Carnegie Mellon University

24 Distributed OLAP Databases

Intro to Database Systems
15-445/15-645
Fall 2020

AP
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Computer Science
Carnegie Mellon University

ADMINISTRIVIA

Project #4: Sunday Dec 13th @ 11:59pm
→ Q&A Session Monday Dec 7th @ 8:00pm
https://piazza.com/class/kdaz9wtp37u3pk?cid=1207

Potpourri + Review: Wednesday Dec 9th
→ Vote for what system you want me to talk about.
https://cmudb.io/f20-systems

Final Exam:
→ Session #1: Thursday Dec 17th @ 8:30am
→ Session #2: Thursday Dec 17th @ 8:00pm

UPCOMING DATABASE TALKS

Snowflake Lecture

→ Monday Dec 7th @ 3:20pm ET

TiDB Tech Talk

→ Monday Dec 14th @ 5pm ET

LAST CLASS

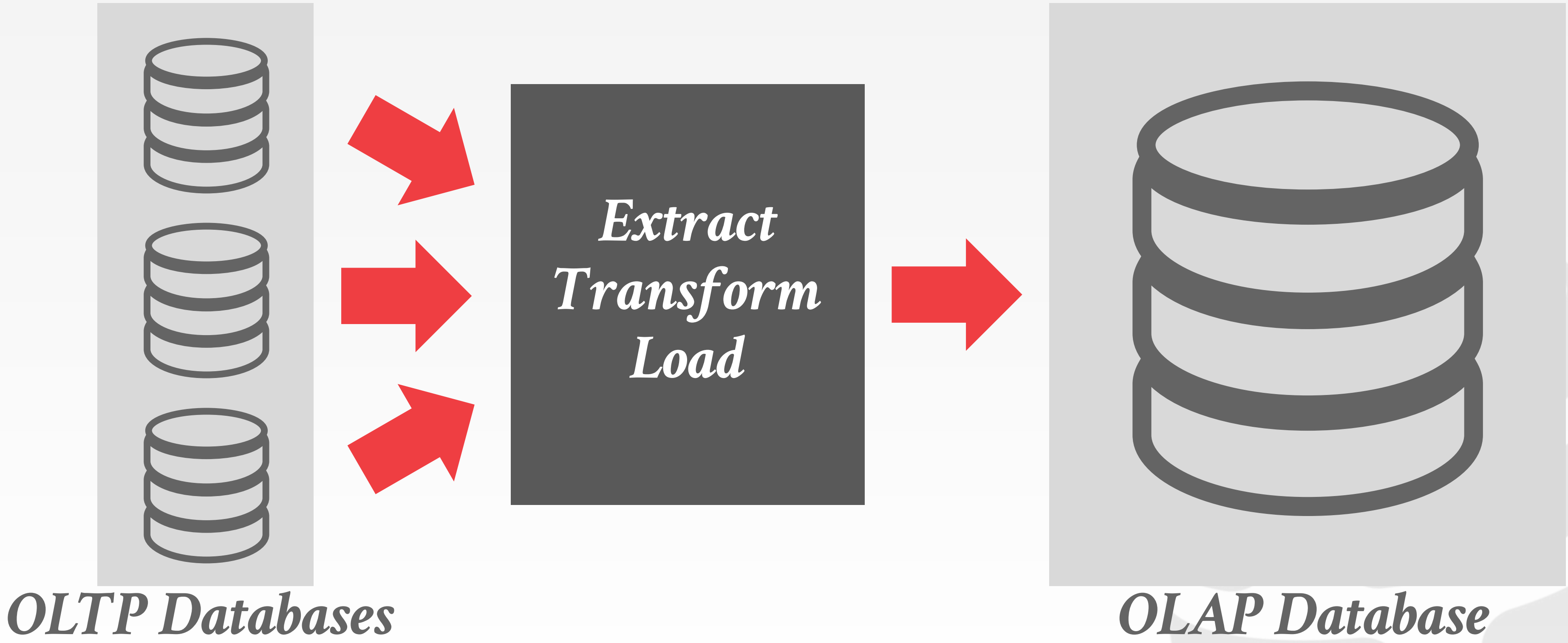
Atomic Commit Protocols

Replication

Consistency Issues (CAP)

