Introduction to Data Management
CSE 344

Unit 5: Parallel Data Processing

Parallel RDBMS
MapReduce
Spark

(4 lectures)

Introduction to Data Management CSE 344

Spark

Class Overview

- Unit 1: Intro
- Unit 2: Relational Data Models and Query Languages
- Unit 3: Non-relational data
- Unit 4: RDMBS internals and query optimization
- Unit 5: Parallel query processing
  - Spark, Hadoop, parallel databases
- Unit 6: DBMS usability, conceptual design
- Unit 7: Transactions
- Unit 8: Advanced topics (time permitting)

Parallelism is of Increasing Importance

- Multi-cores:
  - Most processors have multiple cores
  - This trend will likely increase in the future

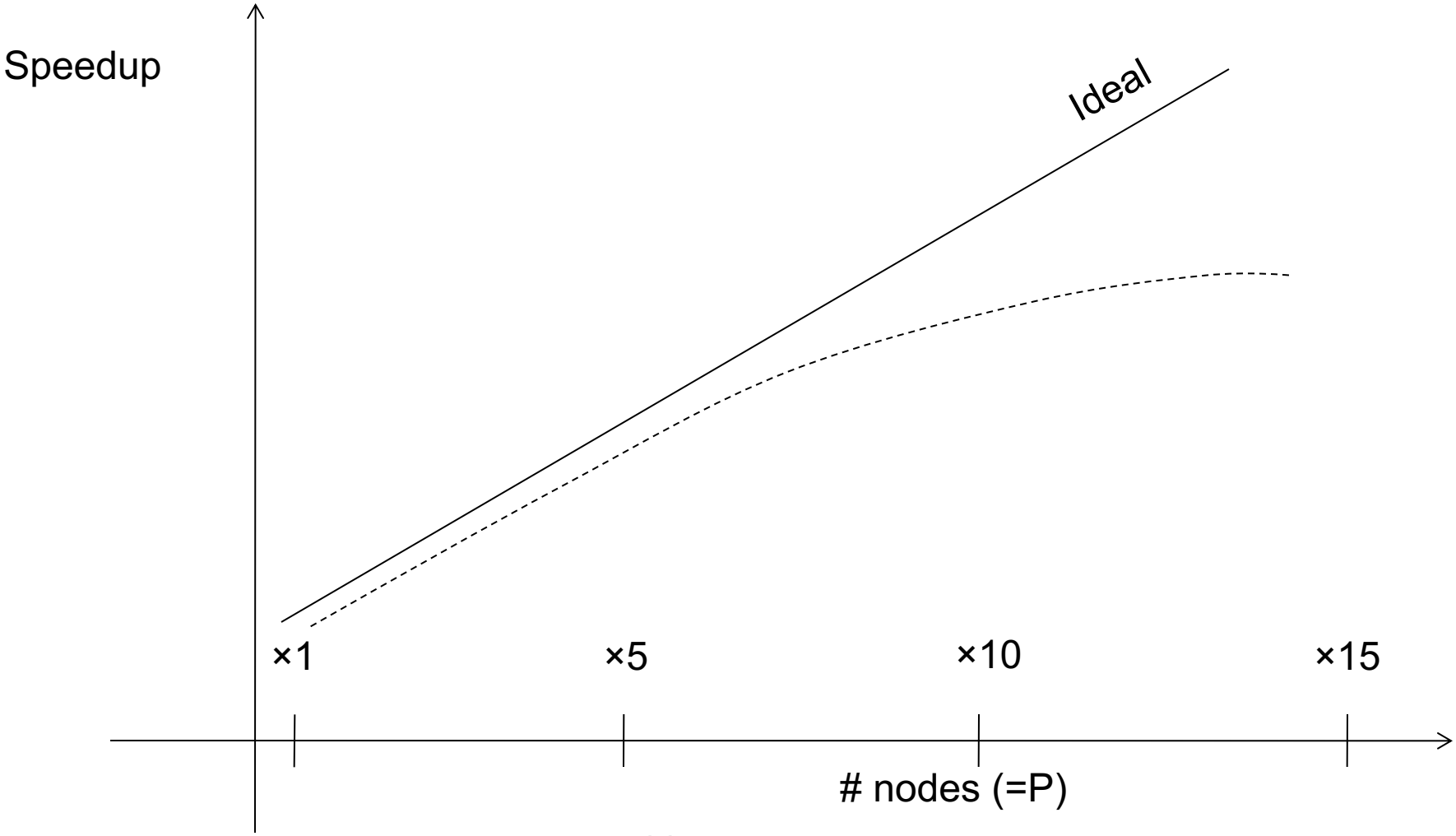
- Big data: too large to fit in main memory
  - Distributed query processing on 100x-1000x servers
  - Widely available now using cloud services

Performance Metrics for Parallel DBMSs

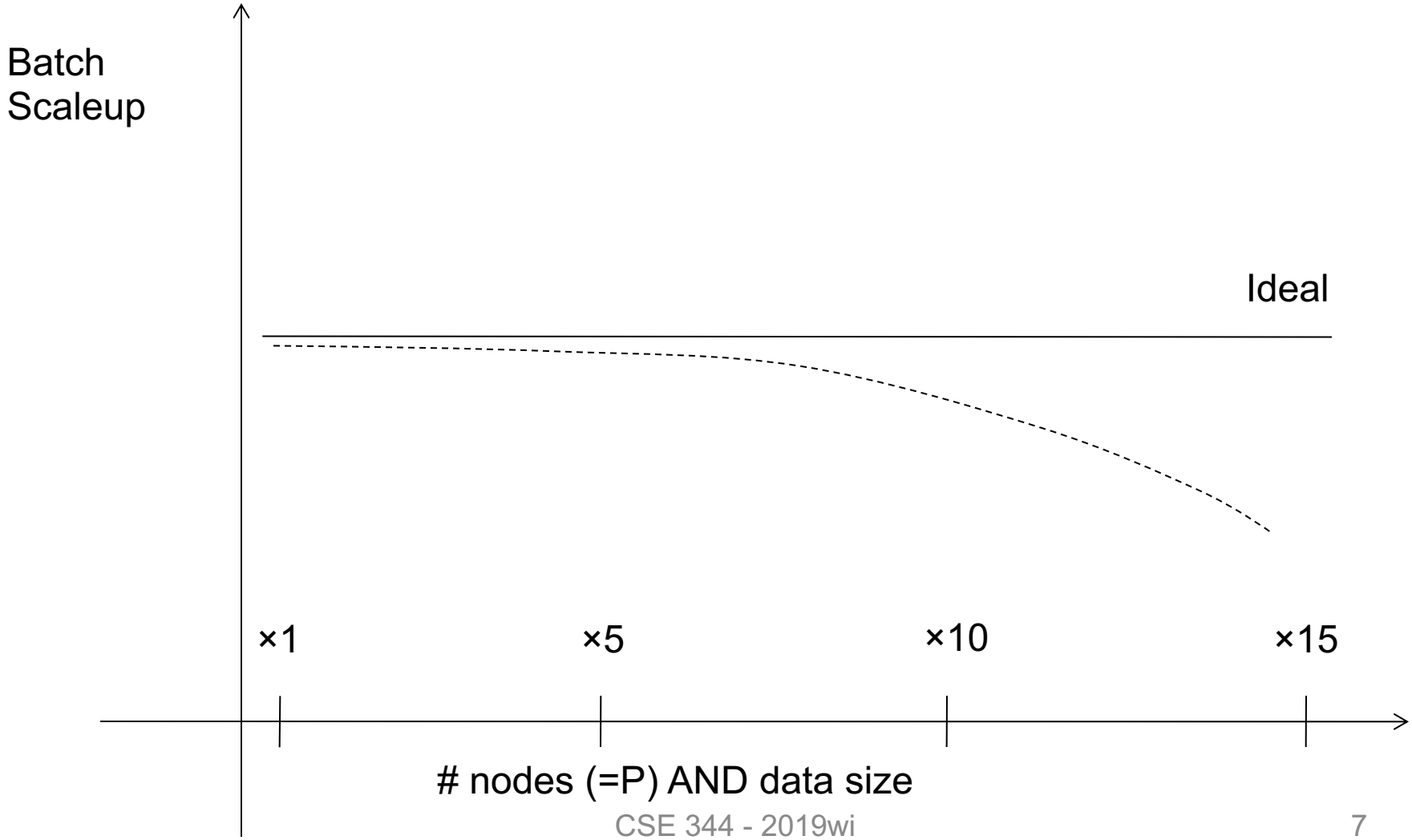
Nodes = processors, computers

- Speedup:
  - More nodes, same data ➔ higher speed
- Scaleup:
  - More nodes, more data ➔ same speed

Linear v.s. Non-linear Speedup



Linear v.s. Non-linear Scaleup



Why Sub-linear?

