

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

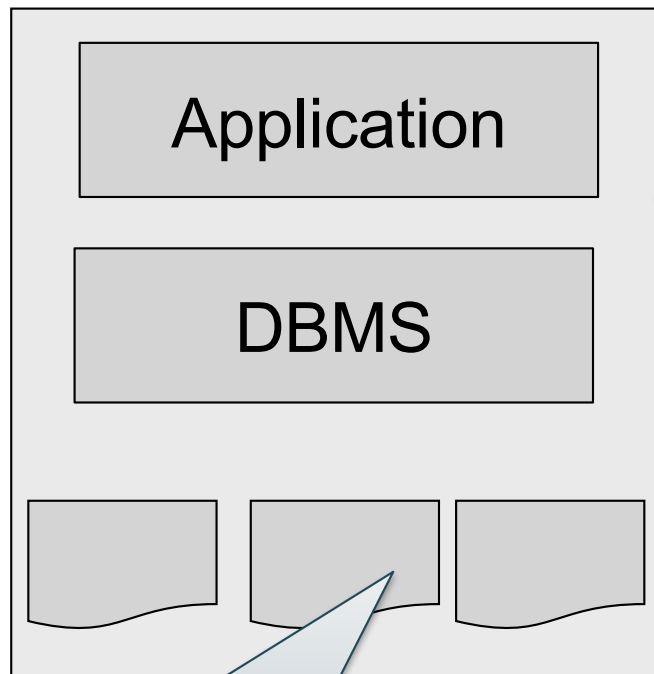
Where We Are Headed Next

- 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



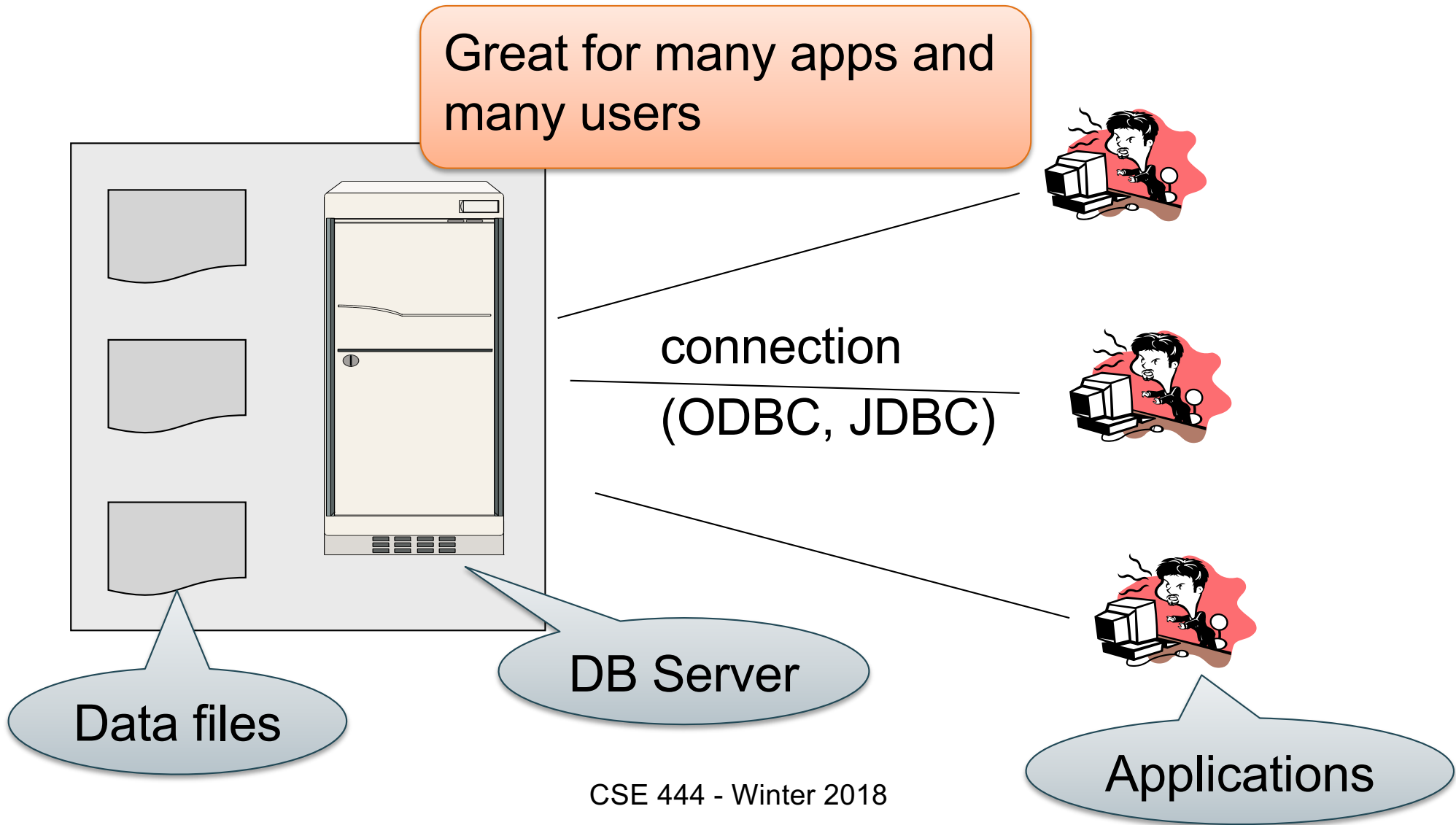
Great for one application
(could be more) and one
user.

