Carnegie Mellon University

24

Distributed OLAP Databases

Intro to Database Systems
15-445/15-645
Fall 2019

AP
Andy Pavlo
Computer Science
Carnegie Mellon University

ADMINISTRIVIA

Homework #5: Monday Dec 3rd @ 11:59pm

Project #4: Monday Dec 10th @ 11:59pm

Extra Credit: Wednesday Dec 10th @ 11:59pm

Final Exam: Monday Dec 9th @ 5:30pm

Systems Potpourri: Wednesday Dec 4th
→ Vote for what system you want me to talk about.
→ https://cmudb.io/f19-systems

ADMINISTRIVIA

Monday Dec 2nd – Oracle Lecture
→ Shasank Chavan (VP In-Memory Databases)

Monday Dec 2nd – Oracle Systems Talk
→ 4:30pm in GHC 6115
→ Pizza will be served

Tuesday Dec 3rd – Oracle Research Talk
→ Hideaki Kimura (Oracle Beast)
→ 12:00pm in CIC 4th Floor (Panther Hollow Room)
→ Pizza will be served.

LAST CLASS

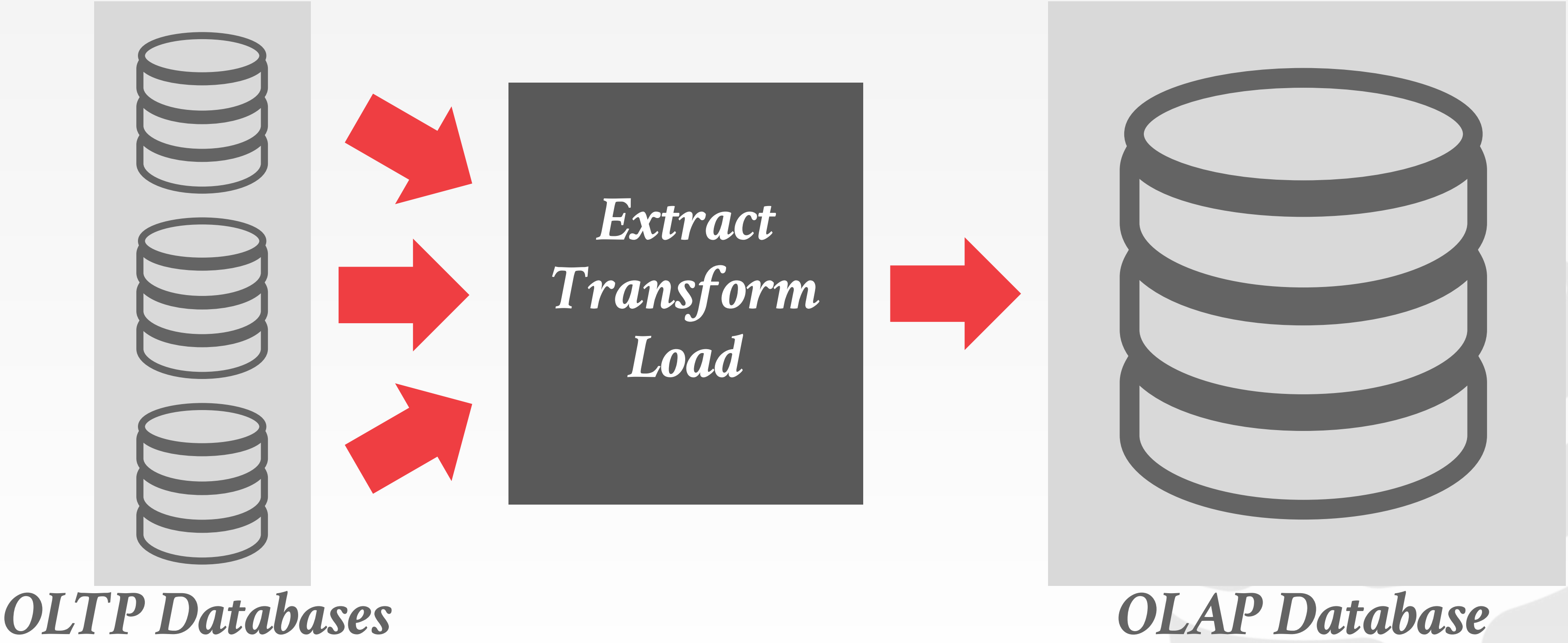
Atomic Commit Protocols

Replication

Consistency Issues (CAP)

Federated Databases

BIFURCATED ENVIRONMENT

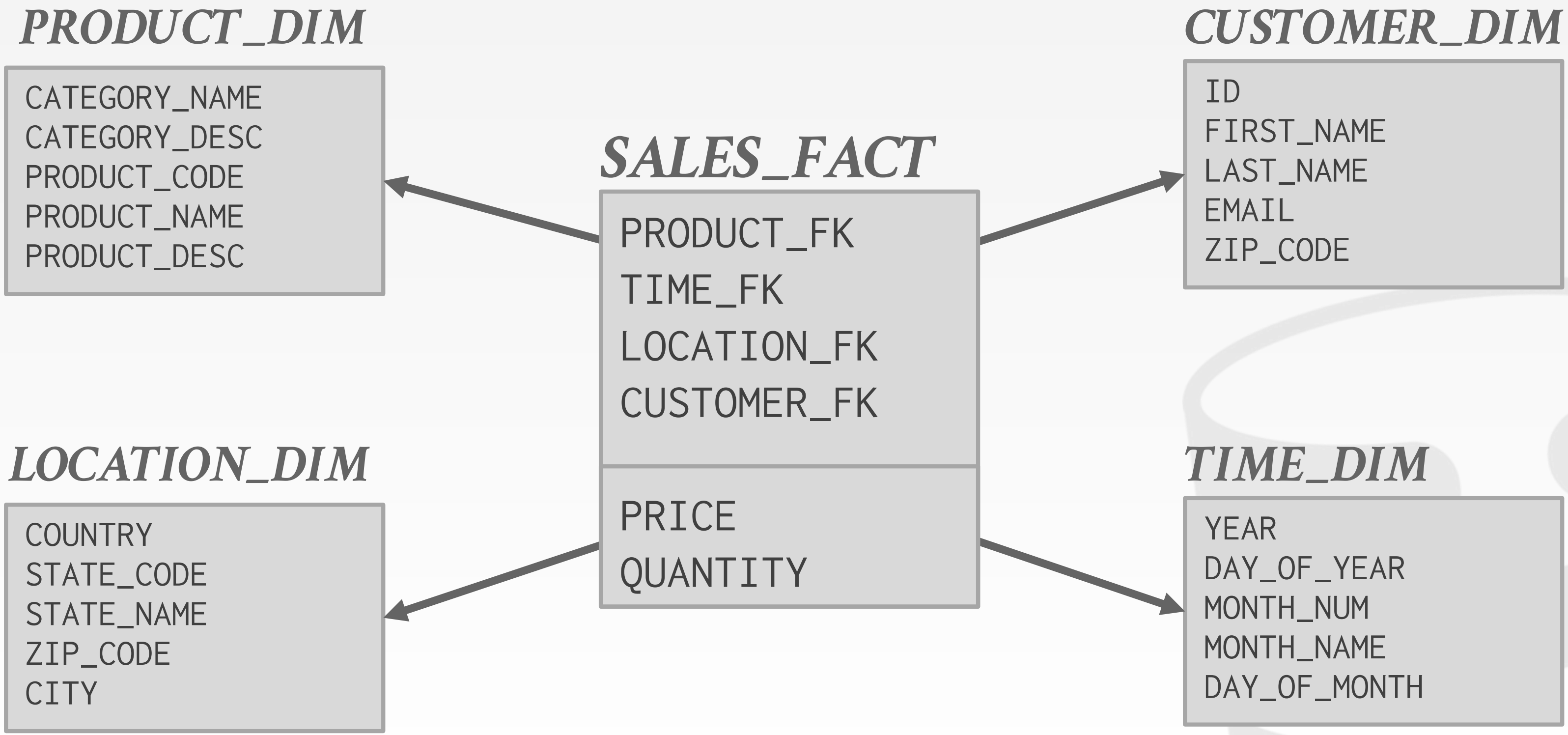


DECISION SUPPORT SYSTEMS

Applications that serve the management, operations, and planning levels of an organization to help people make decisions about future issues and problems by analyzing historical data.