- Startup cost
  - Cost of starting an operation on many nodes
- Interference
  - Contention for resources between nodes
- Skew
  - Slowest node becomes the bottleneck

Spark

A Case Study of the MapReduce Programming Paradigm

Spark

- Open source system from UC Berkeley
- Distributed processing over HDFS
- Differences from MapReduce (CSE322):
  - Multiple steps, including iterations
  - Stores intermediate results in main memory
  - Closer to relational algebra (familiar to you)
- Details: http://spark.apache.org/examples.html

Spark

- Spark supports interfaces in Java, Scala, and Python
  - Scala: extension of Java with functions/closures
- We will illustrate use the Spark Java interface in this class
- Spark also supports a SQL interface (SparkSQL), and compiles SQL to its native Java interface

Programming in Spark

- A Spark program consists of:
  - Transformations (map, reduce, join…). Lazy
  - Actions (count, reduce, save...). Eager

- Eager: operators are executed immediately

- Lazy: operators are not executed immediately
  - A *operator tree* is constructed in memory instead
  - Similar to a relational algebra tree

Collections in Spark

- RDD<T> = an RDD collection of type T
  - Distributed on many servers, not nested
  - Operations are done in parallel
  - Recoverable via lineage; more later
- Seq<T> = a sequence
  - Local to one server, may be nested
  - Operations are done sequentially

Example

Given a large log file hdfs://logfile.log retrieve all lines that:

- Start with “ERROR”
- Contain the string “sqlite”

```
s = SparkSession.builder()...getOrCreate();

lines = s.read().textFile(“hdfs://logfile.log”);

errors = lines.filter(l -> l.startsWith(“ERROR”));

sqlerrors = errors.filter(l -> l.contains(“sqlite”));

sqlerrors.collect();
```

Example

Given a large log file hdfs://logfile.log retrieve all lines that:

`lines has type JavaRDD<String>`

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sqlerrors.collect();
```

Transformation:
Not executed yet…

Action:
triggers execution
of entire program

Example

Recall: anonymous functions
(lambda expressions) starting in Java 8

```
errors = lines.filter(l -> l.startsWith("ERROR"));
```

is the same as:

```
class FilterFn implements Function<Row, Boolean>{
  Boolean call (Row r)
  { return l.startsWith("ERROR"); }
}

errors = lines.filter(new FilterFn());
```

Example

Given a large log file hdfs://logfile.log retrieve all lines that:

- Start with “ERROR”
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              .filter(l -> l.startsWith(“ERROR”))
              .filter(l -> l.contains(“sqlite”))
              .collect();
```

“Call chaining” style

Example

The RDD s:

Error…	Warning…	Warning…	Error…	Abort…	Abort…	Error…	Error…	Warning…	Error…

```
s = SparkSession.builder()...getOrCreate();

sqlerrors = s.read().textFile("hdfs://logfile.log")
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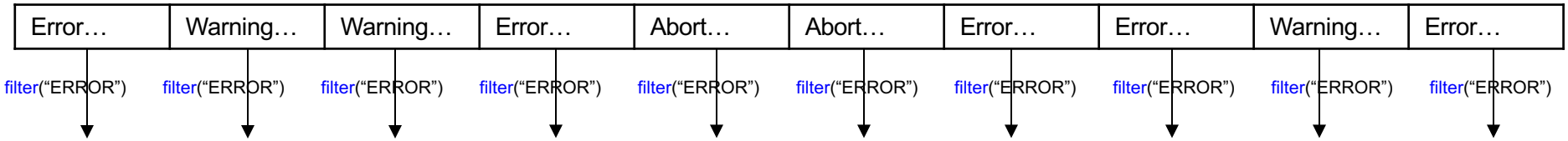
             .collect();
```

Example

The RDD s:

Parallel step 1

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Example

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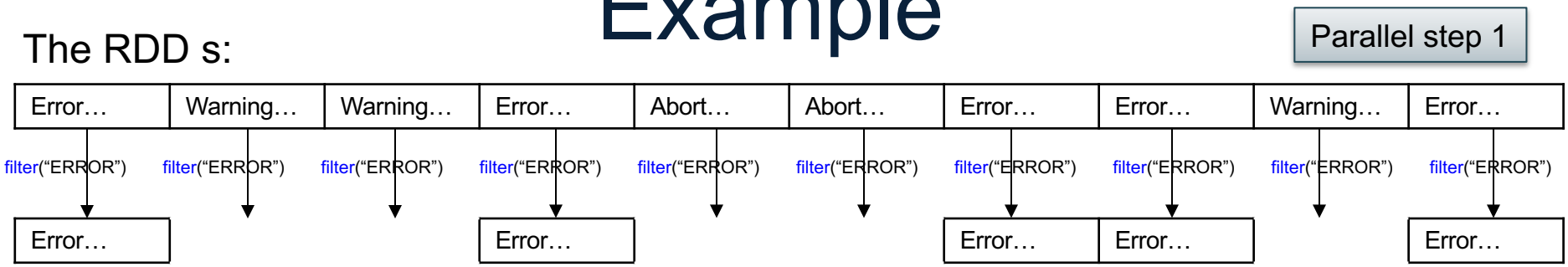


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Example

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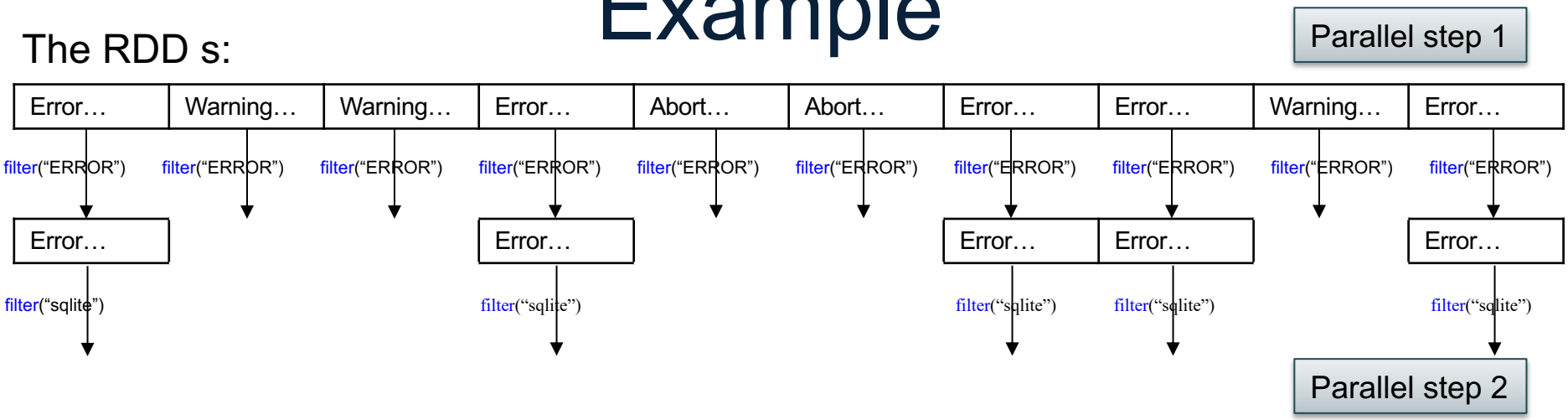


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sqlerrors = s.read().textFile("hdfs://logfile.log")
            .filter(l -> l.startsWith("ERROR"))
            .filter(l -> l.contains("sqlite"))
            .collect();
```

Fault Tolerance

- When a job is executed on x100 or x1000 servers, the probability of a failure is high
- Example: if a server fails once/year, then a job with 10000 servers fails once/hour
- Different solutions:
  - Parallel database systems: restart. Expensive.
  - MapReduce: write everything to disk, redo. Slow.
  - Spark: redo only what is needed. Efficient.

Resilient Distributed Datasets

- RDD = Resilient Distributed Dataset
  - Distributed, immutable and records its *lineage*
  - Lineage = expression that says how that relation was computed = a relational algebra plan
- Spark stores intermediate results as RDD
- If a server crashes, its RDD in main memory is lost. However, the driver (=master node) knows the lineage, and will simply recompute the lost partition of the RDD

Persistence

```
lines = s.read().textFile("hdfs://logfile.log");
errors = lines.filter(l->l.startsWith("ERROR"));
sqlerrors = errors.filter(l->l.contains("sqlite"));
sqlerrors.collect();
```

If any server fails before the end, then Spark must restart

Persistence

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lines = s.read().textFile("hdfs://logfile.log");
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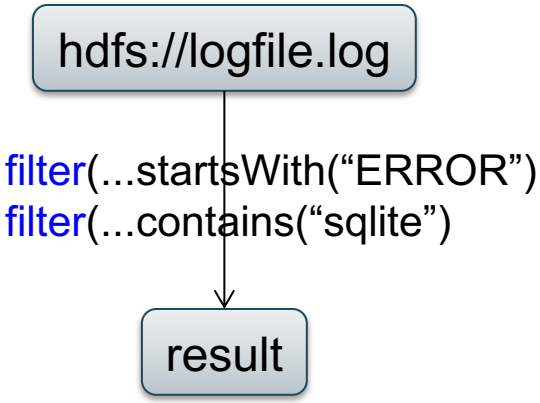
RDD:



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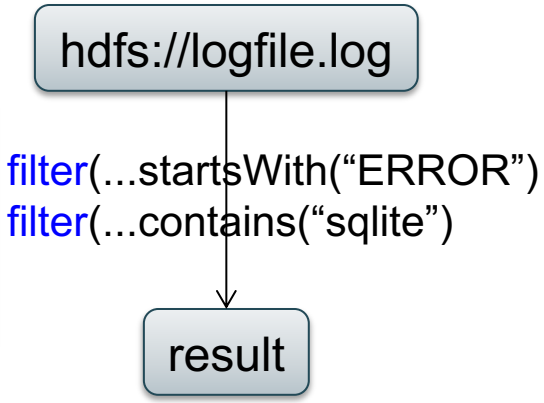
RDD:



If any server fails before the end, then Spark must restart

