### **Parallel Databases**

When/why do we need them?

### Two Kinds to Parallel Data Processing

- Parallel databases, developed starting with the 80s (this lecture)
  - OLTP (Online Transaction Processing)
  - OLAP (Online Analytic Processing, or Decision Support)
- General purpose distributed processing: MapReduce, Spark

– Mostly for Decision Support Queries

### Performance Metrics for Parallel DBMSs

- P = the number of nodes (processors, computers)
- Speedup:
  - More nodes, same data  $\rightarrow$  higher speed
- Scaleup:
  - More nodes, more data  $\rightarrow$  same speed
- OLTP: "Speed" = transactions per second (TPS)
- Decision Support: "Speed" = query time

### **Shared Nothing**



### Approaches to Parallel Query Evaluation

- Inter-query parallelism
  - Transaction per node
  - OLTP
- Inter-operator parallelism
  - Operator per node
  - Both OLTP and Decision Support
- Intra-operator parallelism
  - Operator on multiple nodes
  - Decision Support

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 attr. A as key
  - When a new key is equal to an existing one, add B to the value
- Join: R ⊠ S
  - Scan file S, insert into a hash table using attr. B as key
  - Scan file R, probe the hash table using attr. B

# **Distributed Query Processing**

 Data is horizontally partitioned on many servers

• Operators may require data reshuffling

### Horizontal Data Partitioning



### Horizontal Data Partitioning



## Horizontal Data Partitioning

#### • Block Partition:

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

## Parallel GroupBy

#### Data: $R(\underline{K}, A, B, C)$ Query: $\gamma_{A,sum(C)}(R)$ 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

### Parallel GroupBy

- Data:  $R(\underline{K},A,B,C)$ Query:  $\gamma_{A,sum(C)}(R)$
- R is block-partitioned or hash-partitioned on K



### Parallel Join

Data: R(<u>K1</u>,A, B), S(<u>K2</u>, B, C)
Query: R(<u>K1</u>,A,B) ⋈ S(<u>K2</u>,B,C)

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



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



### Speedup and Scaleup

- Consider:
  - Query:  $\gamma_{A,sum(C)}(R)$
  - 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 ½ 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(K,A,B,C); which of the following partition methods may result in skewed partitions?



### **Example Parallel Query Execution**

Find all orders from today, along with the items ordered



### Order(oid, item, date), Line(item, ...) Example Parallel Query Execution





Order(<u>oid</u>, item, date), Line(item, ...) **Example Parallel** join o.item = i.item **Query Execution** scan Item i



date = today()

Order o

### **Example Parallel Query Execution**