Desktop

Data files on disk

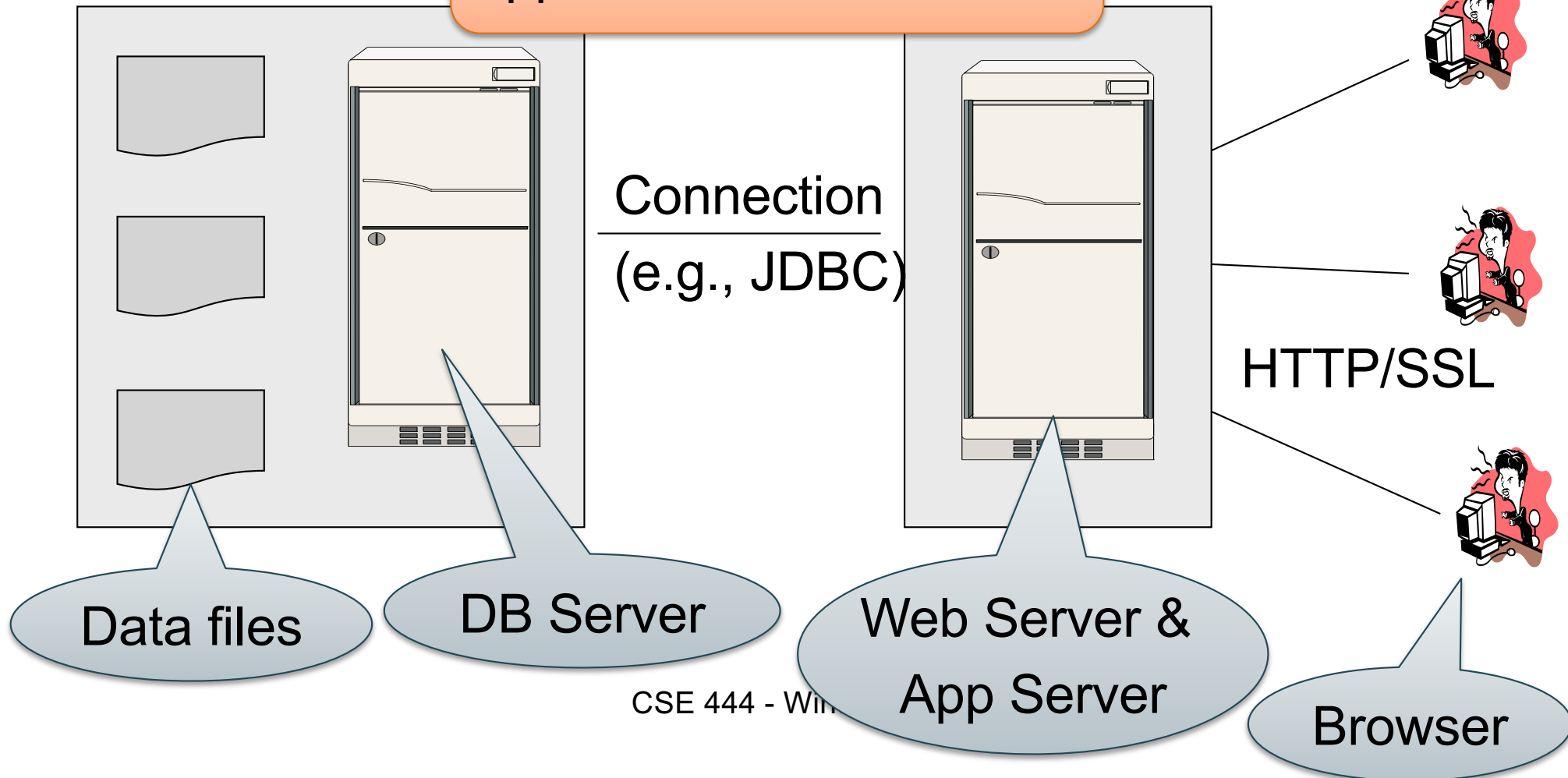
DBMS Deployment: Client/Server

Great for many apps and many users



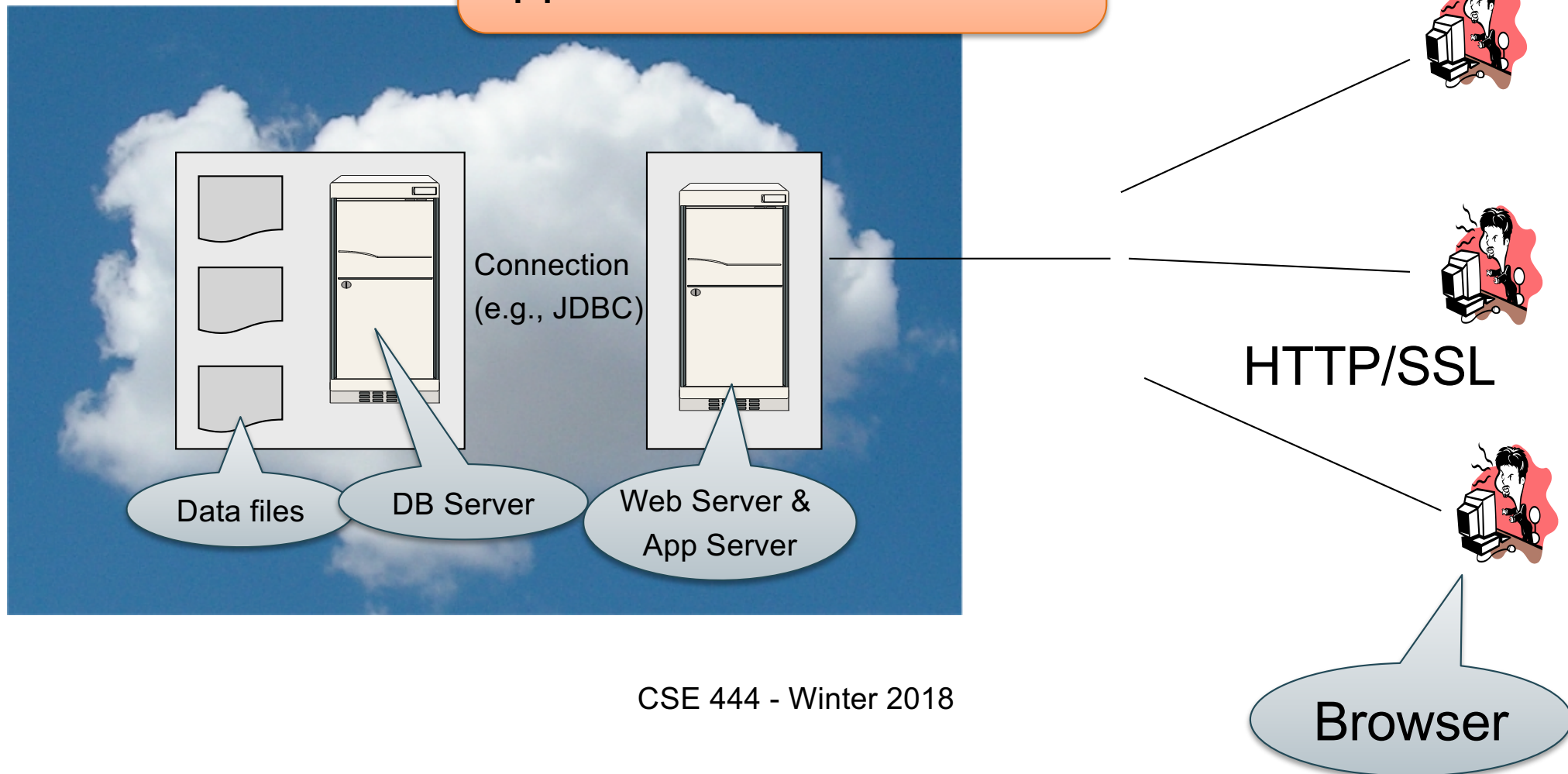
DBMS Deployment: 3 Tiers

Great for web-based applications

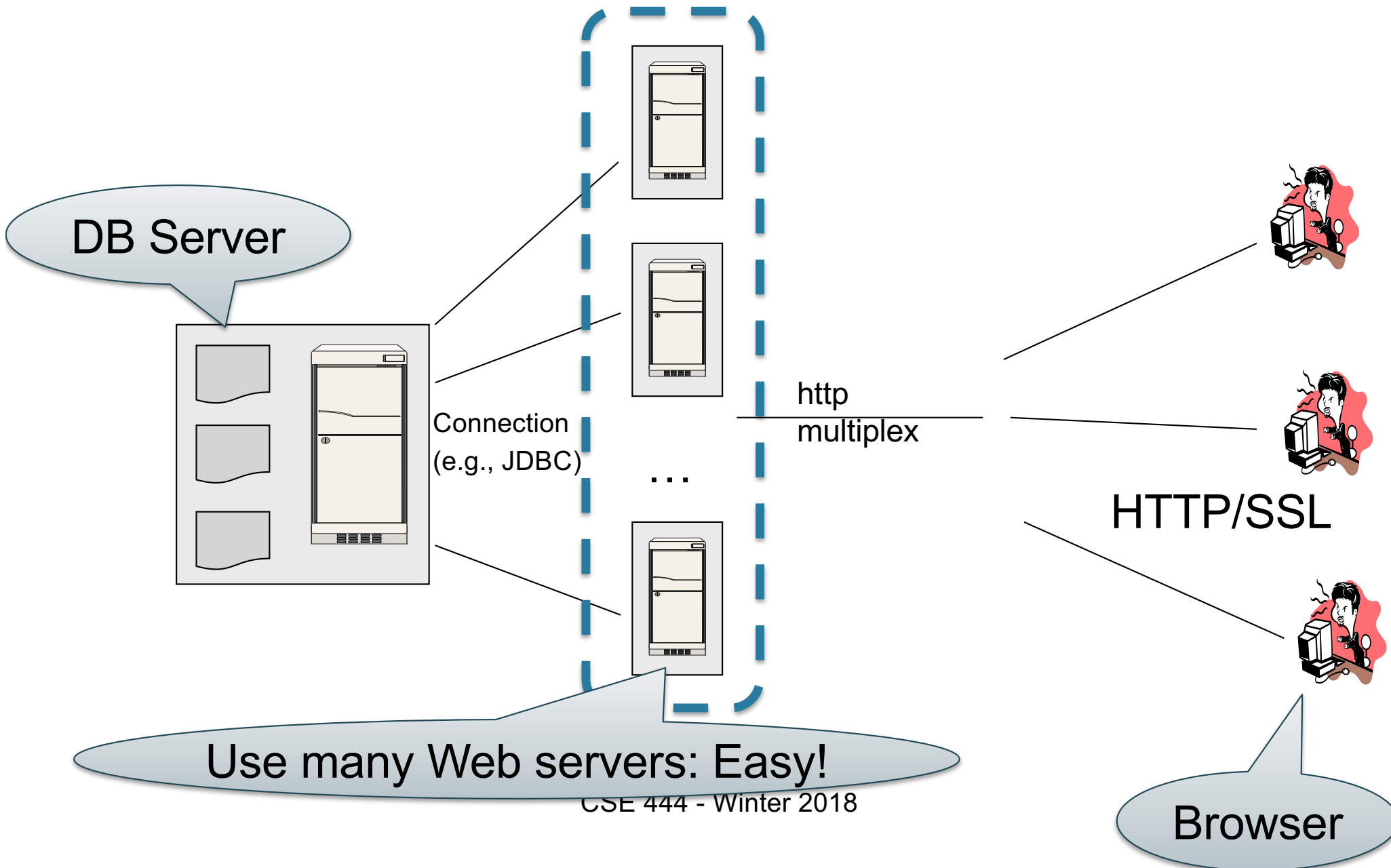


DBMS Deployment: Cloud

Great for web-based applications

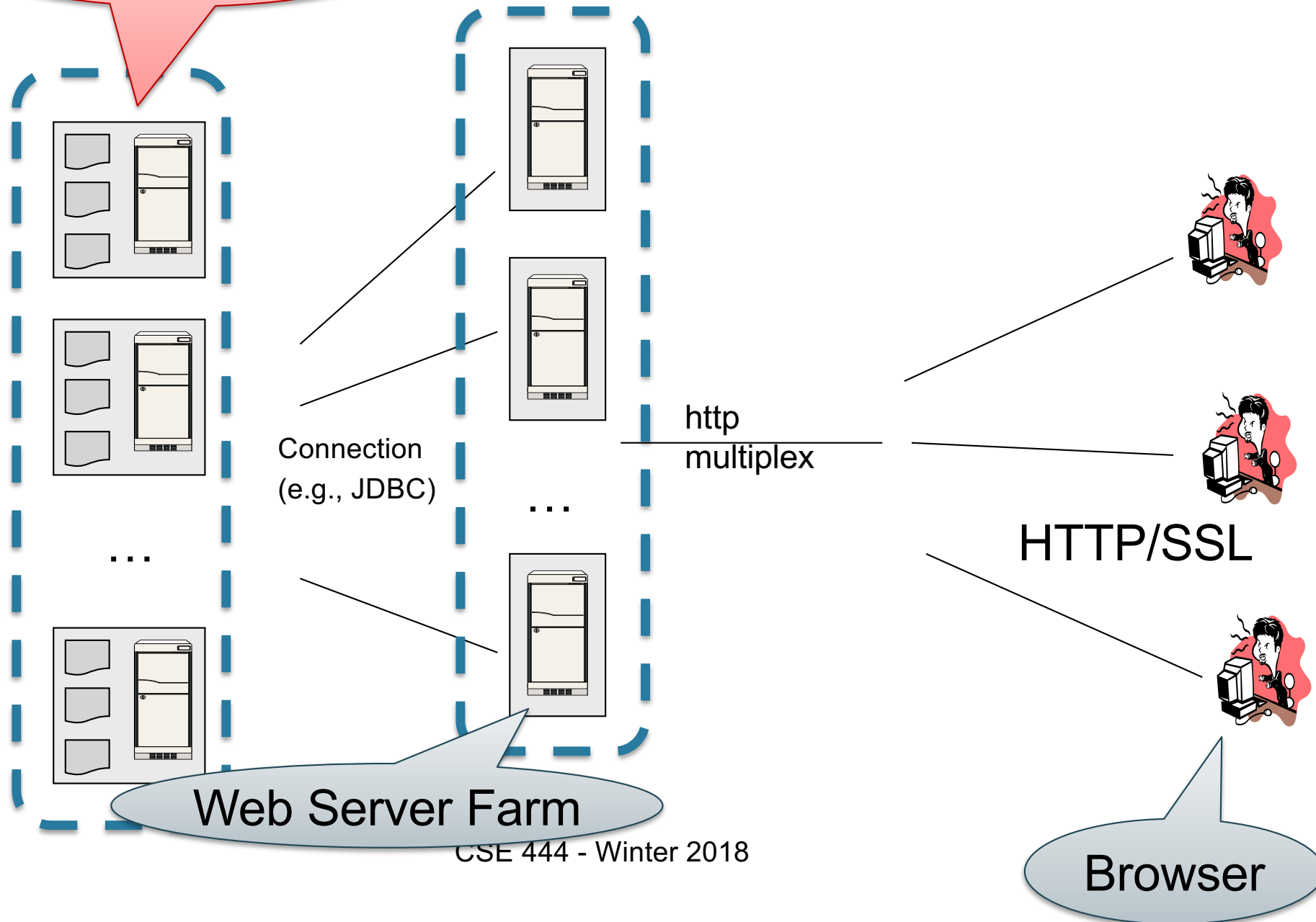


How to Scale?