```
lines = s.read().textFile("hdfs://logfile.log");
errors = lines.filter(l->l.startsWith("ERROR"));
errors.persist();
sqlerrors = errors.filter(l->l.contains("sqlite"));
sqlerrors.collect()
```

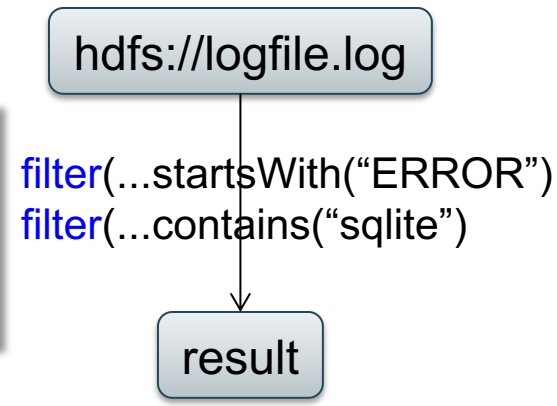
New RDD

Spark can recompute the result from errors

Persistence

```
lines = s.read().textFile("hdfs://logfile.log");
errors = lines.filter(l->l.startsWith("ERROR"));
sqlerrors = errors.filter(l->l.contains("sqlite"));
sqlerrors.collect();
```

RDD:



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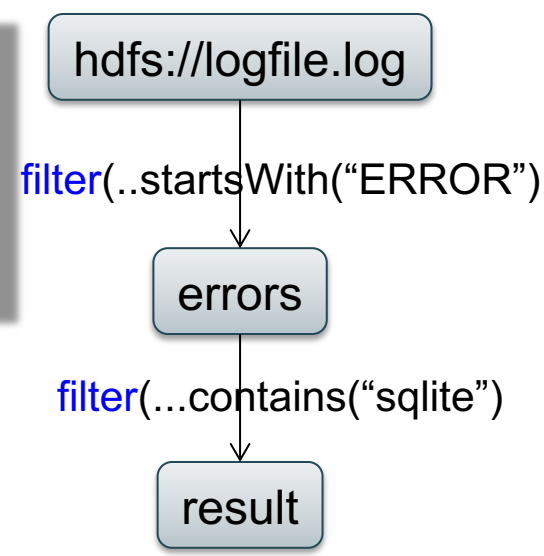
New RDD



Spark can recompute the result from errors

R(A,B)
S(A,C)

SELECT count(*) FROM R, S
WHERE R.B > 200 and S.C < 100 and R.A = S.A

Example

```
R = strm.read().textFile("R.csv").map(parseRecord).persist();
S = strm.read().textFile("S.csv").map(parseRecord).persist();
```

Parses each line into an object

persisting on disk

R(A,B)
S(A,C)

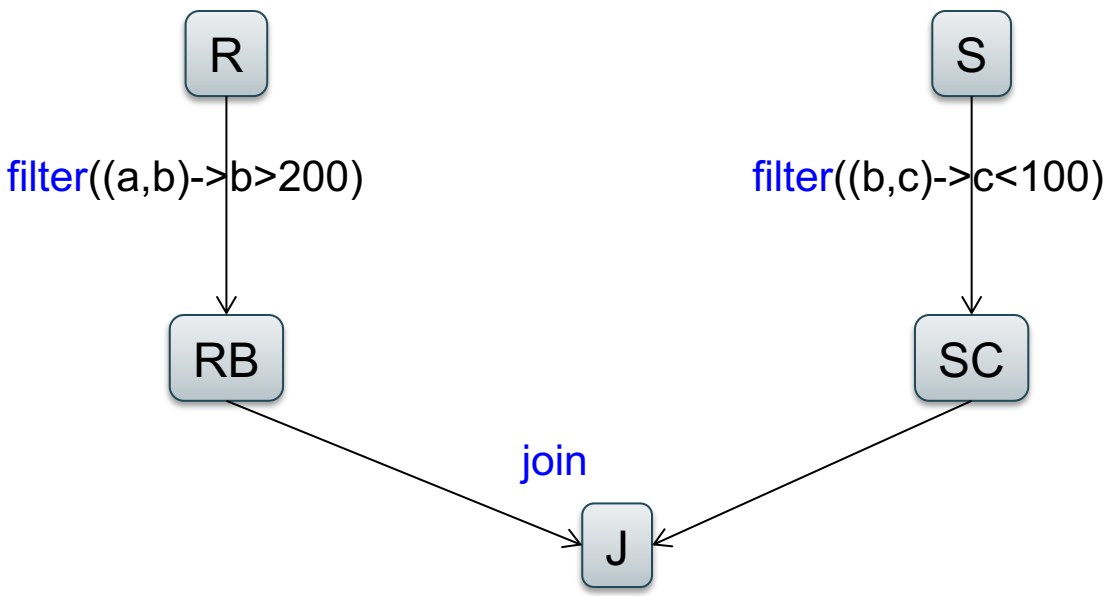
SELECT count(*) FROM R, S
WHERE R.B > 200 and S.C < 100 and R.A = S.A

Example

