Cost-Based Optimizer in Apache Spark 2.2

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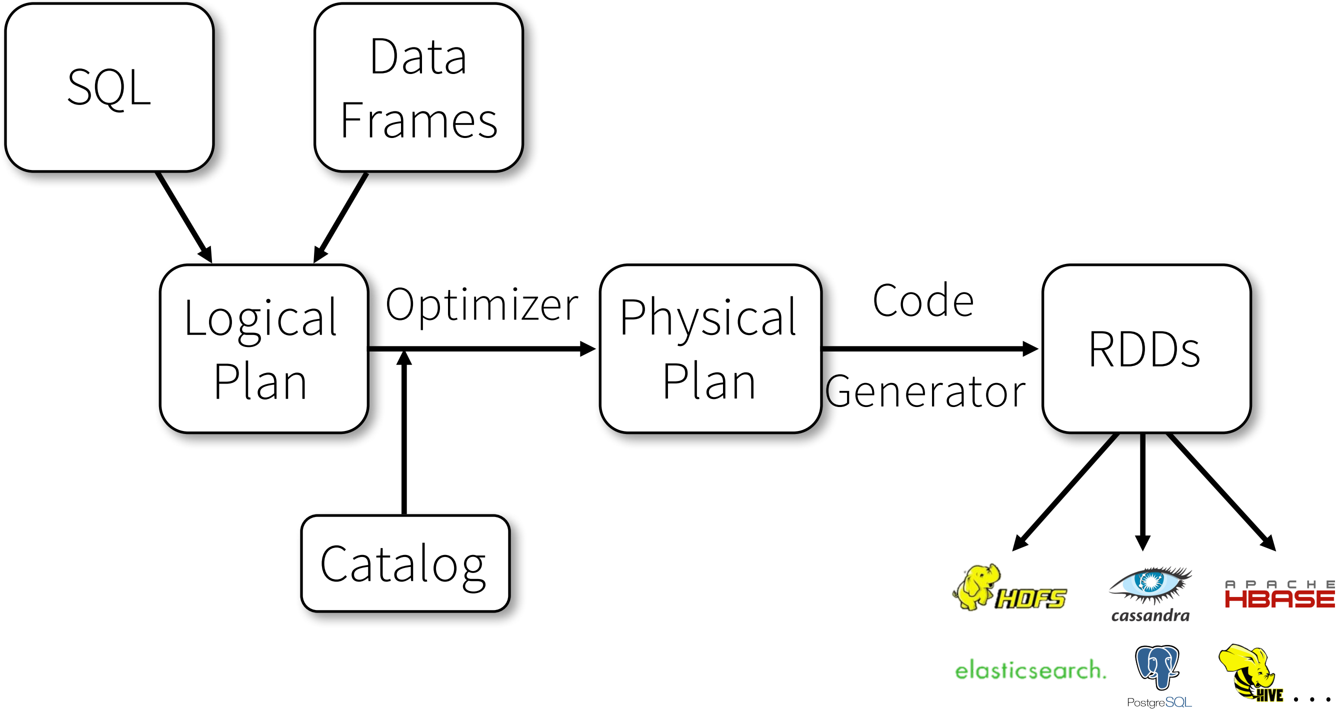
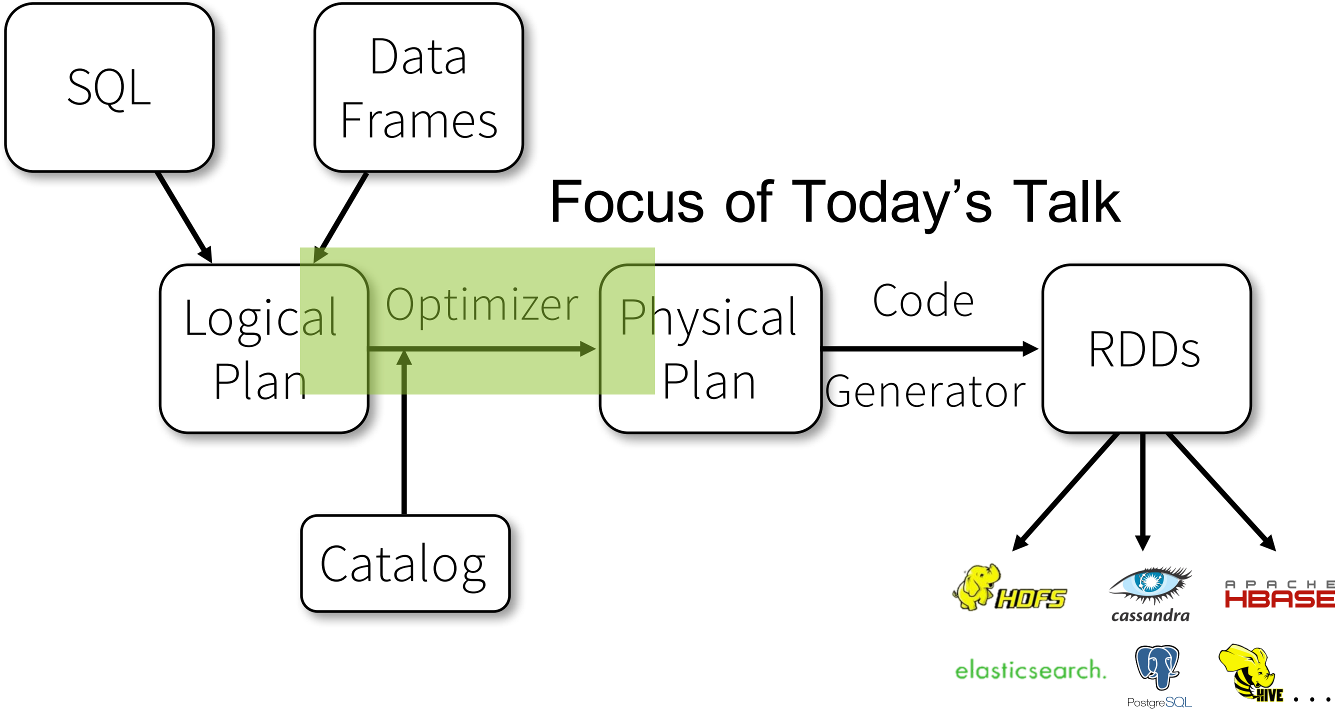
Session 1 Topics

- Motivation
- Statistics Collection Framework
- Cost Based Optimizations
- TPC-DS Benchmark and Query Analysis
- Demo

How Spark Executes a Query?



How Spark Executes a Query?

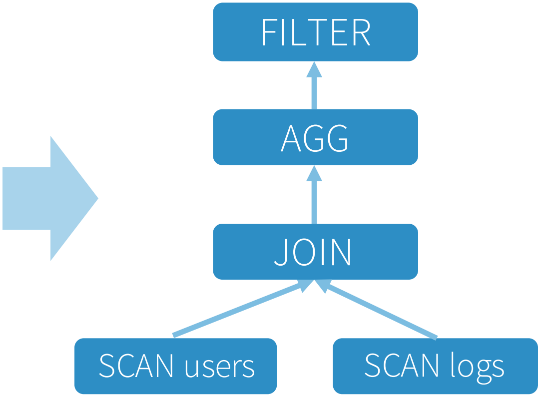


Catalyst Optimizer: An Overview

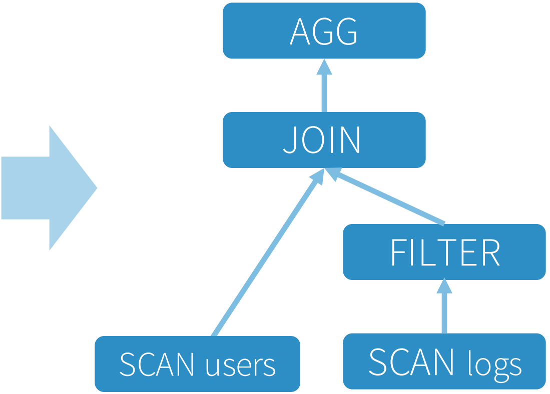
```
events =
 sc.read.json("/logs")

stats =
  events.join(users)
  .groupBy("loc","status")
.avg("duration")


errors = stats.where(
  stats.status == "ERR")
```



Query Plan is an internal representation of a user's program

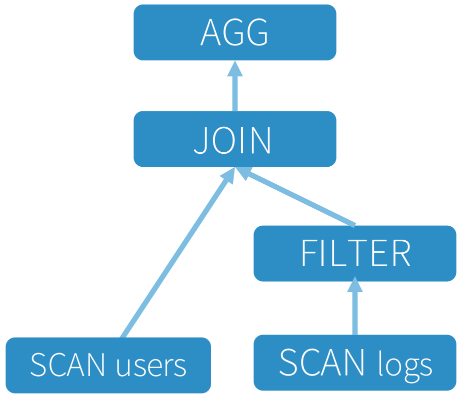


Series of Transformations that convert the initial query plan into an optimized plan

Catalyst Optimizer: An Overview

In Spark, the optimizer's goal is to minimize end-to-end query response time. Two key ideas:

- Prune unnecessary data as early as possible
  - e.g., filter pushdown, column pruning
- Minimize per-operator cost
  - e.g., broadcast vs shuffle, optimal join order



