Apache CarbonData: An indexed columnar file format for interactive query with Spark SQL

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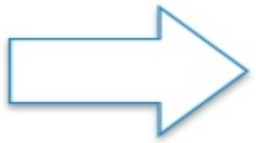
Report & Dashboard

OLAP & Ad-hoc

Batch processing

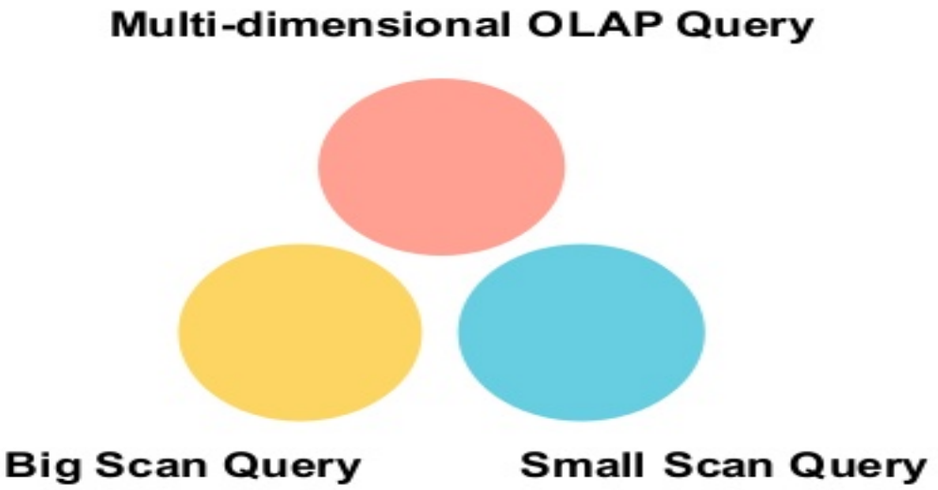
Real Time Analytics

Machine learning



Challenge

- Wide Spectrum of Query Analysis
  - OLAP Vs Detailed Query
  - Full scan Vs Small scan
  - Point queries



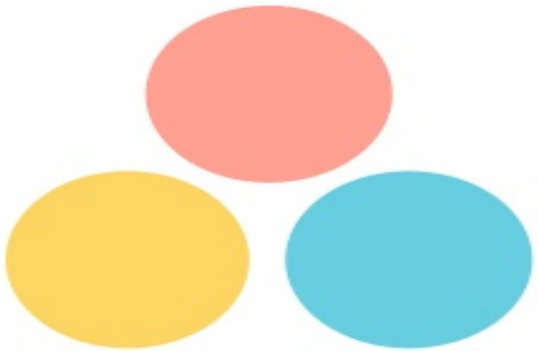
How to choose storage engine to facilitate query execution?

Available Options

1. NoSQL Database
   - Key-Value store: low latency, <5ms
   - No Standard SQL support
2. MPP relational Database
   - Shared-nothing enables fast query execution
   - Poor scalability: < 100 cluster size, no fault-tolerance
3. Search Engine
   - Advanced indexing technique for fast search
   - 3~4X data expansion in size, no SQL support
4. SQL on Hadoop
   - Modern distributed architecture and high scalability
   - Slow on point queries

Motivation for A New File Format

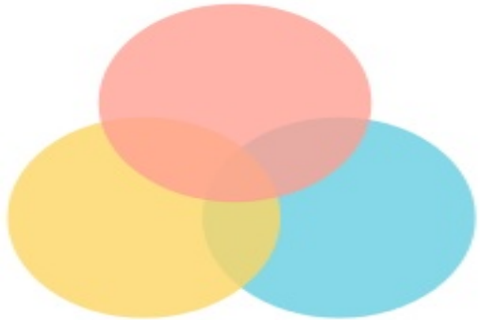
Multi-dimensional OLAP Query



Big Scan Query

Small Scan Query

CarbonData: Unified File Format



A single copy of data
balanced to fit all data access

Apache CarbonData

- Apache Incubator Project since June, 2016
- Apache releases
  - 4 stable releases
  - **Latest 1.0.0, Jan 28, 2017**
- Contributors:

Alibaba Group, ebay, HUAWEI, hulu, INMOBI, intel, Letv, 美团 meituan.com, talend, 交通銀行 BANK OF COMMUNICATIONS

- In Production:

交通銀行 BANK OF COMMUNICATIONS, HUAWEI, hulu

Compute

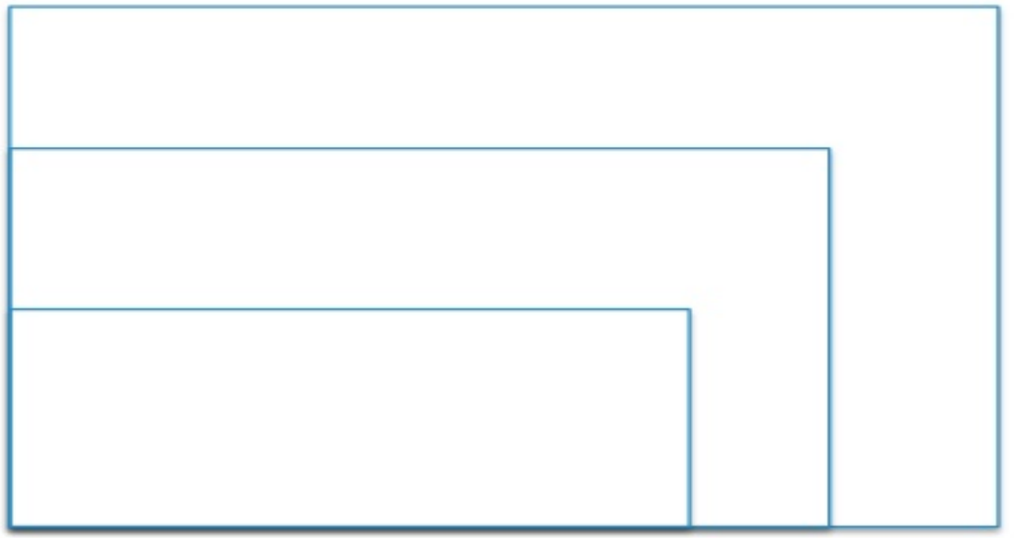
Spark, Flink, HIVE

Storage

CarbonData, hadoop

Introducing CarbonData

- What it takes to deeply integrate with distributed processing engine like Spark?
- What forms a CarbonData table on disk?
- What is CarbonData file format?



CarbonData:

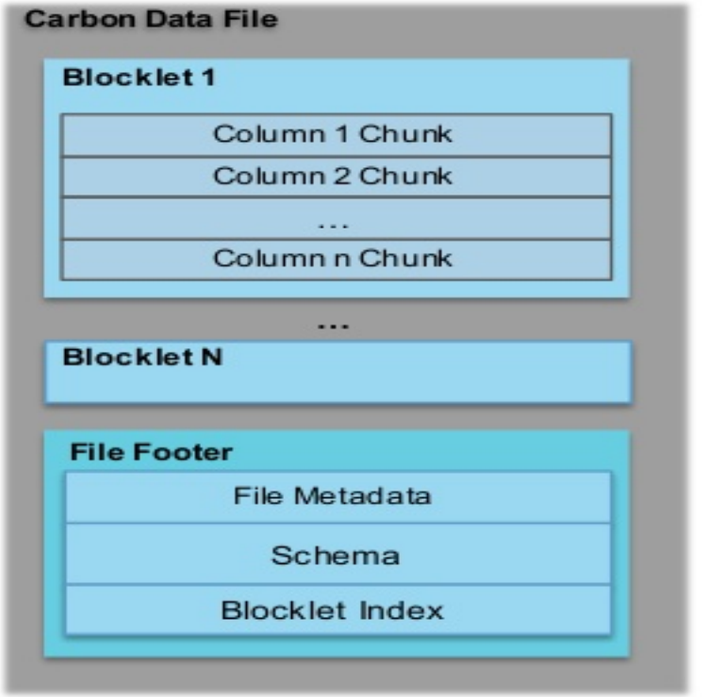
An Indexed Columnar File Format

CarbonData File Structure

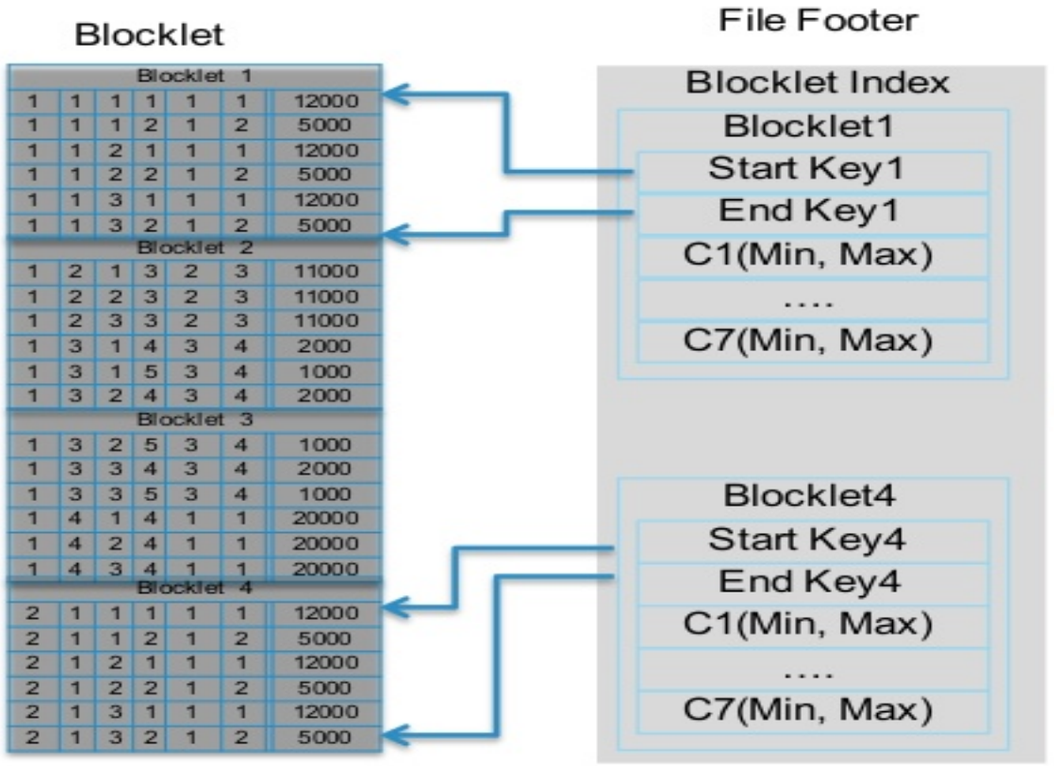
- **Built-in Columnar & Index**
  - Multi-dimensional Index (B+ Tree)
  - Min/Max index
  - Inverted index
- **Encoding:**
  - RLE, Delta, Global Dictionary
  - Snappy for compression
  - Adaptive Data Type Compression
- **Data Type:**
  - Primitive type and nested type

CarbonData File Layout

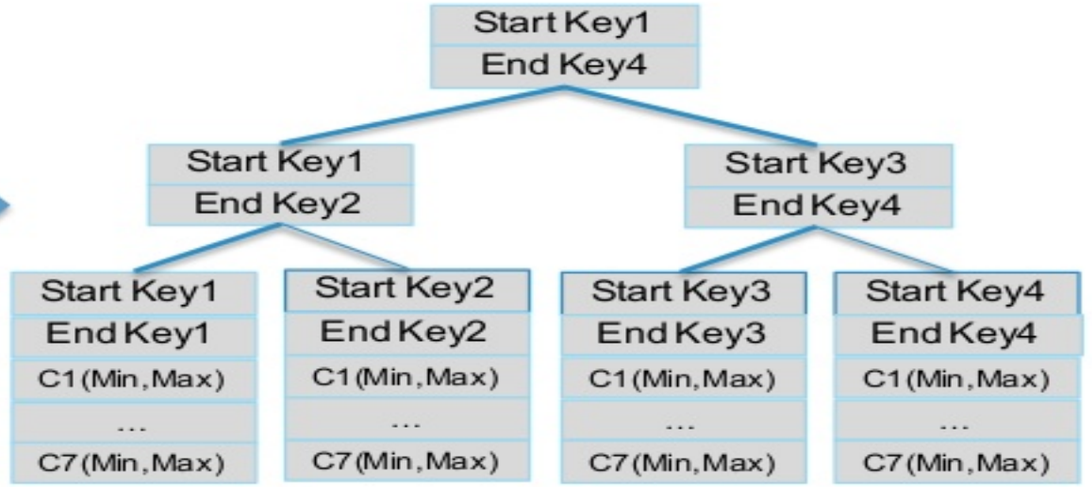
- Blocklet: A set of rows in columnar format
  - Data are sorted along MDK (multi-dimensional keys)
  - Clustered data enabling efficient filtering and scan
- Column chunk: Data for one column in a Blocklet
- Footer: Metadata information
  - File level metadata & statistics
  - Schema
  - Blocklet Index



File Level Blocklet Index

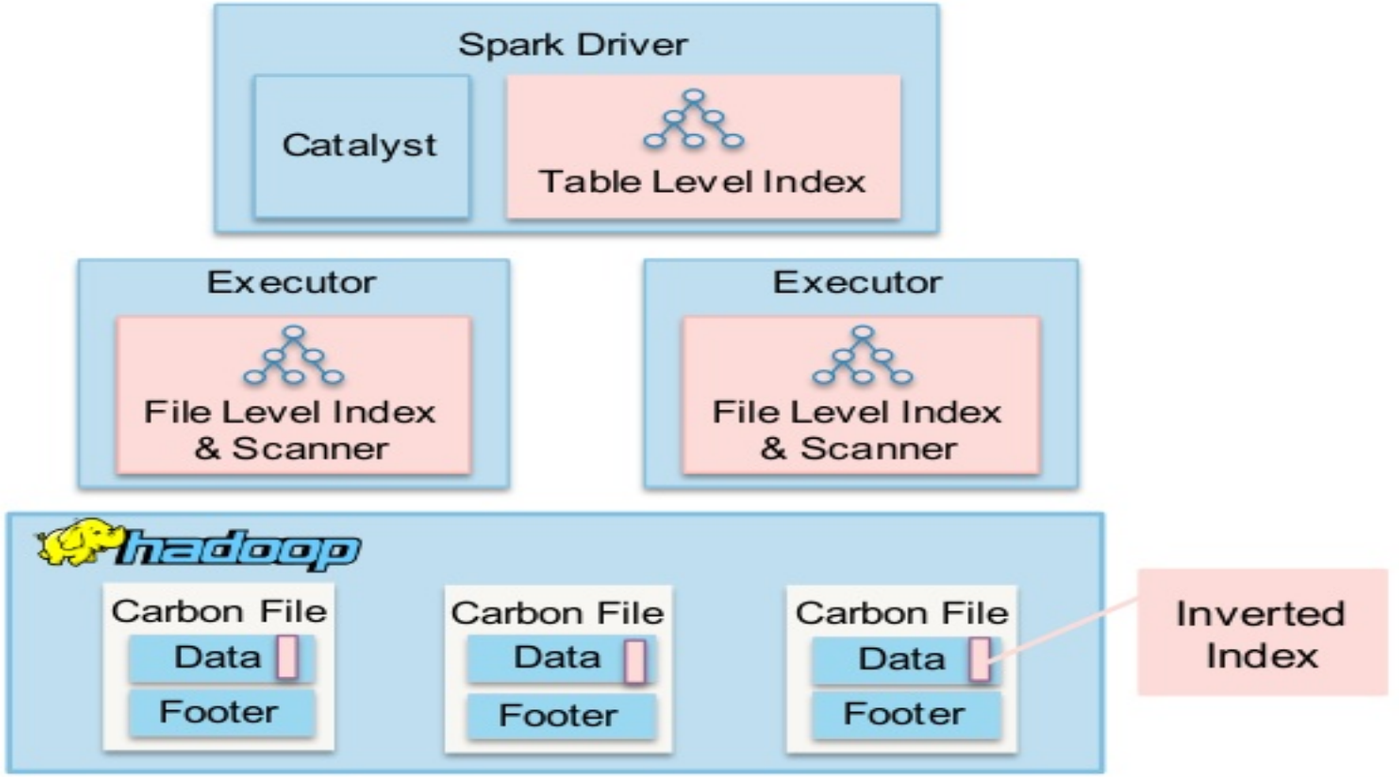


- Build in-memory file level MDK index tree for filtering
- Major optimization for efficient scan



Rich Multi-Level Index Support

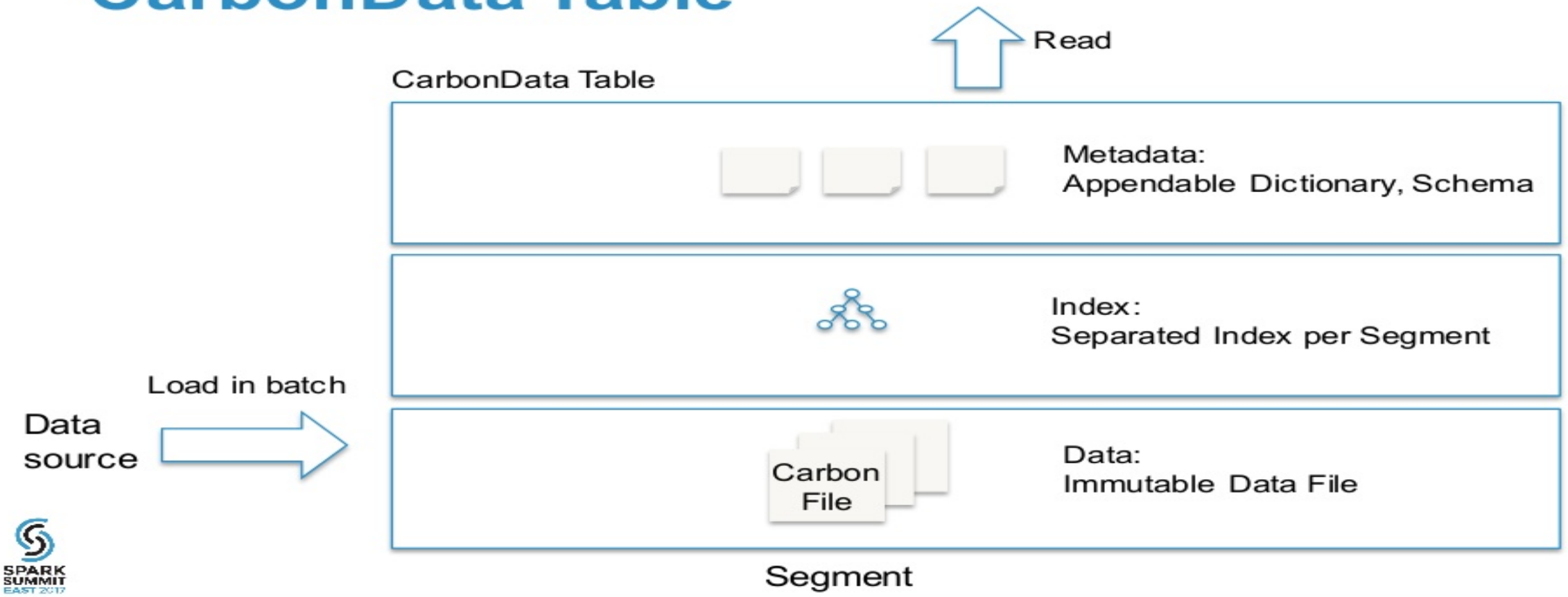
- Using the index info in footer, two level B+ tree index can be built:
  - File level index: local B+ tree, efficient blocklet level filtering
  - Table level index: global B+ tree, efficient file level filtering
- Column chunk inverted index: efficient column chunk scan