Federated Databases

BIFURCATED ENVIRONMENT

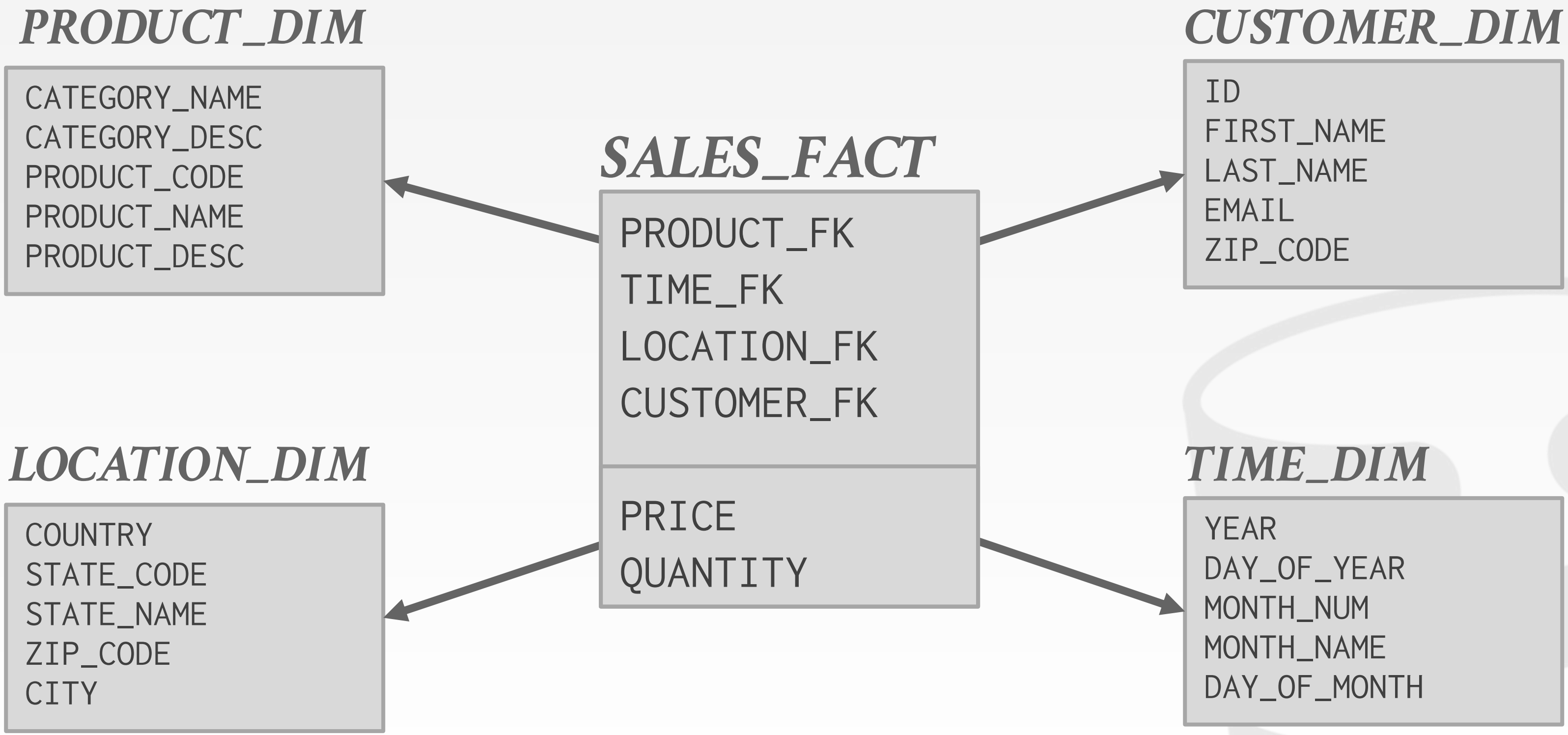


DECISION SUPPORT SYSTEMS

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
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SALES_FACT
PRODUCT_FK
TIME_FK
LOCATION_FK
CUSTOMER_FK
PRICE
QUANTITY
CUSTOMER_DIM
ID
FIRST_NAME
LAST_NAME
EMAIL
ZIP_CODE
LOCATION_DIM
COUNTRY
STATE_CODE
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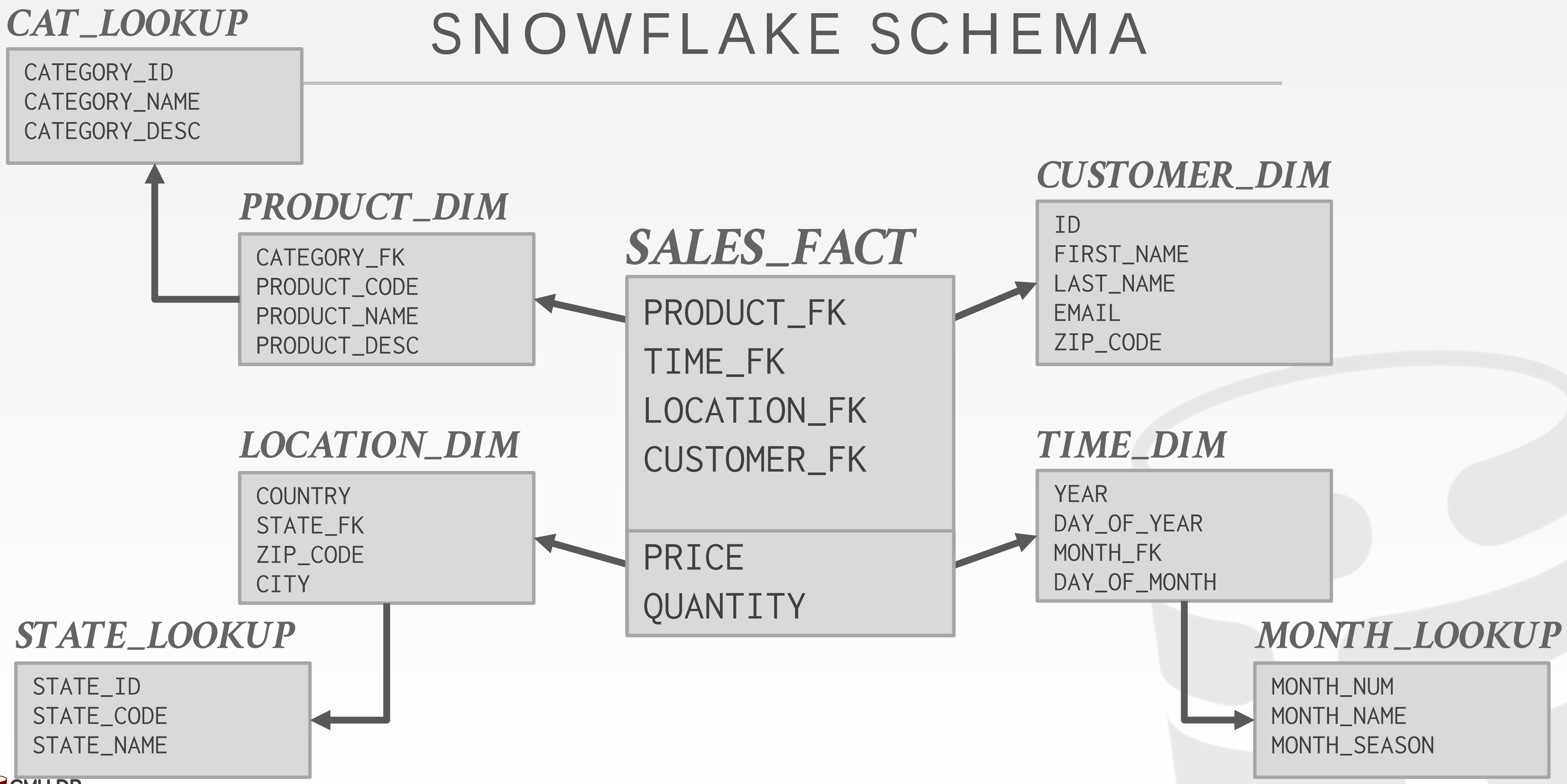
YEAR
DAY_OF_YEAR
MONTH_NUM
MONTH_NAME
DAY_OF_MONTH

SNOWFLAKE SCHEMA



STAR VS. SNOWFLAKE SCHEMA

Issue #1: Normalization

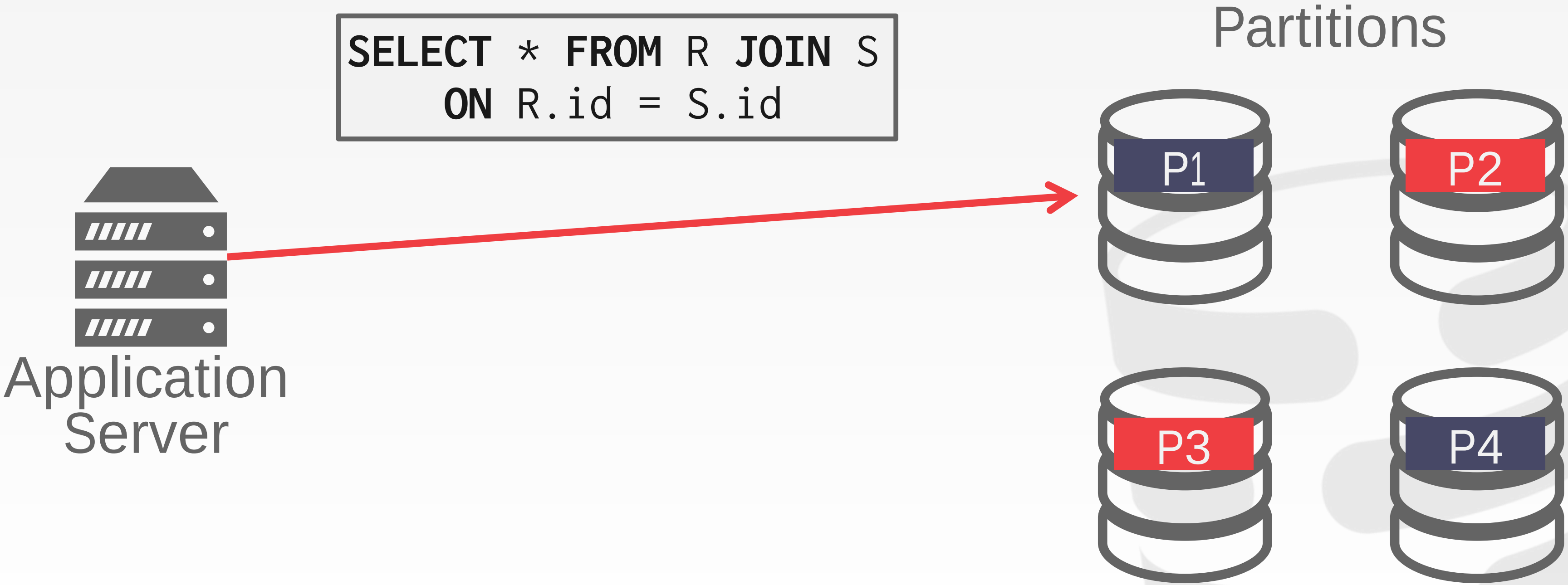
→ Snowflake schemas take up less storage space.
→ Denormalized data models may incur integrity and consistency violations.

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

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



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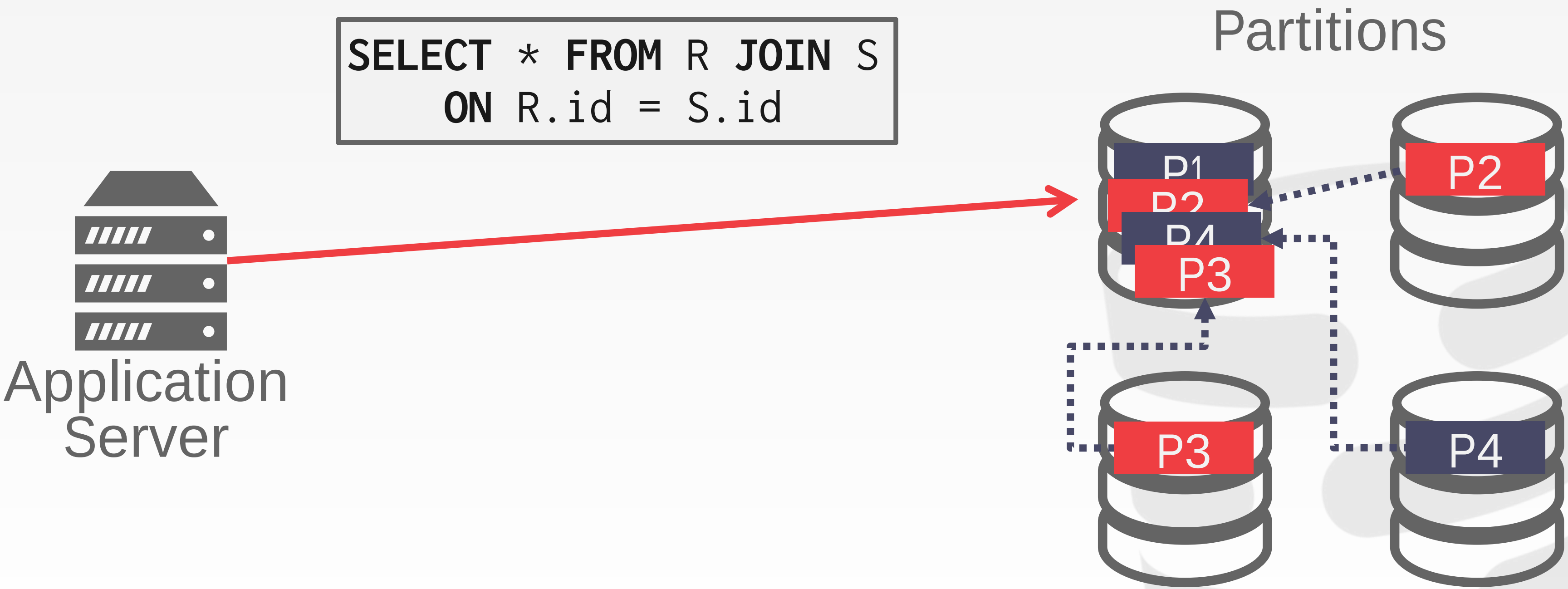


