Carnegie Mellon University

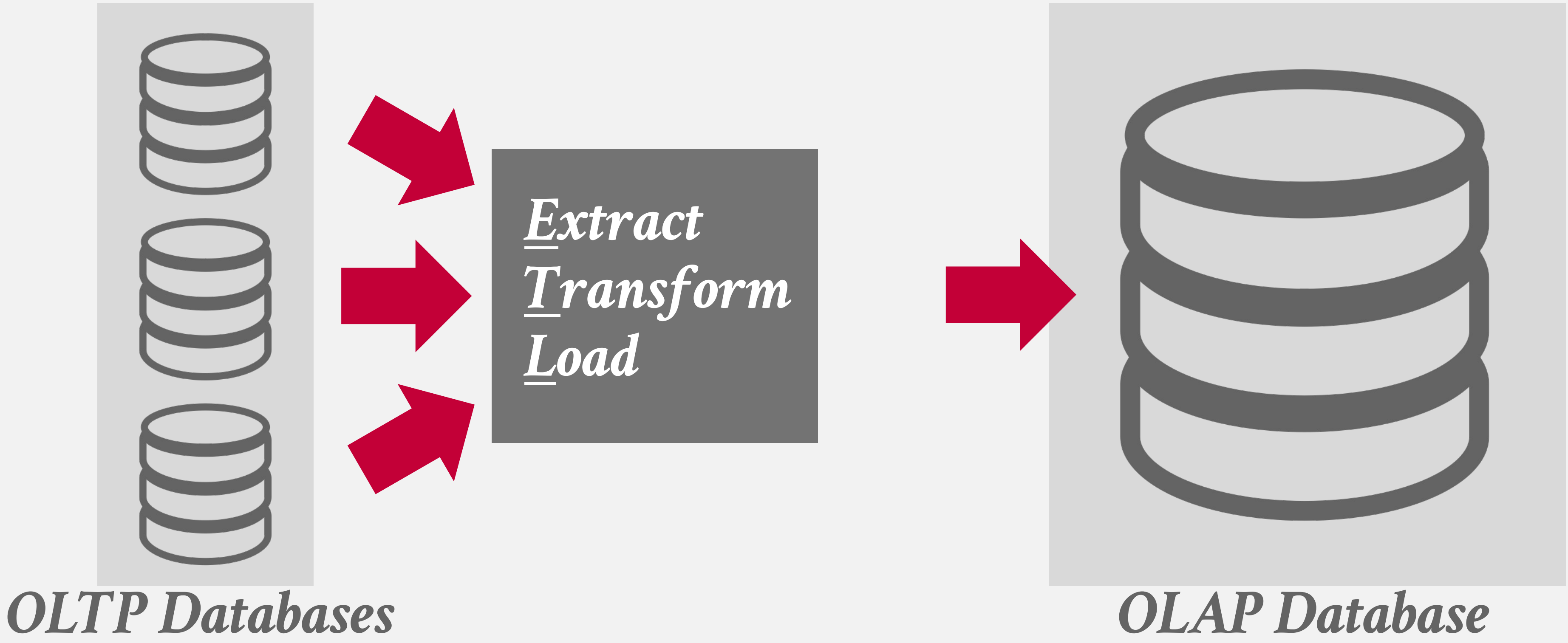
Intro to Database Systems (15-445/645)

Lecture #24

Distributed OLAP Databases

SPRING 2024 ❯❯ Prof. Jignesh Patel

BIFURCATED ENVIRONMENT



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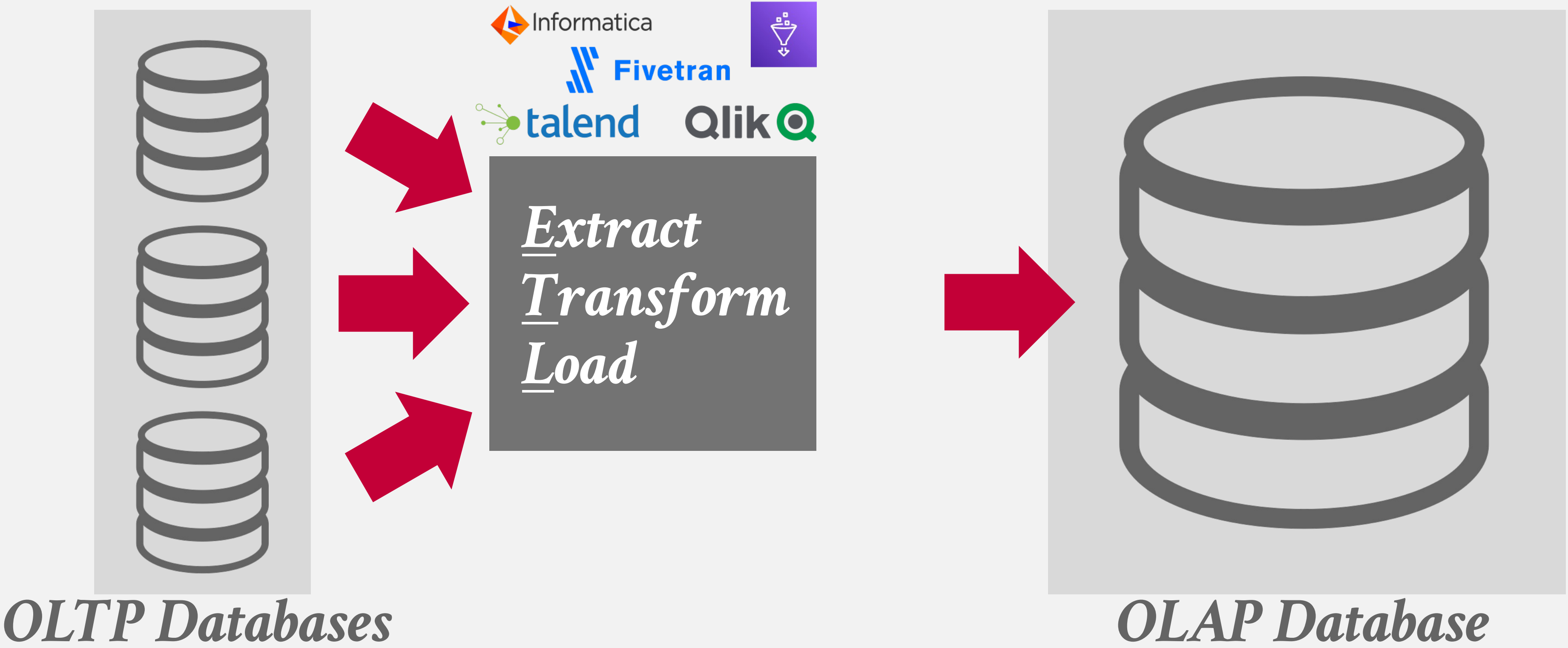

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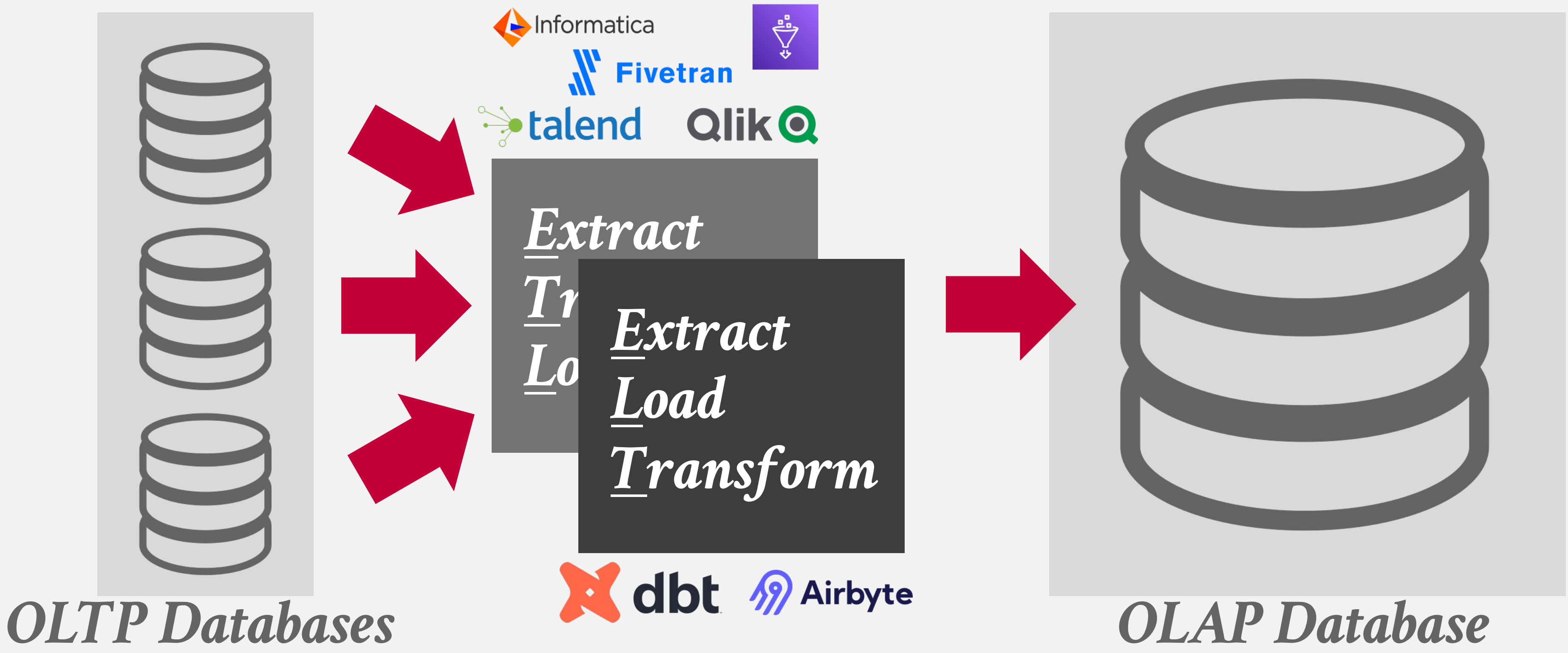

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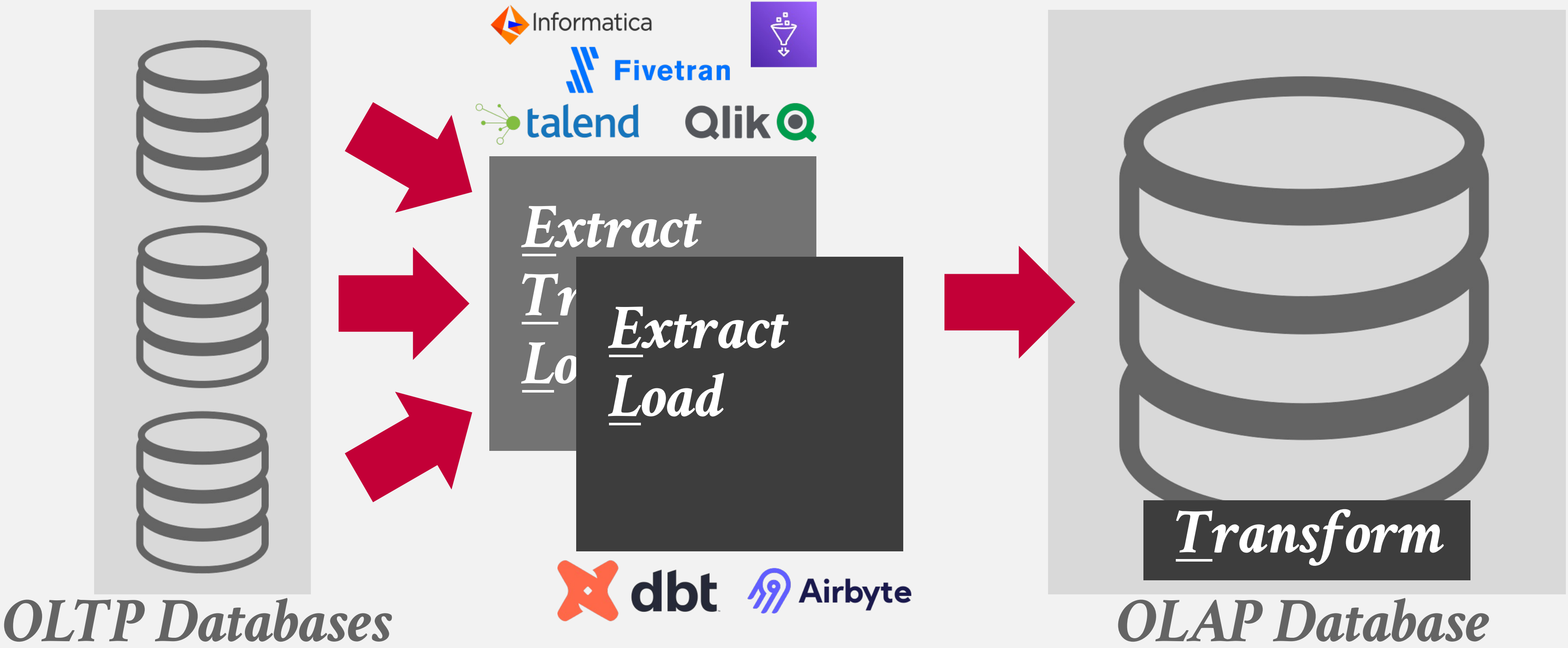
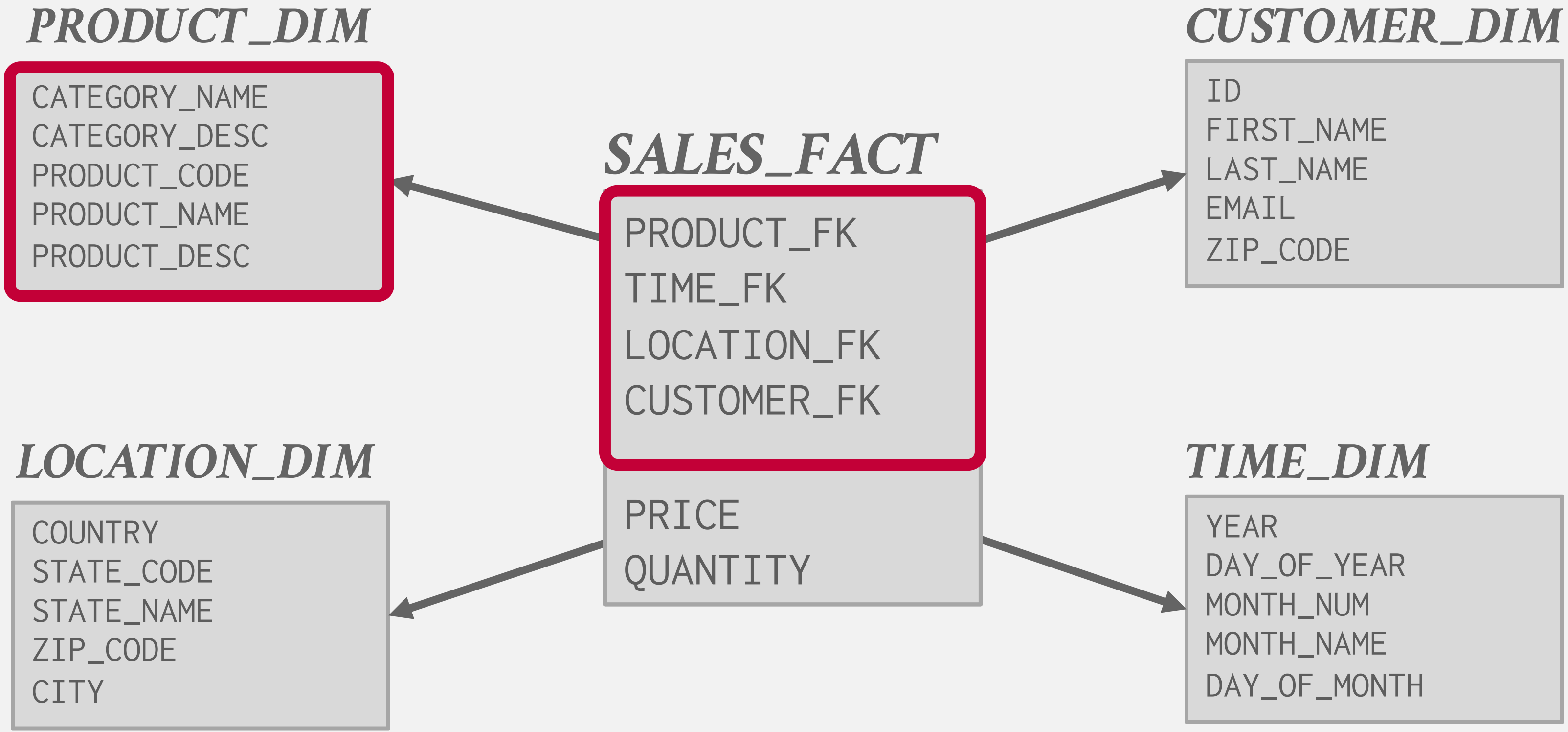