Many DBMS instances: HARD

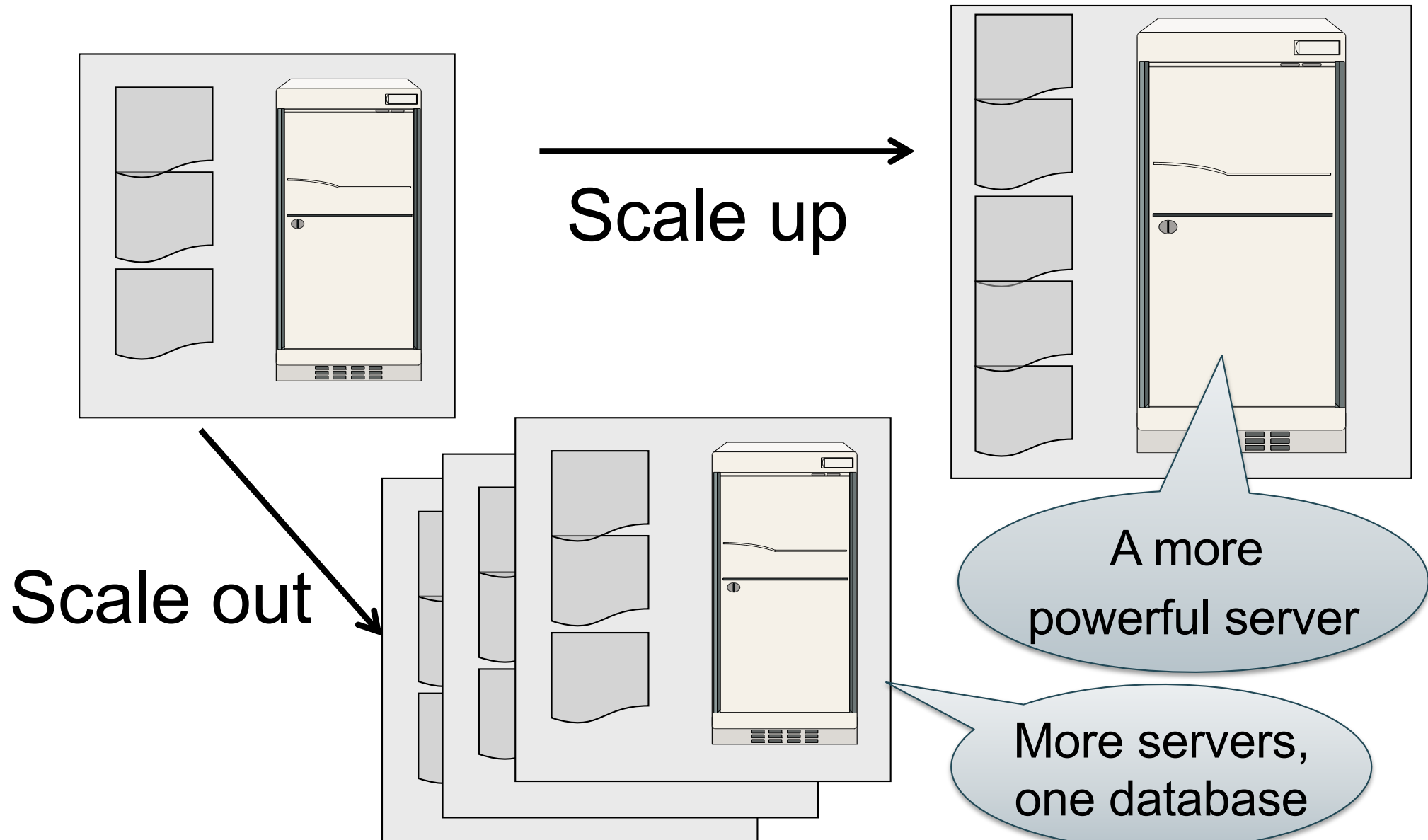
How to Scale?



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 <http://www.gartner.com/newsroom/id/1731916>
 - High Variety
 - High Velocity

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
- [DATAlegro](#) 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 Landscape 2016 (Version 3.0)

Infrastructure

Hadoop On-Premise
cloudera, Hortonworks, MAPR, Pivotal, IBM InfoSphere, bluedata, jethro

Hadoop in the Cloud
amazon web services, Microsoft Azure, Google Cloud Platform, IBM InfoSphere, CAZENA, altiscale, Quale

Spark
databricks, GridGain, TACHYON NEXUS

Cluster Services
amazon web services, kubernetes, HPCC SYSTEMS, MESOSPHERE, Core OS, pepperdata, StackIQ

Analytics

Analyst Platforms
Palantir, AYASDI, Quid, enigma, Digital Reasoning, ORBITAL INSIGHT

Analytics Platforms
Microsoft, guavus, Datameer, Bottlenose, interlana

Data Science Platforms
context relevant, DataRobot, Alpine, MODE, dataiku, DOMINO, yhat, ARIMO, sense, ALGORITHMIA

Visualization
tableau, Google Cloud Platform, Qlik, looker, Roambi, Sisense, Goomdata, datorama, CHARTIO

Applications

Sales & Marketing
RADIUS, Gainsight, bloomreach, Zeta, EVERSTRING, livefyre, blueyonder, Lattice, kahuna, infer, SAILTHRU, persado, AVISO, bsense, QUANTIFIND, ACTIONIQ, fuse|machines, ENGAGIO

Customer Service
MEDALLIA, ATTENSTY, CLARABRIDGE, CLICKFOX, STELLA Service, NGDATA, Preact, DigitalGenius, appuri, Wise.io

Human Capital
gild, Connectifier, textic, entelo, hiQ

Legal
RAVEL, JUDICATA, Everlaw, Brevia, PREMONITION

NoSQL Databases
amazon dynamodb, Google Cloud Platform, Microsoft Azure, MarkLogic, mongoDB, DATASTAX, CERO SPIKE, Couchbase, SequoiaDB, redislabs, influxdata

NewSQL Databases
SAP HANA, Clustrix, Pivotal, memsql, paradigm4, nuodb, splice machine, MariaDB, VOLTD, citusdata, deep db, Trifacta, Cockroach LABS

BI Platforms
Power BI, amazon web services, Domo, Wave Analytics, GoodData, birst, kyvos insights, platforma, atscale, arcadia, sisense

Statistical Computing
sas, SPSS, MATLAB

Log Analytics
splunk, sumologic, kibana, CLOUD PHYSICS, loggly

Social Analytics
Hootsuite, NETBASE, DATA SIFT, tracx, bitly, synthsis, simple reach

Ad Optimization
AppNexus, MediaMath, critico, OpenX, rocketfuel, Integral, theTradeDesk, Ad Science, Adgorithms, distillery, DataXu, Uppier, MOAT

Security
CYLANCE, CounterTack, cybereason, ThreatMetrix, AREA 1 SECURITY, SentinelOne, Recorded Future, Guardian Analytics, FORTSCALE, sift science, Keybase, feedzai, SIGNIFYD

Vertical AI Applications
facebook, Clara, KASIST, lumiata

Graph Databases
neo4j, OrientDB, InfiniteGraph

MPP Databases
TERADATA, VERTICA, Netezza, Action, koginitio, BASOL, dremio

Cloud EDW
amazon web services, Microsoft Azure, Pivotal, snowflake, WATERLINE DATA, Infoworks

Data Transformation
alteryx, talend, TRIFACTA, tamr, Paxata, StreamSets, Alation

Data Integration
informatica, Put potential to work, MuleSoft, snapLogic, Bedrock Data, xplenty

Real-Time
amazon web services, METAMARKETS, striim, confluent, DATATORRENT, dataArtisans

Machine Learning
Azure Machine Learning, H2O, amazon, Dato, SKYTREE, rapidminer, DATARPM, deepsense, VISENZE, PredictionIO, glowfish

Speech & NLP
NarrativeScience, Nuance, WolframAlpha, semantic, ARRIA, Gridspace, ari.ai, cortical.io, maluba, MindMeld, iDIBON, yseop

Horizontal AI
IBM Watson, Cortana, sentient, viv, nora, Numenta, Descartes Labs, clarifai, MetaMind

Publisher Tools
outbrain, Taboola, quantcast, Chartbeat, yieldbot, Yieldmo

Govt / Regulation
Socrata, OPENGOV, FN FiscalNote, enigma, PREDDOL, mark43, OpenDataSoft

Finance
Affirm, LendingClub, OnDeck, Kreditech, zest finance, LendUp, Kabbage, tidemark, Pave, INSIGHT, ZUORA, Dataminr, Lenddo, KENSHO, AIDYIA, ISENTIUM, Quantopian, sentient

Management / Monitoring
New Relic, APPDYNAMICS, amazon, actifio, Numerify, splunk, DATADOG, Yrcona, DRIVEN, Anodot

Security
TANUM, illumio, CODE42, DataGravity, CipherCloud, VECTRA, sqrl, BlueTalon

Storage
amazon web services, Microsoft Azure, panasas, nimblestorage, COHO DATA, Qumulo

App Dev
apigee, CASK, Keen IO, Typesafe, DRIVEN

Crowd-sourcing
amazon mechanical turk, CrowdFlower, WorkFusion

Search
hp, Autonomy, ORACLE, ENDECA, EXALEAD, Lucidworks, elastic, ThoughtSpot, MAANA, swifttype, Algolia, SINEQUA

