Query processing on raw files

Vítor Uwe Reus

Outline

1. Introduction
2. Adaptive Indexing
3. Hybrid MapReduce
4. NoDB
5. Summary

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Raw Files

Information Storing

Sometimes human-readable, open format

Not physically optimized for querying

Might be useful in some cases

Big Data

Traditional DBMS may not be a good option

Internet-scale business

Scientific data

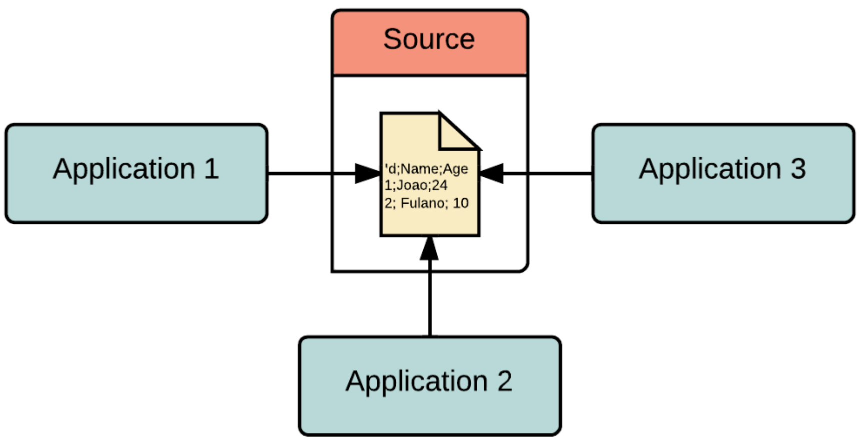
The fourth paradigm

For scientific discovery

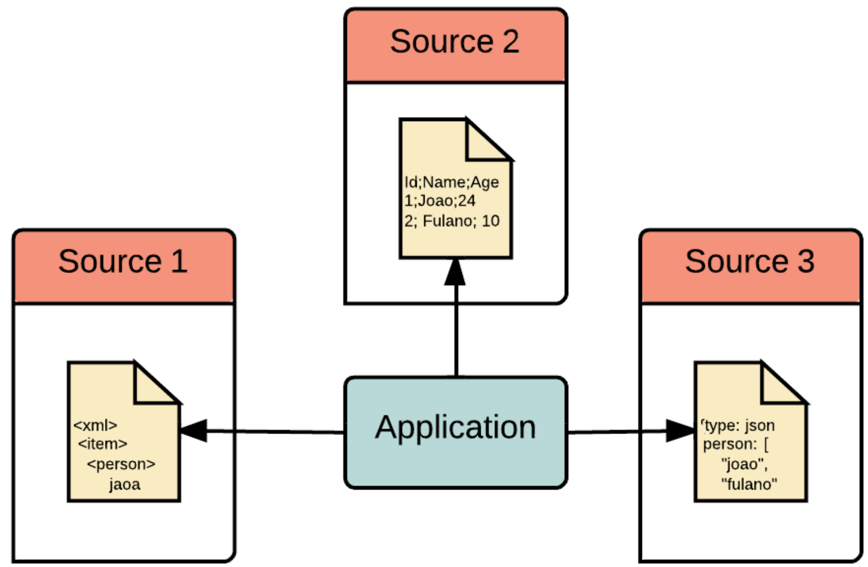
- Experimental
- Theoretical
- Computational (simulations)
- **Data driven**

Interoperability

Interoperability



Information interoperability



Application interoperability

Human-sourced Information

How to query raw files?

State of the art

Raw file as storage

A-priori loading

Raw file parsing

AWK

Oracle external table

MySQL CSV engine

MapReduce

Read entire data all times

No indexing features

A-priori loading

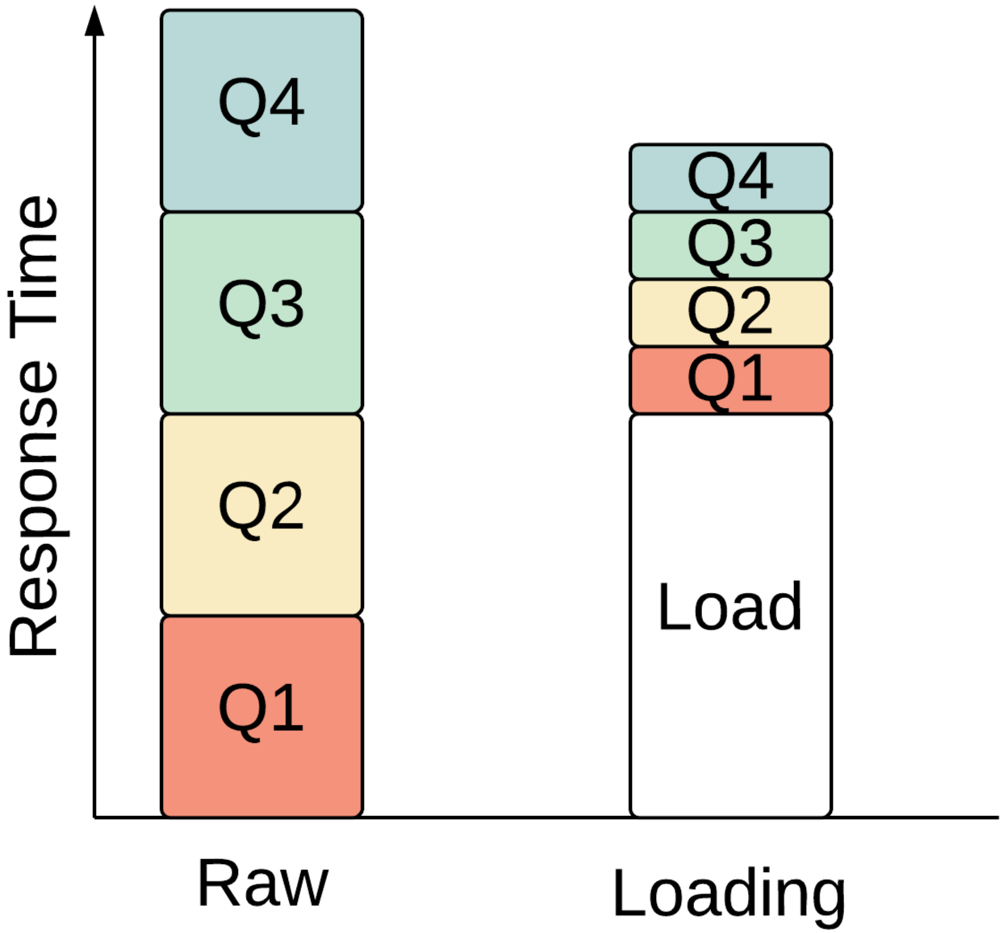
Load into a DBMS and then query
- Benefit from indexes

Time

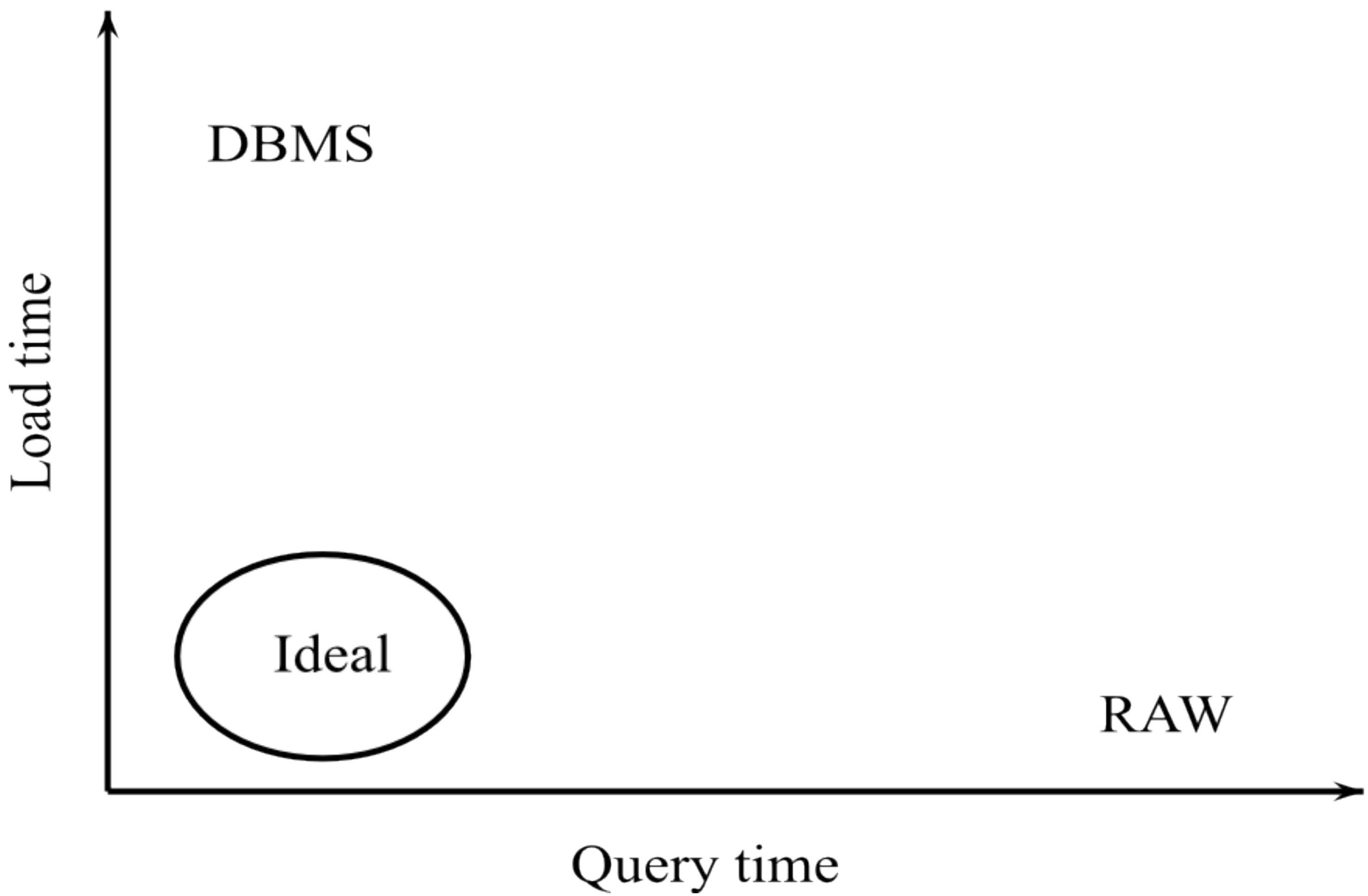
Labor intensive
- Loading scripts, schemas