DECISION SUPPORT SYSTEMS

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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EMAIL
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SALES_FACT
PRODUCT_FK
TIME_FK
LOCATION_FK
CUSTOMER_FK
PRICE
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LOCATION_DIM
COUNTRY
STATE_CODE
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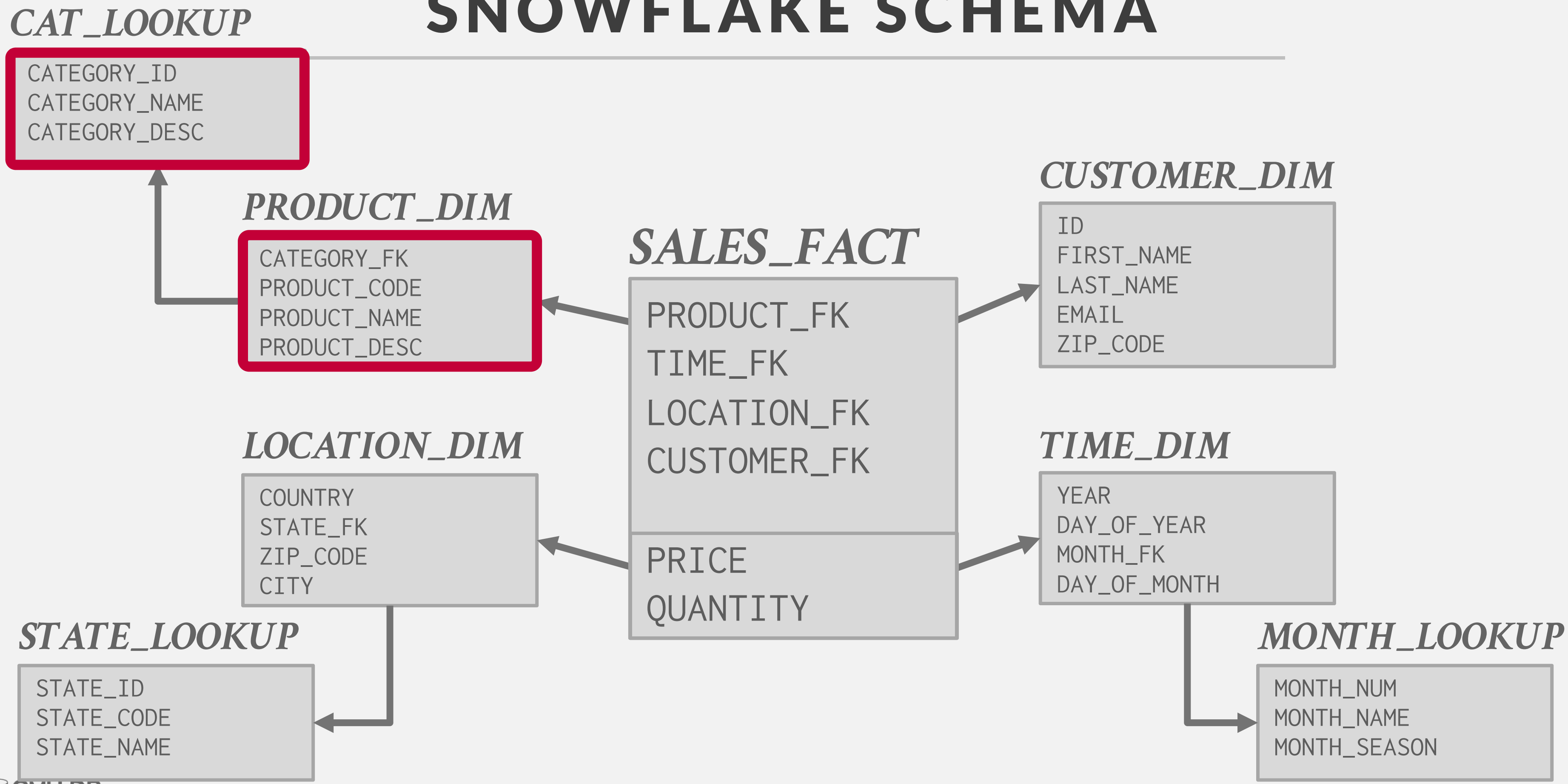
MONTH_NAME
DAY_OF_MONTH

SNOWFLAKE SCHEMA



STAR VS. SNOWFLAKE SCHEMA

Issue #1: Normalization

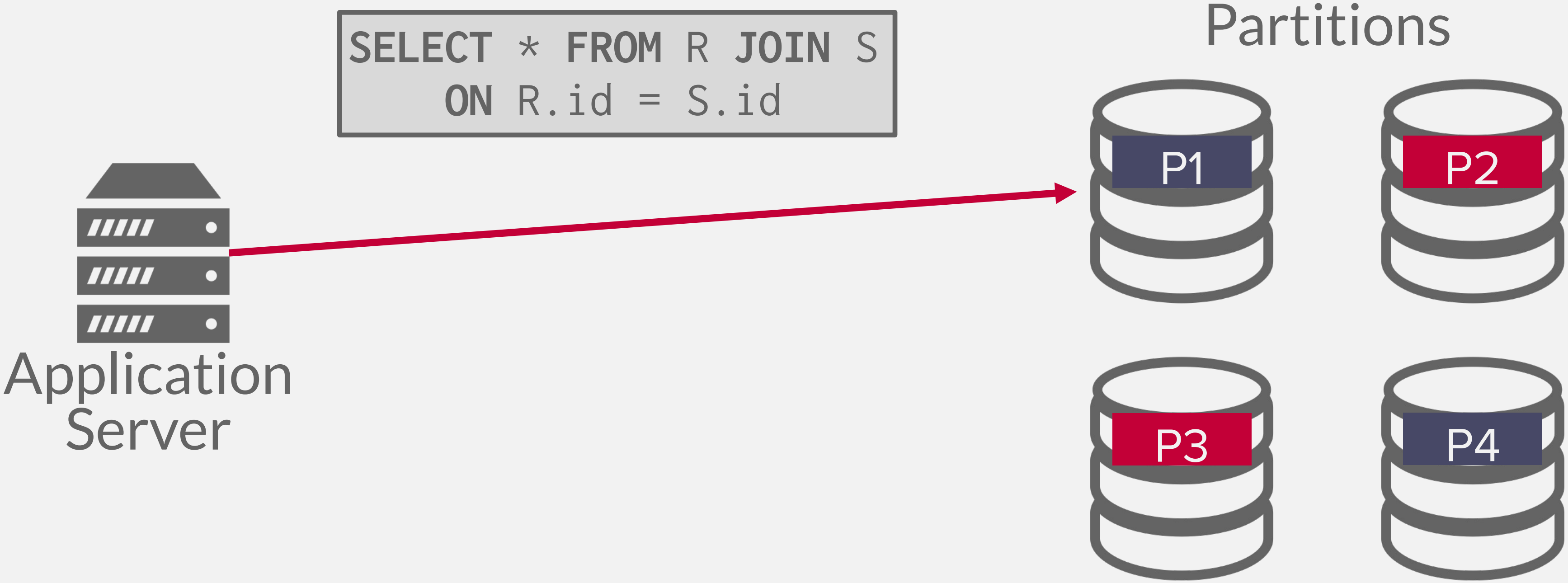
→ Snowflake schemas take up less storage space.
→ Denormalized data models may incur integrity and consistency violations.

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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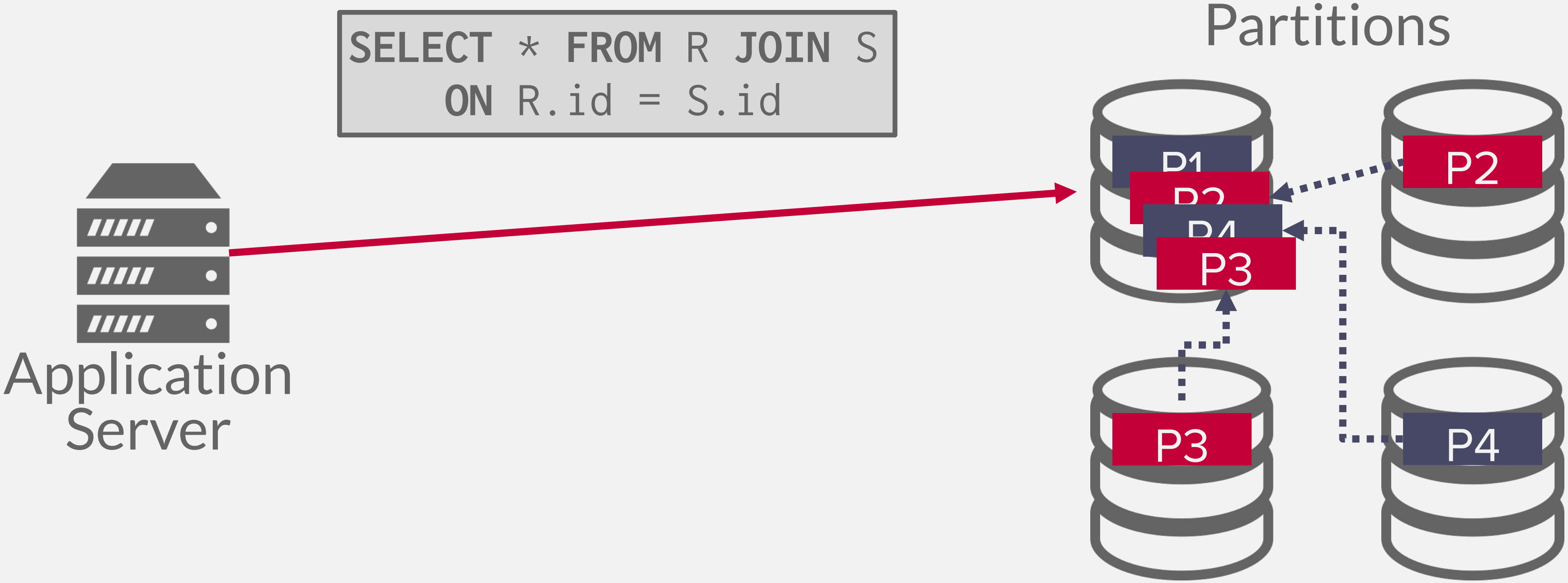

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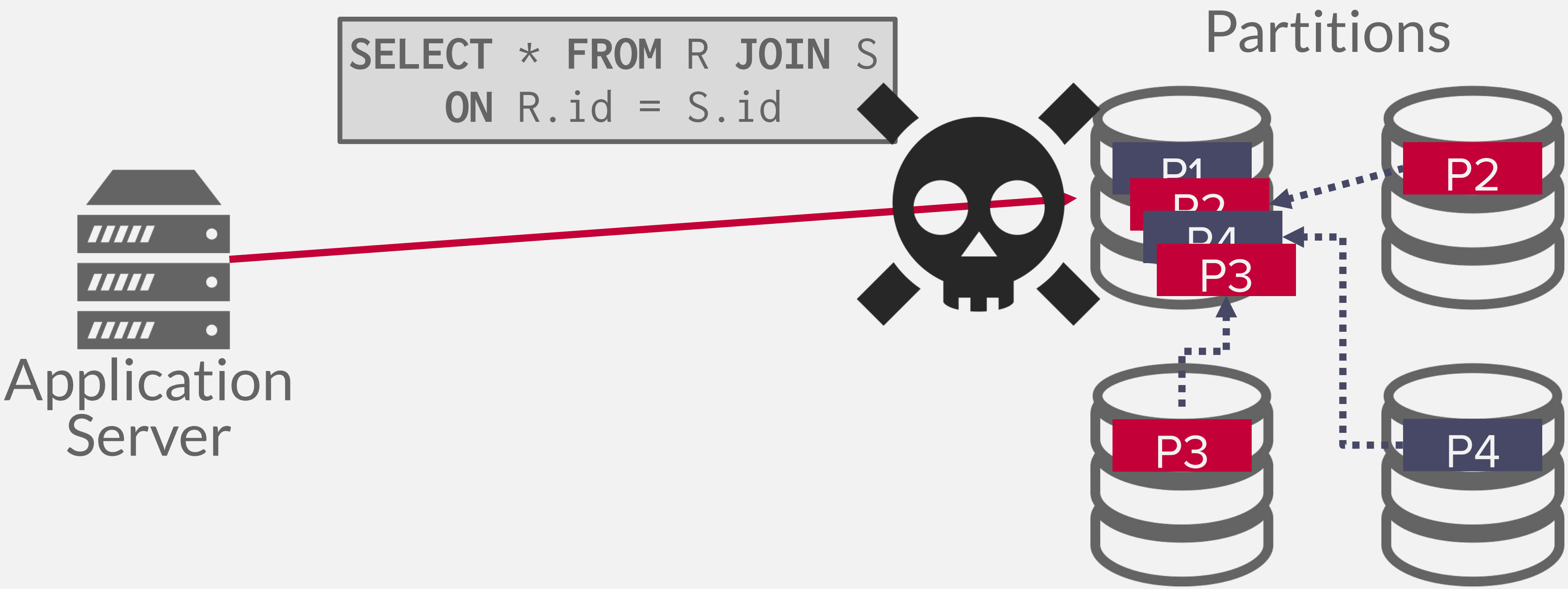

TODAY'S AGENDA

Execution Models

Query Planning

Distributed Join Algorithms

Cloud Systems

DISTRIBUTED QUERY EXECUTION

Executing an OLAP query in a distributed DBMS is roughly the same as on a single-node DBMS.

→ Query plan is a DAG of physical operators.

For each operator, the DBMS considers where input is coming from and where to send output.

→ Table Scans
→ Joins
→ Aggregations
→ Sorting

DISTRIBUTED SYSTEM ARCHITECTURE

A distributed DBMS's system architecture specifies the location of the database's data files. This affects how nodes coordinate with each other and where they retrieve/store objects in the database.

Two approaches (not mutually exclusive):
→ **Push Query to Data**
→ **Pull Data to Query**

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.
→ This is necessary when there is no compute resources available where database files are located.

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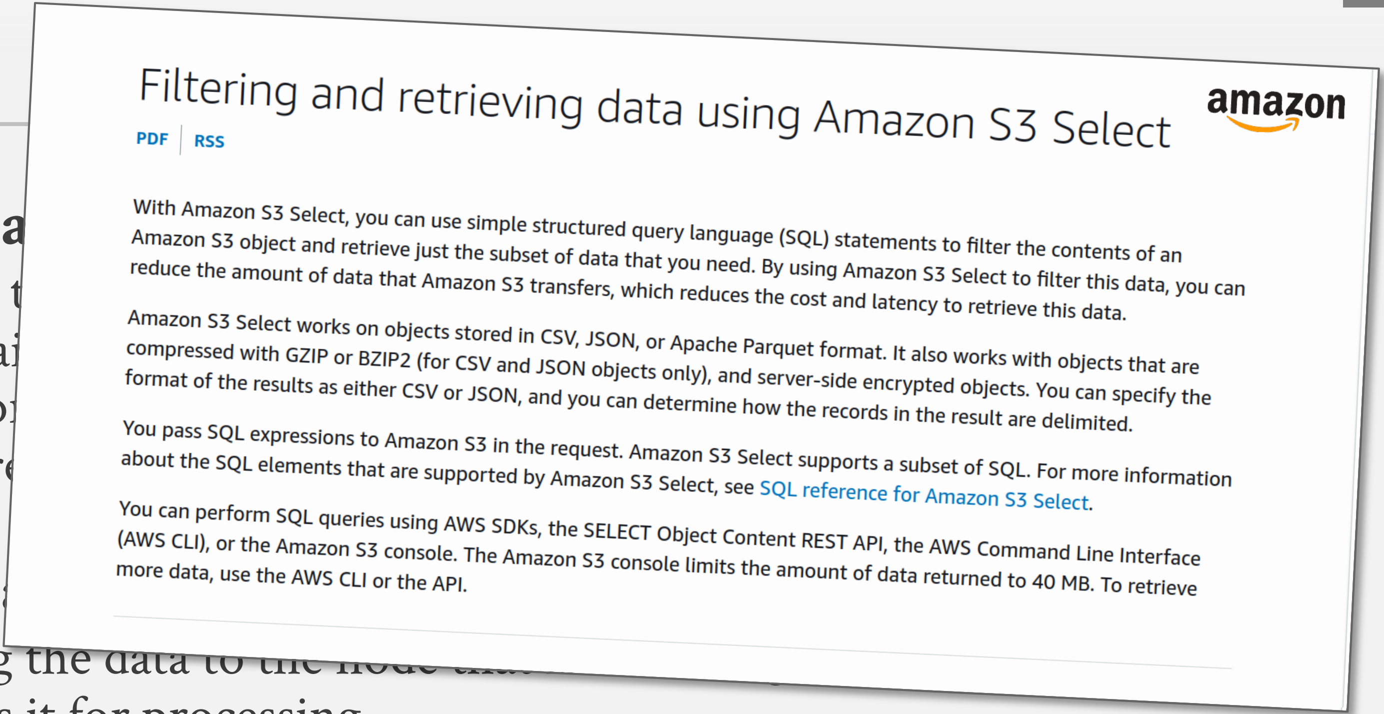

Filtering and retrieving data using Amazon S3 Select

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With Amazon S3 Select, you can use simple structured query language (SQL) statements to filter the contents of an Amazon S3 object and retrieve just the subset of data that you need. By using Amazon S3 Select to filter this data, you can reduce the amount of data that Amazon S3 transfers, which reduces the cost and latency to retrieve this data.

Amazon S3 Select works on objects stored in CSV, JSON, or Apache Parquet format. It also works with objects that are compressed with GZIP or BZIP2 (for CSV and JSON objects only), and server-side encrypted objects. You can specify the format of the results as either CSV or JSON, and you can determine how the records in the result are delimited.

You pass SQL expressions to Amazon S3 in the request. Amazon S3 Select supports a subset of SQL. For more information about the SQL elements that are supported by Amazon S3 Select, see SQL reference for Amazon S3 Select.

You can perform SQL queries using AWS SDKs, the SELECT Object Content REST API, the AWS Command Line Interface (AWS CLI), or the Amazon S3 console. The Amazon S3 console limits the amount of data returned to 40 MB. To retrieve more data, use the AWS CLI or the API.

Approa

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amazon

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Object Content REST API, the AWS Command Line Interface
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Query Blob Contents

Microsoft

Feedback

Article • 07/20/2021 • 10 minutes to read • 3 contributors

The `Query Blob Contents` API applies a simple Structured Query Language (SQL) statement on a blob's contents and returns only the queried subset of the data. You can also call `Query Blob Contents` to query the contents of a version or snapshot.

