CSE 444: Database Internals

Lectures 20-21

Parallel DBMSs

What We Have Already Learned

- Overall architecture of a DBMS
- Internals of query execution:
  - Data storage and indexing
  - Buffer management
  - Query evaluation including operator algorithms
  - Query optimization
- Internals of transaction processing:
  - Concurrency control: pessimistic and optimistic
  - Transaction recovery: undo, redo, and undo/redo

Where We Are Headed Next

- Scaling the execution of a query
  - Parallel DBMS
  - MapReduce
  - Spark and Myria

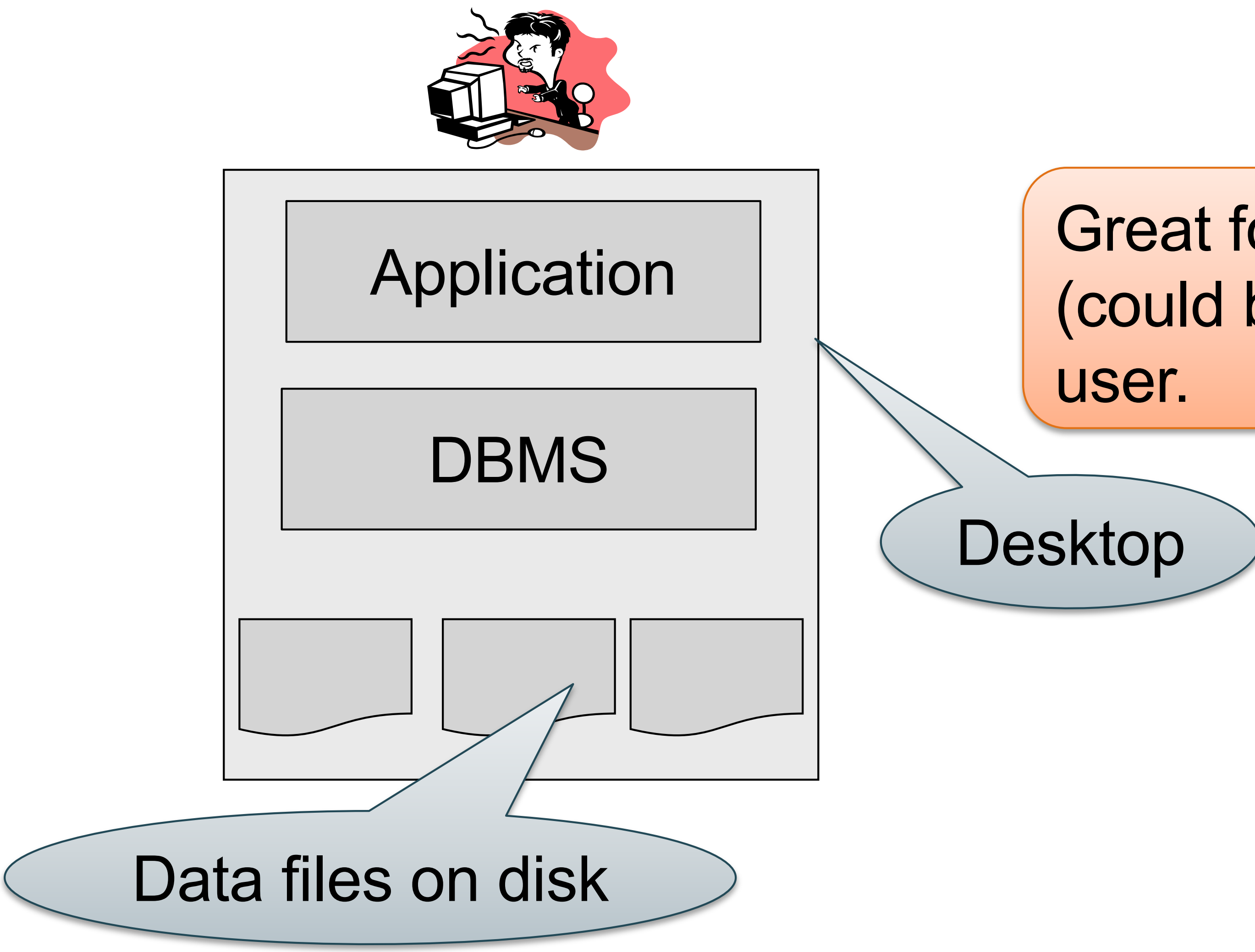
- Scaling transactions
  - Distributed transactions
  - Replication

- Scaling with NoSQL and NewSQL

Reading Assignments

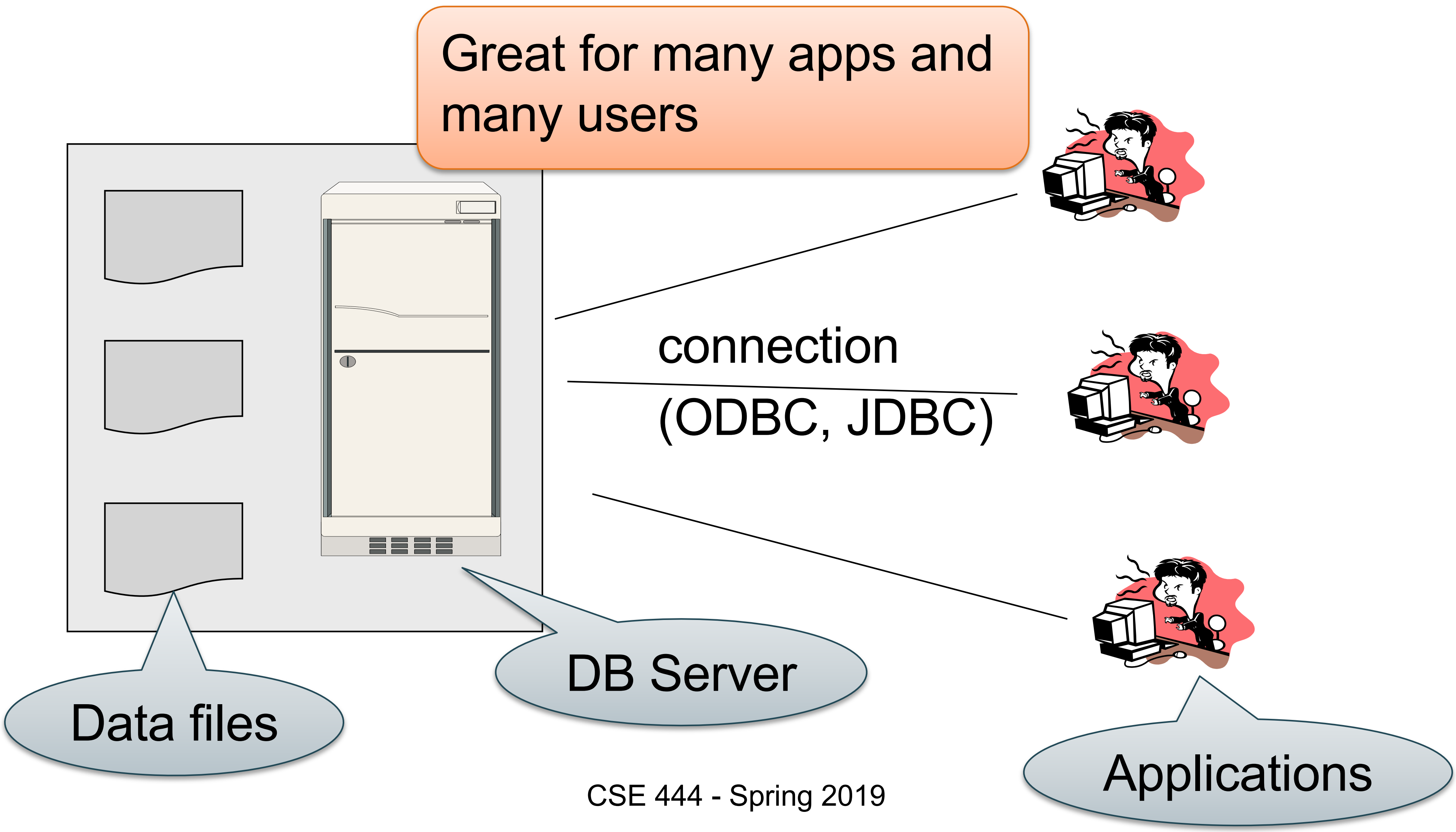
- Main textbook Chapter 20.1
- Database management systems.
  Ramakrishnan&Gehrke.
  Third Ed. Chapter 22.11

DBMS Deployment: Local

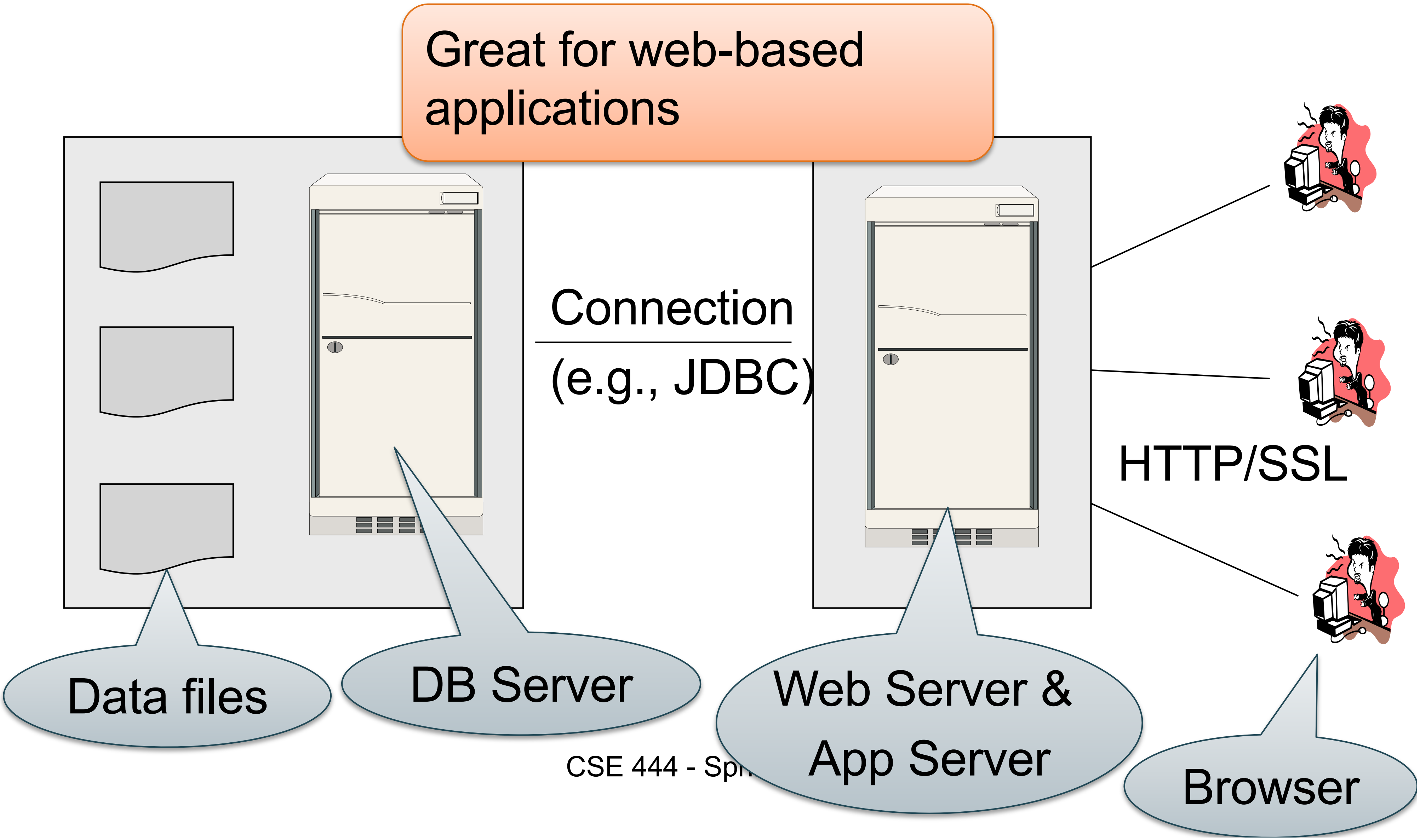


Great for one application (could be more) and one user.