Star Schema vs. Snowflake Schema

STAR SCHEMA


PRODUCT_DIM
CATEGORY_NAME
CATEGORY_DESC
PRODUCT_CODE
PRODUCT_NAME
PRODUCT_DESC
CUSTOMER_DIM
ID
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LAST_NAME
EMAIL
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SALES_FACT
PRODUCT_FK
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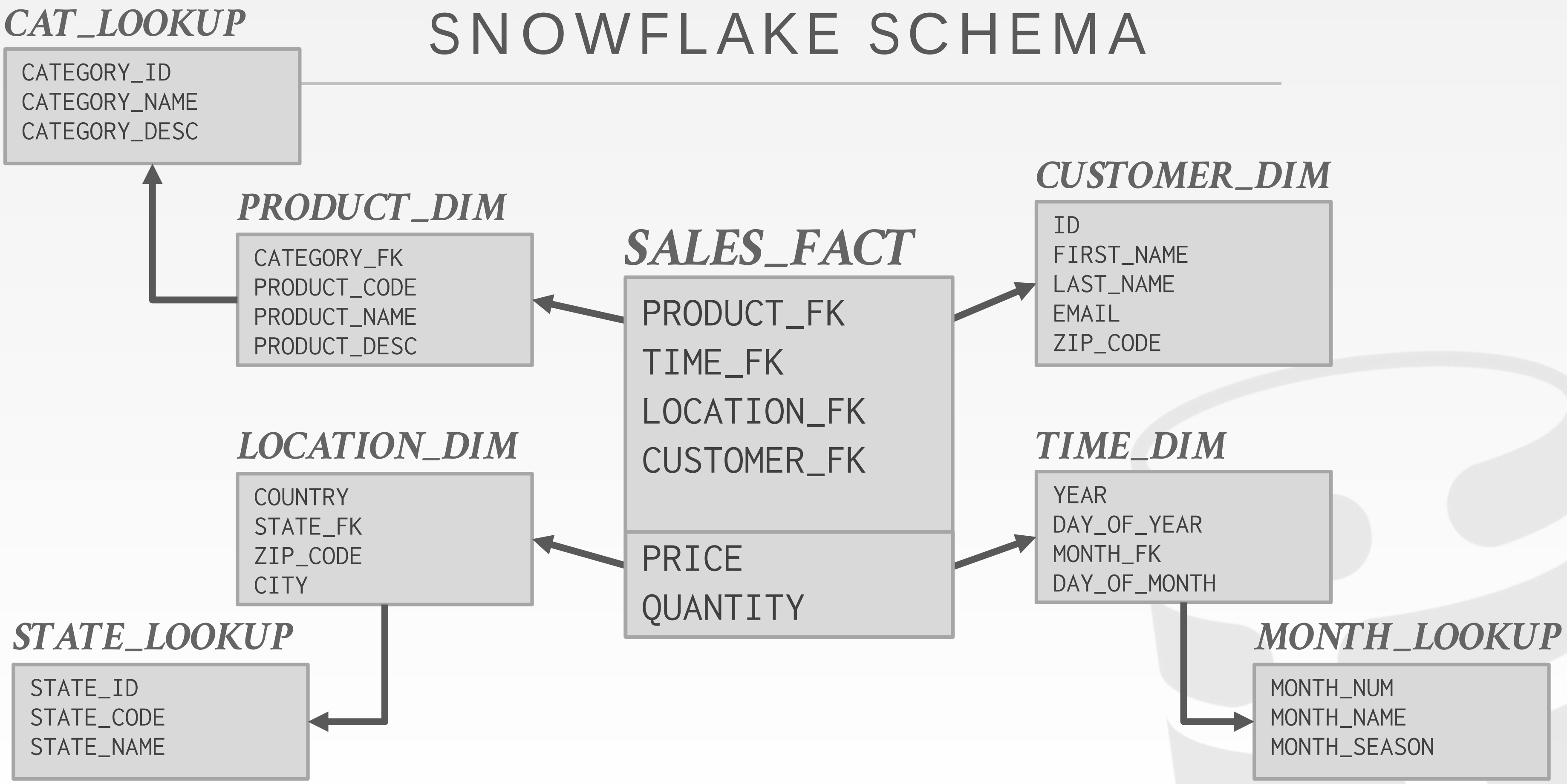
SNOWFLAKE SCHEMA



STAR VS. SNOWFLAKE SCHEMA

Issue #1: Normalization

→ Snowflake schemas take up less storage space.
→ Denormalized data models may incur integrity and consistency violations.

Issue #2: Query Complexity

→ Snowflake schemas require more joins to get the data needed for a query.
→ Queries on star schemas will (usually) be faster.