Request

The `Query Blob Contents` request may be constructed as follows. HTTPS is recommended. Replace *myaccount* with the name of your storage account:

POST Method Request URI	HTTP Version
`https://myaccount.blob.core.windows.net/mycontainer/myblob?comp=query`	HTTP/1.0
`https://myaccount.blob.core.windows.net/mycontainer/myblob?comp=query&snapshot=<DateTime>`	HTTP/1.1
`https://myaccount.blob.core.windows.net/mycontainer/myblob?comp=query&versionid=<DateTime>`	

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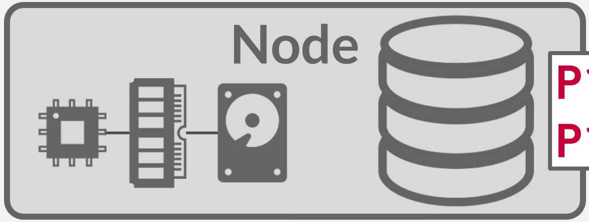
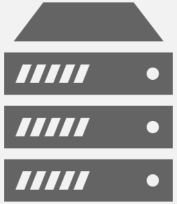
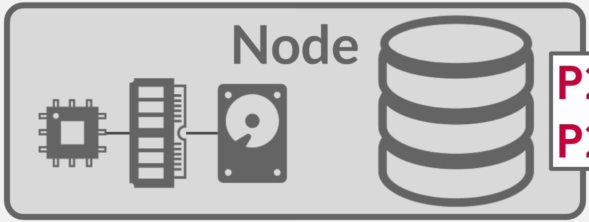
PUSH QUERY TO DATA



P1→R.id:1-100
P1→S.id:1-100



Application Server



P2→R.id:101-200
P2→S.id:101-200

PUSH QUERY TO DATA

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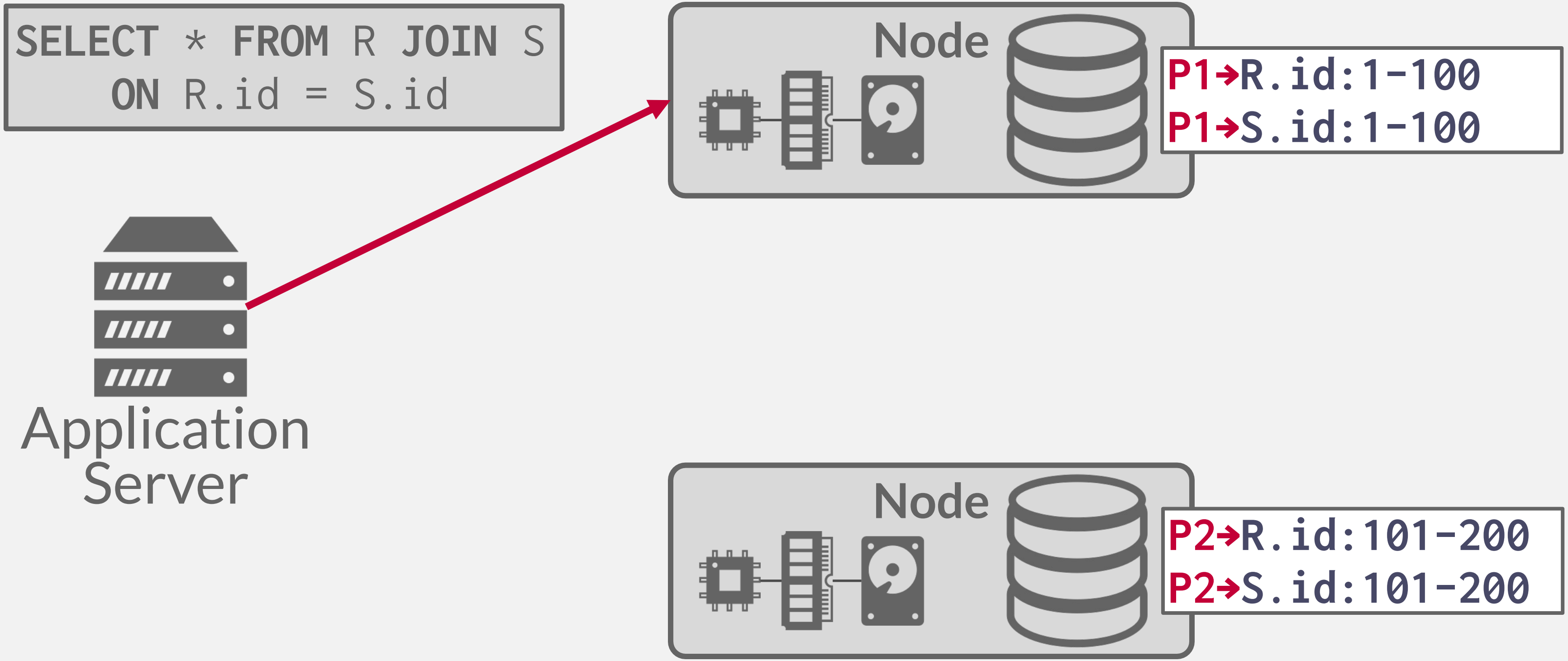

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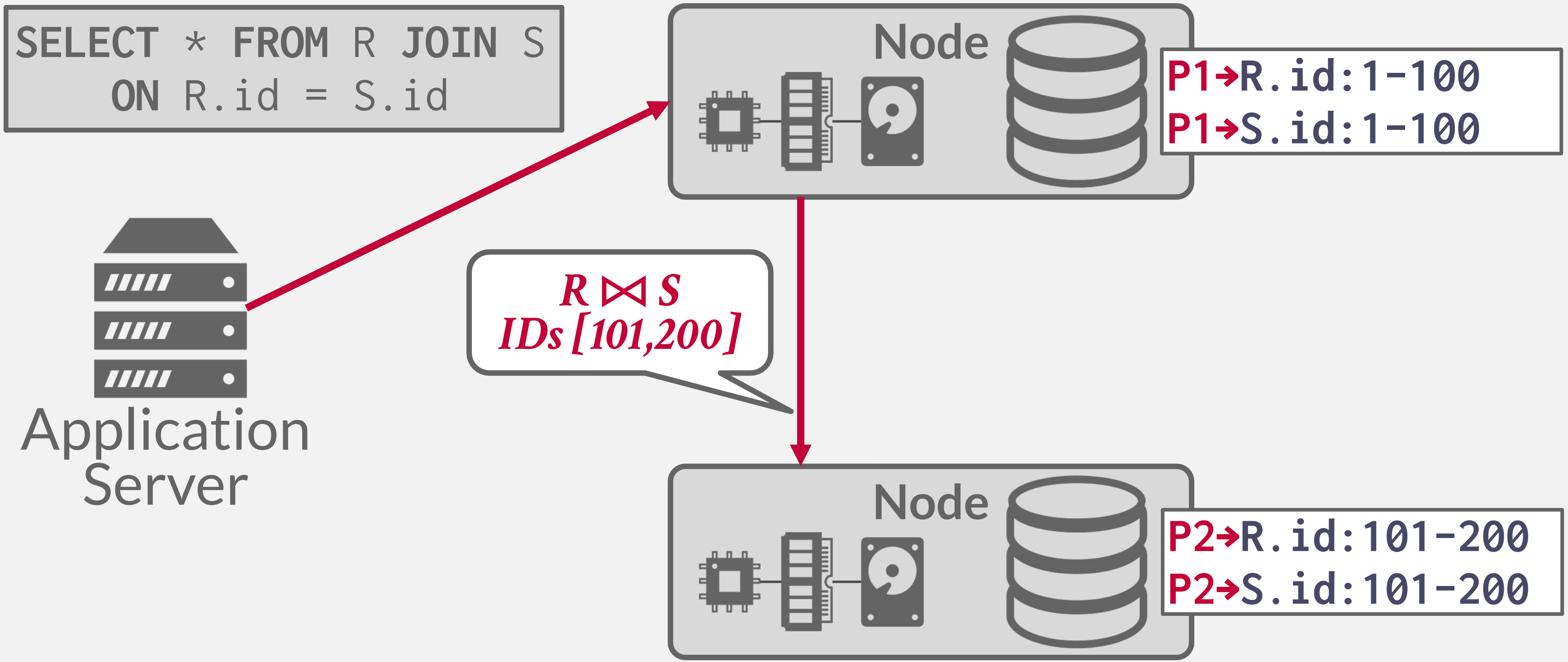

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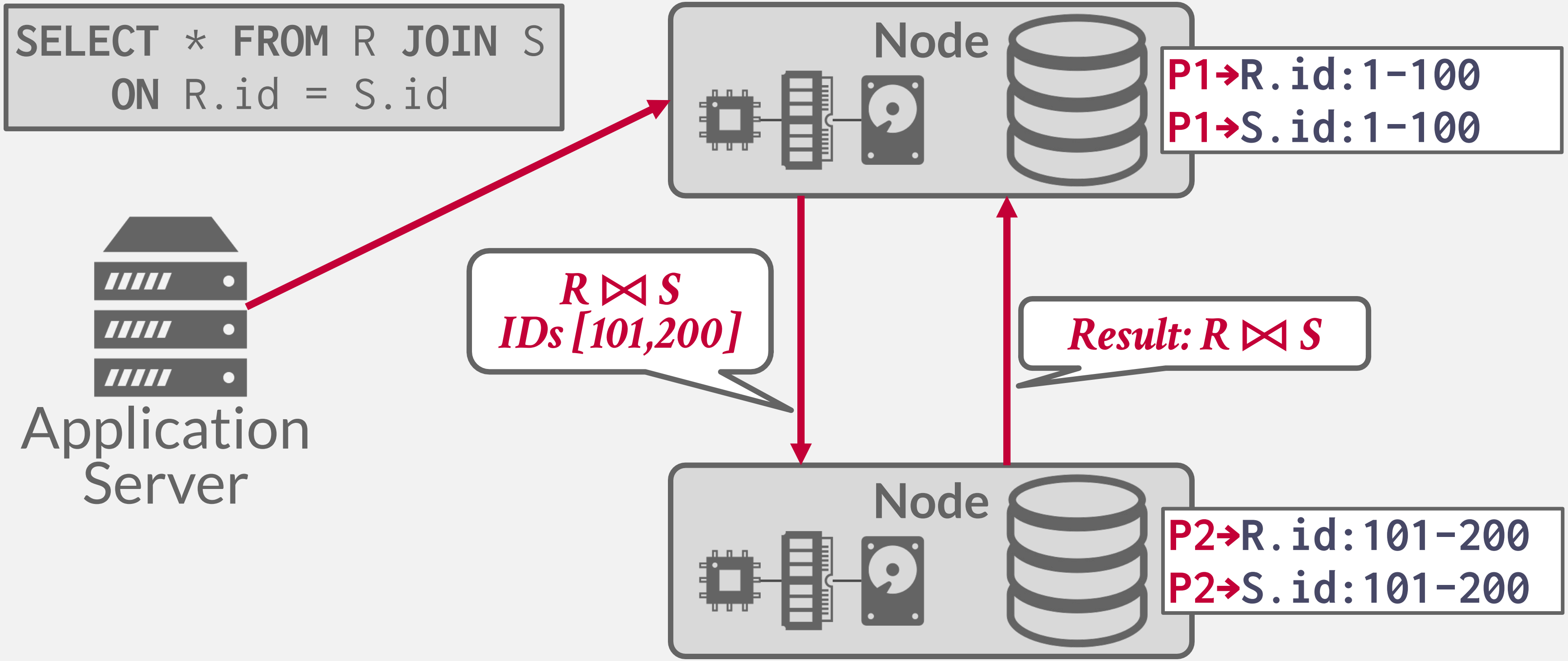

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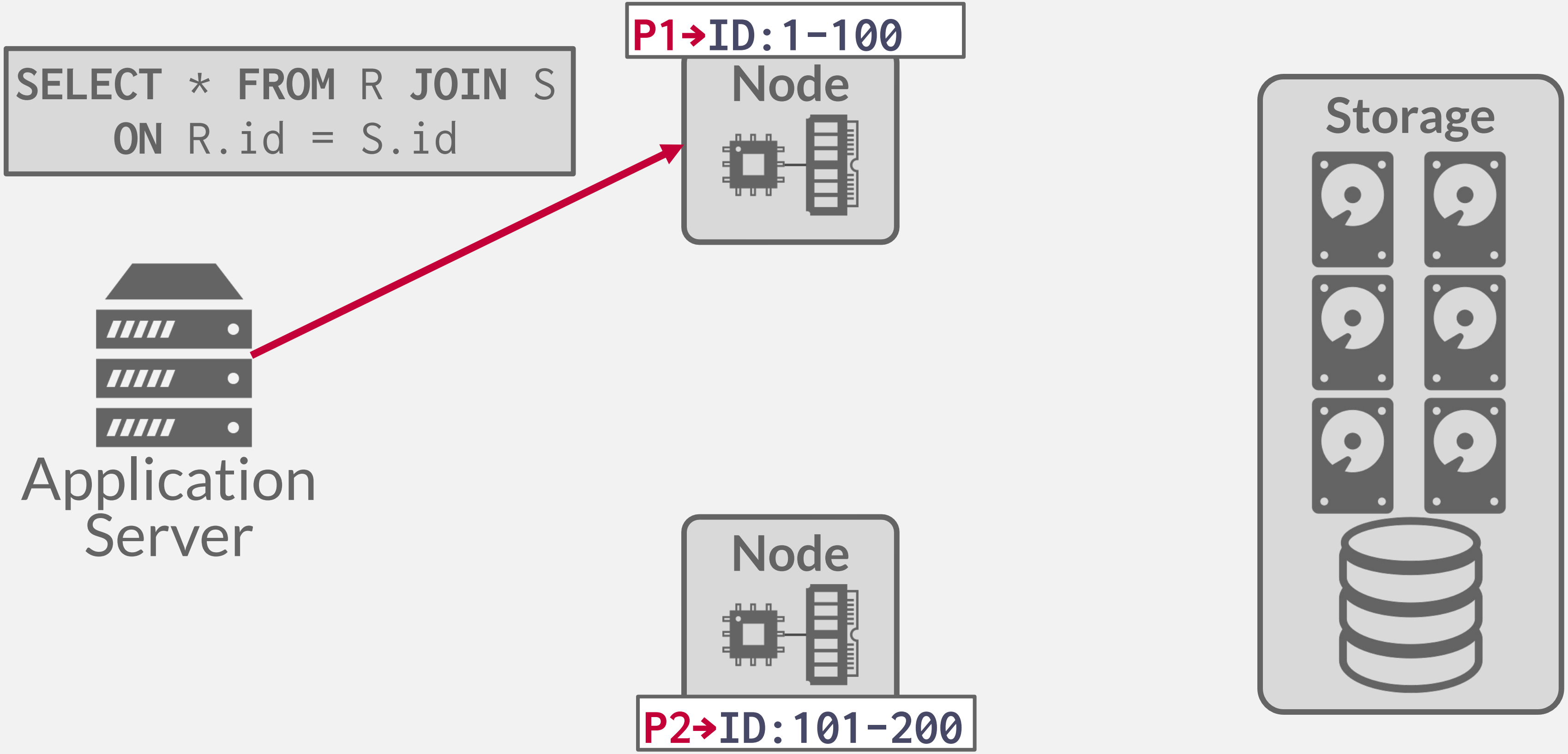

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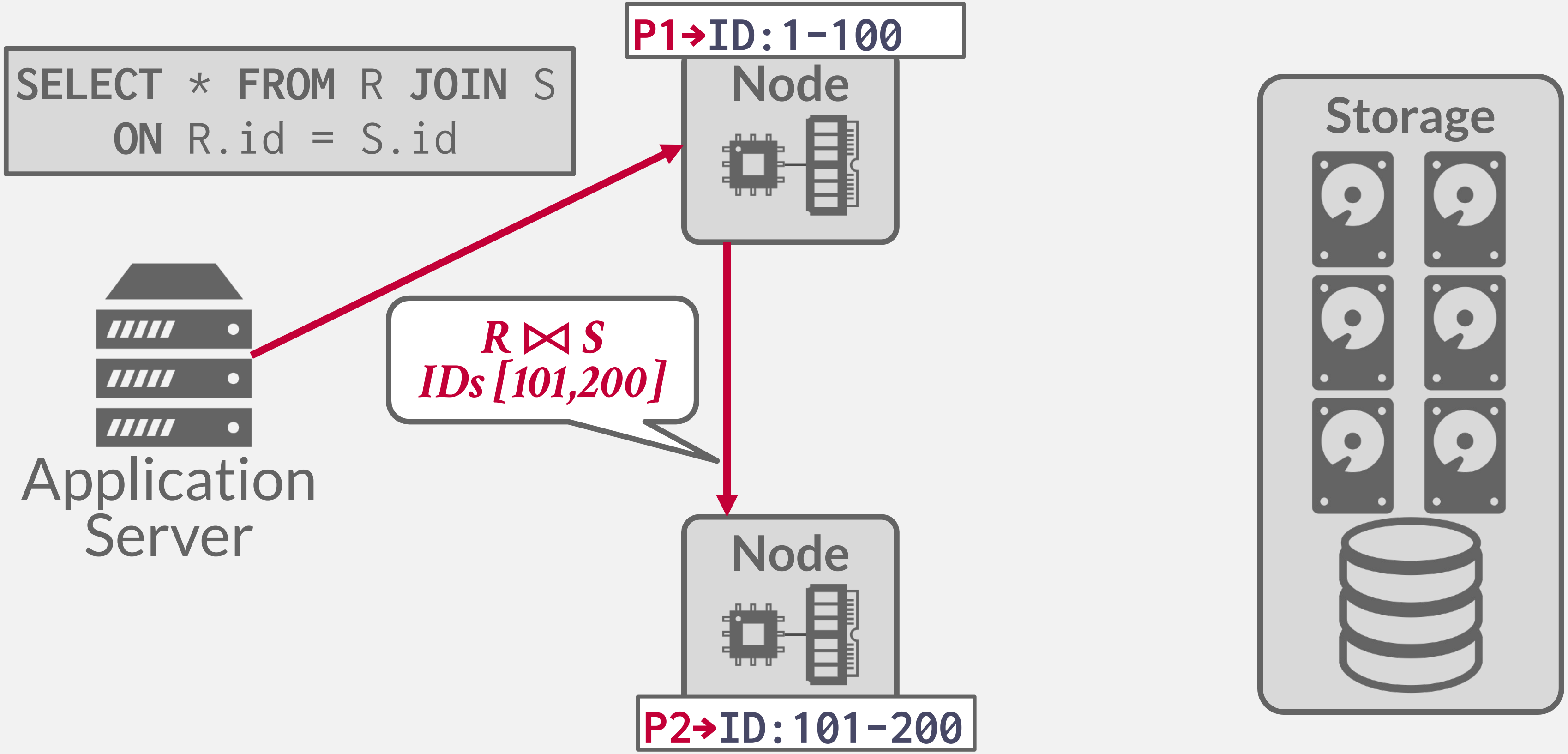

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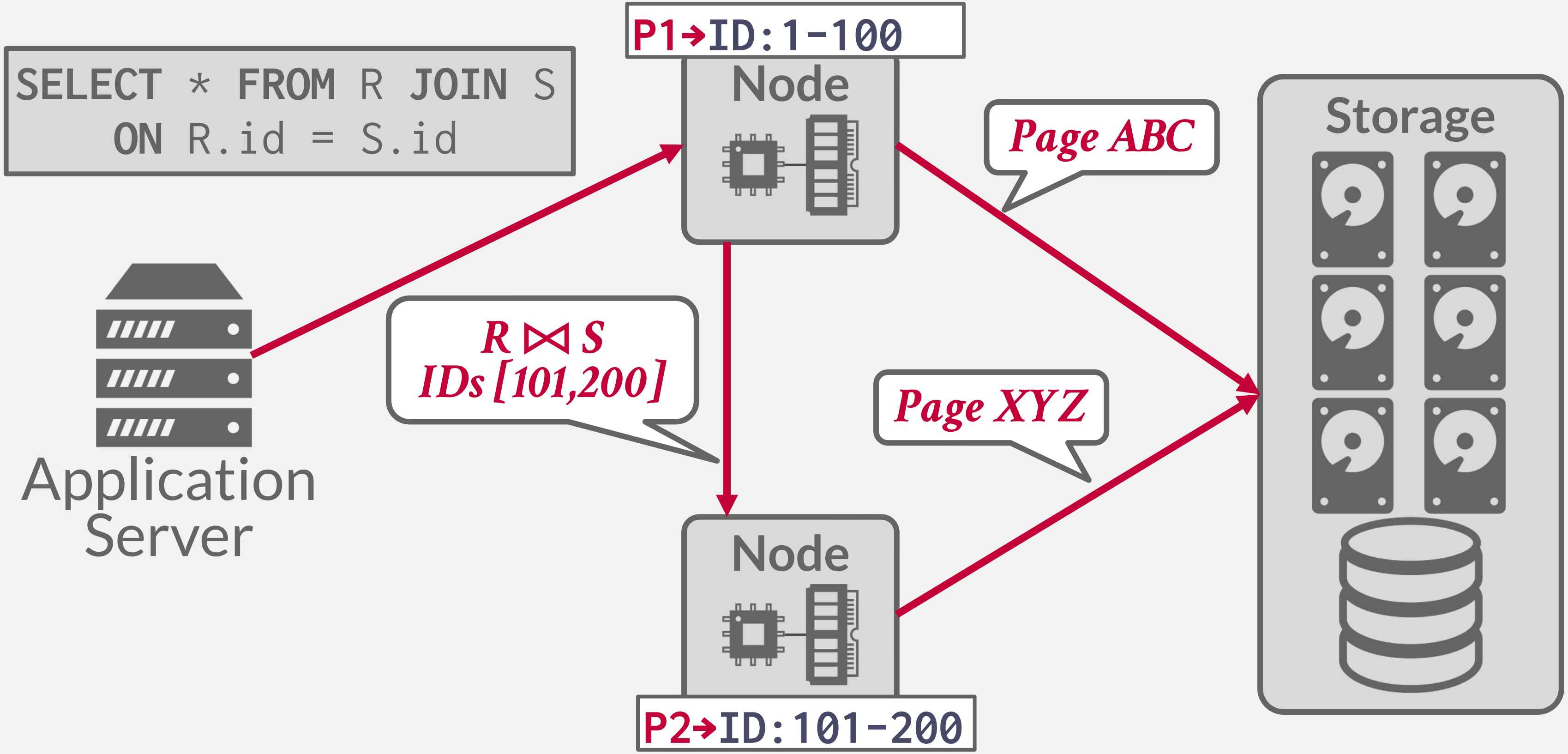