DBMS Deployment: Client/Server

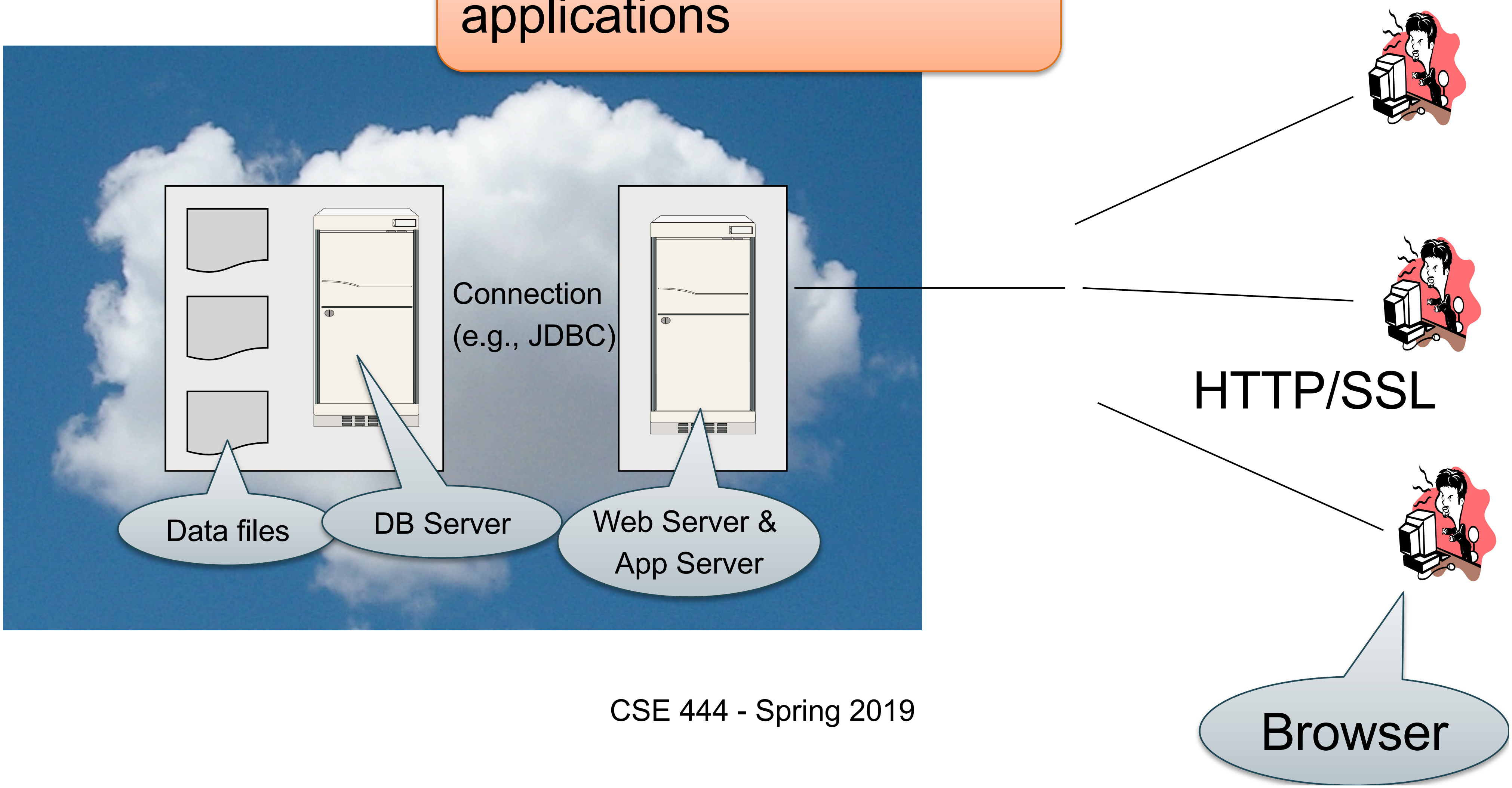


DBMS Deployment: 3 Tiers

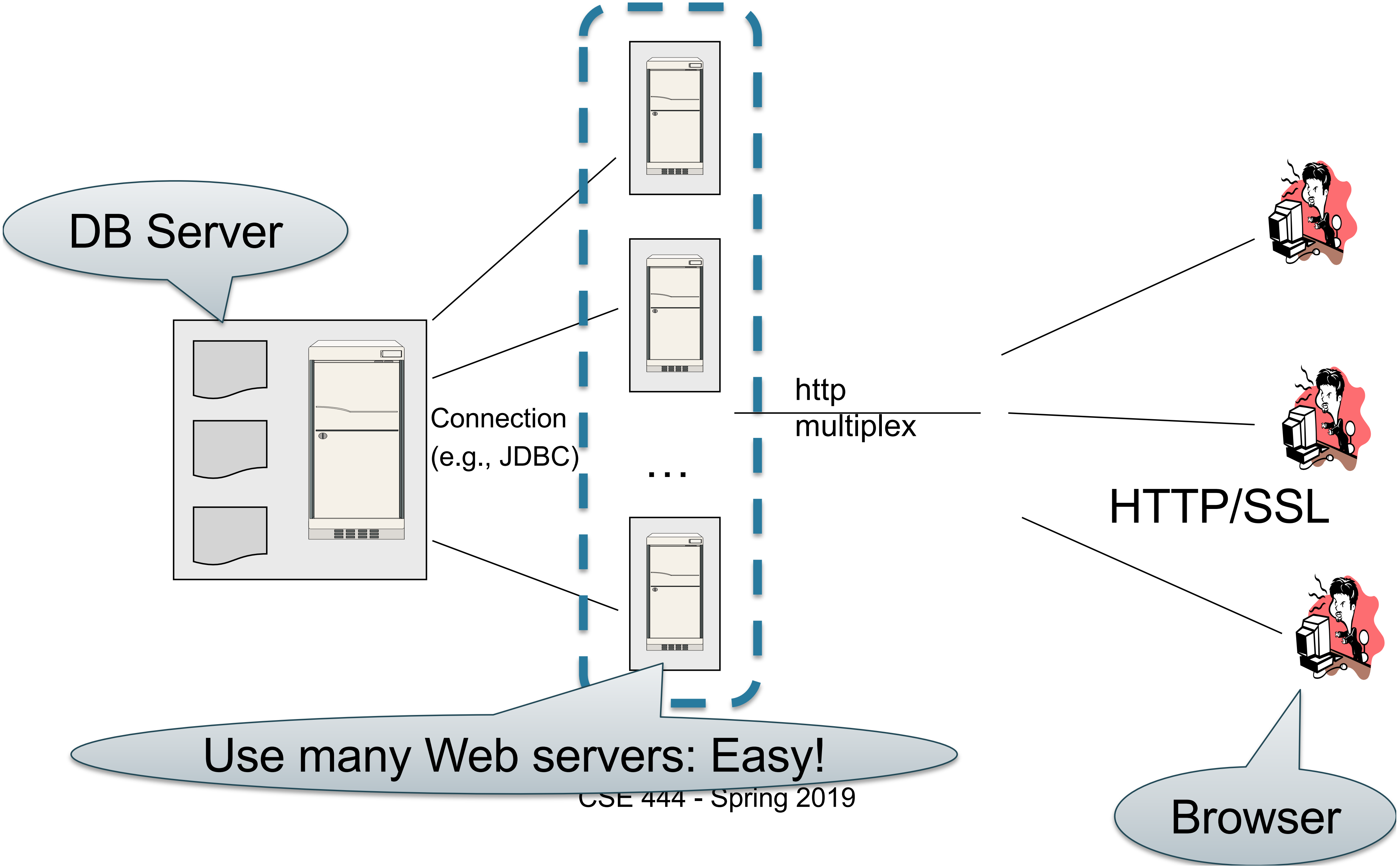


DBMS Deployment: Cloud

Great for web-based applications

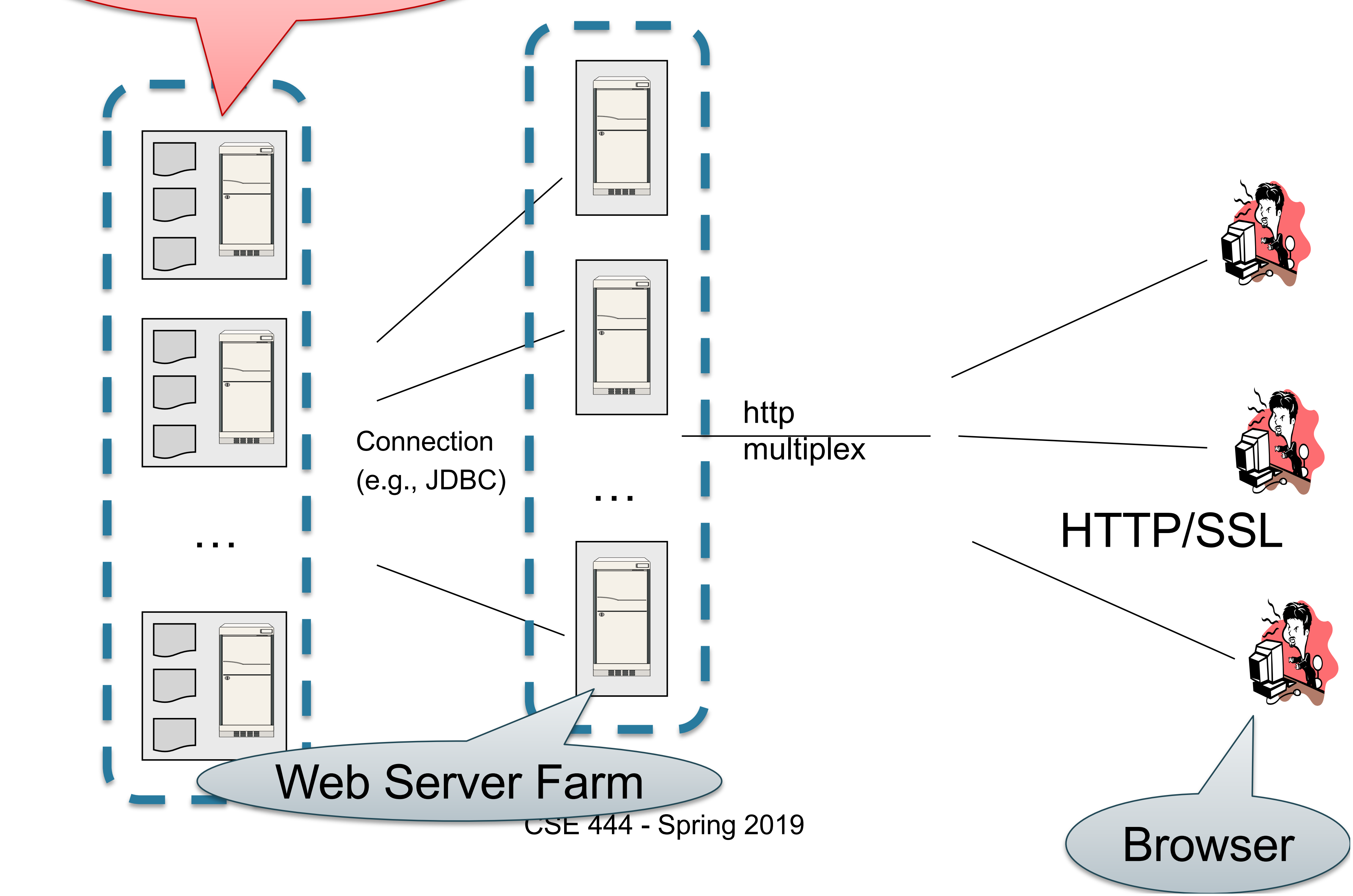


How to Scale?