Data duplication
- Big data
- Versioning

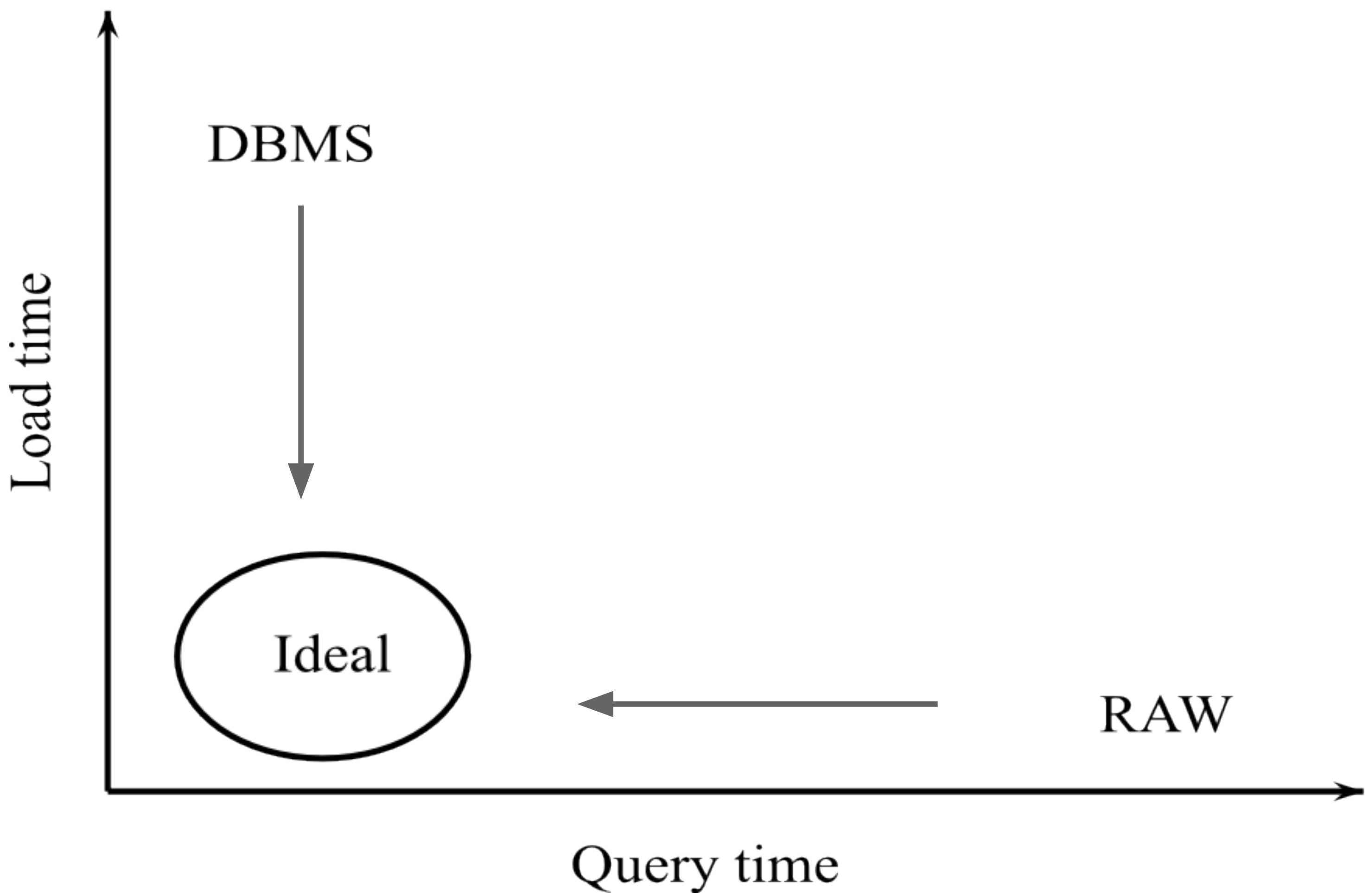
Workload behavior



Load time vs Query time



Hybrid querying techniques



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Adaptive indexing

Automatic tuning based on workload

Keep an auxiliary structure

Can benefit raw file parsing

Database Cracking

Adaptive Merging

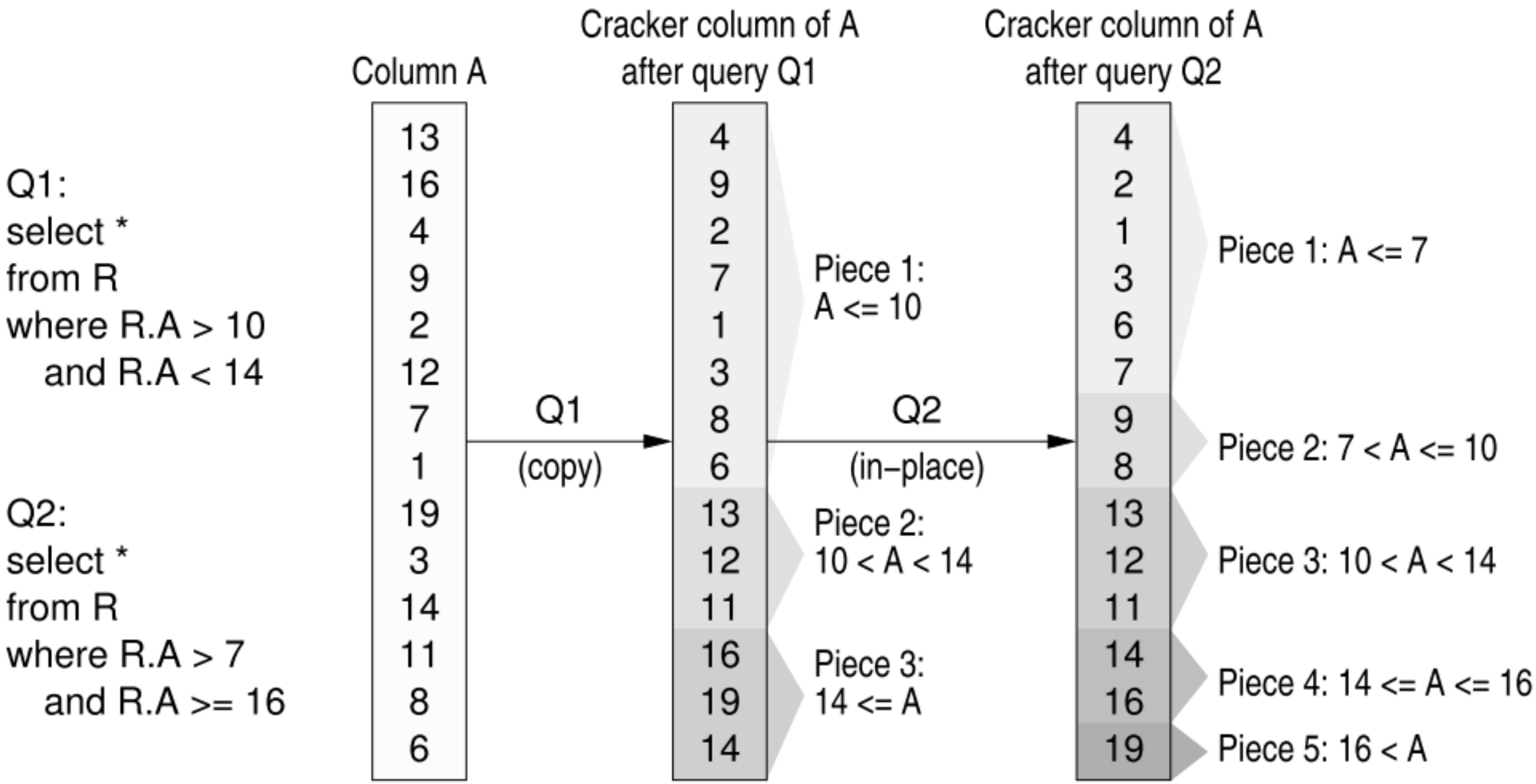
Database cracking

Physical reorganization of columns

Implemented on MonetDB

- A column store, but can be generalized (raw)

Database Cracking



Cracking a column

Database Cracking

Column A $\rightarrow$ Copy to cracker column A_{CRK}

AVL tree indexing

Refinement

Tuple reconstruction

Fast if columns are in same order

Cracking compromises original positions

Cracker columns: Value selection

Original columns: Tuple reconstruction

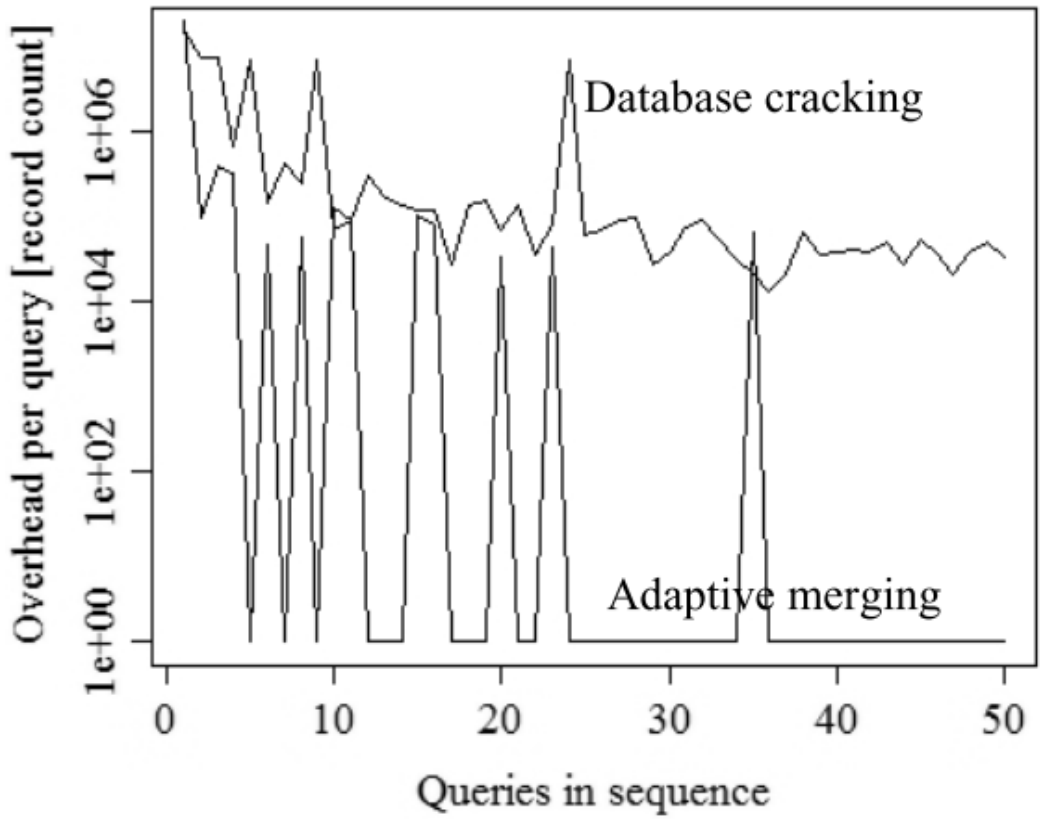
Adaptive merging

Incremental index creation as in cracking

Partitioned B-trees

Focus on merging instead of partitioning

Merging vs cracking



Typical result of merging compared to cracking

*In this case, all queries focus on the same 10^6 keys in the center of the domain

Merging vs cracking

	Cracking	Merging
Converge	Stable	Faster
Storage	AVL	B-Tree
Data is	Partitioned	...and Sorted
as in..	Quick Sort	Merge Sort

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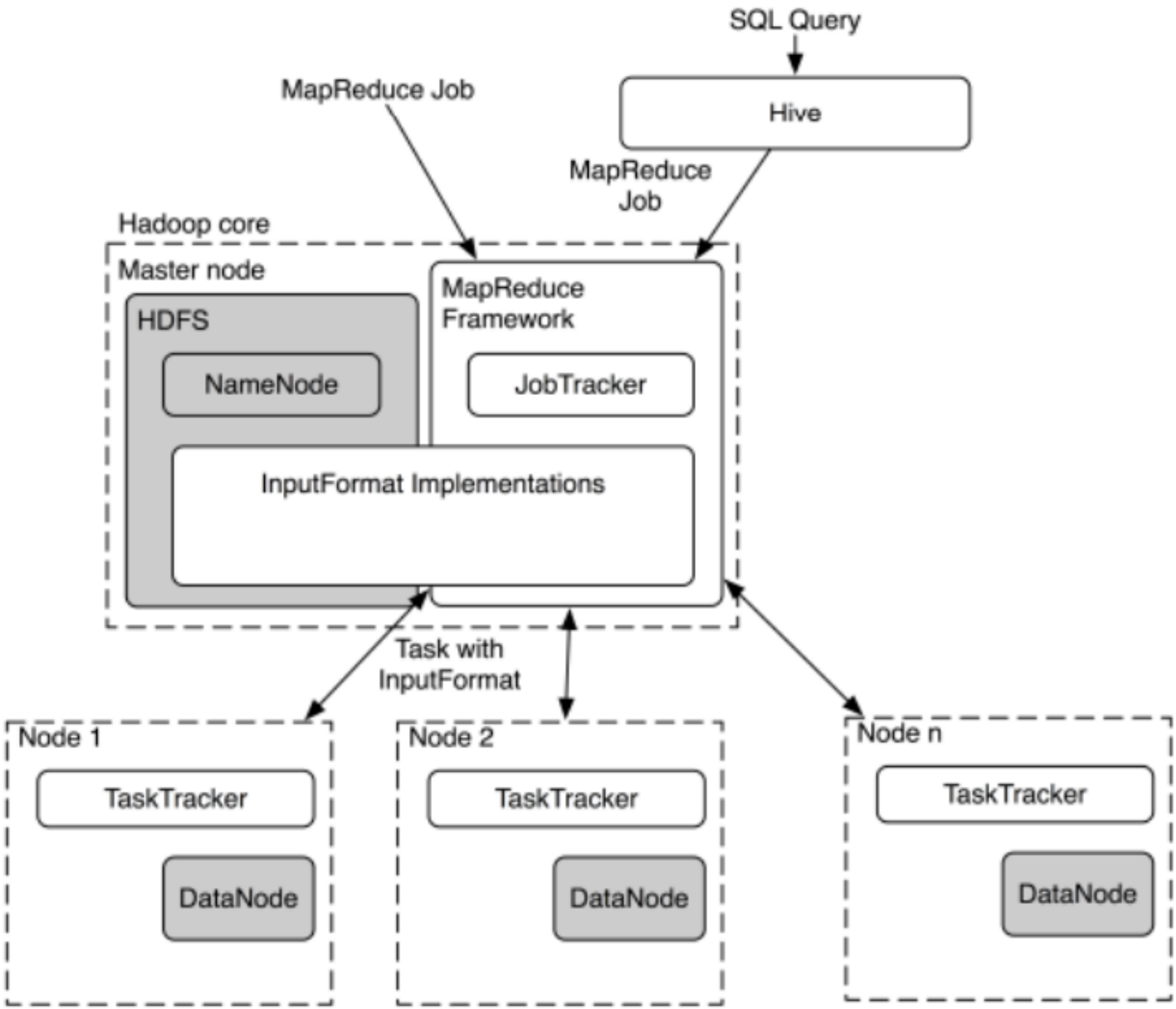
Hybrid MapReduce