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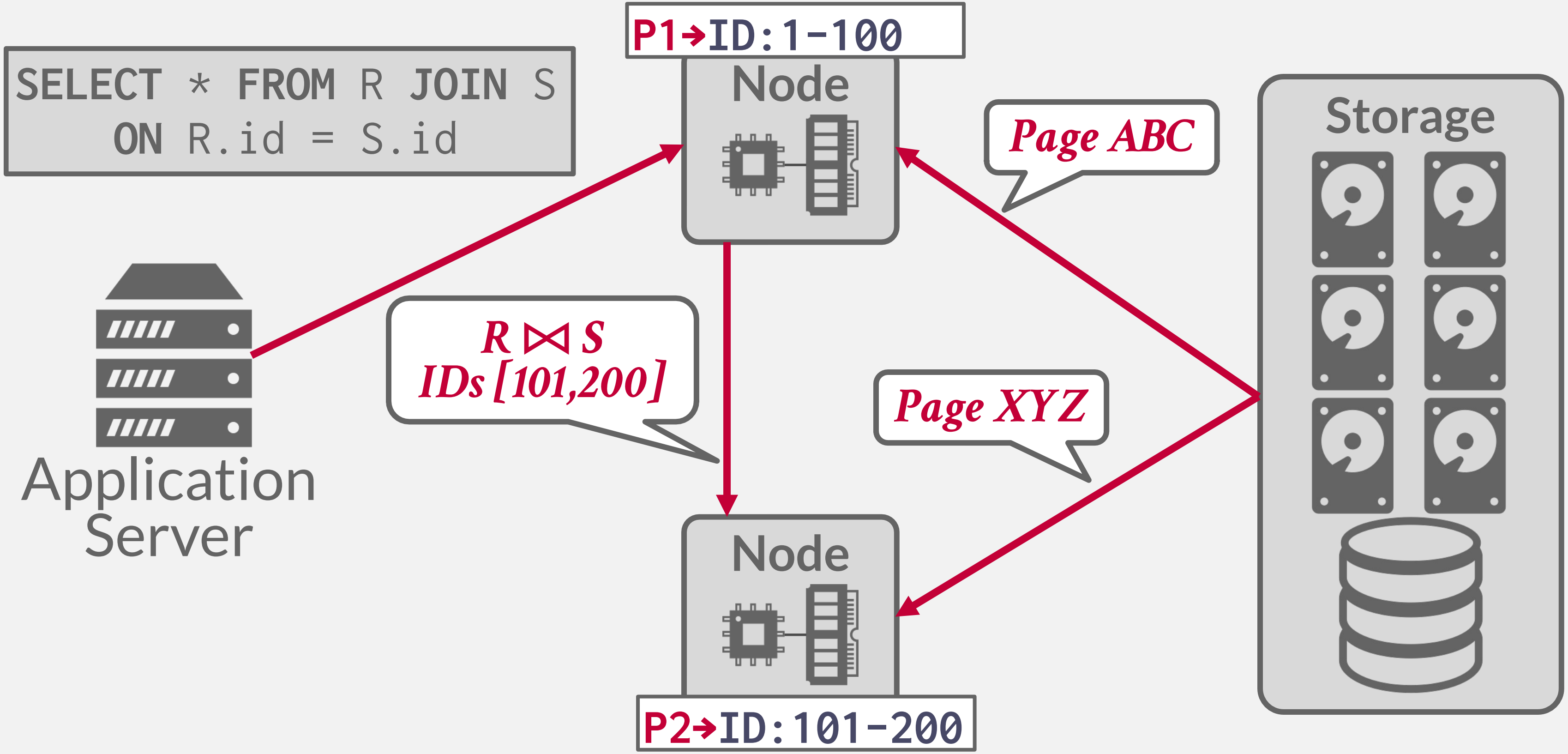

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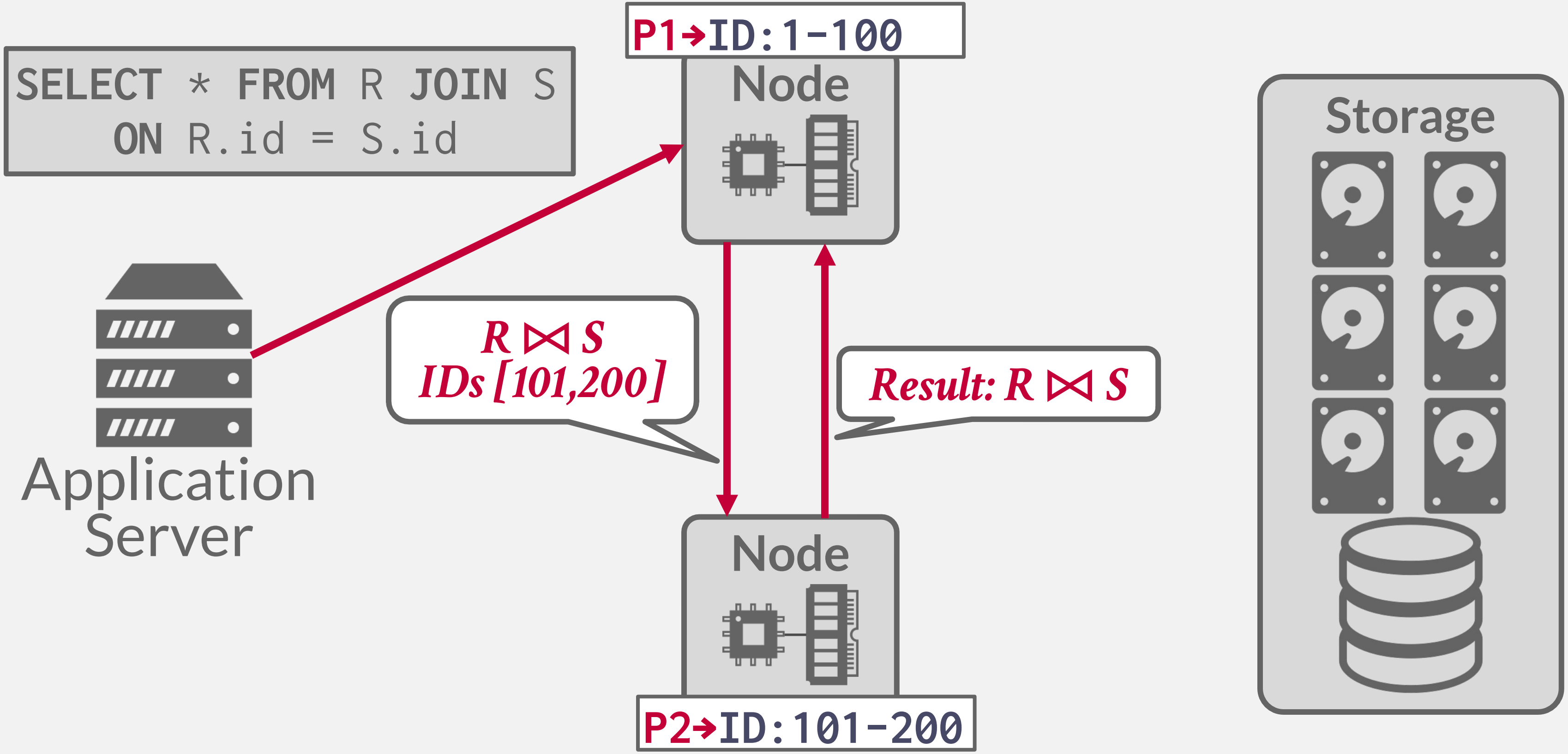

OBSERVATION

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 <u>not</u> 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.

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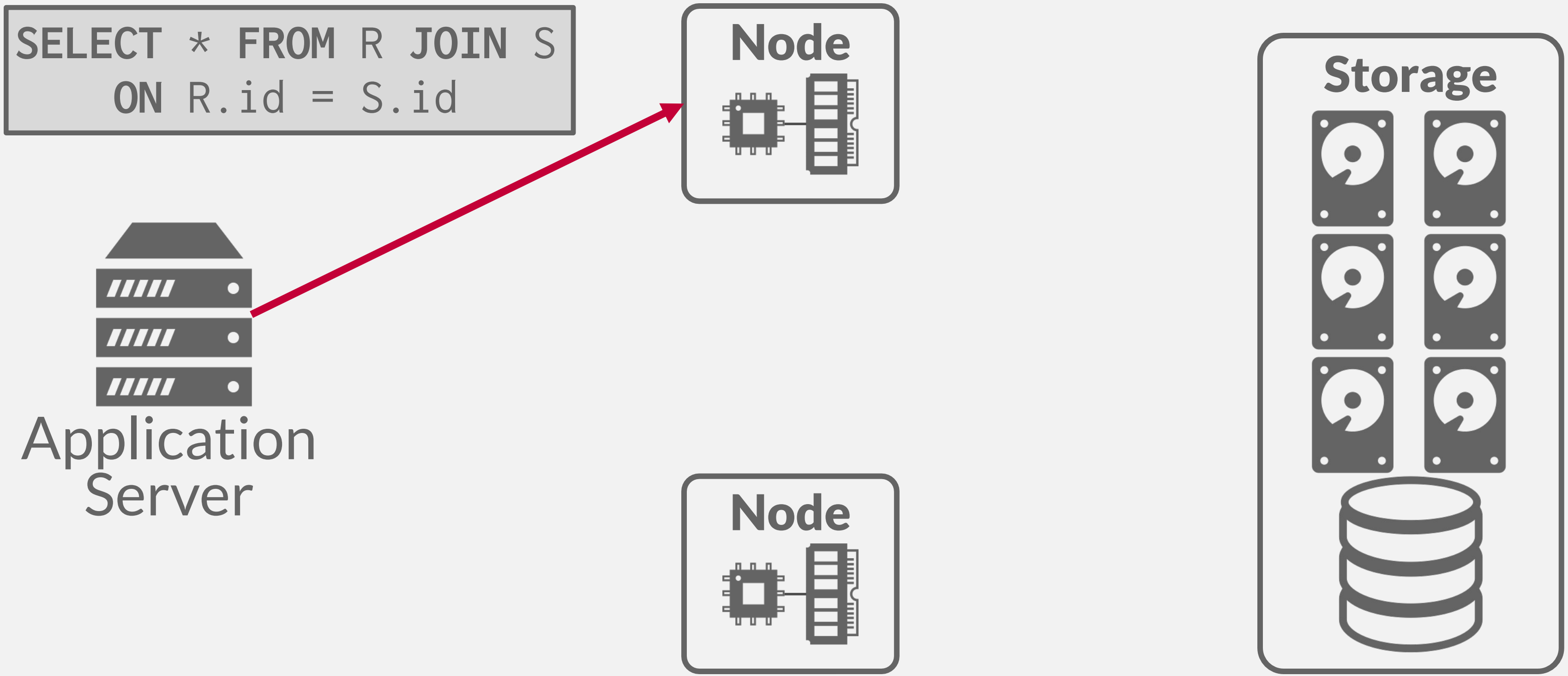

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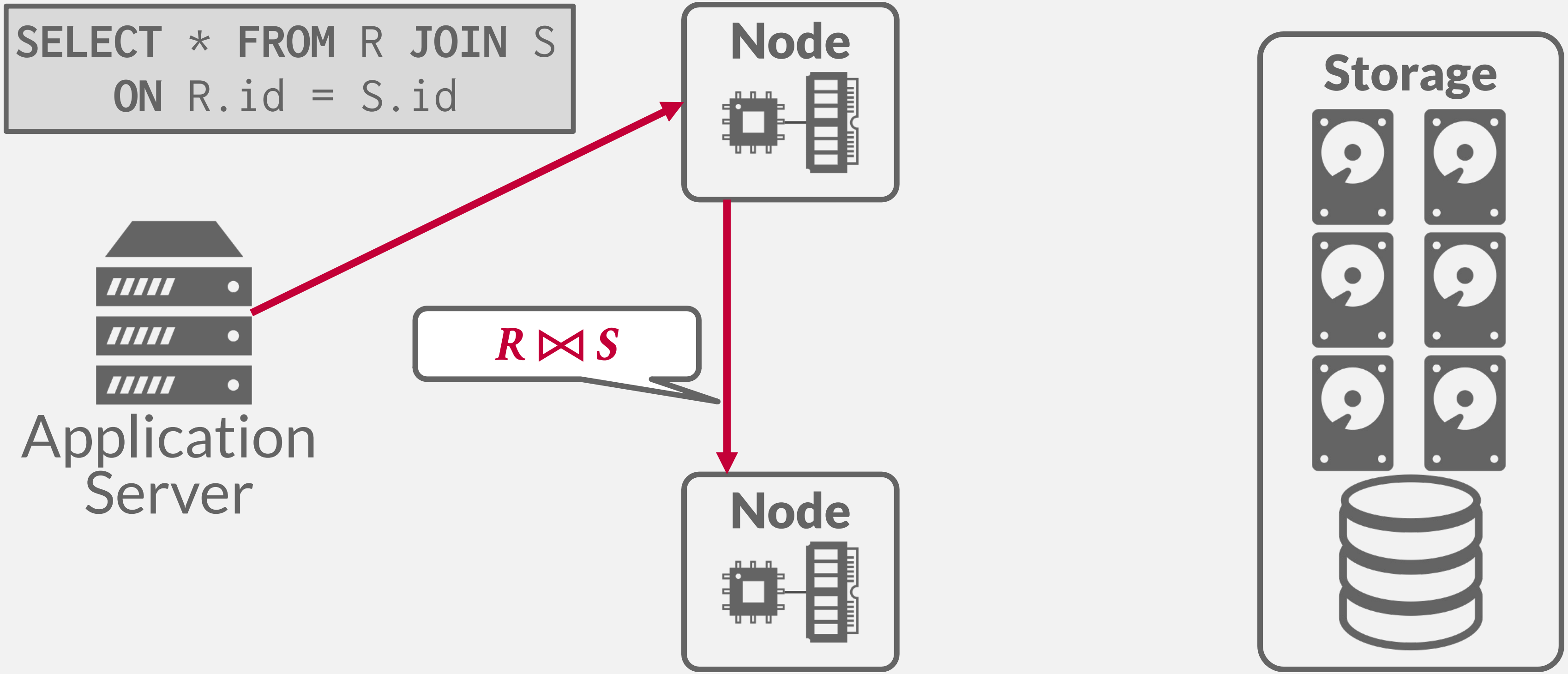

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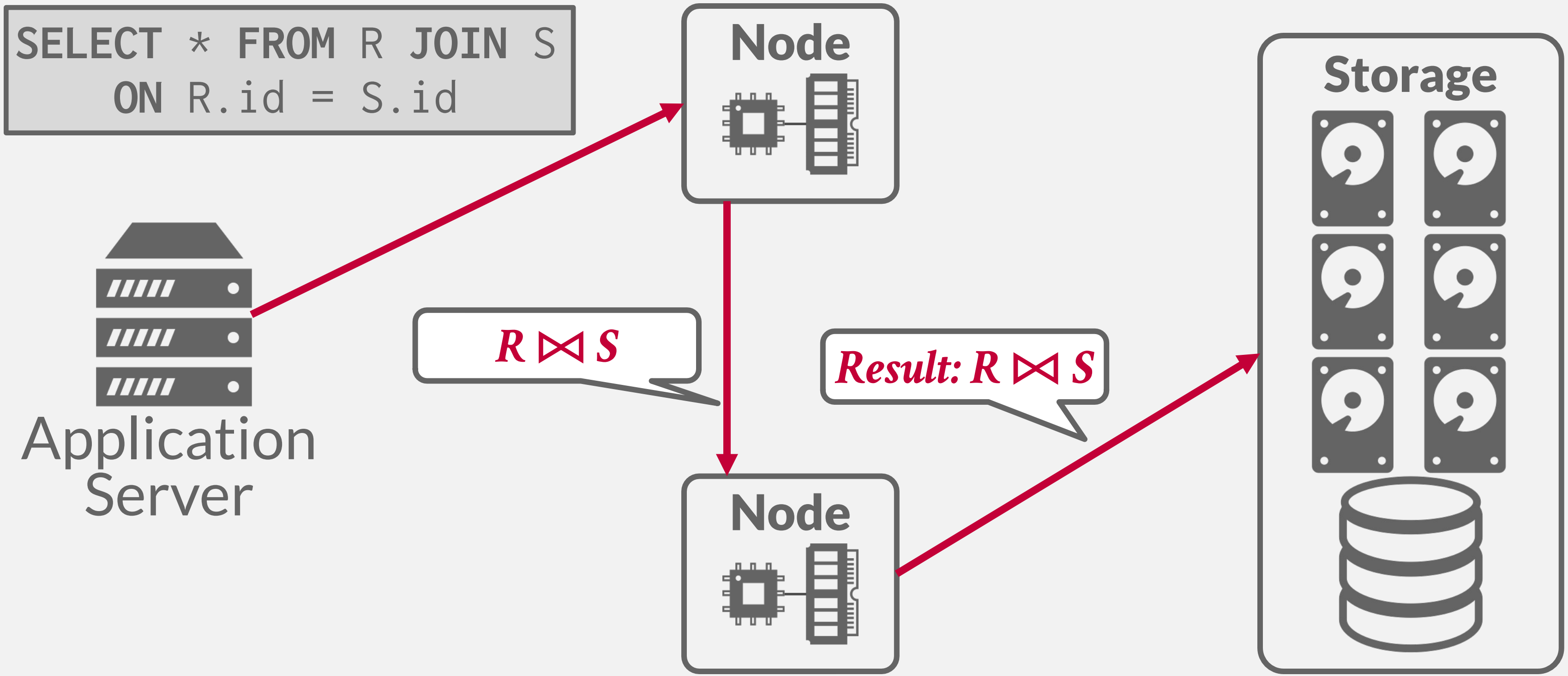