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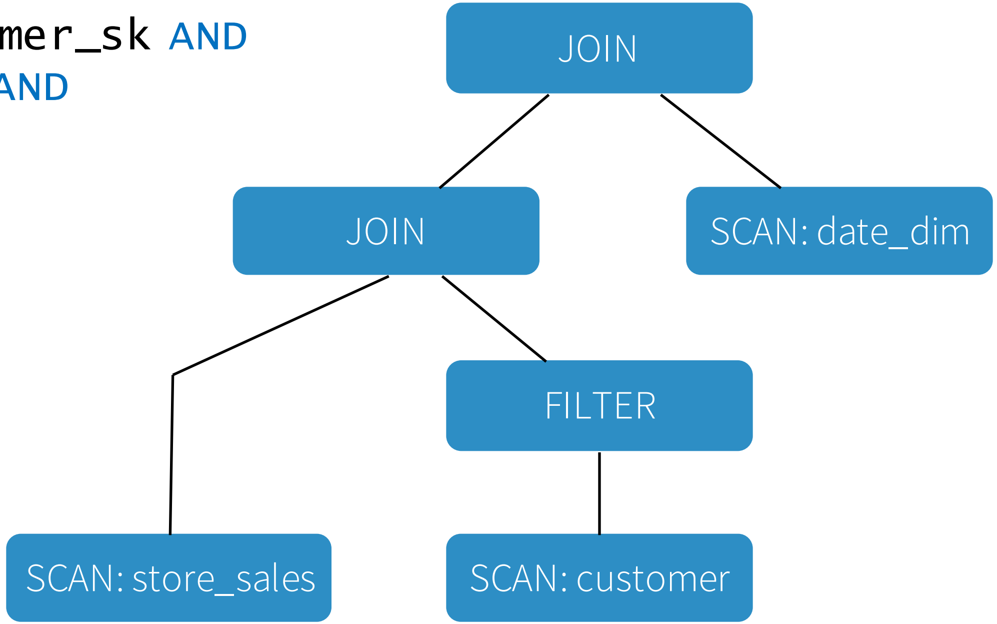
Rule-based Optimizer in Spark 2.1

- Most of Spark SQL optimizer's rules are heuristics rules.
  - `PushDownPredicate`, `ColumnPruning`, `ConstantFolding`,…
- Does NOT consider the cost of each operator
- Does NOT consider selectivity when estimating join relation size

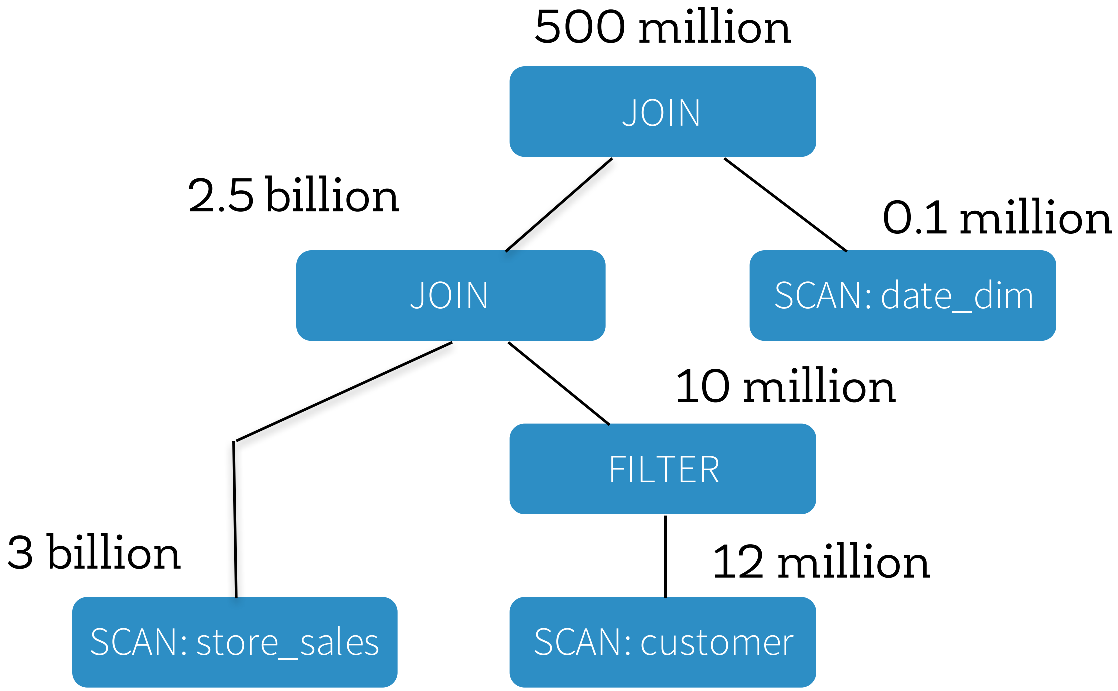
- Therefore:
  - Join order is mostly decided by its position in the SQL queries
  - Physical Join implementation is decided based on heuristics

An Example (TPC-DS q11 variant)

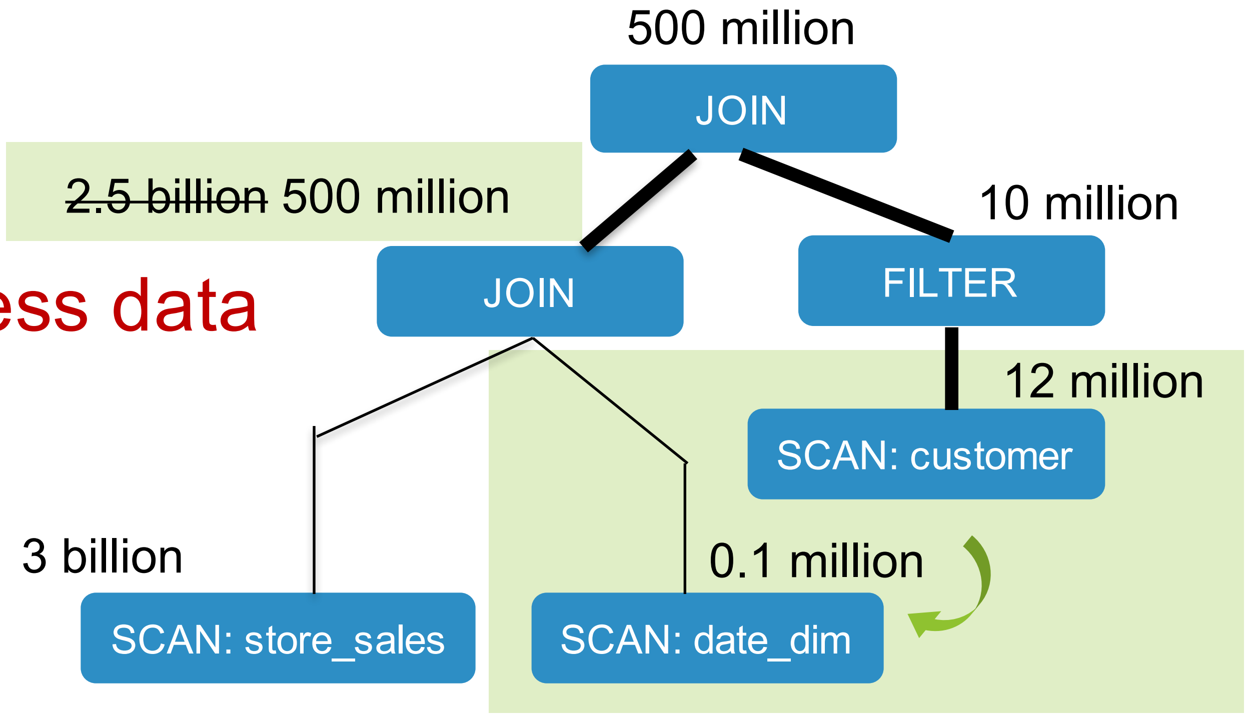
```
SELECT customer_id
FROM customer, store_sales, date_dim
WHERE c_customer_sk = ss_customer_sk AND
  ss_sold_date_sk = d_date_sk AND
  c_customer_sk > 1000
```



An Example (TPC-DS q11 variant)