	Scalability*	High Performance**
MapReduce	✓	✗
Parallel Databases	✗	✓
What is needed	✓	✓

** 1000s of nodes*
*** Queries on structured data*

HadoopDB

MapReduce using a DBMS instead of HDFS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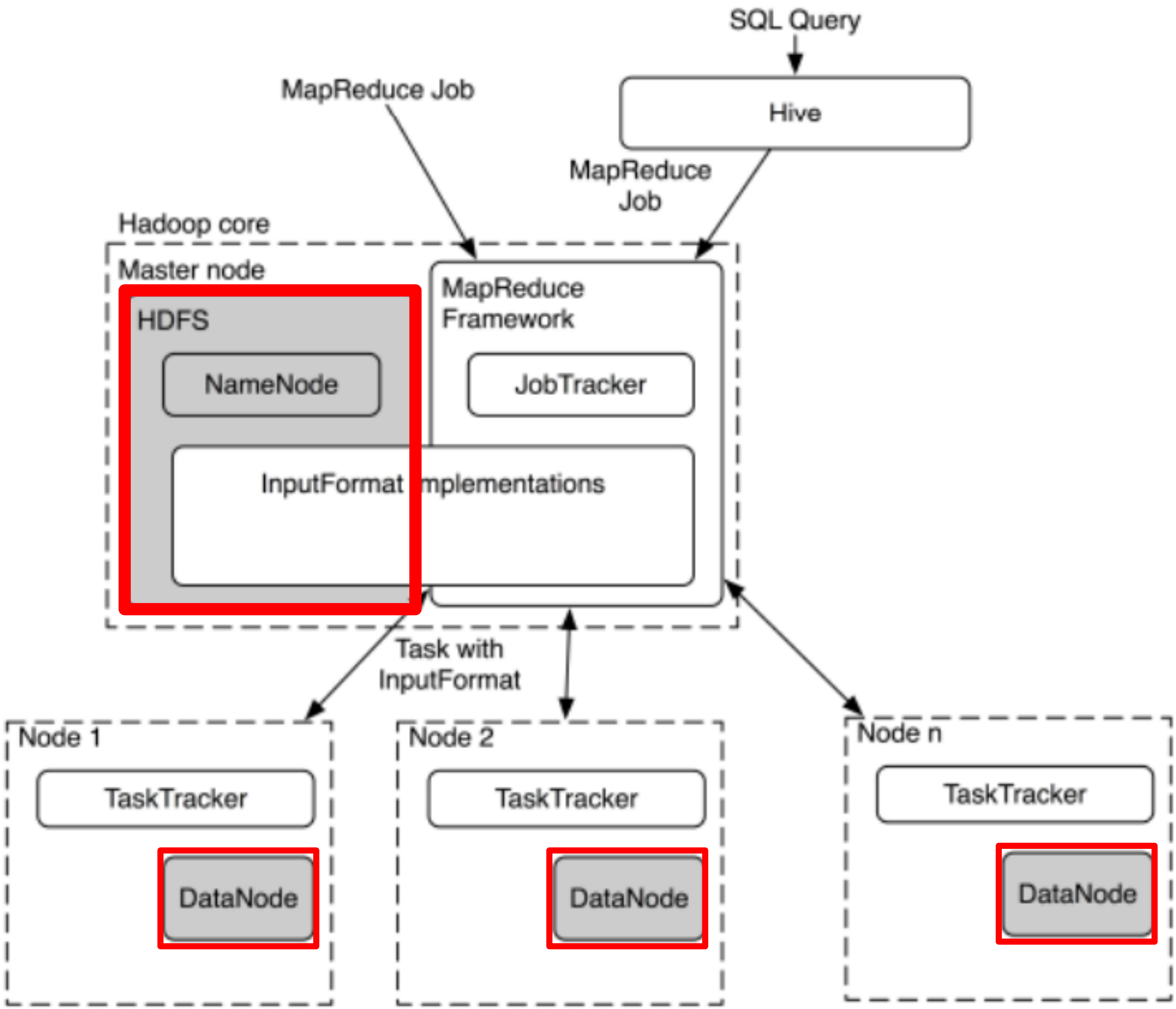
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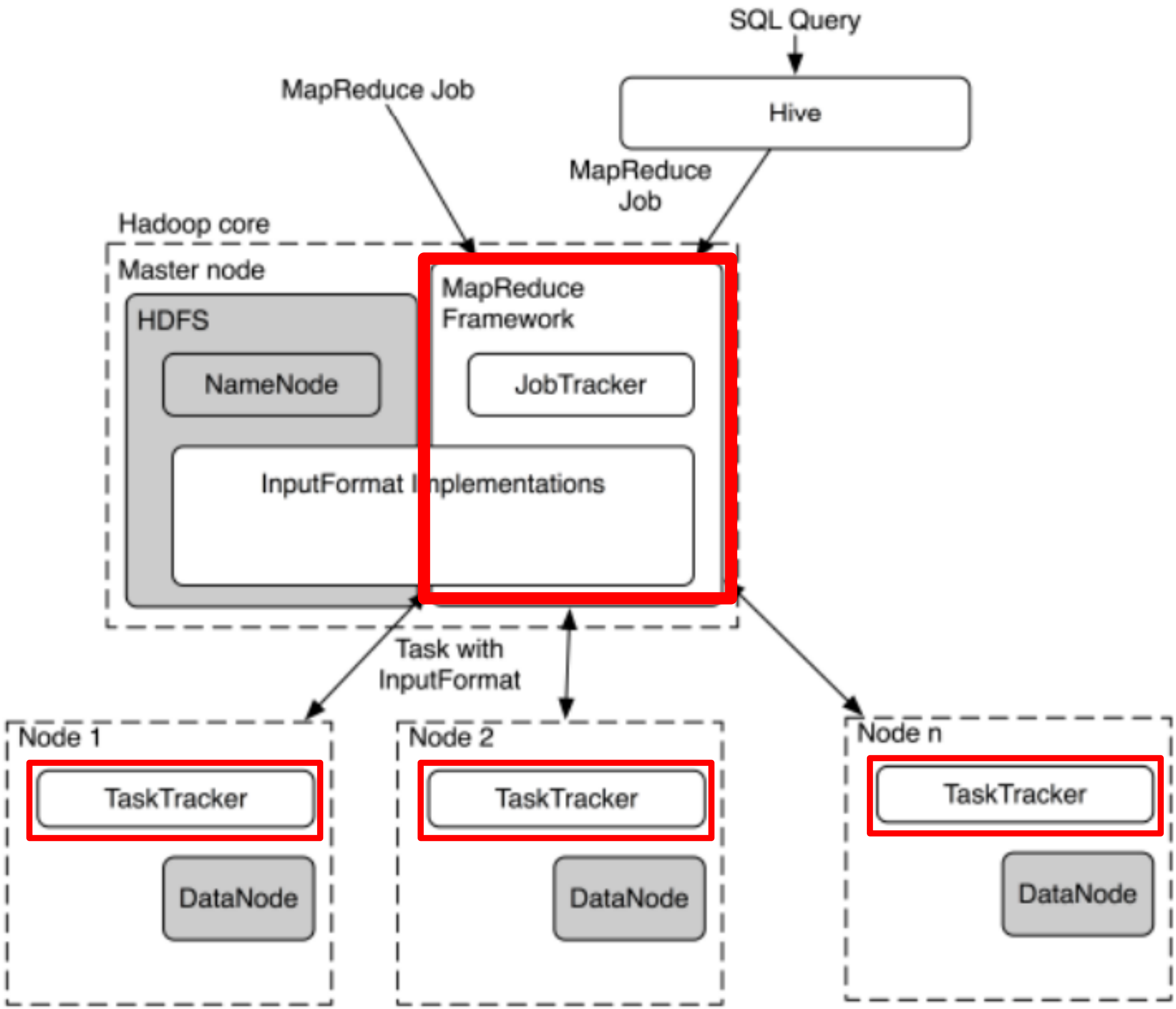
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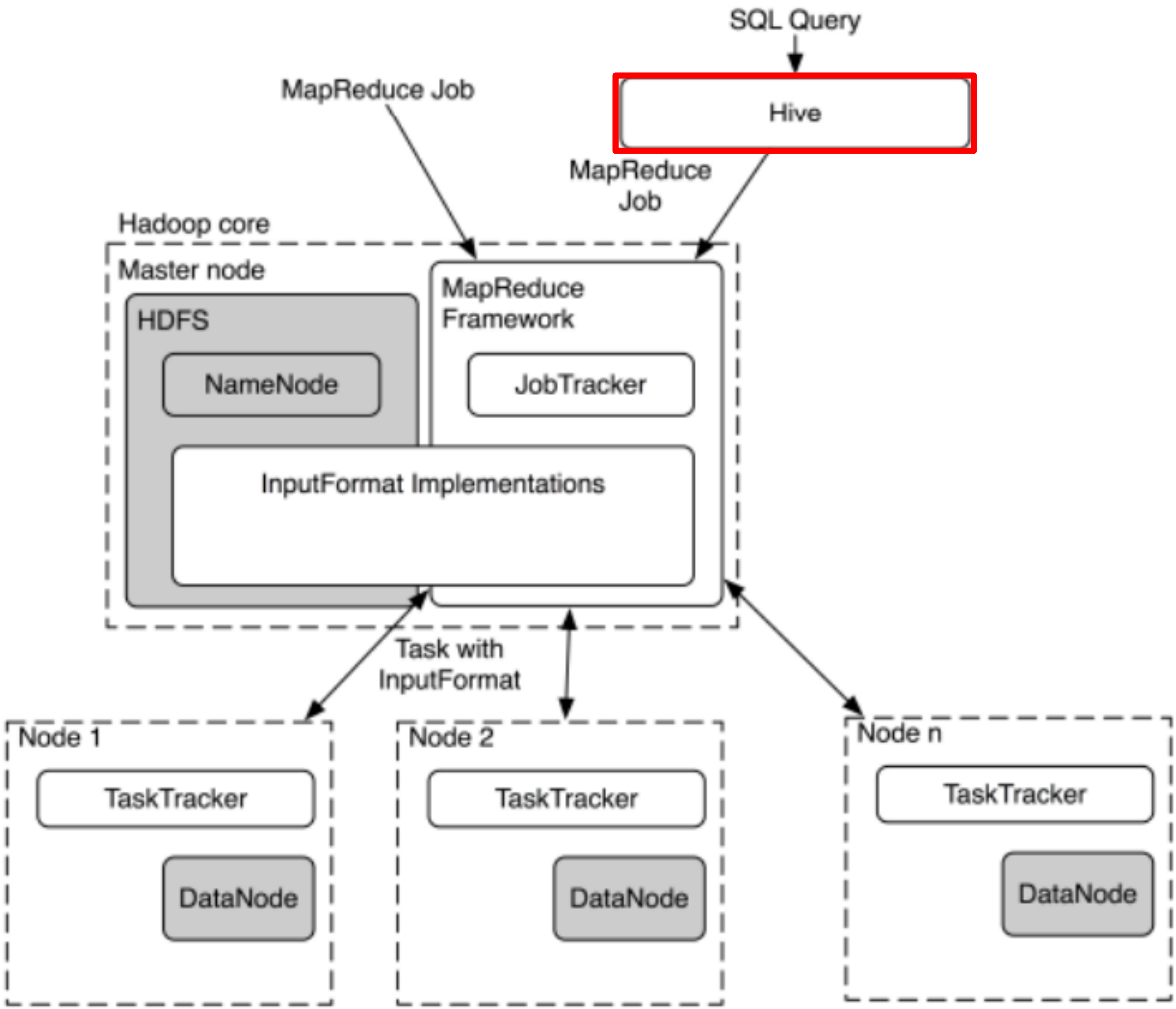
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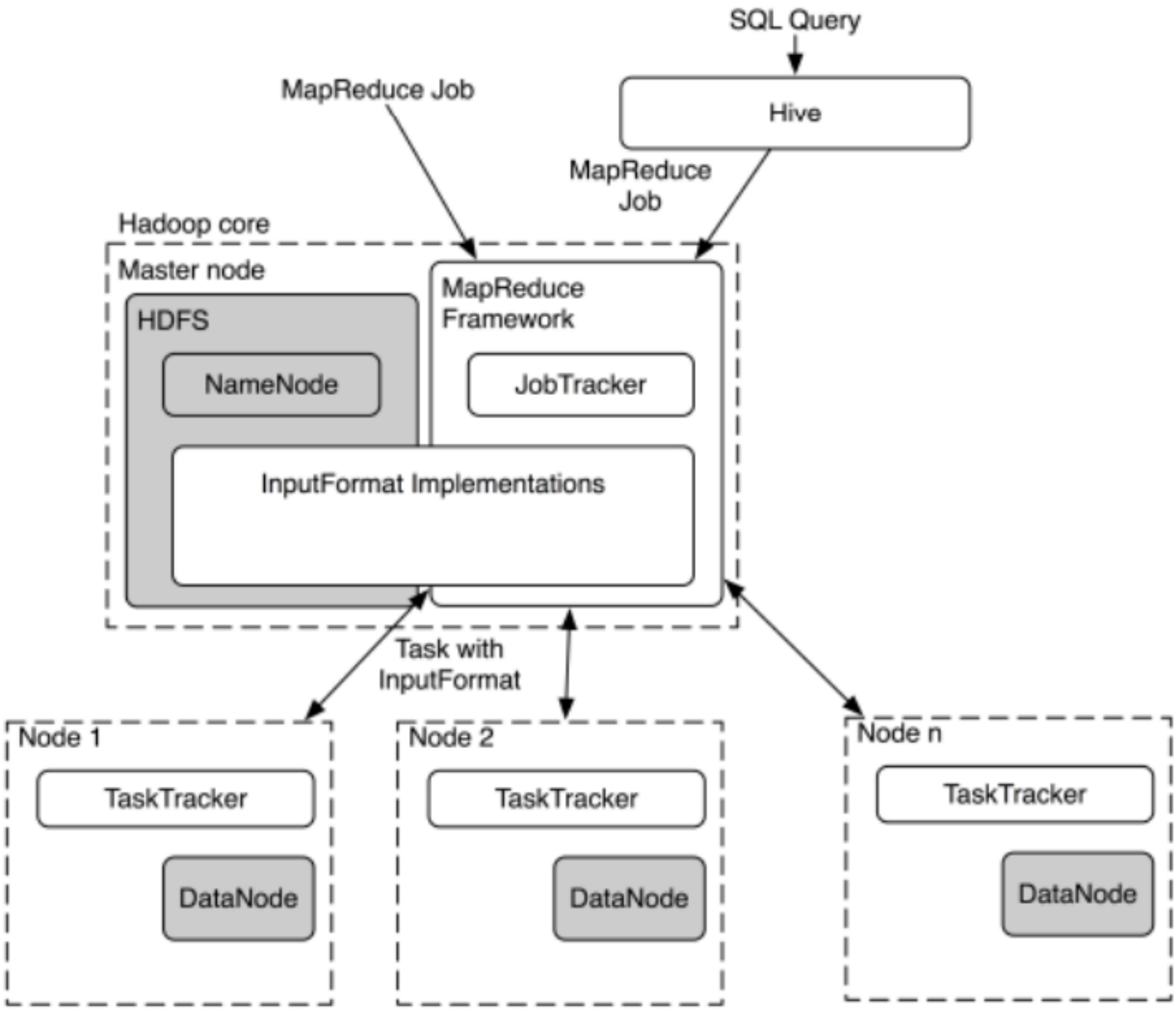
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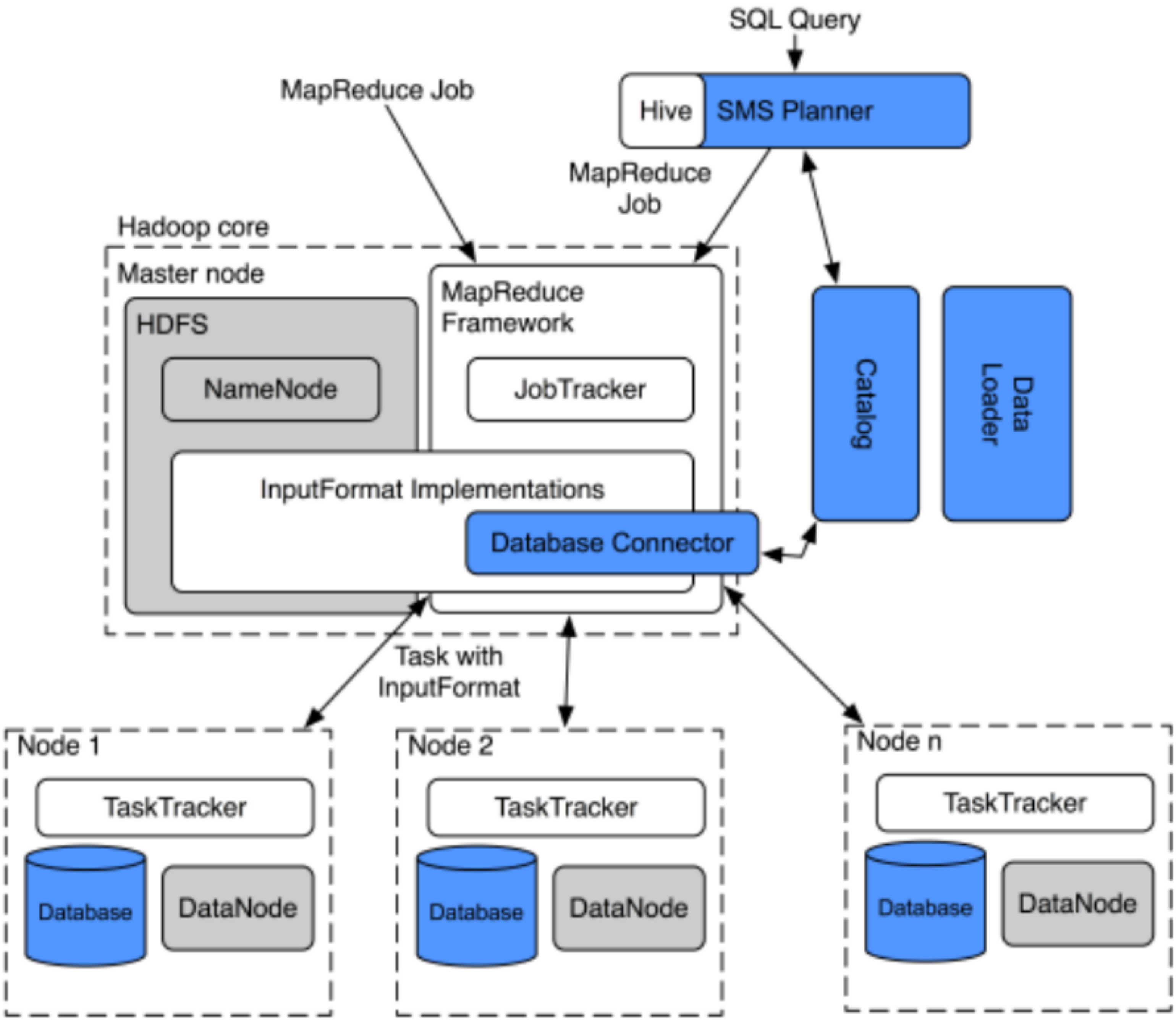