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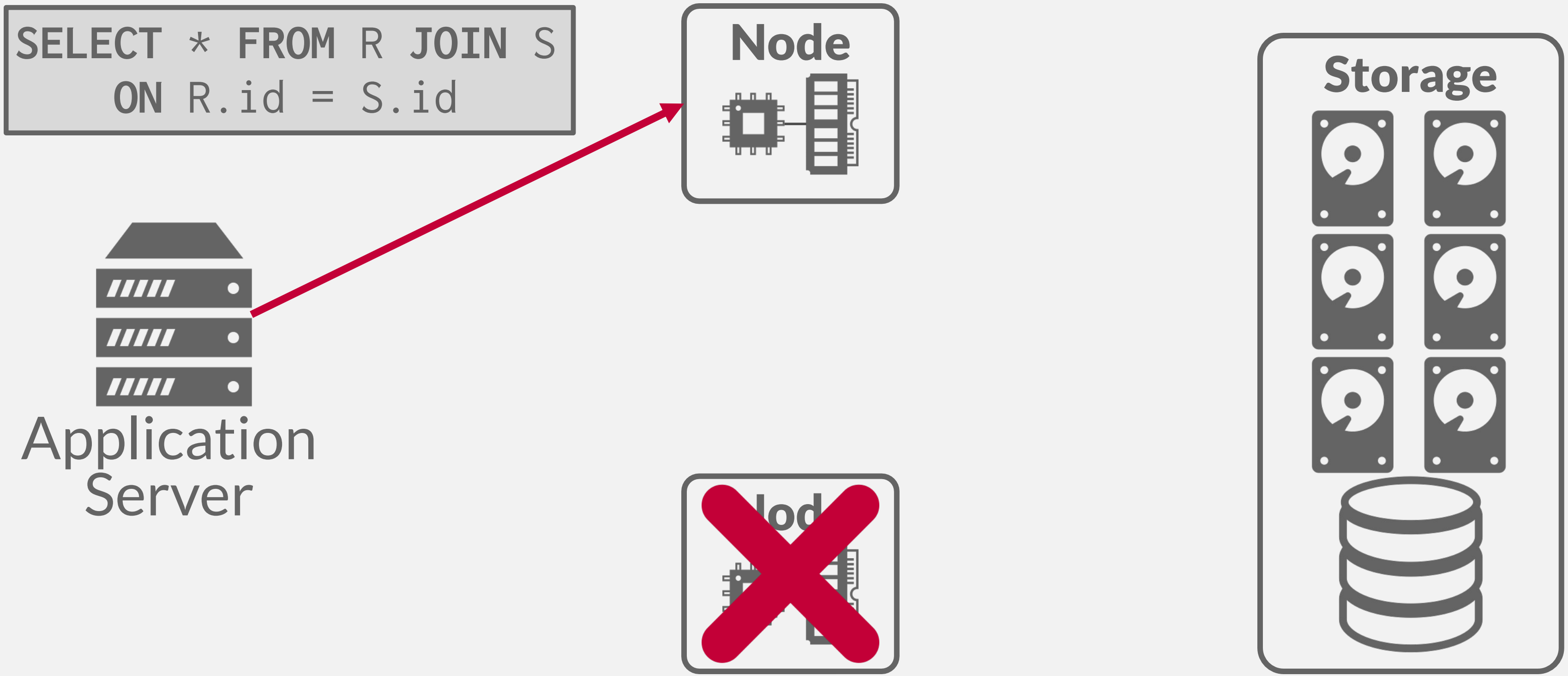

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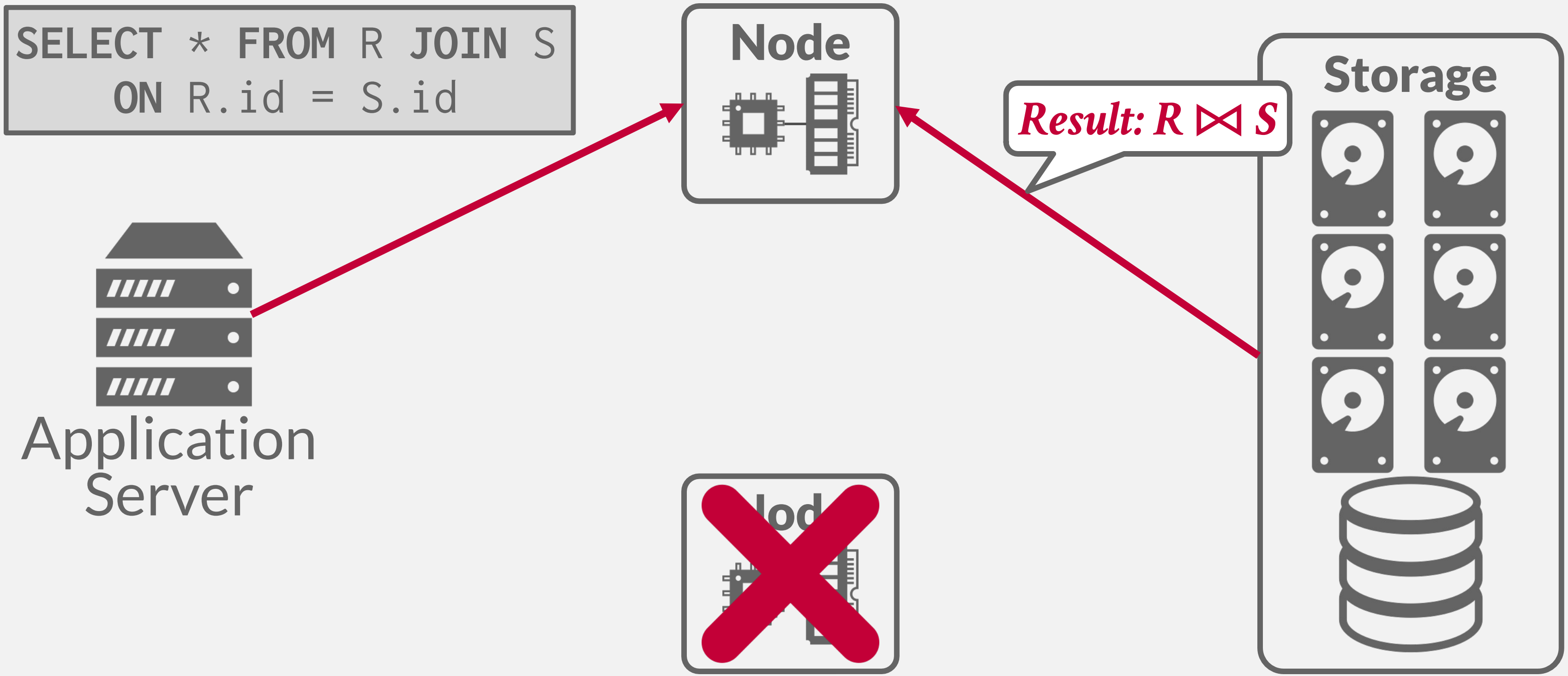

QUERY PLANNING

All the optimizations that we talked about before are still applicable in a distributed environment.

→ Predicate Pushdown
→ Projection Pushdown
→ 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 we know that use this approach.

QUERY PLAN FRAGMENTS

```
SELECT * FROM R JOIN S
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QUERY PLAN FRAGMENTS