```
R = strm.read().textFile("R.csv").map(parseRecord).persist();
S = strm.read().textFile("S.csv").map(parseRecord).persist();
RB = R.filter(t -> t.b > 200).persist();
SC = S.filter(t -> t.c < 100).persist();
J = RB.join(SC).persist();
J.count();
```

transformations

action



Recap: Programming in Spark

- A Spark/Scala program consists of:
  - Transformations (map, reduce, join…). Lazy
  - Actions (count, reduce, save...). Eager
- RDD<T> = an RDD collection of type T
  - Partitioned, recoverable (through lineage), not nested
- Seq<T> = a sequence
  - Local to a server, may be nested

Transformations:	
map(f : T -> U):	RDD<T> -> RDD<U>
flatMap(f: T -> Seq(U)):	RDD<T> -> RDD<U>
filter(f:T->Bool):	RDD<T> -> RDD<T>
groupByKey():	RDD<(K,V)> -> RDD<(K,Seq[V])>
reduceByKey(F:(V,V)-> V):	RDD<(K,V)> -> RDD<(K,V)>
union():	(RDD<T>,RDD<T>) -> RDD<T>
join():	(RDD<(K,V)>,RDD<(K,W)>) -> RDD<(K,(V,W))>
cogroup():	(RDD<(K,V)>,RDD<(K,W)>)-> RDD<(K,(Seq<V>,Seq<W>))>
crossProduct():	(RDD<T>,RDD<U>) -> RDD<(T,U)>

Actions:	
count():	RDD<T> -> Long
collect():	RDD<T> -> Seq<T>
reduce(f:(T,T)->T):	RDD<T> -> T
save(path:String):	Outputs RDD to a storage system e.g., HDFS

Spark 2.0

The DataFrame and Dataset Interfaces

DataFrames

- Like RDD, also an immutable distributed collection of data

- Organized into *named columns* rather than individual objects
  - Just like a relation
  - Elements are untyped objects called `Row`'s

- Similar API as RDDs with additional methods
  -
```
people = spark.read().textFile(…);
ageCol = people.col("age");
ageCol.plus(10); // creates a new DataFrame
```

Datasets

- Similar to DataFrames, except that elements must be typed objects
- E.g.: `Dataset<People>` rather than `Dataset<Row>`
- Can detect errors during compilation time