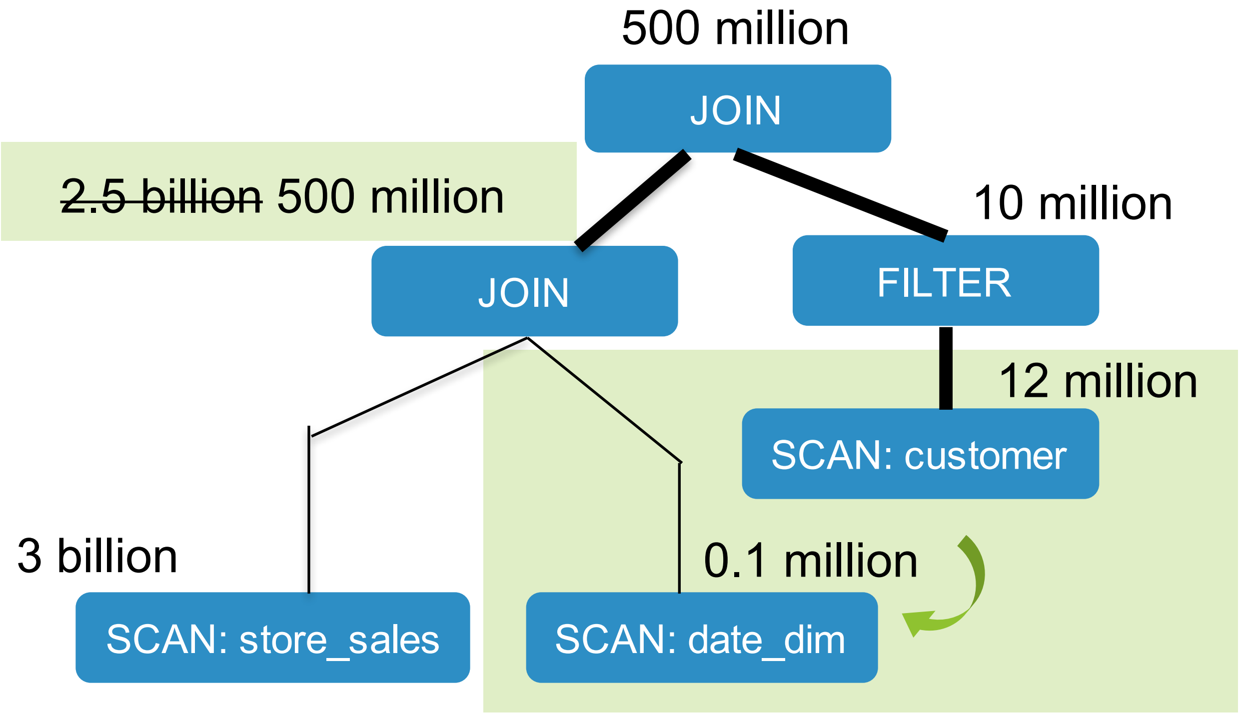
An Example (TPC-DS q11 variant)



80% less data

40% faster

An Example (TPC-DS q11 variant)



How do we automatically optimize queries like these?

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Cost Based Optimizer (CBO)

- Collect, infer and propagate table/column statistics on source/intermediate data
- Calculate the cost for each operator in terms of number of output rows, size of output, etc.
- Based on the cost calculation, pick the most optimal query execution plan

Rest of the Talk

- Statistics Collection Framework
  - Table/Column Level Statistics Collected
  - Cardinality Estimation (Filters, Joins, Aggregates etc.)
- Cost-based Optimizations
  - Build Side Selection
  - Multi-way Join Re-ordering
- TPC-DS Benchmarks
- Demo

Statistics Collection Framework and Cost Based Optimizations

Ron Hu
Huawei Technologies

Step 1: Collect, infer and propagate table and column statistics on source and intermediate data

Table Statistics Collected

- Command to collect statistics of a table.
  – Ex: `ANALYZE TABLE table-name COMPUTE STATISTICS`
- It collects table level statistics and saves into metastore.
  – Number of rows
  – Table size in bytes

Column Statistics Collected

- Command to collect column level statistics of individual columns.
  - Ex: `ANALYZE TABLE table-name COMPUTE STATISTICS FOR COLUMNS column-name1, column-name2, ….`
- It collects column level statistics and saves into meta-store.

Numeric/Date/Timestamp type

✓ Distinct count
✓ Max
✓ Min
✓ Null count
✓ Average length (fixed length)
✓ Max length (fixed length)

String/Binary type

✓ Distinct count
✓ Null count
✓ Average length
✓ Max length

Filter Cardinality Estimation

- Between Logical expressions: AND, OR, NOT
- In each logical expression: =, <, <=, >, >=, in, etc
- Current support type in Expression
  - For <, <=, >, >=, <=>: Integer, Double, Date, Timestamp, etc
  - For = , <=>: String, Integer, Double, Date, Timestamp, etc.
- Example: A <= B
  - Based on A, B's min/max/distinct count/null count values, decide the relationships between A and B. After completing this expression, we set the new min/max/distinct count/null count
  - Assume all the data is evenly distributed if no histogram information.

Filter Operator Example

- ***Column A (op) literal B***
  - (op) can be “=“, “<”, “<=”, “>”, “>=”, “like”
  - Like the styles as “l_orderkey = 3”, “l_shipdate <= “1995-03-21”
  - Column’s max/min/distinct count/null count should be updated
  - Example: **Column A < value B**

Filtering Factor = 100%
no need to change A’s statistics

Filtering Factor = 0%
need to change A’s statistics

Without histograms, suppose data is evenly distributed
Filtering Factor = (B.value – A.min) / (A.max – A.min)
A.min = no change
A.max = B.value
*A.ndv = A.ndv * Filtering Factor*

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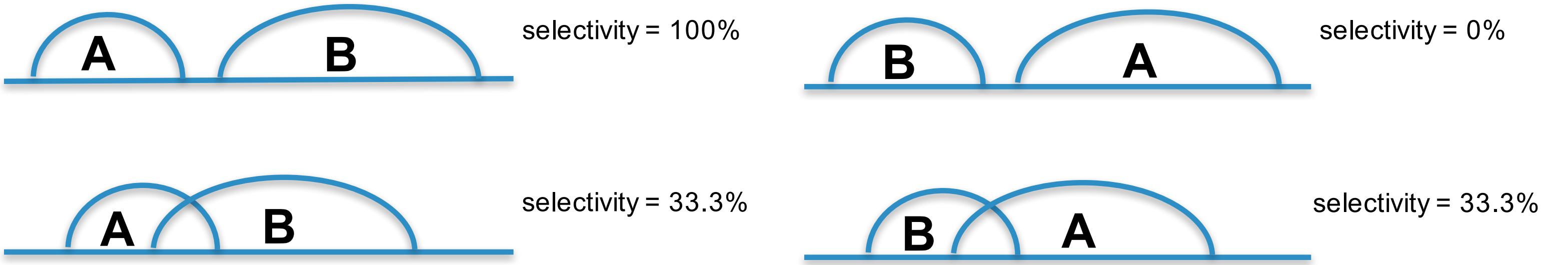
Filter Operator Example

- ***Column A (op) Column B***
  - (op) can be “<”, “<=”, “>”, “>=”
  - We cannot suppose the data is evenly distributed, so the empirical filtering factor is set to **1/3**
  - Example: **Column A < Column B**



Join Cardinality Estimation

- *Inner-Join:* The number of rows of “A join B on A.k1 = B.k1” is estimated as: `num`(A⋈ B) = `num`(A) * `num`(B) / `max` (`distinct`(A.k1), `distinct`(B.k1)),
  - where `num`(A) is the number of records in table A, `distinct` is the number of distinct values of that column.
  - The underlying assumption for this formula is that each value of the smaller domain is included in the larger domain.

- We similarly estimate cardinalities for Left-Outer Join, Right-Outer Join and Full-Outer Join

Other Operator Estimation

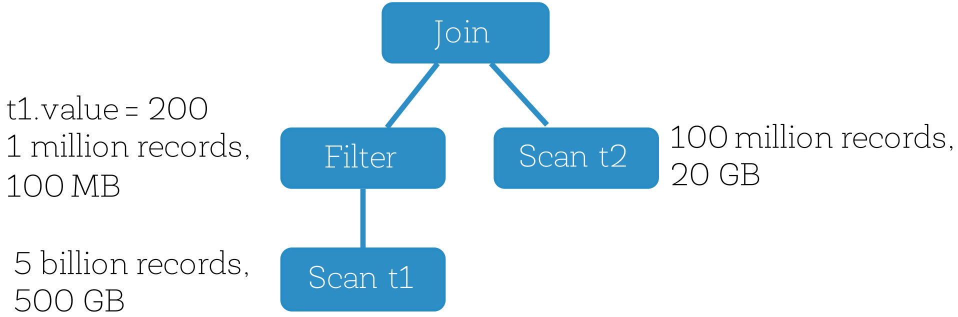
- Project: does not change row count
- Aggregate: consider uniqueness of group-by columns
- Limit, Sample, etc.

Step 2: Cost Estimation and Optimal Plan Selection

Build Side Selection

- For two-way hash joins, we need to choose one operand as build side and the other as probe side.