```
SELECT * FROM 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

N FRAGMENTS

Union the output of each join to produce final result.

```
ROM R JOIN S
ON    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.

→ Need to produce the correct answer as if all the data is located in a single node system.

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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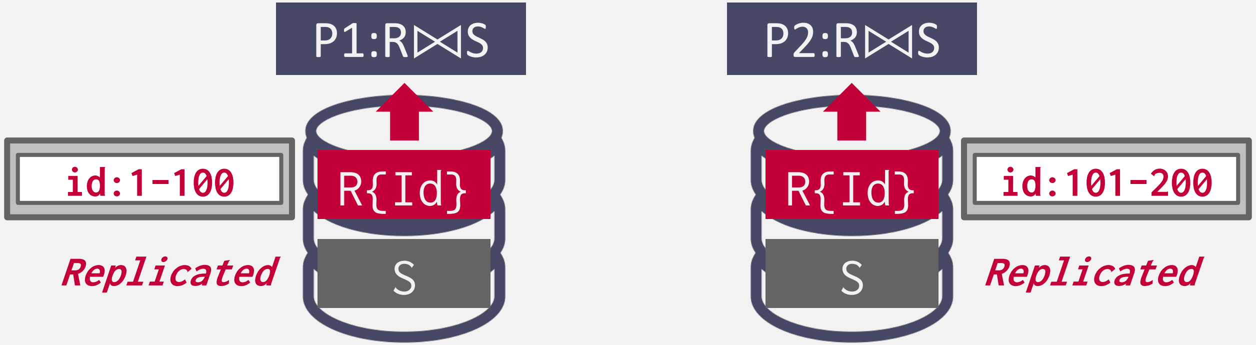

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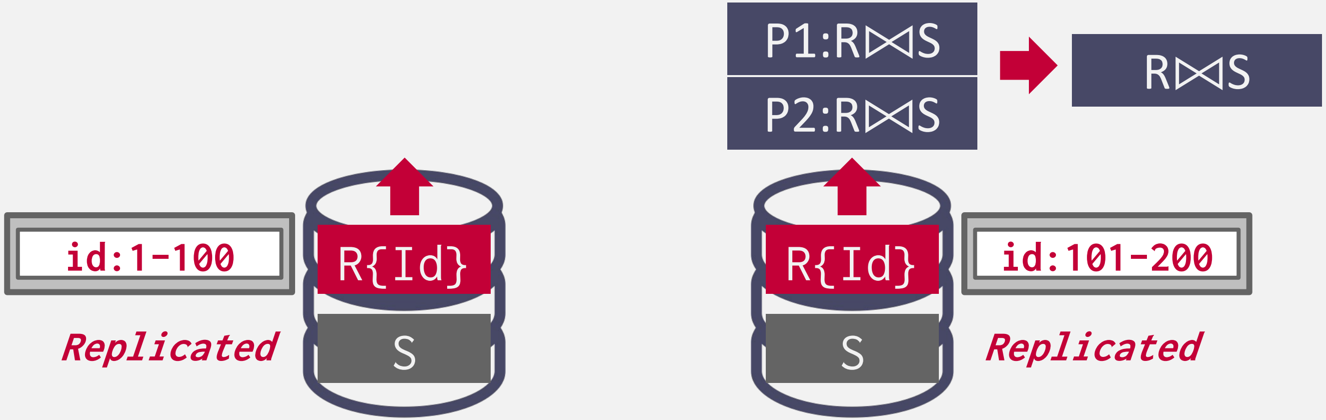

SCENARIO #2

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

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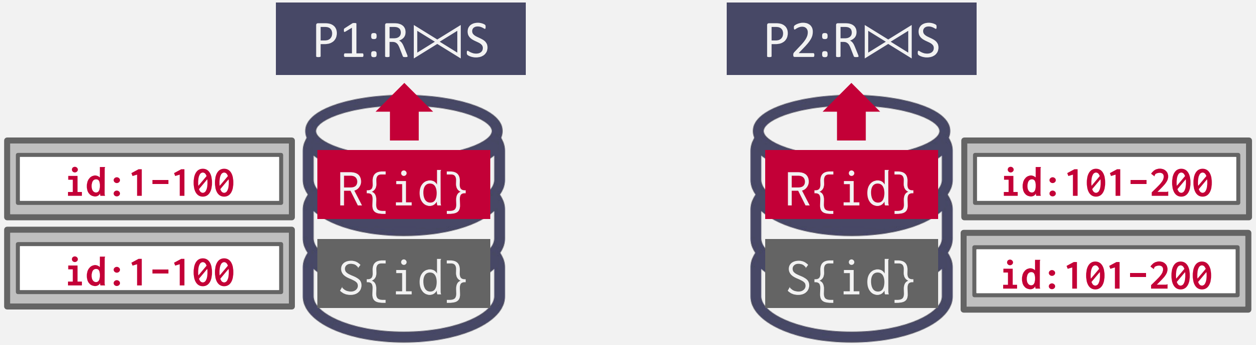

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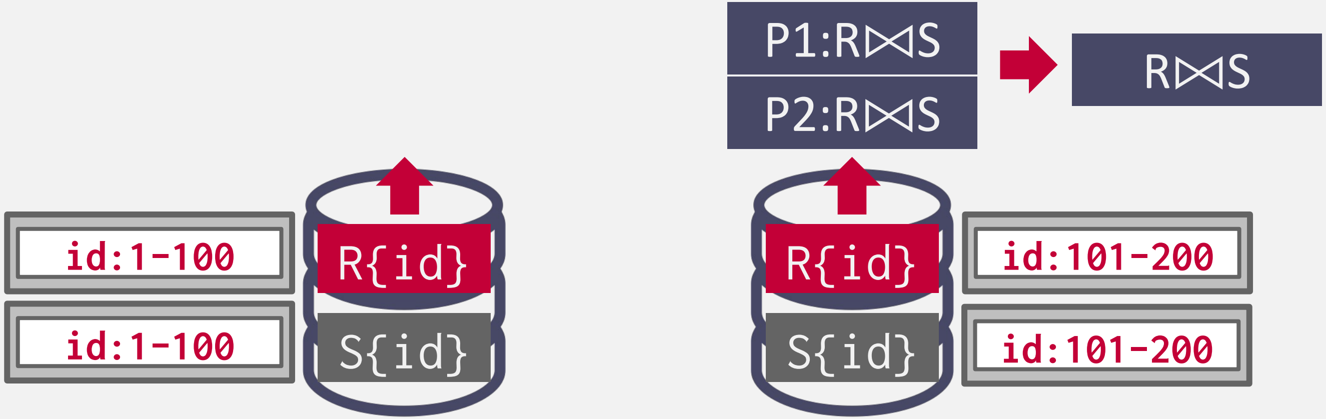

SCENARIO #3

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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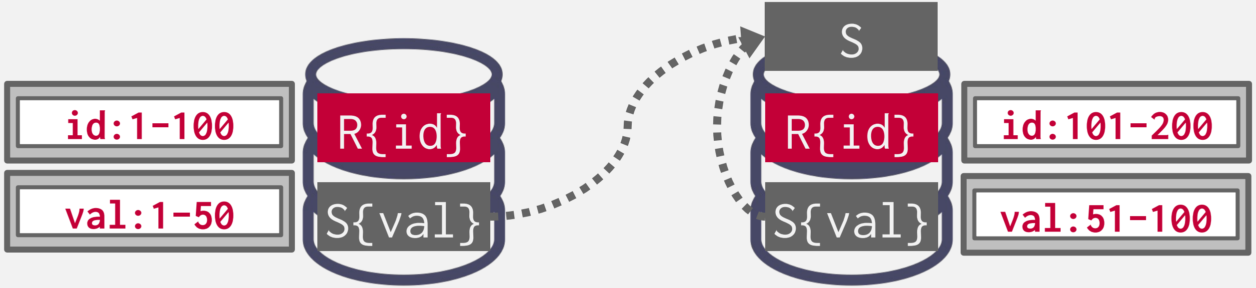

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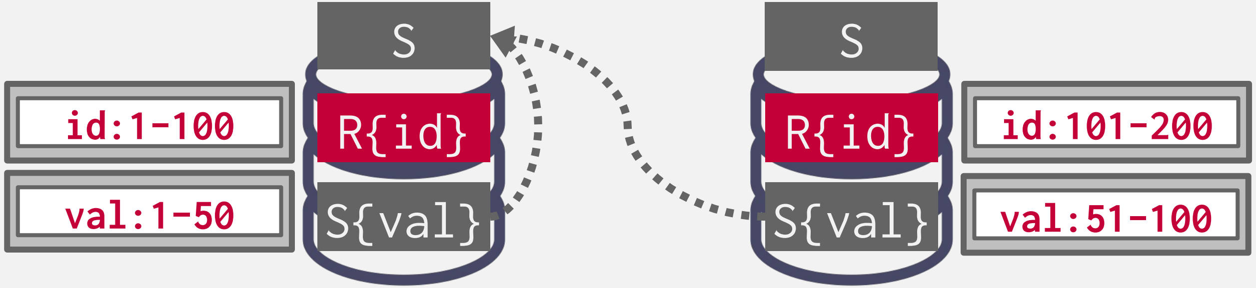

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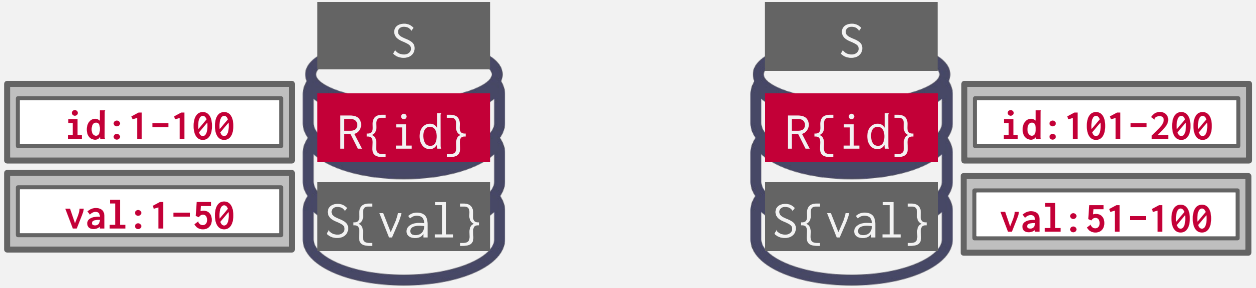

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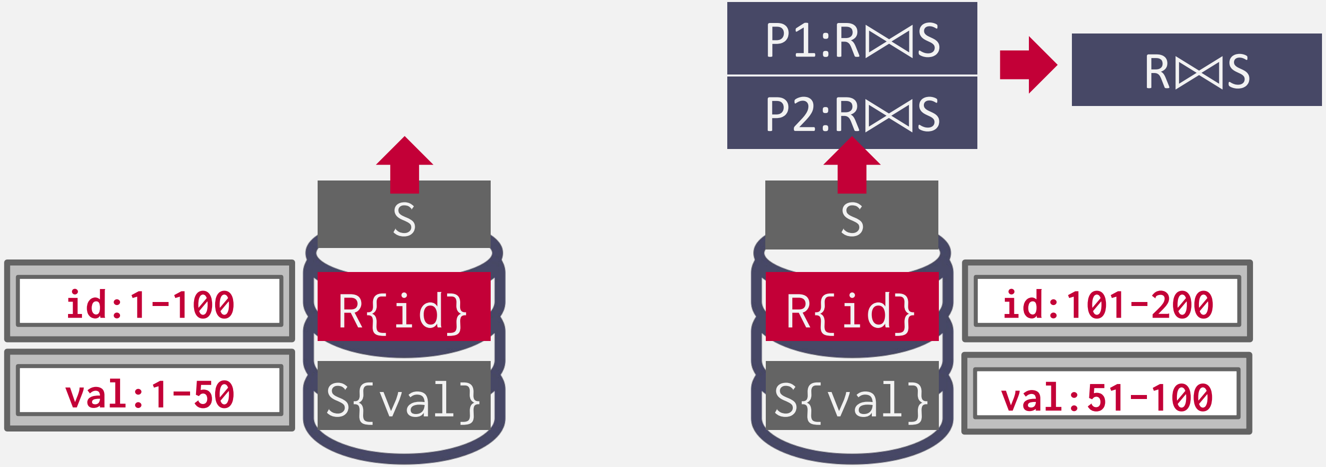

SCENARIO #4

Both tables are not partitioned on the join key. The DBMS copies/re-partitions the tables on-the-fly across nodes.

→ This repartitioned data is generally deleted when the query is done.

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SELECT * FROM R JOIN S
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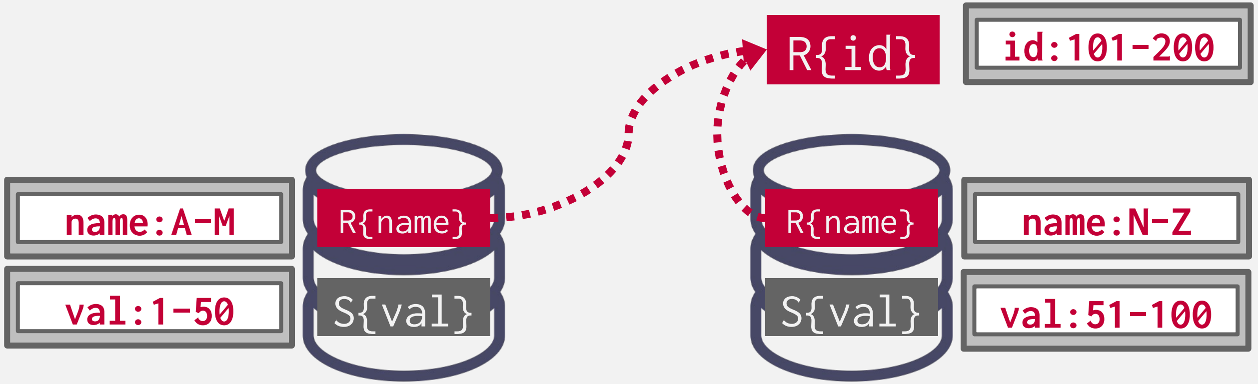

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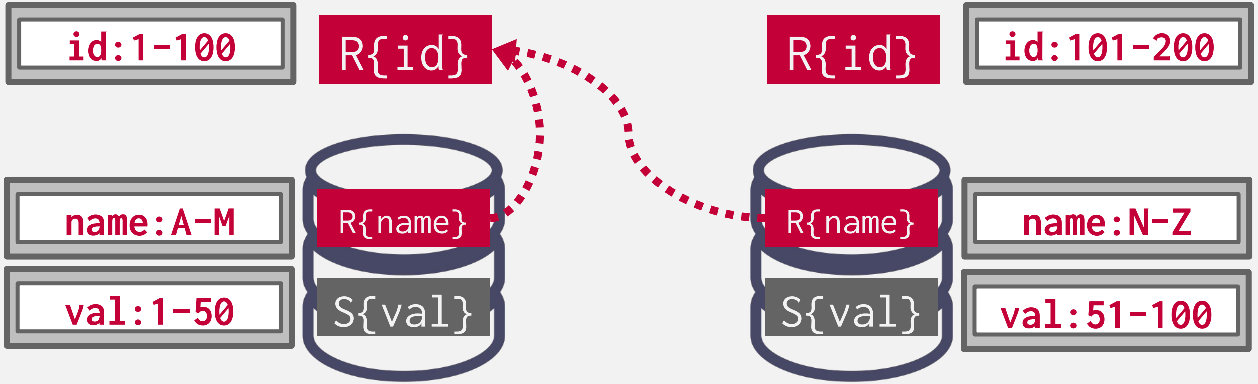

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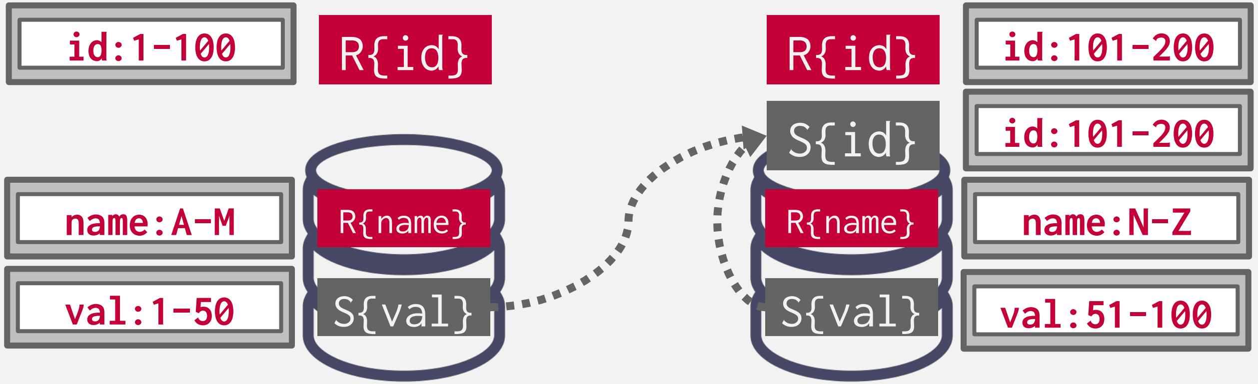

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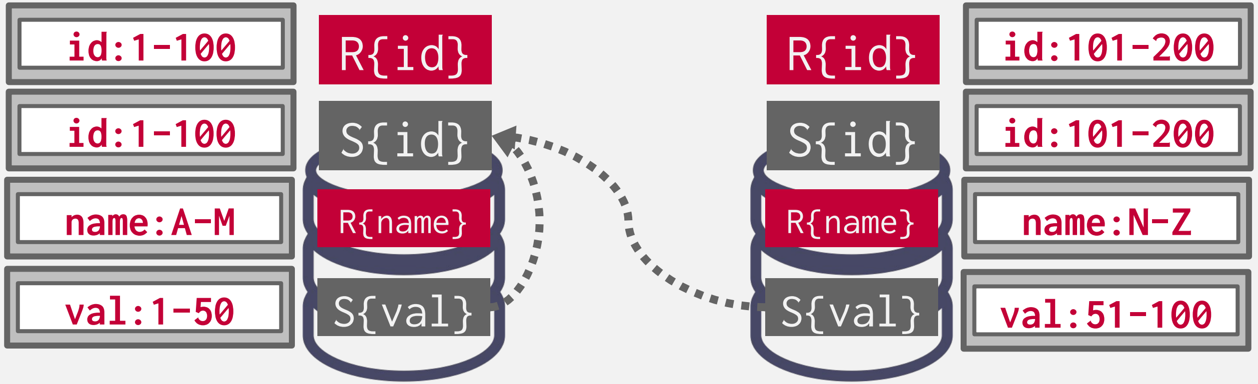

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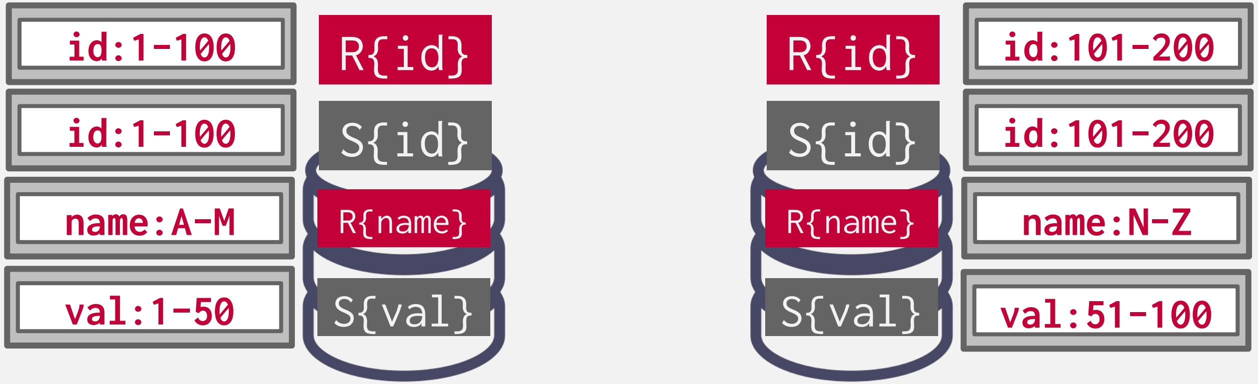

SCENARIO #4

Both tables are not partitioned on the join key. The DBMS copies/re-partitions the tables on-the-fly across nodes.

→ This repartitioned data is generally deleted when the query is done.

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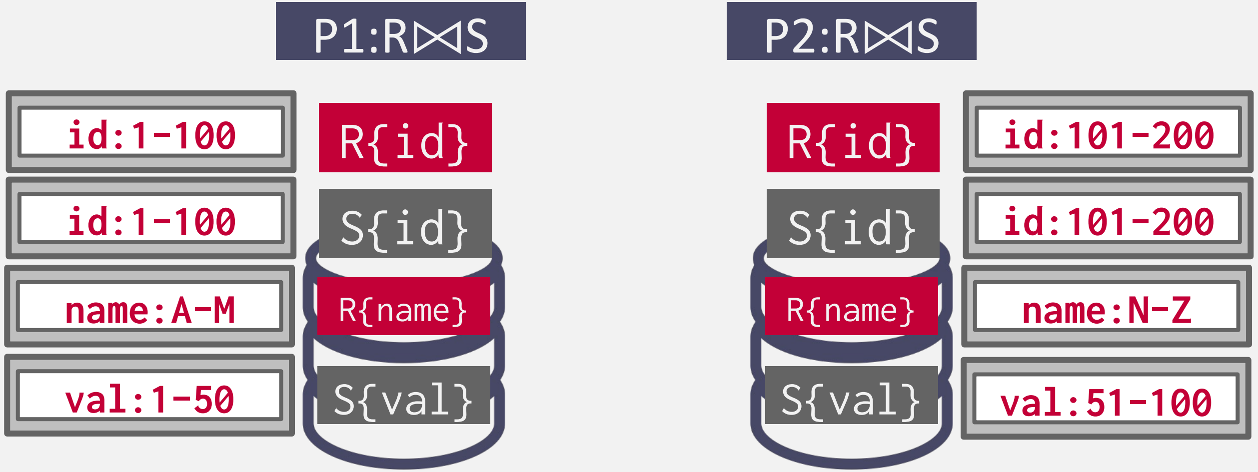

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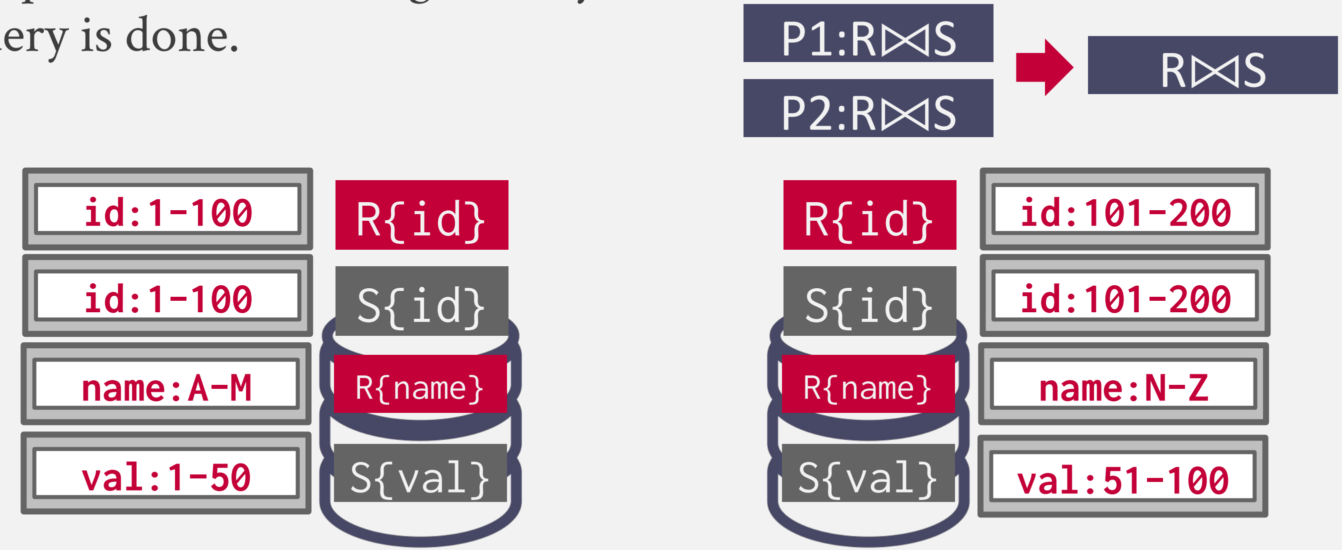

SEMI-JOIN: REDUCE DATA MOVEMENT

Can use this technique to reduce data movement