PROBLEM SETUP

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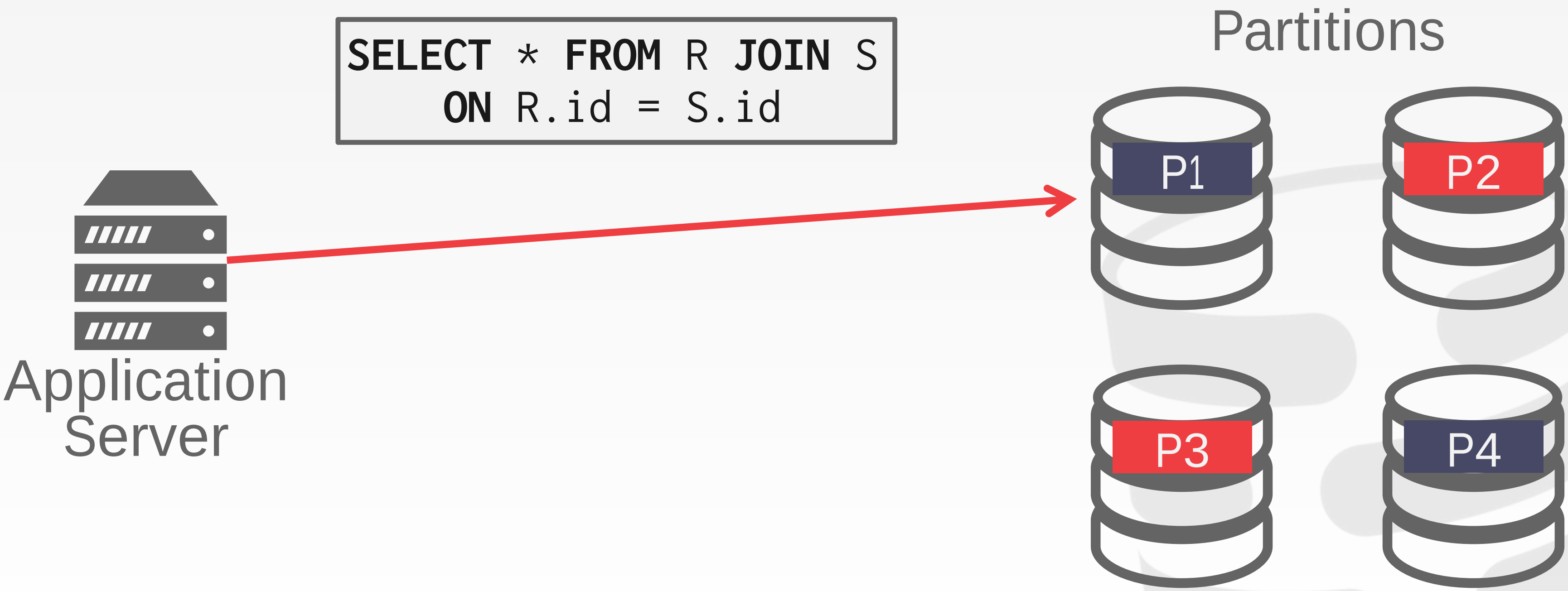
SELECT * FROM R JOIN S
ON R.id = S.id
```



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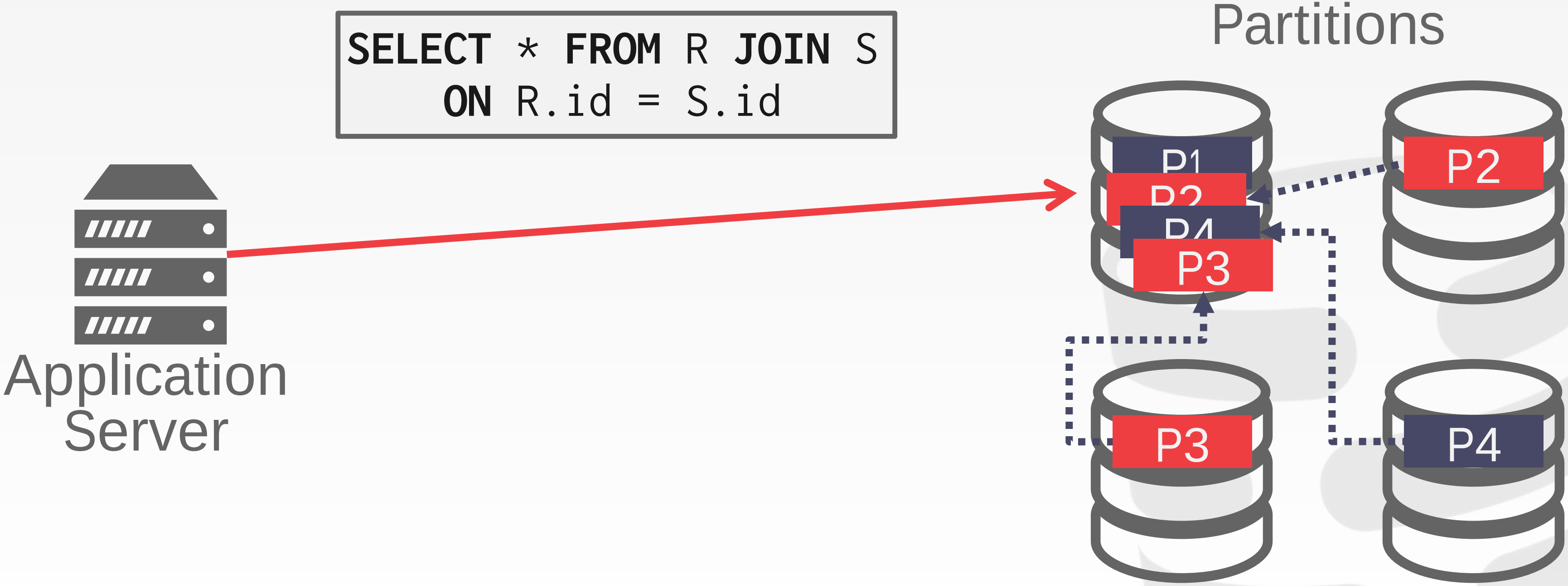

TODAY'S AGENDA

Execution Models

Query Planning

Distributed Join Algorithms

Cloud Systems

PUSH VS. PULL

Approach #1: Push Query to Data

→ Send the query (or a portion of it) to the node that contains the data.

→ Perform as much filtering and processing as possible where data resides before transmitting over network.

Approach #2: Pull Data to Query

→ Bring the data to the node that is executing a query that needs it for processing.

PUSH QUERY TO DATA

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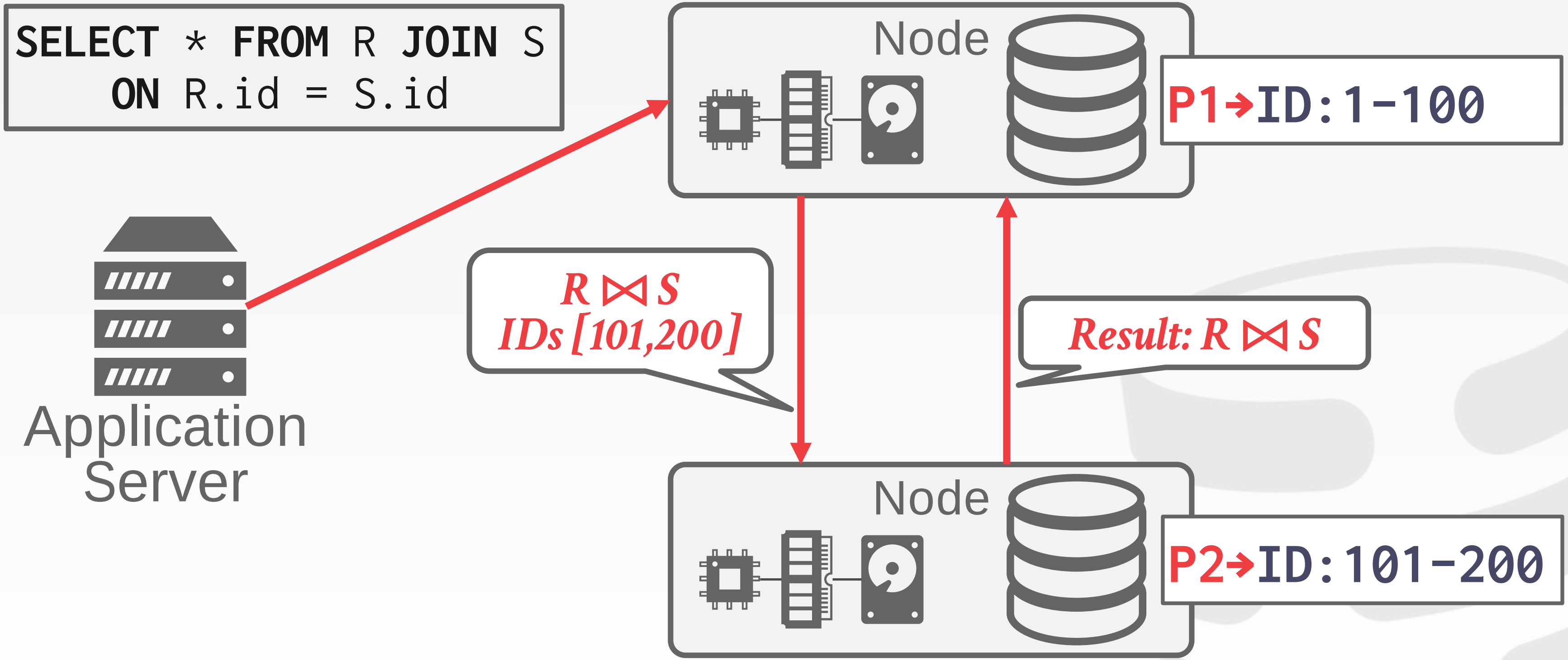

PULL DATA TO QUERY

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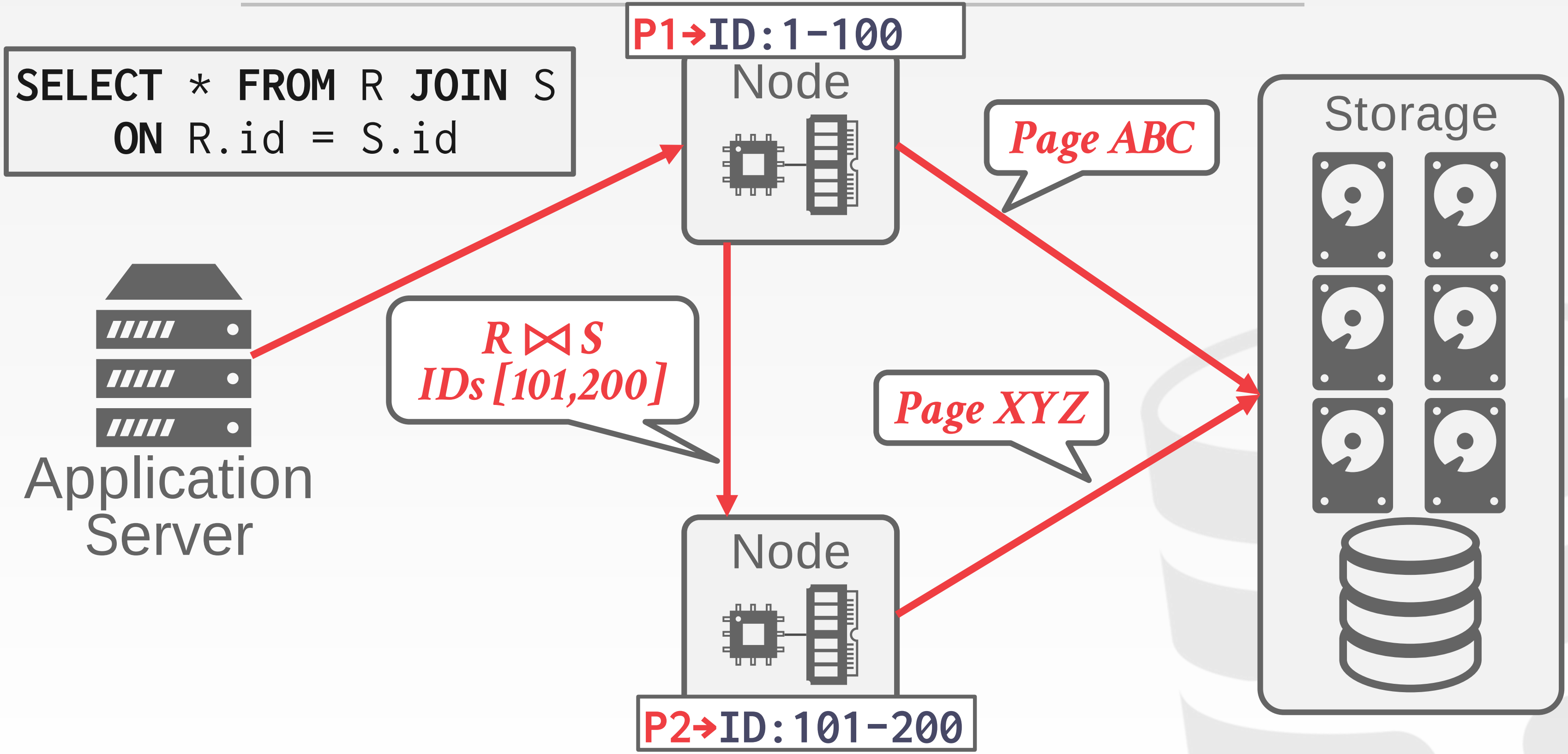

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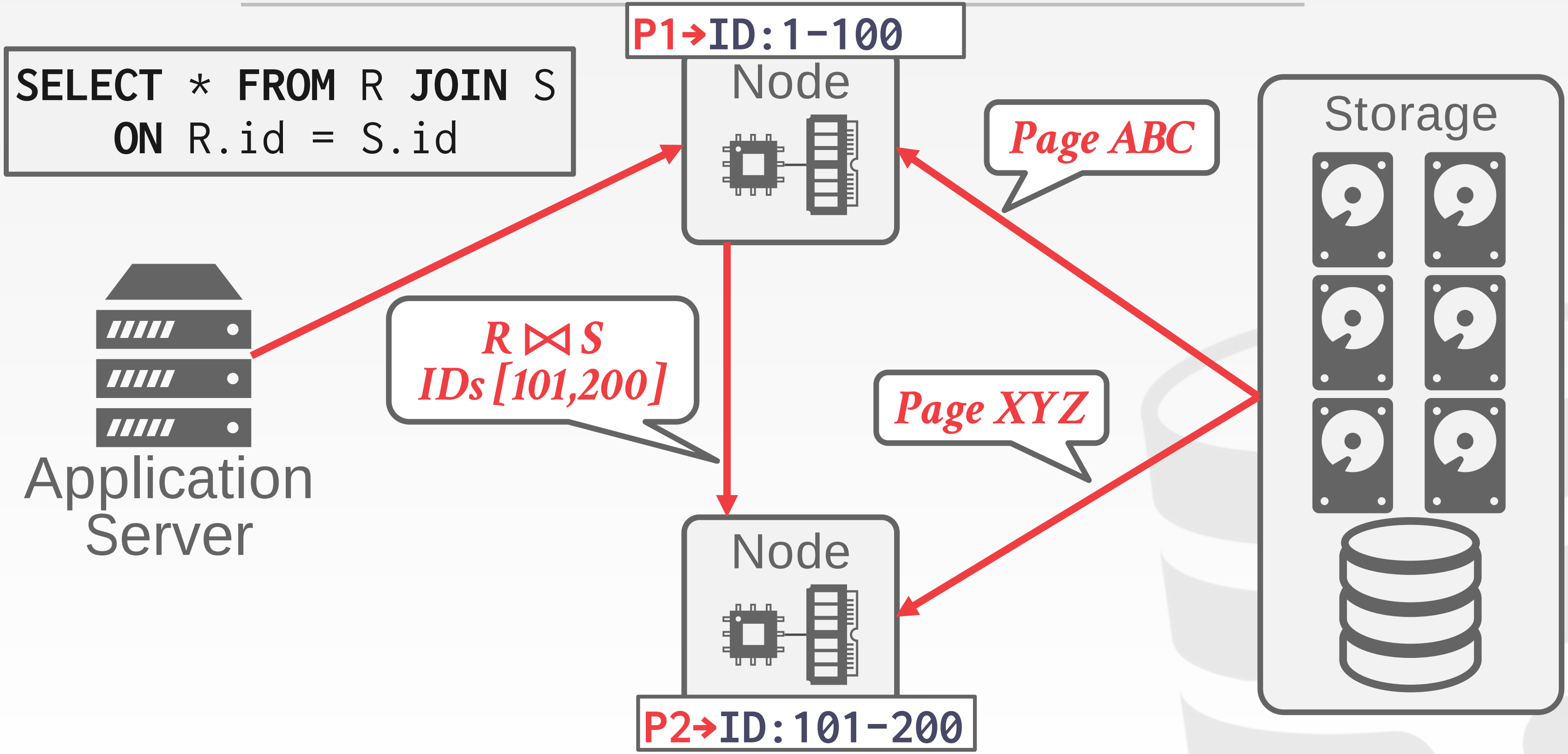

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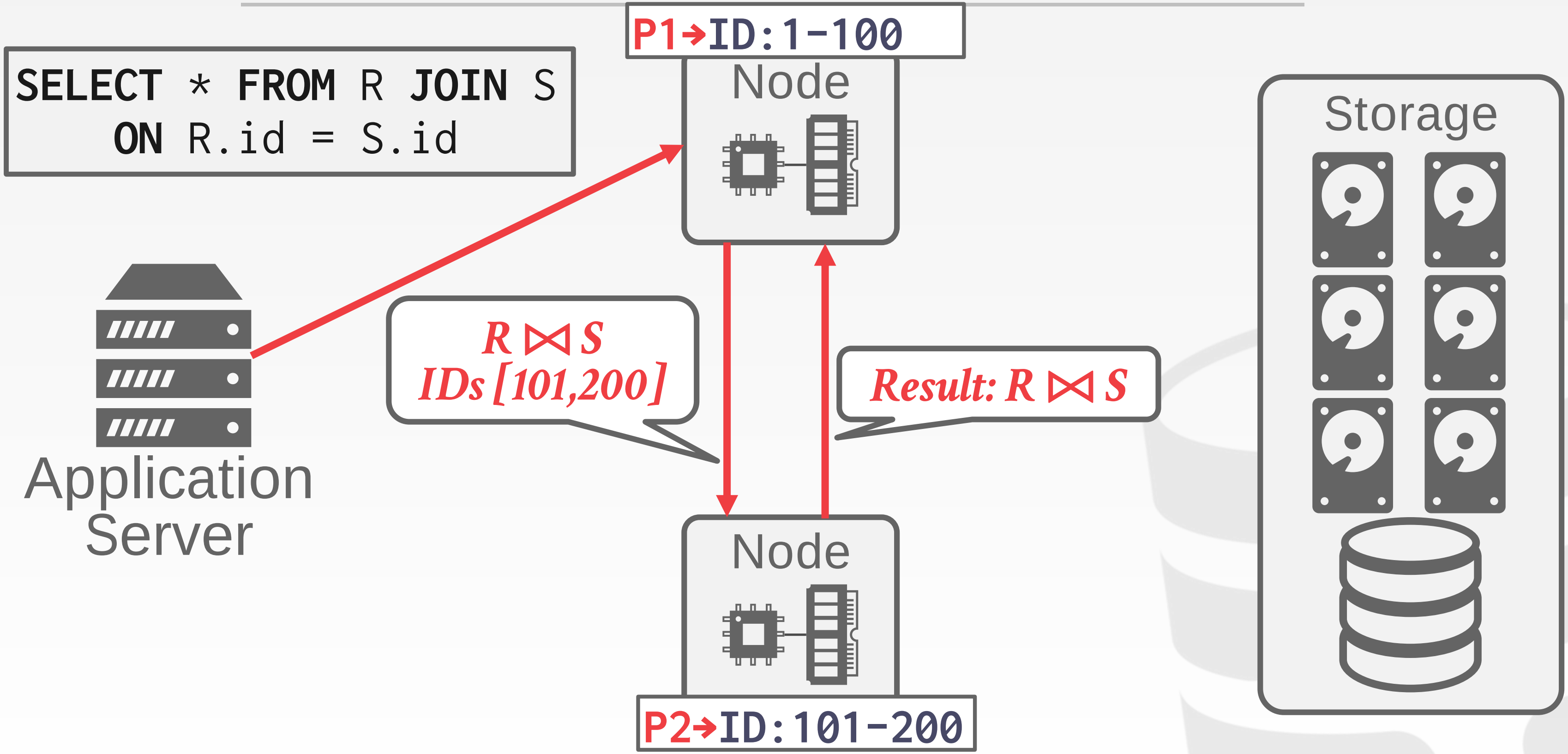

OBSERVATION

The data that a node receives from remote sources are cached in the buffer pool.

→ This allows the DBMS to support intermediate results that are large than the amount of memory available.

→ Ephemeral pages are not persisted after a restart.

