

Introduction to Data Management

CSE 344

Lecture 23: Parallel Databases

Announcements

- HW7 due tomorrow
- HW8 is posted (1 late day, setup in tomorrow's section)
- Review session schedule (problem solving)

Topic	Date	Venue/Time	Who
RC/RA/Datalog	3/6 (Th) Sections	Sections	Yi-Shu
BCNF/ ERD	3/10 (M)	CSE 303, 4:30-5:30pm	Vaspol
Transaction	3/13 (Th) Sections	Sections	Yi-Shu
Parallel DB/MR	3/14 (F) Class	Class	Sudeepa

- Additional review session: **March 15 (Sat), 2-4 pm, CSE 303**, Sudeepa, office hour format (review of lecture/ assignments/old exams together if you have questions)

HW8

- Will take more hours than other HWs, start early
 - complex setup, queries run for many hours
- MapReduce (Hadoop) w/ declarative language (Pig)
- Cluster will run in Amazon's cloud (AWS)
 - Give your credit card
 - Click, click, click... and you have a MapReduce cluster
- We will analyze a real 0.5TB graph
- Processing the entire data takes hours
 - Problems #1,#2,#3: queries on a subset only
 - Problem #4: entire data

Amazon Warning

- “We **HIGHLY** recommend you remind students to turn off any instances after each class/session – as this can quickly diminish the credits and start charging the card on file. **You are responsible for the overages.**”
- “AWS customers can now use **billing alerts** to help monitor the charges on their AWS bill. You can get started today by visiting your [Account Activity page](#) to enable monitoring of your charges. Then, you can set up a billing alert by simply specifying a bill threshold and an e-mail address to be notified as soon as your estimated charges reach the threshold.”

Outline

- Today: Query Processing in Parallel DBs
- Next Lecture: Parallel Data Processing at Massive Scale (MapReduce)
 - Reading assignment:
Chapter 2 (Sections 1,2,3 only) of Mining of Massive Datasets, by Rajaraman and Ullman
<http://i.stanford.edu/~ullman/mmds.html>

What we did in last lecture

- Why parallel processing?
- What are the possible architectures for a parallel database system?
- What are speedup and scaleup?

Basic Query Processing: Quick Review in Class

Basic query processing **on one node**.

Given relations $R(A,B)$ and $S(B, C)$, **no indexes**, how do we compute:

- **Selection:** $\sigma_{A=123}(R)$
- **Group-by:** $\gamma_{A, \text{sum}(B)}(R)$
- **Join:** $R \bowtie S$

Basic Query Processing: Quick Review in Class

Basic query processing **on one node**.

Given relations $R(A,B)$ and $S(B, C)$, **no indexes**, how do we compute:

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

Parallel Query Processing

How do we **compute** these operations on a **shared-nothing parallel** db?

- **Selection**: $\sigma_{A=123}(R)$ (that's easy, won't discuss...)
- **Group-by**: $\gamma_{A, \text{sum}(B)}(R)$
- **Join**: $R \bowtie S$