Data Services
UO OPERA, Mu Sigma, EXL, DATA SCIENCE, KAGGLE, dataSCOPE, DataKind

For Business Analysts
OrigamiLogic, ClearStory, CIRRO, import.io

Web / Mobile / Commerce
Google Analytics, mixpanel, RJMetrics, BLUECORE, AMPLITUDE, granify, sumall, Airtable, retention, custora

Education / Learning
KNEWTON, Clever, Declara, PANORAMA, knowre

Life Sciences
23andMe, Counsyl, Recombine, KYRUUS, FLATIRON, zymergen, HealthTap, METABIOTA, ZEPHYR HEALTH, ovia, Ginger.io, transcriptic, Glow, Atomwise, enlitic, AiCure, Atomwise

Industries
OPower, eHarmony, RetailNext, STITCH FIX, WorkFusion, TACHYUS, Seeq, FarmLogs, SwiftKey, HowGood, select, SIGHT MACHINE, statmuse, BOXXEVER

Cross-Infrastructure/Analytics

amazon web services, Google, Microsoft, IBM, SAP, SAS, data, hp, Autonomy, VERTICA, vmware, TIBCO, TERADATA, ORACLE, NetApp

Open Source

Framework
hadoop, HDFS, YARN, Spark, MESOS, TEZ, Flink, CDAP

Query / Data Flow
SLAMDATA, DRILL, Google Cloud Dataflow

Data Access
cassandra, HBASE, mongoDB, kafka, CouchDB, riak, OPEN TSOB, nifi

Coordination
talend, Apache Zookeeper, Apache Ambari

Real-Time
STORM, Spark, APEX, Flink, TACHYON, druid

Stat Tools
ScalaLab, NumPy, SciPy

Machine Learning
mlib, Aerosolve, Apache, SINGA, MADlib, CNTK, TensorFlow, jupyter, DL4J

Search
elasticsearch, Solr, Lucene

Security
Apache Ranger, Zeppelin

Data Sources & APIs

Health
JAWBONE, GARMIN, practicefusion, fitbit, Withings, VALIDIC, netatmo, kinsa, Human API

IOT
UPTAKE, ThingWorx, helium, samsara, AUGURY, estimate

Financial & Economic Data
Bloomberg, DOW JONES, THOMSON REUTERS, S&P CAPITAL IQ, YODLEE, PREMISE, quandl, xignite, CB INSIGHTS, mattermark, StockTwits, estimate, PLAID

Air / Space / Sea
PLANET LABS, spire, WINDWARD, CRUISE, SKYCATCH, Airware, DroneDeploy

Location / People / Entities
acxiom, Experian, EPSILON, InsideView, GARMIN, foursquare, STREETLINE, esri, Crimson Hexagon, CARTODB, factual, PlaceIQ, CIRCULATE, placemeter, BASIS, Sense

Other
qualtrics, panjiva, DATA.GOV

Incubators & Schools
GA, PLURALSIGHT, DataCamp, INSIGHT, DataElite, The Data Incubator, METIS

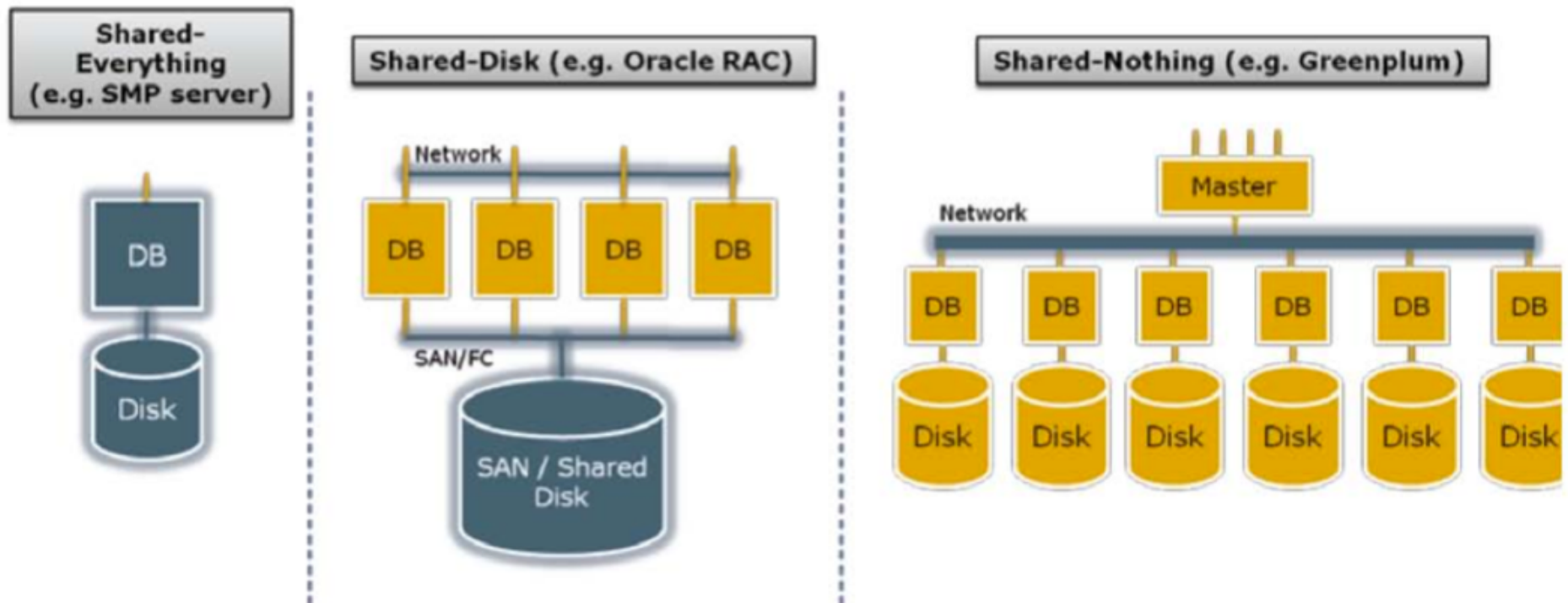
Two Fundamental Approaches to Parallel Data Processing

- **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 DMBSSs

Figure 1 - Types of database architecture



From: Greenplum Database Whitepaper

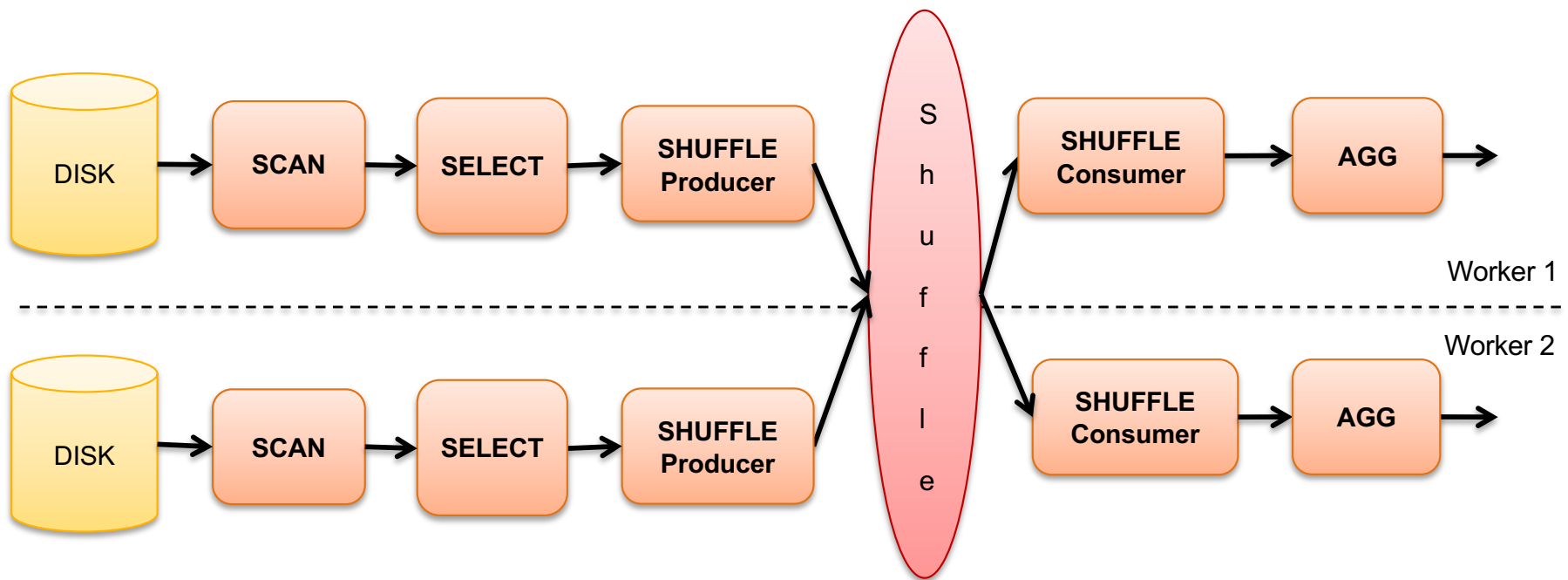
SAN = “Storage Area Network”

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:** $\gamma_{A, \text{sum}(B)}(R)$
- **Join:** $R \bowtie S$

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

Horizontal Data Partitioning

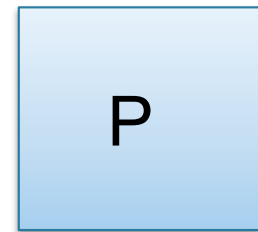
Data:

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

Servers:



. . .