What happens to a long-running OLAP query if a node crashes during execution?

QUERY FAULT TOLERANCE

Most shared-nothing distributed OLAP DBMSs are designed to assume that nodes do not fail during query execution.

→ If one node fails during query execution, then the whole query fails.

The DBMS could take a snapshot of the intermediate results for a query during execution to allow it to recover if nodes fail.

QUERY FAULT TOLERANCE

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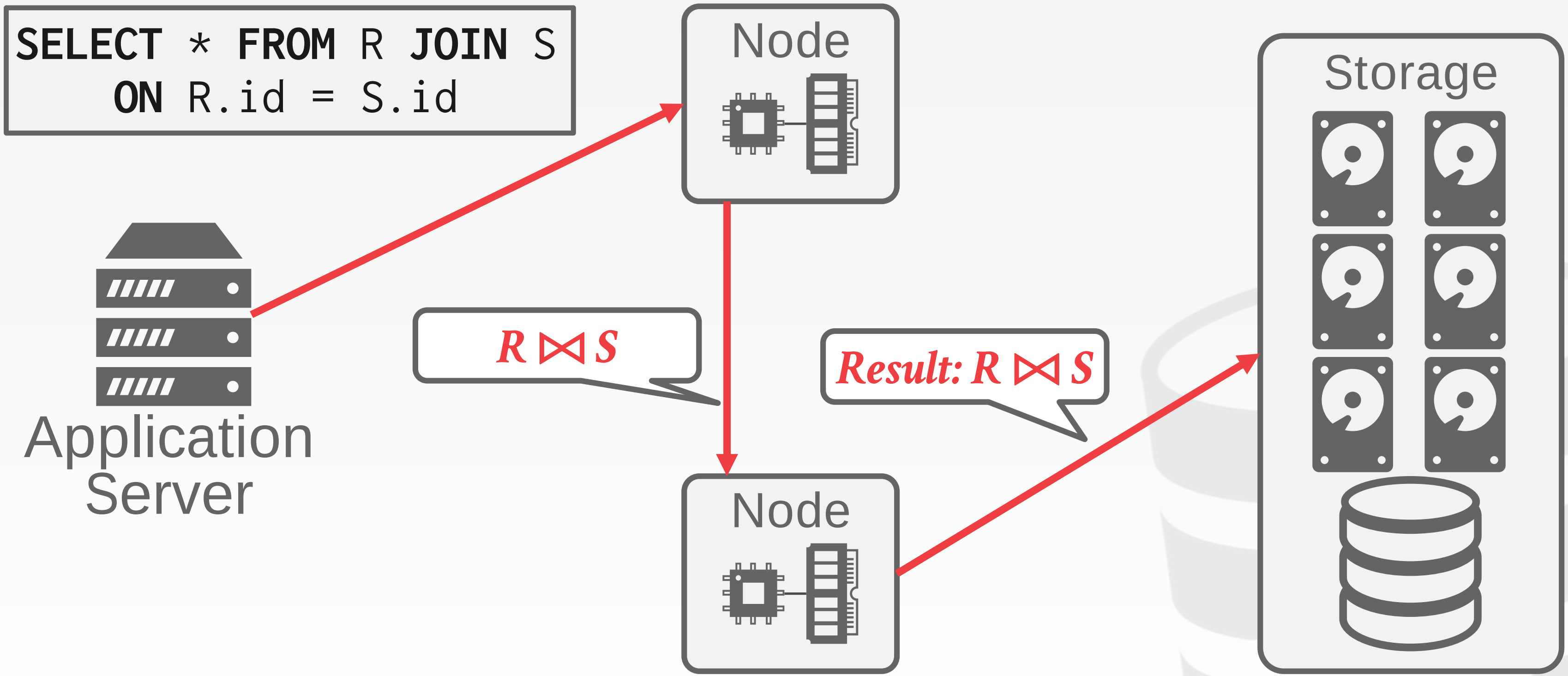

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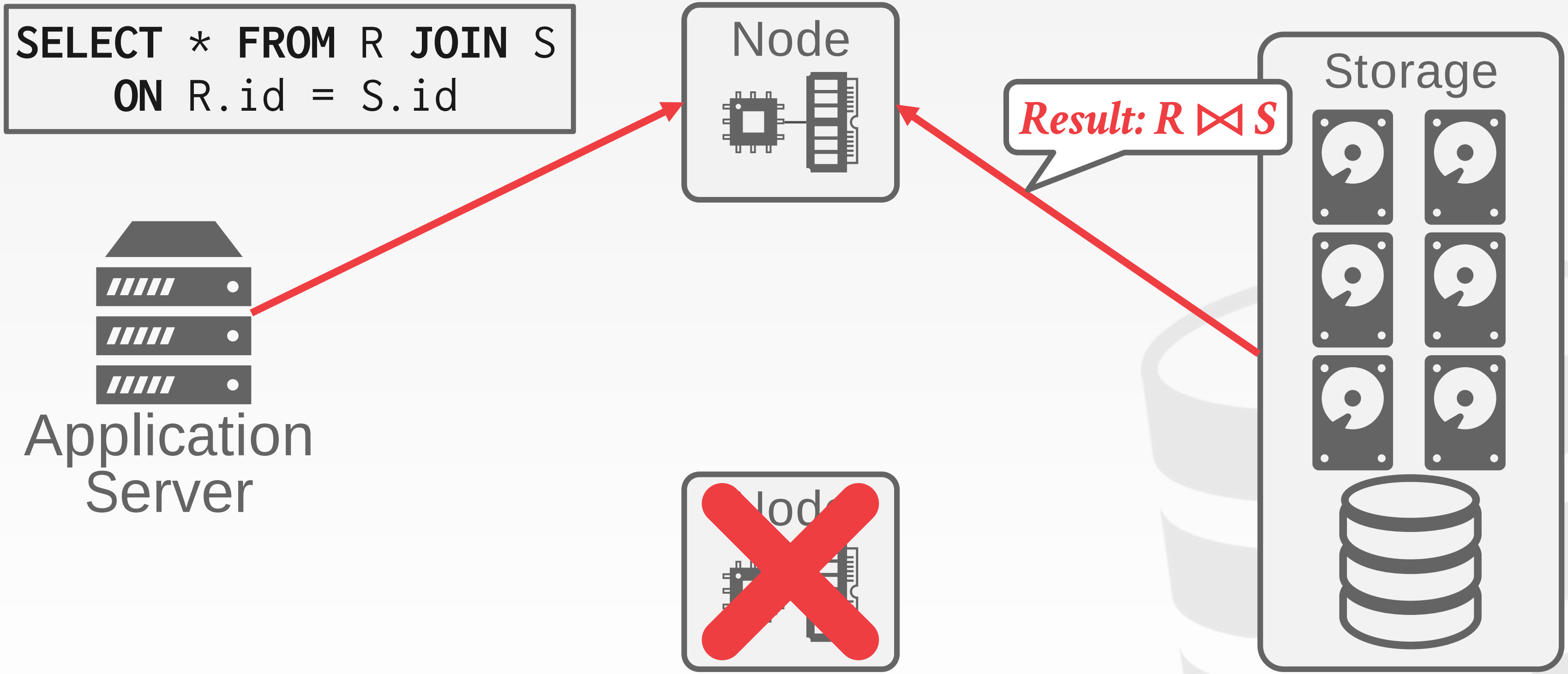


QUERY PLANNING

All the optimizations that we talked about before are still applicable in a distributed environment.
- → Predicate Pushdown
- → Early Projections
- → Optimal Join Orderings

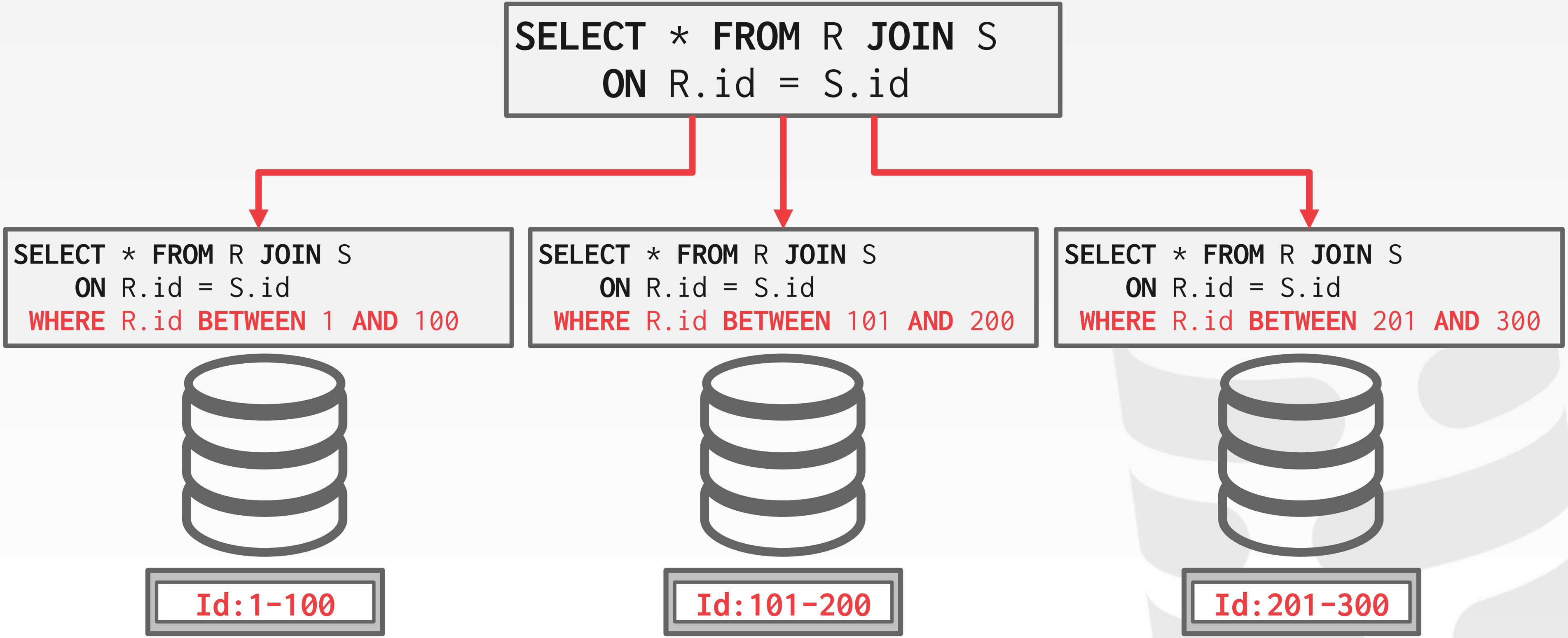
Distributed query optimization is even harder because it must consider the location of data in the cluster and data movement costs.

QUERY PLAN FRAGMENTS

Approach #1: Physical Operators
→ Generate a single query plan and then break it up into partition-specific fragments.
→ Most systems implement this approach.

Approach #2: SQL
→ Rewrite original query into partition-specific queries.
→ Allows for local optimization at each node.
→ MemSQL is the only system that I know that does this.

QUERY PLAN FRAGMENTS



N FRAGMENTS

Union the output of each join to produce final result.