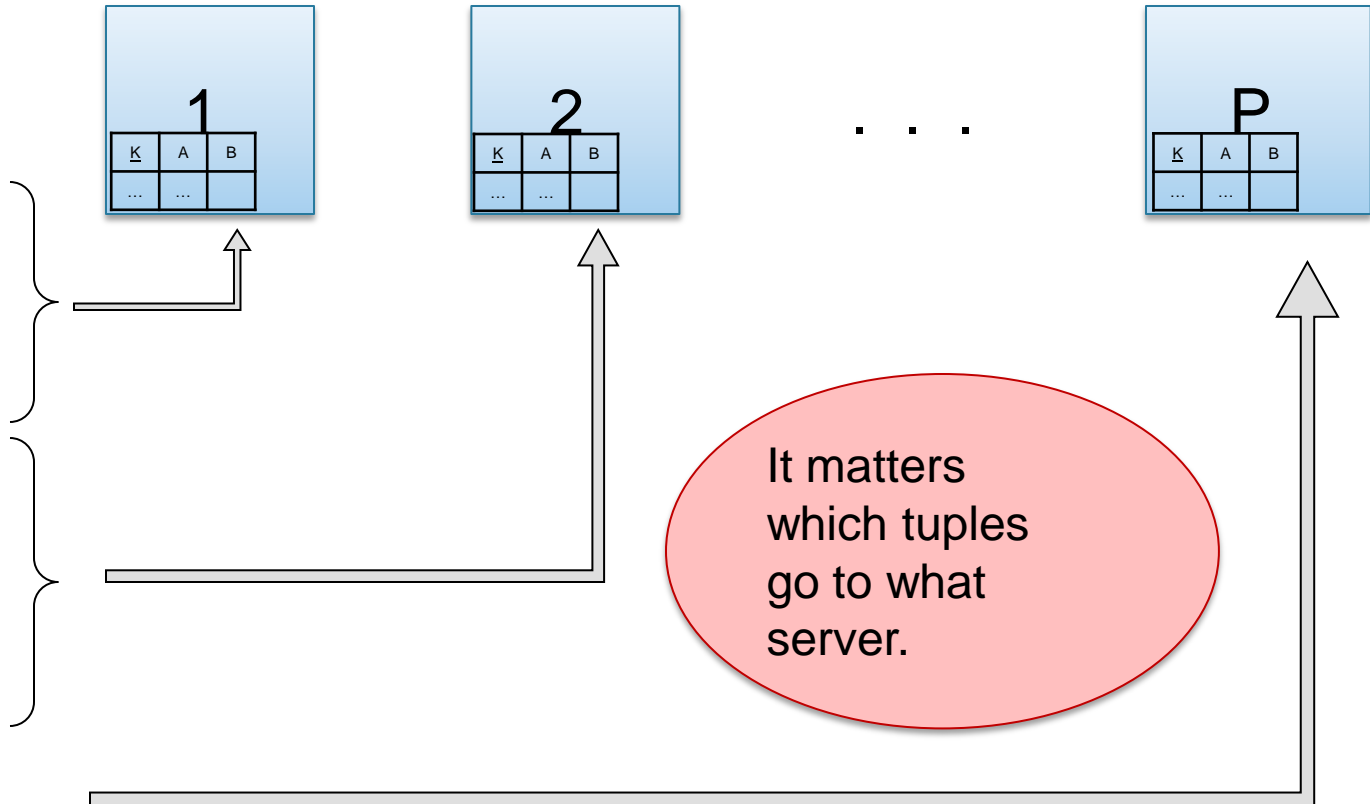
Before we answer that: how do we **store** R (and S) on a shared-nothing parallel db?

Horizontal Data Partitioning

Data:

Servers:

<u>K</u>	A	B
...	...	



Horizontal Data Partitioning

- **Block Partition:**
 - Partition tuples arbitrarily s.t. $\text{size}(R_1) \approx \dots \approx \text{size}(R_P)$
- **Hash partitioned on attribute A:**
 - Tuple t goes to chunk i , where $i = h(t.A) \bmod P + 1$
- **Range partitioned on attribute A:**
 - Partition the range of A into $-\infty = v_0 < v_1 < \dots < v_P = \infty$
 - Tuple t goes to chunk i , if $v_{i-1} < t.A < v_i$

Parallel GroupBy

Data: $R(\underline{K}, A, B, C)$

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

Discuss in class how to compute in each case:

- R is hash-partitioned on A
- R is block-partitioned
- R is hash-partitioned on K (key)

