B S_i$$

Strategy 1: Parity Bit

Node 1 sending too much is ok!
(Node 2 still needs to compute $\bowtie_B$)

Node 1

<1,A>1
<2,B>0
<2,C>0
<3,D>1
<4,E>0

<2,B>
<2,C>
<4,E>

Send me data with a parity bit of ‘0’

Node 2

0<2,X>
0<6,Y>

Problem: <u>One</u> parity bit is too little

Sending Hints

$$R_k \bowtie_B S_i$$

Strategy 2: Parity Bits

Node 1

<1,A> 01
<2,B> 10
<2,C> 10
<3,D> 11
<4,E> 00

<2,B>
<2,C>
<3,D>

Node 2

Send me data with parity bits 10 or 11

10 <2,X>
11 <3,Y>
10 <6,Y>

Problem: Almost as much data as π_B

Sending Hints

Can we summarize the parity bits?

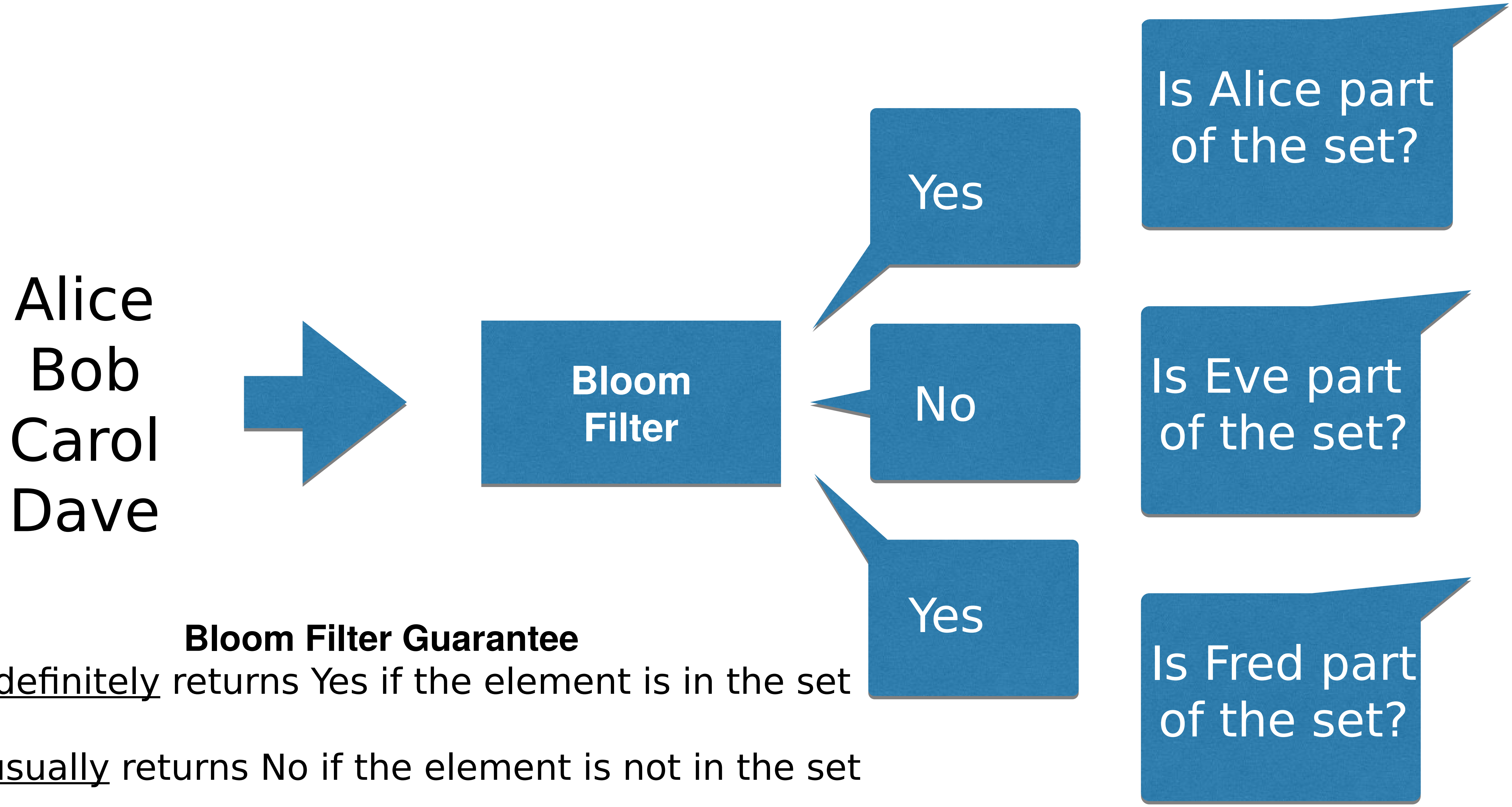
Bloom Filters

Alice
Bob
Carol
Dave

Bloom Filters

Alice
Bob
Carol
Dave

Bloom Filters



Bloom Filter Guarantee

Test <u>definitely</u> returns Yes if the element is in the set

Test <u>usually</u> returns No if the element is not in the set

Bloom Filters

A Bloom Filter is a bit vector

M - # of bits in the bit vector

K - # of hash functions

For ONE key (or record):
For i between 0 and K:
bitvector[$hash_i$ (key) % M] = 1

Each bit vector has ~K bits set

Bloom Filters

Key 1 00101010

Key 2 01010110

Key 3 10000110

Key 4 01001100

Filters are combined by Bitwise-OR

e.g. (Key 1 | Key 2)