TODAY'S AGENDA

Execution Models

Query Planning

Distributed Join Algorithms

Cloud Systems

PUSH VS. PULL

Approach #1: Push Query to Data

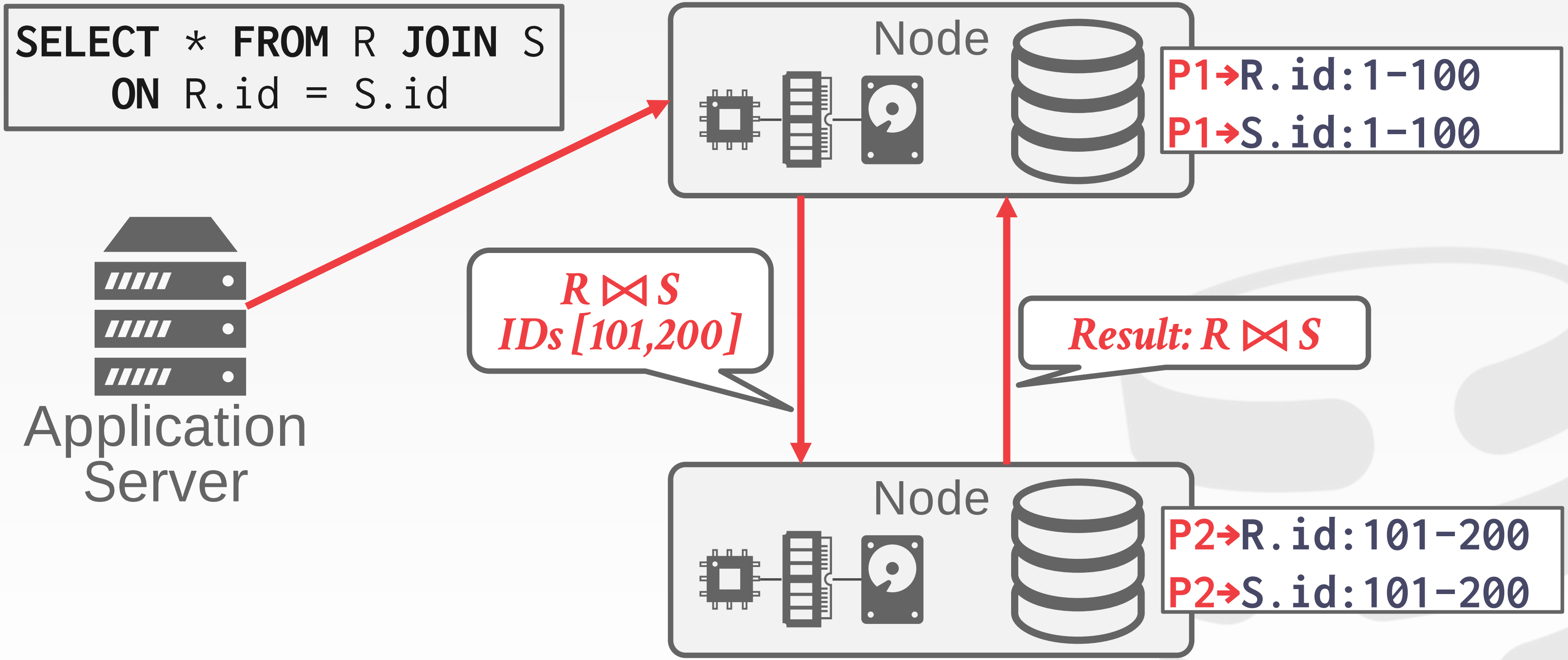
→ Send the query (or a portion of it) to the node that contains the data.