- DataFrames are aliased as `Dataset<Row>` (as of Spark 2.0)
- You will use both Datasets and RDD APIs in HW6

Datasets API: Sample Methods

- Functional API
  - `agg(Column expr, Column... exprs)`
    Aggregates on the entire Dataset without groups.
  - `groupBy(String col1, String... cols)`
    Groups the Dataset using the specified columns, so that we can run aggregation on them.
  - `join(Dataset<?> right)`
    Join with another DataFrame.
  - `orderBy(Column... sortExprs)`
    Returns a new Dataset sorted by the given expressions.
  - `select(Column... cols)`
    Selects a set of column based expressions.
- "SQL" API
  - `SparkSession.sql("select * from R");`
- Look familiar?

Introduction to Data Management CSE 344

Parallel Databases

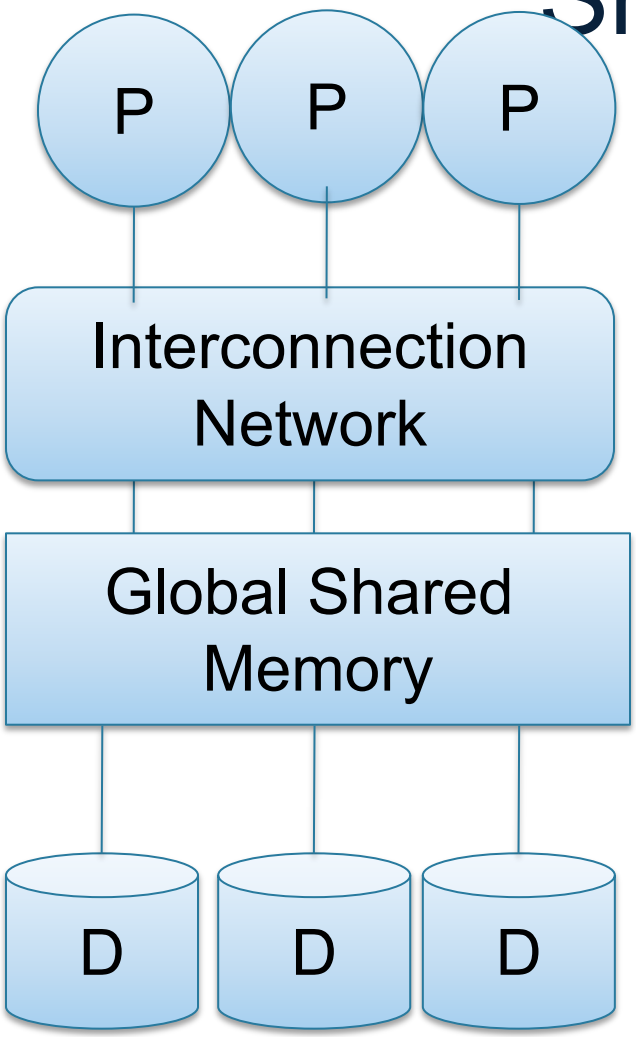
Announcements

- Jack and Jonathan are traveling to ACM SIGCSE this week; updated sections
  - (AA) 12:30pm-1:20pm, MGH 238 (Walter+Ying).
    (AB) 1:30pm-2:20pm, AND 010 (~~Jack~~ Natalie).
    (AC) 2:30pm-3:20pm, JHN 026 (~~Jonathan~~ Walter).
    (AD) 3:30pm-4:20pm, MEB 242 (Shana).
- Makeup lecture Thursday 4:30, BAG 131
- HW6 due on Friday evening

Architectures for Parallel Databases

- Shared memory
- Shared disk
- Shared nothing

Shared Memory



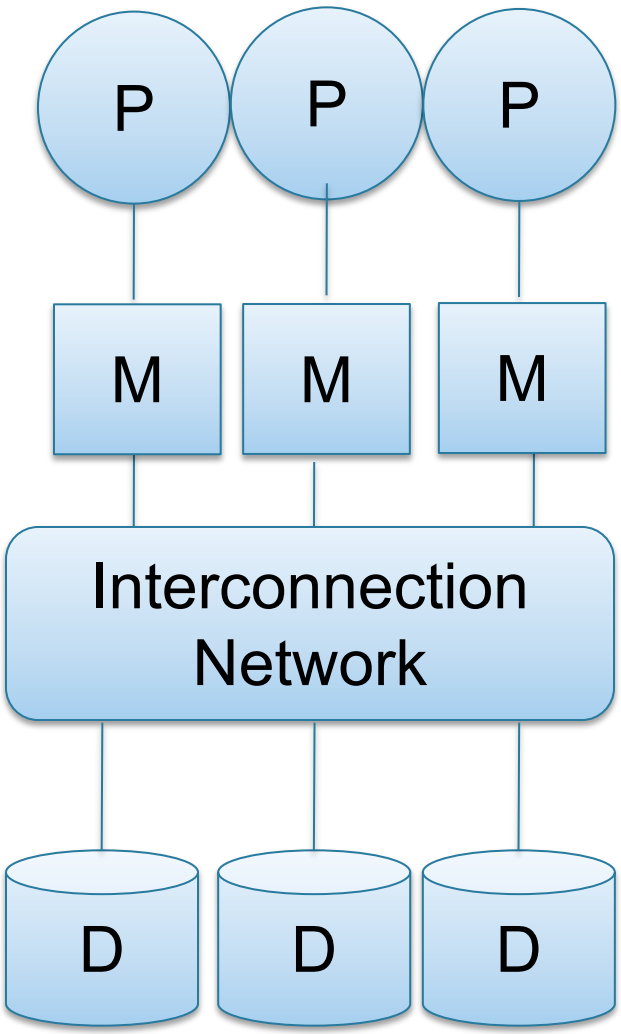
- Nodes share both RAM and disk
- Dozens to hundreds of processors

Example: SQL Server runs on a single machine and can leverage many threads to speed up a query

- check your HW3 query plans

- Easy to use and program
- Expensive to scale

Shared Disk



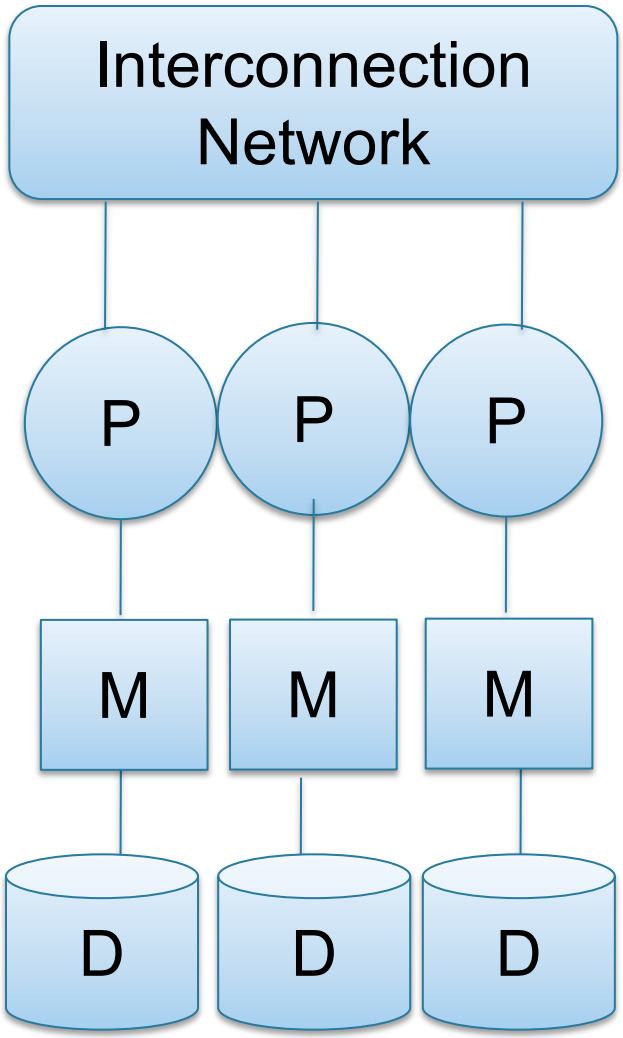
- All nodes access the same disks
- Found in the largest "single-box" (non-cluster) multiprocessors

Example: Oracle

- No more memory contention

- Harder to program