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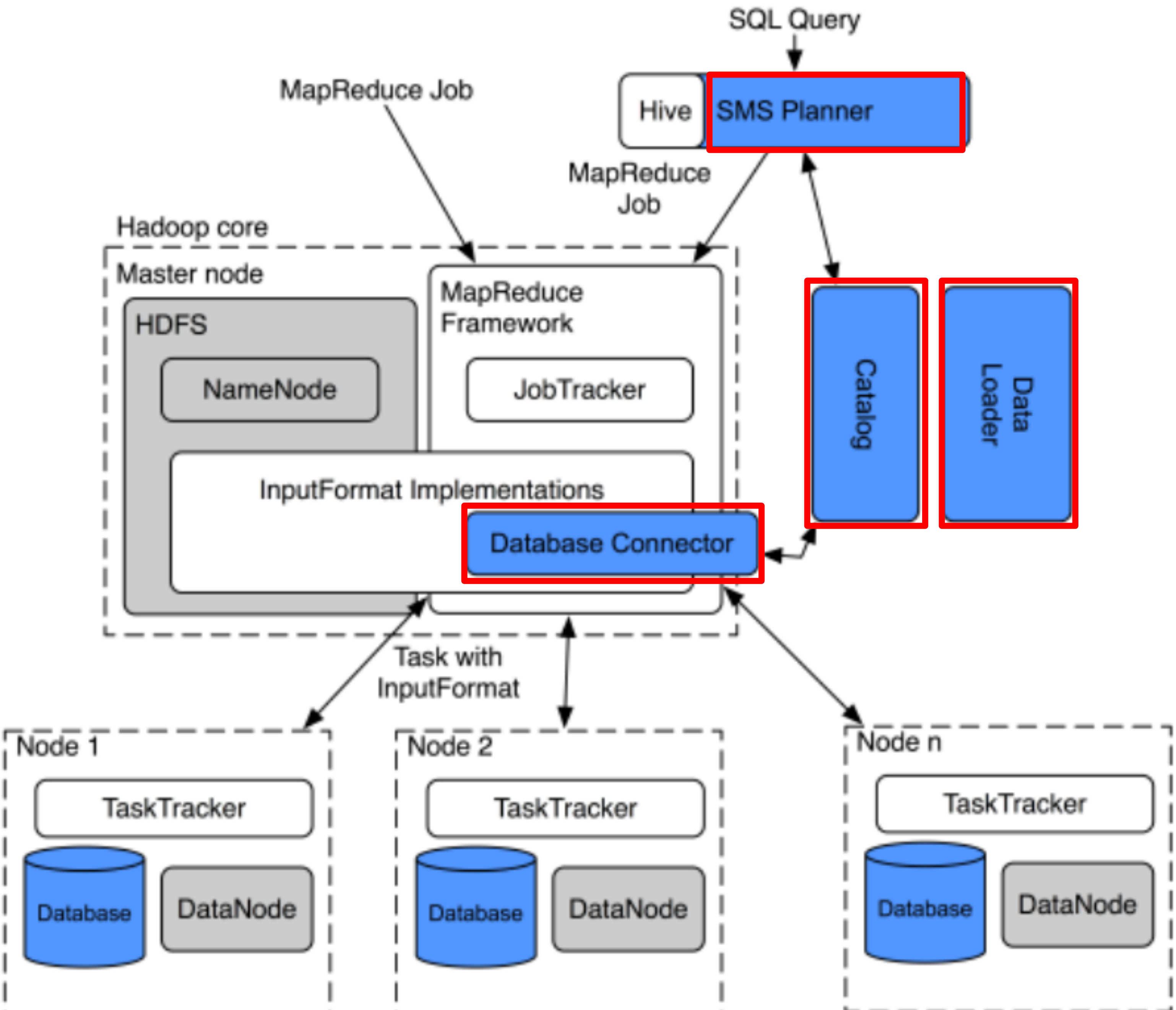
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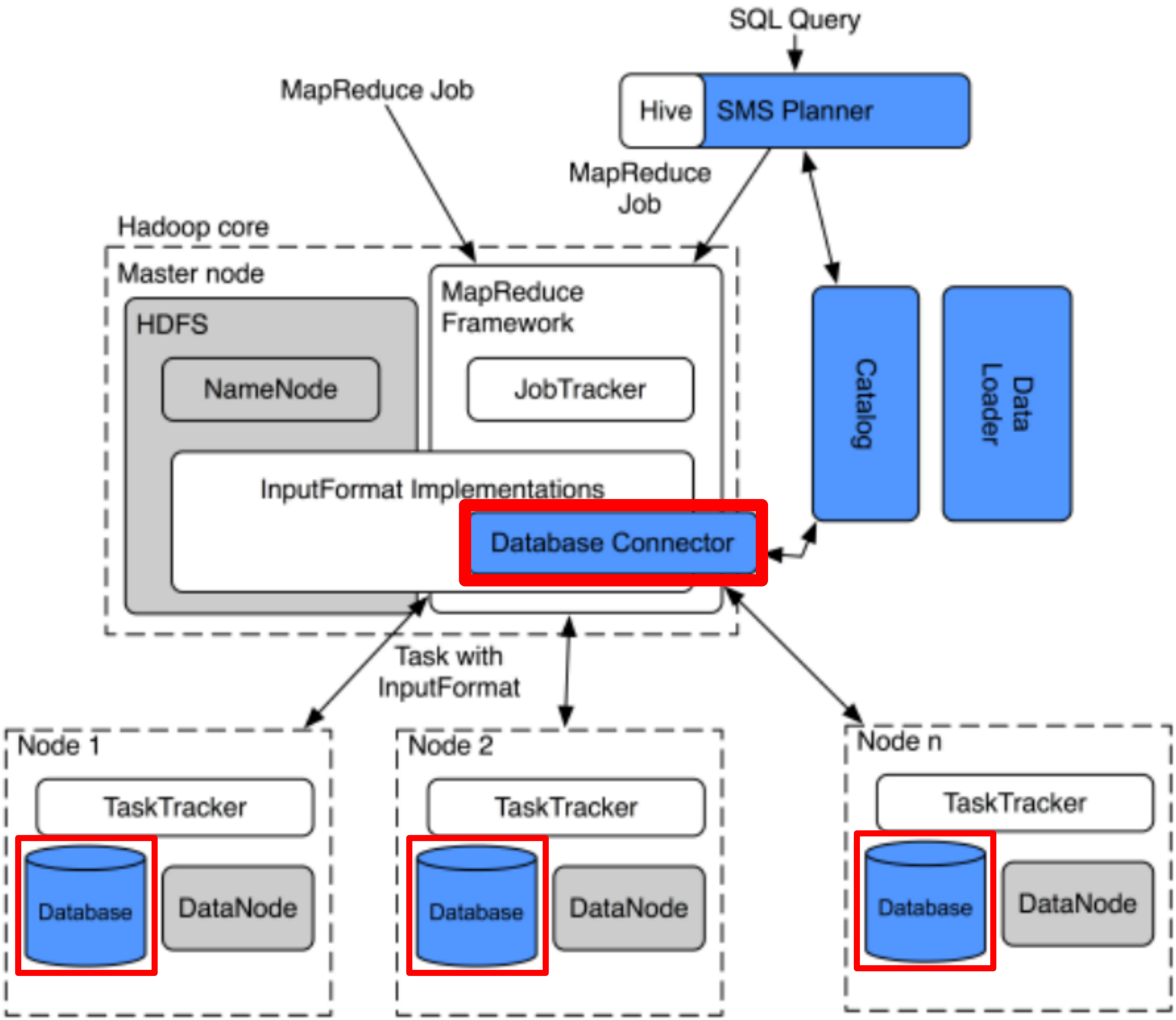
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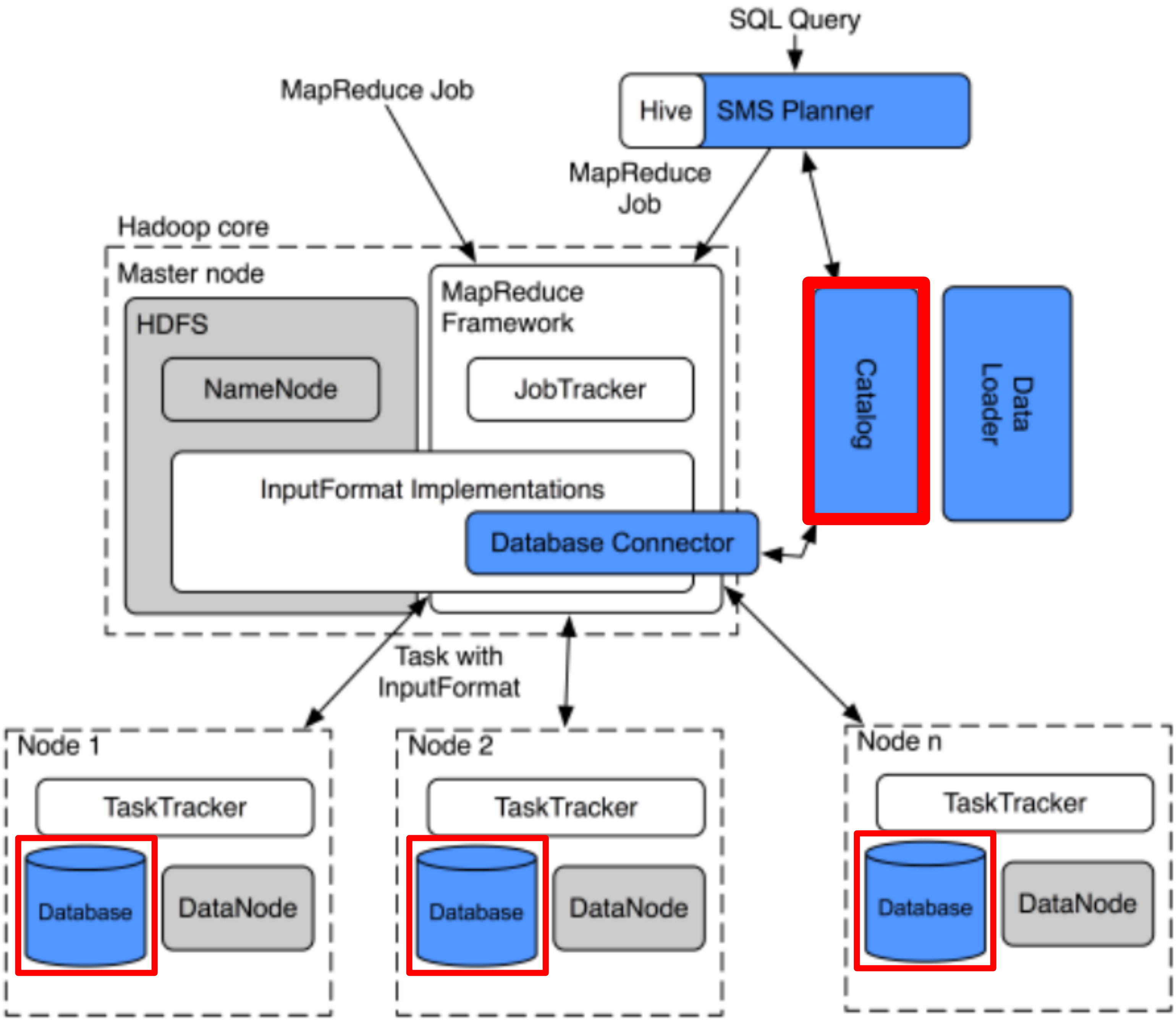