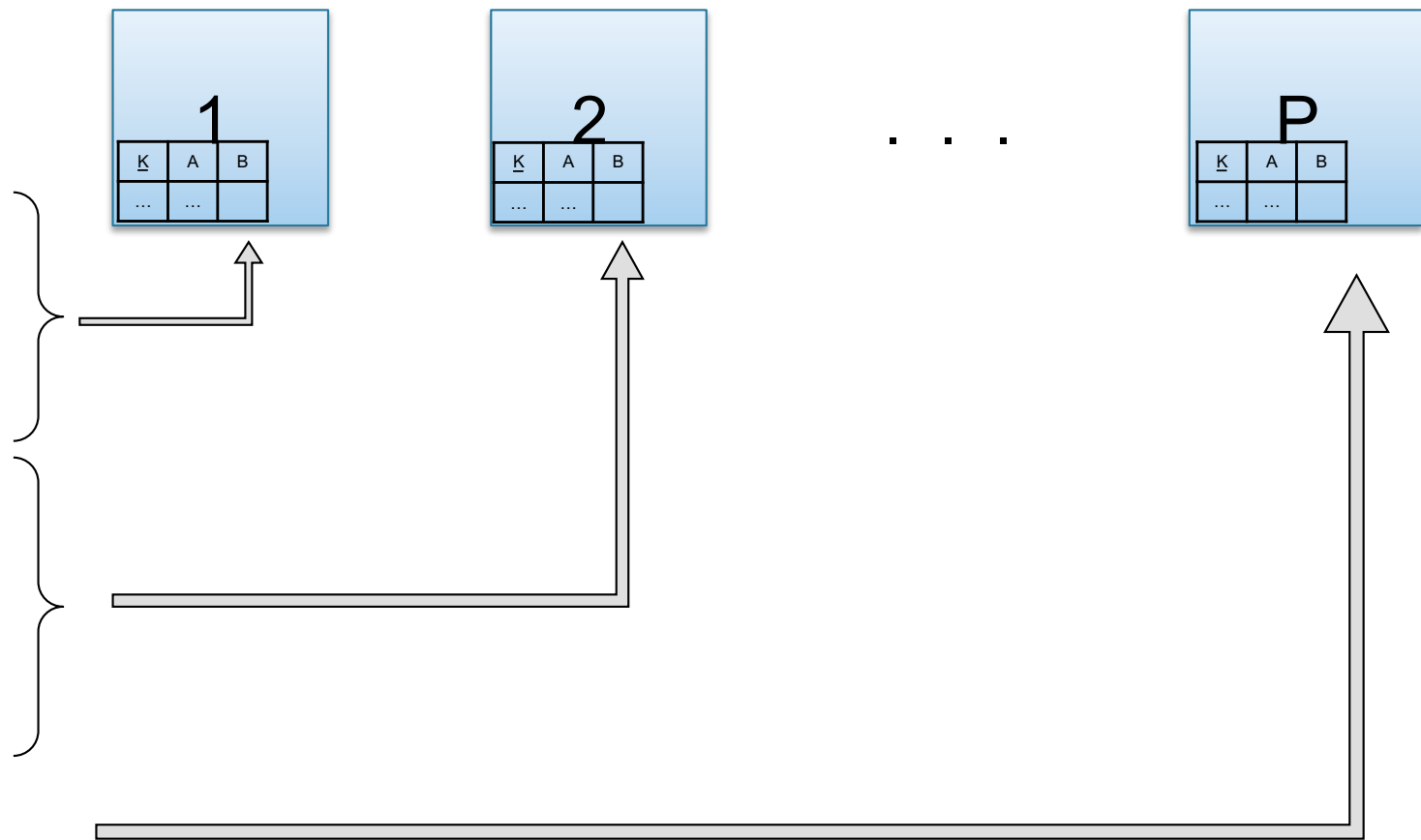


Horizontal Data Partitioning

Data:

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

Servers:

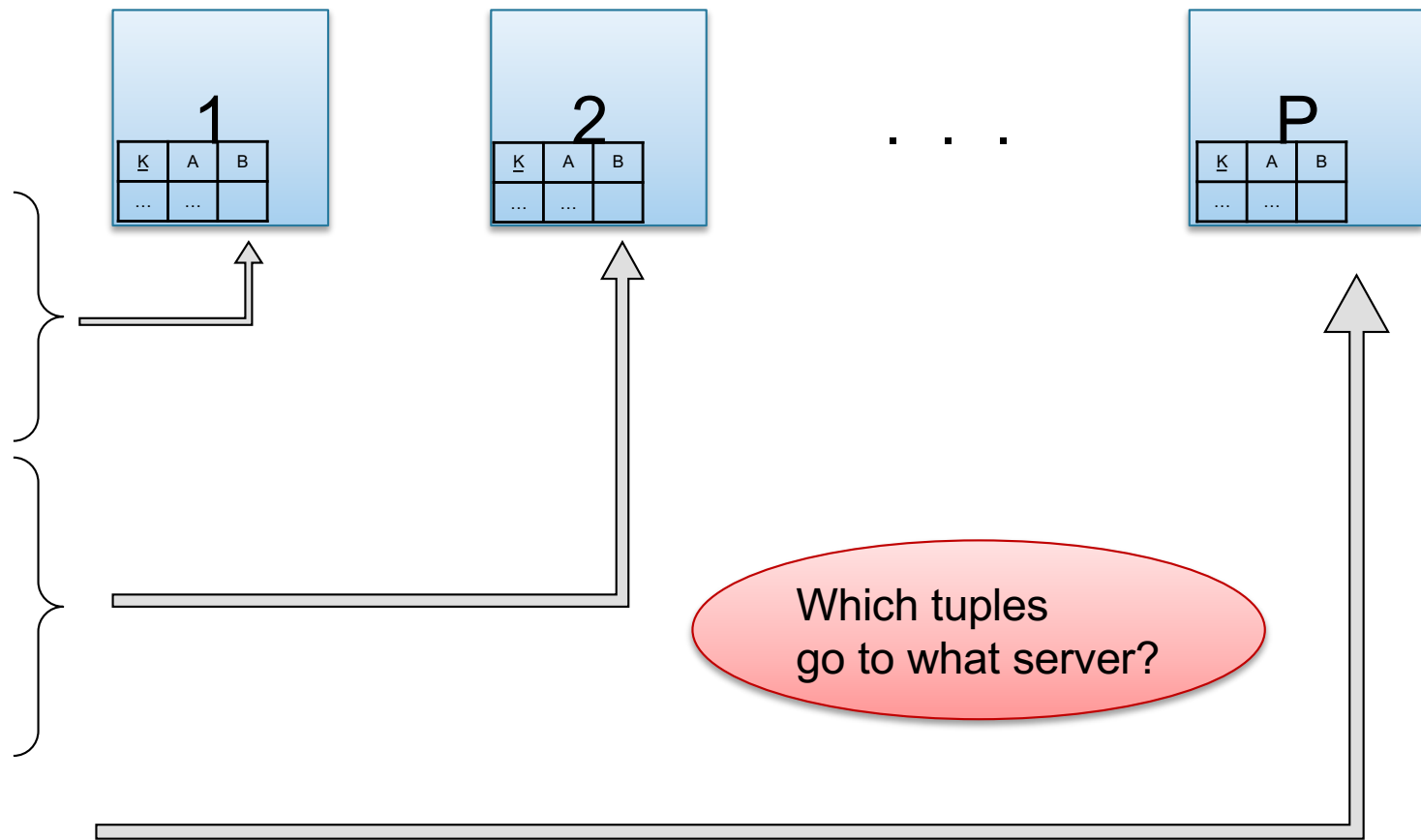


Horizontal Data Partitioning

Data:

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

Servers:



Horizontal Data Partitioning

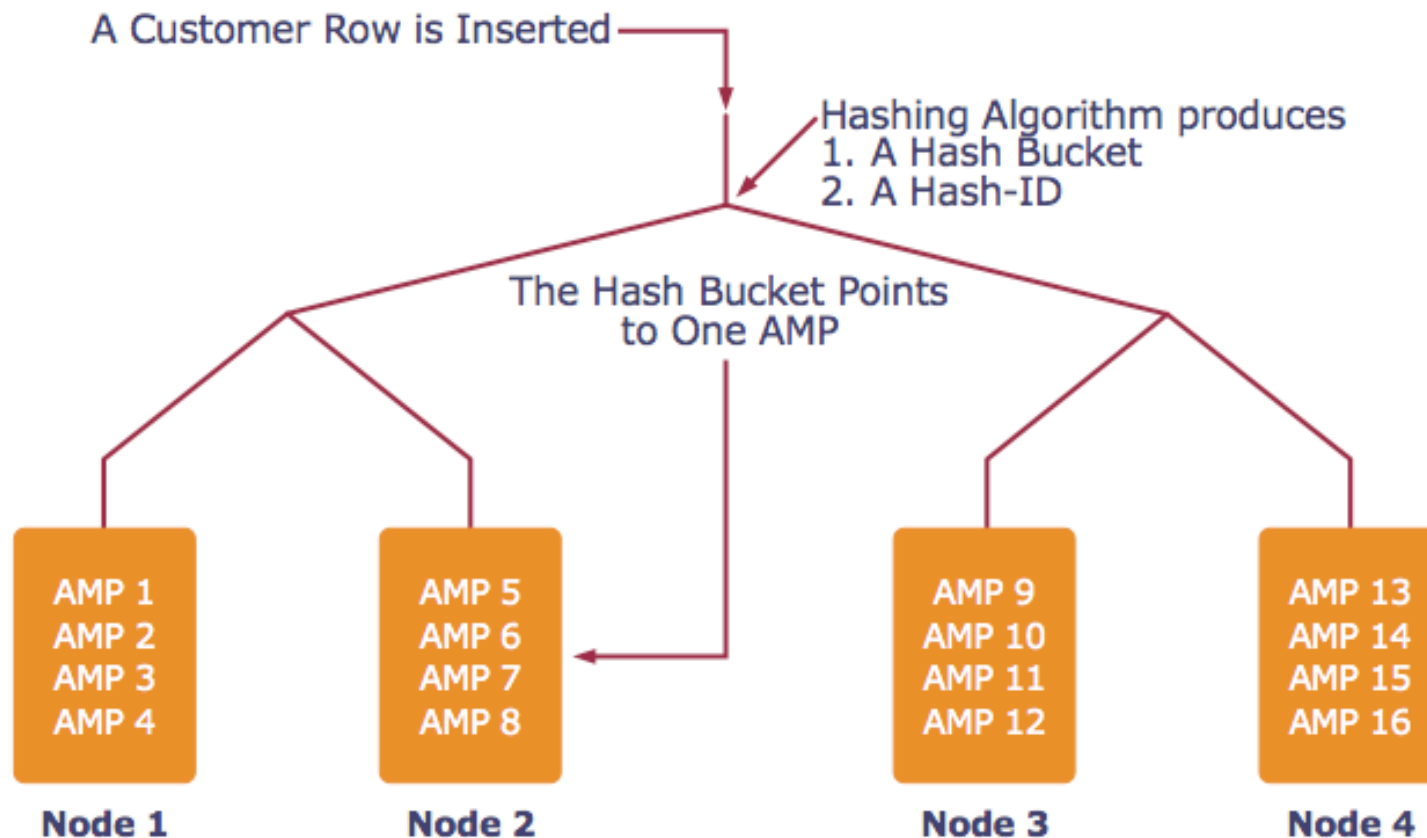
- Relation R split into P chunks R_0, \dots, R_{P-1} , stored at the P nodes
- Block partitioned
 - Each group of k tuples goes to a different node
- Hash based partitioning on attribute A :
 - Tuple t to chunk $h(t.A) \bmod P$
- Range based partitioning on attribute A :
 - Tuple t to chunk i if $v_{i-1} < t.A < v_i$
- 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