Q. Which one can leverage locality of tuples (less communication)?

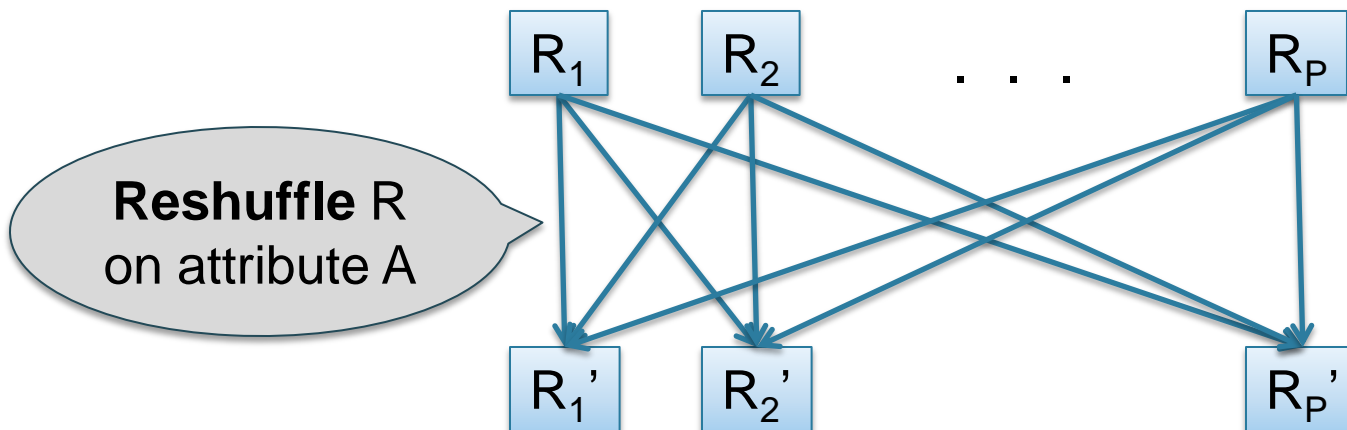
What will the others do?

Parallel GroupBy

Data: $R(\underline{K}, A, B, C)$

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

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



Parallel Join

- **Data:** $R(\underline{K1}, A, B)$, $S(\underline{K2}, B, C)$
- **Query:** $R(\underline{K1}, A, B) \bowtie_{B=B} S(\underline{K2}, B, C)$

Initially, both R and S are horizontally partitioned on K1 and K2

R_1, S_1

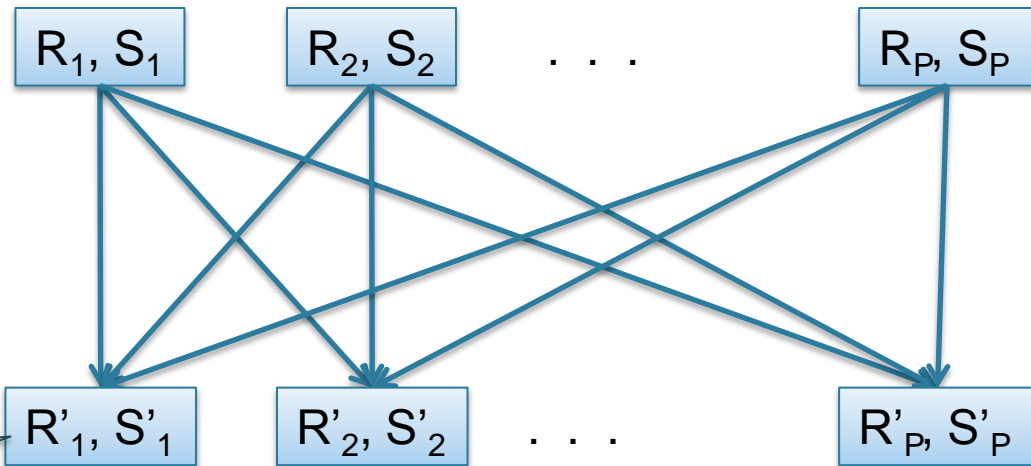
R_2, S_2

R_P, S_P

Parallel Join

- **Data:** $R(\underline{K1}, A, B)$, $S(\underline{K2}, B, C)$
- **Query:** $R(\underline{K1}, A, B) \bowtie S(\underline{K2}, B, C)$

Initially, both R and S are horizontally partitioned on K1 and K2



Reshuffle R on R.B
and S on S.B

Each server computes
the join locally

Speedup and Scaleup

- Consider:
 - Query: $\gamma_{A, \text{sum}(C)}(R)$
 - Runtime: dominated by reading chunks from disk
- If we double the number of nodes P , what is the new running time?
- If we double both P and the size of R , what is the new running time?