DB Server
Connection
(e.g., JDBC)
…
http
multiplex
HTTP/SSL
Use many Web servers: Easy!
Browser

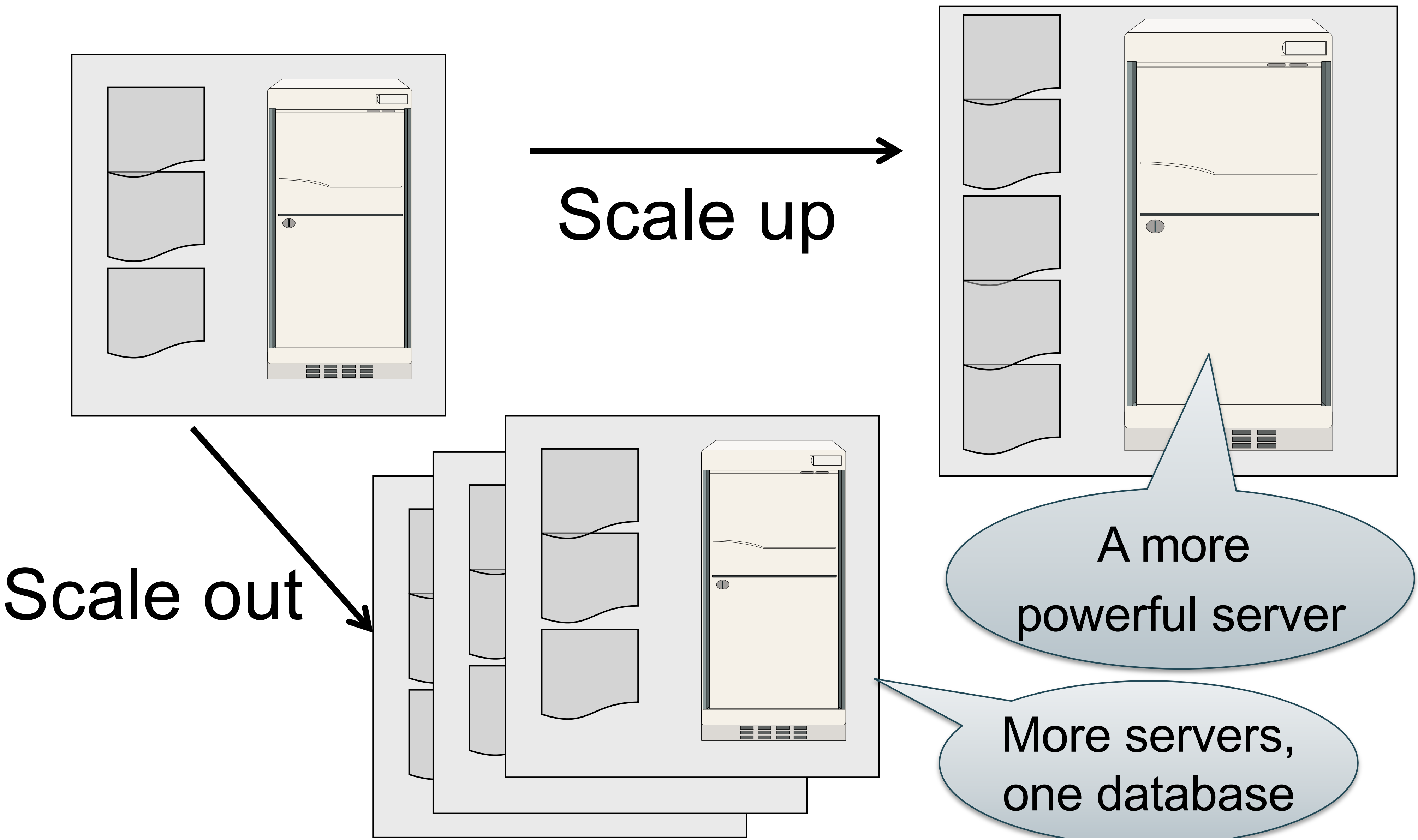
ow to Scale?


Many DBMS instances: HARD
...
Connection (e.g., JDBC)
...
http multiplex
HTTP/SSL
Web Server Farm
Browser

How to Scale?

- We can easily replicate the web servers and the application servers
- We cannot so easily replicate the database servers, because the database is unique
- We need to design ways to scale up the DBMS

How to Scale a DBMS?



What to scale?

- OLTP: Transactions per second
  - OLTP = Online Transaction Processing
- OLAP: Query response time
  - OLAP = Online Analytical Processing

Scaling Transactions Per Second

- Amazon
- Facebook
- Twitter
- … your favorite Internet application…

- Goal is to scale OLTP workloads

- We will get back to this next week

Scaling Single Query Response Time

- Goal is to scale OLAP workloads
- That means the analysis of massive datasets

This Week: Focus on Scaling a Single Query

Big Data

- Buzzword?

- Definition from industry:
  - High Volume
  - High Variety
  - High Velocity

http://www.gartner.com/newsroom/id/1731916

Big Data

Volume is not an issue

- Databases *do* parallelize easily; techniques available from the 80's
  - Data partitioning
  - Parallel query processing
- SQL is *embarrassingly parallel*

- We will learn how to do this

Big Data

New workloads are an issue

- Big volumes, small analytics
  - OLAP queries: join + group-by + aggregate
  - Can be handled by today's RDBMSs (e.g., Teradata)

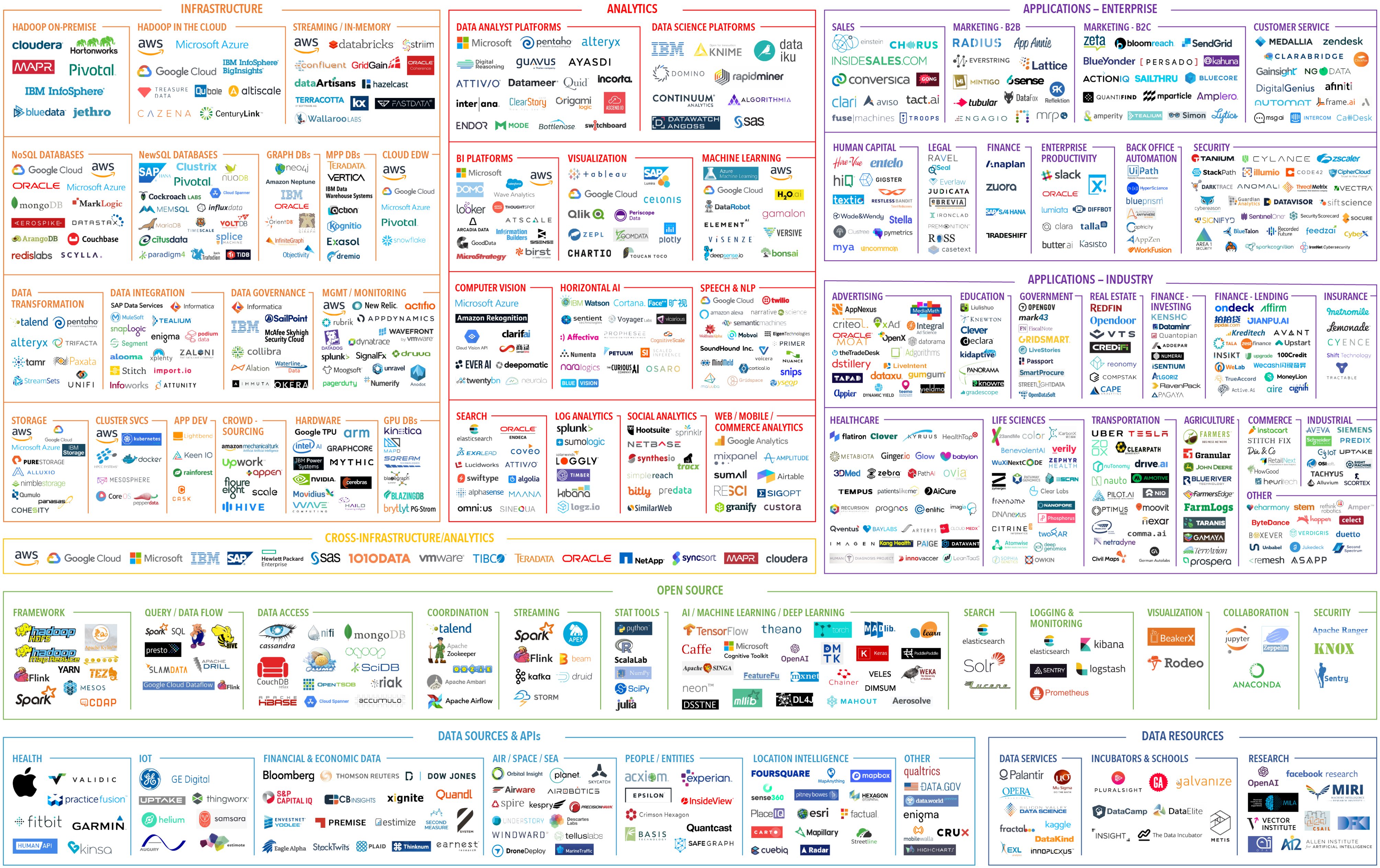
- Big volumes, big analytics
  - More complex Machine Learning, e.g. click prediction, topic modeling, SVM, k-means
  - Requires innovation – Active research area

Data Analytics Companies

Fifteen years ago, explosion of db analytics companies

- Greenplum founded in 2003 acquired by EMC in 2010; A parallel shared-nothing DBMS (this lecture)
- Vertica founded in 2005 and acquired by HP in 2011; A parallel, column-store shared-nothing DBMS
- DATAllegro founded in 2003 acquired by Microsoft in 2008; A parallel, shared-nothing DBMS
- Aster Data Systems founded in 2005 acquired by Teradata in 2011; A parallel, shared-nothing, MapReduce-based data processing system (in two lectures). SQL on top of MapReduce
- Netezza founded in 2000 and acquired by IBM in 2010. A parallel, shared-nothing DBMS.