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

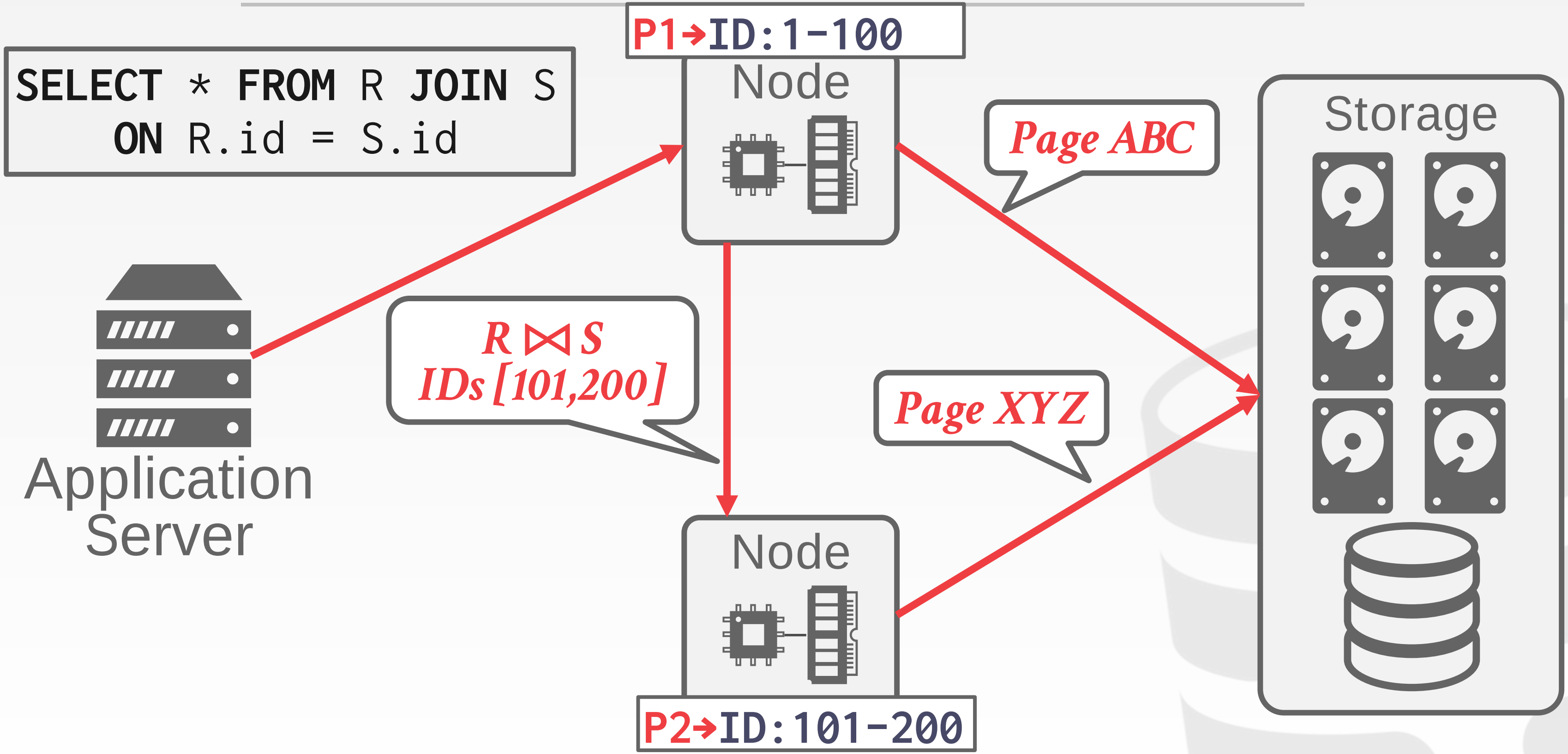
Approach #2: Pull Data to Query

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

PUSH QUERY TO DATA



PULL DATA TO QUERY



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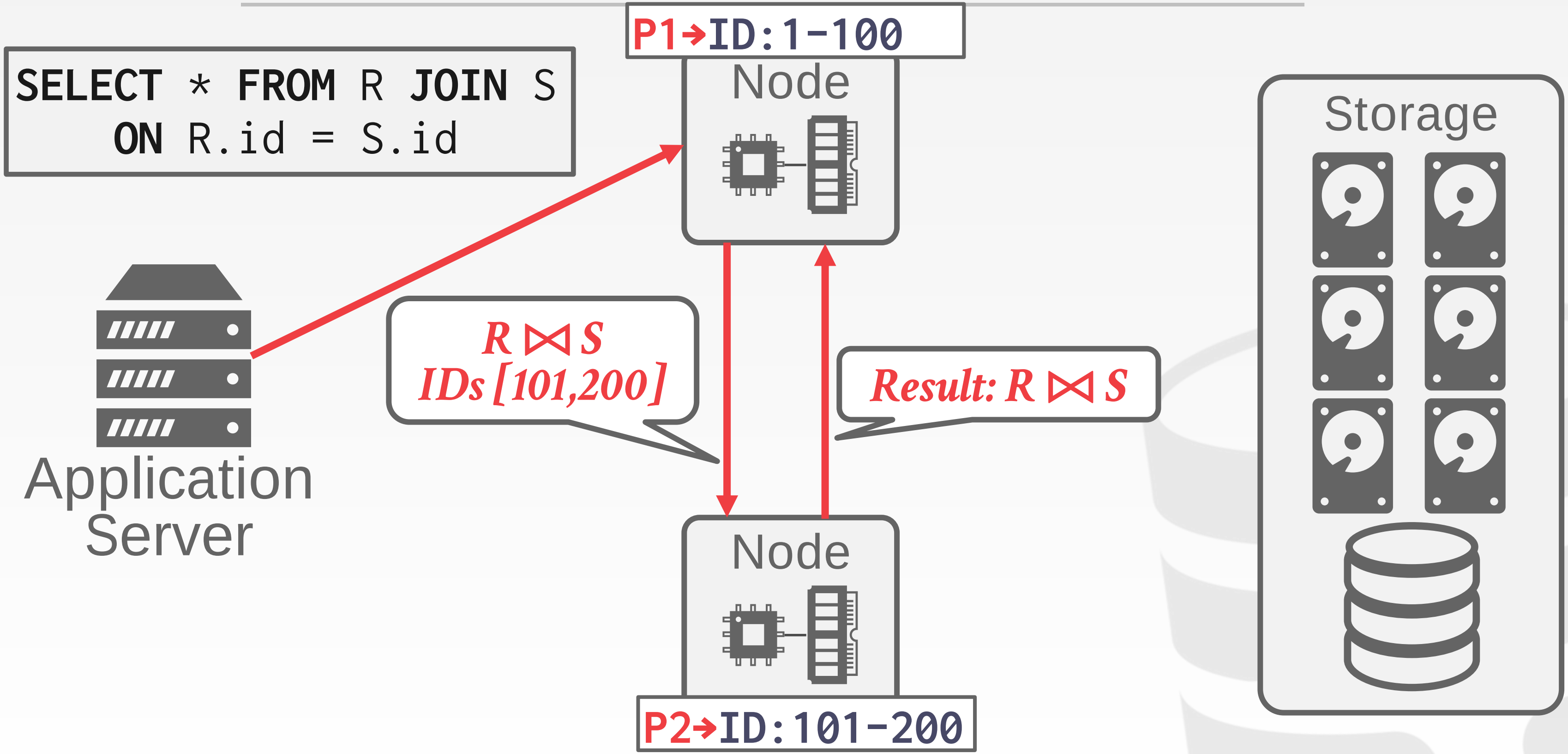

OBSERVATION

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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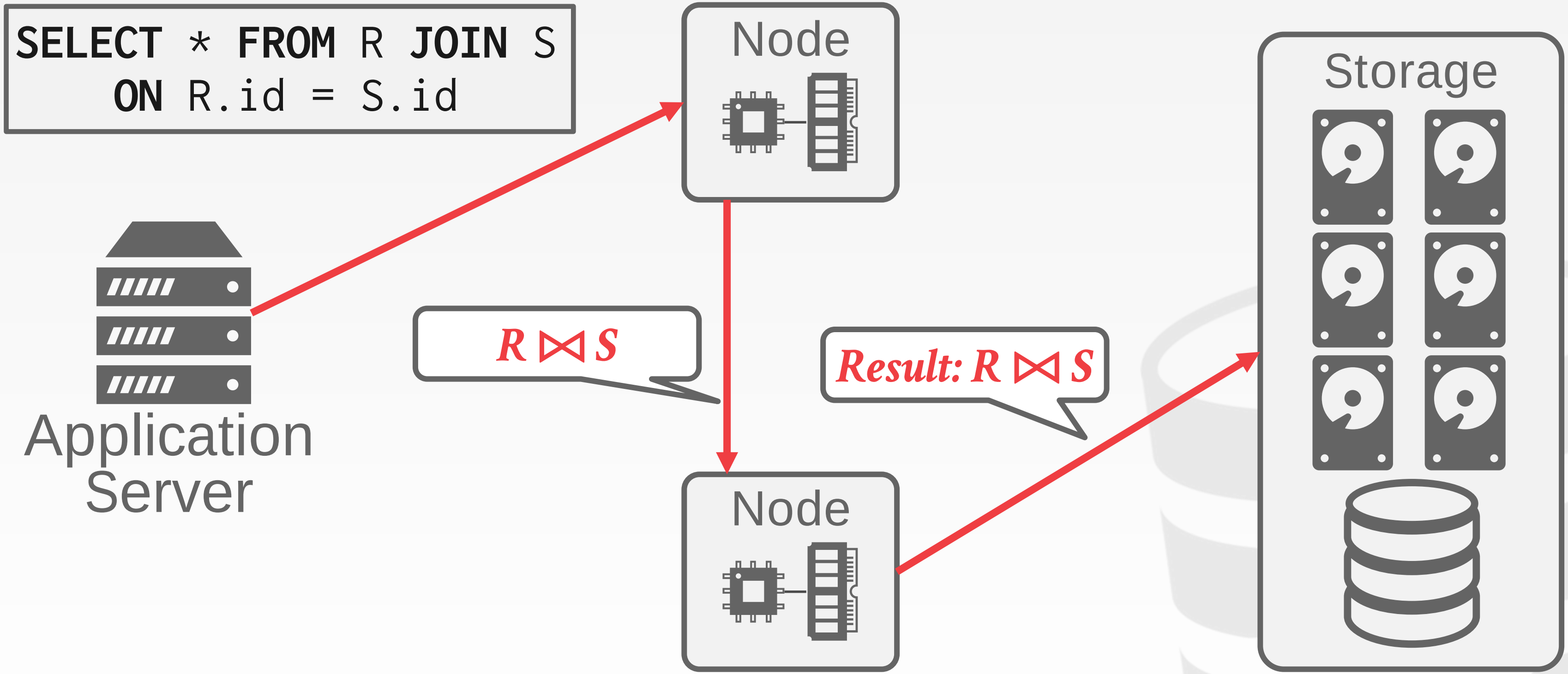

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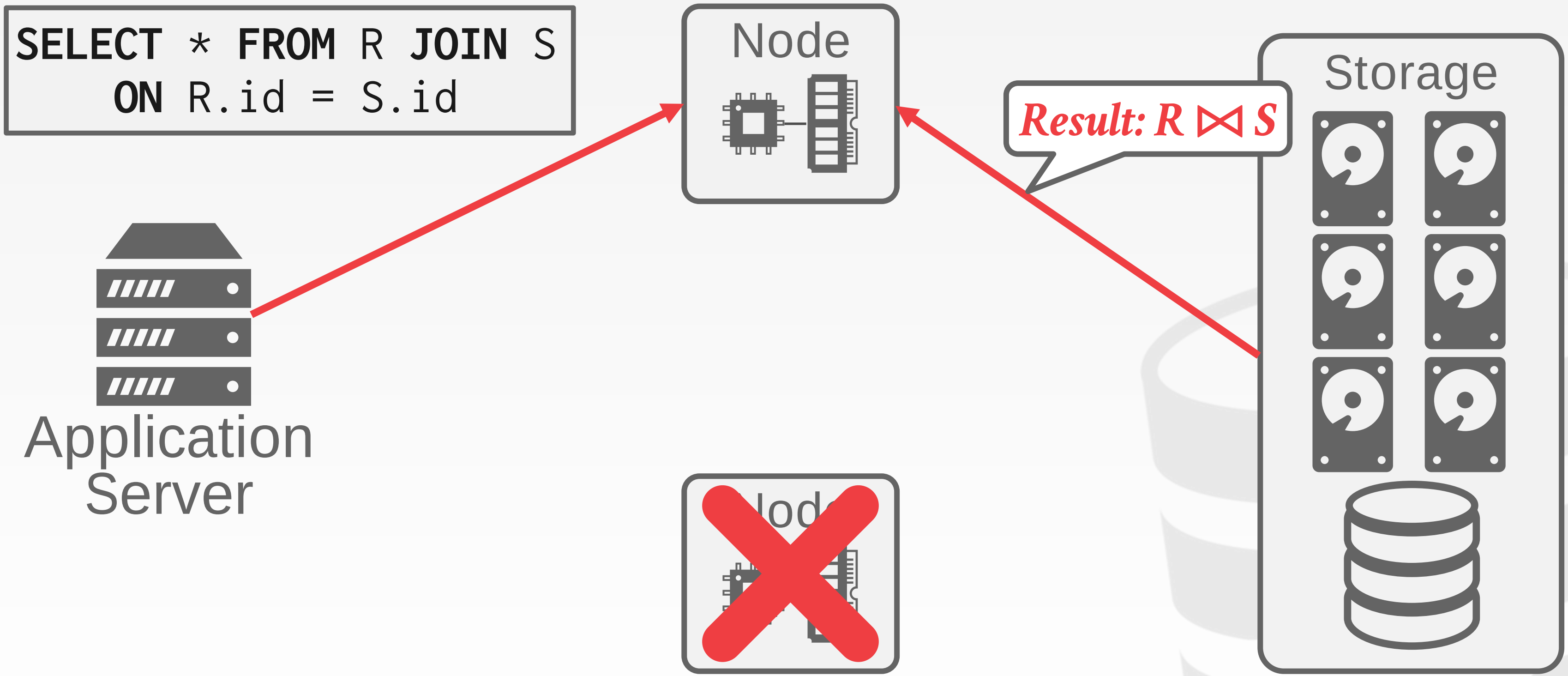


QUERY PLANNING

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 physical location of data and network transfer costs.