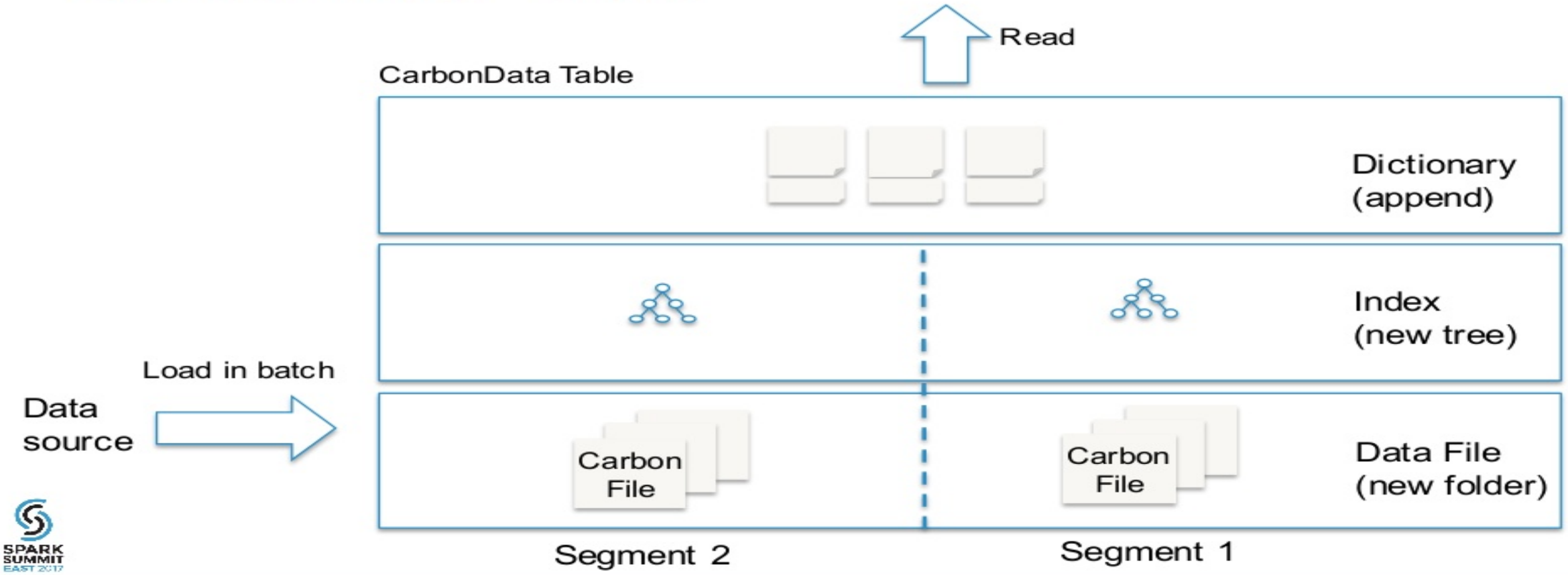
CarbonData Table:

Data Segment + Metadata

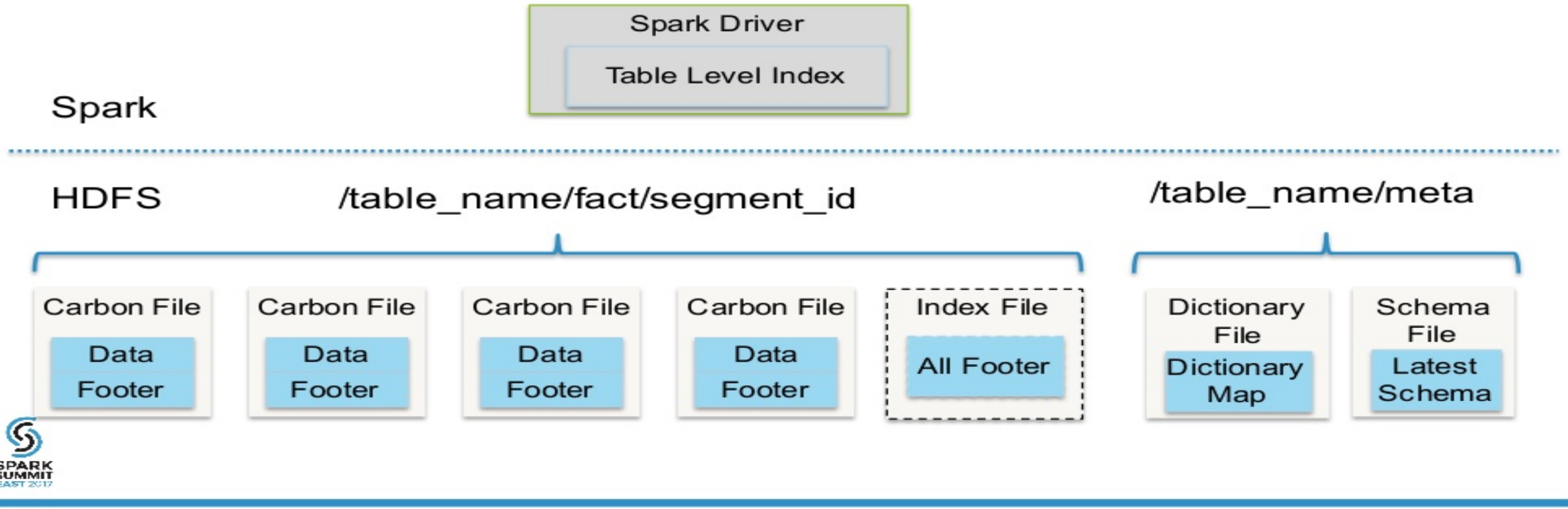
CarbonData Table



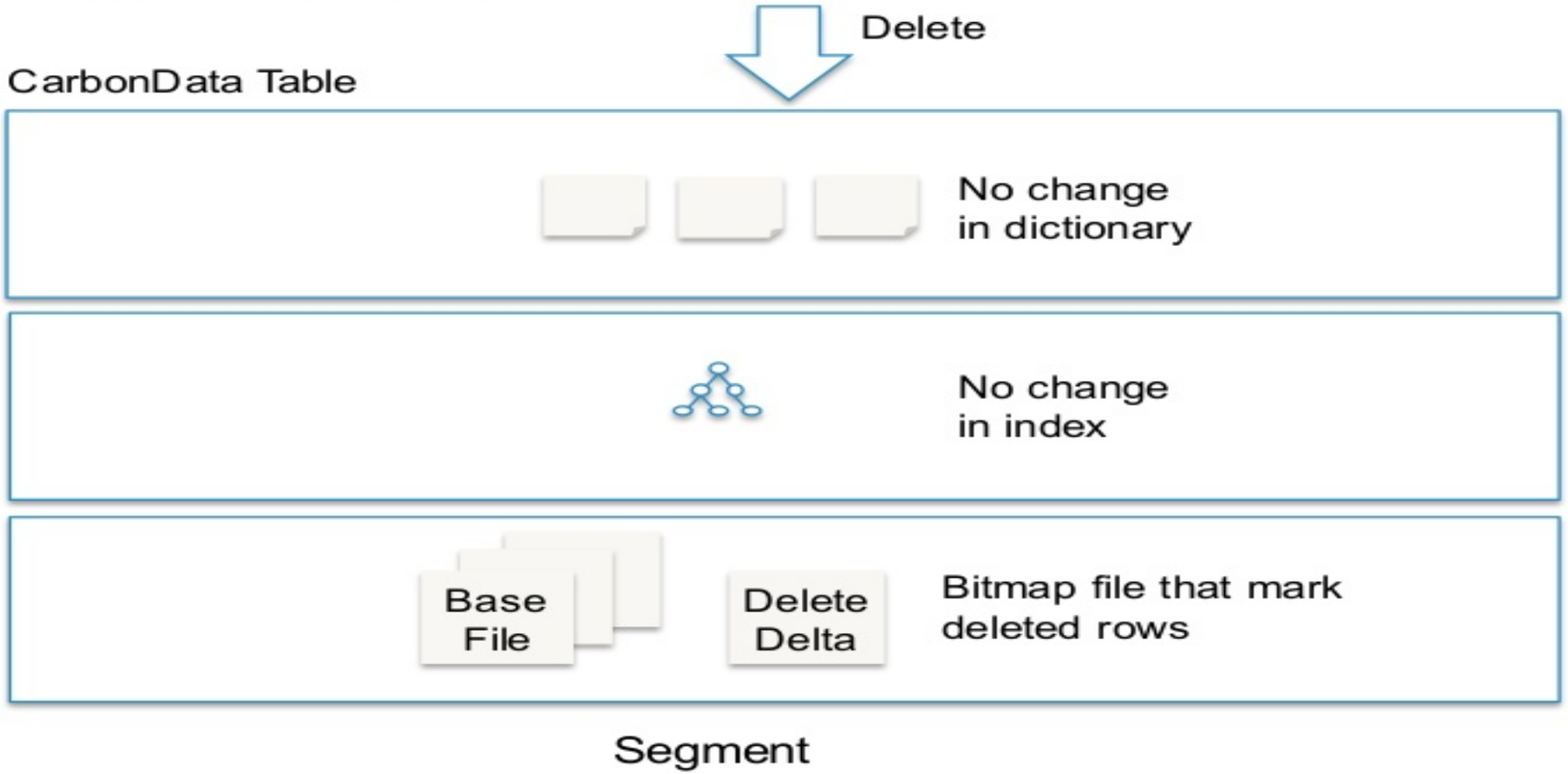
CarbonData Table



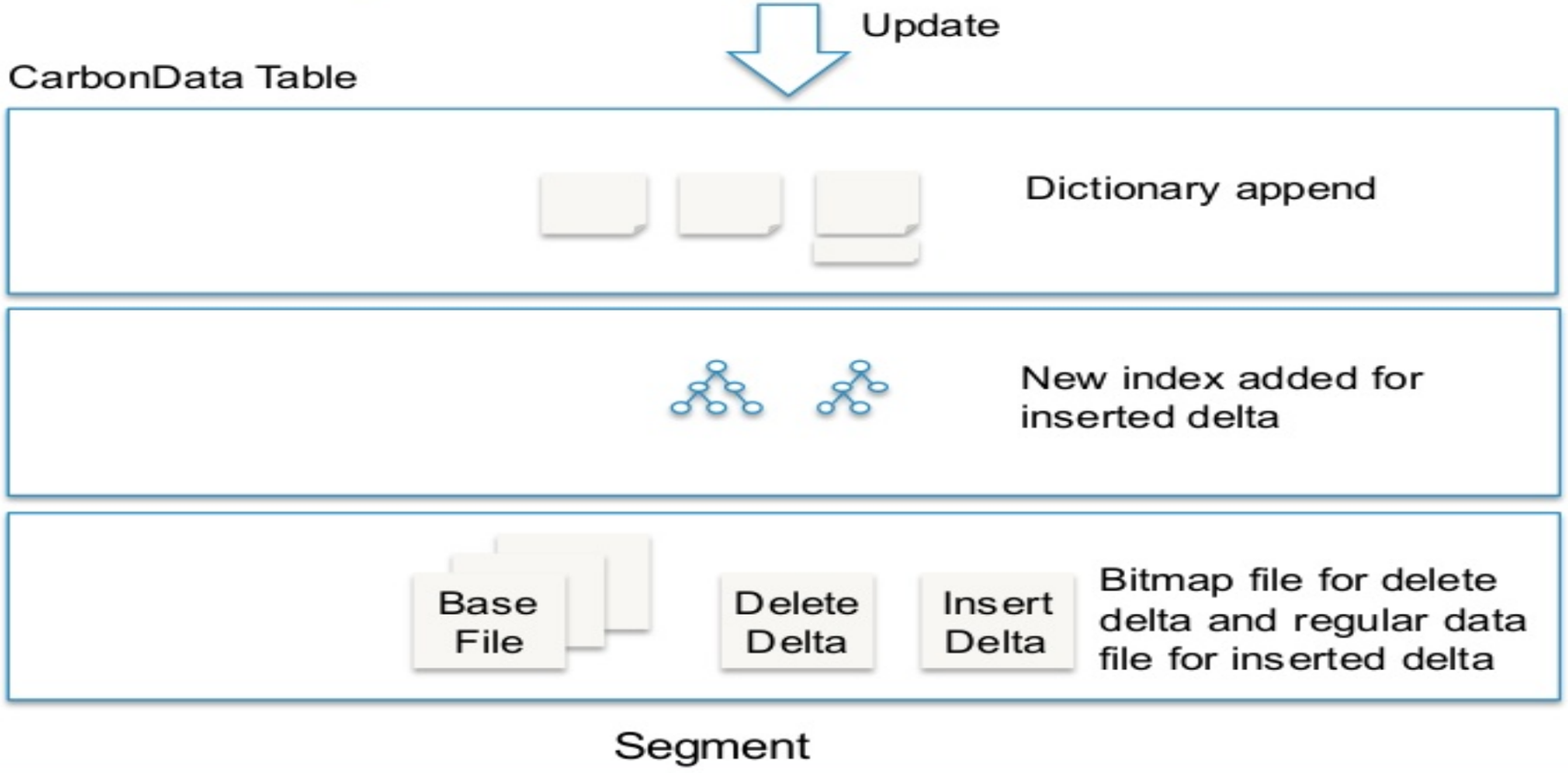
CarbonData Table Layout