```
ROM R JOIN S
ON R.id = S.id
```

```
SELECT * FROM R JOIN S
    ON R.id = S.id
 WHERE R.id BETWEEN 1 AND 100
```

```
SELECT * FROM R JOIN S
    ON R.id = S.id
 WHERE R.id BETWEEN 101 AND 200
```

```
SELECT * FROM R JOIN S
    ON R.id = S.id
 WHERE R.id BETWEEN 201 AND 300
```

Id:1-100

Id:101-200

Id:201-300

OBSERVATION

The efficiency of a distributed join depends on the target tables' partitioning schemes.

One approach is to put entire tables on a single node and then perform the join.

→ You lose the parallelism of a distributed DBMS.
→ Costly data transfer over the network.

DISTRIBUTED JOIN ALGORITHMS

To join tables **R** and **S**, the DBMS needs to get the proper tuples on the same node.

Once there, it then executes the same join algorithms that we discussed earlier in the semester.

SCENARIO #1

One table is replicated at every node. Each node joins its local data and then sends their results to a coordinating node.

```
SELECT * FROM R JOIN S
    ON R.id = S.id
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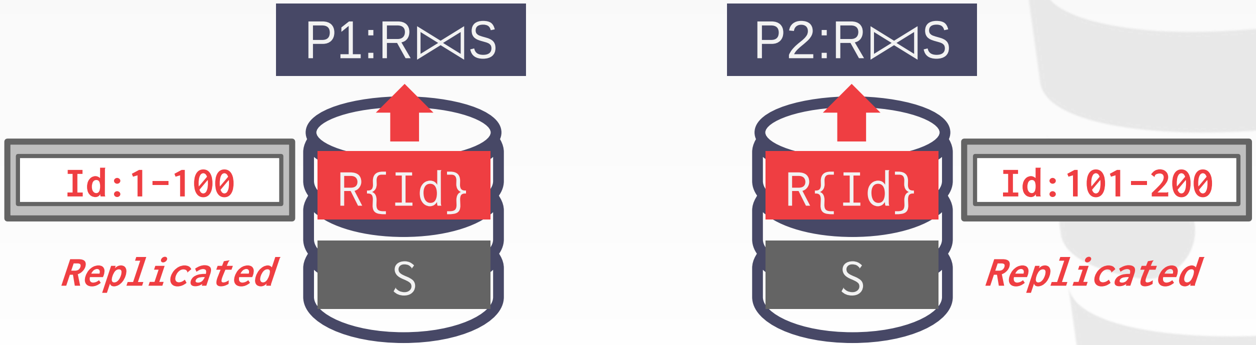

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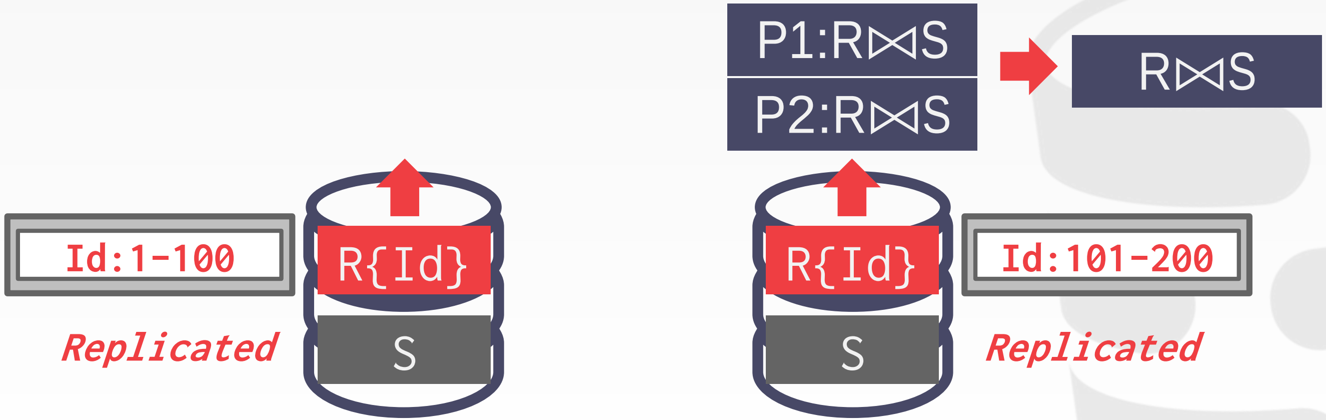

SCENARIO #2

Tables are partitioned on the join attribute. Each node performs the join on local data and then sends to a node for coalescing.