QUERY PLAN FRAGMENTS

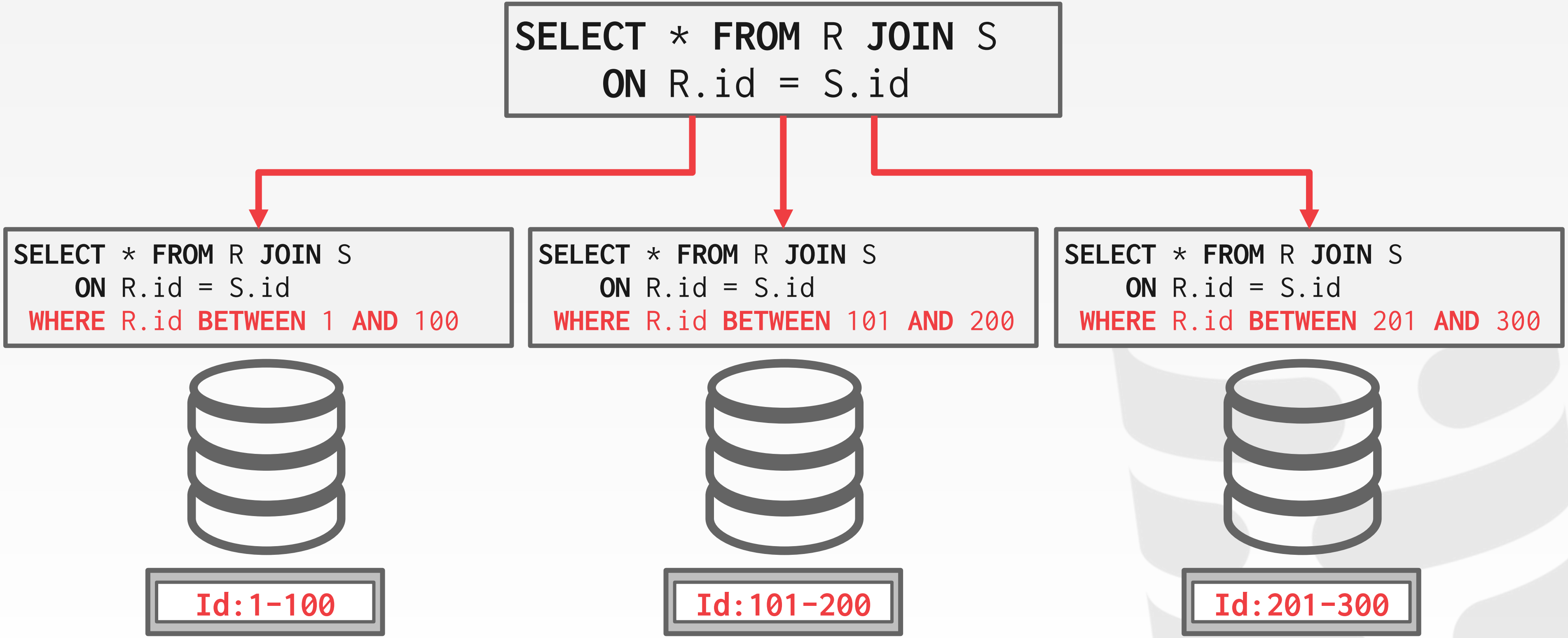
Approach #1: Physical Operators

→ 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.
→ SingleStore + Vitess are the only systems that Andy knows about that uses this approach.

QUERY PLAN FRAGMENTS



N FRAGMENTS

Union the output of each join to produce the 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 the data is at the node, the DBMS 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 in parallel and then sends their results to a coordinating node.

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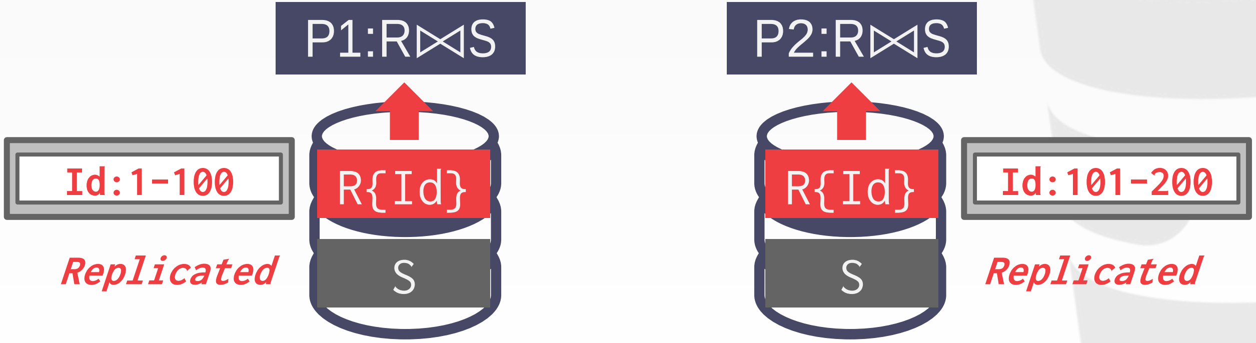

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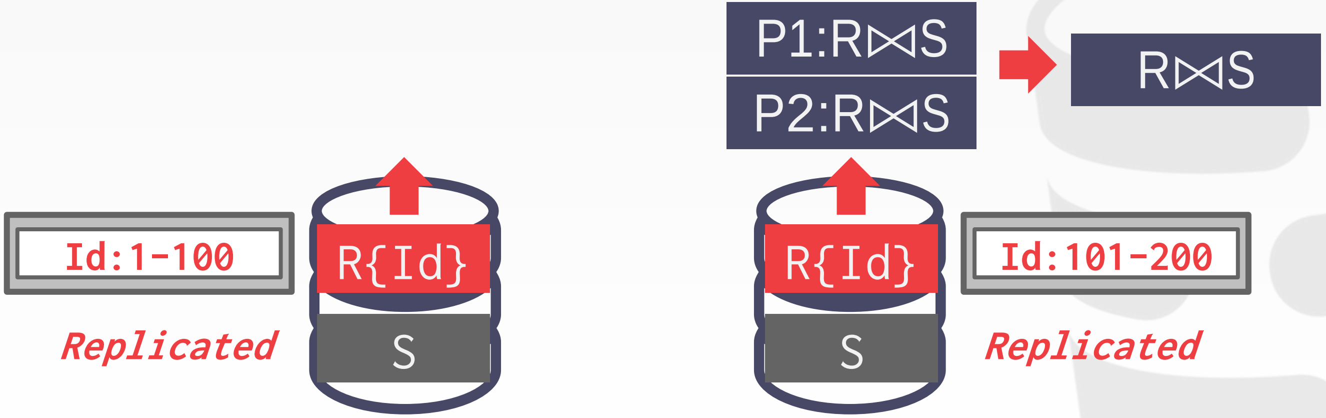

SCENARIO #2

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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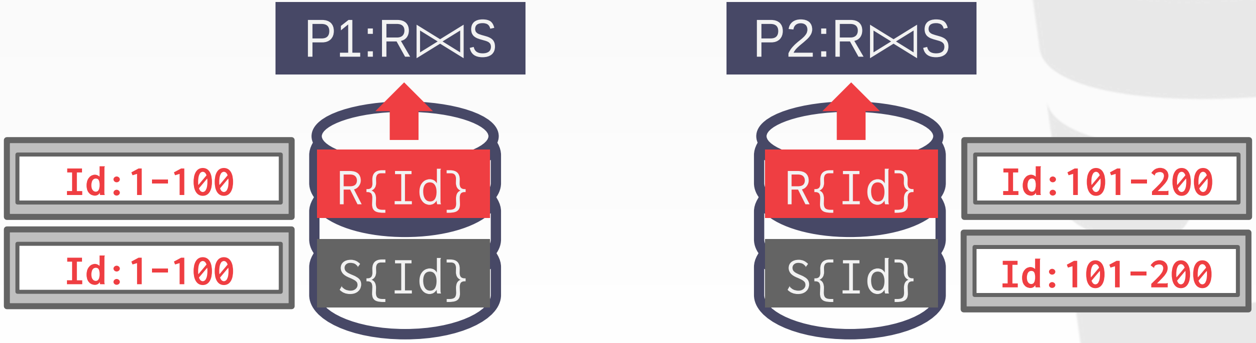