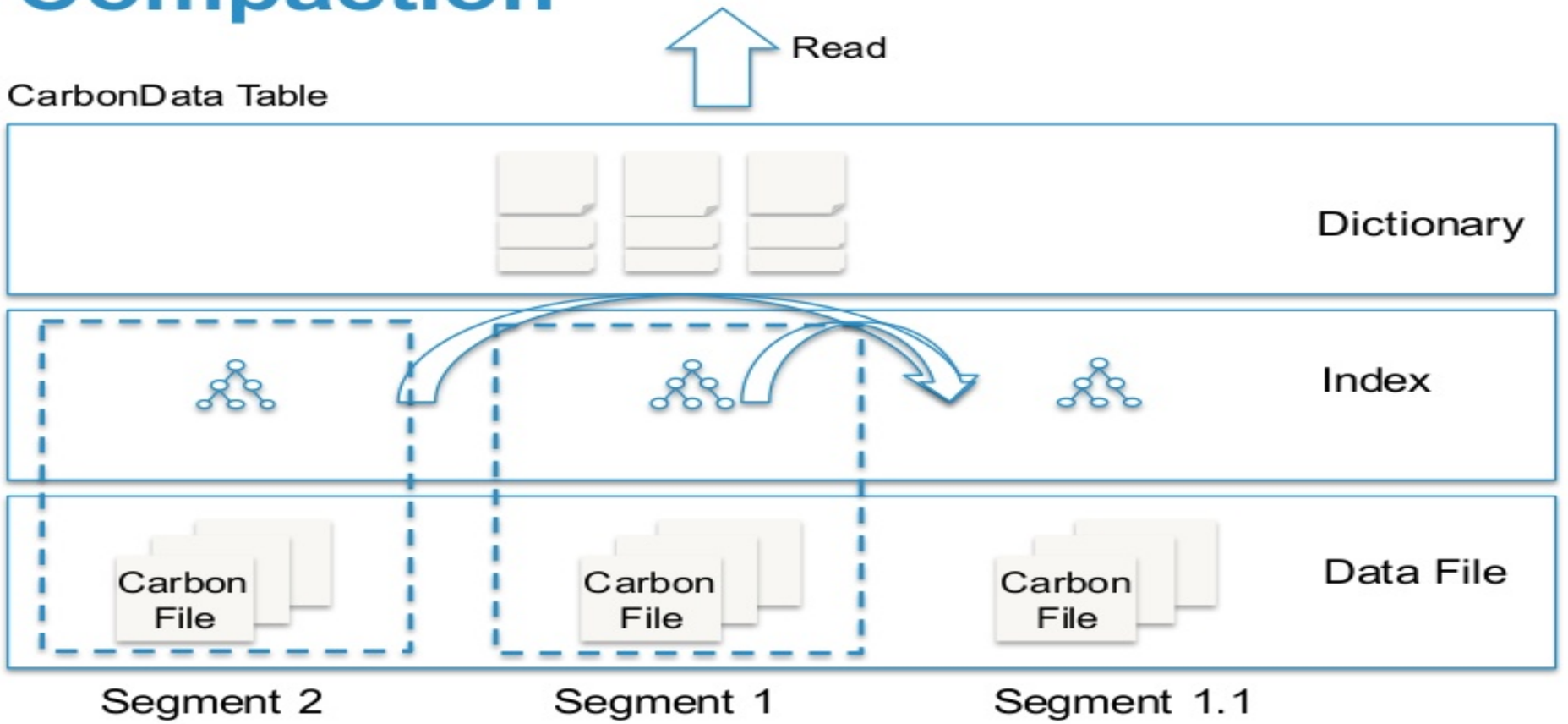
Mutation: Delete



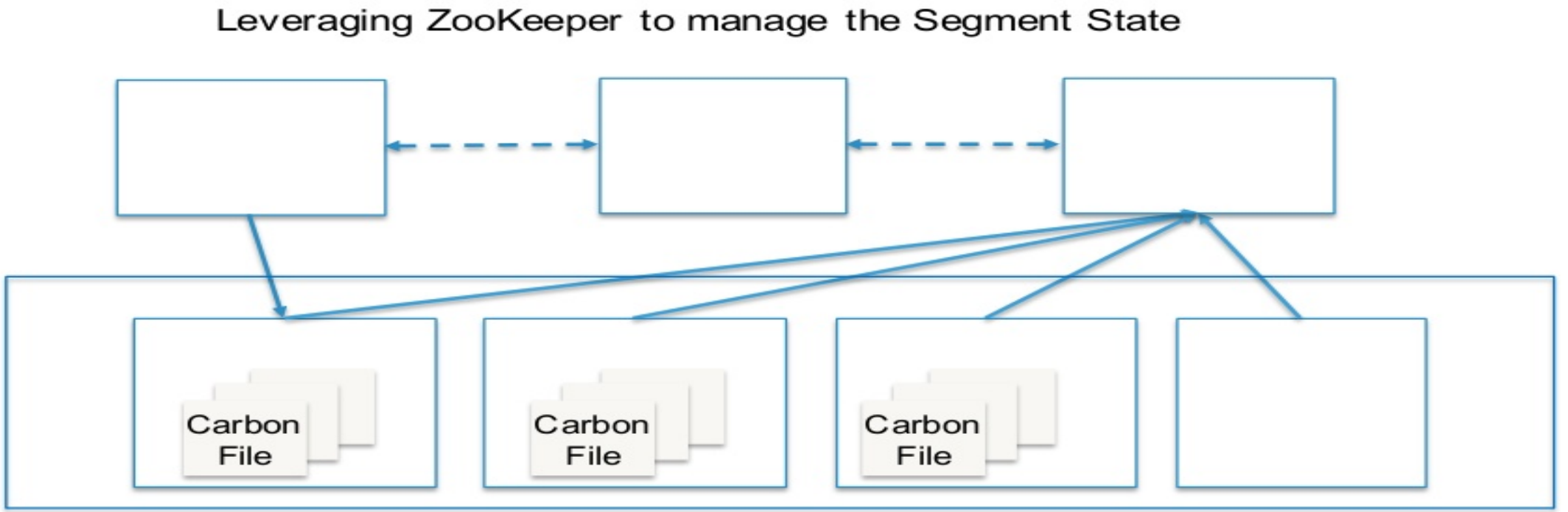
Mutation: Update



Data Compaction



Segment Management

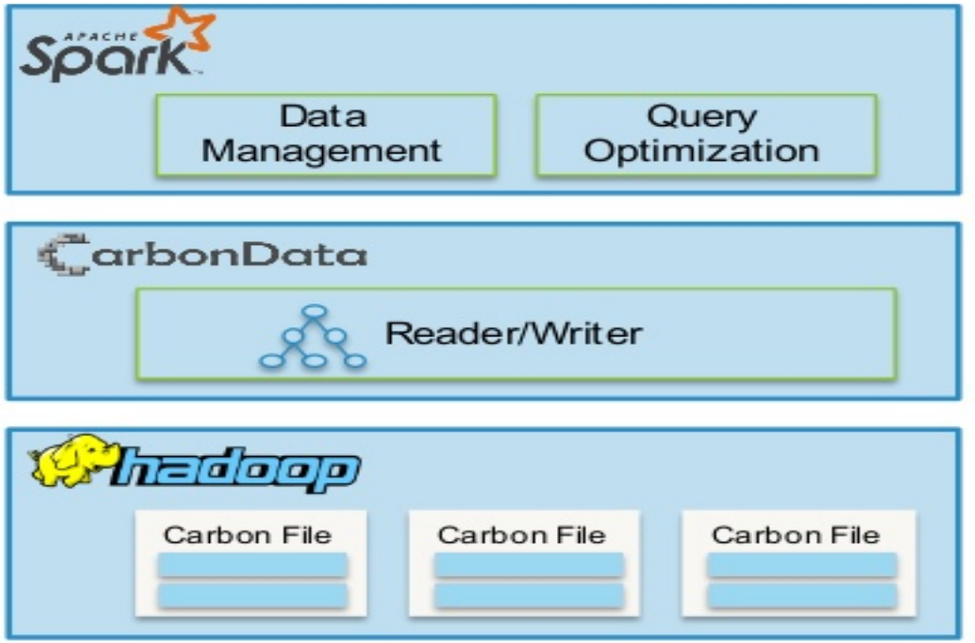


SparkSQL + CarbonData:

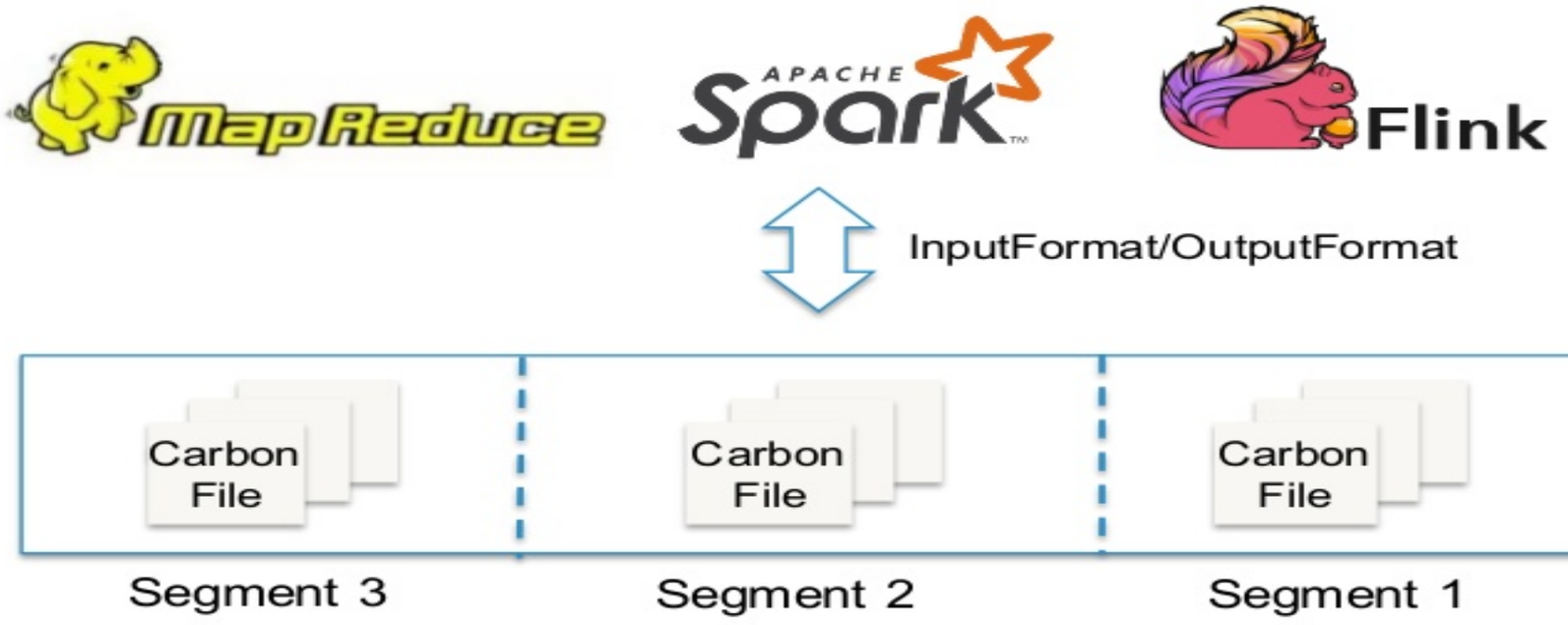
Enables fast interactive data analysis

Carbon-Spark Integration

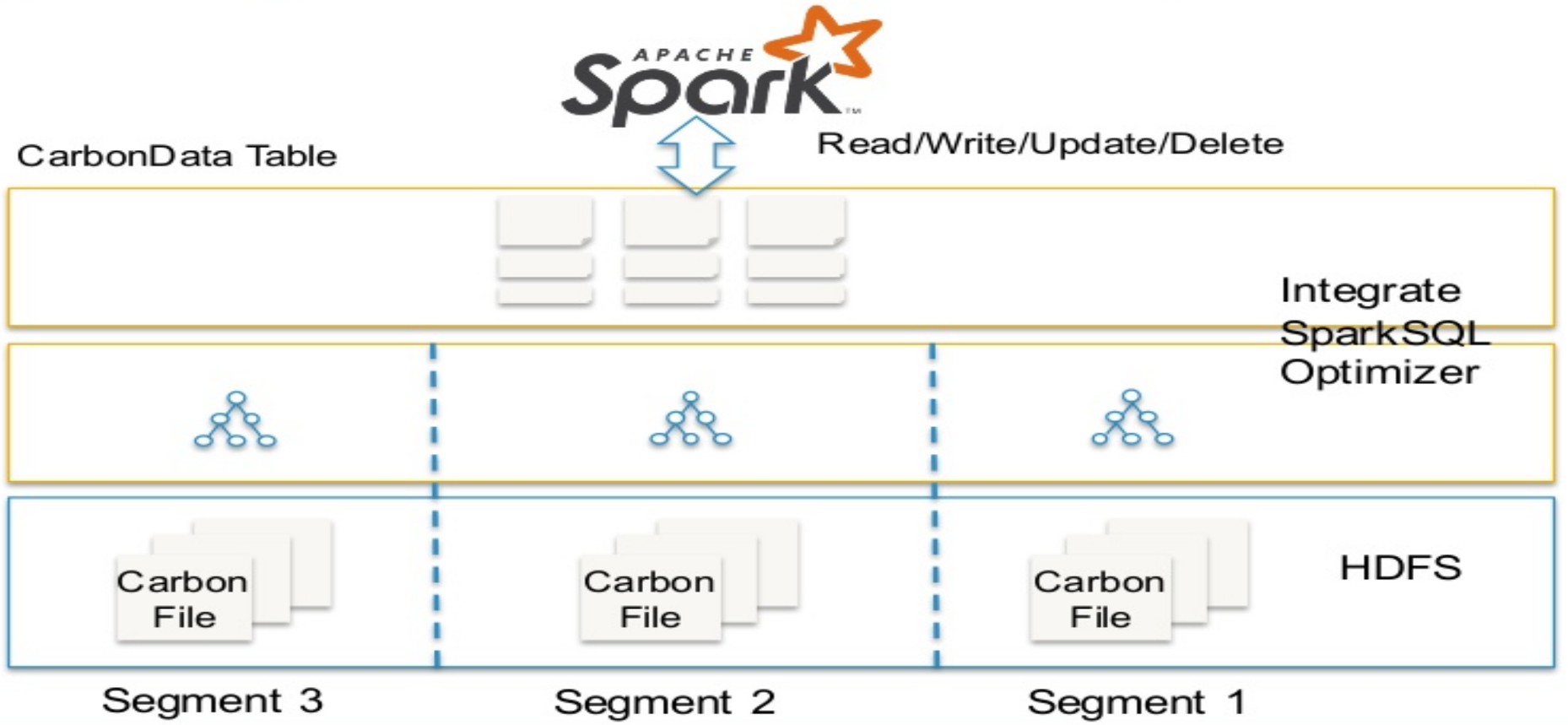
- Built-in Spark integration
  - Spark 1.5, 1.6, 2.1
- Interface
  - SQL
  - DataFrame API
- Operation:
  - Load, Query (with optimization)
  - Update, Delete, Compaction, etc