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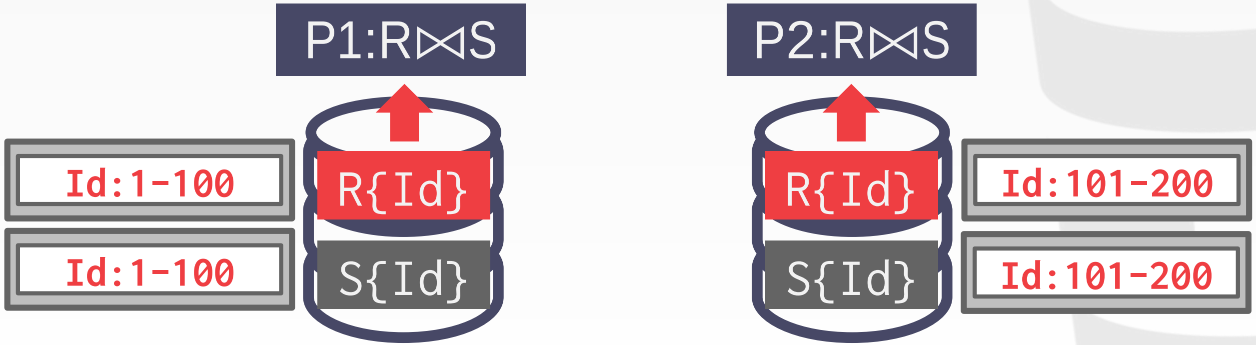

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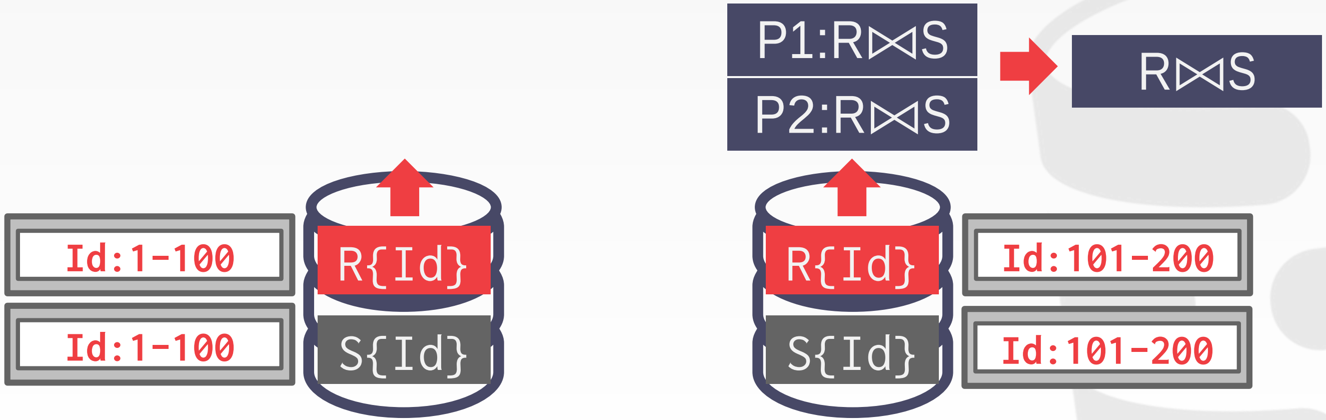

SCENARIO #3

Both tables are partitioned on different keys. If one of the tables is small, then the DBMS **broadcasts** that table to all nodes.

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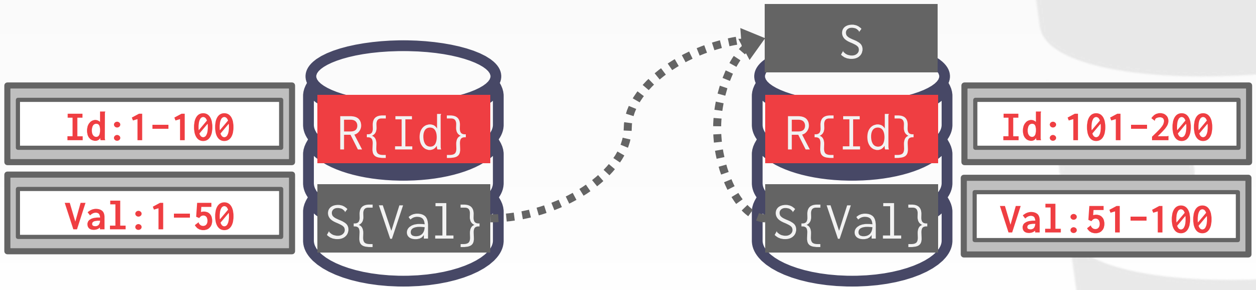

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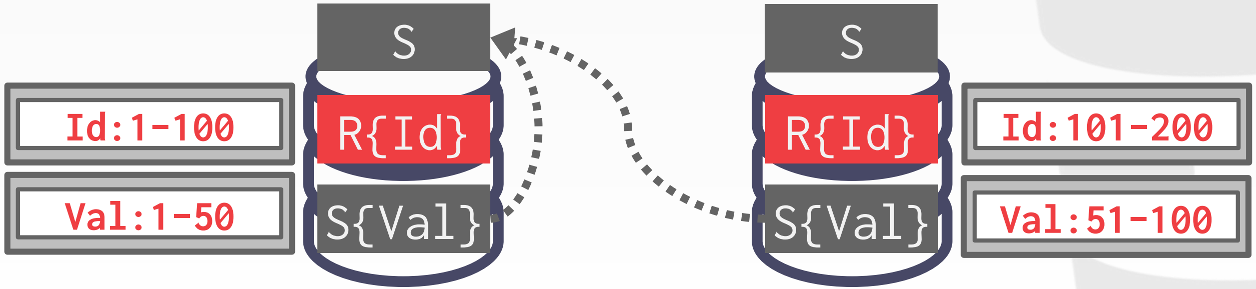

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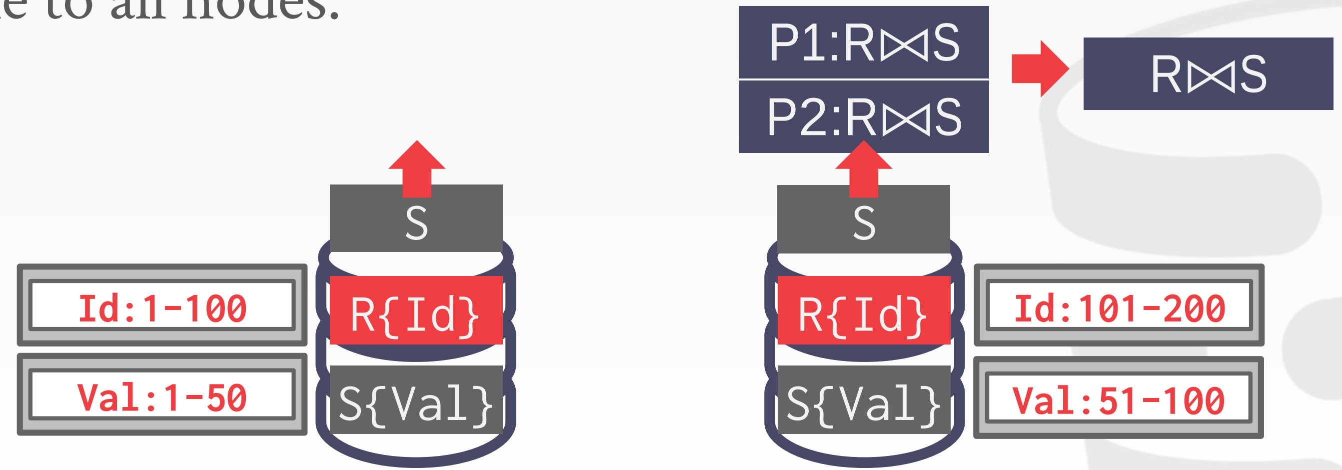

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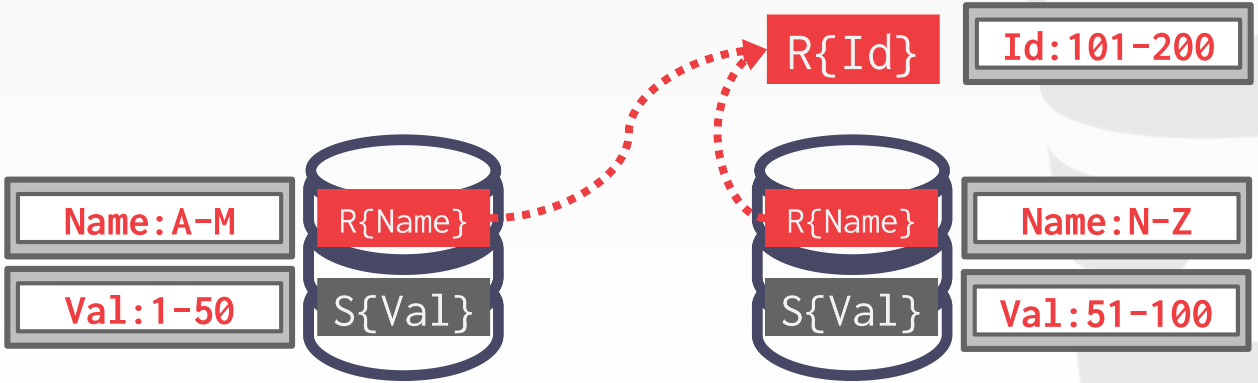

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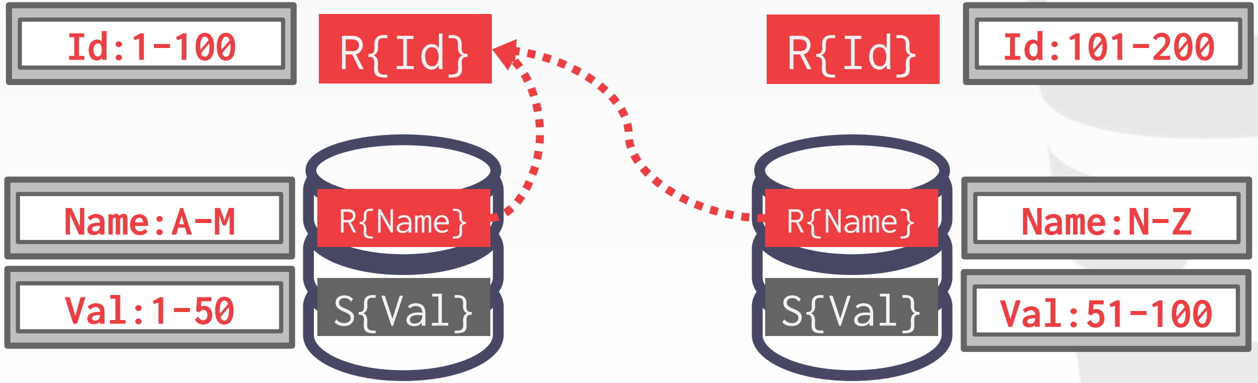