- Choose lower-cost child as build side of hash join.
  - Before: build side was selected based on original table sizes. ➔ BuildRight
  - Now with CBO: build side is selected based on estimated cost of various operators before join. ➔ BuildLeft



Hash Join Implementation: Broadcast vs. Shuffle

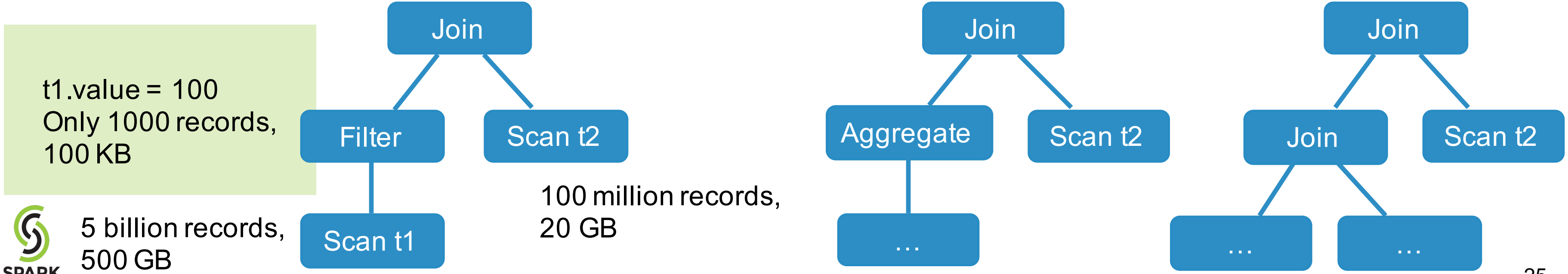
Logical Plan

- Equi-join
  - Inner Join
  - LeftSemi/LeftAnti Join
  - LeftOuter/RightOuter Join
- Theta-join

Physical Plan

- SortMergeJoinExec/ BroadcastHashJoinExec/ ShuffledHashJoinExec
- CartesianProductExec/ BroadcastNestedLoopJoinExec

- Broadcast Criterion: whether the join side's output size is small (default 10MB).



Multi-way Join Reorder

- Reorder the joins using a dynamic programming algorithm.
  1. First we put all items (basic joined nodes) into level 0.
  2. Build all two-way joins at level 1 from plans at level 0 (single items).
  3. Build all 3-way joins from plans at previous levels (two-way joins and single items).
  4. Build all 4-way joins etc, until we build all n-way joins and pick the best plan among them.

- When building m-way joins, only keep the best plan (optimal sub-solution) for the same set of m items.
  - E.g., for 3-way joins of items {A, B, C}, we keep only the best plan among: `(A J B) J C`, `(A J C) J B` and `(B J C) J A`

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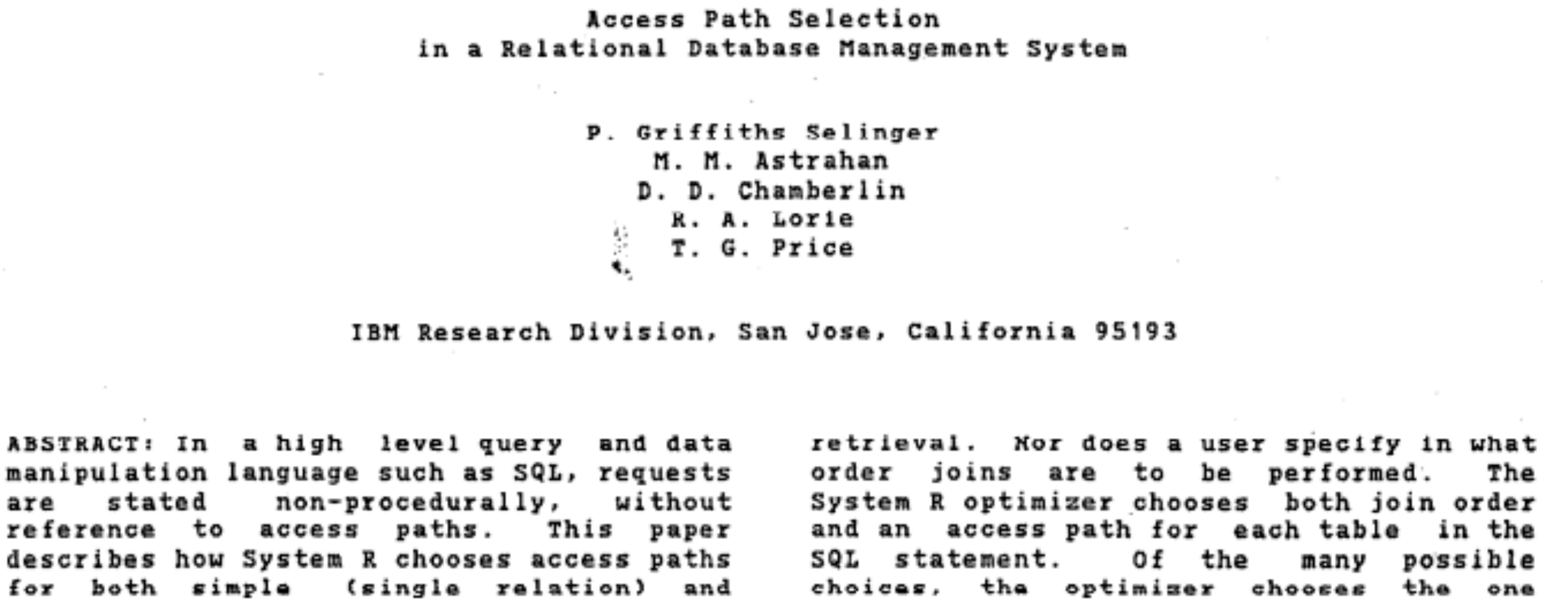
Multi-way Join Reorder



Access Path Selection
in a Relational Database Management System

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ABSTRACT: In a high level query and data manipulation language such as SQL, requests are stated non-procedurally, without reference to access paths. This paper describes how System R chooses access paths for both simple (single relation) and retrieval. Nor does a user specify in what order joins are to be performed. The System R optimizer chooses both join order and an access path for each table in the SQL statement. Of the many possible choices, the optimizer chooses the one

Selinger et al. Access Path Selection in a Relational Database Management System. In SIGMOD 1979

Join Cost Formula

- The cost of a plan is the sum of costs of all intermediate tables.
- `Cost = weight * Cost`$_{cpu}$ `+ Cost`$_{IO}$ `* (1 - weight)`
  - In Spark, we use
    `weight * cardinality + size * (1 – weight)`
  - `weight` is a tuning parameter configured via `spark.sql.cbo.joinReorder.card.weight` (0.7 as default)

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TPC-DS Benchmarks and Query Analysis

Zhenhua Wang

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Session 2 Topics

- Motivation
- Statistics Collection Framework
- Cost Based Optimizations
- TPC-DS Benchmark and Query Analysis
- Demo

Preliminary Performance Test

- Setup:
  - TPC-DS size at 1 TB (scale factor 1000)
  - 4 node cluster (Huawei FusionServer RH2288: 40 cores, 384GB mem)
  - Apache Spark 2.2 RC (dated 5/12/2017)

- Statistics collection
  - A total of 24 tables and 425 columns

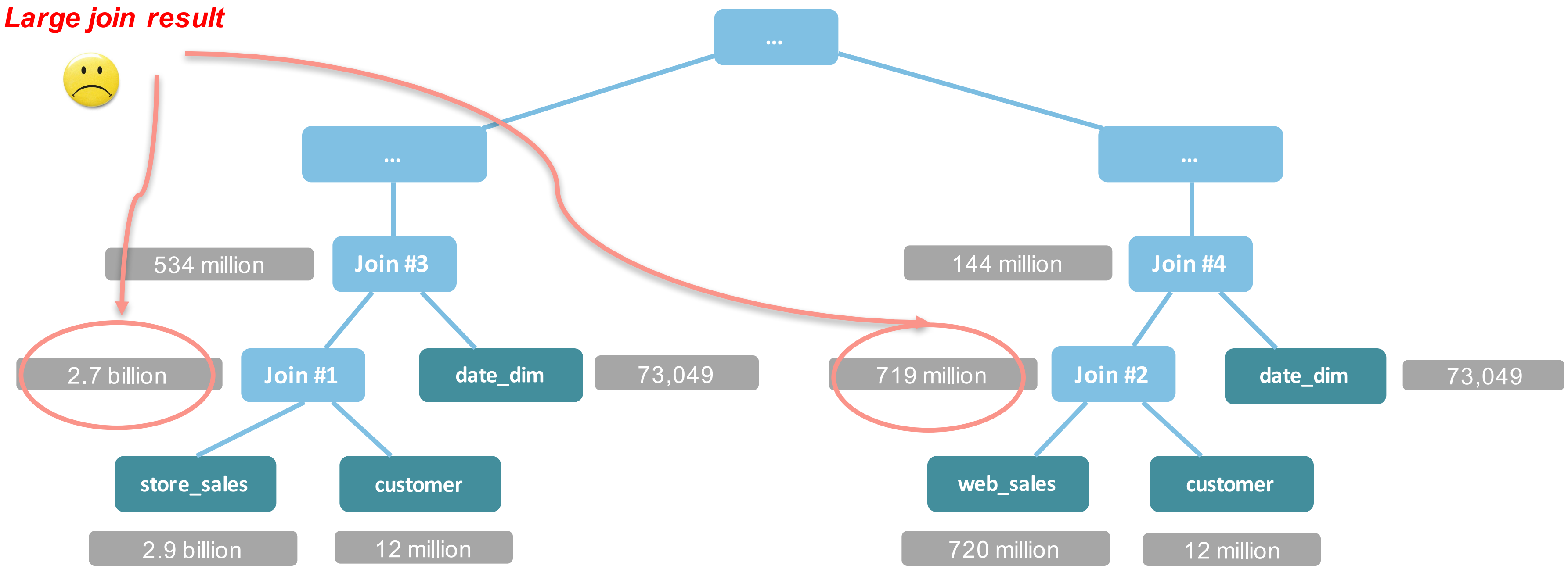
➢ Take 14 minutes to collect statistics for ***all* tables and *all* columns**.
  - Fast because all statistics are computed by integrating with Spark’s built-in aggregate functions.
  - Should take much less time if we collect statistics for columns used in predicate, join, and group-by only.