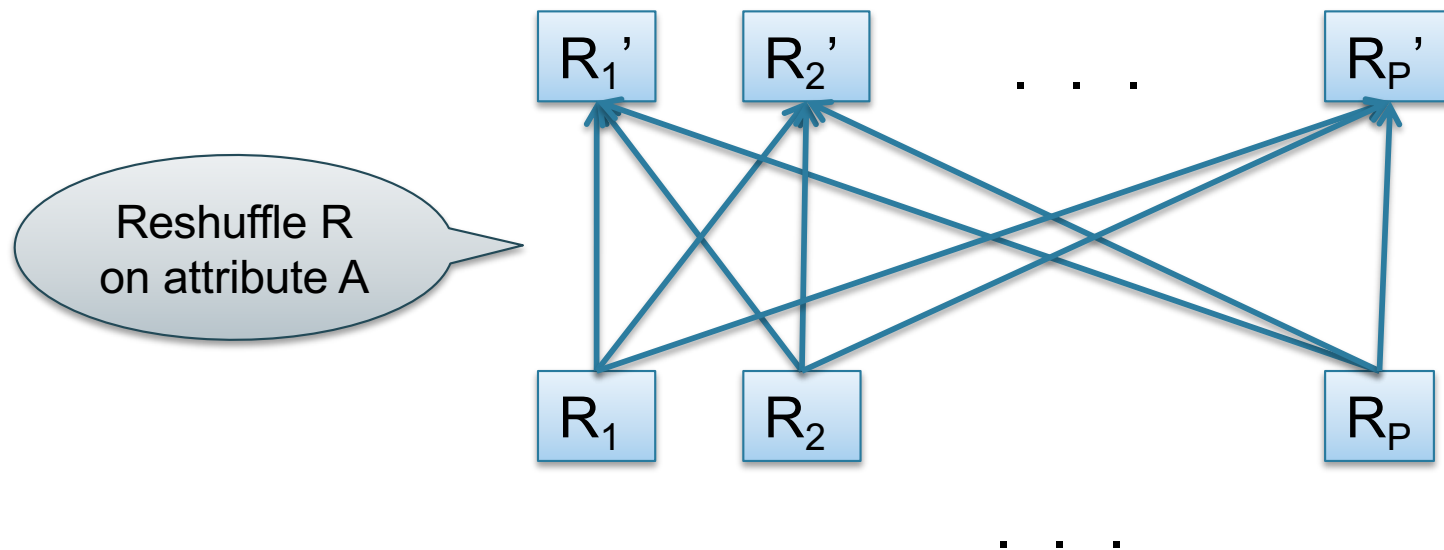
Compute $\sigma_{A=v}(R)$, or $\sigma_{v1 < A < v2}(R)$

- 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: $R(\underline{K}, A, B, C)$ -- hash-partitioned on K

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



Basic Parallel GroupBy

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

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)

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
$\text{sum}(a_1+a_2+\dots+a_9)=$ $\text{sum}(\text{sum}(a_1+a_2+a_3)+$ $\text{sum}(a_4+a_5+a_6)+$ $\text{sum}(a_7+a_8+a_9))$	$\text{avg}(B) =$ $\text{sum}(B)/\text{count}(B)$	$\text{median}(B)$

YES

- Compute partial aggregates before shuffling

Example Query with Group By

```
SELECT a, max(b) as topb  
FROM R WHERE a > 0  
GROUP BY a
```