BIG DATA & AI LANDSCAPE 2018



Final 2018 version, updated 07/15/2018

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mattturck.com/bigdata2018

FIRSTMARK
EARLY STAGE VENTURE CAPITAL

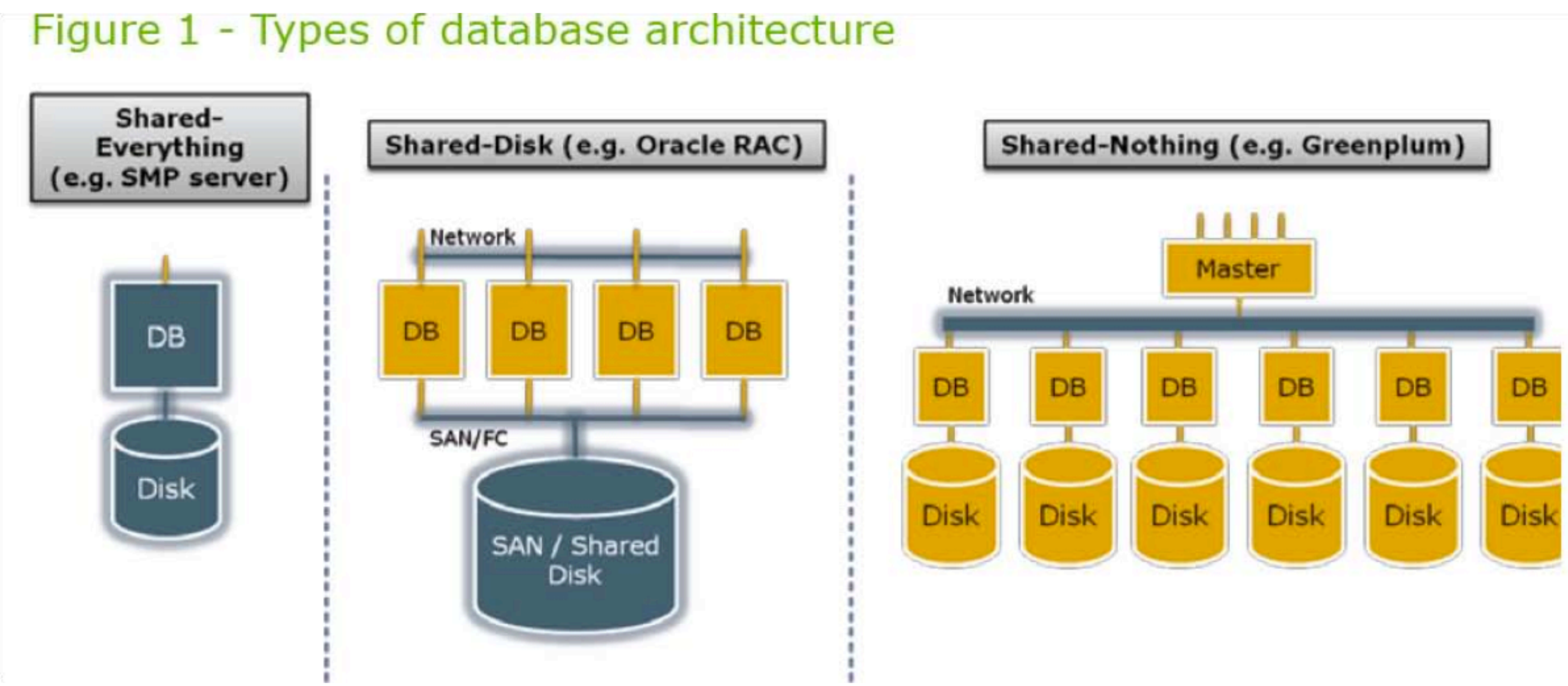
Two Fundamental Approaches to Parallel Data Processing

- Parallel databases, developed starting with the 80s (this lecture)
  - For both OLTP (transaction processing)
  - And for OLAP (decision support queries)

- MapReduce, first developed by Google, published in 2004 (in two lectures)
  - Only for decision support queries

Today we see convergence of the two approaches

Architectures for Parallel DMBSs



From: Greenplum Database Whitepaper

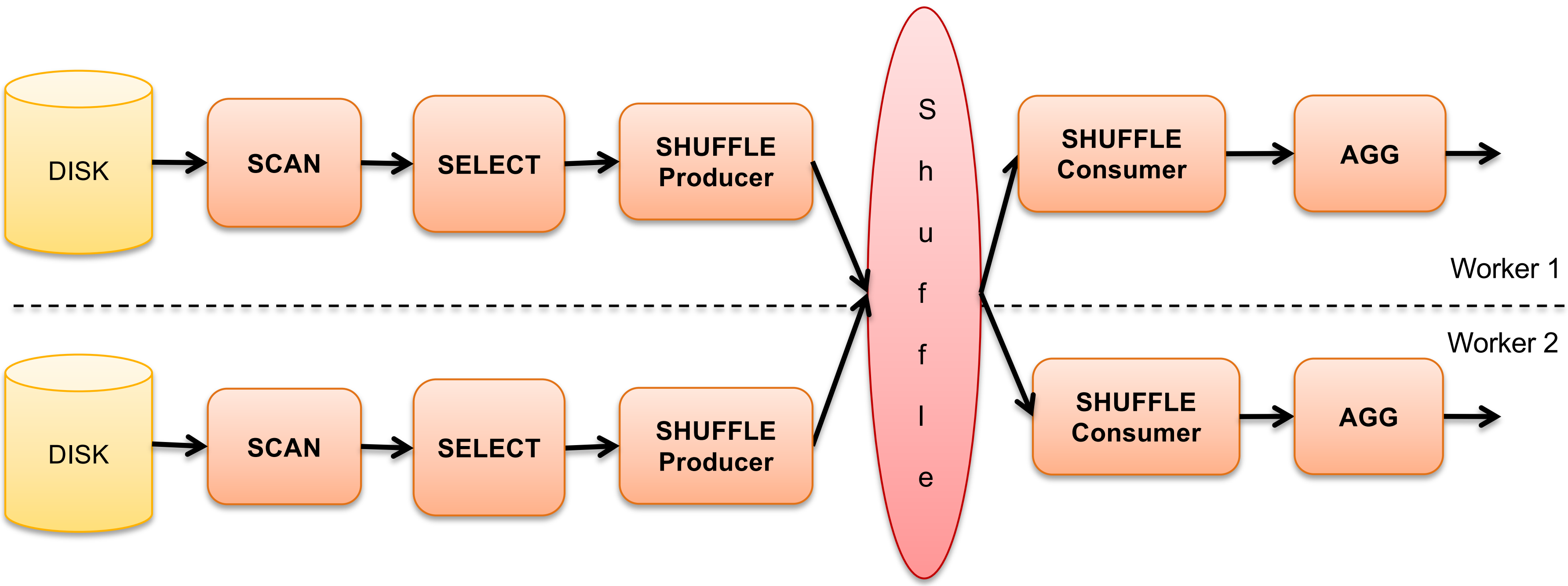
SAN = "Storage Area Network"

Our Focus: Shared-Nothing DBMS

Parallel Query Evaluation

- Multiple DBMS instances (= processes) also called "nodes" execute on machines in a cluster
  - One instance plays role of the coordinator
  - Other instances play role of workers
- Applications interact with coordinator
- Workers execute queries
  - Typically **all workers execute the same plan**
    - **Intra-operator parallelism & intra-query parallelism**
  - Some operations may execute at subsets of workers
  - Workers can execute **multiple queries at the same time**
    - **Inter-query parallelism**

Parallel Query Execution



Parallel Query Evaluation

New operator: Shuffle

- Origin: **Exchange** operator from Volcano system
- Serves to re-shuffle data between processes
  - Handles data routing, buffering, and flow control
- Two parts: ShuffleProducer and ShuffleConsumer
- Producer:
  - Pulls data from child 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

Parallel DBMSs

- Performance metrics
  - **Speedup**: More nodes, same data -> higher speed
  - **Scaleup**: More nodes, more data -> same speed
  - Speed = query execution time
- Key challenges
  - Start-up costs
  - Interference
  - Skew

Parallel Query Processing

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

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

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

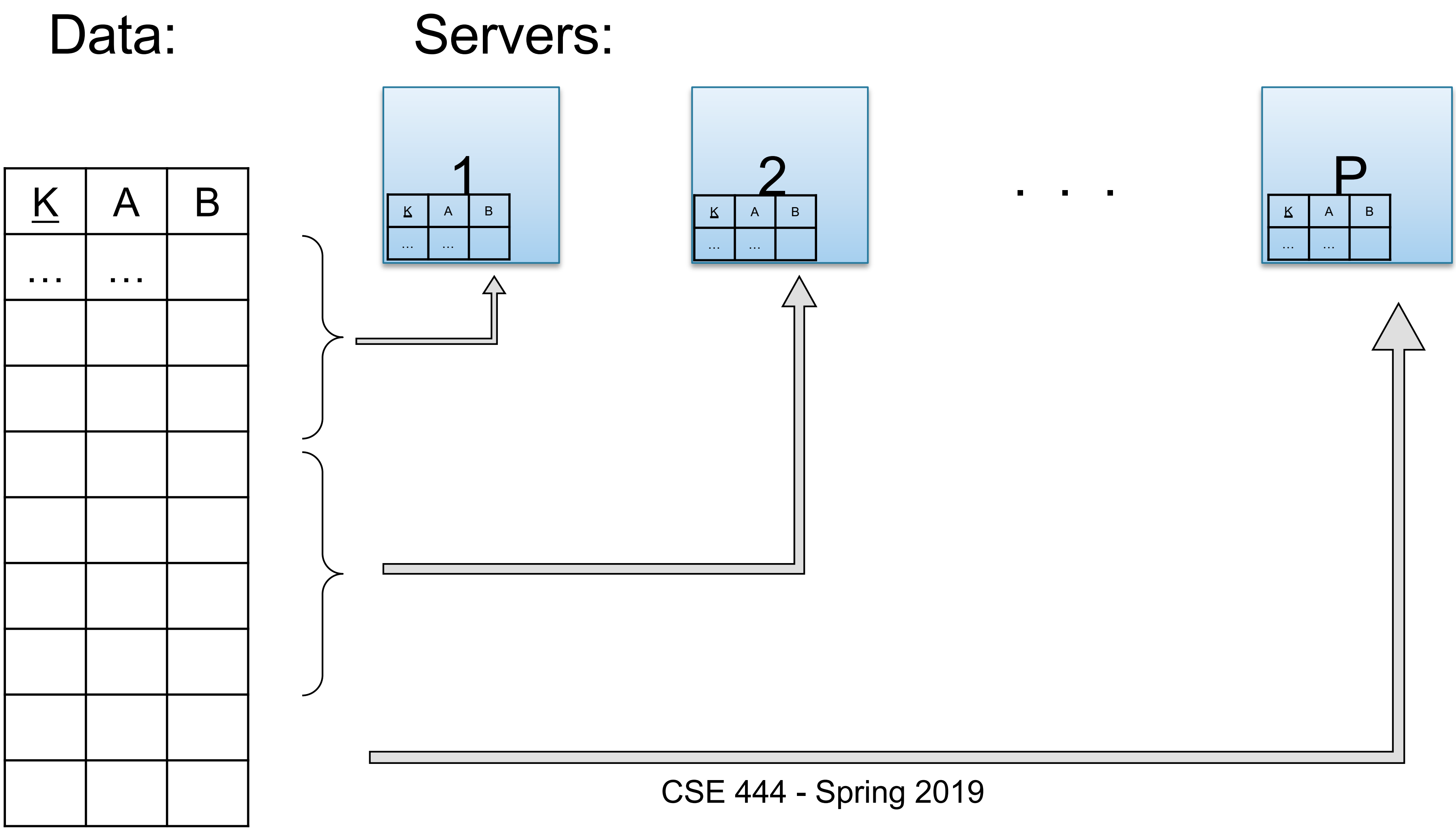
Horizontal Data Partitioning

Data:

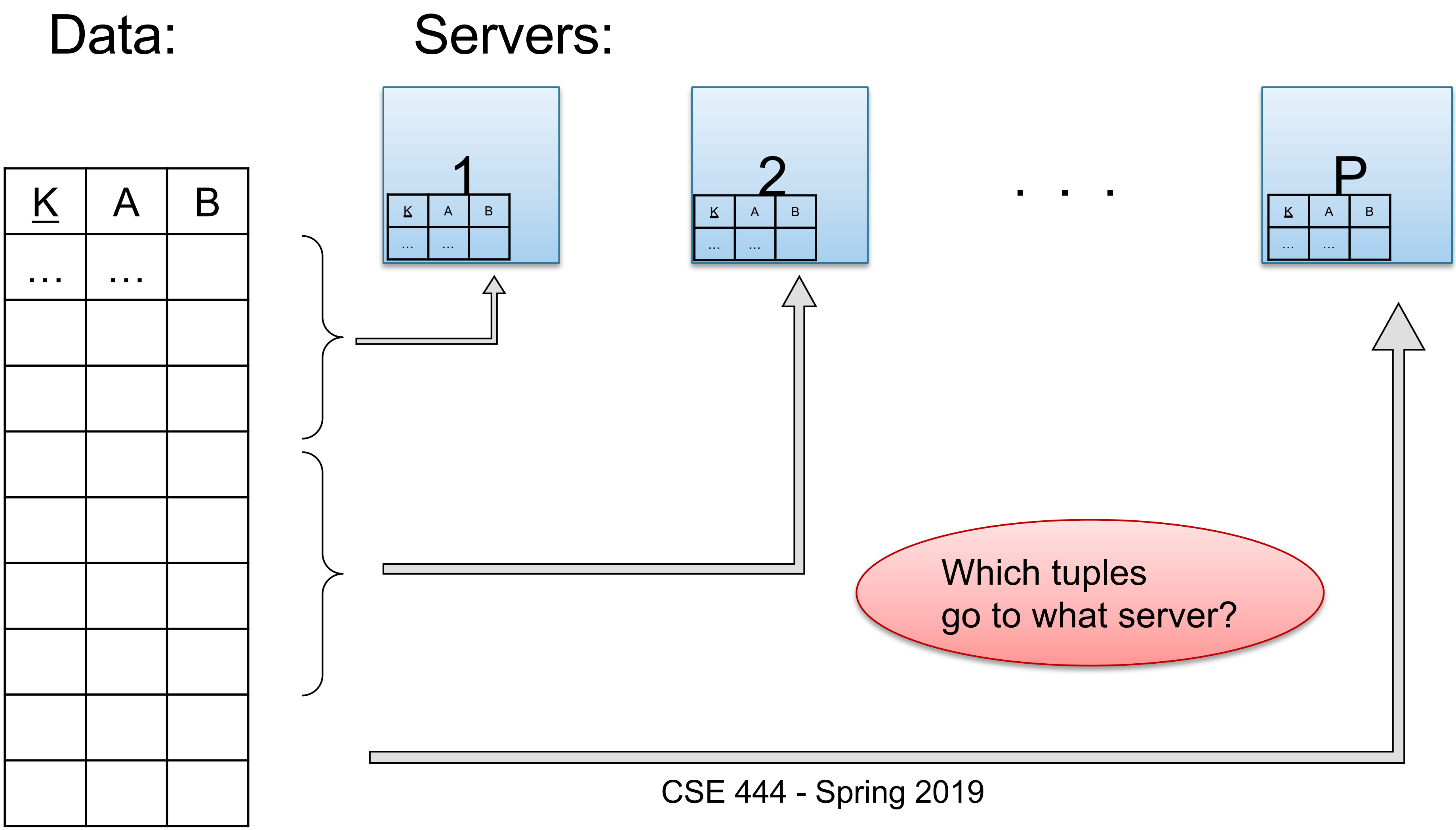
<u>K</u>	A	B
…	…	

Servers:

Horizontal Data Partitioning



Horizontal Data Partitioning



Horizontal Data Partitioning

- Relation R split into P chunks $R_0, \ldots, R_{P-1}$, stored at the P nodes

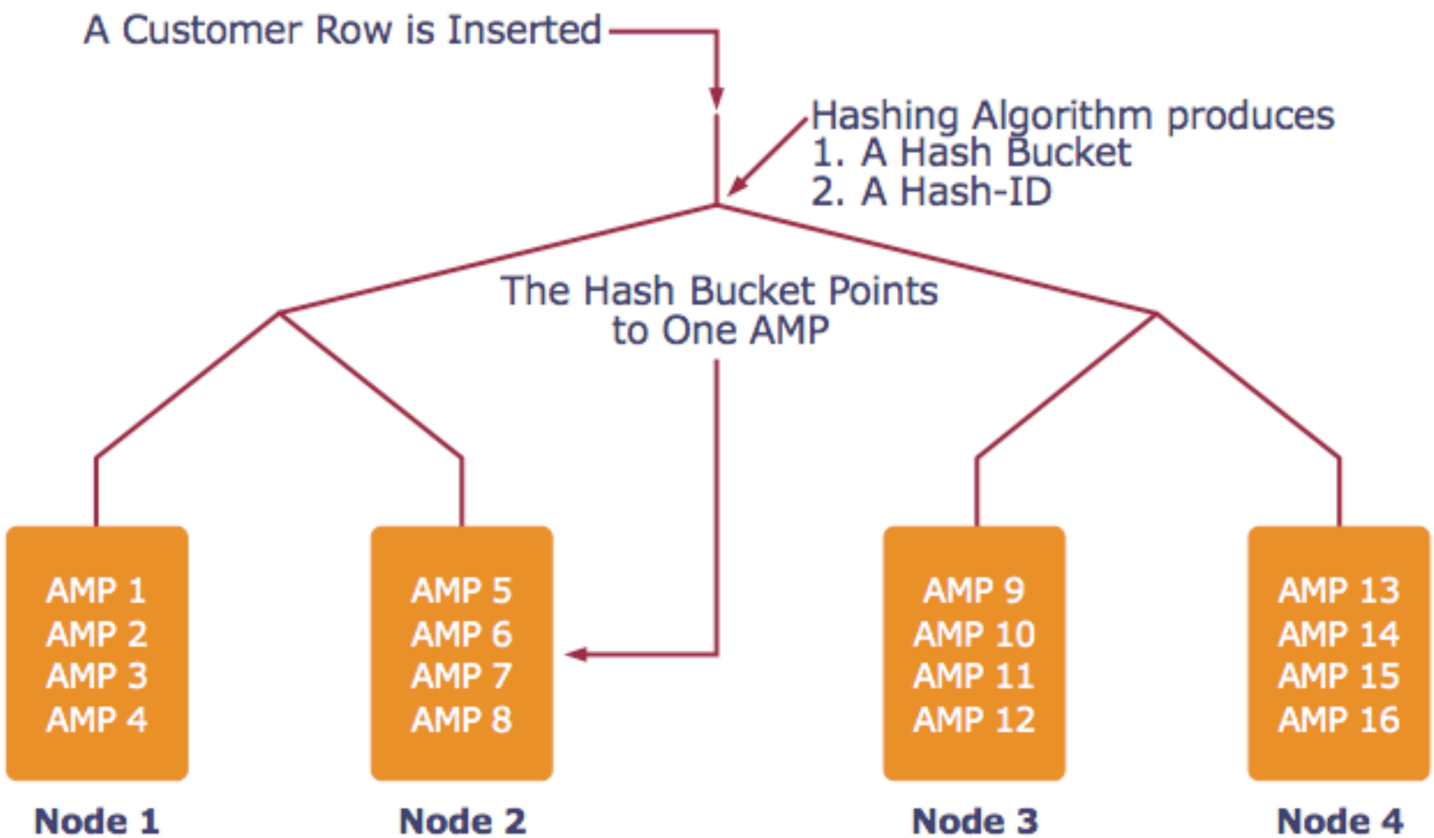
- Block partitioned
  - Each group of k tuples goes to a different node
- Hash based partitioning on attribute A:
  - Tuple t to chunk h(t.A) mod P
- Range based partitioning on attribute A:
  - Tuple t to chunk i if $v_{i-1} < t.A < v_i$
- For hash and range partitioning: Beware of skew

Horizontal Data Partitioning

All three choices are just special cases:

- For each tuple, compute *bin = f(t)*
- Different properties of the function *f* determine hash vs. range vs. round robin vs. anything

Example: Teradata – Loading



AMP = "Access Module Processor" = unit of parallelism

Parallel Selection

Compute $\sigma_{A=v}(R)$, or $\sigma_{v1<A<v2}(R)$

- On a conventional database: cost = B(R)

- Q: What is the cost on a parallel database with P processors ?
  - Block partitioned
  - Hash partitioned
  - Range partitioned

Parallel Selection

Compute $\sigma_{A=v}(R)$, or $\sigma_{v1<A<v2}(R)$

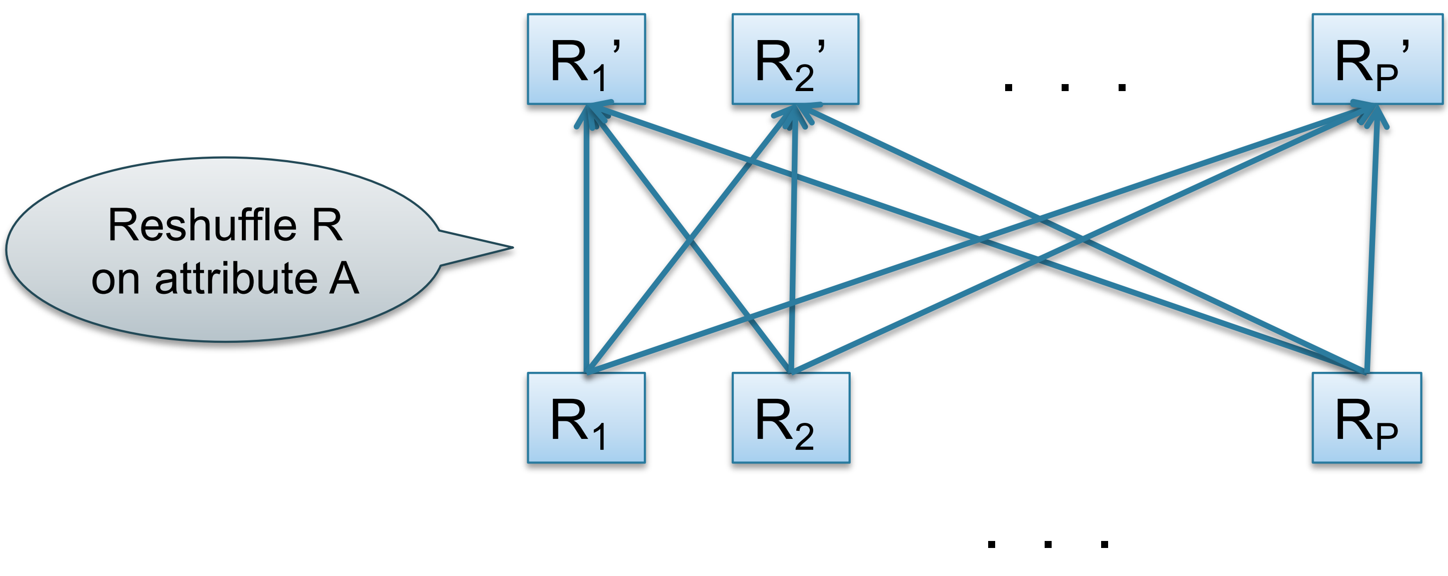
- On a conventional database: cost = B(R)

- Q: What is the cost on a parallel database with P processors ? A: B(R) / P, but
  - Block partitioned -- all servers do the work
  - Hash partitioned -- some servers do the work
  - Range partitioned -- some servers do the work

Basic Parallel GroupBy

Data: R(K,A,B,C) -- hash-partitioned on K

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



Basic Parallel GroupBy

- Step 1: each server i partitions its chunk R_i using a hash function h(t.A) mod P: $R_{i,0}, R_{i,1}, \ldots, R_{i,P-1}$
- Step 2: server j computes $\gamma_{A,\ sum(B)}$ on $R_{0,j}, R_{1,j}, \ldots, R_{P-1,j}$

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?
- If we double both P and the size of R, what is the new running time?