TPC-DS Query Q11

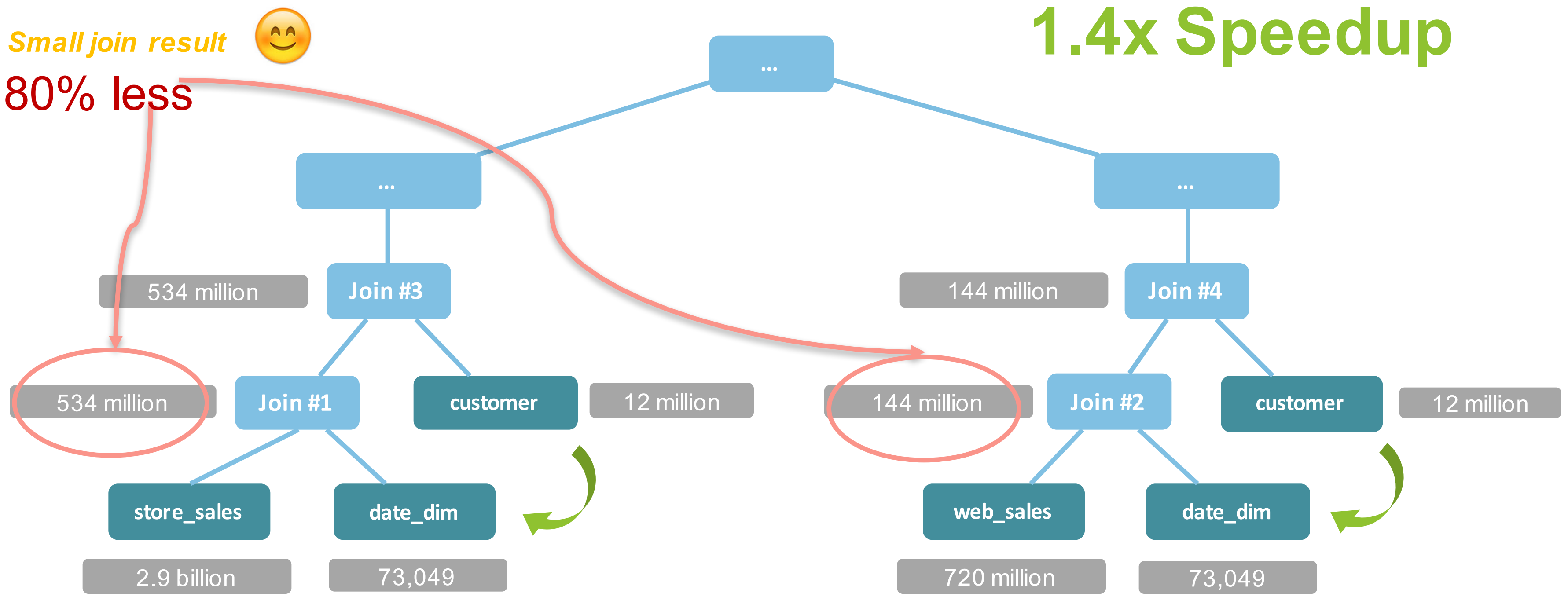
```
WITH year_total AS (
 SELECT
  c_customer_id customer_id,
  c_first_name customer_first_name,
  c_last_name customer_last_name,
  c_preferred_cust_flag customer_preferred_cust_flag,
  c_birth_country customer_birth_country,
  c_login customer_login,
  c_email_address customer_email_address,
  d_year dyear,
  sum(ss_ext_list_price - ss_ext_discount_amt) year_total,
  's' sale_type
 FROM customer, store_sales, date_dim
 WHERE c_customer_sk = ss_customer_sk
  AND ss_sold_date_sk = d_date_sk
 GROUP BY c_customer_id, c_first_name, c_last_name, d_year
  , c_preferred_cust_flag, c_birth_country, c_login, c_email_address, d_year
 UNION ALL
 SELECT
  c_customer_id customer_id,
  c_first_name customer_first_name,
  c_last_name customer_last_name,
  c_preferred_cust_flag customer_preferred_cust_flag,
  c_birth_country customer_birth_country,
  c_login customer_login,
  c_email_address customer_email_address,
  d_year dyear,
  sum(ws_ext_list_price - ws_ext_discount_amt) year_total,
  'w' sale_type
 FROM customer, web_sales, date_dim
 WHERE c_customer_sk = ws_bill_customer_sk AND ws_sold_date_sk = d_date_sk
 GROUP BY c_customer_id, c_first_name, c_last_name, c_preferred_cust_flag,
  c_birth_country, c_login, c_email_address, d_year)
```

```
SELECT t_s_secyear.customer_preferred_cust_flag
FROM year_total t_s_firstyear
 , year_total t_s_secyear
 , year_total t_w_firstyear
 , year_total t_w_secyear
WHERE t_s_secyear.customer_id = t_s_firstyear.customer_id
 AND t_s_firstyear.customer_id = t_w_secyear.customer_id
 AND t_s_firstyear.customer_id = t_w_firstyear.customer_id
 AND t_s_firstyear.sale_type = 's'
 AND t_w_firstyear.sale_type = 'w'
 AND t_s_secyear.sale_type = 's'
 AND t_w_secyear.sale_type = 'w'
 AND t_s_firstyear.dyear = 2001
 AND t_s_secyear.dyear = 2001 + 1
 AND t_w_firstyear.dyear = 2001
 AND t_w_secyear.dyear = 2001 + 1
 AND t_s_firstyear.year_total > 0
 AND t_w_firstyear.year_total > 0
 AND CASE WHEN t_w_firstyear.year_total > 0
 THEN t_w_secyear.year_total / t_w_firstyear.year_total
   ELSE NULL END
 > CASE WHEN t_s_firstyear.year_total > 0
 THEN t_s_secyear.year_total / t_s_firstyear.year_total
  ELSE NULL END
ORDER BY t_s_secyear.customer_preferred_cust_flag
LIMIT 100
```