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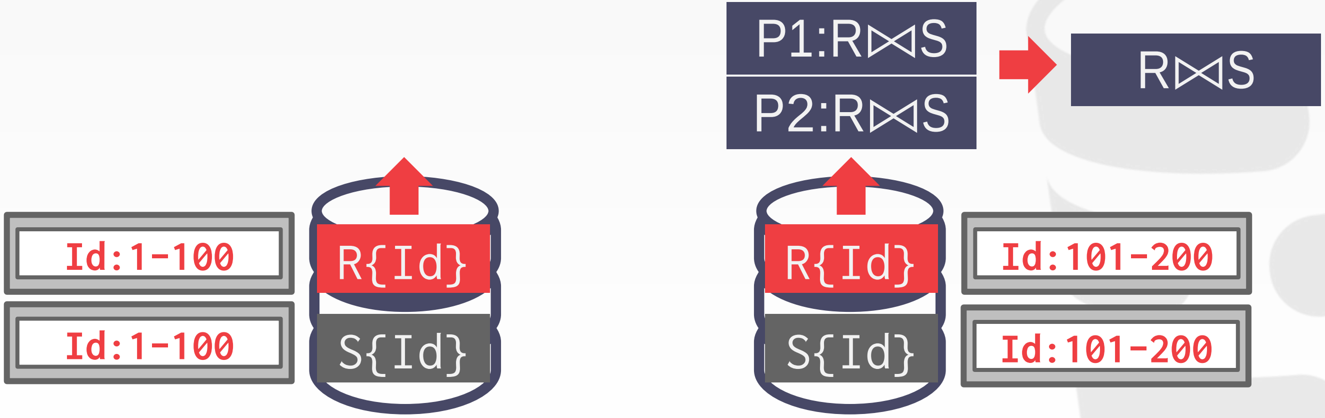

SCENARIO #3

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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SELECT * FROM R JOIN S
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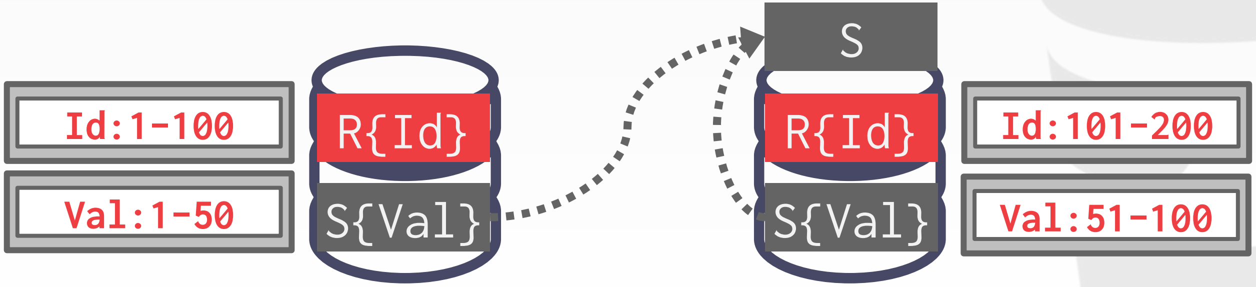

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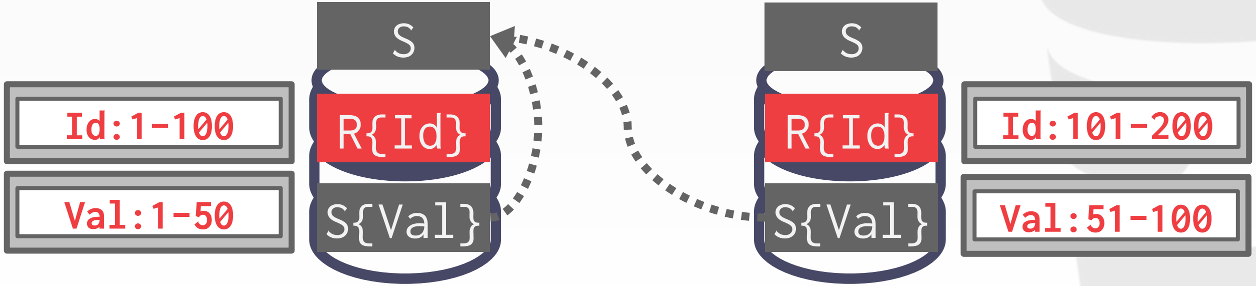

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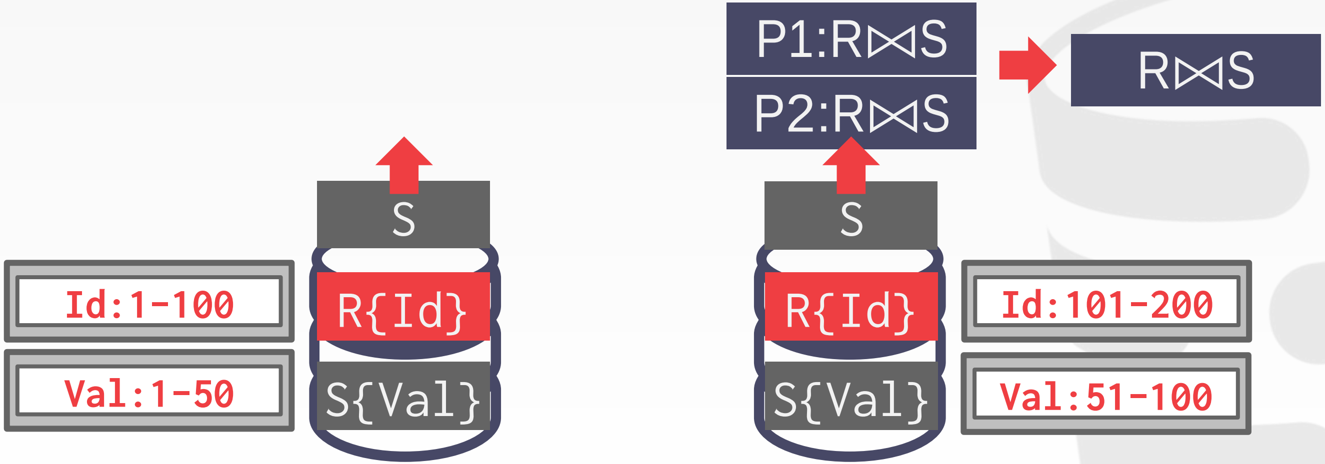

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Both tables are not partitioned on the join key. The DBMS copies the tables by "shuffling" them across nodes.

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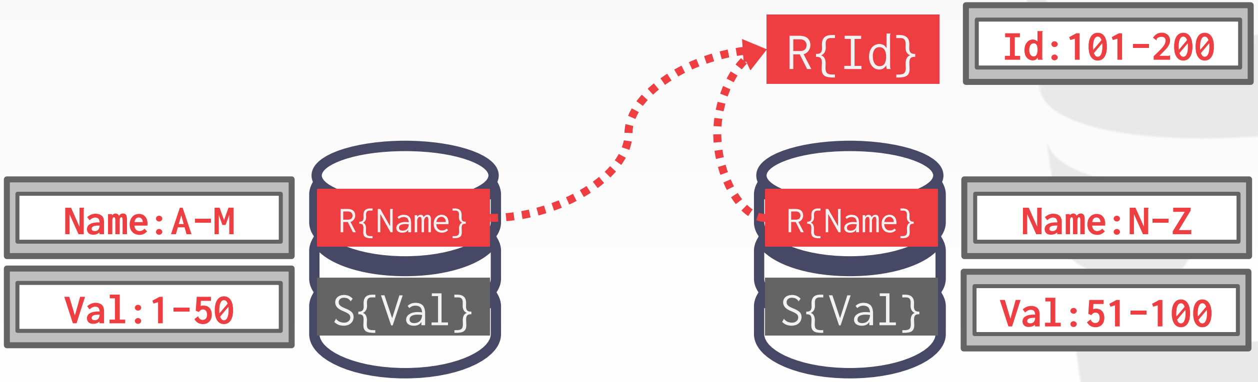

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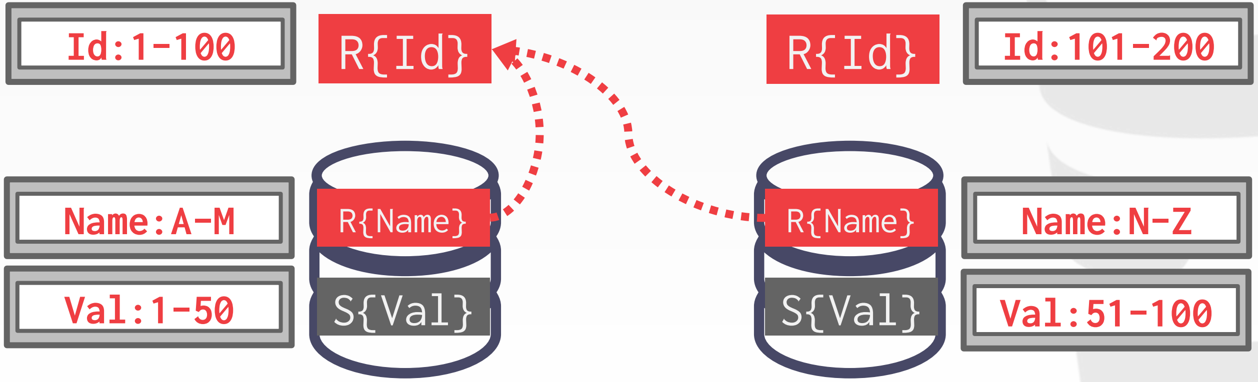