→ Before pulling data from another node, send a semi-join filter to reduce data movement.

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SELECT Fact.price, Dim.*
  FROM Fact JOIN Dim
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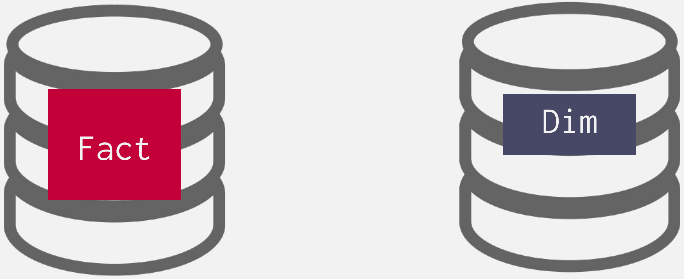

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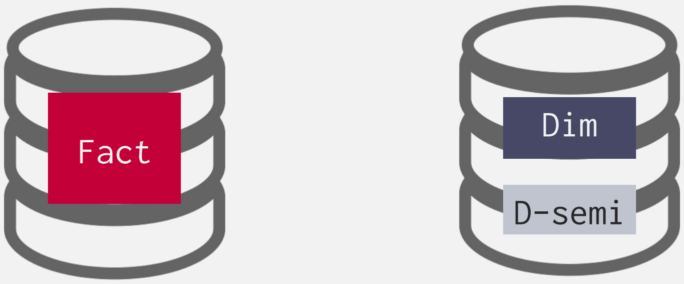

$$\text{D-semi} = \Pi_{id}\,(\sigma_{zip\,=\,15213}\ \text{Dim})$$

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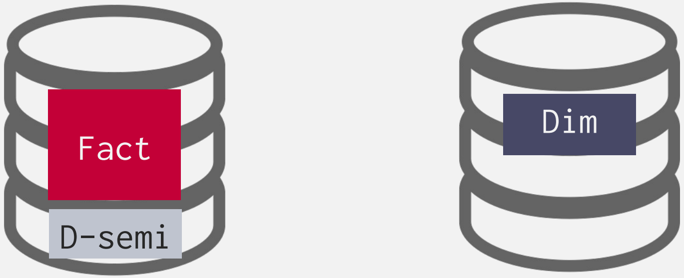

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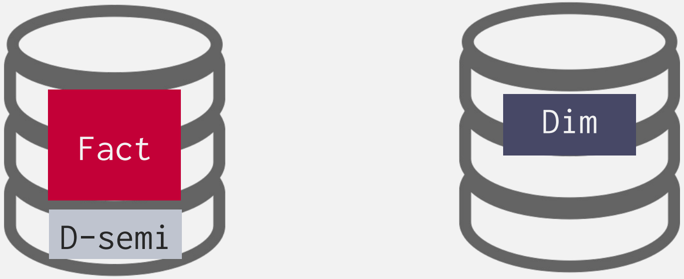

F-small = Fact $\bowtie$ D-semi

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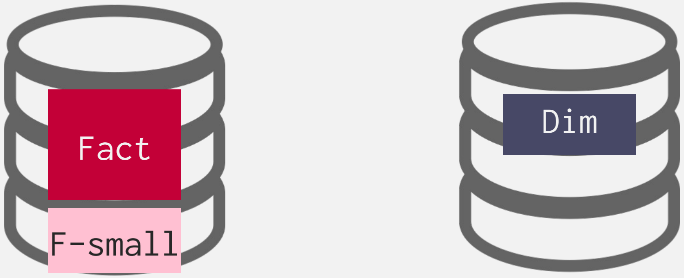

D-semi = Π_{id} ($\sigma_{zip\ =\ 15213}$ Dim)

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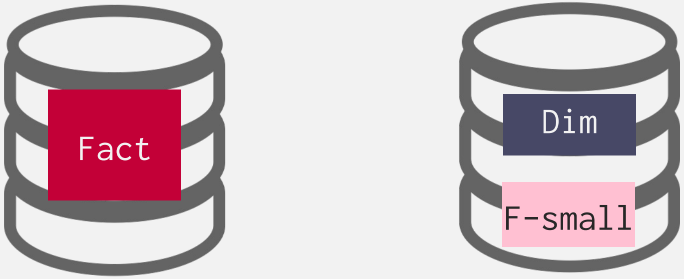

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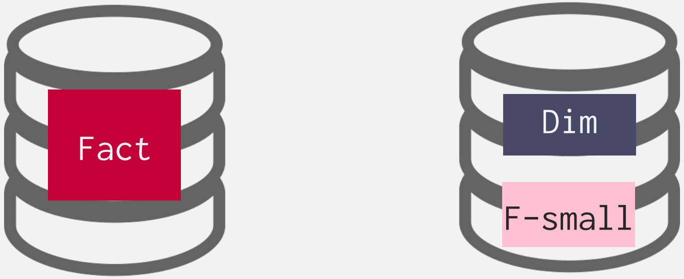


Result = $\Pi_{price}(\text{Dim} \bowtie \text{F-small})$

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

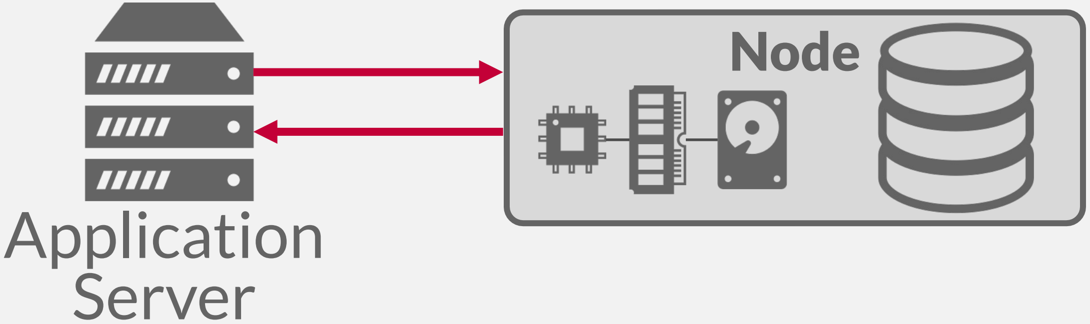
→ No significant modification to the DBMS to be "aware" that it is running in a cloud environment.
→ Examples: Most vendors

Approach #2: Cloud-Native DBMS

→ System designed explicitly to run in a cloud environment.
→ Usually based on a shared-disk architecture.
→ Examples: Snowflake, Google BigQuery

SERVERLESS DATABASES

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



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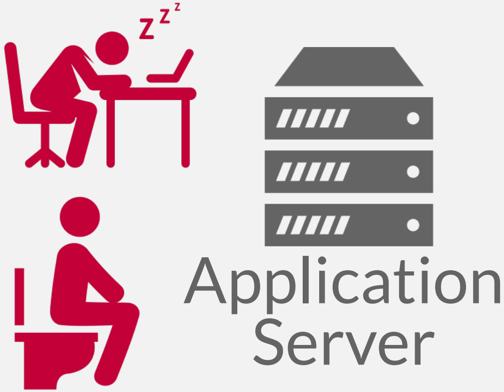

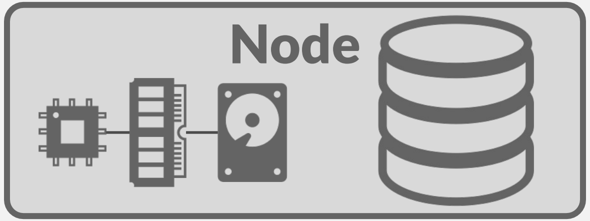

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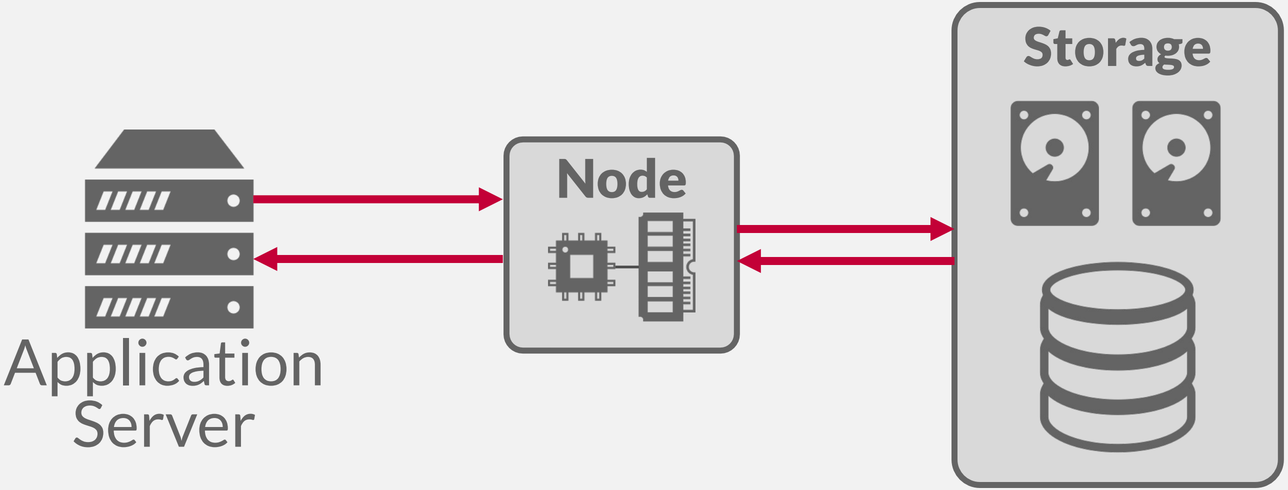

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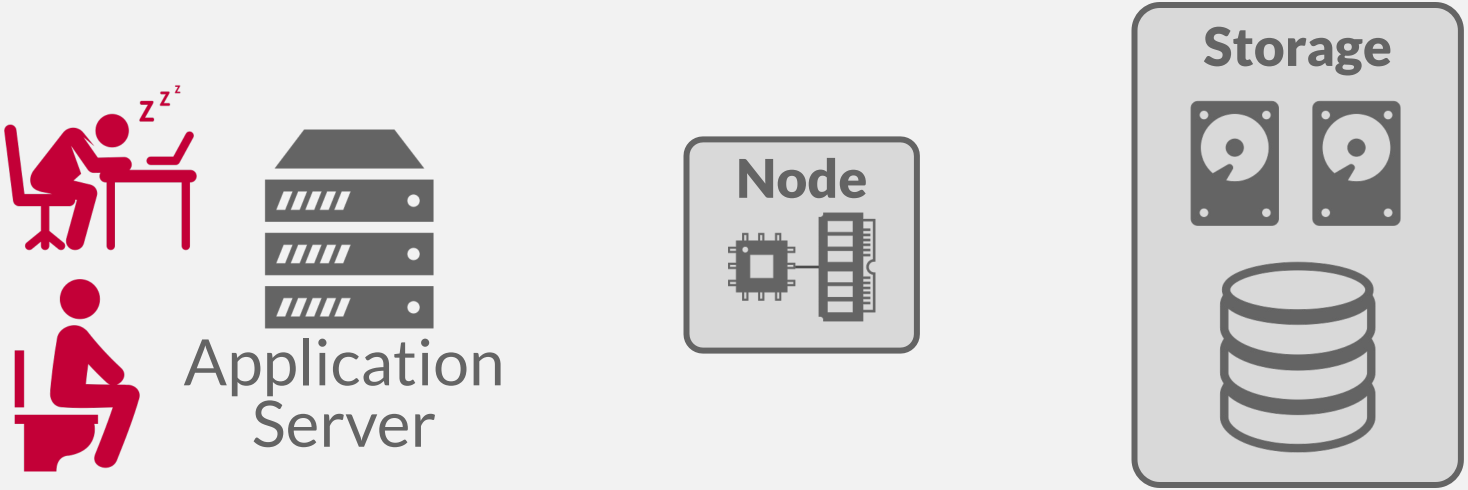

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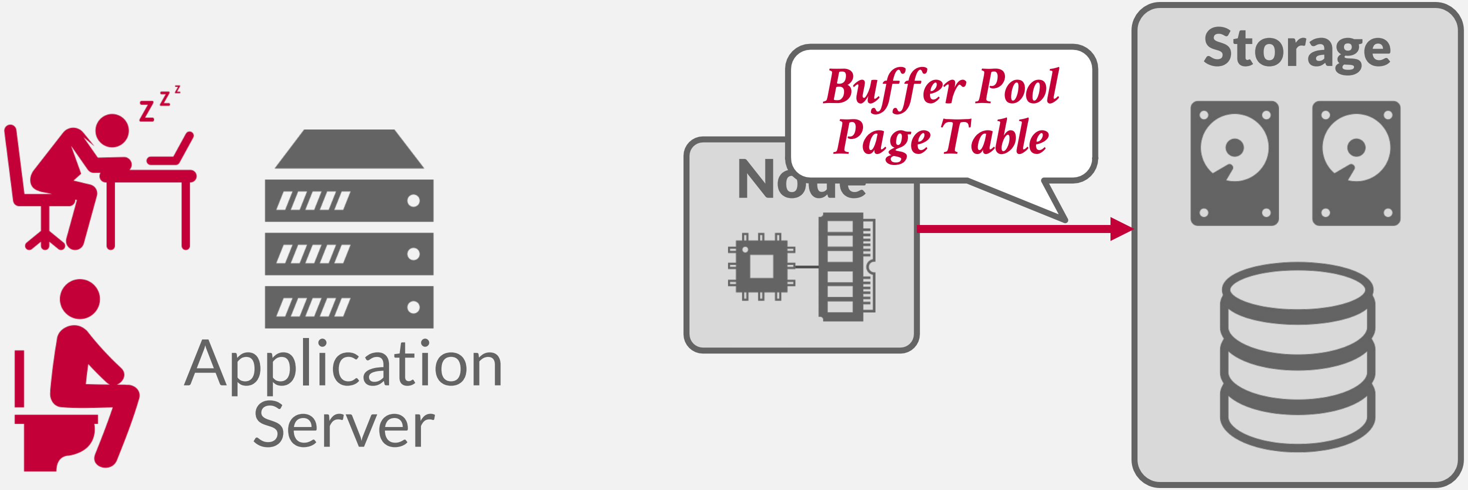

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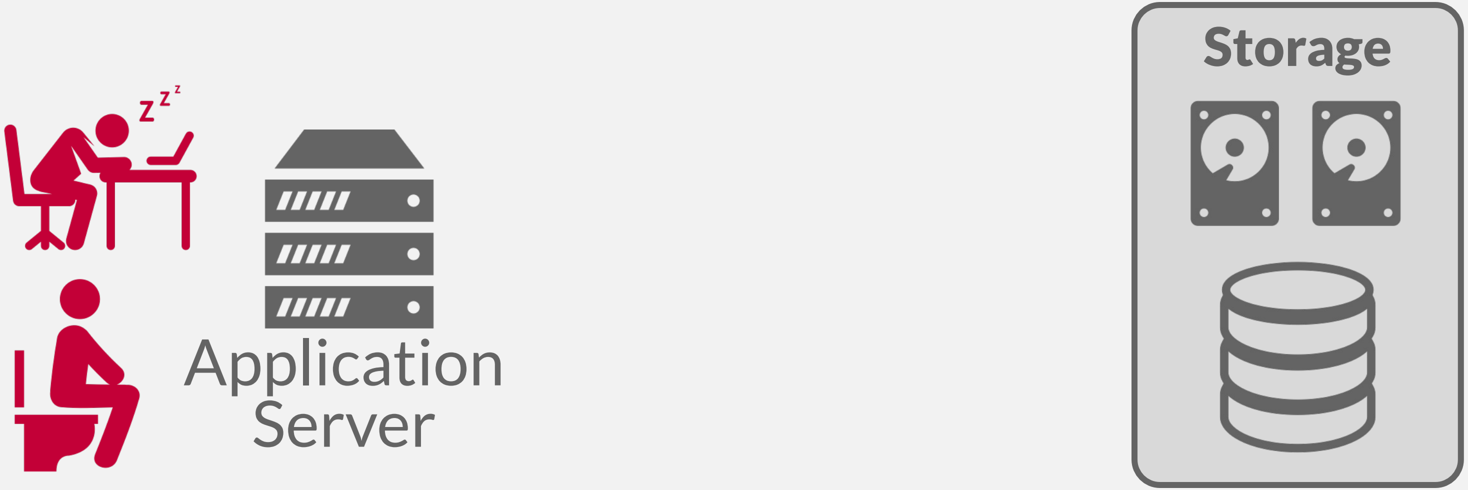

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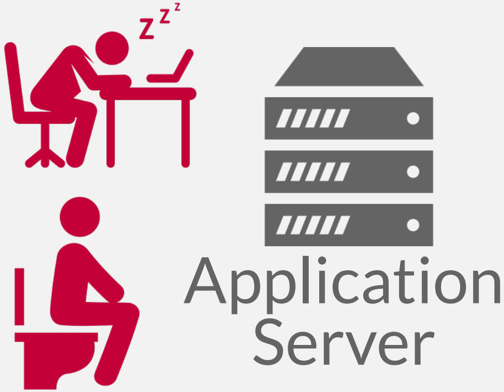

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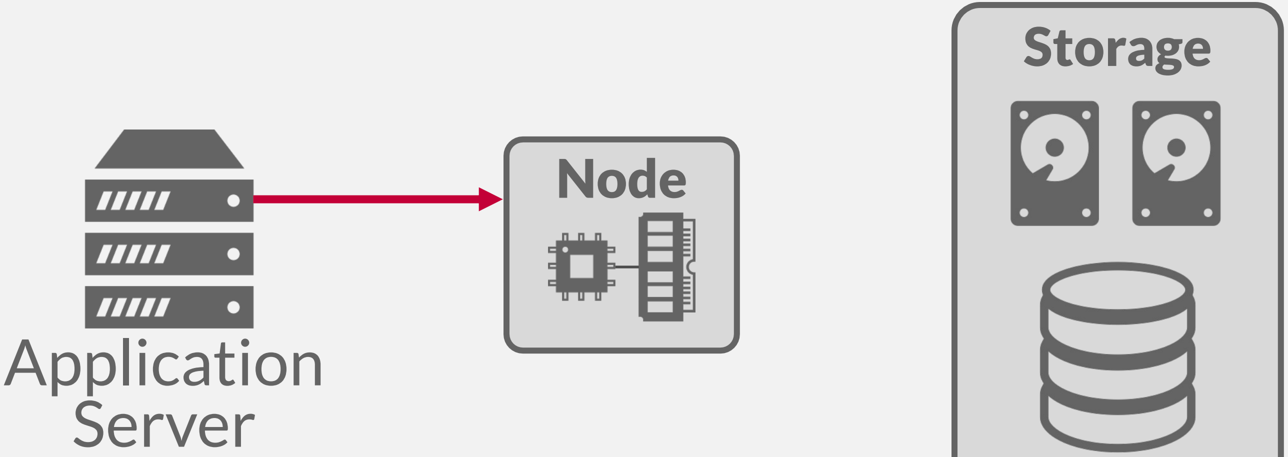

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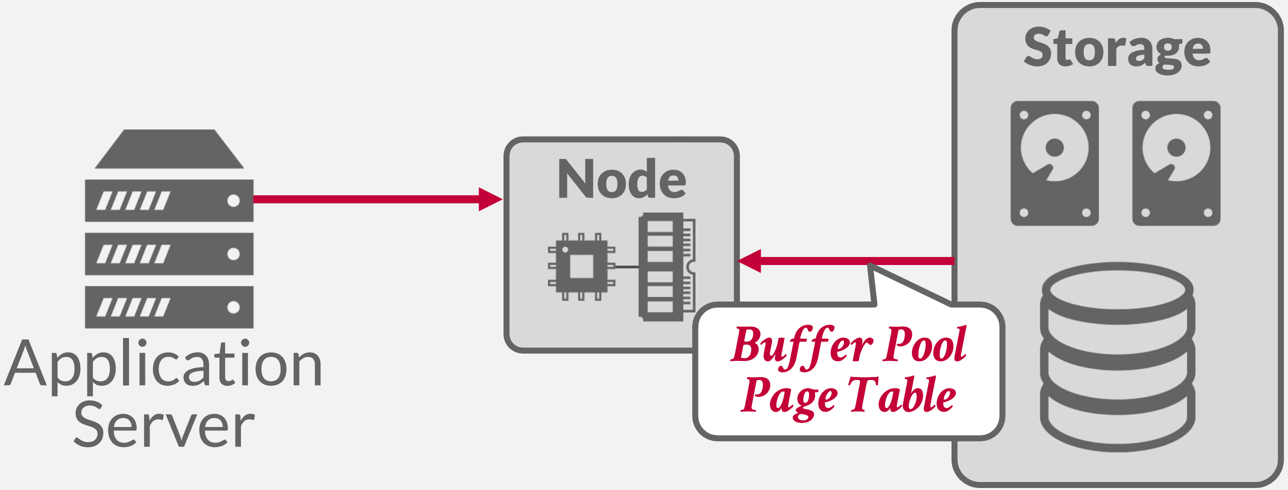

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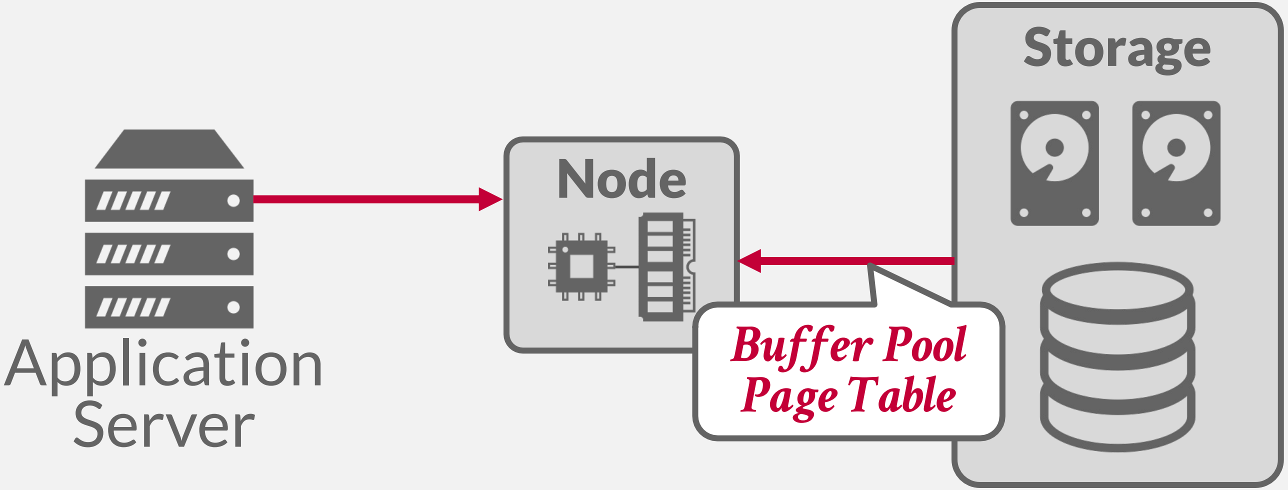
planetscale
CockroachDB
NEON
amazon
fauna
Microsoft SQL Azure



DATA LAKES

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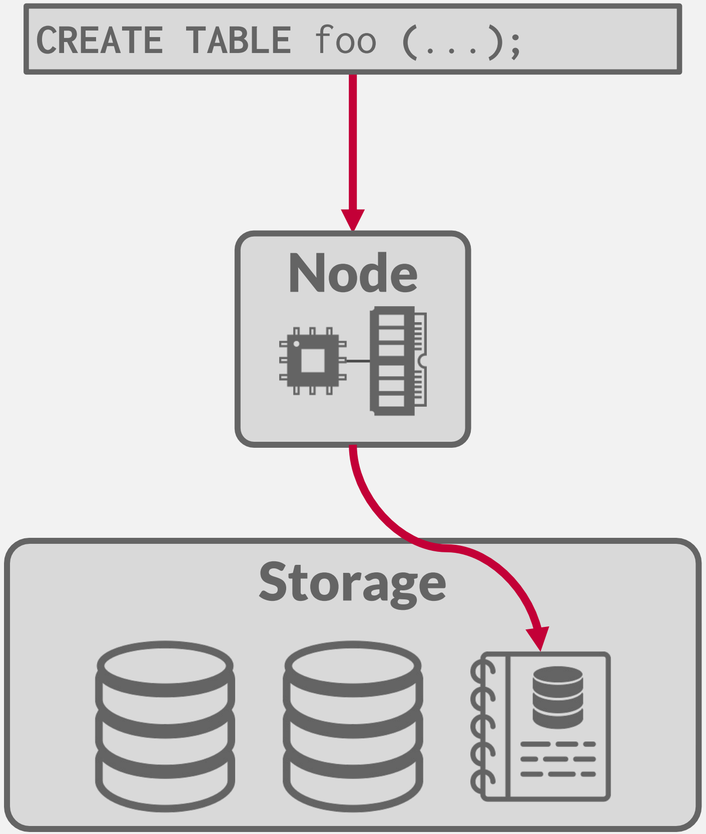