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)

Announcements

- Lab 4 due Friday
- Quiz 3+4 Monday 3/11
- HW 6 released – due 3/18

Basic Parallel GroupBy

Can we do better?

- Sum?
- Count?
- Avg?
- Max?
- Median?

Basic Parallel GroupBy

Can we do better?

- Sum?
- Count?
- Avg?
- Max?
- Median?

Distributive	Algebraic	Holistic
$sum(a_1+a_2+\ldots+a_9)=$ $sum(sum(a_1+a_2+a_3)+$ $sum(a_4+a_5+a_6)+$ $sum(a_7+a_8+a_9))$	avg(B) = sum(B)/count(B)	median(B)

YES

- Compute partial aggregates before shuffling

Basic Parallel GroupBy

Can we do better?

- Sum?
- Count?
- Avg?
- Max?
- Median?

Distributive	Algebraic	Holistic
$sum(a_1+a_2+\ldots+a_9)=$ $sum(sum(a_1+a_2+a_3)+$ $sum(a_4+a_5+a_6)+$ $sum(a_7+a_8+a_9))$	avg(B) = sum(B)/count(B)	median(B)

YES

- Compute partial aggregates before shuffling

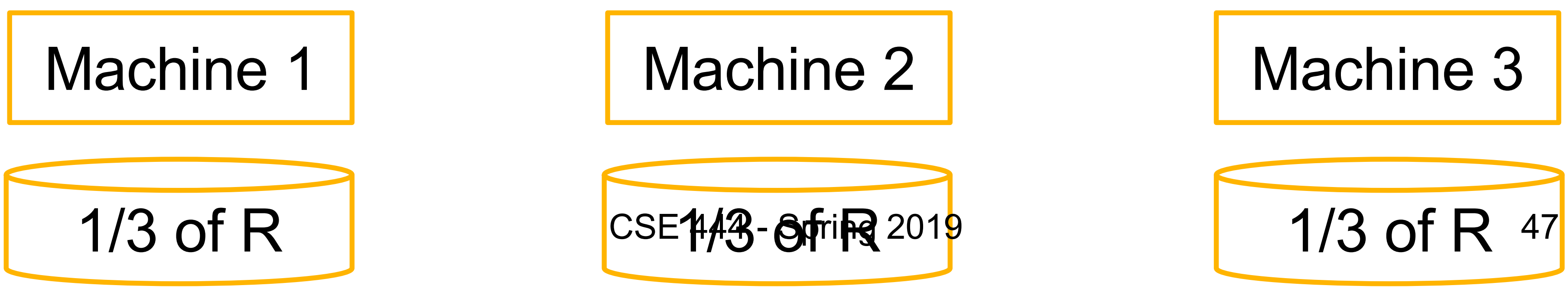
MapReduce implements this as "Combiners"

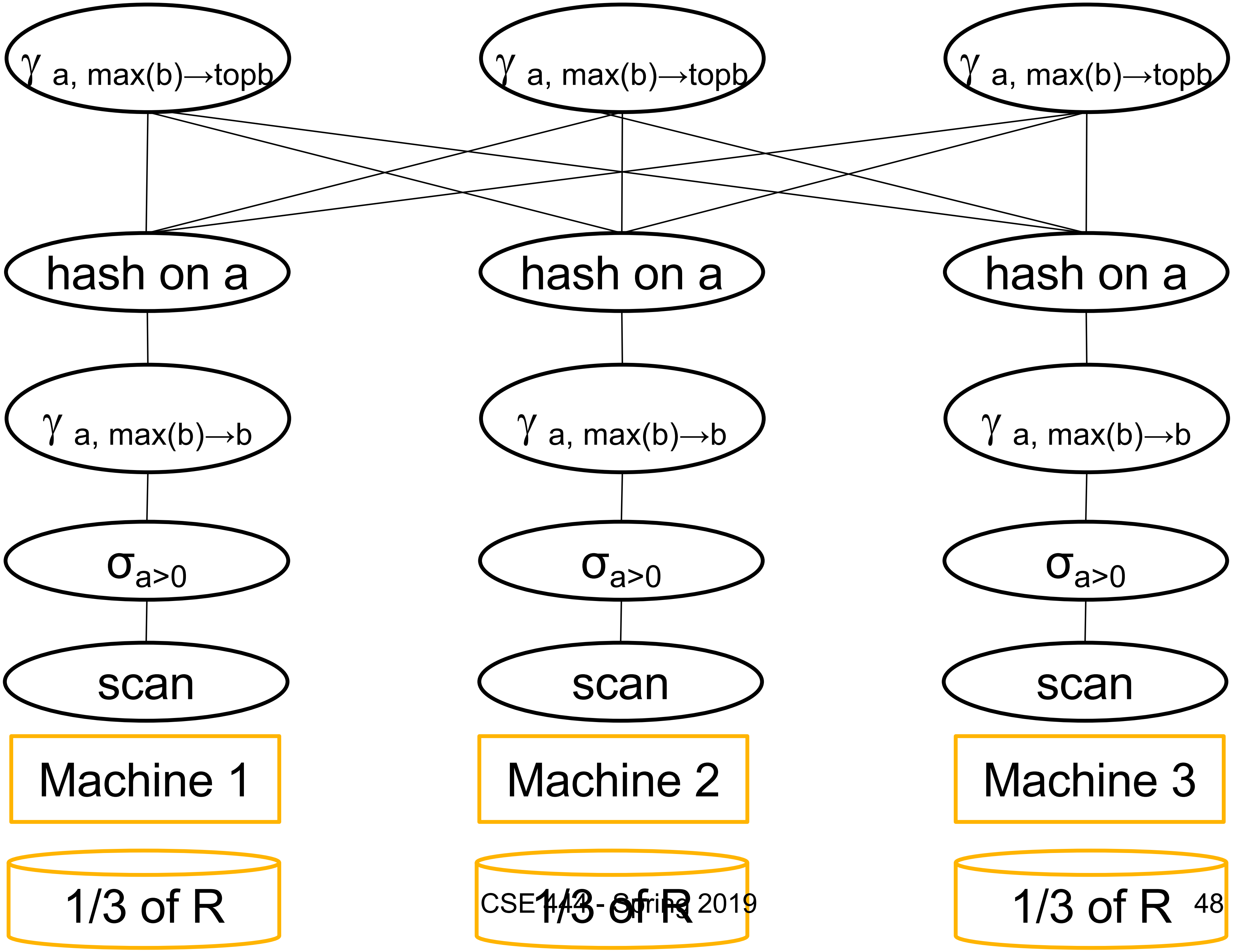
Example Query with Group By

SELECT a, max(b) as topb

FROM R WHERE a > 0

GROUP BY a



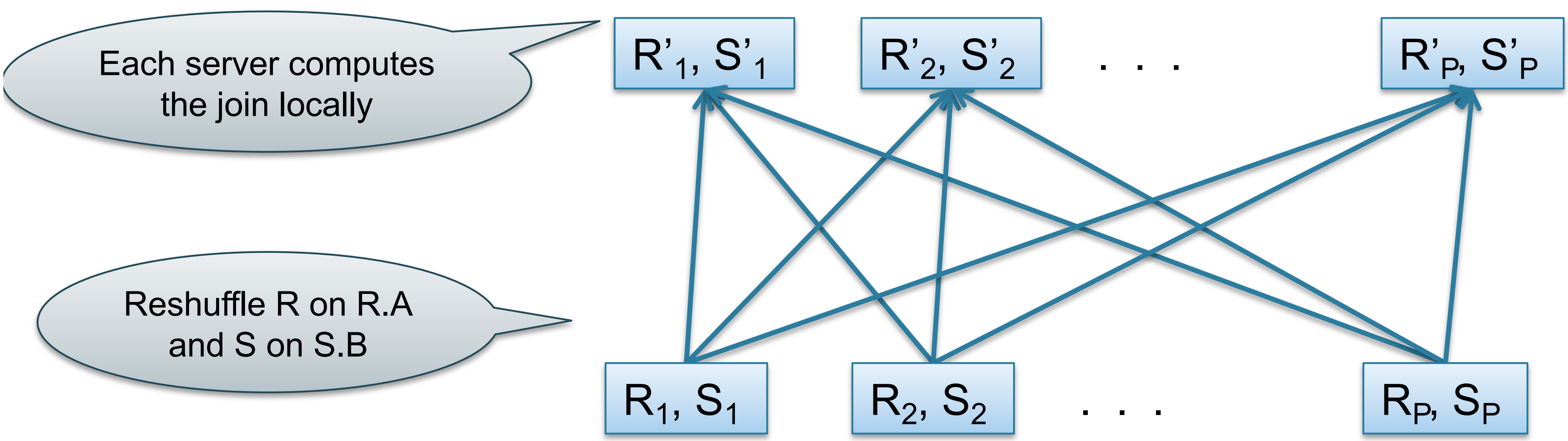

γ a, max(b)→topb
γ a, max(b)→topb
γ a, max(b)→topb
hash on a
hash on a
hash on a
γ a, max(b)→b
γ a, max(b)→b
γ a, max(b)→b
$\sigma_{a>0}$
$\sigma_{a>0}$
$\sigma_{a>0}$
scan
scan
scan
Machine 1
Machine 2
Machine 3
1/3 of R
1/3 of R
1/3 of R

Parallel Join: $R \bowtie_{A=B} S$

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

Parallel Join: R $\bowtie_{A=B}$ S

- Data: R(<u>K1</u>,A, C), S(<u>K2</u>, B, D)
- Query: R(<u>K1</u>,A,C) $\bowtie$ S(<u>K2</u>,B,D)



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

Parallel Join: $R \bowtie_{A=B} S$

- Step 1
  - Every server holding any chunk of R partitions its chunk using a hash function h(t.A) mod P
  - Every server holding any chunk of S partitions its chunk using a hash function h(t.B) mod P
- Step 2:
  - Each server computes the join of its local fragment of R with its local fragment of S

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

Query: R(K1,A,B) ⋈ S(K2,B,C)

Join on R.B = S.B

Local Join

M1

R1'

K1	B
1	20
3	20
4	20

⋈

S1'

K2	B
201	20

M2

R2'

K1	B
2	50

⋈

S2'

K2	B
101	50
102	50
202	50

Shuffle

Partition

M1

R1

K1	B
1	20
2	50

S1

K2	B
101	50
102	50

M2

R2

K1	B
3	20
4	20

S2

K2	B
201	20
202	50

Optimization for Small Relations

When joining R and S

- If |R| >> |S|
  - Leave R where it is
  - Replicate entire S relation across nodes

- Also called a small join or a broadcast join

Other Interesting Parallel Join Implementation

Skew:

- Some partitions get more input tuples than others
  Reasons:
  - Range-partition instead of hash
  - Some values are very popular:
    - Heavy hitters values; e.g. 'Justin Bieber'
  - Selection before join with different selectivities

- Some partitions generate more output tuples than others

Some Skew Handling Techniques

If using range partition:

- Ensure each range gets same number of tuples
- E.g.: {1, 1, 1, 2, 3, 4, 5, 6 } → [1,2] and [3,6]
- Eq-depth v.s. eq-width histograms

Some Skew Handling Techniques

Create more partitions than nodes

- And be smart about scheduling the partitions
- Note: MapReduce uses this technique

Some Skew Handling Techniques

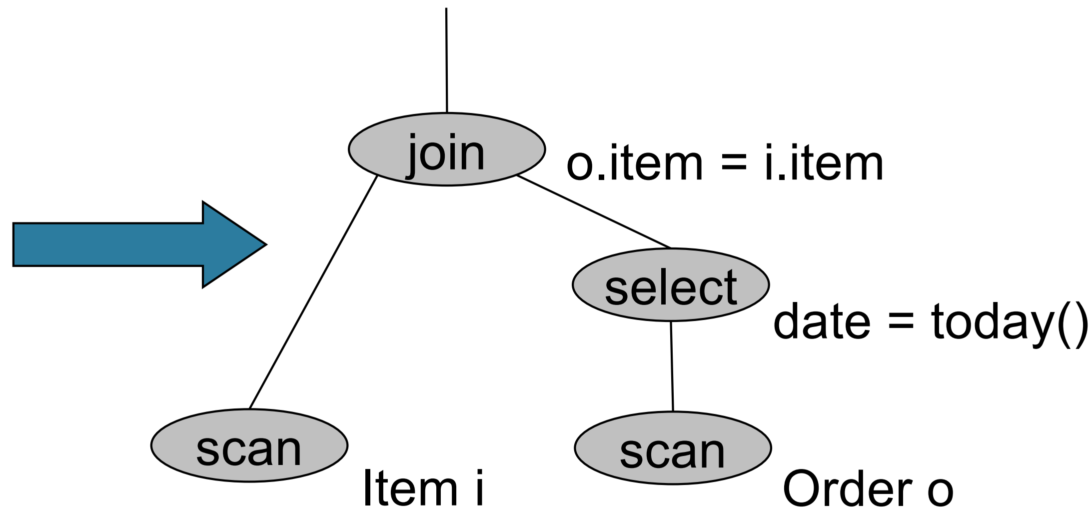
Use subset-replicate (a.k.a. “skewedJoin”)

- Given $R \bowtie_{A=B} S$
- Given a heavy hitter value R.A = ‘v’
  (i.e. ‘v’ occurs very many times in R)
- Partition R tuples with value ‘v’ across all nodes
  e.g. block-partition, or hash on other attributes
- Replicate S tuples with value ‘v’ to all nodes
- R = the build relation
- S = the probe relation

Example: Teradata – Query Execution

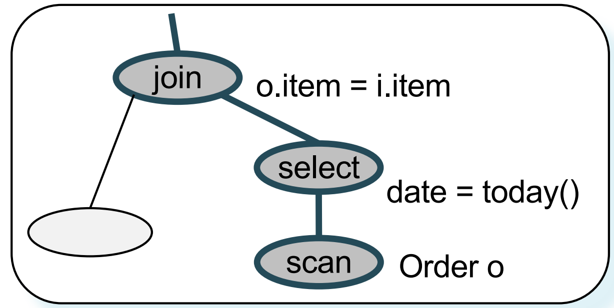
Find all orders from today, along with the items ordered

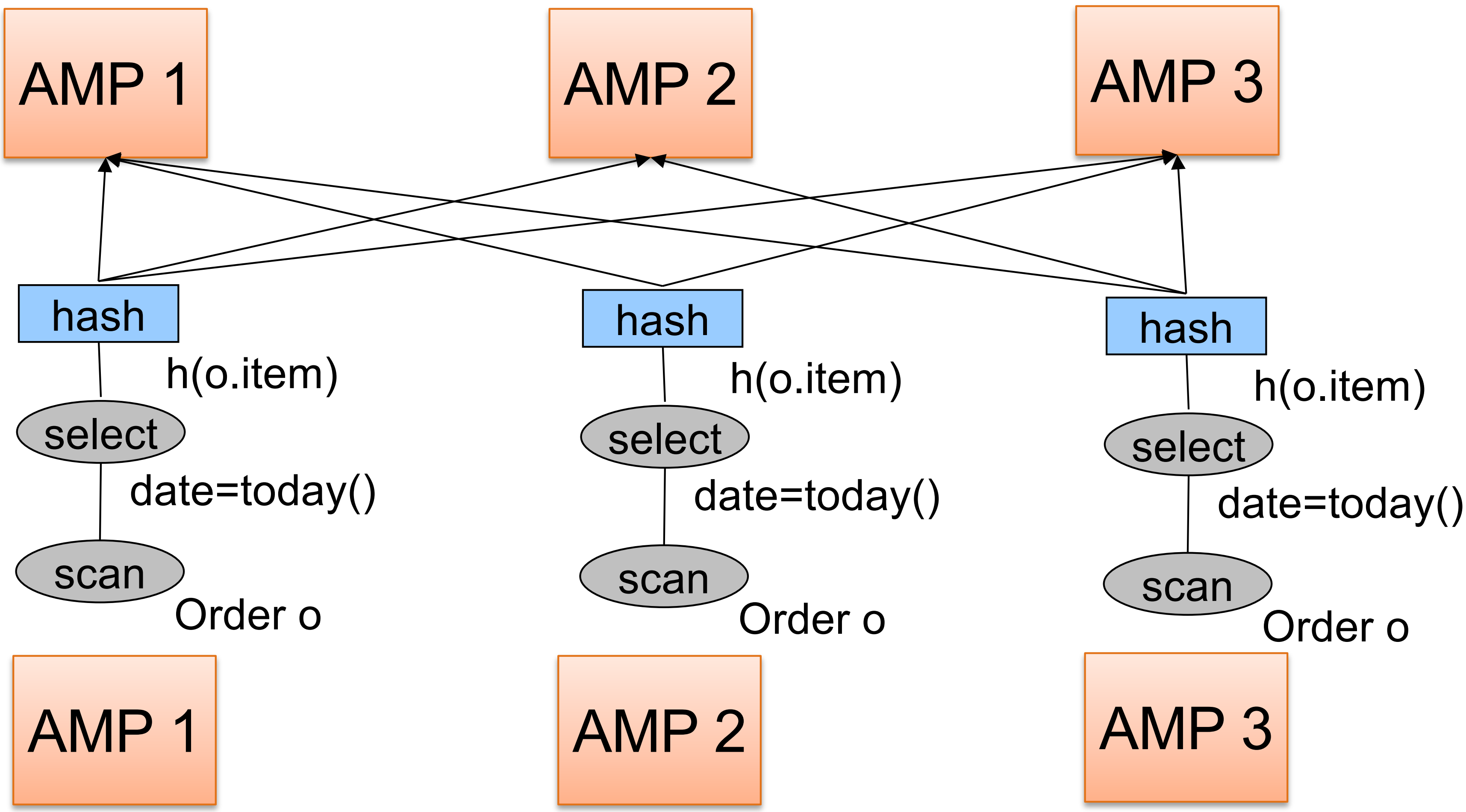
```
SELECT *
  FROM Order o, Line i
 WHERE o.item = i.item
   AND o.date = today()
```



Order(oid, item, date), Line(item, …)