Speedup and Scaleup

- Consider:
 - Query: $\gamma_{A, \text{sum}(C)}(R)$
 - Runtime: dominated by reading chunks from disk
- If we double the number of nodes P , what is the new running time?
 - Half (each server holds $\frac{1}{2}$ as many chunks)
- If we double both P and the size of R , what is the new running time?
 - Same (each server holds the same # of chunks)

Uniform Data v.s. Skewed Data

- Let $R(\underline{K}, A, B, C)$; which of the following partition methods may result in **skewed** partitions?
- Block partition
- Hash-partition
 - On the key K
 - On the attribute A
- Range-partition
 - On the key K
 - On the attribute A

Uniform Data v.s. Skewed Data

- Let $R(\underline{K}, A, B, C)$; which of the following partition methods may result in **skewed** partitions?

- Block partition

Uniform

- Hash-partition

Uniform

Assuming uniform hash function

- On the key K
- On the attribute A

May be skewed

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

- Range-partition

- On the key K
- On the attribute A

May be skewed

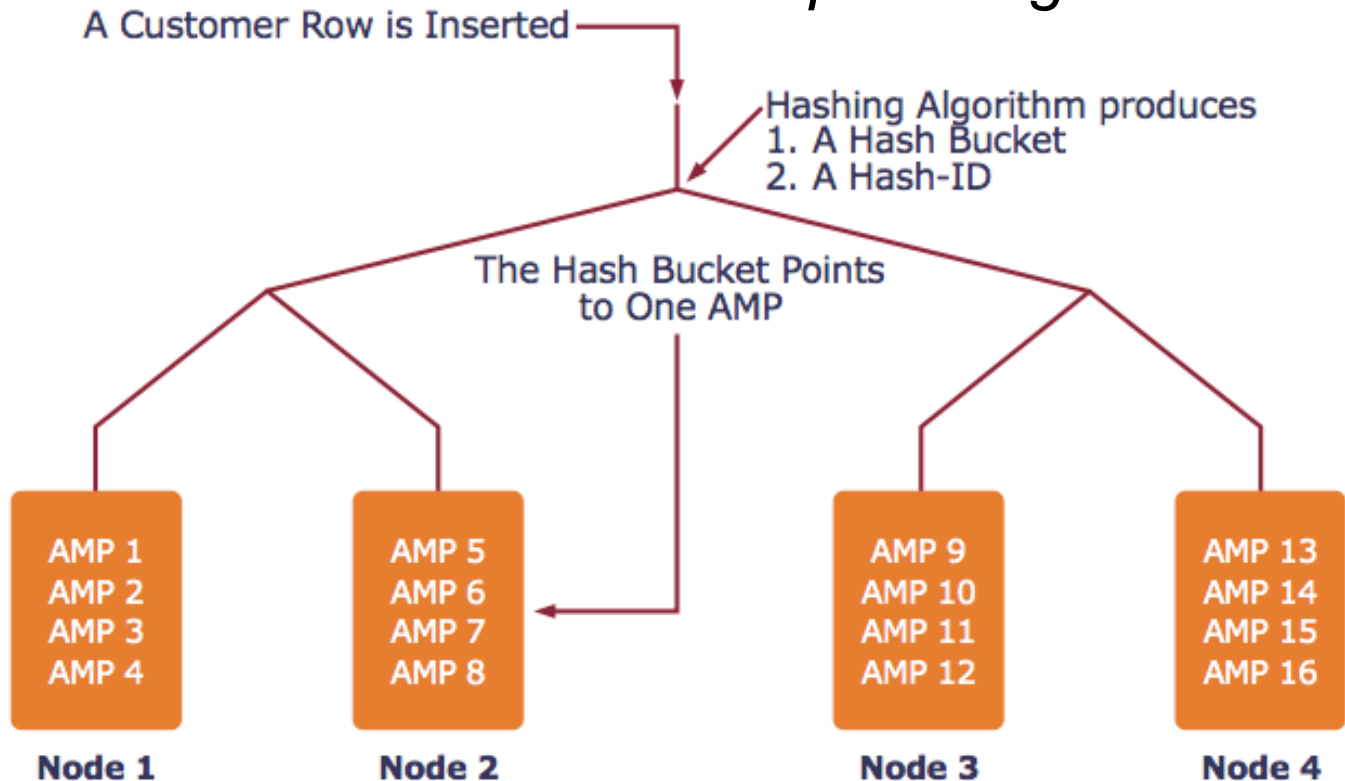
Difficult to partition the range of A uniformly