- Still hard to scale: existing deployments typically have fewer than 10 machines

Shared Nothing



- Cluster of commodity machines on high-speed network
- Called "clusters" or "blade servers"
- Each machine has its own memory and disk: lowest contention.

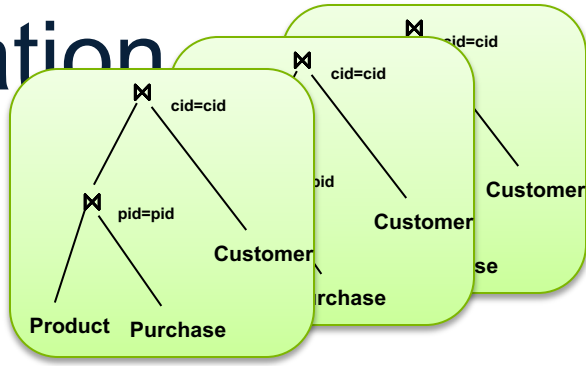
Example: Spark

Because all machines today have many cores and many disks, shared-nothing systems typically run many "nodes" on a single physical machine.

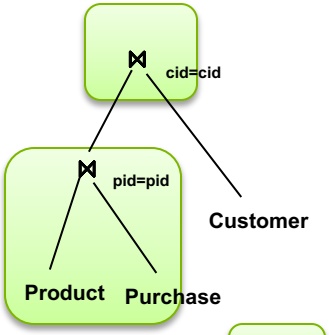
- Easy to maintain and scale
- Most difficult to administer and tune.

We discuss only Shared Nothing in class

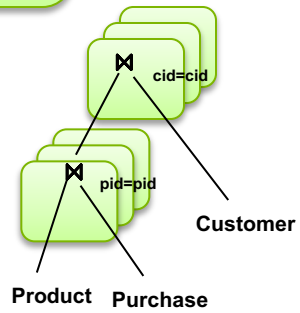
Approaches to Parallel Query Evaluation



- Inter-query parallelism
  - Transaction per node
  - Good for transactional workloads



- Inter-operator parallelism
  - Operator per node
  - Good for analytical workloads



- Intra-operator parallelism
  - Operator on multiple nodes
  - Good for both?

We study only intra-operator parallelism: most scalable

Single Node Query Processing (Review)

Given relations R(A,B) and S(B, C), no indexes:

- Selection: $\sigma_{A=123}(R)$
  - Scan file R, select records with A=123
- Group-by: $\gamma_{A,sum(B)}(R)$
  - Scan file R, insert into a hash table using A as key
  - When a new key is equal to an existing one, add B to the value
- Join: $R \bowtie_{R.B=S.B} S$
  - Scan file S, insert into a hash table using B as key
  - Scan file R, probe the hash table using B

Distributed Query Processing

- Data is horizontally partitioned on servers
- Operators may require data reshuffling

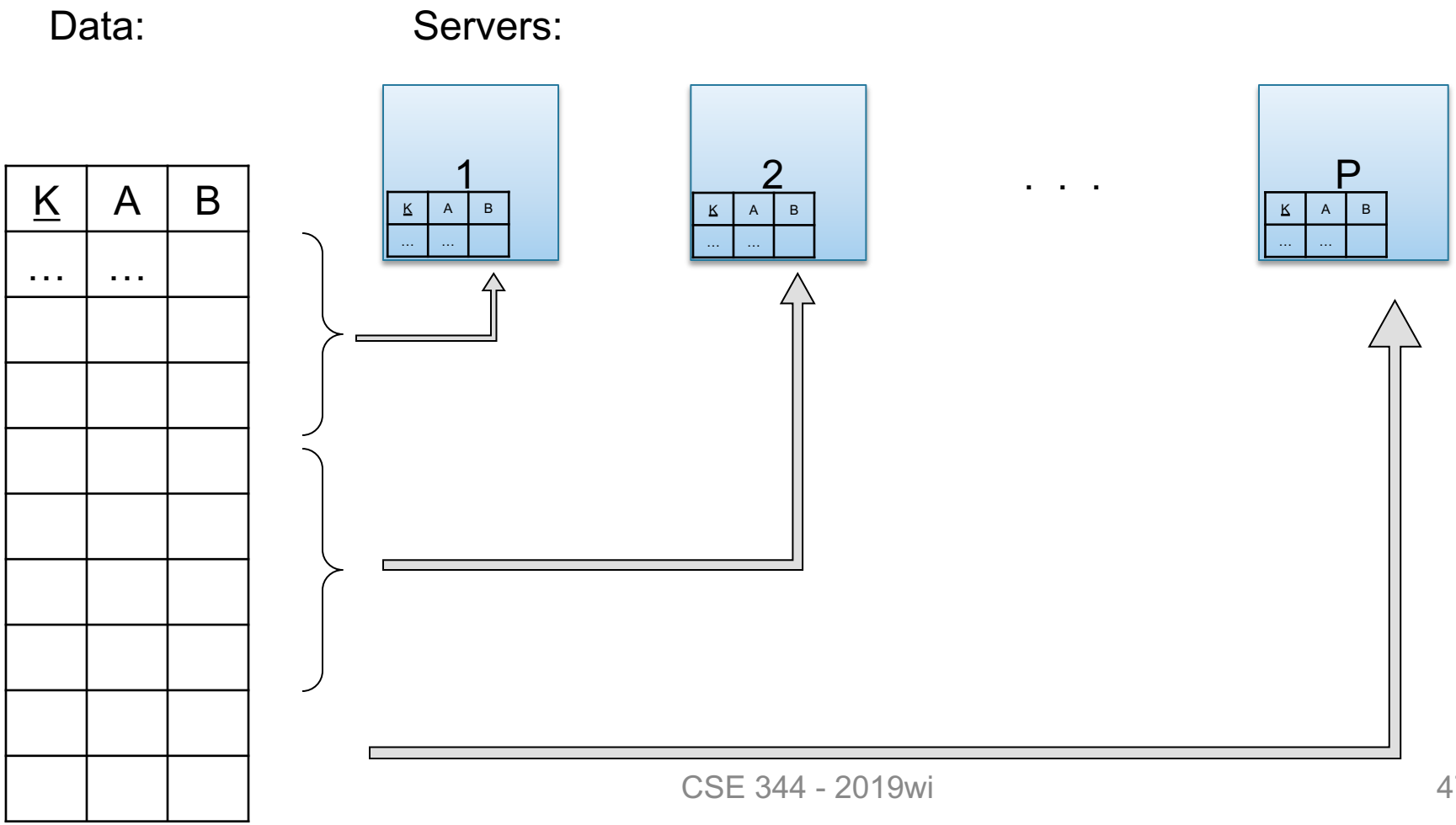
Horizontal Data Partitioning

Data:

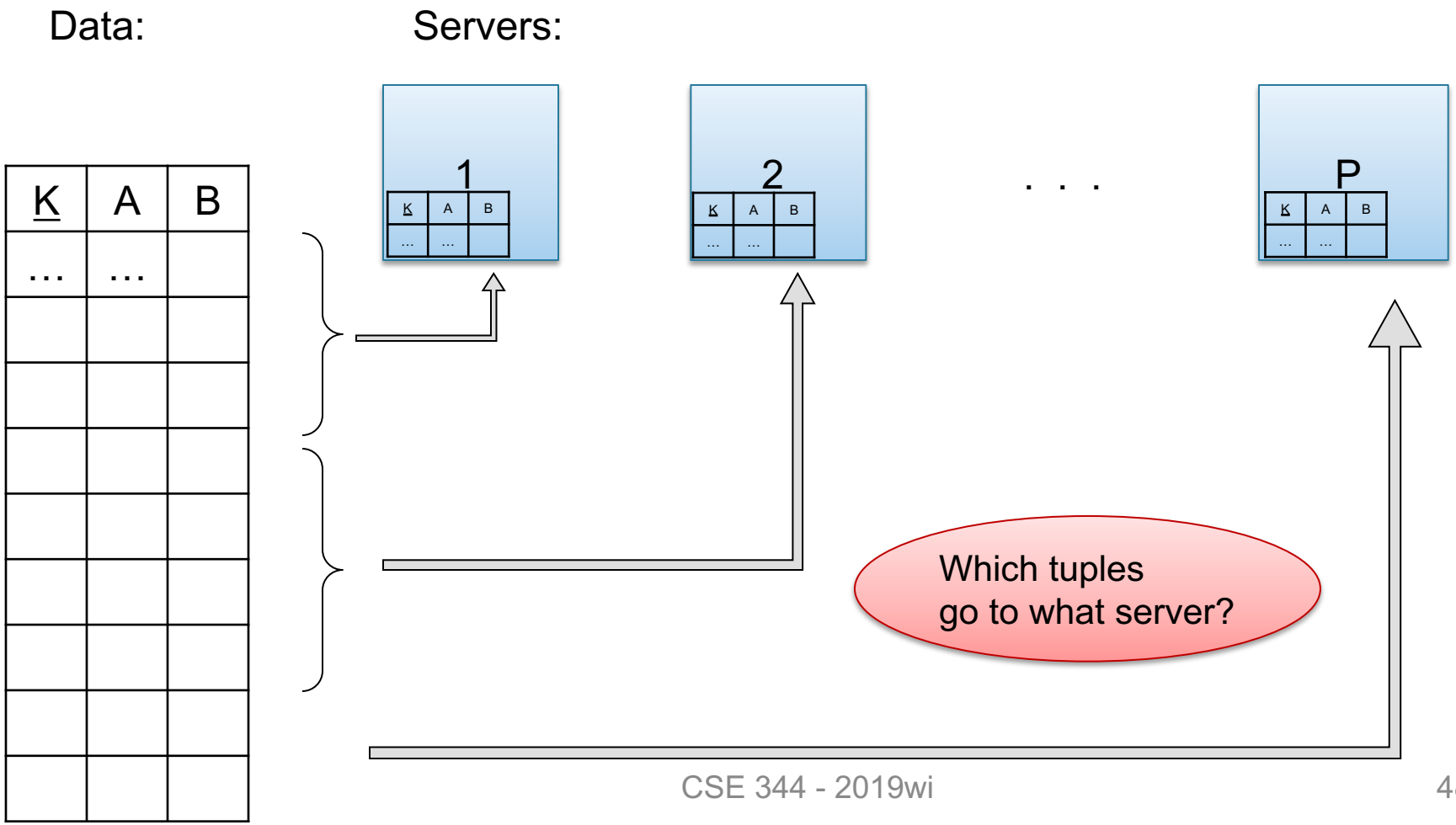
K	A	B
…	…	

Servers:

Horizontal Data Partitioning



Horizontal Data Partitioning