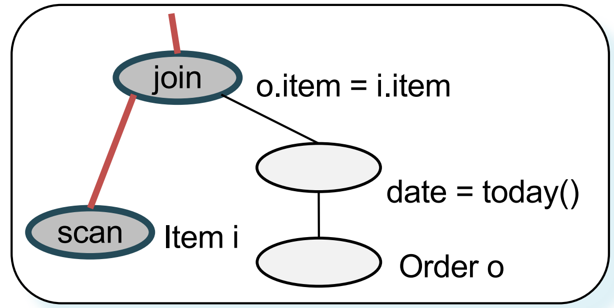
Query Execution

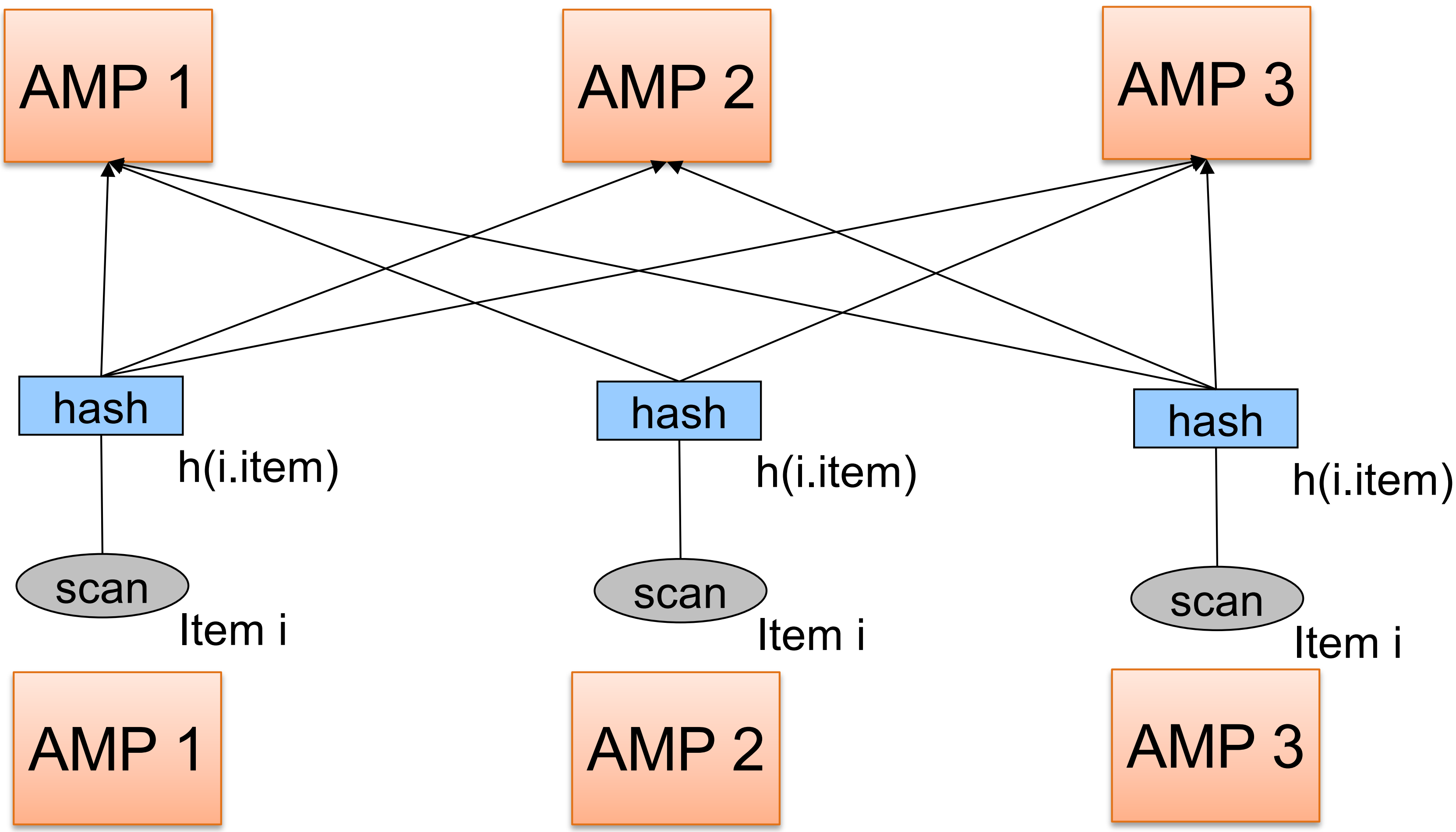




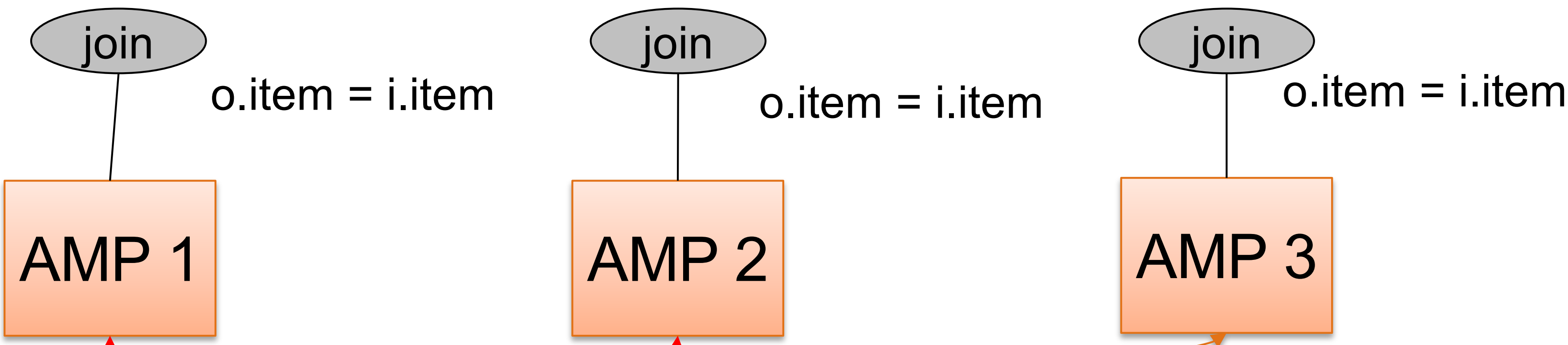
Order(oid, item, date), Line(item, …)

Query Execution





Query Execution



contains all orders and all lines where hash(item) = 3

contains all orders and all lines where hash(item) = 2

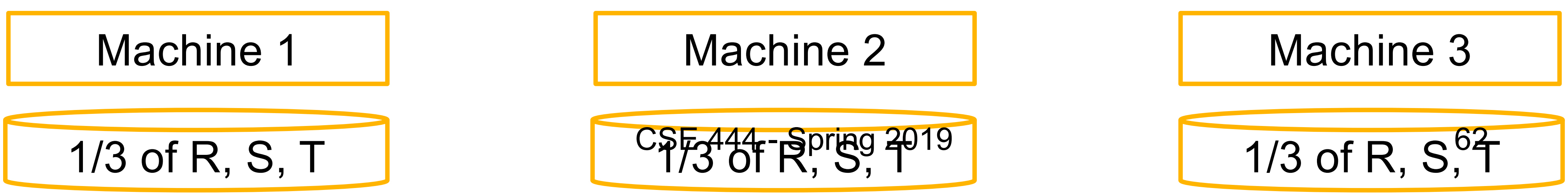
contains all orders and all lines where hash(item) = 1

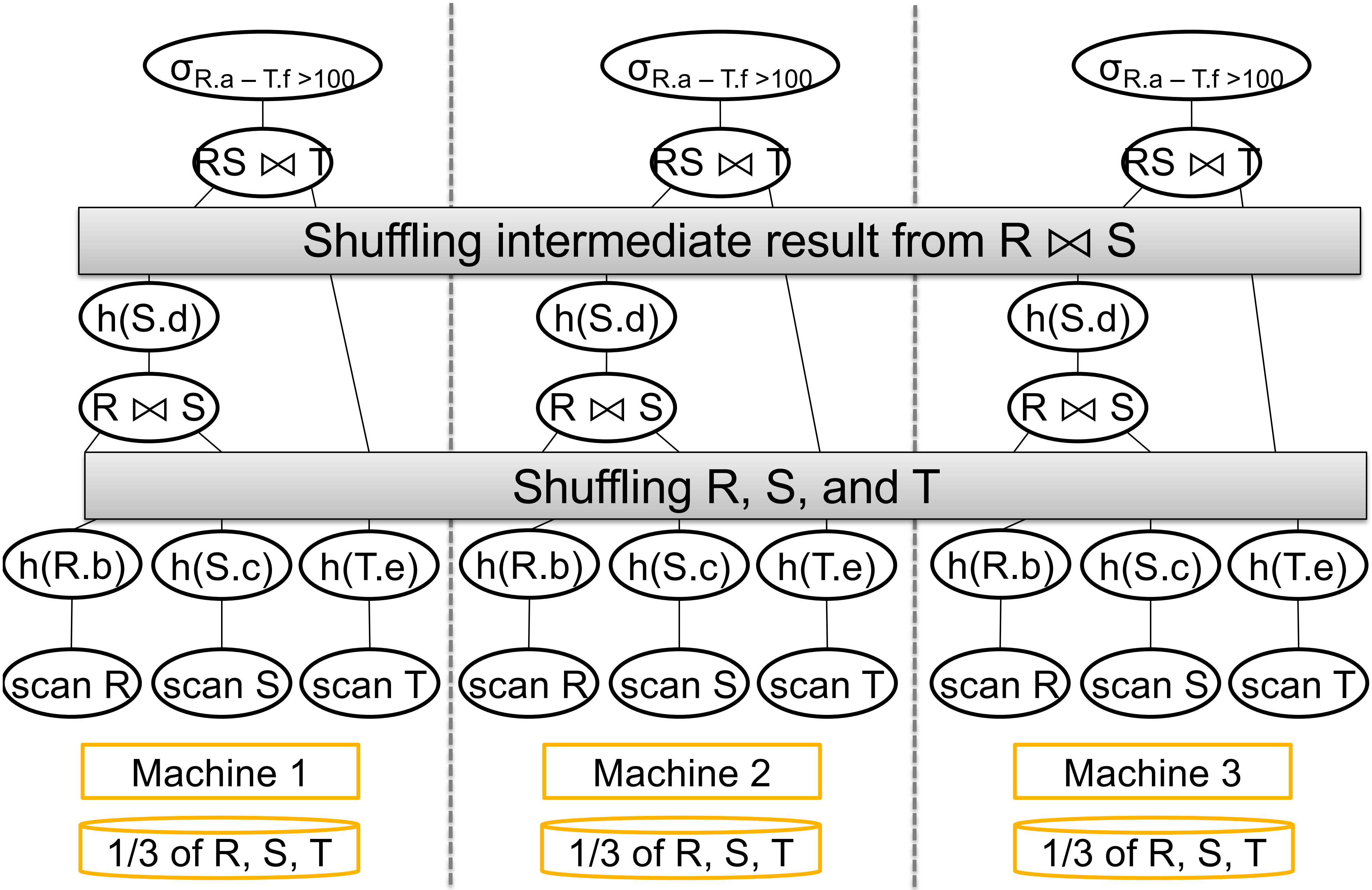
Example 2

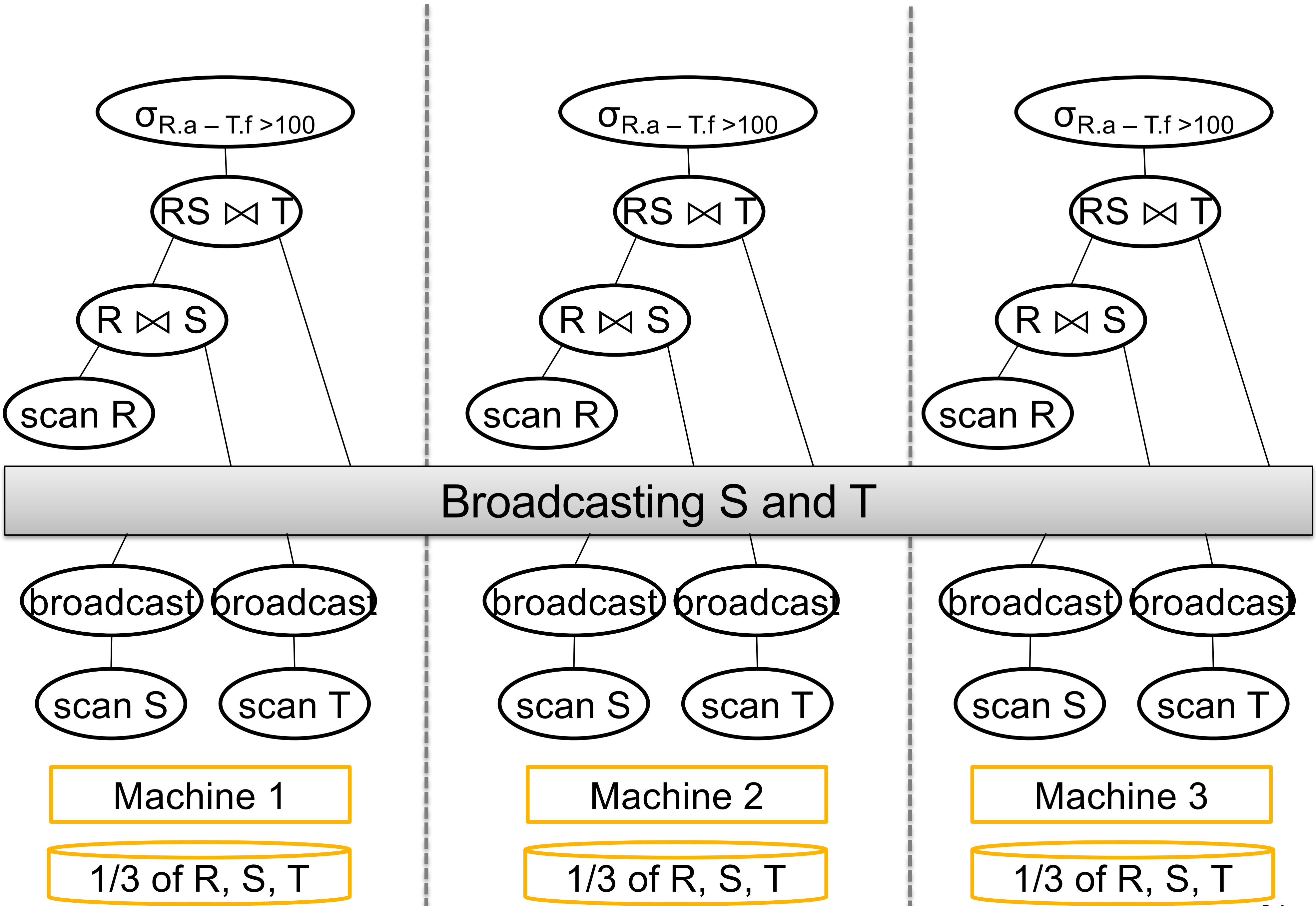
SELECT *

FROM R, S, T

WHERE R.b = S.c AND S.d = T.e AND (R.a - T.f) > 100




σR.a – T.f >100
RS ⋈ T
Shuffling intermediate result from R ⋈ S
h(S.d)
R ⋈ S
Shuffling R, S, and T
h(R.b)
h(S.c)
h(T.e)
scan R
scan S
scan T
Machine 1
Machine 2
Machine 3
1/3 of R, S, T


$\sigma_{R.a - T.f > 100}$
$RS \bowtie T$
$R \bowtie S$
scan R
Broadcasting S and T
broadcast
broadcast
scan S
scan T
Machine 1
Machine 2
Machine 3
1/3 of R, S, T