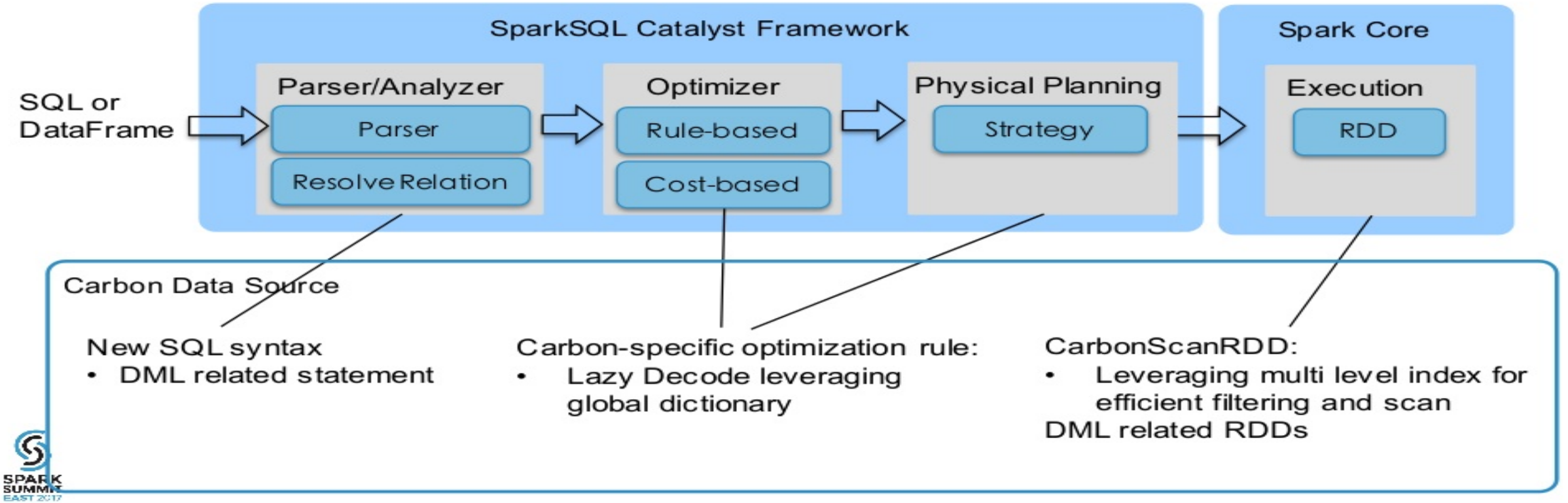
Integration through File Format



Deep Integration with SparkSQL

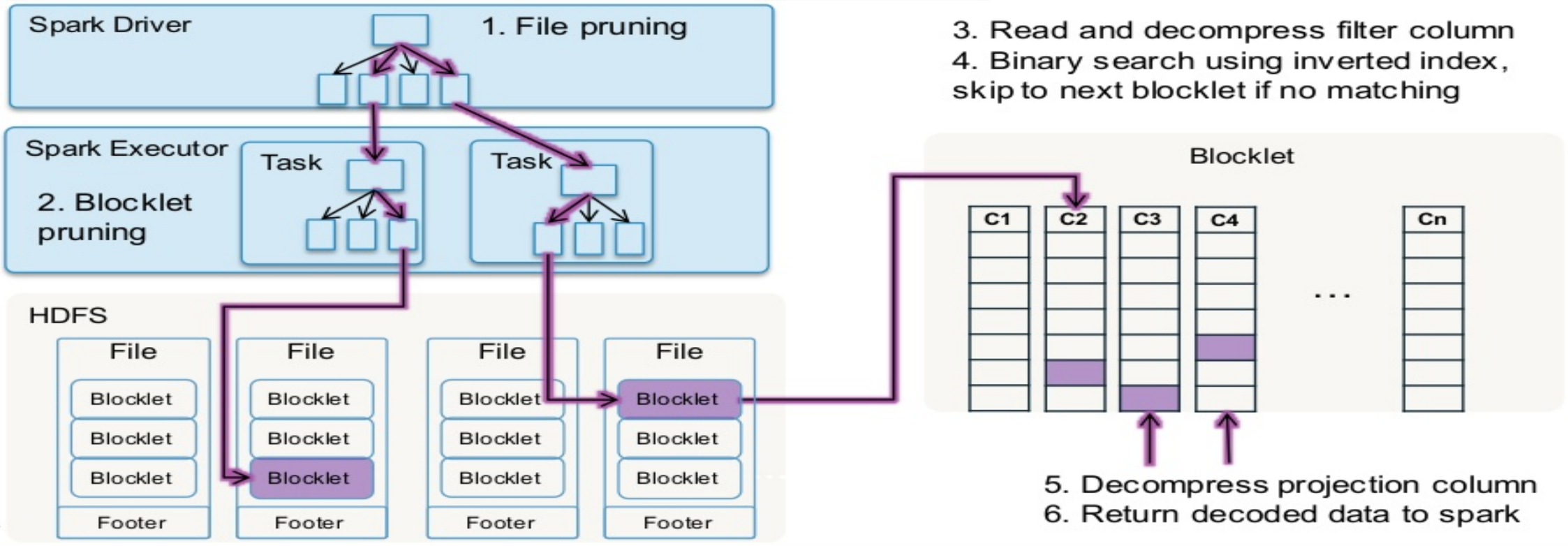


CarbonData as a SparkSQL Data Source



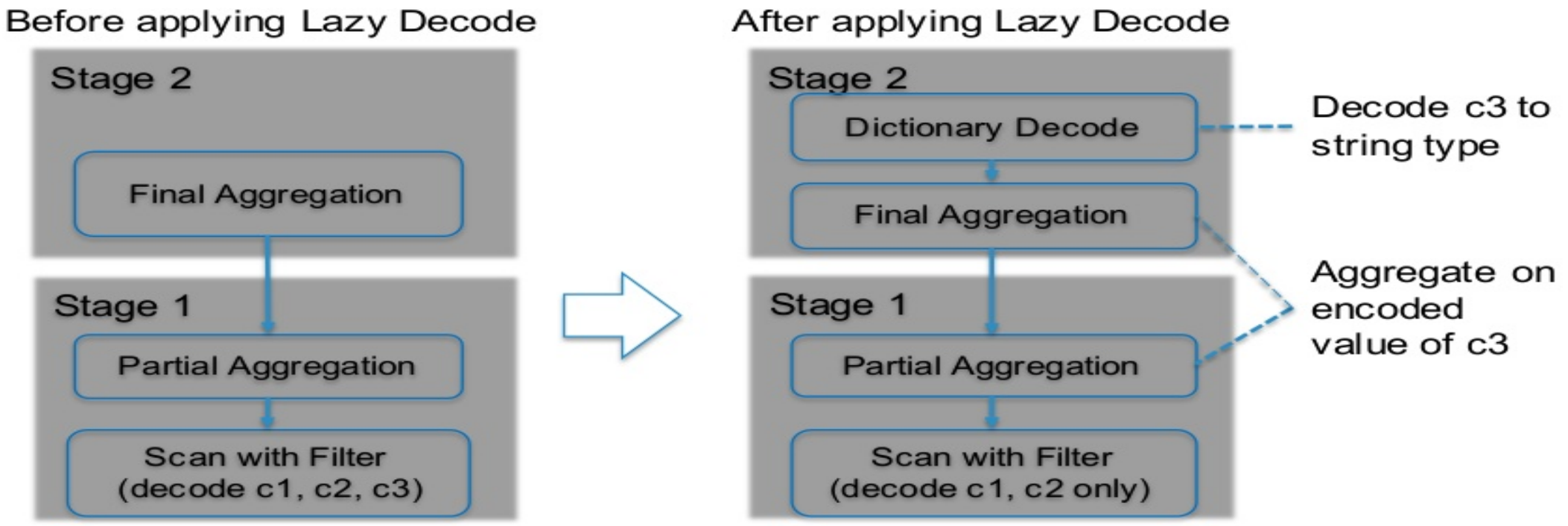
Efficient Filtering via Index

```
SELECT c3, c4 FROM t1 WHERE c2='boston'
```



Lazy Decoding by Leveraging Global Dictionary

```
SELECT c3, sum(c2) FROM t1 WHERE c1>10 GROUP BY c3
```



Usage: Write

- Using SQL

```
CREATE TABLE tablename (name String, PhoneNumber String) STORED BY “carbondata”

LOAD DATA [LOCAL] INPATH 'folder path' [OVERWRITE] INTO TABLE tablename
OPTIONS(property_name=property_value, ...)

INSERT INTO TABLE tablennme  select_statement1 FROM table1;
```

- Using Dataframe

```
df.write
    .format(“carbondata")
    .options("tableName“, “t1"))
    .mode(SaveMode.Overwrite)
    .save()
```

Usage: Read

- Using SQL

```
SELECT project_list FROM t1
WHERE cond_list
GROUP BY columns
ORDER BY columns
```

- Using Dataframe

```
df = sparkSession.read
          .format("carbondata")
          .option("tableName", "t1")
          .load("path_to_carbon_file")

df.select(…).show
```

Usage: Update and Delete

Modify one column in table1

```
UPDATE table1 A
SET A.REVENUE = A.REVENUE - 10
WHERE A.PRODUCT = 'phone'
```

Modify two columns in table1 with values from table2

```
UPDATE table1 A
SET (A.PRODUCT, A.REVENUE) =
     (
      SELECT PRODUCT, REVENUE
      FROM table2 B
      WHERE B.CITY = A.CITY AND B.BROKER = A.BROKER
     )
WHERE A.DATE BETWEEN '2017-01-01' AND '2017-01-31'
```

Delete records in table1

```
DELETE FROM table1 A
WHERE A.CUSTOMERID = '123'
```

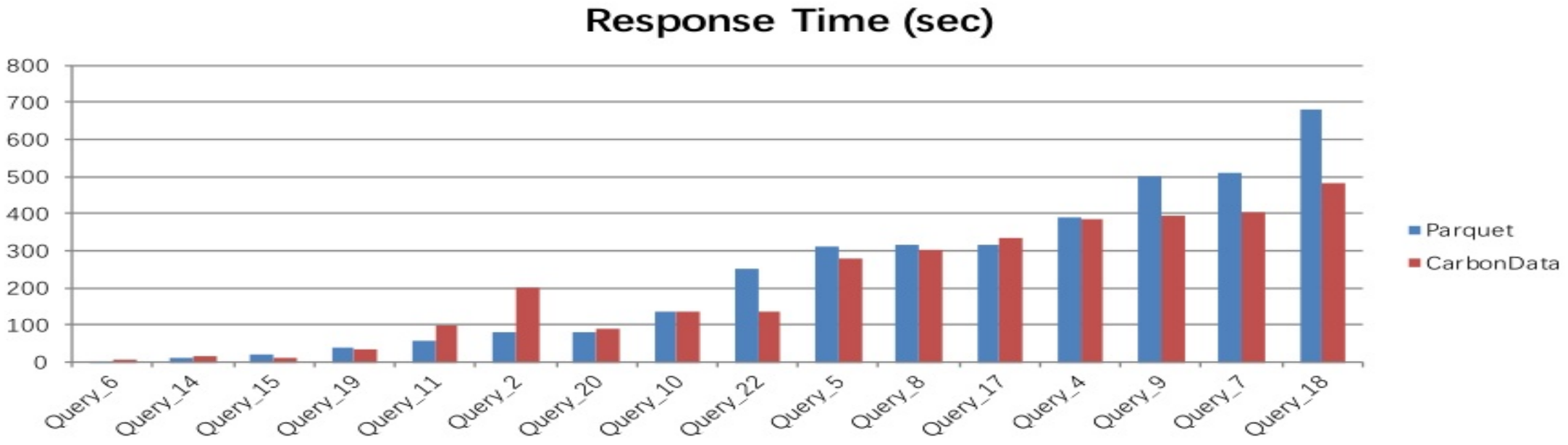
Performance Result

Test

1. TPC-H benchmark (500GB)
2. Test on Production Data Set (Billions of rows)
3. Test on Large Data Set for Scalability (1000B rows, 103TB)

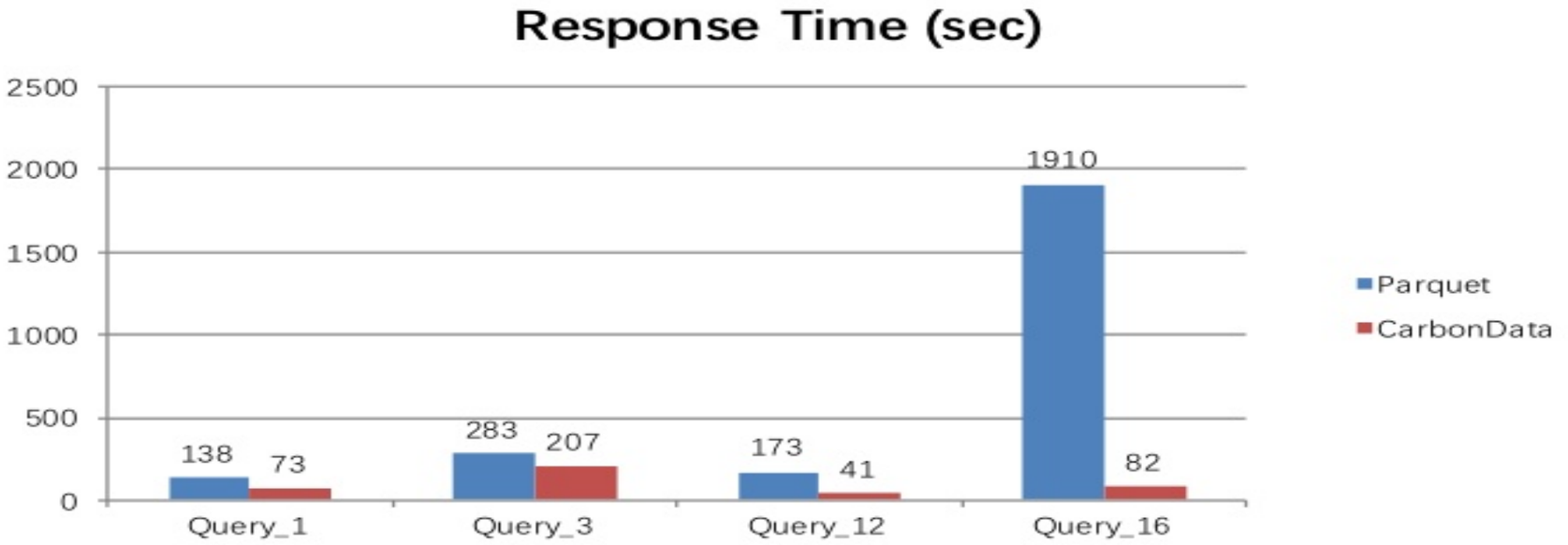
- Storage
  - Parquet:
    - Partitioned by time column (c1)
  - CarbonData:
    - Multi-dimensional Index by c1~c10
- Compute
  - Spark 2.1

TPC-H: Query



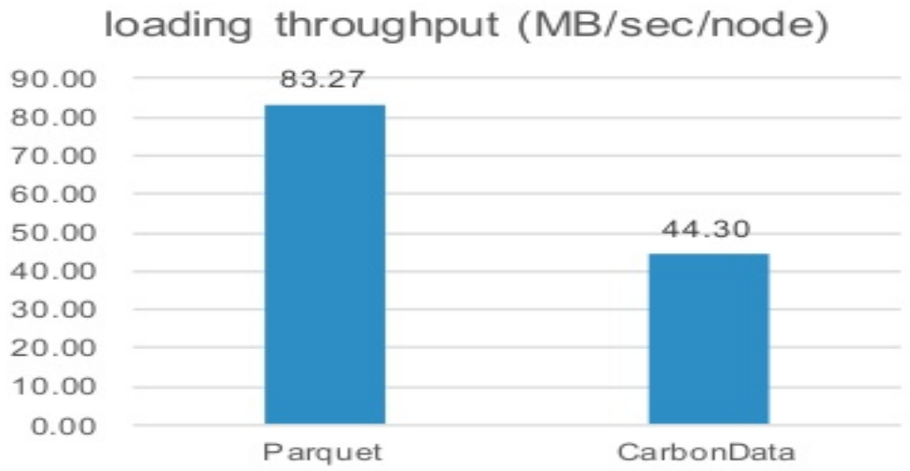
For big scan queries, similar performance, ±20%