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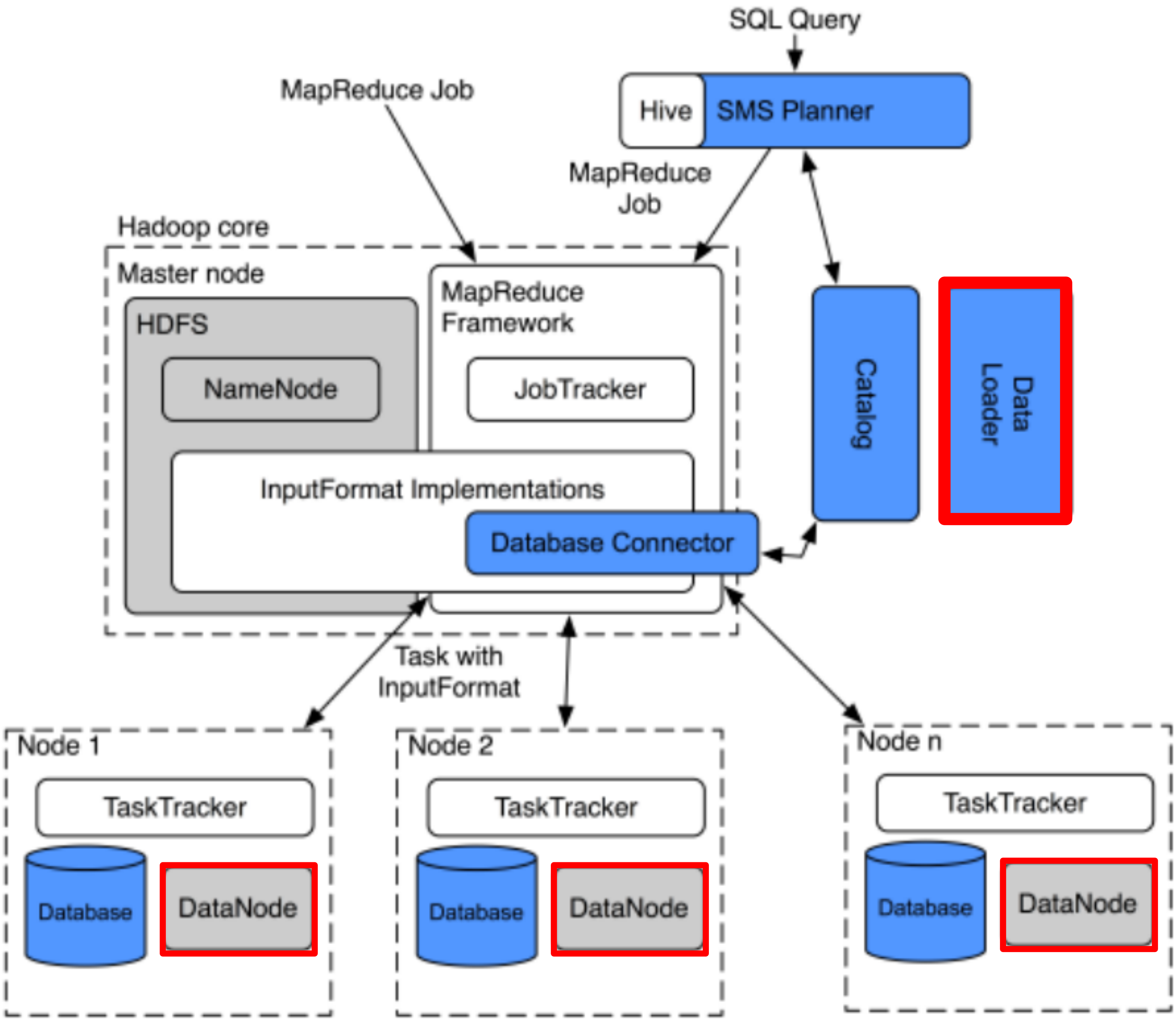
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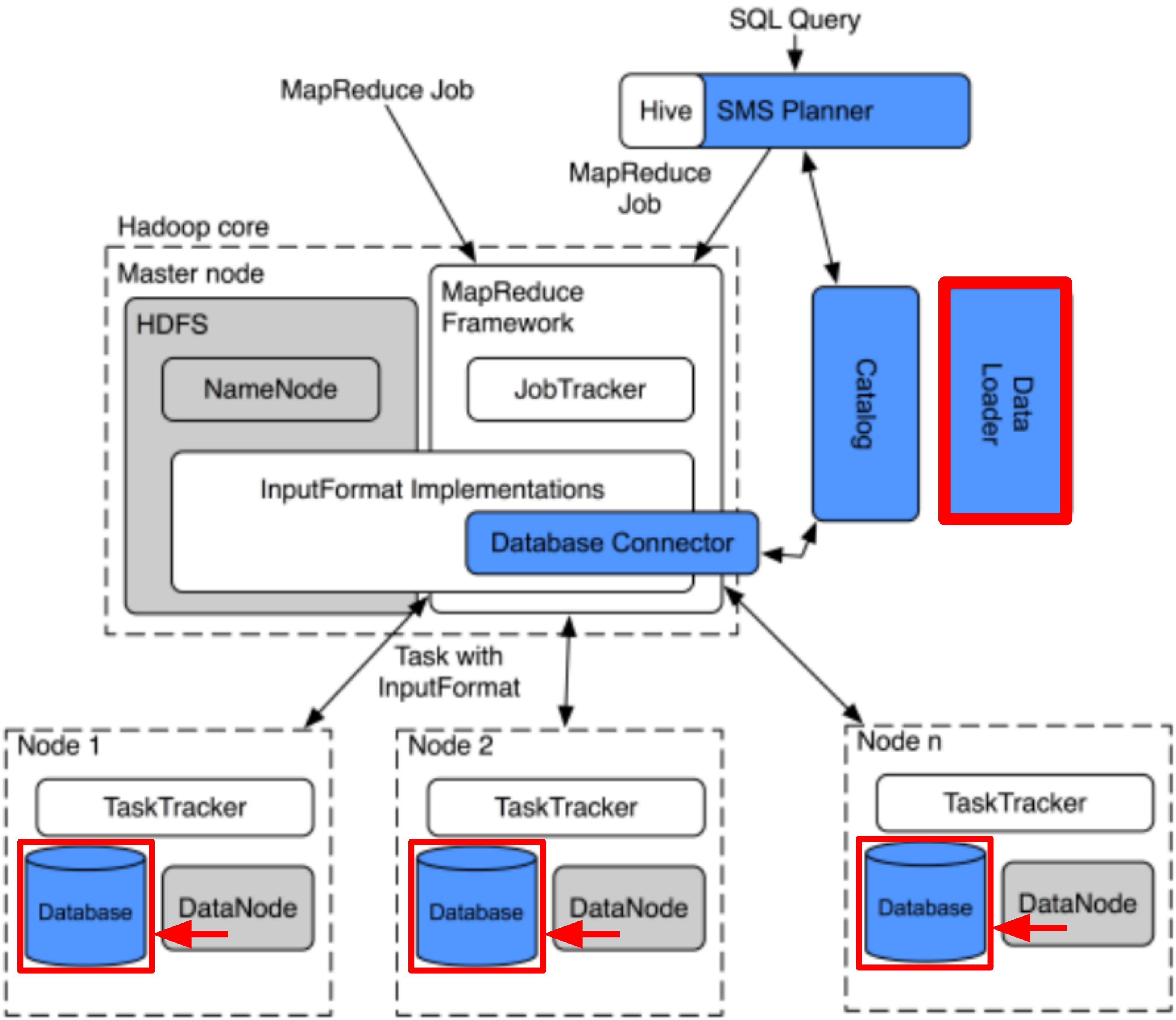
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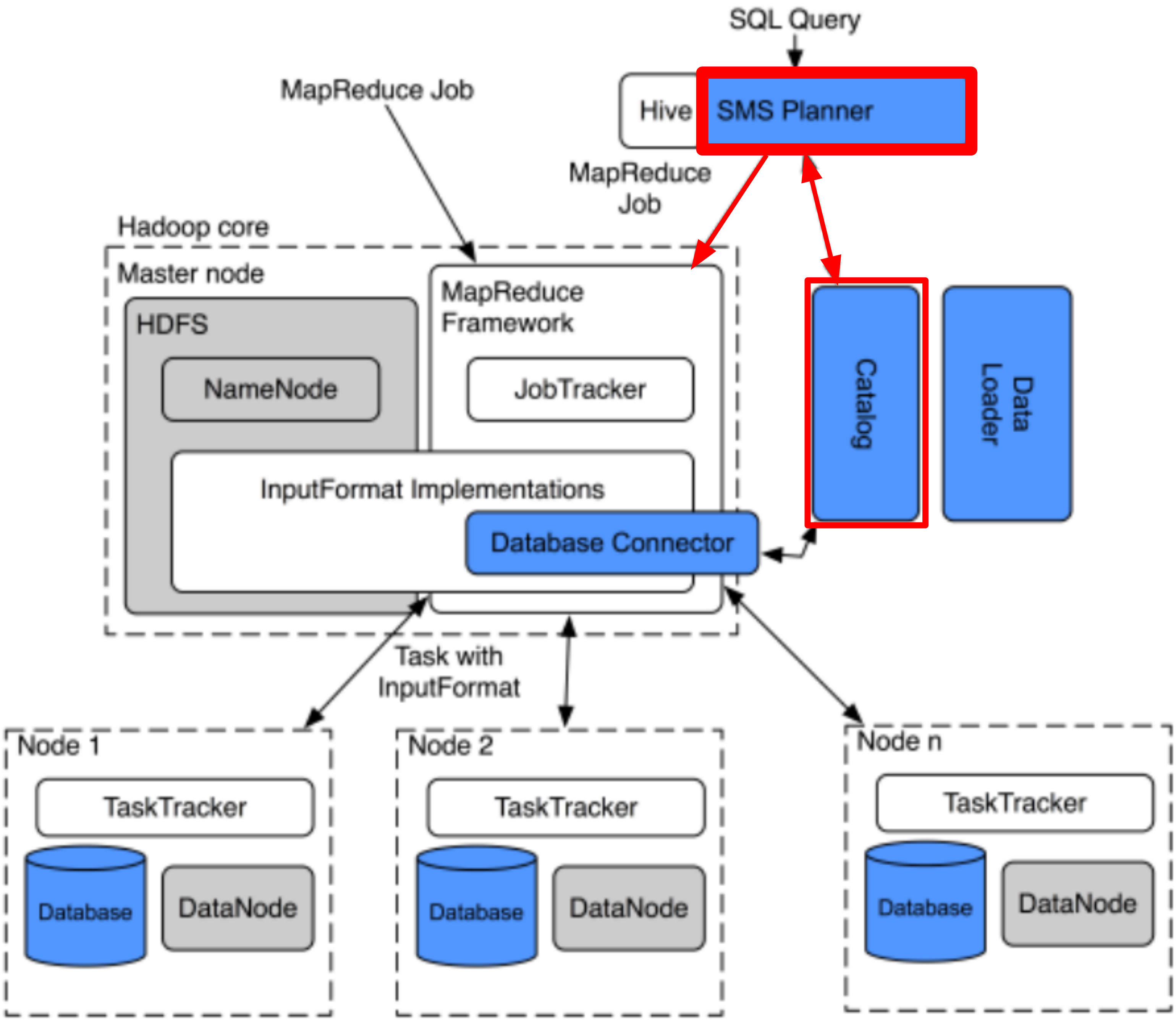
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SMS Planner