Query Analysis – Q11 CBO OFF



Query Analysis – Q11 CBO ON

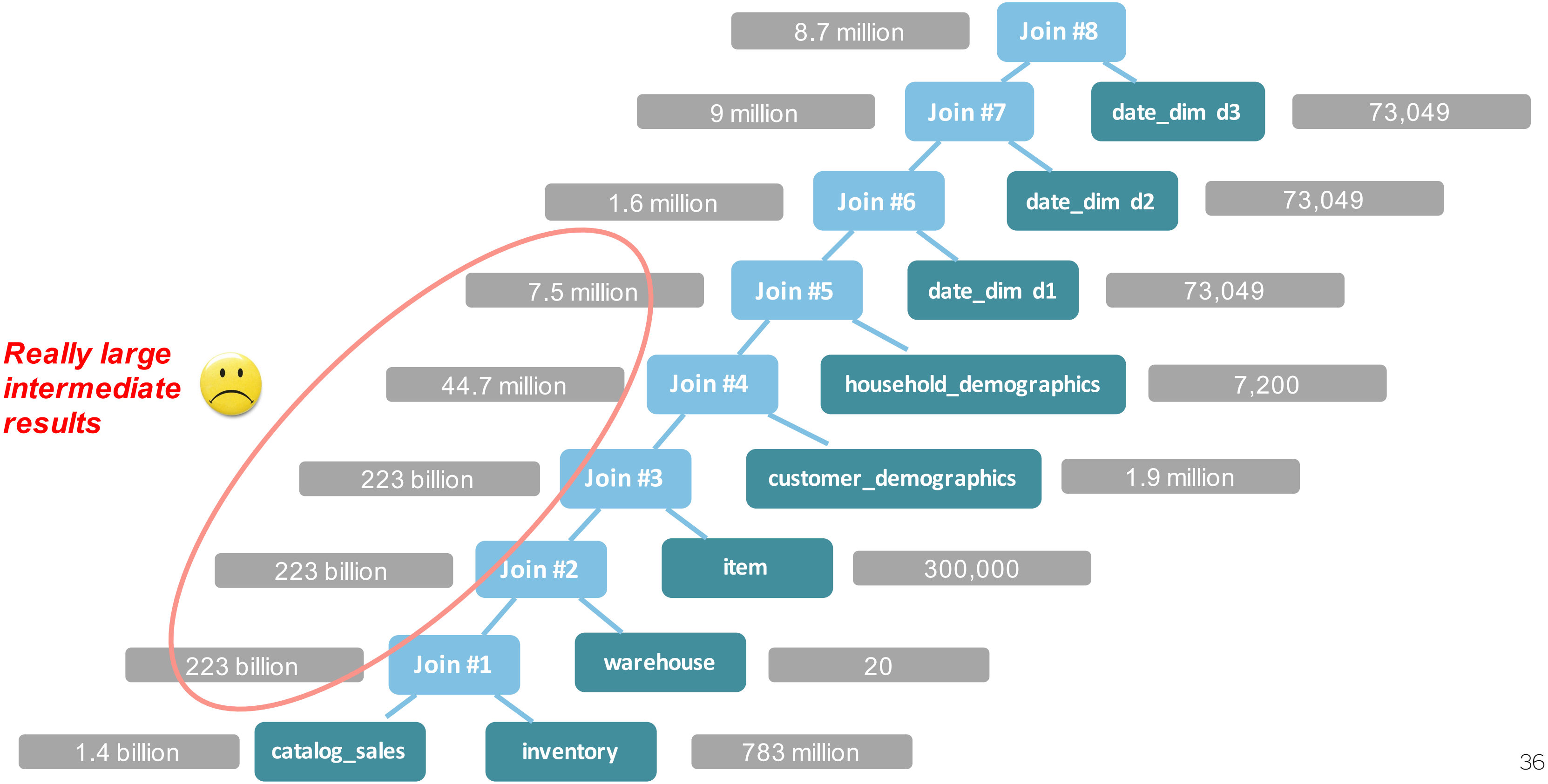


TPC-DS Query Q72

```
SELECT
  i_item_desc,
  w_warehouse_name,
  d1.d_week_seq,
  count(CASE WHEN p_promo_sk IS NULL
    THEN 1
        ELSE 0 END) no_promo,
  count(CASE WHEN p_promo_sk IS NOT NULL
    THEN 1
        ELSE 0 END) promo,
  count(*) total_cnt
FROM catalog_sales
  JOIN inventory ON (cs_item_sk = inv_item_sk)
  JOIN warehouse ON (w_warehouse_sk = inv_warehouse_sk)
  JOIN item ON (i_item_sk = cs_item_sk)
  JOIN customer_demographics ON (cs_bill_cdemo_sk = cd_demo_sk)
  JOIN household_demographics ON (cs_bill_hdemo_sk = hd_demo_sk)
  JOIN date_dim d1 ON (cs_sold_date_sk = d1.d_date_sk)
  JOIN date_dim d2 ON (inv_date_sk = d2.d_date_sk)
  JOIN date_dim d3 ON (cs_ship_date_sk = d3.d_date_sk)
  LEFT OUTER JOIN promotion ON (cs_promo_sk = p_promo_sk)
  LEFT OUTER JOIN catalog_returns ON (cr_item_sk = cs_item_sk AND cr_order_number = cs_order_number)
WHERE d1.d_week_seq = d2.d_week_seq
  AND inv_quantity_on_hand < cs_quantity
  AND d3.d_date > (cast(d1.d_date AS DATE) + interval 5 days)
  AND hd_buy_potential = '>10000'
  AND d1.d_year = 1999
  AND hd_buy_potential = '>10000'
  AND cd_marital_status = 'D'
  AND d1.d_year = 1999
GROUP BY i_item_desc, w_warehouse_name, d1.d_week_seq
ORDER BY total_cnt DESC, i_item_desc, w_warehouse_name, d_week_seq
LIMIT 100
```

Query Analysis – Q72 CBO OFF

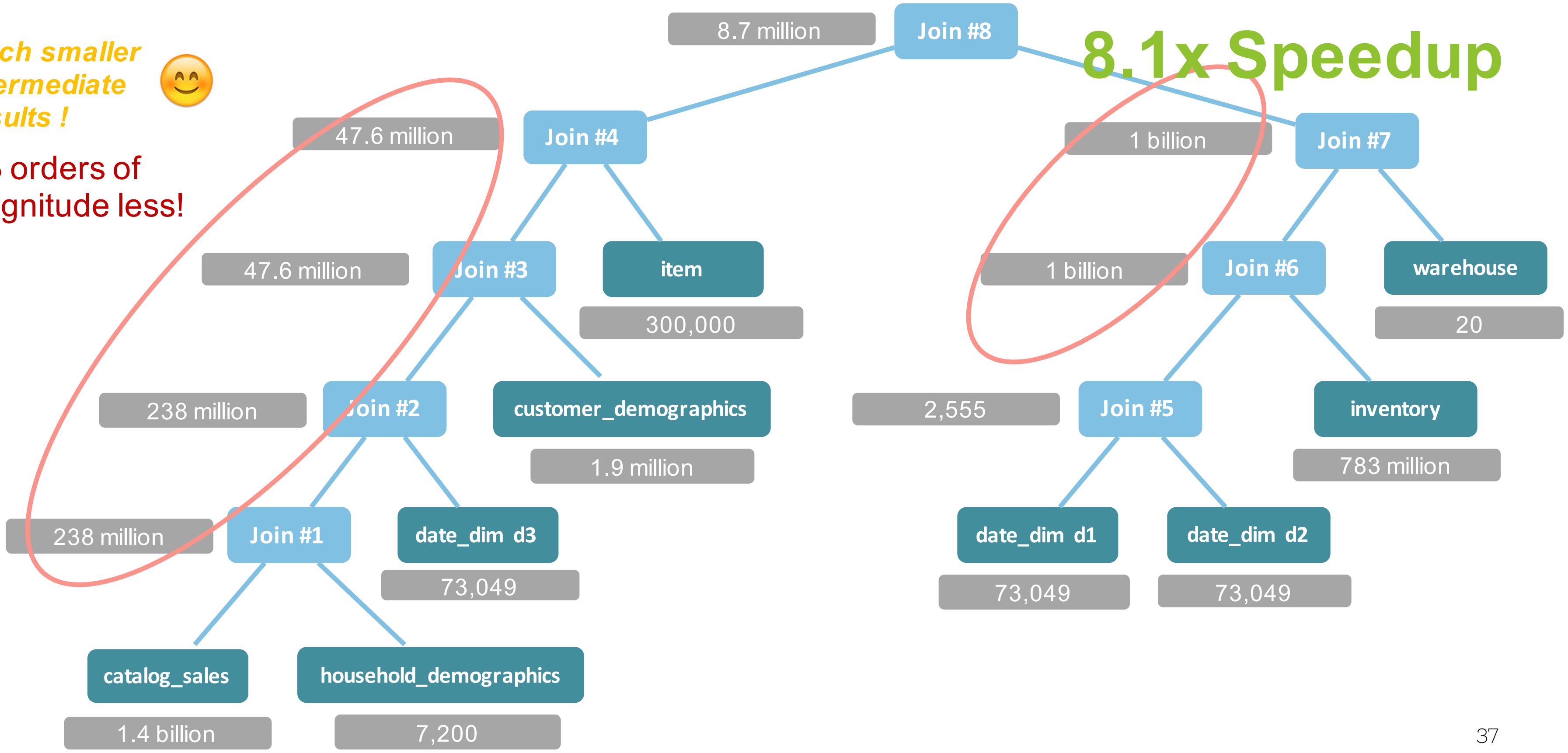
Really large intermediate results



Query Analysis – Q72 CBO ON

Much smaller intermediate results !

2-3 orders of magnitude less!



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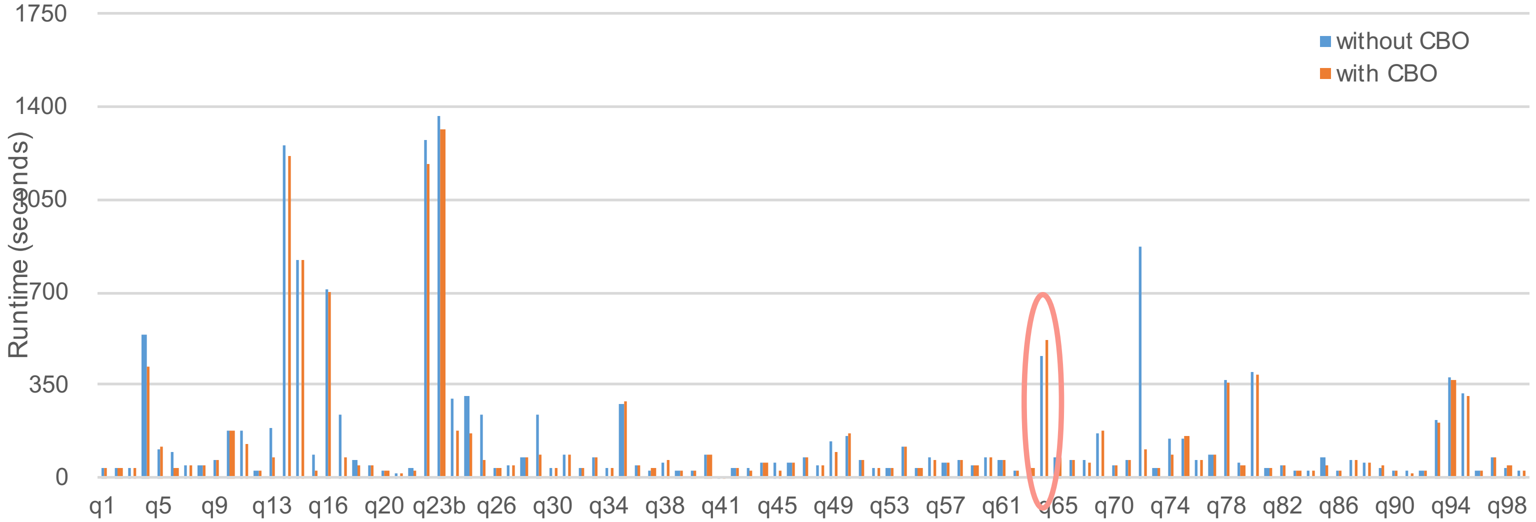
TPC-DS Query Performance