Machine 1

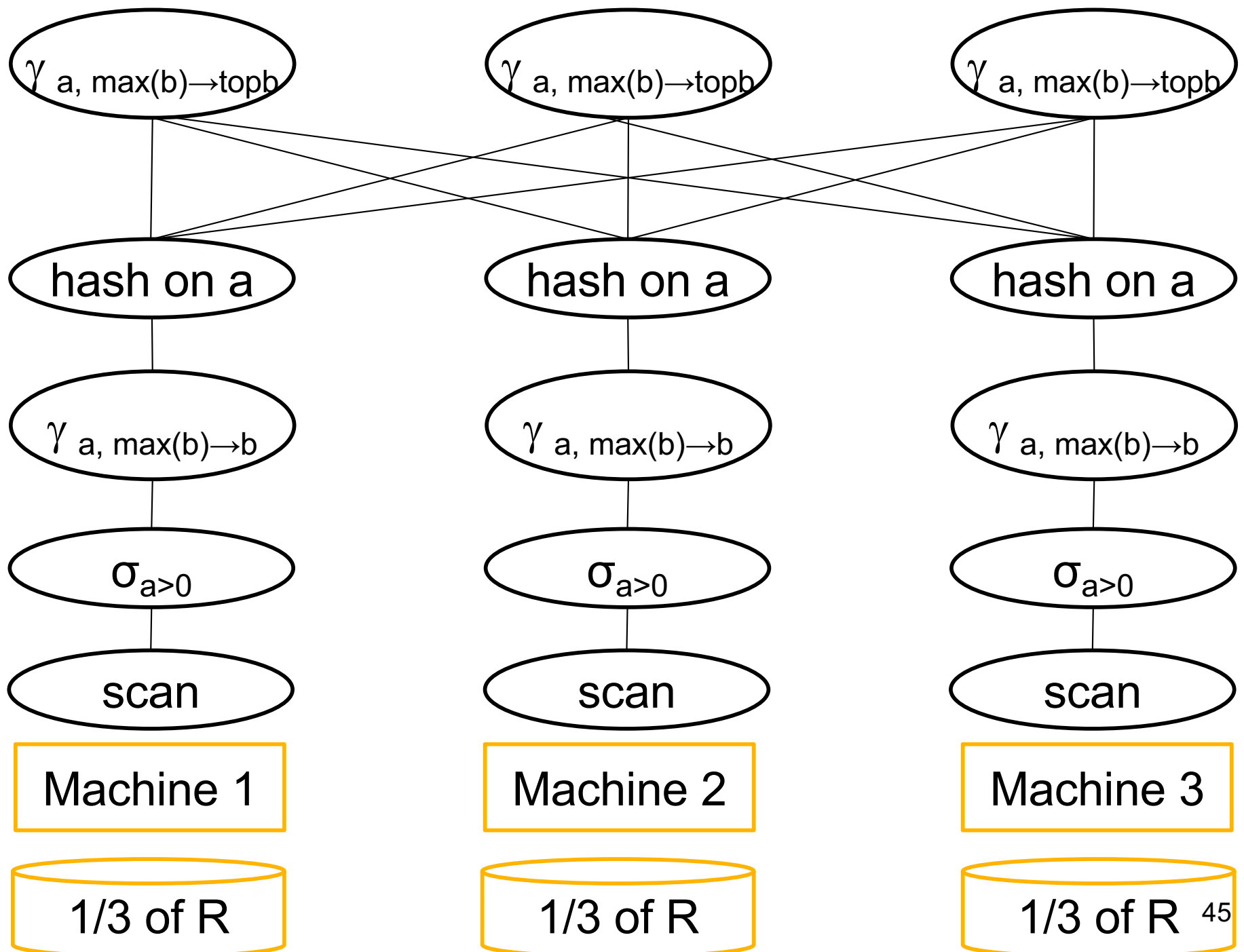
1/3 of R

Machine 2

1/3 of R

Machine 3

1/3 of R ⁴⁴

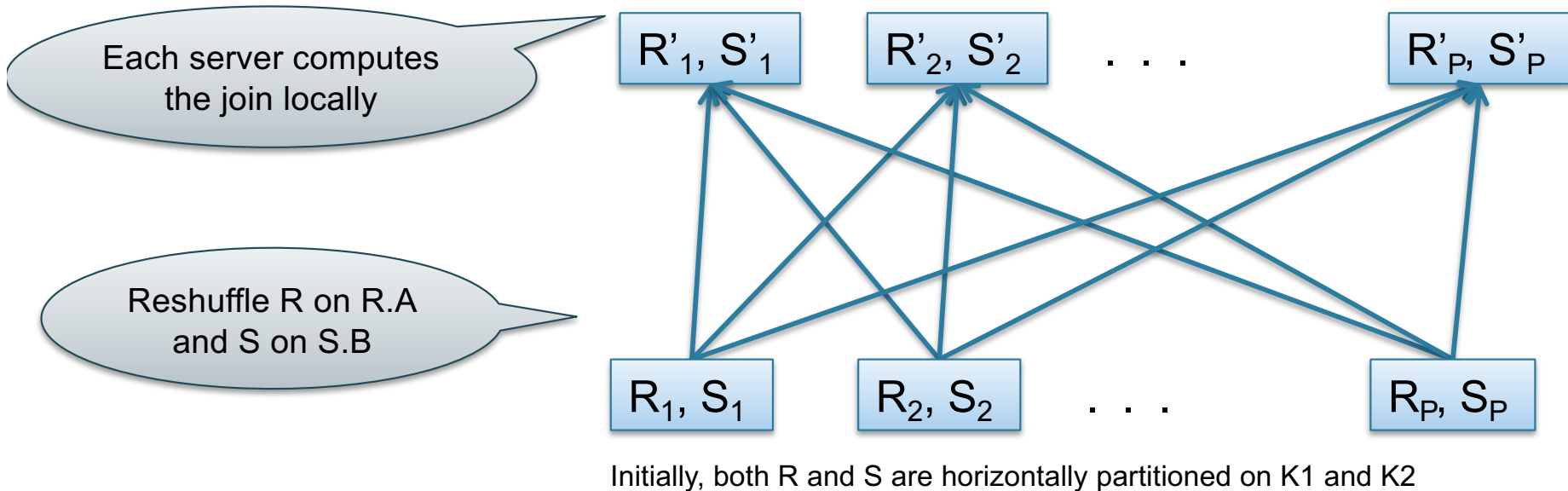


Parallel Join: $R \bowtie_{A=B} S$

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

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

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



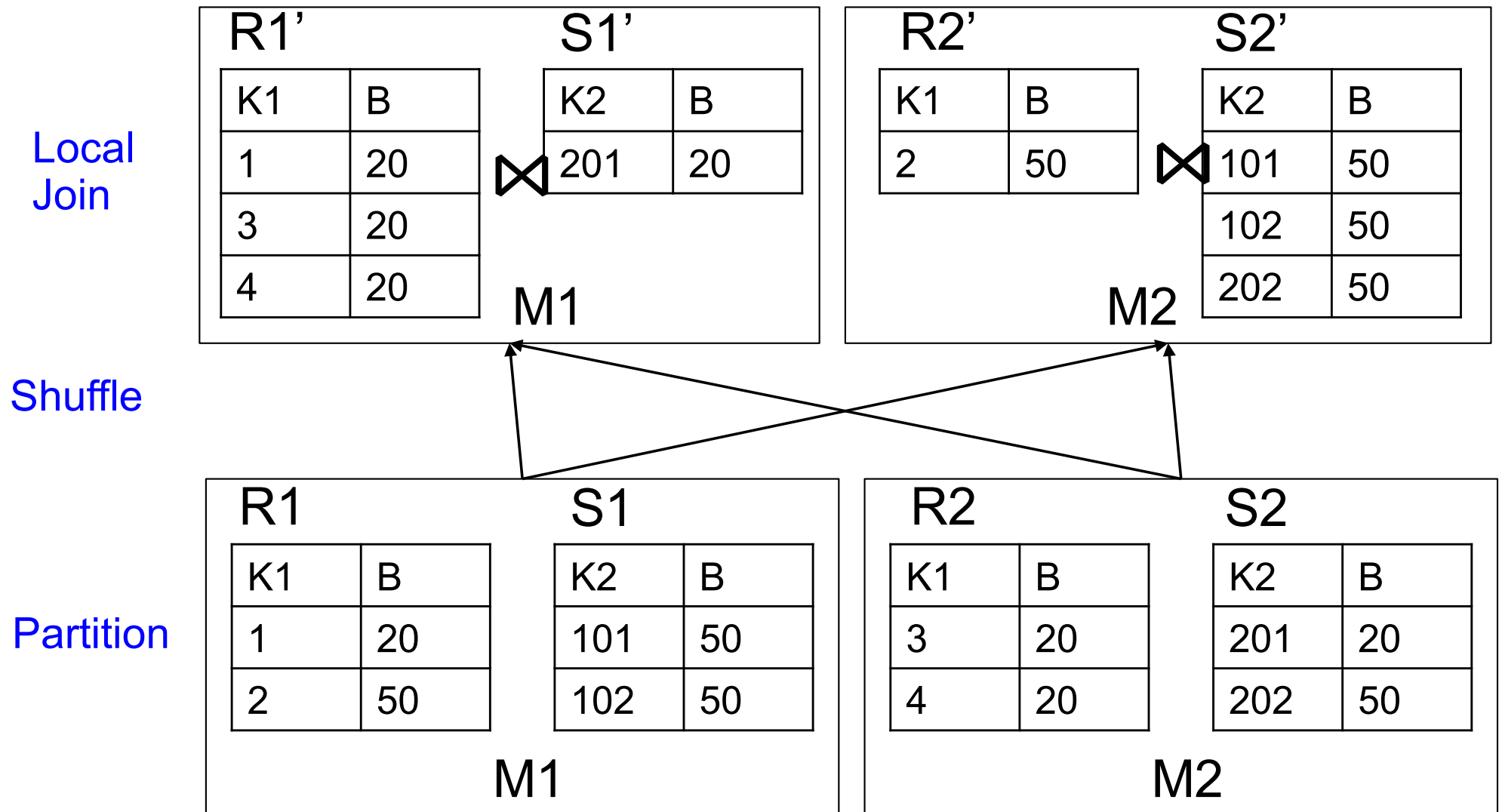
Parallel Join: $R \bowtie_{A=B} S$

- Step 1
 - Every server holding any chunk of R partitions its chunk using a hash function $h(t.A) \bmod P$
 - Every server holding any chunk of S partitions its chunk using a hash function $h(t.B) \bmod P$
- 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



Optimization for Small Relations

When joining R and S

- If $|R| \gg |S|$
 - 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.: $\{1, 1, 1, 2, 3, 4, 5, 6\} \rightarrow [1,2]$ 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”)

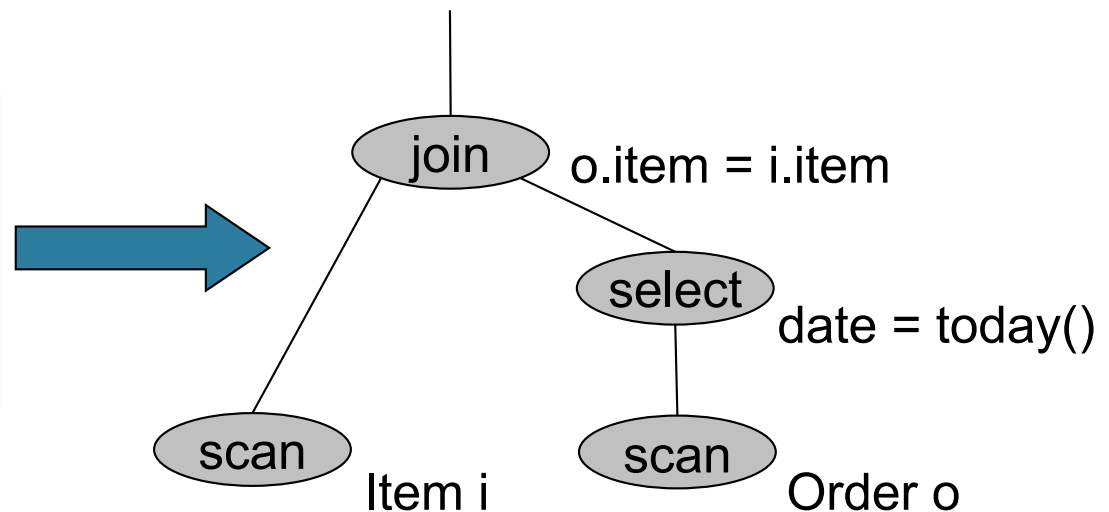
- Given $R \bowtie_{A=B} S$
- Given a heavy hitter value $R.A = 'v'$
(i.e. $'v'$ occurs very many times in R)
- Partition R tuples with value $'v'$ across all nodes
e.g. block-partition, or hash on other attributes
- Replicate S tuples with value $'v'$ to all nodes
- R = the build relation
- S = the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

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

Example: Teradata – Query Execution

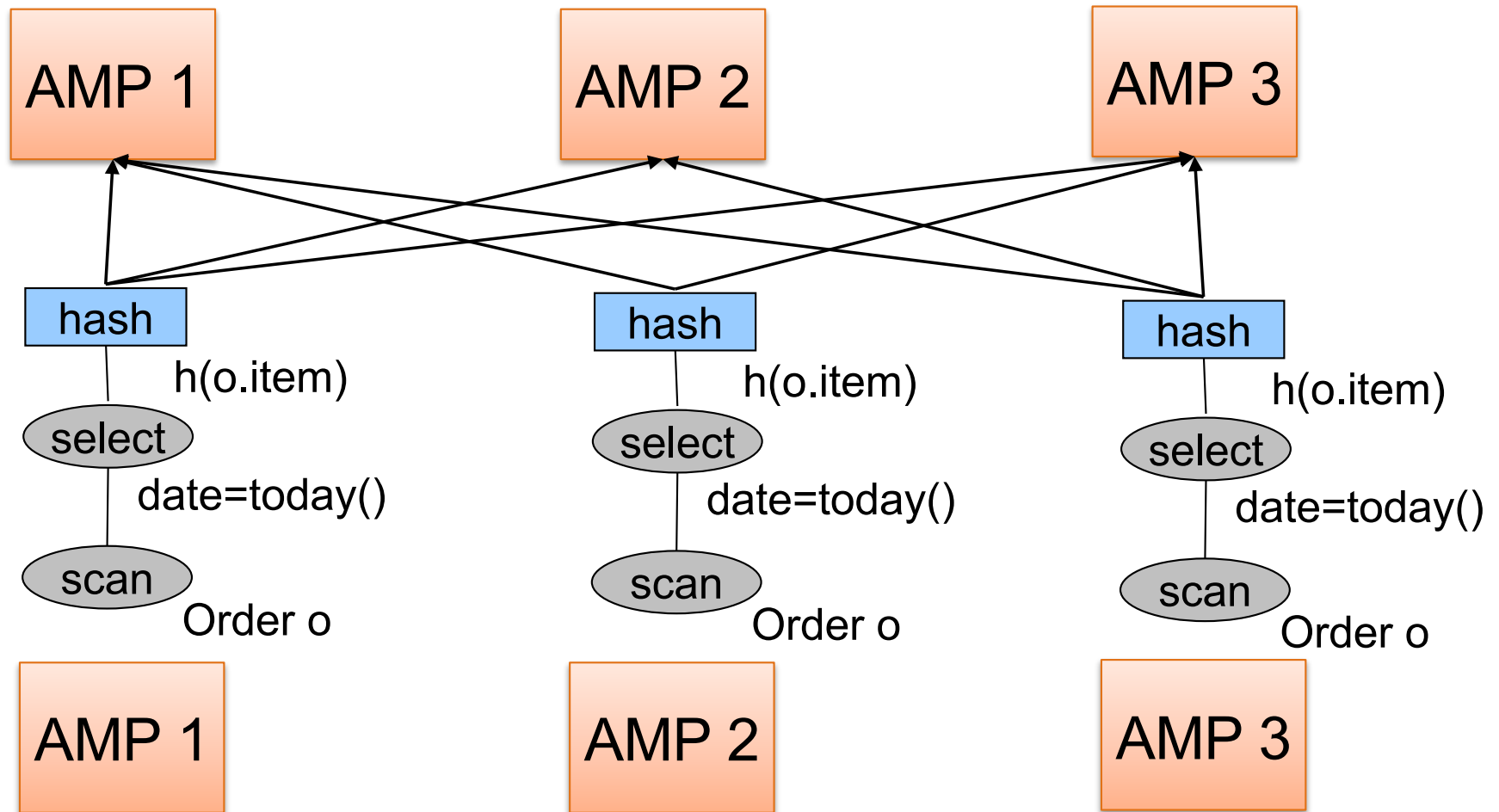
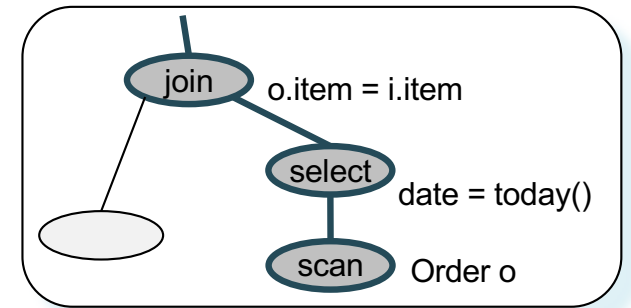
Find all orders from today, along with the items ordered