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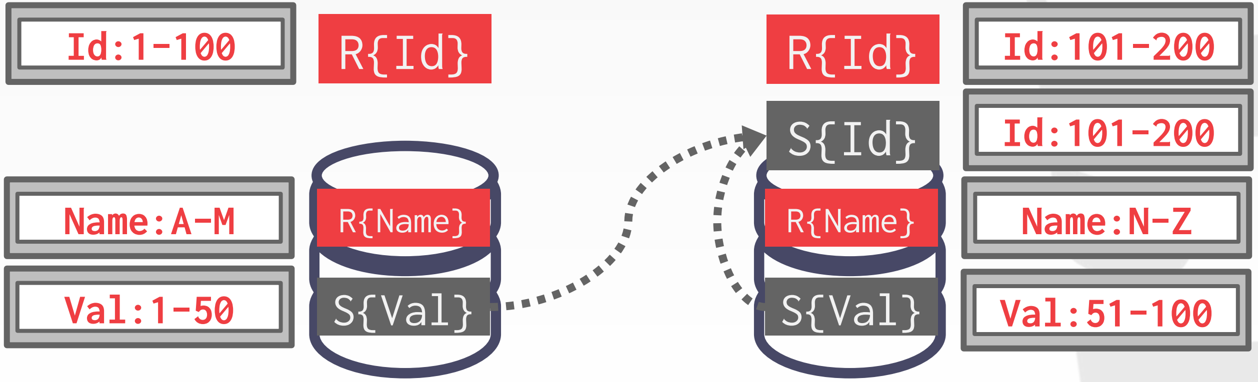

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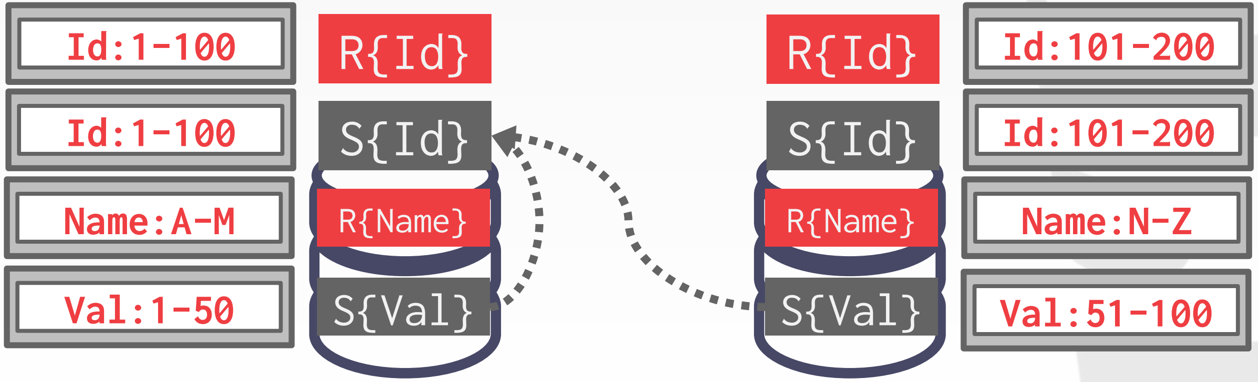

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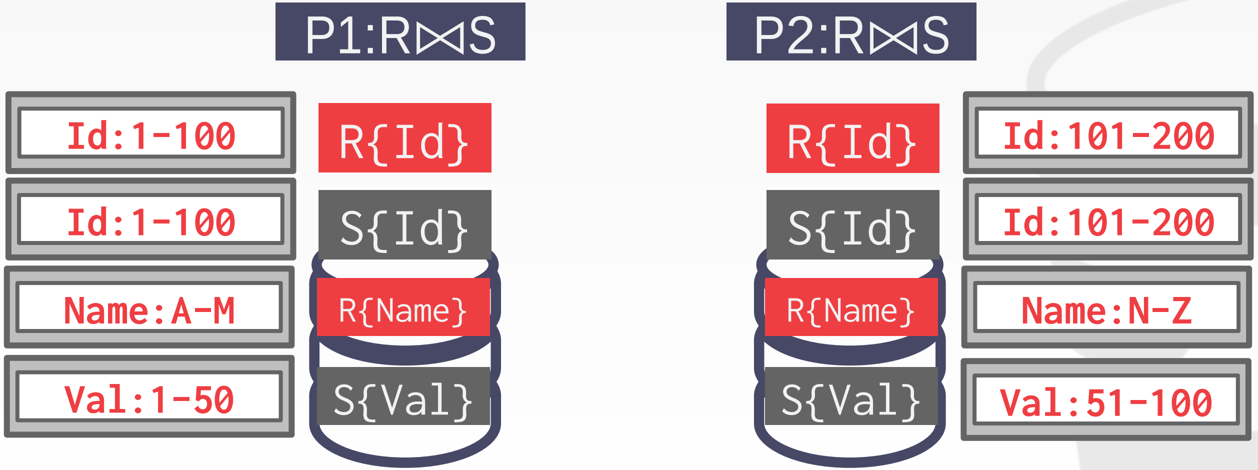

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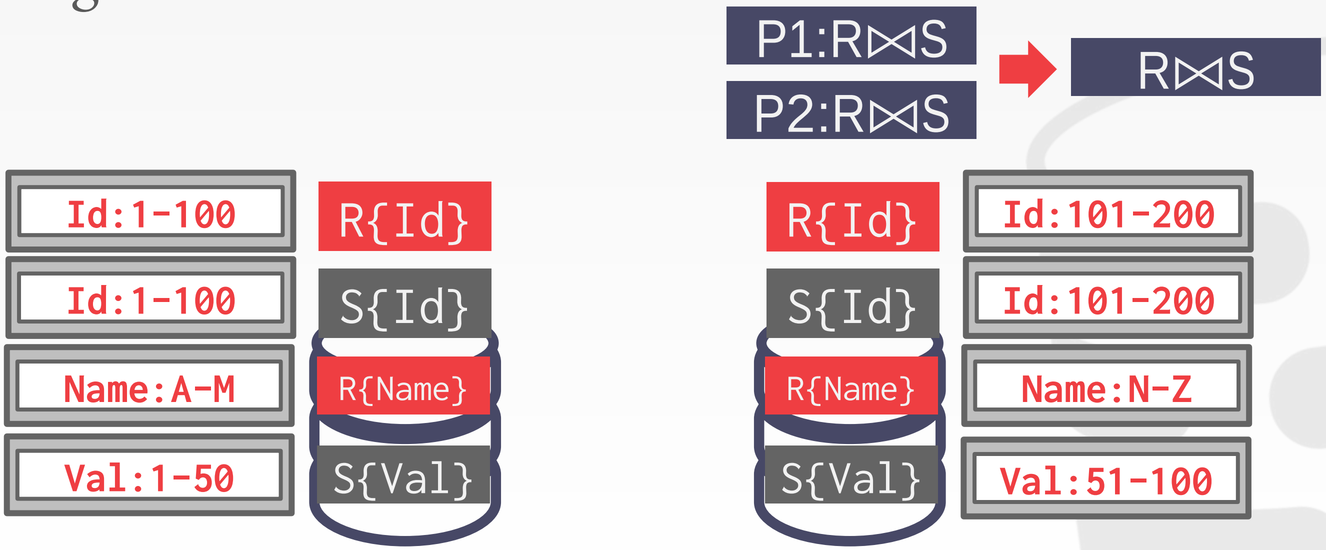

SEMI-JOIN

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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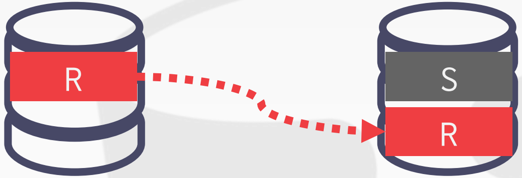

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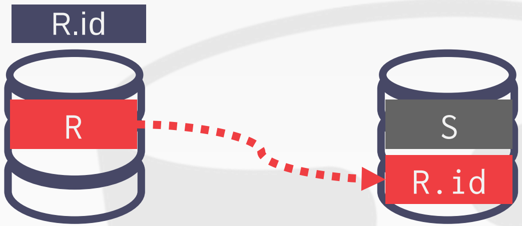