Hive query processor

1. Convert HiveQL query to AST
2. Get schema from catalog
3. Create a Query Plan
4. Optimize
5. Converted plan to one or more MR Jobs

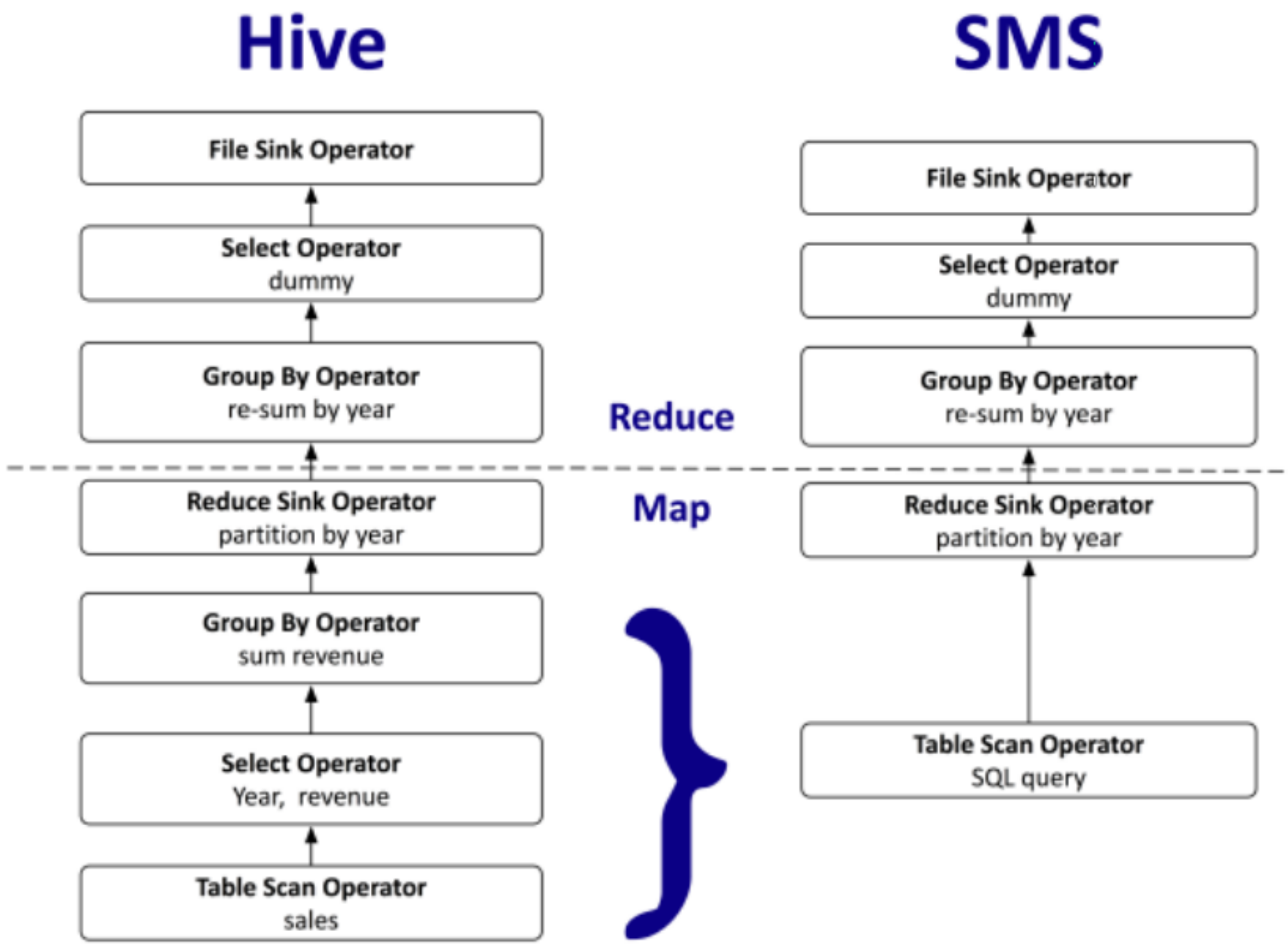
SMS Planner

1. Convert HiveQL query to AST

   Update Catalog with DB information
2. Get schema from catalog
3. Create a Query Plan
4. Optimize

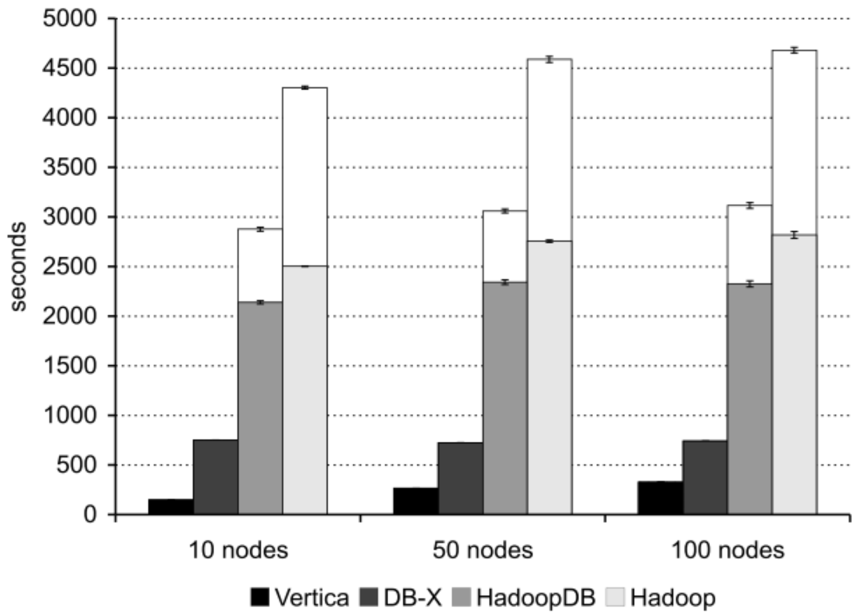
   Reconstruc some SQL to push it to the DB
5. Converted plan to one or more MR Jobs

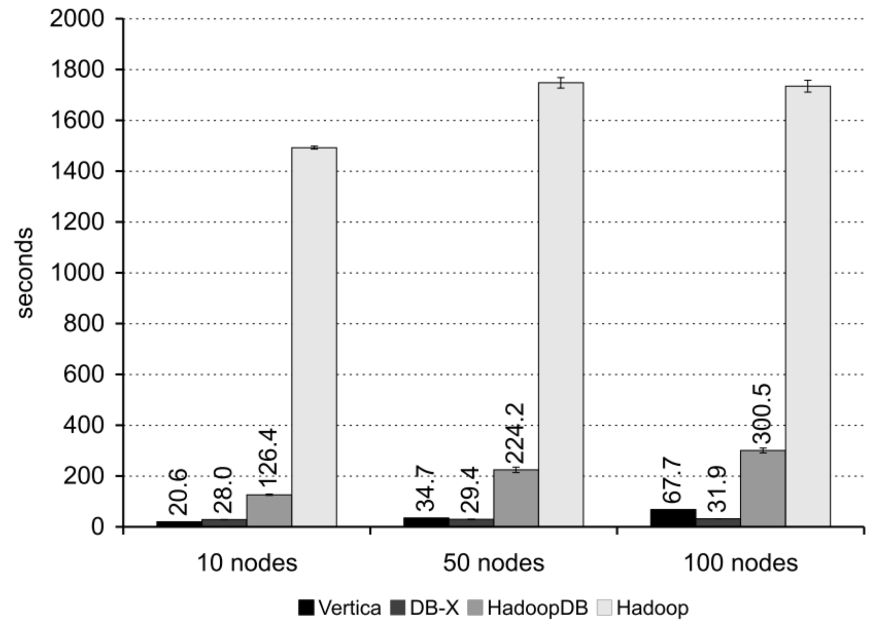
SMS Planner



SELECT YEAR(saleDate), SUM(revenue) FROM sales GROUP BY YEAR(saleDate);