Horizontal Data Partitioning

- Block Partition:
  - Partition tuples arbitrarily s.t. size(R_1)≈ … ≈ size(R_P)

Will discuss mostly this

- Hash partitioned on attribute A:
  - Tuple t goes to chunk i, where i = h(t.A) mod P + 1
  - Recall: calling hash fn's is free in this class

- Range partitioned on attribute A:
  - Partition the range of A into $-\infty = v_0 < v_1 < \ldots < v_P = \infty$
  - Tuple t goes to chunk i, if $v_{i-1} < t.A < v_i$

Uniform Data v.s. Skewed Data

- Let R(K,A,B,C); which of the following partition methods may result in skewed partitions?

- Block partition

Uniform

- Hash-partition
  - On the key K
  - On the attribute A

Assuming good hash function

Uniform

E.g. when all records have the same value of the attribute A, then all records end up in the same partition

May be skewed

Keep this in mind in the next few slides

Parallel Execution of RA Operators: Grouping

Data: R(K,A,B,C)

Query: $\gamma_{A,sum(C)}(R)$

How to compute group by if:

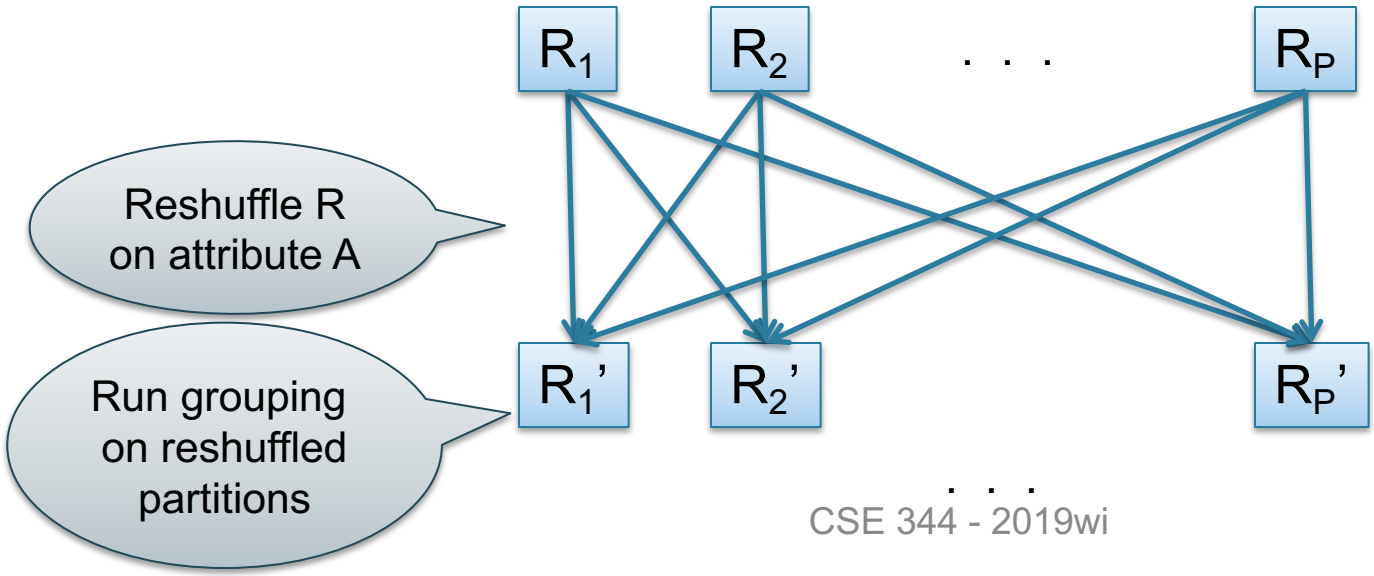
- R is hash-partitioned on A ?
- R is hash-partitioned on K ?

Parallel Execution of RA Operators: Grouping

Data: R(K,A,B,C)

Query: $\gamma_{A,sum(C)}(R)$

- R is block-partitioned or hash-partitioned on K



Speedup and Scaleup

Consider the Query: $\gamma_{A,sum(C)}(R)$

- If we double the number of nodes P, what is the new running time?
  - Half (each server holds ½ as many records)
- If we double both P and the size of R, what is the new running time?
  - Same (each server holds the same # of records)

But only if the data is without skew!

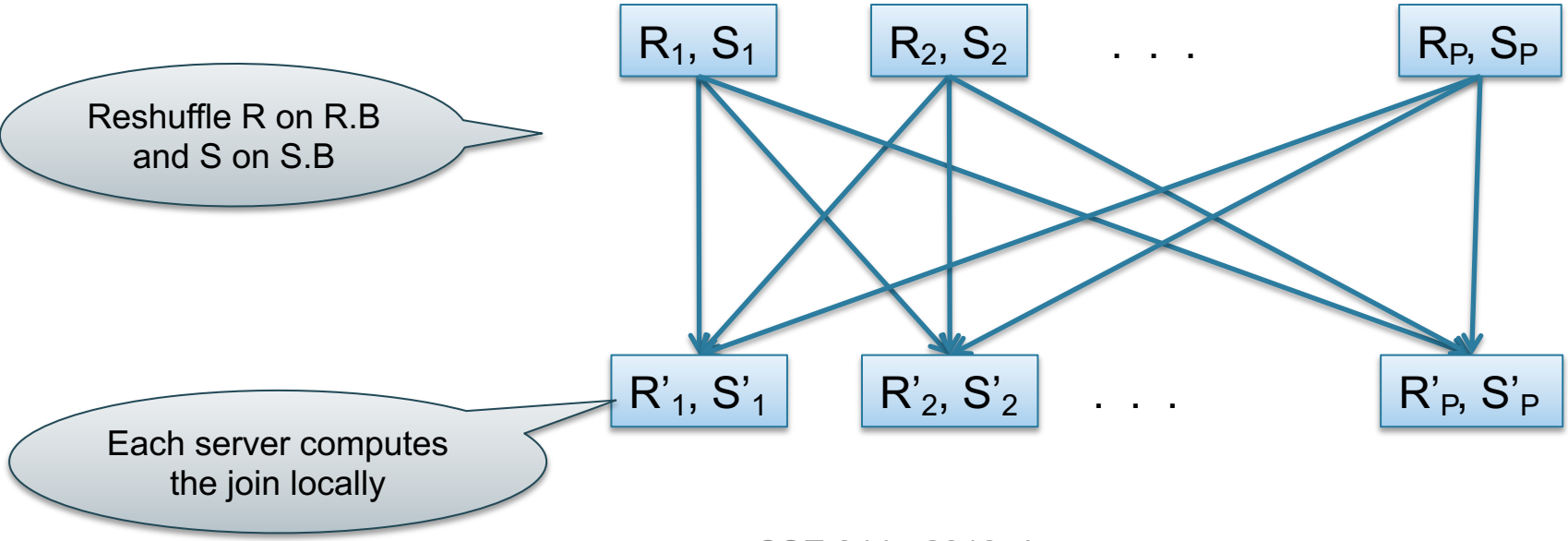
Skewed Data

Data: R(K,A,B,C)

- Informally: we say that the data is skewed if one server holds much more data that the average