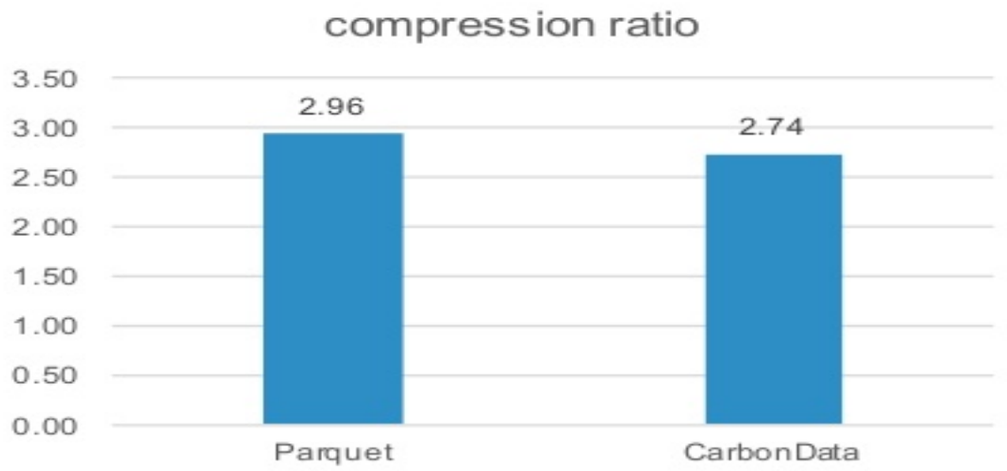
TPC-H: Query



For queries include filter on fact table,
CarbonData get 1.5-20X performance by leveraging index

TPC-H: Loading and Compression





Test on Production Data Set

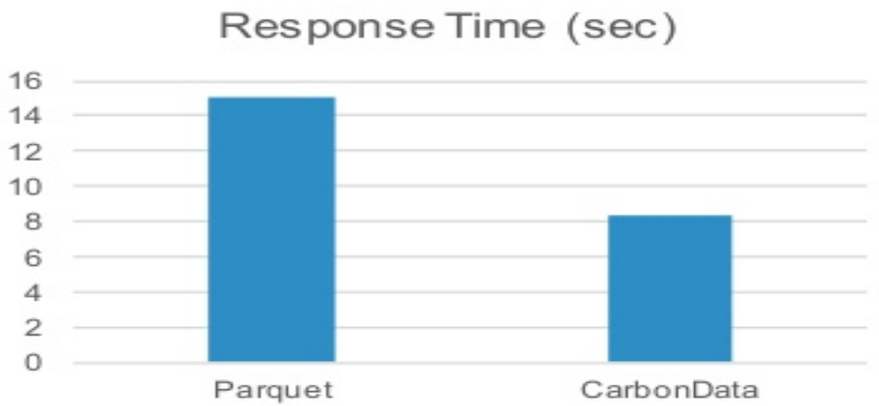
Filter Query

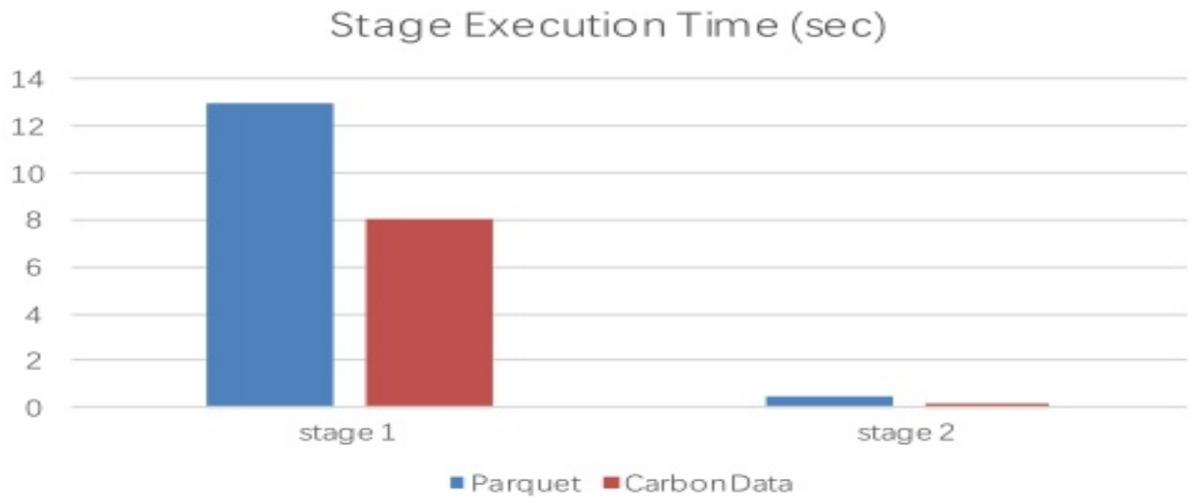
	Filter								Response Time (sec)		Number of Task	
Query	c1	c2	c3	c4	c5	c6	...	c10	Parquet	CarbonData	Parquet	CarbonData
Q1	✓	✓	✓	✓					6.4	1.3	55	5
Q2		✓	✓						65	1.3	804	5
Q3		✓		✓					71	5.2	804	9
Q5		✓			✓				64	4.7	804	9
Q4			✓	✓					67	2.7	804	161
Q6			✓			✓			62	3.7	804	161
Q7				✓		✓			63	21.85	804	588
Q8								✓	69	11.2	804	645

Observation:
Less scan task (resource) is needed because of more efficient filtering by leveraging multi-level index

Test on Production Data Set

Aggregation Query: no filter, group by c5 (dictionary encoded column)





Observation: both partial aggregation and final aggregation are faster, because aggregation operates on dictionary encoded value

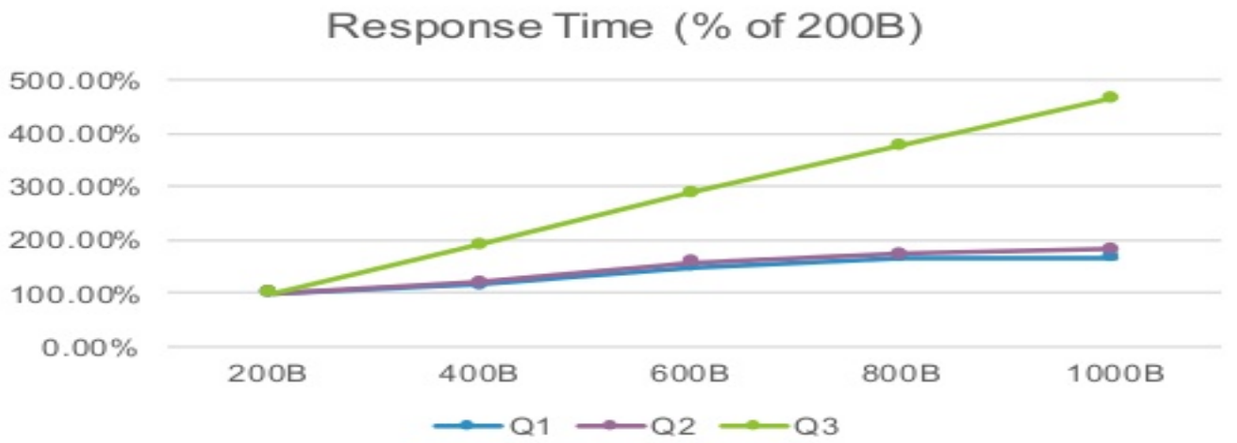
Test on large data set

Data: 200 to 1000 Billion Rows (half year of telecom data in one china province)

Cluster: 70 nodes, 1120 cores

Query:

Q1: filter (c1~c4), select *
Q2: filter (c10), select *
Q3: full scan aggregate



Observation

When data increase:

- Index is efficient to reduce response time for IO bound query: Q1, Q2
- Spark can scale linearly for CPU bound query: Q3

What's Coming Next

What's coming next

- Enhancement on data loading & compression
- Streaming Ingest:
  - Introduce row-based format for fast ingestion
  - Gradually compact row-based to column-based for analytic workload
  - Optimization for time series data
- Broader Integration across big data ecosystem: Beam, Flink, Kafka, Kylin

Apache CarbonData

- Love feedbacks, try out, any kind of contribution!
  - Code: https://github.com/apache/incubator-carbondata
  - JIRA: https://issues.apache.org/jira/browse/CARBONDATA
  - dev mailing list: dev@carbondata.incubator.apache.org
  - Website: http://http://carbondata.incubator.apache.org

  - **Current Contributor: 64**
  - **Monthly resolved JIRA issue: 100+**

Thank You.

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