HadoopDB Performance





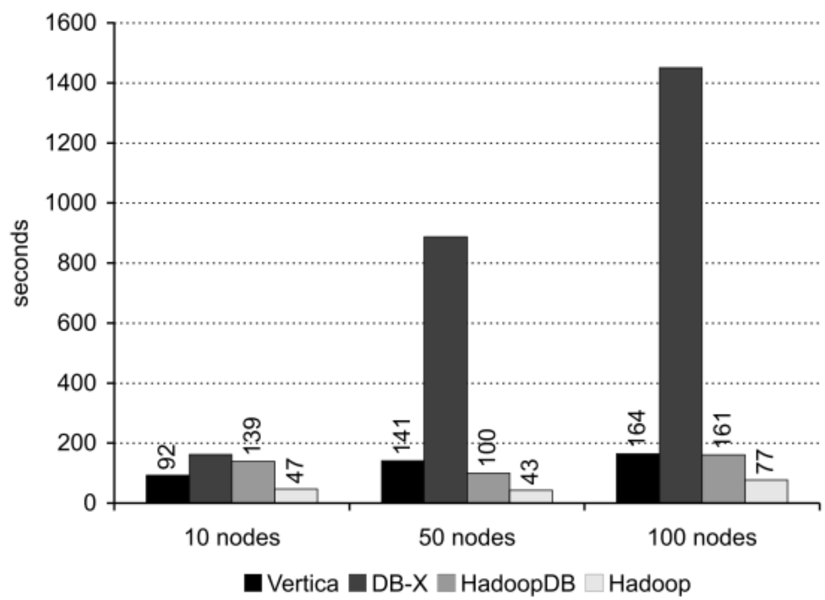
Group By

2,500,000 unique groups
over 20gb of data

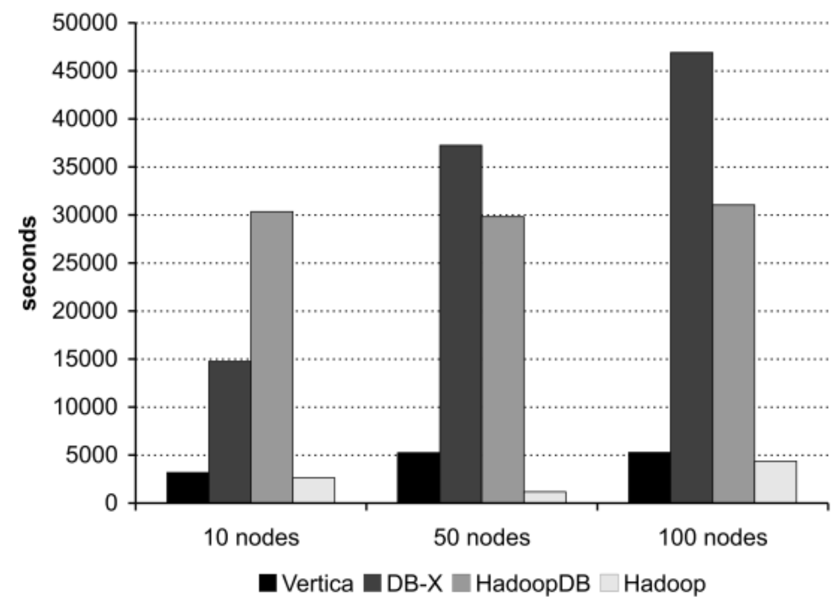
Join

134,000 joined records
over 20gb of date

HadoopDB loading times



Load Grep (0.5GB/node)



Load UserVisits (20GB/node)

HadoopDB

☺ Good performance

☺ Scalable

☺ Fault tolerant

☺ Heterogeneous node compatible

☺ Make any DBMS a distributed system

☹ Data Loader: All *a-priori* loading problems

Invisible loading

Load DBMS with data from Hadoop at run-time

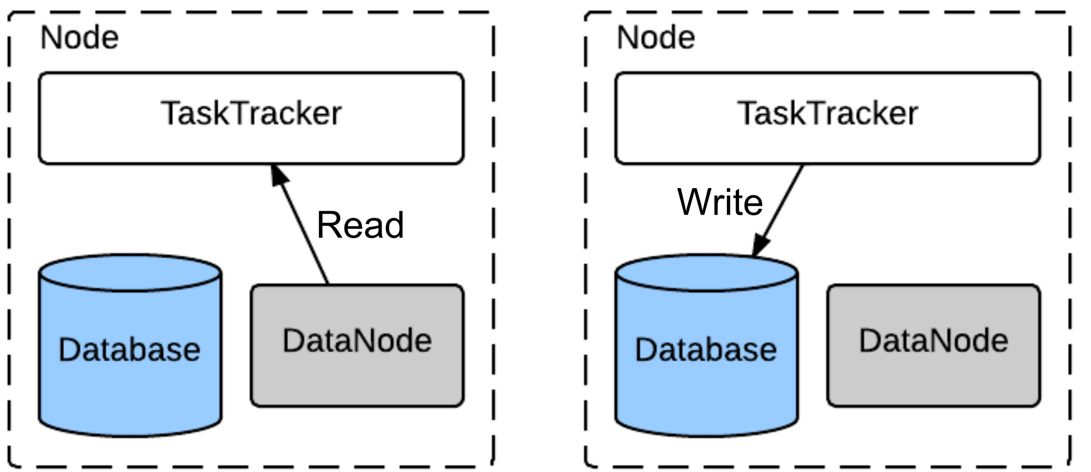
Invisibility objective

- Minimal human effort
- Minimal increase in response time

Use a DBMS as a cache for the raw data

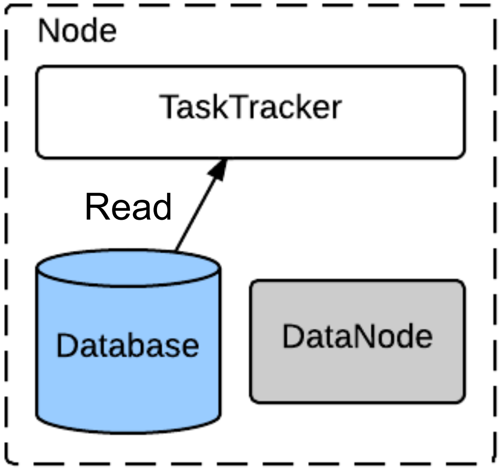
Invisible loading

Use code for tuple parsing and extraction to invisibly load the parsed tuples into a DBMS



Invisible loading

On next data access, it can be read from DBMS



Invisible loading: Parser

Parser extends inputFormat

- `getAttribute(int index)`
- Code for tuple parsing and extraction

Map takes a Parser as input

Invisible loading

☺ Incremental data reorganization

☺ Almost no overhead on MR Jobs

☺ Optimizes future access speeds

☹ Data duplication (No GC)

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NoDB

New DBMS paradigm

Do not require data loading

Maintains feature set of modern DBMS

Replaces physical storage with raw files

PostgresRaw

NoDB Implementation

Replaces TableScan Operator

CSV Files

Optimizations

PostgresRaw Optimizations

Selective...

a. Tokenizing
b. Parsing
c. Tuple formation

Indexing

Auto Tuning

Caching

Statistics

a. Selective tokenizing

111;222;"third";garbage;...

Supposing we want attributes **1** and **3**

We can stop tokenizing at the third

Saves CPU time

b. Selective parsing

111;222;"third";garbage;...

In memory:

111	`6F`	Parsed to int
222	`32 32 32`	Keep as string
"third"	`74 68 69 72 64`	

Also: delayed parsing

c. Selective tuple formation

111;222;"third";garbage;...

```
(111, "third")
```

Final tuple containing only attributes 1 and 3

CPU bound

Indexing

```
Year;  Make;      Model;   Liters
1997;  BMW;       E89;     2,34
2011;  Mercedes;  SLS;     2
```

Looks nice :)

Indexing

NOT :(

```
Year;Make;Model;Liters¶1997;BMW;E89;2,34¶2011;Mercedes;SLS;2
```

Sequentially reading each time is not an option

Solution

- Keep an index of the already used attributes
- Skip file reading to this positions

Indexing

Positional Map

Dynamically created according to queries

Tuple 1		Tuple 2		Tuple 3	
Attribute 1	Attribute 3	Attribute 1	Attribute 3	Attribute 1	Attribute 3
0	10	23	32	41	55

```
Year;Make;Model;Liters¶1997;BMW;E89;2,34¶2011;Mercedes;SLS;2
```

Updates

First case, no positions change

Tuple 1		Tuple 2		Tuple 3	
Attribute 1	Attribute 3	Attribute 1	Attribute 3	Attribute 1	Attribute 3
0	10	23	32	41	55

`Year;Make;Model;Liters¶`**`1989;BBB;CCC;4,44`**`¶2011;Mercedes;SLS;2`

Updates

Second case, positions change.

First option, update index.

Tuple 1		Tuple 2		Tuple 3	
Attribute 1	Attribute 3	Attribute 1	Attribute 3	Attribute 1	Attribute 3
0	10	23	~~32~~ 30 (-2)	~~41~~ 37 (-4)	~~55~~ 51 (-4)

```
Year;Make;Model;Liters¶1989;B;C;4,44¶2011;Mercedes;SLS;2
```

Updates

Second case, positions change.
Second option, throw it partially (or fully) away.

Tuple 1		Tuple 2
Attribute 1	Attribute 3	Attribute 1
0	10	23

Year;Make;Model;Liters¶1**989;B;C;4,44**¶2011;Mercedes;SLS;2

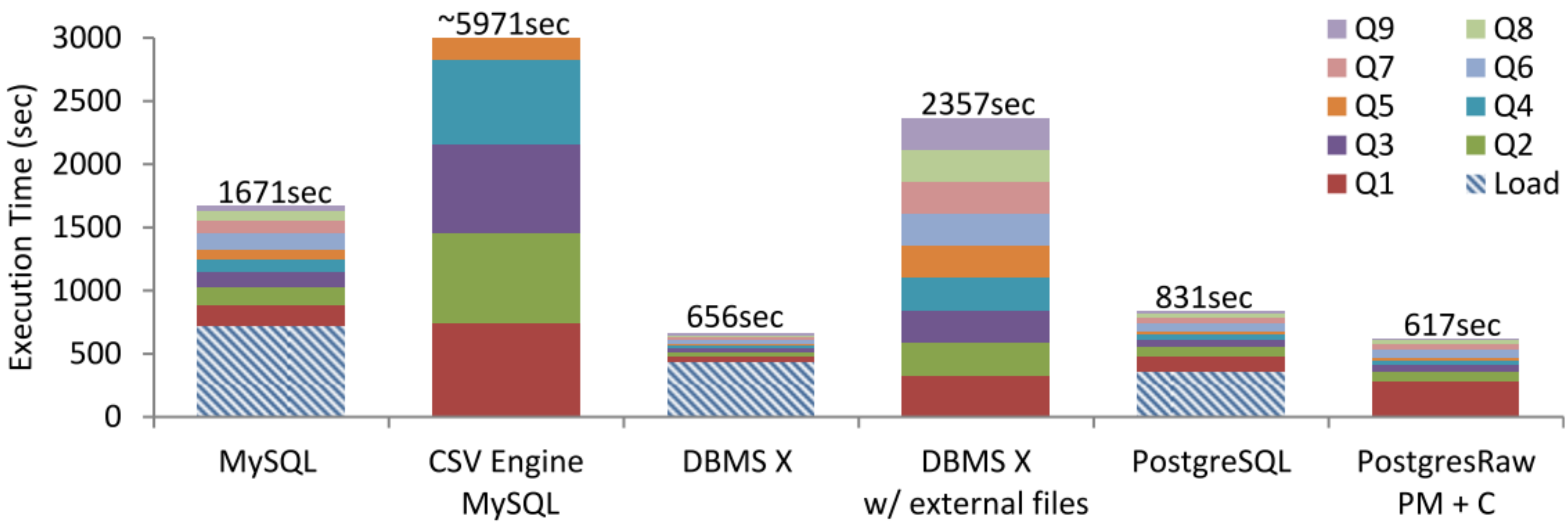
Index will automatically reconstruct itself

Traditional optimizations

Caching

Statistics

NoDB Performance Compared



NoDB

- ☺ Great DBMS + Raw hybrid
- ☺ Competitive performance with traditional DBs
- ☺ Eliminates loading times
- ☺ Queries get faster with time