Parallel DBMS

- Parallel query plan: tree of parallel operators
Intra-operator parallelism
 - Data streams from one operator to the next
 - Typically all cluster nodes process all operators
- Can run multiple queries at the same time
Inter-query parallelism
 - Queries will share the nodes in the cluster
- Notice that user does not need to know how his/her SQL query was processed

Loading Data into a Parallel DBMS

Example using Teradata System

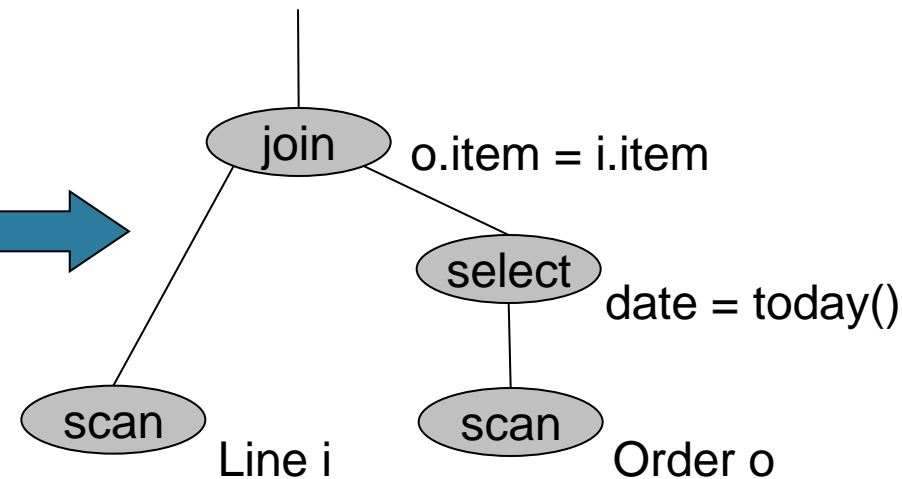


AMP = “Access Module Processor” = unit of parallelism

Example Parallel Query Execution

Find all orders from today, along with the items ordered

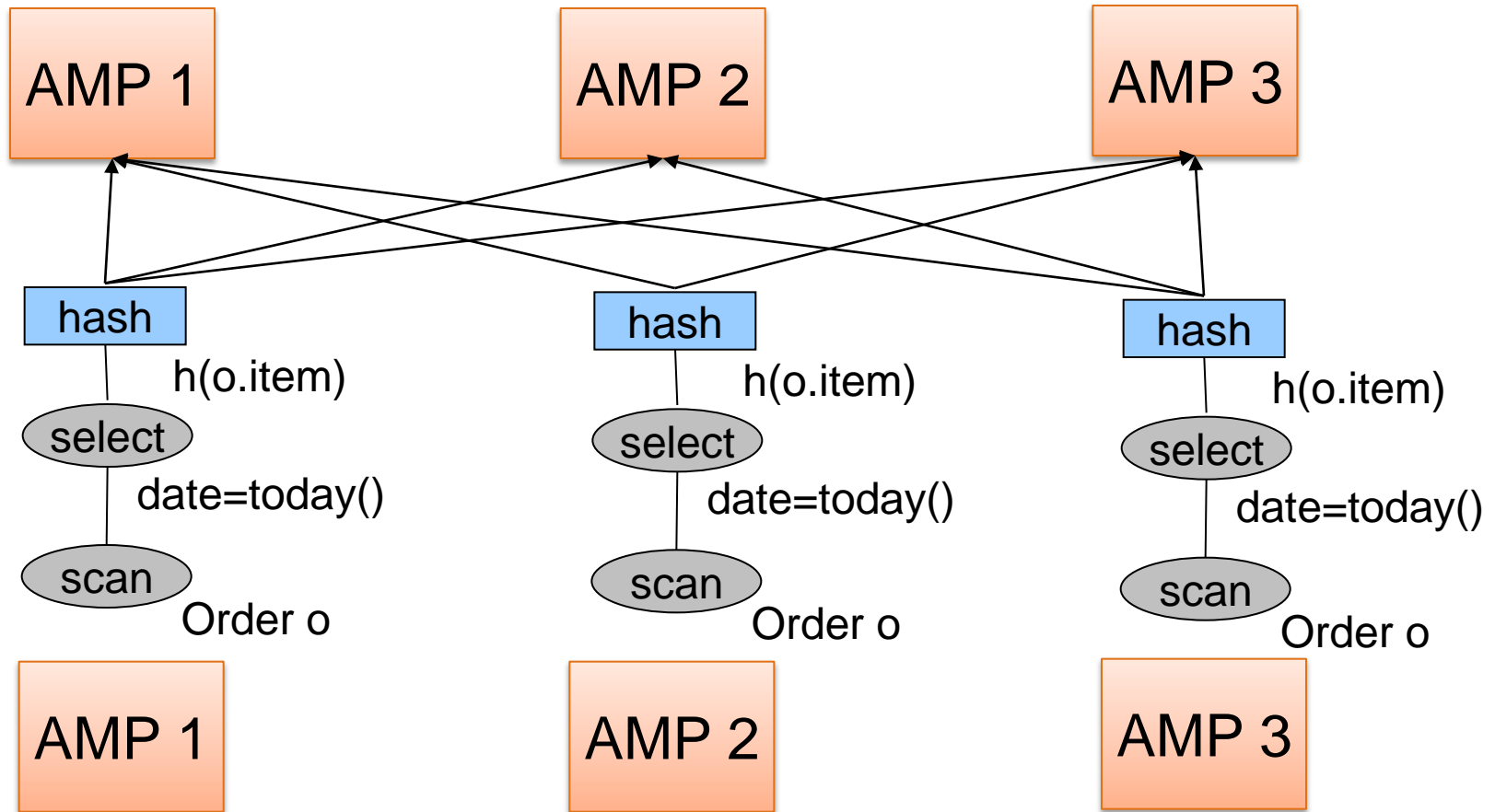
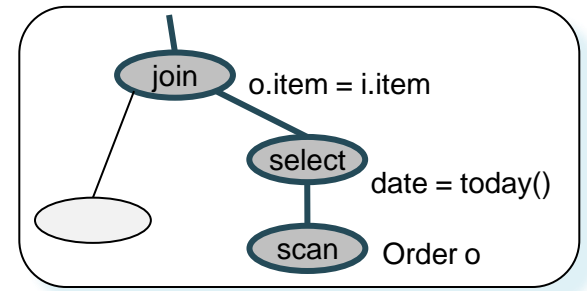
```
SELECT *  
  FROM Order o, Line i  
 WHERE o.item = i.item  
    AND o.date = today()
```



Order(oid, item, date), Line(item, ...)