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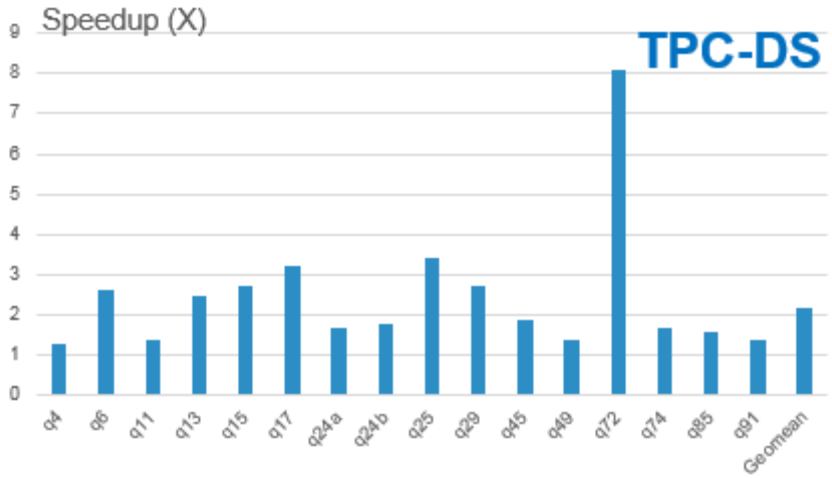
TPC-DS Query Speedup

- TPC-DS query speedup ratio with CBO versus without CBO

- 16 queries show speedup > 30%
- The max speedup is 8X.
- The geo-mean of speedup is 2.2X.



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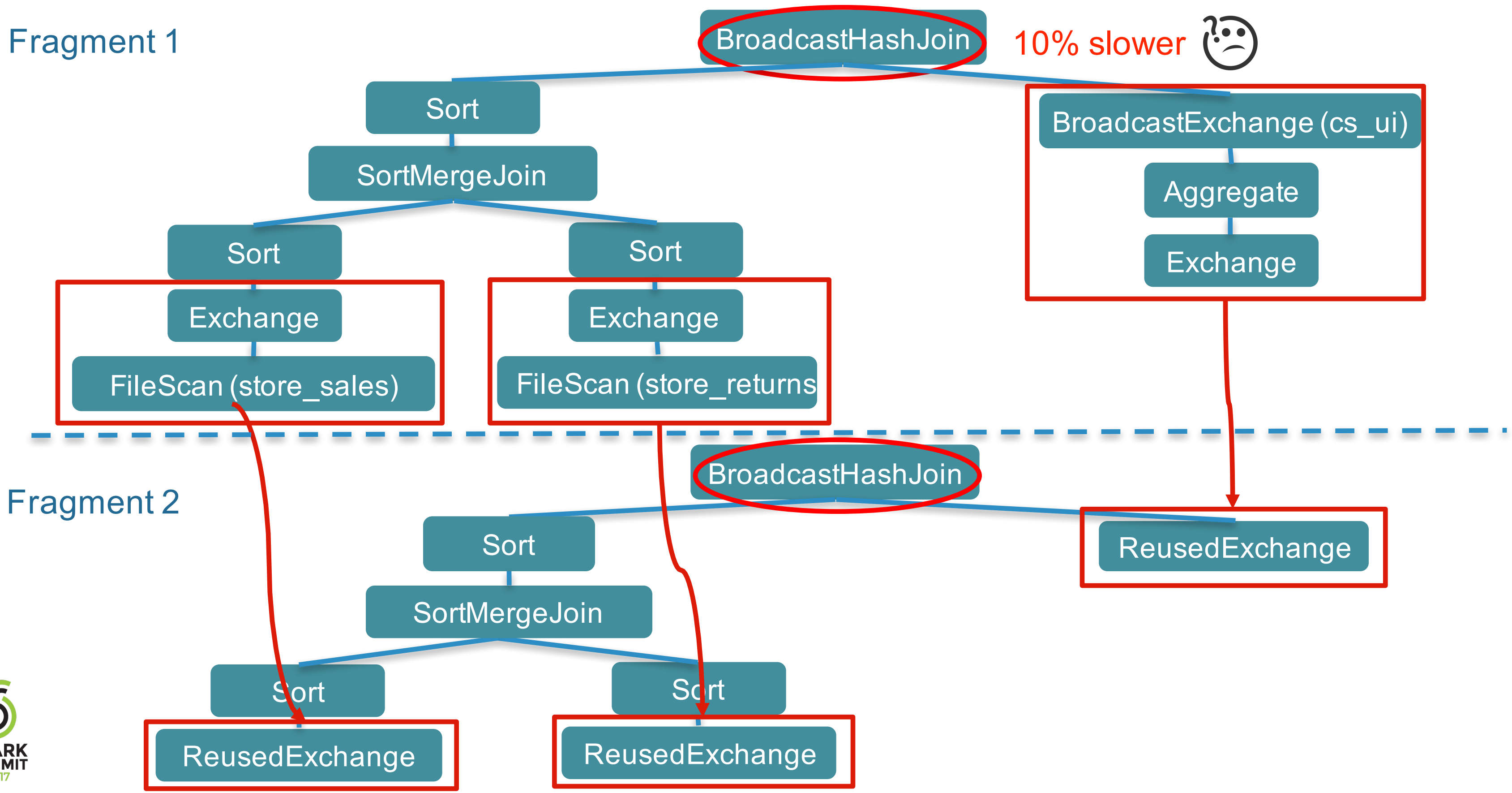
TPC-DS Query 64