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



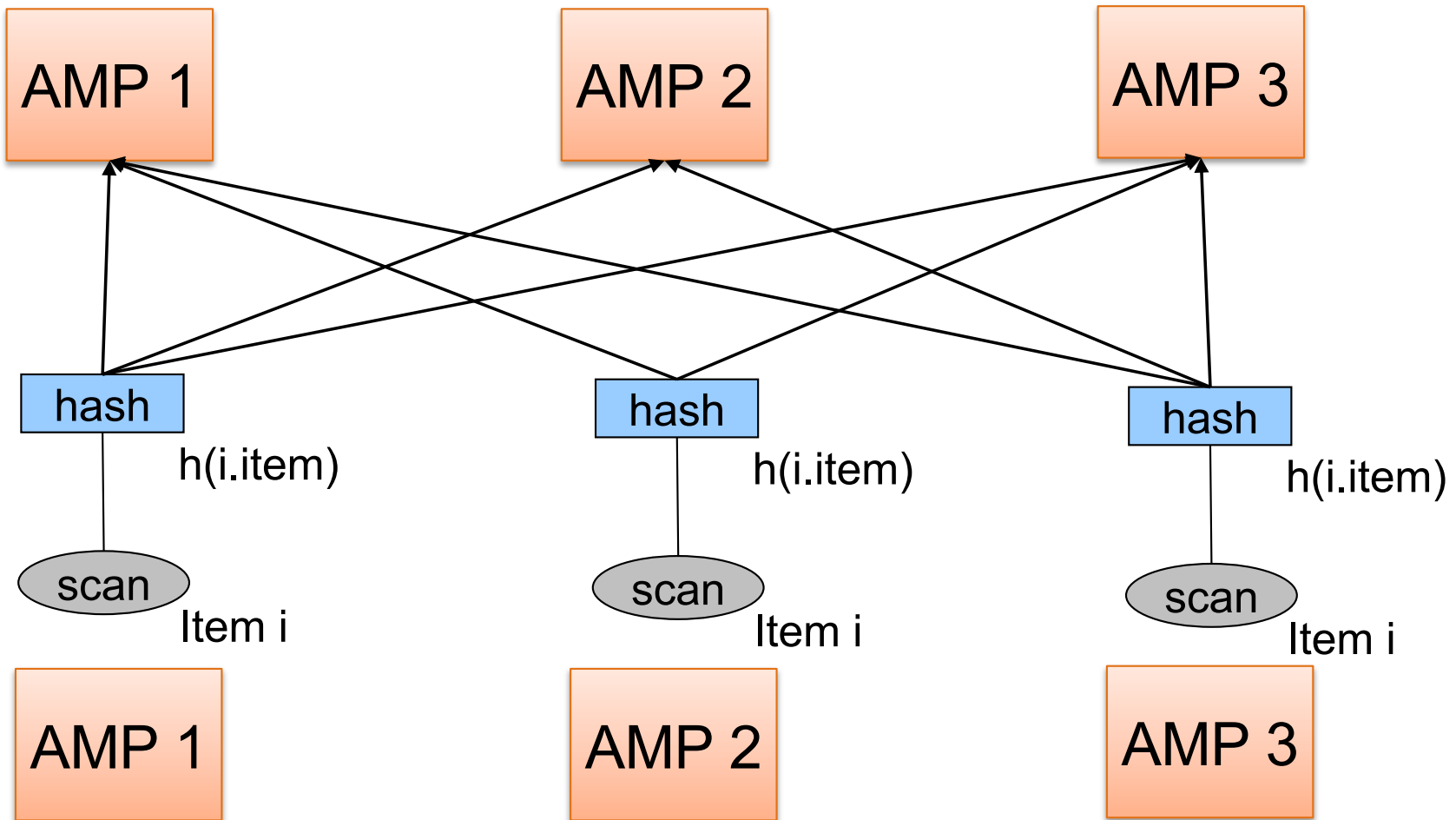
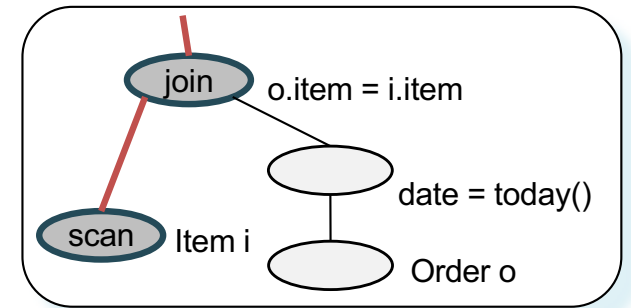
Order(oid, item, date), Line(item, ...)

Query Execution

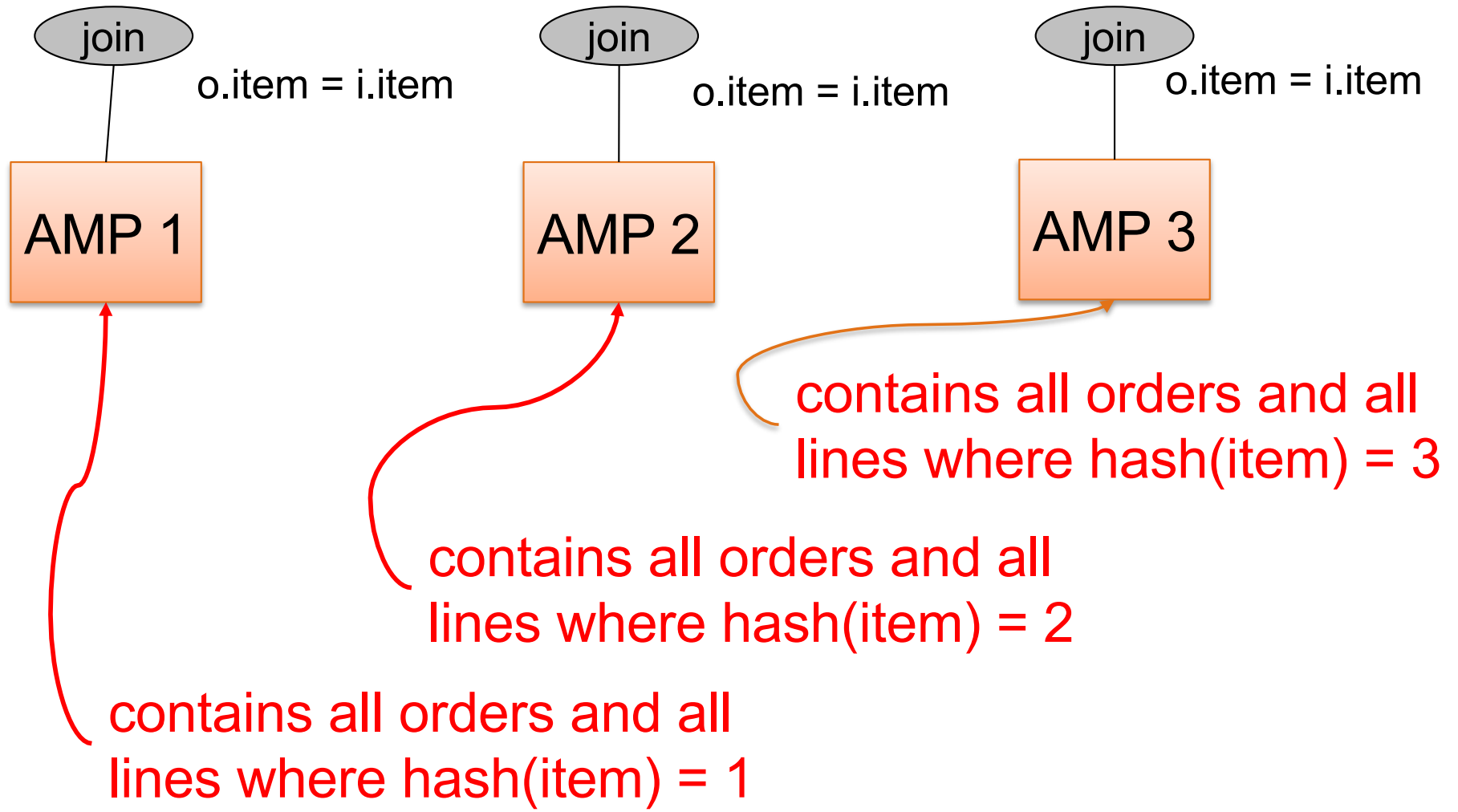


Order(oid, item, date), Line(item, ...)

Query Execution



Query Execution



Example 2

SELECT *

FROM R, S, T

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

Machine 1

1/3 of R, S, T

Machine 2

1/3 of R, S, T

Machine 3

1/3 of R, S, T

