Distributed query optimization

Data Management for Big Data
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These slides are a modified version of the slides provided with the book
Özsu and Valduriez, *Principles of Distributed Database Systems* (3rd Ed.), 2011
The original version of the slides is available at: extras.springer.com

Outline (distributed DB)

- Introduction (Ch. 1) *
- Distributed Database Design (Ch. 3) *
- Distributed Query Processing (Ch. 6-8) *
  - Overview (Ch. 6) *
  - Query decomposition and data localization (Ch. 7) *
  - **Distributed query optimization (Ch. 8)** *
- Distributed Transaction Management (Ch. 10-12) *

* Özsu and Valduriez, *Principles of Distributed Database Systems* (3rd Ed.), 2011

Outline (today)

- Distributed query optimization (Ch. 8) *
  - Overview
  - Join Ordering in Localized Queries
  - Semijoin-based Algorithm
  - Distributed query optimization strategies
  - Hybrid approaches

* Özsu and Valduriez, *Principles of Distributed Database Systems* (3rd Ed.), 2011

Distributed Query Optimization

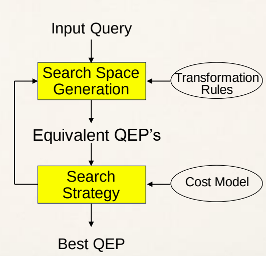
- In previous chapter (Ch. 7) *:
  - A distributed query is mapped into a query over fragments (decomposition and data localization)
  - Simplification ("optimization") independent from relation (fragment) statistics (e.g., cardinality)
- In this chapter (Ch. 8) *:
  - Optimization based on DB statistics (order of operations and operands, algorithm to perform simple operations) to produce a query execution plan (QEP)
    - In the distributed case a QEP is further extended with communication operations to support execution of queries over fragment sites
  - Once again: the problem is NP-hard, so not looking for the optimal solution
  - Statement of the problem
    - Input: Fragment query
    - Output: the *best* (not necessarily optimal) global schedule
  - Additional problems specific to the distributed setting
    - Where to execute (partial) queries? Which relation to ship where?
    - Choose between data transfer methods : ship-whole vs. fetch-as-needed
    - Decide on the use of semijoins (semijoins save on communication at the expense of more local processing)

* Özsu and Valduriez, *Principles of Distributed Database Systems* (3rd Ed.), 2011

Structure of the Optimizer

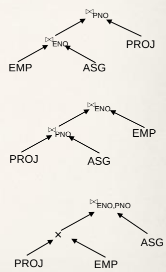
- Similar to the centralized case
  - Solution space (aka search space)
    - The set of equivalent QEP: algebra expressions enriched with implementation details **and communication choices**
  - Cost model
    - Cost prediction for local and global operations based on catalog statistics
    - Cost function (in terms of time)
      - I/O cost + CPU cost + **communication cost**
      - These might have different weights in different distributed environments (LAN vs WAN)
      - Can also maximize throughput
      - In early approach only communication costs were considered; due to fast communication technology, communication and I/O costs become comparable
  - Search algorithm (aka search strategy)
    - How do we move inside the solution space?
      - Exhaustive search, heuristic algorithms (iterative improvement, simulated annealing, genetic,...)
    - Goal is finding a good strategy according to the cost model
- Difference between centralized and distributed settings: search space and cost model (*search strategy* remains the same)