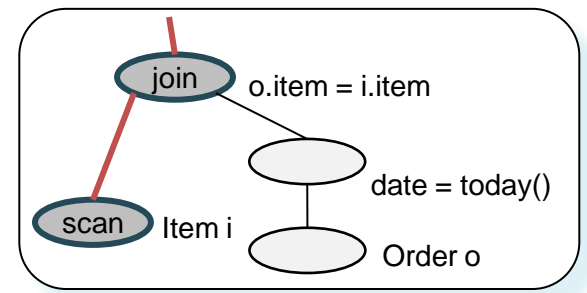
Example Parallel Query Execution

Scan, select, hash Order

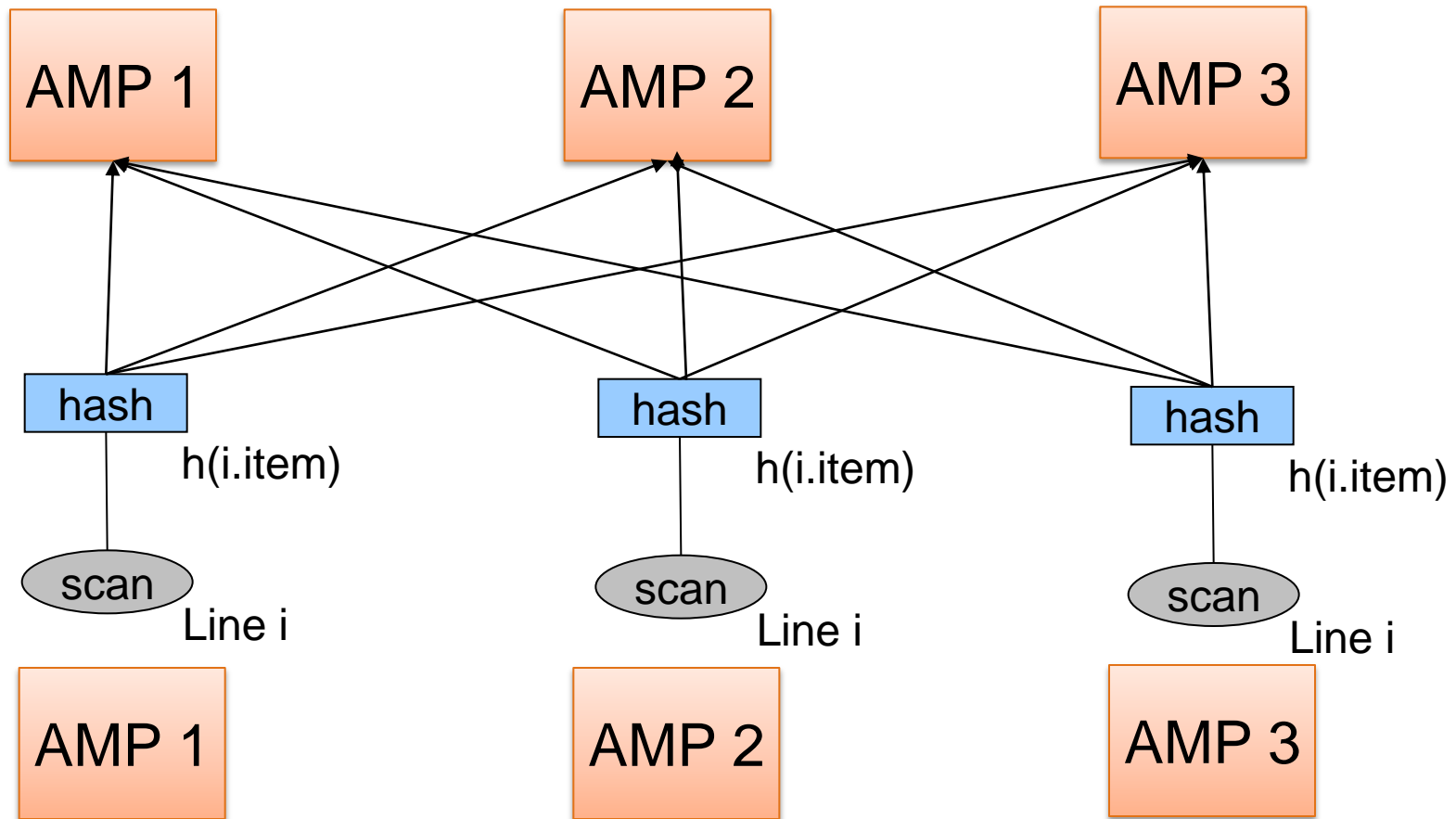


Order(oid, item, date), Line(item, ...)