= 01111110

How do we test for inclusion?

(Key & Filter) == Key?

(Key 1 & S) = 00101010 √

(Key 3 & S) = 00000110 X

(Key 4 & S) = 01001100 √

False Positive

Sending Hints

$$\mathbf{R_k} \bowtie_B \mathbf{S_i}$$

Strategy 3: Bloom Filters

Node 1

<1,A>
<2,B>
<2,C>
<3,D>
<4,E>

Node 2

<2,X>
<3,Y>
<6,Y>

Sending Hints

$$\mathbf{R_k} \bowtie_B \mathbf{S_i}$$

Strategy 3: Bloom Filters

Node 1

<1,A>
<2,B>
<2,C>
<3,D>
<4,E>

Send me rows with a ‘B’ in the bloom filter summarizing the set {2,3,6}

Node 2

<2,X>
<3,Y>
<6,Y>

Sending Hints

$\mathbf{R}_k \bowtie_B \mathbf{S}_i$

Strategy 3: Bloom Filters

Node 1

<1,A>
<2,B>
<2,C>
<3,D>
<4,E>

<2,B>
<2,C>
<3,D>
<4,E>

Send me rows with a ‘B’ in the bloom filter summarizing the set {2,3,6}

Node 2

<2,X>
<3,Y>
<6,Y>

This is called a <u>bloom-join</u>.

Bloom Filters

Probability that 1 bit is set by 1 hash fn

1/m

Bloom Filters

Probability that 1 bit is not set by 1 hash fn

$1 - 1/m$

Bloom Filters

Probability that 1 bit is not set by k hash fns

$$(1 - 1/m)^k$$

Bloom Filters

Probability that 1 bit is not set by k hash fns
for n records

$$(1 - 1/m)^{kn}$$

So for an arbitrary record, what is the probability
that all of its bits will be set?