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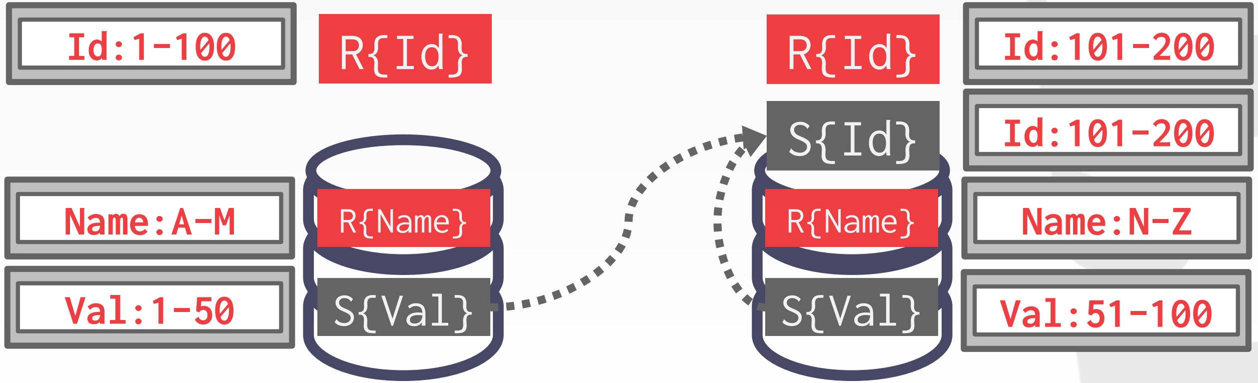

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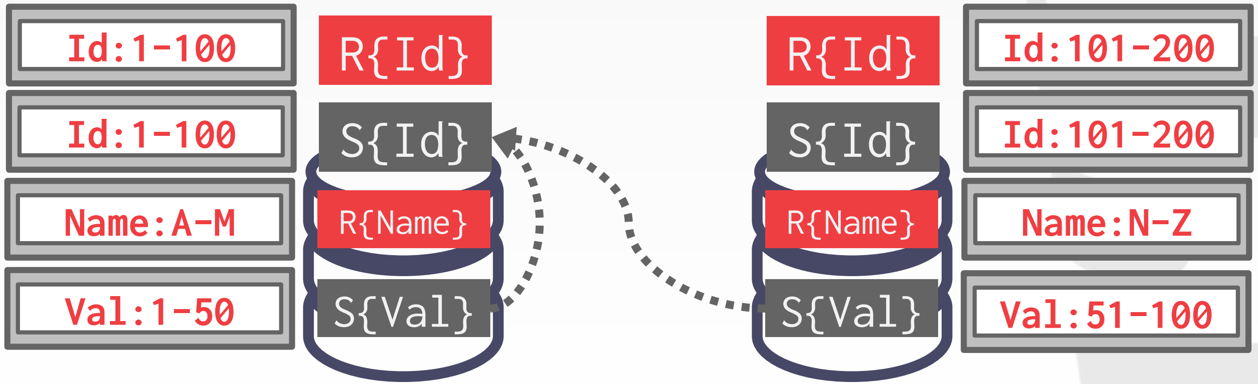

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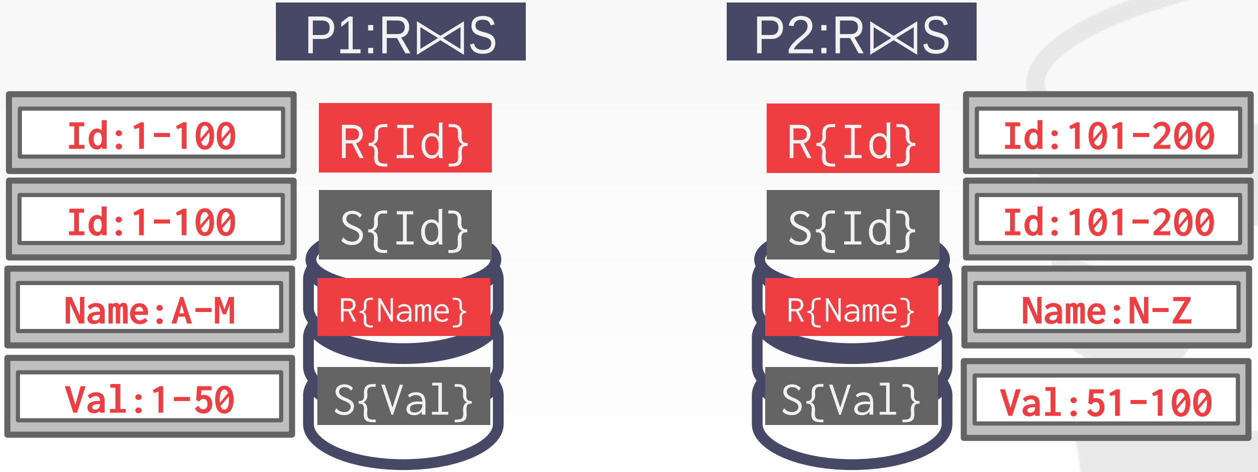

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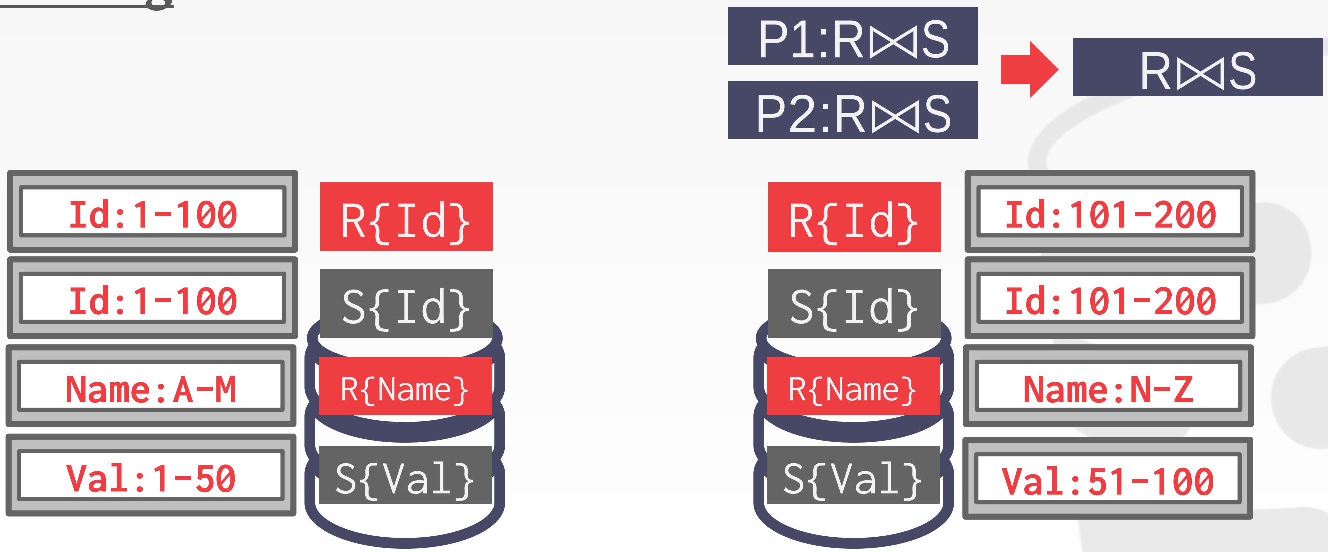

SEMI-JOIN

Join operator where the result only contains columns from the left table.

Distributed DBMSs use semi-join to minimize the amount of data sent during joins.

→ This is like a projection pushdown.

Some DBMSs support **SEMI JOIN** SQL syntax. Otherwise you fake it with **EXISTS**.

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SELECT R.id FROM R
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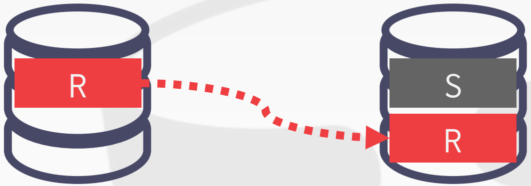

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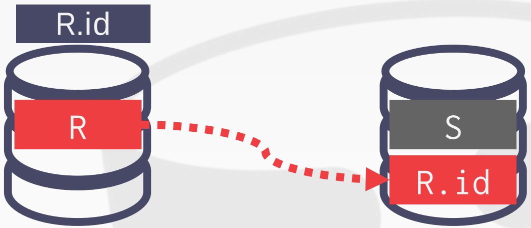


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RELATIONAL ALGEBRA: SEMI-JOIN

Like a natural join except that the attributes on the right table that are <u>not</u> used to compute the join are restricted.

Syntax: **(R ⋉ S)**

R(a_id,b_id,xxx)

a_id	b_id	xxx
a1	101	X1
a2	102	X2
a3	103	X3

S(a_id,b_id,yyy)

a_id	b_id	yyy
a3	103	Y1
a4	104	Y2
a5	105	Y3

(R ⋉ S)

a_id	b_id	xxx
a3	103	X3

CLOUD SYSTEMS

Vendors provide ***database-as-a-service*** (DBaaS) offerings that are managed DBMS environments.

Newer systems are starting to blur the lines between shared-nothing and shared-disk.

→ Example: You can do simple filtering on Amazon S3 before copying data to compute nodes.