☹ Updates

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Summary

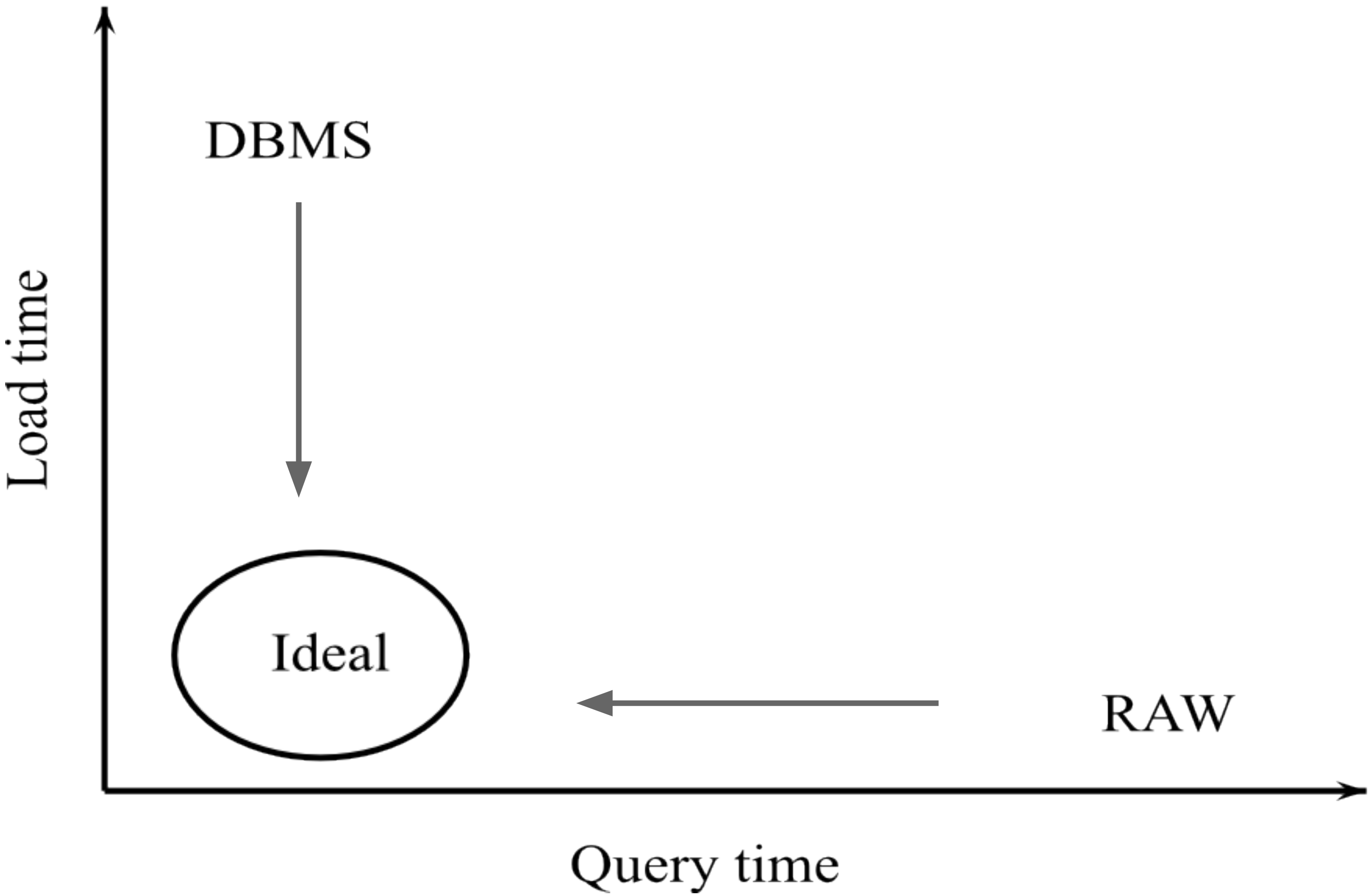
Mature solutions: high load or query time

- No index → High query time
- Load all data → High delay (load time)

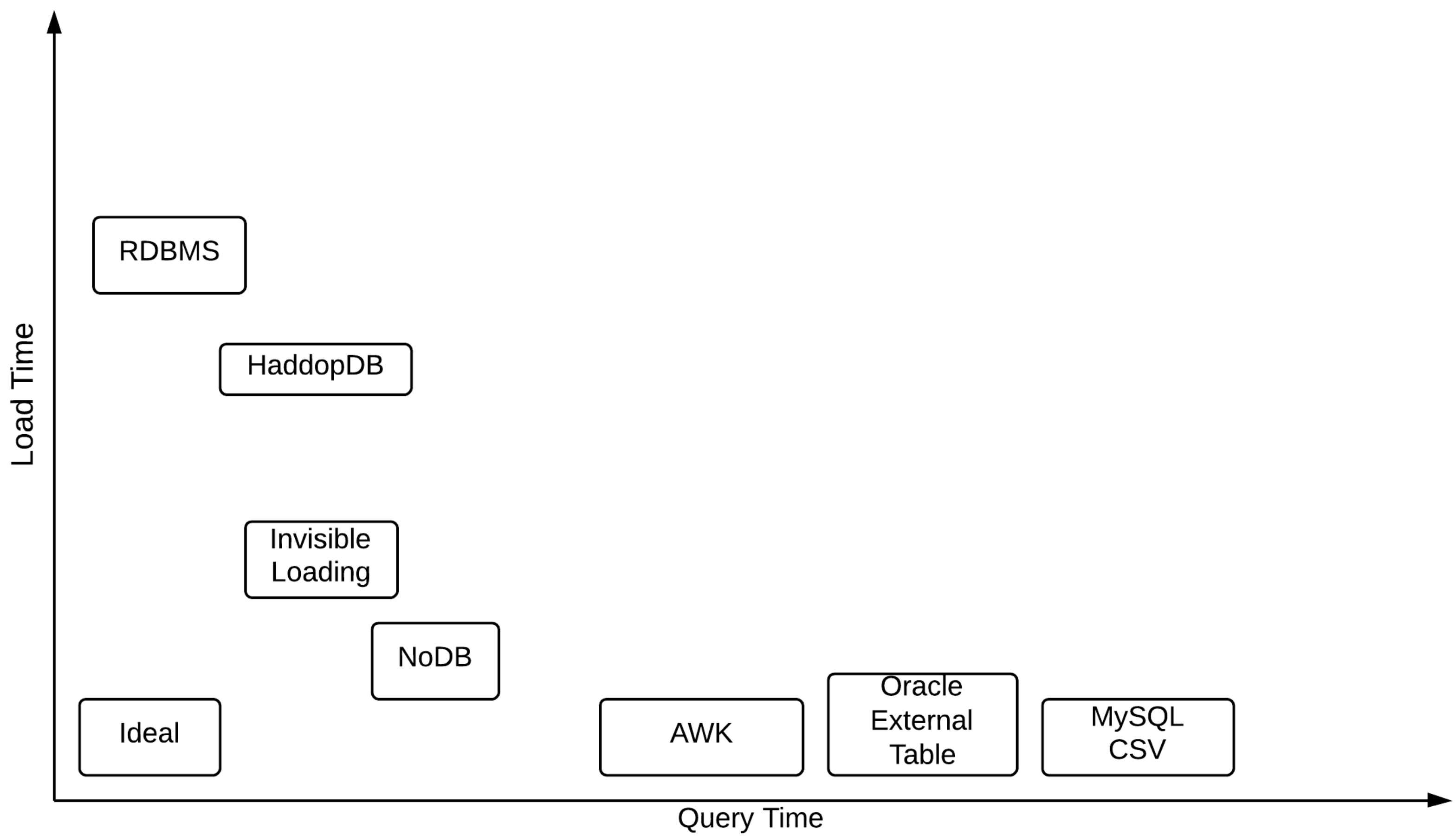
Hybrid solutions

- Bring indexes to in-situ processing
- Adaptive indexing
- HadoopDB
- NoDB

Remember..



Conclusions



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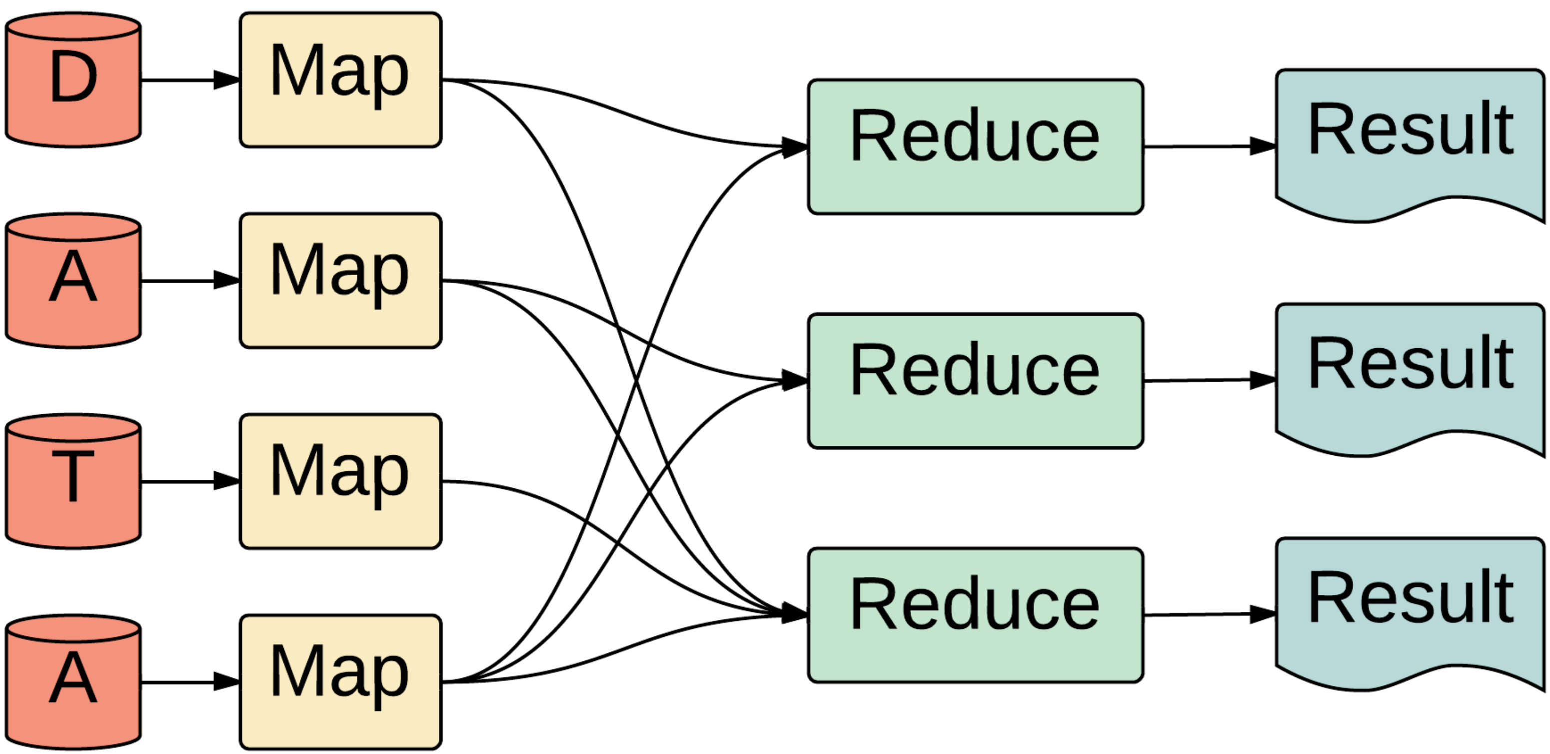
Questions?

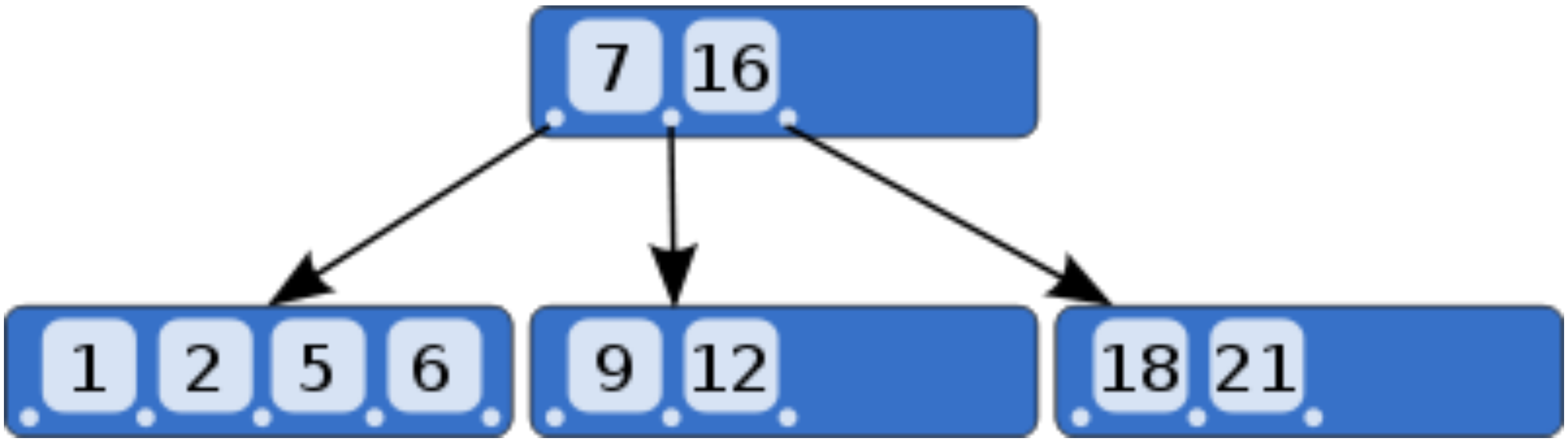
Thank you!

MapReduce

Can be classified as distributed raw file parsing



Adaptive merging



Database Cracking