Query Optimization Process



Search Space

- Search space is large
  - *N* relations ➡ ((2(N-1))!)/((N-1)!) * equivalent join trees (by join commutativity and associativity)
  - ```
    SELECT   ENAME,RESP
    FROM     EMP, ASG,PROJ
    WHERE    EMP.ENO=ASG.ENO
    AND      ASG.PNO=PROJ.PNO
    ```
- Focus on join trees
- A difference
  - A good heuristics for centralized context: left-deep trees
  - In distributed context: non left-deep trees allow for parallelization



* In Özsu and Valduriez, *Principles of Distributed Database Systems* (3rd Ed.), 2011: it is said *O(N!)*, which is incorrect

Centralized vs. Distributed Query Optimization

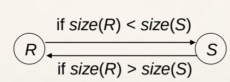
- Relation between centralized and distributed query optimization
  - Distributed query optimization (DQO) employs techniques and solutions from the centralized context
    - A distributed query is translated into local ones (localized queries): centralized query optimization (CQO) techniques
    - Distributed query optimization is a more general (and thus difficult) problem
      - Most solution to DQO extend solutions to CQO
  - We focus on communication costs (local CPU and I/O costs are ignored)
    - Clearly, cost of localized queries (handled with CQO techniques) is computed as in the centralized case (mainly I/O costs)

Join Ordering in Localized Queries

- Join ordering is important in centralized query optimization
- It is even more in distributed query optimization (reduce communication costs)
- Use of semijoins to reduce relation sizes (and thus communication costs) before performing join operations

Join Ordering – 2 relations

- We assume query to be already localized (i.e., on fragments)
  - Fragments are relations entirely stored at a single site
    - We often use "fragments" and "relations" indistinguishably (no technical reason to distinguish them)
- We first focus on ordering issues without using semijoins
  - Consider two relations only: $R \bowtie S$ (*R* and *S* are at different sites)
    - Move the smaller relation to the site of the larger one

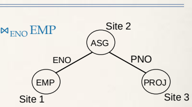


Join Ordering – Multiple Relations

- Multiple relations case: more difficult because too many alternatives
- Goal is still transmit small operands (relations)
  - Compute the cost of all alternatives and select the best one
    - Necessary to compute the size of intermediate relations which is difficult
      - In distributed context it is even more because information may be not available on site

Join Ordering – Example

Consider PROJ $\bowtie_{PNO}$ ASG $\bowtie_{ENO}$ EMP



Join graph of distributed query

Execution alternatives:

1. EMP → Site 2
   Site 2 computes EMP'=EMP ⋈ ASG
   EMP' → Site 3
   Site 3 computes EMP' ⋈ PROJ
2. ASG → Site 1
   Site 1 computes EMP'=EMP ⋈ ASG
   EMP' → Site 3
   Site 3 computes EMP' ⋈ PROJ
3. ASG → Site 3
   Site 3 computes ASG'=ASG ⋈ PROJ
   ASG' → Site 1
   Site 1 computes ASG' ⋈ EMP
4. PROJ → Site 2
   Site 2 computes PROJ'=PROJ ⋈ ASG
   PROJ' → Site 1
   Site 1 computes PROJ' ⋈ EMP
5. EMP → Site 2
   PROJ → Site 2
   Site 2 computes EMP ⋈ PROJ ⋈ ASG
    ```

Semijoin Algorithms

- Semijoins can be used to reduce the sizes of operands to transfer (similar to what selections do)
  - Reduced communication costs
- Consider the join of two relations:
  - R (at site 1)
  - S (at site 2)
- Alternatives:
  1. Do the join $R \bowtie_A S$
  2. Perform one of the semijoin-based equivalent options

$$R \bowtie_A S \Leftrightarrow (R \ltimes_A S) \bowtie_A S$$
$$\Leftrightarrow R \bowtie_A (S \ltimes_A R)$$
$$\Leftrightarrow (R \ltimes_A S) \bowtie_A (S \ltimes_A R)$$

Tradeoff between

a) cost to compute and send semijoin to other site (and then perform the join there)

b) Cost to send the whole relation to other site (and then perform the join there)

Semijoin Algorithms – Example

- Perform the join
  - Send R to Site 2
  - Site 2 computes $R \bowtie_A S$
- Consider semijoin $(R \ltimes_A S) \bowtie_A S$
  - $S' = \Pi_A(S)$
  - $S' \rightarrow$ Site 1
  - Site 1 computes $R' = R \ltimes_A S'$
  - $R' \rightarrow$ Site 2
  - Site 2 computes $R' \bowtie_A S$
- Semijoin is better if

$$size(\Pi_A(S)) + size(R \ltimes_A S)) < size(R)$$

  - Only communication costs (time to transfer relations)

Semijoin Algorithms – Sum up

- Using semijoin is convenient if $R \ltimes_A S$ has high selectivity (select few tuples) and/or size of R is large
- It is bad otherwise, due to the additional transfer of $\Pi_A(S)$
- Cost of transferring $\Pi_A(S)$ can be reduced by using bit arrays
- A disadvantage of using semijoin is the loss of indices

Bit arrays

- Let h be a hash function that distributes possible values for A into n buckets:

$$h : Dom(A) \longrightarrow \{ 0, \ldots, n\text{-}1 \}$$

- Bit array $BA[0 .. n\text{-}1]$ over relation S is defined as:

$BA[i] = 1$ iff $\exists$ value v for attribute A in S s.t. $h(v) = i$

- Transfer BA (n bits) rather than $\Pi_A(S)$
- A tuple of R with value v for attribute A belongs to R' iff $BA[h(v)] = 1$
- R' is an (over-)approximation of $R \ltimes_A S$

Bit Arrays for Seminoins

R

id_R	A
1	1
2	2
3	2
4	5
5	4
6	5
7	4
8	5

S

id_S	A
1	5
2	5
3	3
4	5
5	3

$R' \supsetneq R \ltimes_A S$

id_R	A
1	1
4	5
6	5
8	5

id_S	A
4	5
6	5
8	5

R' : $R \ltimes_A S$ computed with bit array

- Recall:
  - $BA[i] = 1$ iff $\exists$ value v for attribute A in S s.t. $h(v) = i$
  - a tuple of R with value v for A belongs to R' iff $BA[h(v)] = 1$
- $h(x) = x \bmod 4$
- $n = 4$ (4 buckets)
- $h(1) = h(5) = 1$
- $BA[0] = 0$ (no value v occurs in $S.A$ s.t. $h(v) = 0$)
- $BA[1] = 1$ (due to occurrence of 5 for attribute A in S)
- $BA[2] = 0$ (no value v occurs in $S.A$ s.t. $h(v) = 2$)
- $BA[3] = 1$ (due to occurrence of 3 for attribute A in S)

R′ contains tuple <1,1> that does not belong to $R \ltimes_A S$

However, R' is a good approximation because h has only one conflict ($h(1) = h(5)$) among values for attribute A in R and S

Semijoins for Joins among Multiple Relations

- Semijoins to optimize joins among more than 2 operands

$$\text{EMP} \bowtie \text{ASG} \bowtie \text{PROJ} = \text{EMP}' \bowtie \text{ASG}' \bowtie \text{PROJ}$$

where $\text{EMP}' = \text{EMP} \ltimes \text{ASG}$
and $\text{ASG}' = \text{ASG} \ltimes \text{PROJ}$

- Each operand can be further reduced using more than one semijoin in cascade

$$\text{EMP}'' = \text{EMP} \bowtie (\text{ASG} \bowtie \text{PROJ})$$

Semijoin program

We have $size(\text{ASG} \bowtie \text{PROJ}) <= size(\text{ASG})$
Therefore $size(\text{EMP}'') <= size(\text{EMP}')$

- Full reducer for a relation is the semijoin program that reduces the relation the most
- Finding full reducer for a relation with exhaustive brute force approach
  - For cyclic queries full reducer cannot be found
    - Solution: break the cycle
  - With other queries: inefficient (NP-hard)
    - Solution: only use semijoin when problem is simple
      - e.g., for chained queries, where relations are in sequence and each one joins with the next one

Distributed Query Optimization

- We focus on optimization of joins
- The algorithm for optimizing a join is adapted from the one for the centralized case
- In distributed context
  - There is a coordinator (master site) where query is initiated
  - Coordinator chooses
    1. execution site and
    2. transfer method
  - Apprentice sites (where fragments are stored and queries are executed)
    - Apprentices behave as in the case of centralized query optimization in optimizing localized queries (over fragments) assigned to them
      - Choose best join ordering, join algorithm, and access method for relations

Choices of the Master Site

1. Choice of the execution sites
   - E.g., $R \bowtie S$ can be executed:
     - at the site where R is stored
     - at the site where S is stored
     - at a third site (e.g., where a 3rd relation waits to be joined – allows for parallel transfer)
2. Transfer method
   - *ship-whole*: relation is transferred to the join execution site entirely
     - In some cases (e.g., for outer relations of in case of merge join) there is no need to store the relation: join as it arrives, in pipelined mode
   - *fetch-as-needed* (only needed tuples are transferred, i.e., tuples selected by the join):
     - equivalent to perform semijoin of one relation with tuple of the other one (to reduce size of the former) before executing the join
     - e.g., semi-join of inner relation wrt outer one (only needed tuples of inner relation are transferred)
       - ✓ tuples of the outer relation are sent (only the join attribute) to the site of the inner relation
       - ✓ matching tuples of the inner relation are sent to the site of the external relation to execute the join

Choices of the master produce 4 strategies (not all combinations are worth being considered)

Strategy 1 – *ship-whole/inner* site

1. *ship-whole*/site of *inner* relation: move outer relation (R) to the site of the inner relation (S)

   (a) Retrieve outer tuples

   (b) Send them to the inner relation site

   (c) Join them as they arrive

- $CT(x)$: communication time to transfer x bytes
- $LT(x)$: local processing time to perform op. x
- $s = card(S \ltimes_A R)/card(R)$: average number of tuples of S that match a tuple of R

Total Cost = LT (retrieve $card(R)$ tuples from R)
+ CT ($size(R)$)
+ LT (retrieve s tuples from S) * $card(R)$

Join is done as R comes because R is the outer relation

Strategy 2 – *ship-whole/outer* site