Bloom Filters

Probability that 1 bit is set by k hash fns for n records

$$1 - (1 - 1/m)^{kn}$$

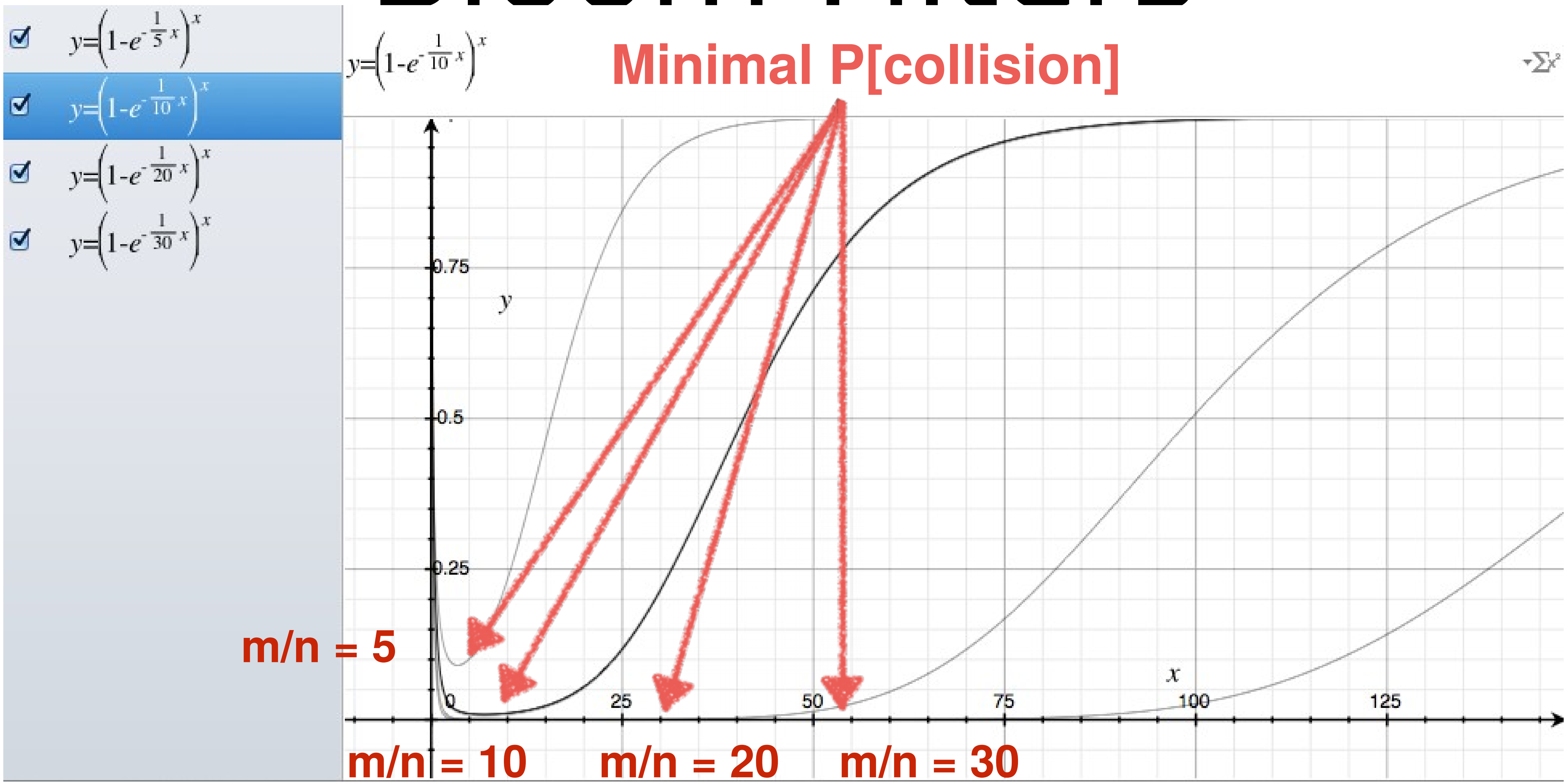
Bloom Filters

Probability that all k bits are set by k hash fns
for n records

$$\approx \left(1 - \left(1 - 1/m\right)^{kn}\right)^{k}$$

$$\approx \left(1 - e^{-kn/m}\right)^{k}$$

Bloom Filters



Minimal P[collision] is at k ≈ c • m/n

Bloom Filters

$$k \approx c \bullet m/n$$

$$\begin{matrix} m \\ k \end{matrix} \approx cn$$

m is linearly related to n (for a fixed k)

Bloom Join

- Node 2 Computes Bloom Filter for Local Records
- Node 2 Sends Bloom Filter to Node 1
- Node 1 Matches Local Records Against Bloom Filter
- Node 1 Sends Matched Records to Node 2
    - Superset of “useful” records
- Node 2 Performs Join Locally