CLOUD SYSTEMS

Approach #1: Managed DBMSs

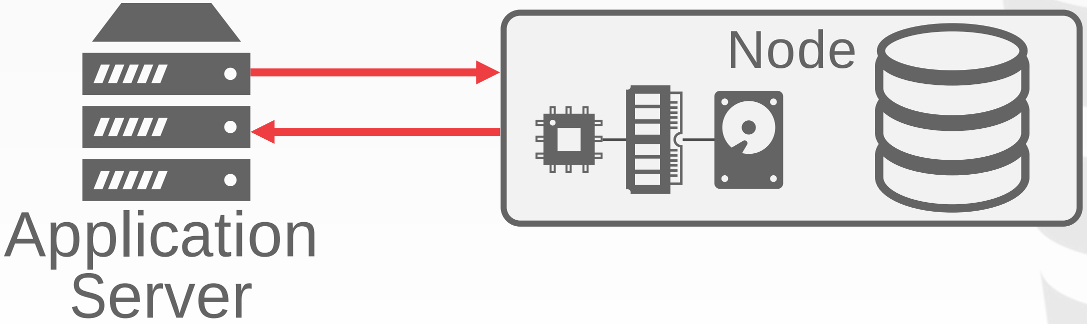
- → No significant modification to the DBMS to be "aware" that it is running in a cloud environment.
- → Examples: Most vendors

Approach #2: Cloud-Native DBMS

- → The system is designed explicitly to run in a cloud environment.
- → Usually based on a shared-disk architecture.
- → Examples: Snowflake, Google BigQuery, Amazon Redshift, Microsoft SQL Azure

SERVERLESS DATABASES

Rather than always maintaining compute resources for each customer, a "serverless" DBMS evicts tenants when they become idle.



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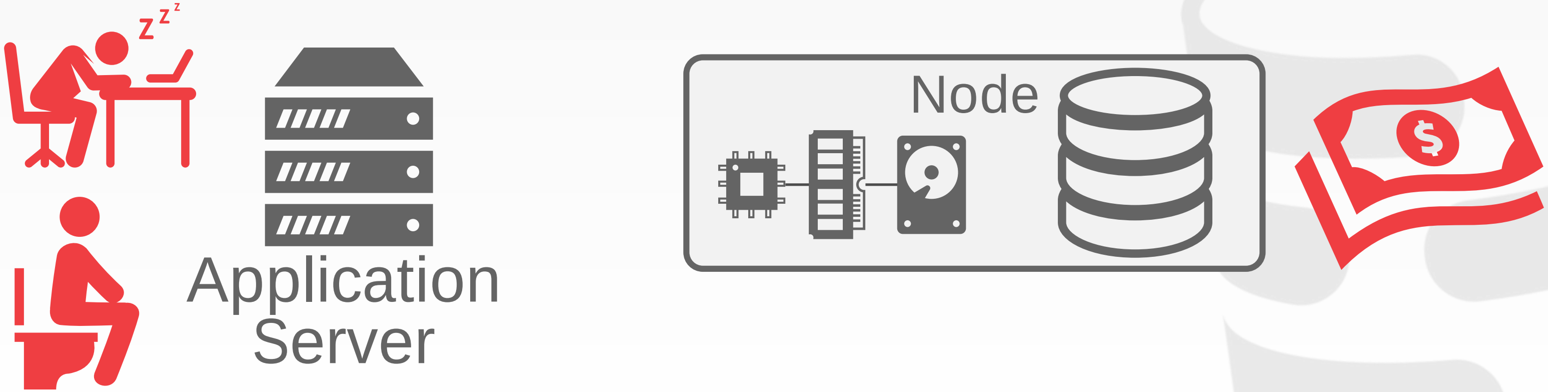

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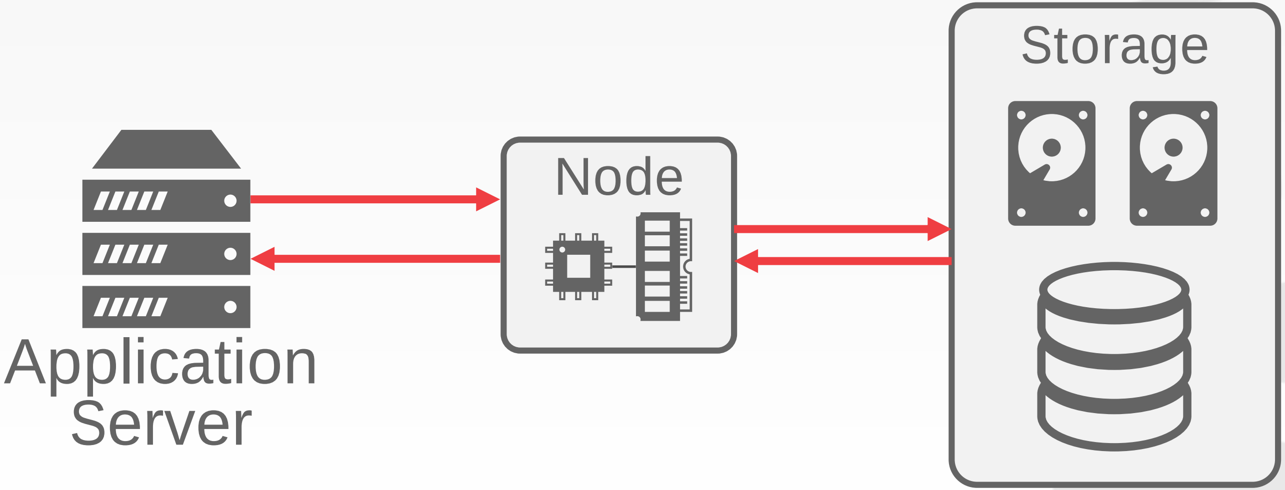

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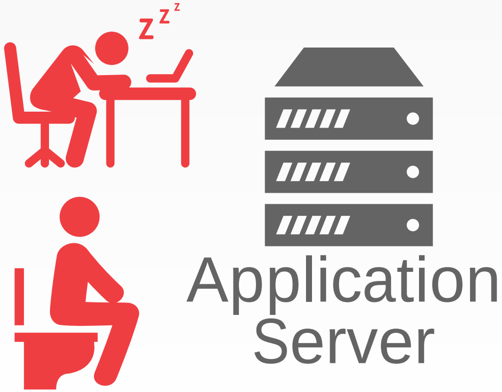

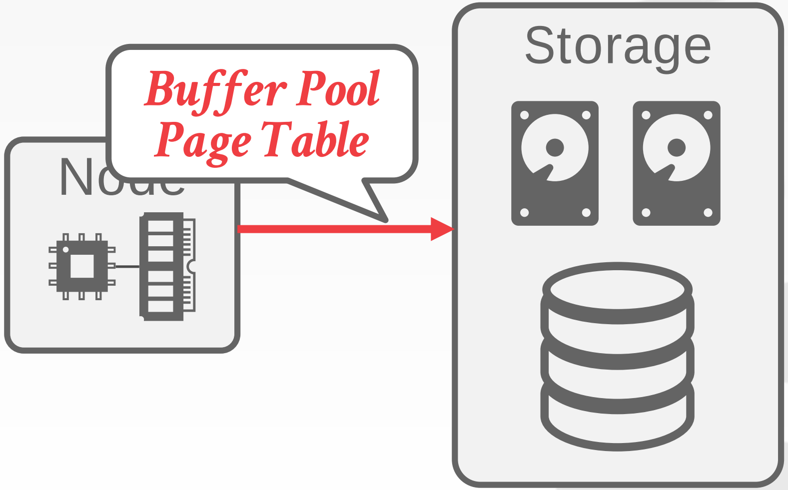

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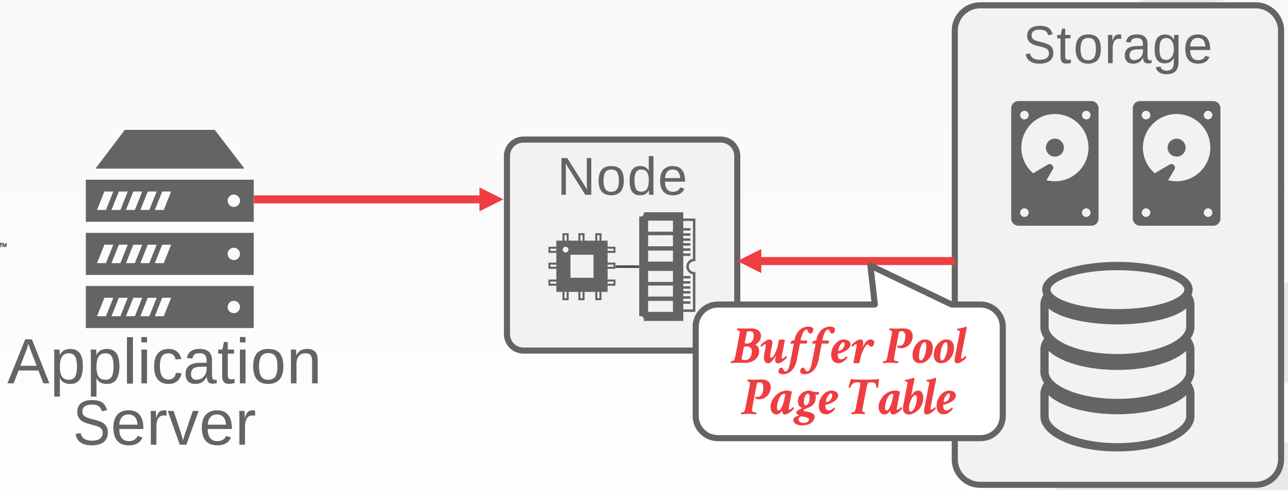

DISAGGREGATED COMPONENTS

System Catalogs

→ HCatalog, Google Data Catalog, Amazon Glue Data Catalog

Node Management

→ Kubernetes, Apache YARN, Cloud Vendor Tools

Query Optimizers

→ Greenplum Orca, Apache Calcite

UNIVERSAL FORMATS

Most DBMSs use a proprietary on-disk binary file format for their databases.

→ Think of the BusTub page types…

The only way to share data between systems is to convert data into a common text-based format

→ Examples: CSV, JSON, XML

There are new open-source binary file formats that make it easier to access data across systems.

UNIVERSAL FORMATS

Apache Parquet
→ Compressed columnar storage from Cloudera/Twitter

Apache ORC
→ Compressed columnar storage from Apache Hive.

Apache CarbonData
→ Compressed columnar storage with indexes from Huawei.

Apache Iceberg
→ Flexible data format that supports schema evolution from Netflix.

HDF5
→ Multi-dimensional arrays for scientific workloads.

Apache Arrow
→ In-memory compressed columnar storage from Pandas/Dremio.

CONCLUSION

More money, more data, more problems…

Cloud OLAP Vendors:

On-Premise OLAP Systems:

NEXT CLASS

Oracle Guest Speaker