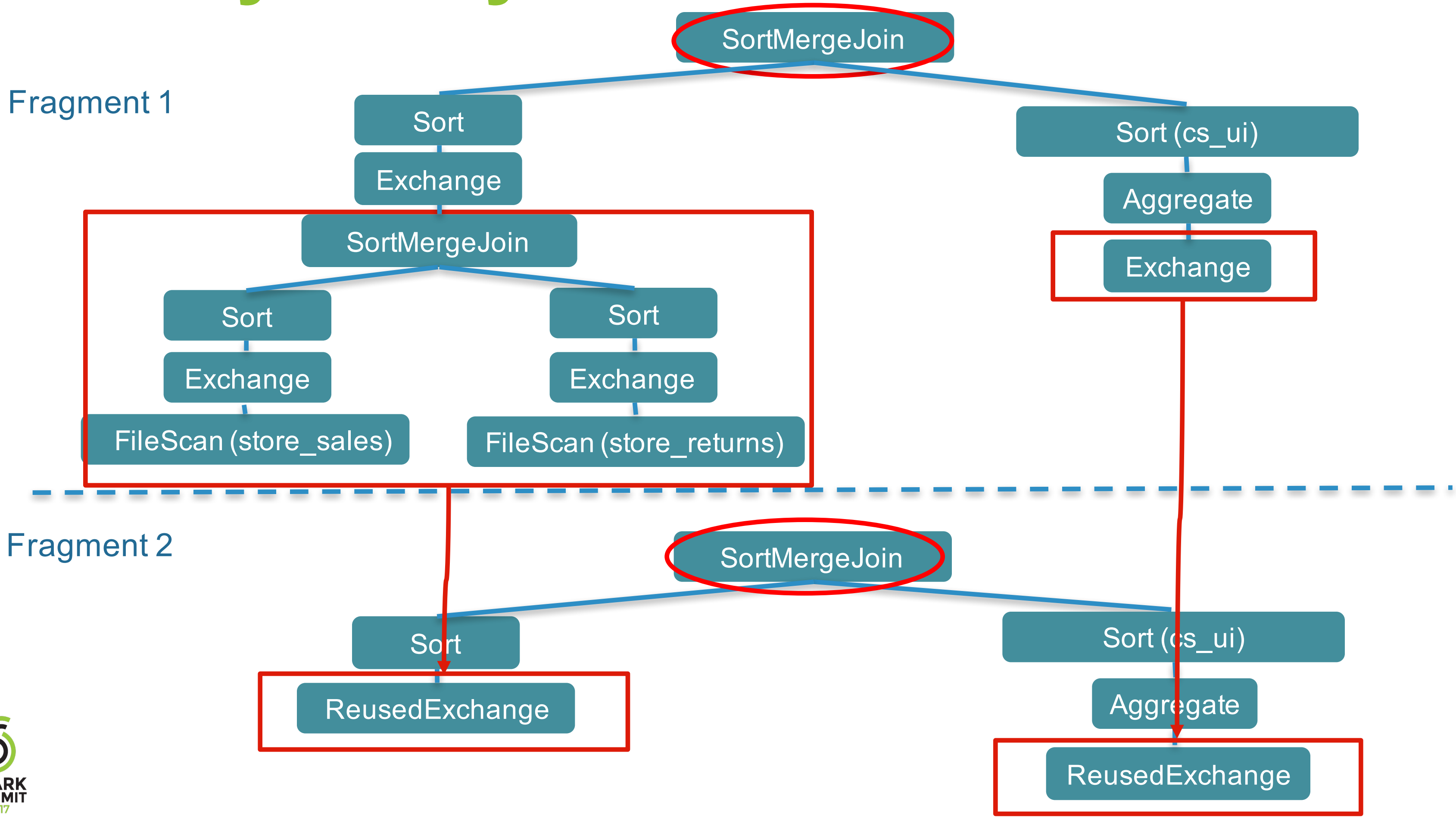
```
WITH cs_ui AS
 (SELECT
    cs_item_sk,
    sum(cs_ext_list_price) AS sale,
    sum(cr_refunded_cash + cr_reversed_charge + cr_store_credit) AS refund
  FROM catalog_sales, catalog_returns
  WHERE cs_item_sk = cr_item_sk AND cs_order_number = cr_order_number
  GROUP BY cs_item_sk
  HAVING sum(cs_ext_list_price) > 2 * sum(cr_refunded_cash + cr_reversed_charge + cr_store_credit)),
    cross_sales AS
  (SELECT
    i_product_name product_name, i_item_sk item_sk, s_store_name store_name,
    s_zip store_zip, ad1.ca_street_number b_street_number, ad1.ca_street_name b_streen_name,
    ad1.ca_city b_city, ad1.ca_zip b_zip, ad2.ca_street_number c_street_number,
    ad2.ca_street_name c_street_name, ad2.ca_city c_city, ad2.ca_zip c_zip,
    d1.d_year AS syear, d2.d_year AS fsyear, d3.d_year s2year,
    count(*) cnt, sum(ss_wholesale_cost) s1, sum(ss_list_price) s2, sum(ss_coupon_amt) s3
  FROM store_sales, store_returns, cs_ui, date_dim d1, date_dim d2, date_dim d3,
    store, customer, customer_demographics cd1, customer_demographics cd2,
    promotion, household_demographics hd1, household_demographics hd2,
    customer_address ad1, customer_address ad2, income_band ib1, income_band ib2, item
  WHERE ss_store_sk = s_store_sk AND ss_sold_date_sk = d1.d_date_sk AND
    ss_customer_sk = c_customer_sk AND ss_cdemo_sk = cd1.cd_demo_sk AND
    ss_hdemo_sk = hd1.hd_demo_sk AND ss_addr_sk = ad1.ca_address_sk AND
    ss_item_sk = i_item_sk AND ss_item_sk = sr_item_sk AND
    ss_ticket_number = sr_ticket_number AND ss_item_sk = cs_ui.cs_item_sk AND
    c_current_cdemo_sk = cd2.cd_demo_sk AND c_current_hdemo_sk = hd2.hd_demo_sk AND
    c_current_addr_sk = ad2.ca_address_sk AND c_first_sales_date_sk = d2.d_date_sk AND
    c_first_shipto_date_sk = d3.d_date_sk AND ss_promo_sk = p_promo_sk AND
    hd1.hd_income_band_sk = ib1.ib_income_band_sk AND
    hd2.hd_income_band_sk = ib2.ib_income_band_sk AND
    cd1.cd_marital_status <> cd2.cd_marital_status AND
    i_color IN ('purple', 'burlywood', 'indian', 'spring', 'floral', 'medium') AND
    i_current_price BETWEEN 64 AND 64 + 10 AND i_current_price BETWEEN 64 + 1 AND 64 + 15
  GROUP BY i_product_name, i_item_sk, s_store_name, s_zip, ad1.ca_street_number,
    ad1.ca_street_name, ad1.ca_city, ad1.ca_zip, ad2.ca_street_number,
    ad2.ca_street_name, ad2.ca_city, ad2.ca_zip, d1.d_year, d2.d_year, d3.d_year)
```

```
SELECT
  cs1.product_name,
  cs1.store_name,
  cs1.store_zip,
  cs1.b_street_number,
  cs1.b_streen_name,
  cs1.b_city,
  cs1.b_zip,
  cs1.c_street_number,
  cs1.c_street_name,
  cs1.c_city,
  cs1.c_zip,
  cs1.syear,
  cs1.cnt,
  cs1.s1,
  cs1.s2,
  cs1.s3,
  cs2.s1,
  cs2.s2,
  cs2.s3,
  cs2.syear,
  cs2.cnt
FROM cross_sales cs1, cross_sales cs2
WHERE cs1.item_sk = cs2.item_sk AND
  cs1.syear = 1999 AND
  cs2.syear = 1999 + 1 AND
  cs2.cnt <= cs1.cnt AND
  cs1.store_name = cs2.store_name AND
  cs1.store_zip = cs2.store_zip
ORDER BY cs1.product_name, cs1.store_name, cs2.cnt
```

Query Analysis – Q64 CBO ON



Query Analysis – Q64 CBO OFF



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CBO Demo

Wenchen Fan
Databricks

Current Status, Credits and Future Work

Ron Hu

Huawei Technologies

Available in Apache Spark 2.2

- Configured via `spark.sql.cbo.enabled`
- ‘Off By Default’. Why?
  - Spark is used in production
  - Many Spark users may already rely on “human intelligence” to write queries in best order
  - Plan on enabling this by default in Spark 2.3
- We encourage you test CBO with Spark 2.2!

Current Status

- SPARK-16026 is the umbrella jira.
  - 32 sub-tasks have been resolved
  - A big project spanning 8 months
  - 10+ Spark contributors involved
  - 7000+ lines of Scala code have been contributed
- Good framework to allow integrations
  - Use statistics to derive if a join attribute is unique
  - Benefit star schema detection and its integration into join reorder

Birth of Spark SQL CBO

- Prototype
  - In 2015, Ron Hu, Fang Cao, etc. of Huawei’s research department prototyped the CBO concept on Spark 1.2.
  - After a successful prototype, we shared technology with Zhenhua Wang, Fei Wang, etc of Huawei’s product development team.
- We delivered a talk at Spark Summit 2016:
  - “Enhancing Spark SQL Optimizer with Reliable Statistics”.
- The talk was well received by the community.
  - https://issues.apache.org/jira/browse/SPARK-16026

Collaboration

- Good community support
  - Developers: Zhenhua Wang, Ron Hu, Reynold Xin, Wenchen Fan, Xiao Li
  - Reviewers: Wenchen, Herman, Reynold, Xiao, Liang-chi, Ioana, Nattavut, Hyukjin, Shuai, …..
  - Extensive discussion in JIRAs and PRs (tens to hundreds conversations).
  - All the comments made the development time longer, but improved code quality.
- It was a pleasure working with community.

Future Work: Cost Based Optimizer

- Current cost formula is coarse.

  Cost = cardinality * weight + size * (1 - weight)

- Cannot tell the cost difference between sort-merge join and hash join
  - spark.sql.join.preferSortMergeJoin defaults to true.
- Underestimates (or ignores) shuffle cost.
- Will improve cost formula in next release.

Future Work: Statistics Collection Framework

- Advanced statistics: e.g. histograms, sketches.
- Hint mechanism.
- Partition level statistics.
- Speed up statistics collection by sampling data for large tables.

Conclusion

- Motivation
- Statistics Collection Framework
  - Table/Column Level Statistics Collected
  - Cardinality Estimation (Filters, Joins, Aggregates etc.)
- Cost-based Optimizations
  - Build Side Selection
  - Multi-way Join Re-ordering
- TPC-DS Benchmarks
- Demo

Thank You.

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Sameer’s Office Hours @ 4:30pm Today
Wenchen’s Office Hours @ 3pm Tomorrow

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Multi-way Join Reorder – Example

- Given A J B J C J D with join conditions A.k1 = B.k1 and B.k2 = C.k2 and C.k3 = D.k3

level 0: p({A}), p({B}), p({C}), p({D})

level 1: p({A, B}), p({A, C}), p({A, D}), p({B, C}), p({B, D}), p({C, D})

level 2: p({A, B, C}), p({A, B, D}), p({A, C, D}), p({B, C, D})

level 3: p({A, B, C, D}) -- final output plan

Multi-way Join Reorder – Example

- Pruning strategy: exclude cartesian product candidates. This significantly reduces the search space.

level 0: p({A}), p({B}), p({C}), p({D})

level 1: p({A, B}), ~~p({A, C})~~, ~~p({A, D})~~, p({B, C}), ~~p({B, D})~~, p({C, D})

level 2: p({A, B, C}), ~~p({A, B, D})~~, ~~p({A, C, D})~~, p({B, C, D})

level 3: p({A, B, C, D}) -- final output plan

New Commands in Apache Spark 2.2

- CBO commands
  - Collect table-level statistics
    - *ANALYZE TABLE table_name COMPUTE STATISTICS*
  - Collect column-level statistics
    - *ANALYZE TABLE table-name COMPUTE STATISTICS FOR COLUMNS column_name1, column_name2, …*
  - Display statistics in the optimized logical plan

```
> EXPLAIN COST
> SELECT cc_call_center_sk, cc_call_center_id FROM call_center;
…
== Optimized Logical Plan ==
Project [cc_call_center_sk#75, cc_call_center_id#76], Statistics(sizeInBytes=1680.0 B, rowCount=42, hints=none)
+- Relation[…31 fields] parquet, Statistics(sizeInBytes=22.5 KB, rowCount=42, hints=none)
…
```

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