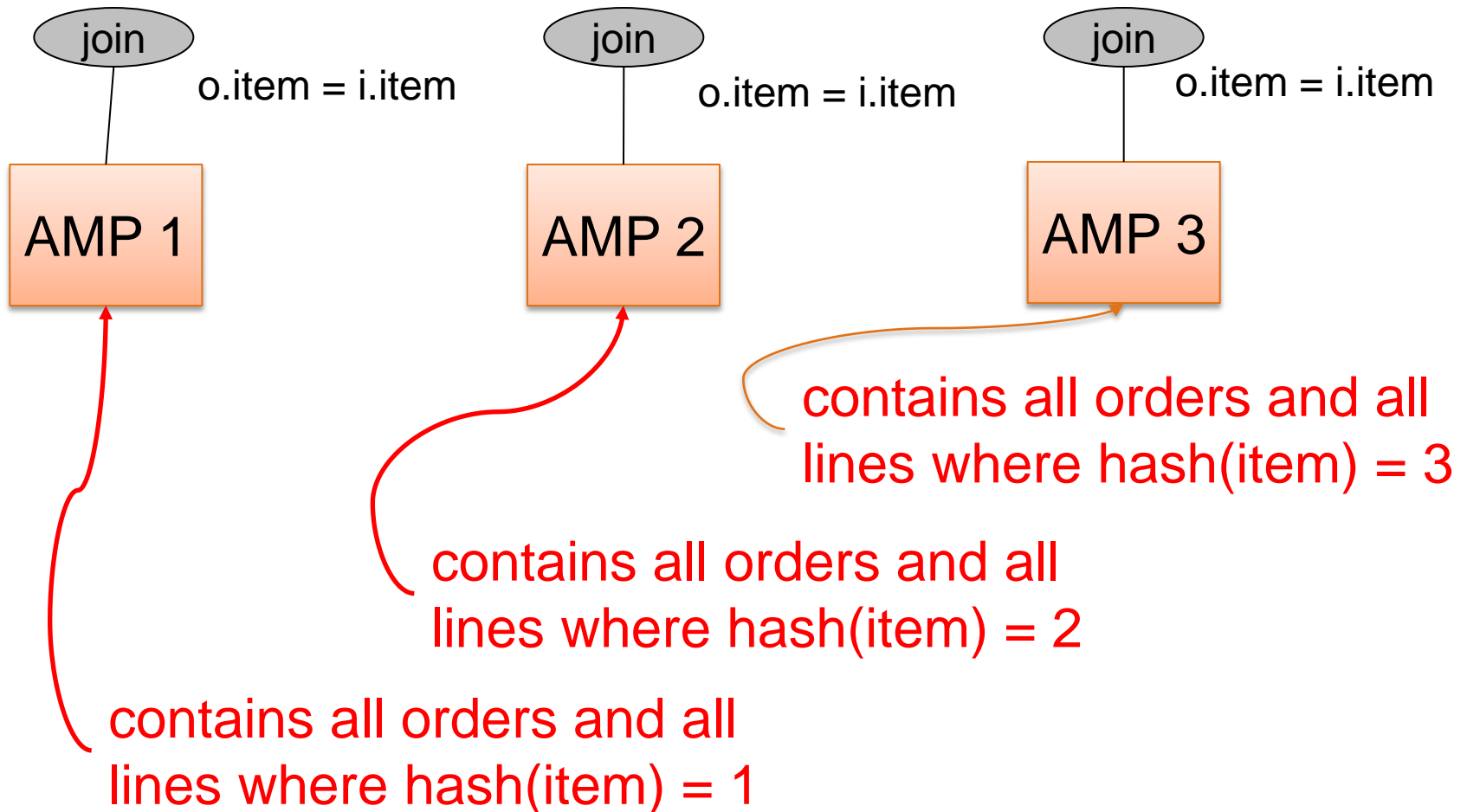
Example Parallel Query Execution



Scan, hash Line



Example Parallel Query Execution



Parallel Dataflow Implementation

- Use relational operators unchanged
- Add a special *shuffle* operator
 - Handle data routing, buffering, and flow control
 - Inserted between consecutive operators in the query plan
 - Two components: ShuffleProducer and ShuffleConsumer
 - Producer pulls data from operator and sends to n consumers
 - Producer acts as driver for operators below it in query plan
 - Consumer buffers input data from n producers and makes it available to operator through getNext interface
- You will use this extensively in 444

Review: Parallel DBMS

Figure 5 - Master server performs global planning and dispatch