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CLOUD SYSTEMS

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

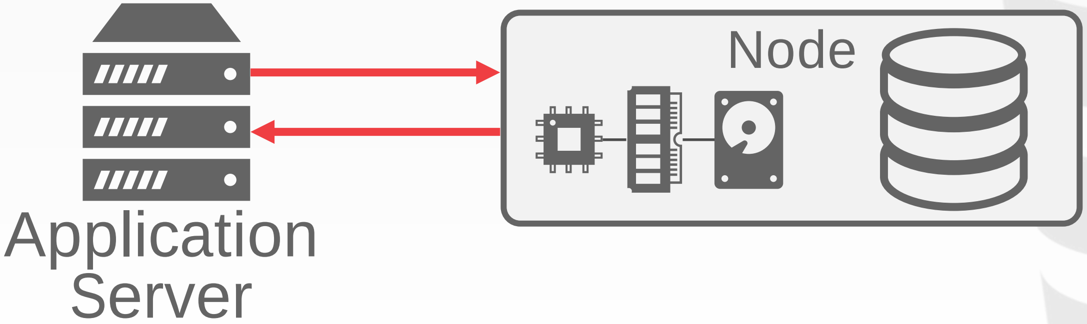
→ No significant modification to the DBMS to be "aware" that it is running in a cloud environment.
→ Examples: Most vendors

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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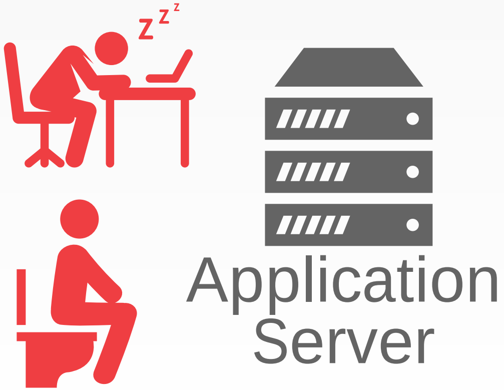

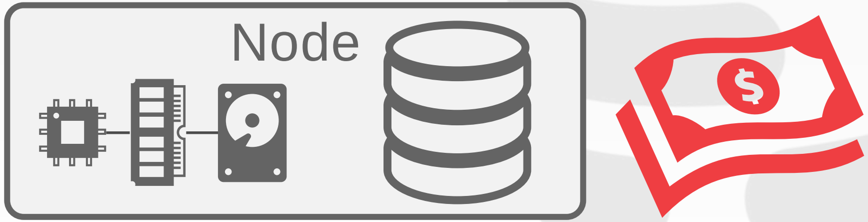

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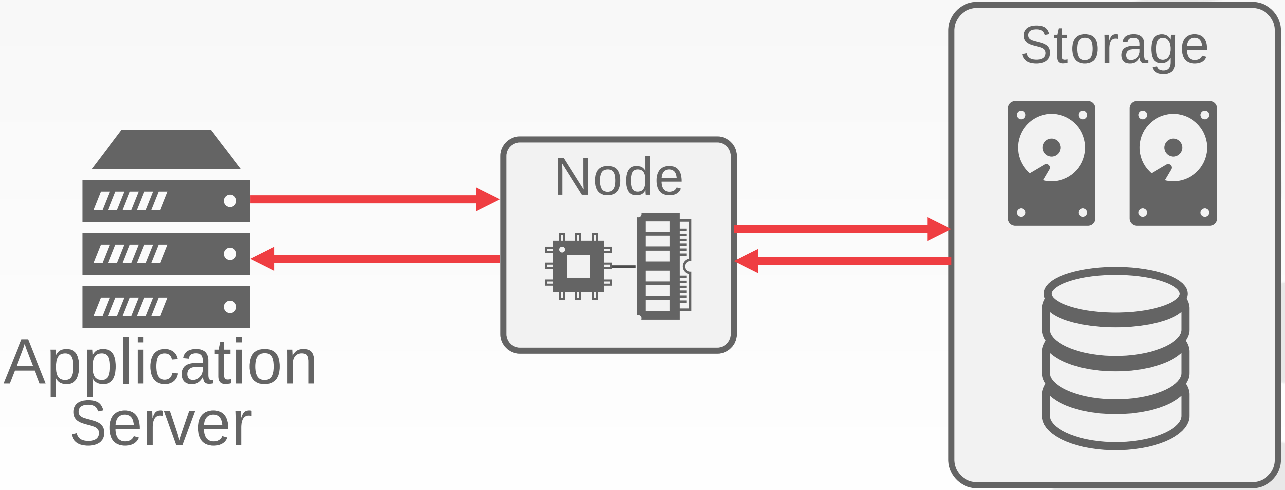

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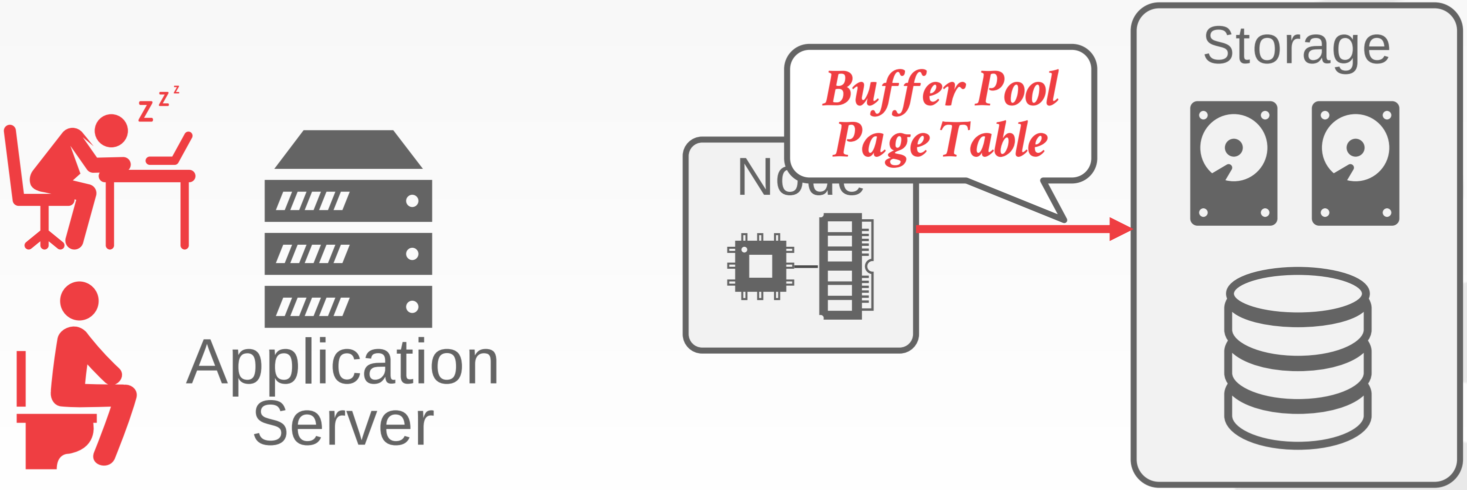

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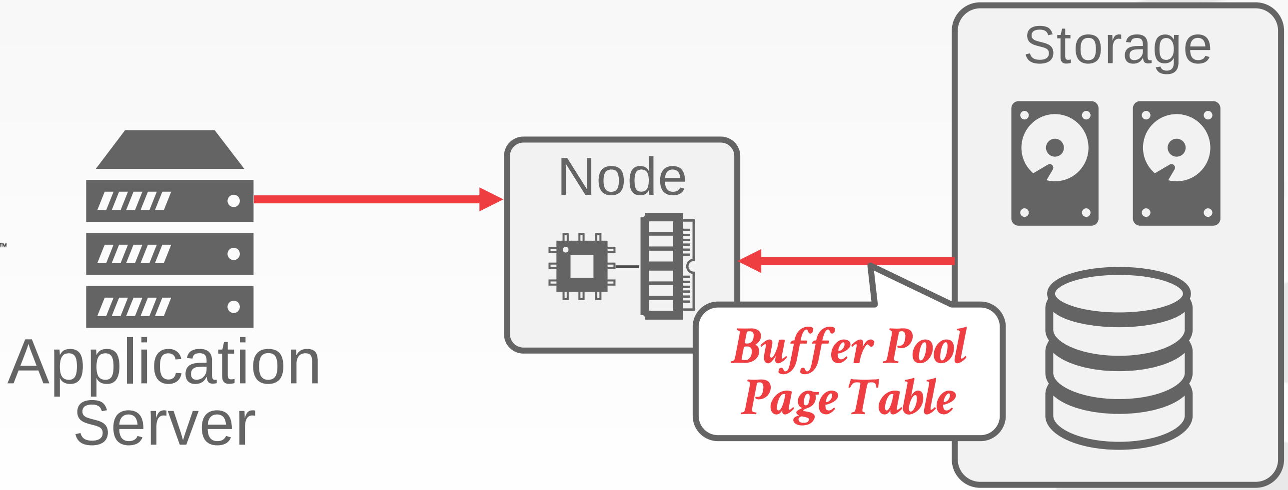

DISAGGREGATED COMPONENTS

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:

amazon REDSHIFT
ORACLE
snowflake
Microsoft SQL Azure

On-Premise OLAP Systems:

ClickHouse
splice MACHINE
VERTICA
ORACLE EXADATA
presto
Greenplum
TERADATA

NEXT CLASS

Snowflake Guest Speakers