- E.g. we hash-partition on A, and some value of A occurs very many times (“Justin Bieber”)
- Then the server holding that value will be skewed

Parallel Execution of RA Operators: Partitioned Hash-Join

- Data: R(K1, A, B), S(K2, B, C)
- Query: R(K1, A, B) $\bowtie_{R.B=S.B}$ S(K2, B, C)
  - Initially, R and S are partitioned on K1 and K2



Data: R(K1,A, B), S(K2, B, C)
Query: R(K1,A,B) ⋈ S(K2,B,C)

Parallel Join Illustration

Partition

R1

K1	B
1	20
2	50

S1

K2	B
101	50
102	50

M1

R2

K1	B
3	20
4	20

S2

K2	B
201	20
202	50

M2

Shuffle on B

Local Join

R1'

K1	B
1	20
3	20
4	20

S1'

K2	B
201	20

⋈

M1

R2'

K1	B
2	50

S2'

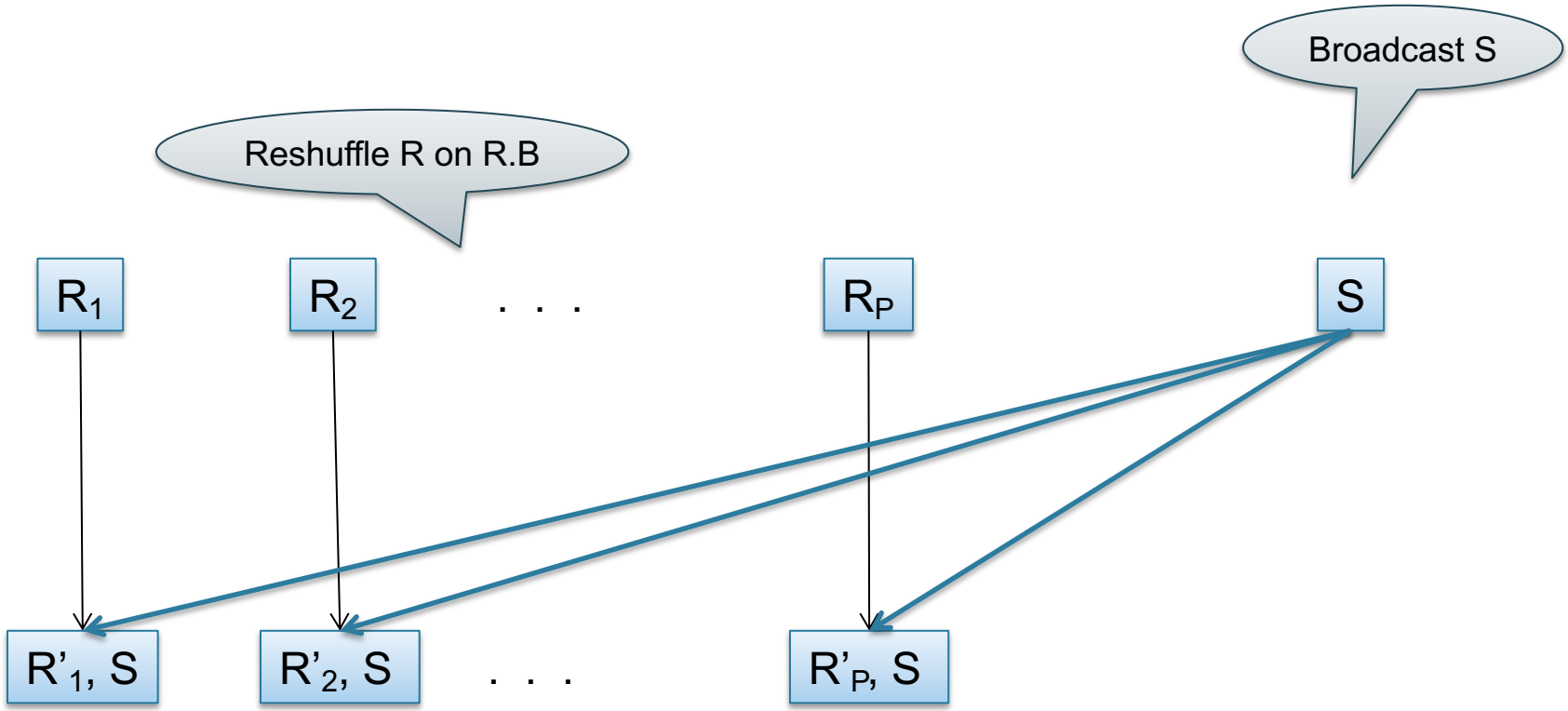
K2	B
101	50
102	50
202	50

⋈

M2

Data: R(A, B), S(C, D)
Query: $R(A,B) \bowtie_{B=C} S(C,D)$

Broadcast Join



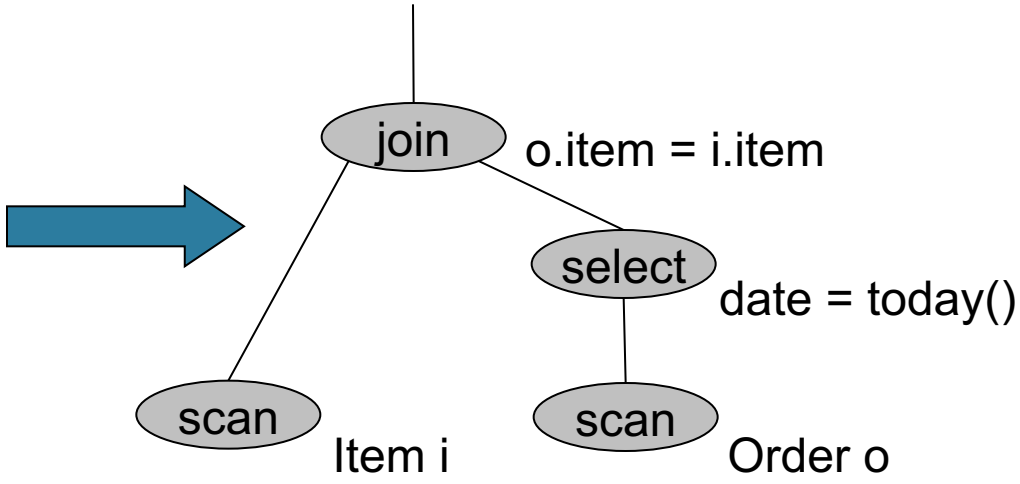
Why would you want to do this?

Order(oid, item, date), Line(item, …)

Putting it Together: Example Parallel Query Plan

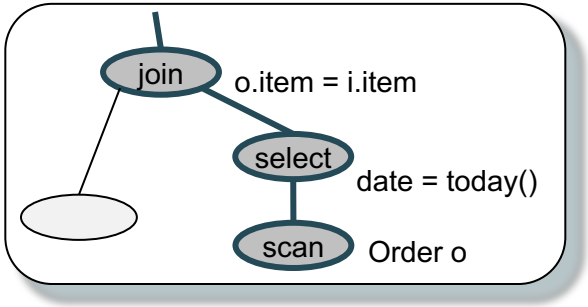
Find all orders from today, along with the items ordered

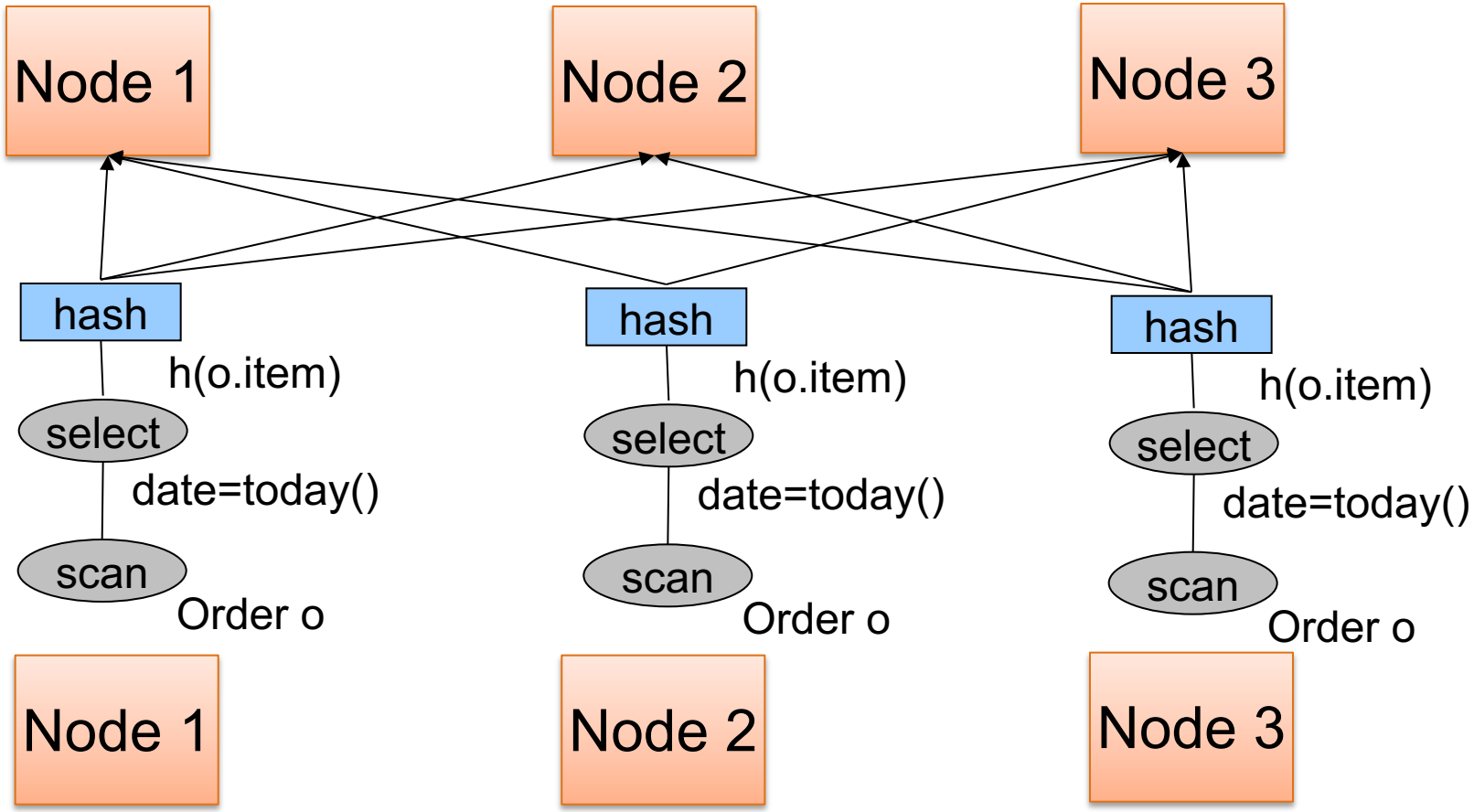
```
SELECT *
  FROM Order o, Line i
 WHERE o.item = i.item
   AND o.date = today()
```



Order(oid, item, date), Line(item, …)

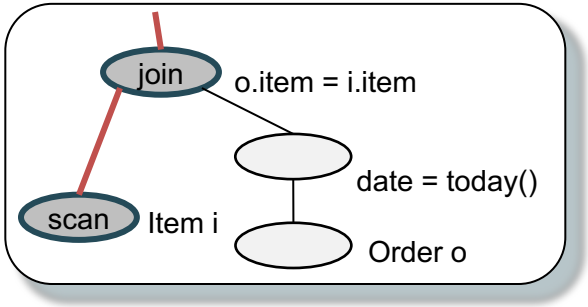
Example Parallel Query Plan

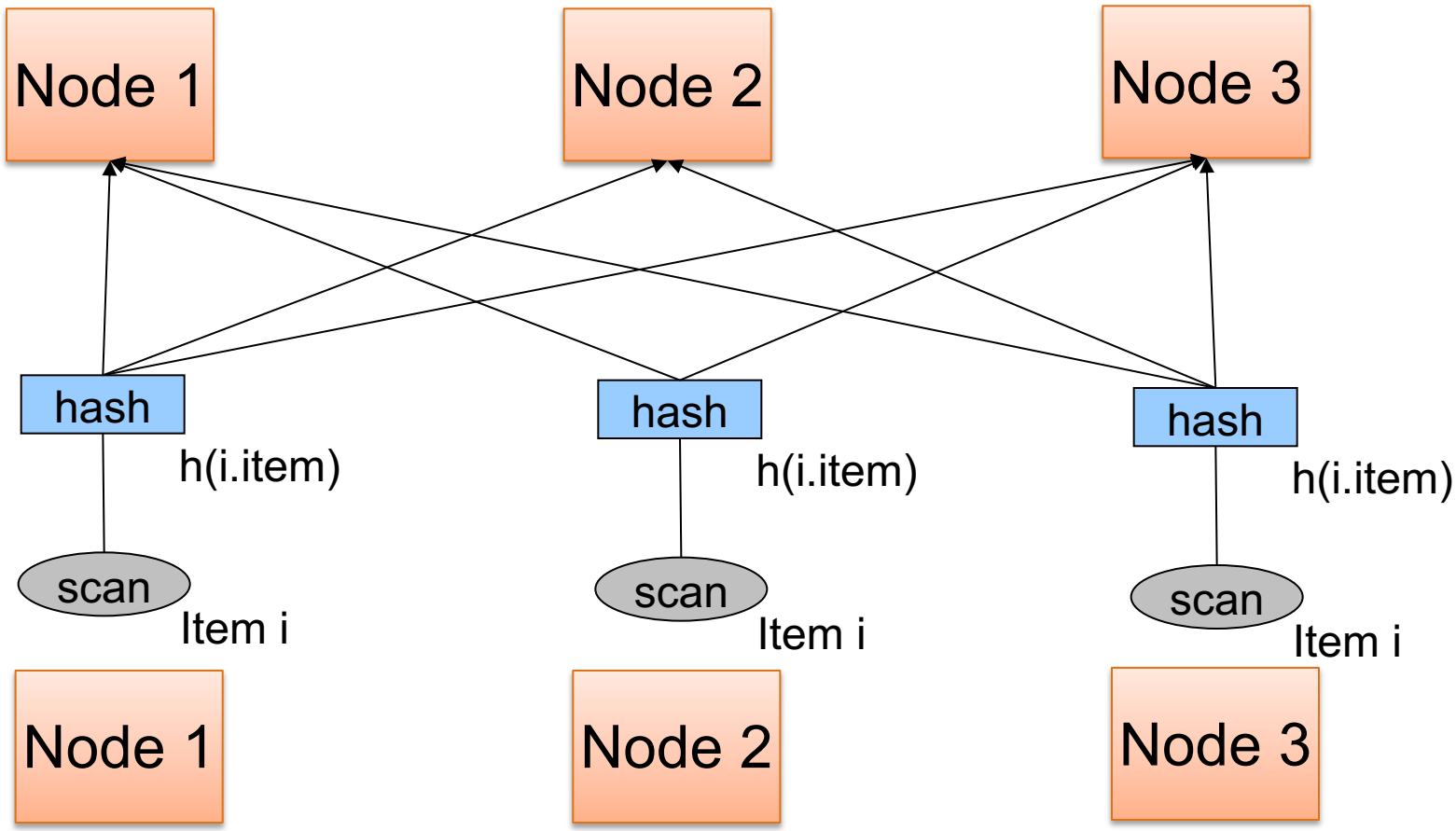




Order(oid, item, date), Line(item, …)

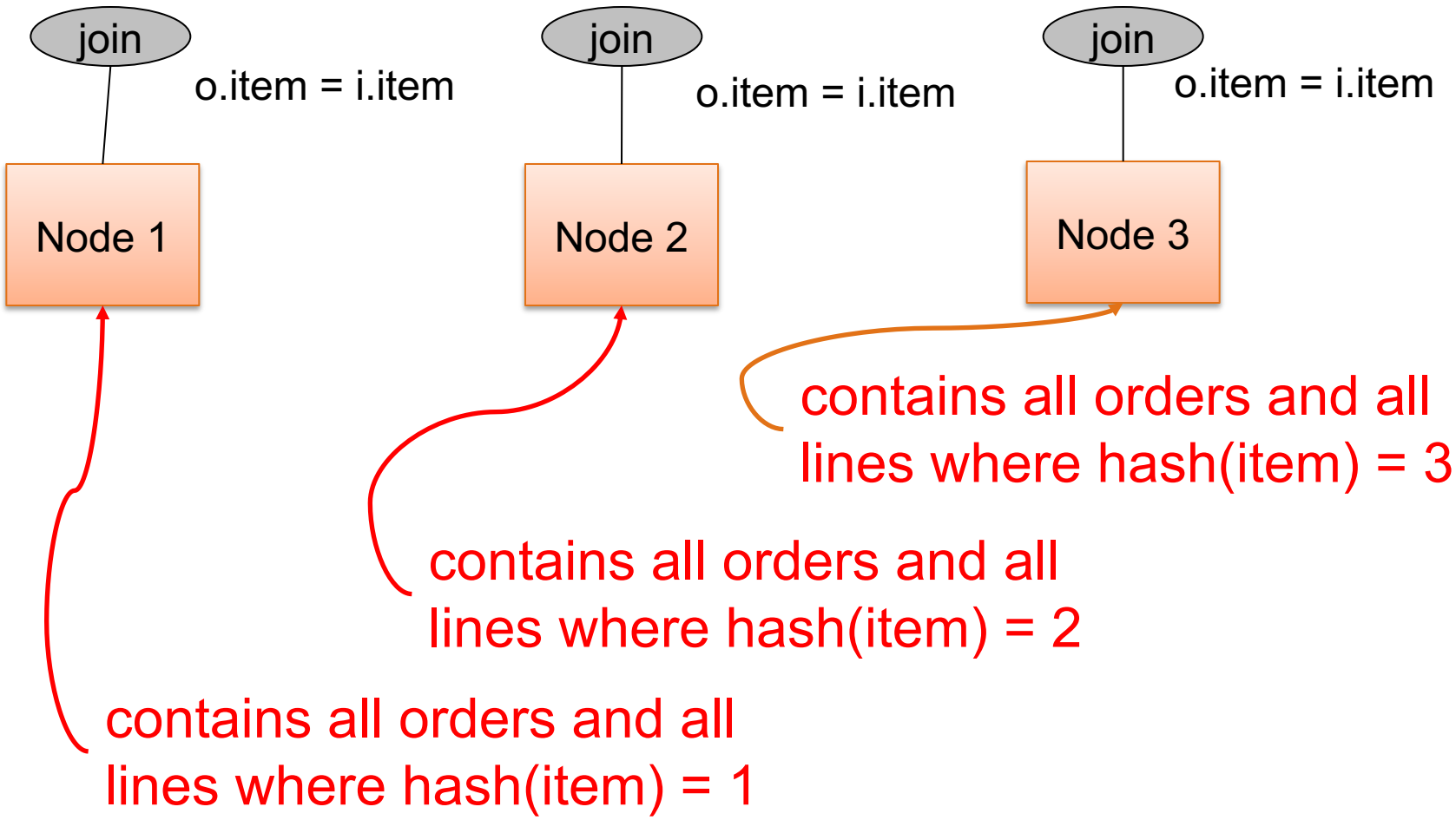
Example Parallel Query Plan





Order(oid, item, date), Line(item, …)

Example Parallel Query Plan



Summary

- Parallel query evaluation is based on data partitioning
- Main challenge: skew
- When the data is skewed (has “heavy hitter” values) then hash partitioning will lead to uneven load, and poor performace
- Skewed data values must be broadcast, e.g. Broadcast join