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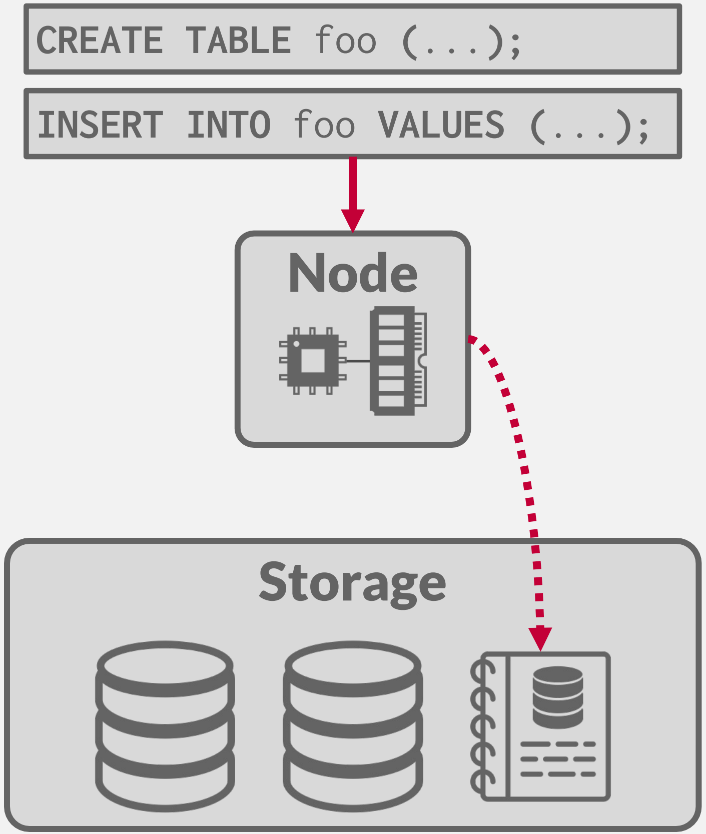

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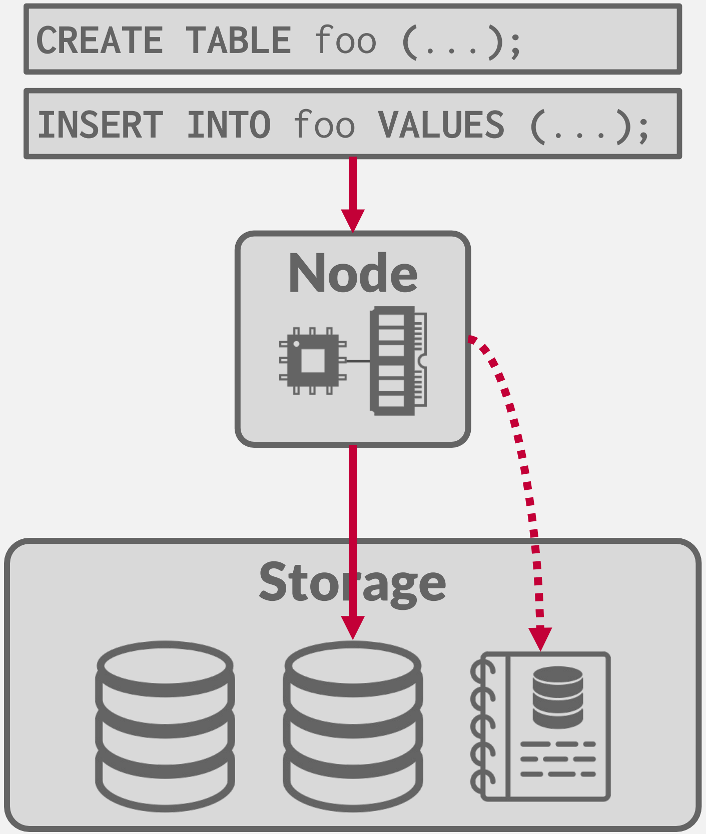

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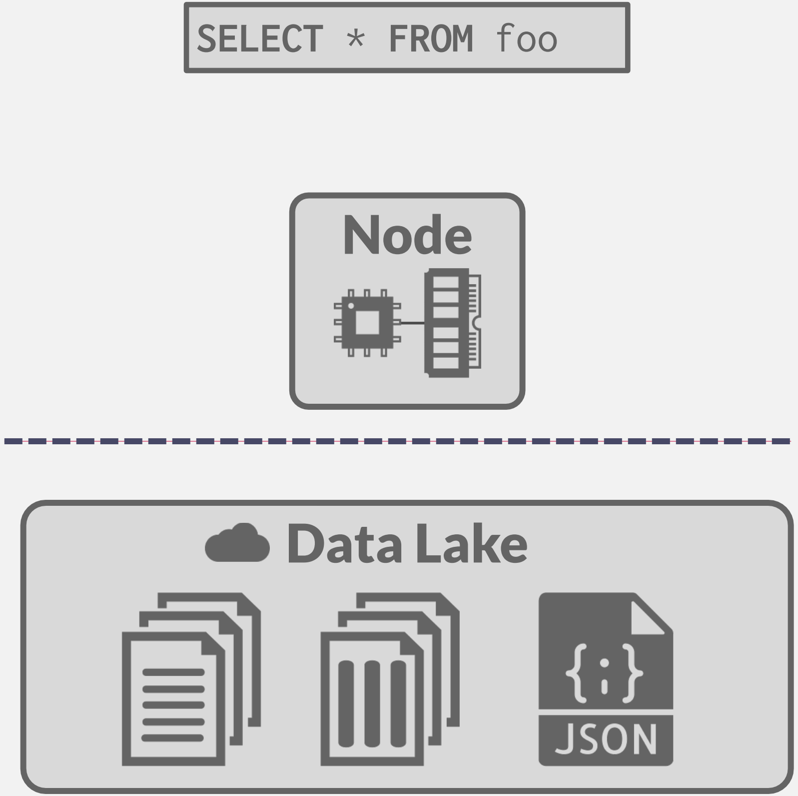

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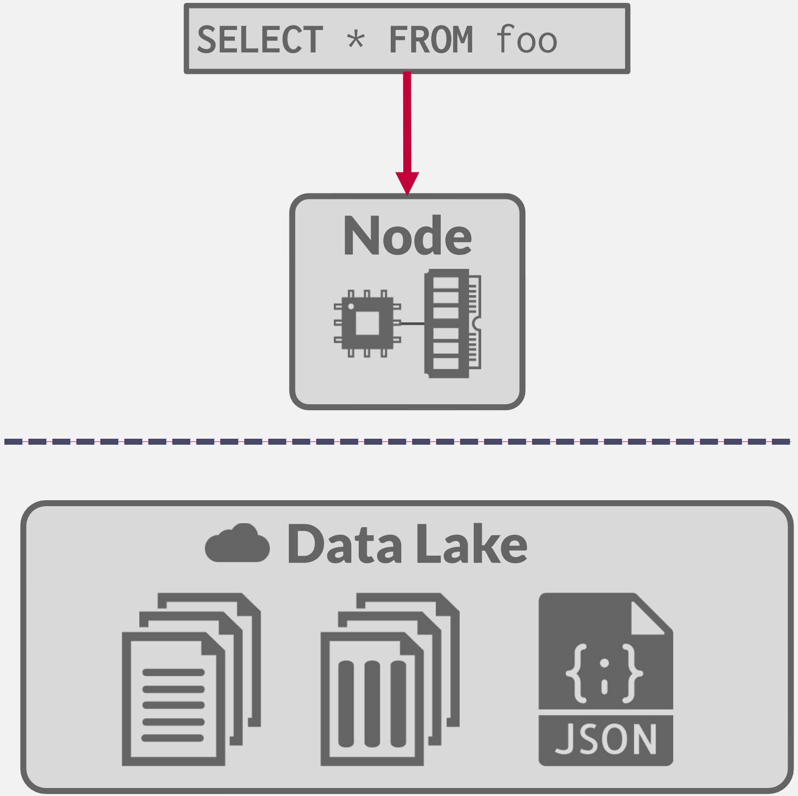

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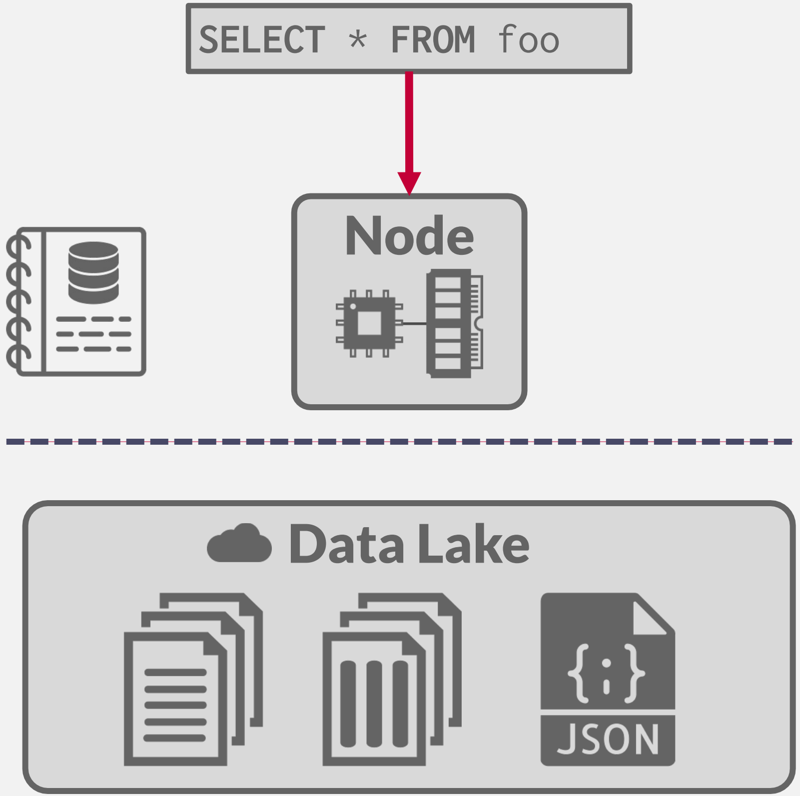

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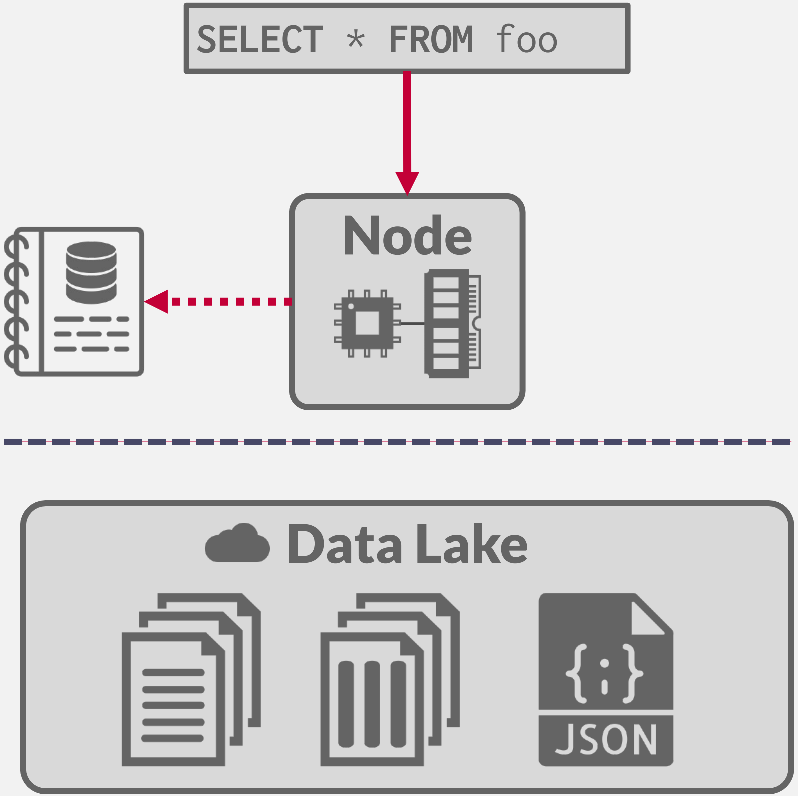

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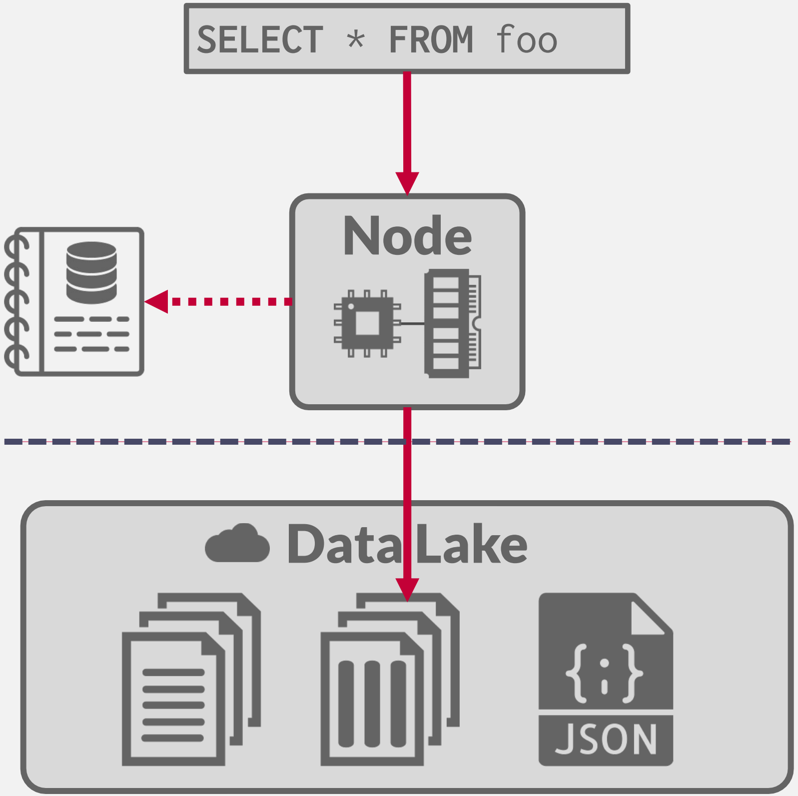

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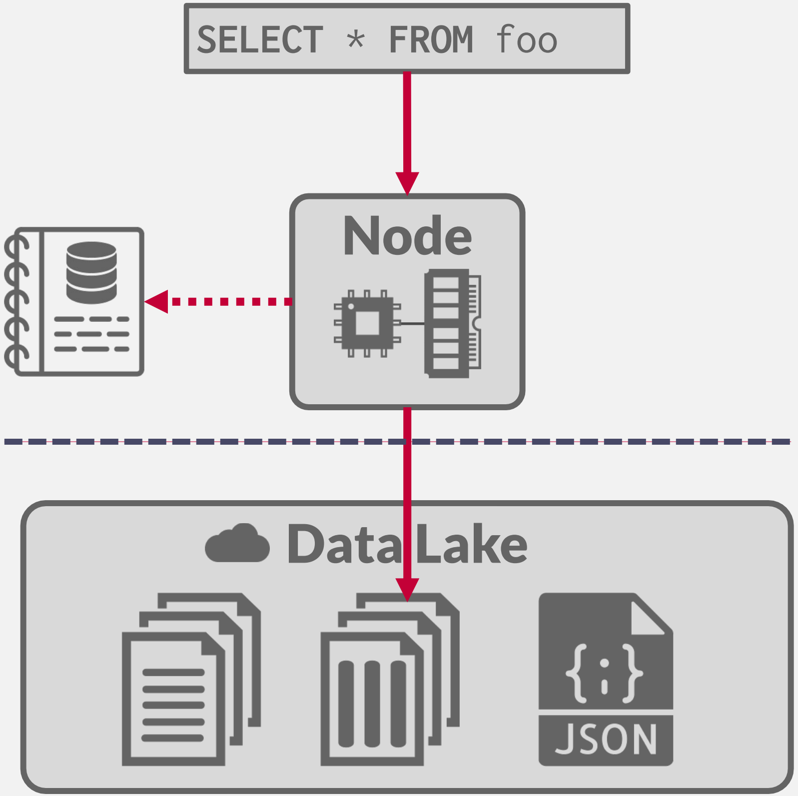

trino amazon REDSHIFT Google Big Query HIVE databricks snowflake presto

OLAP COMMODITIZATION

One recent trend of the last decade is the breakout OLAP engine sub-systems into standalone open-source components.

→ This is typically done by organizations not in the business of selling DBMS software.

Examples:

→ System Catalogs
→ Query Optimizers
→ File Format / Access Libraries
→ Execution Engines

SYSTEM CATALOGS

A DBMS tracks a database's schema (table, columns) and data files in its catalog.

→ If the DBMS is on the data ingestion path, then it can maintain the catalog incrementally.

→ If an external process adds data files, then it also needs to update the catalog so that the DBMS is aware of them.

Notable implementations:

→ HCatalog

→ Google Data Catalog

→ Amazon Glue Data Catalog

QUERY OPTIMIZERS

Extendible search engine framework for heuristic- and cost-based query optimization.

→ DBMS provides transformation rules and cost estimates.

→ Framework returns either a logical or physical query plan.

This is the hardest part to build in any DBMS.

Notable implementations:

→ Greenplum Orca

→ Apache Calcite

DATA FILE 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.

DATA FILE 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.

EXECUTION ENGINES

Standalone libraries for executing vectorized query operators on columnar data.

→ Input is a DAG of physical operators.
→ Require external scheduling and orchestration.

Notable implementations:

→ Velox
→ DataFusion
→ Intel OAP

CONCLUSION

The cloud has made the distributed OLAP DBMS market flourish. Lots of vendors. Lots of money.

But more money, more data, more problems…

NEXT CLASS

Review: Come to class. No recording.