2. *ship-whole*/site of *outer* relation: move inner relation (S) to the site of outer relation (R)

   Cannot join as S arrives; it needs to be stored

Total cost = LT (retrieve $card(S)$ tuples from S)
+ CT ($size(S)$)
+ LT (store $card(S)$ tuples in temporary relation T)
+ LT (retrieve $card(R)$ tuples from R)
+ LT (retrieve s tuples from T) * $card(R)$

- $CT(x)$: communication time to transfer x bytes
- $LT(x)$: local processing time to perform op. x
- $s = card(S \ltimes_A R)/card(R)$: average number of tuples of S that match a tuple of R

Strategy 3 – *fetch-as-needed/outer* site

3. *fetch-as-needed*/site of *outer* relation
   (a) Retrieve tuples at outer relation (R) site
   (b) For each tuple of R, send join attribute values to inner relation (S) site
   (c) Retrieve matching inner tuples at inner relation site
   (d) Send the matching inner tuples to outer relation site
   (e) Join as they arrive

Total Cost = LT (retrieve $card$(R) tuples from R)
+ CT ($length$ (A)) * $card$ (R)
+ LT (retrieve s tuples from S) * $card$ (R)
+ CT (s * $length$ (S)) * $card$ (R)

- $CT(x)$: communication time to transfer x bytes
- $LT(x)$: local processing time to perform op. x
- $s = card(S \ltimes_A R)/card(R)$: average number of tuples of S that match a tuple of R

Strategy 4 – Move Both Relation at Third Site

4. move both inner (S) and outer (R) relations to another site

Total cost = LT (retrieve $card$ (S) tuples from S)
+ CT ($size$ (S))
+ LT (store $card(S)$ tuples in temporary relation T)
+ LT (retrieve $card$ (R) tuples from R)
+ CT ($size$(R))
+ LT (retrieve s tuples from T) * $card$ (R)

- $CT(x)$: communication time to transfer x bytes
- $LT(x)$: local processing time to perform op. x
- $s = card(S \ltimes_A R)/card(R)$: average number of tuples of S that match a tuple of R

Moving inner relation S first is better so we can then join as outer relation R arrives

Strategy comparison

PROJ $\bowtie_{PNO}$ ASG

- PROJ (outer rel.) and ASG (inner rel.) are stored at different sites
- Index on PNO for relation ASG

1. Ship whole PROJ at site of ASG — CT ($size$(PROJ))
2. Ship whole ASG at site of PROJ — CT ($size$(ASG))
3. Fetch tuples of ASG as needed at site of PROJ — CT ($length$ (A)) * $card$ (PROJ) + CT (s * $length$ (ASG)) * $card$ (PROJ)
4. Move both ASG and PROJ to a third site — CT ($size$ (ASG)) + CT ($size$ (PROJ))

- If there is no upper level operation then **4** is a bad choice
- If $size$ ($PROJ$) >> $size$ (ASG), then **2** is a good choice (if local processing time is not too bad compared with **1** and **3** (**1** and **3** can exploit index on ASG in their local processing)
- If $PROJ$ is large/few tuples of ASG match, then **3** is better than **1**
- Otherwise, **1** is better than **3**

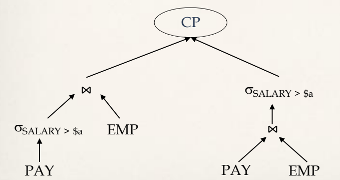
Hybrid approach

- So far, focus on *static* approaches, i.e., strategies (QEP, expressed as decorated trees) are evaluated and compared at compile time
- Advantages: query optimization is done once and used for several query executions
- Disadvantages: cost evaluation is not that accurate
  - it is not always done on exact values but on estimations based on statistics
    - e.g., size of intermediate results
  - some parameter of a query might be known only at runtime
- Problems of static query optimization are much more severe in the distributed context: more infomation variability at runtime
  - Sites may become unavailable or overloaded
  - Selection of site and fragment copy should be done at runtime to increase availability and load balancing
- An hybrid solution (some decisions are taken at runtime) is implemented by means of the CP (choose-plan) operator, which is resolved at runtime, when an exact plan comparison can be done

The CP (choose-plan) Operator

SELECT *
FROM EMP, PAY
WHERE SALARY > $a

where $a is a variable whose value is specified by the user at runtime

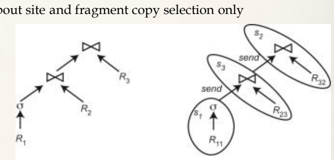


Normally, pushing σ inside ⋈ is a good heuristics, but it can be bad if selection rate of ⋈ is higher than the one of σ

2-Step Optimization

- 2-Step optimization: a simpler approach (more efficient, less exhaustive) than the one based on CP operator; it reduces workload at runtime (no CP operator)
  - At runtime labels are added about site and fragment copy selection only

1. At compile time, generate a static plan with operation ordering and access methods only
2. At startup time, carry out site and copy selection and allocate operations to sites



(a) Static plan (b) Run-time plan

- Site (and copy) selection is done in a greedy fashion
  - best load balancing,
  - best benefit (# of queries already executed at the site, possible saving of communication costs as the site might have already data available)