Cluster-Based Join Algorithms

Basic Join Algorithm

More Efficient Joins Via Replication

Optimization of Multiway Joins

Data-Volume Cost

- *Data-volume cost* = sum of sizes of inputs to all tasks of an algorithm.
- Assumes transport between compute nodes is significant.
- Also assumes computation by a task is linear in input size or negligible compared with communication.

Why Not Count Output Size?

- Outputs of one task are inputs to at least one other, or are algorithm output.
- Algorithm outputs tend to be small because users can't make use of too much information.

Joins

The Natural Join

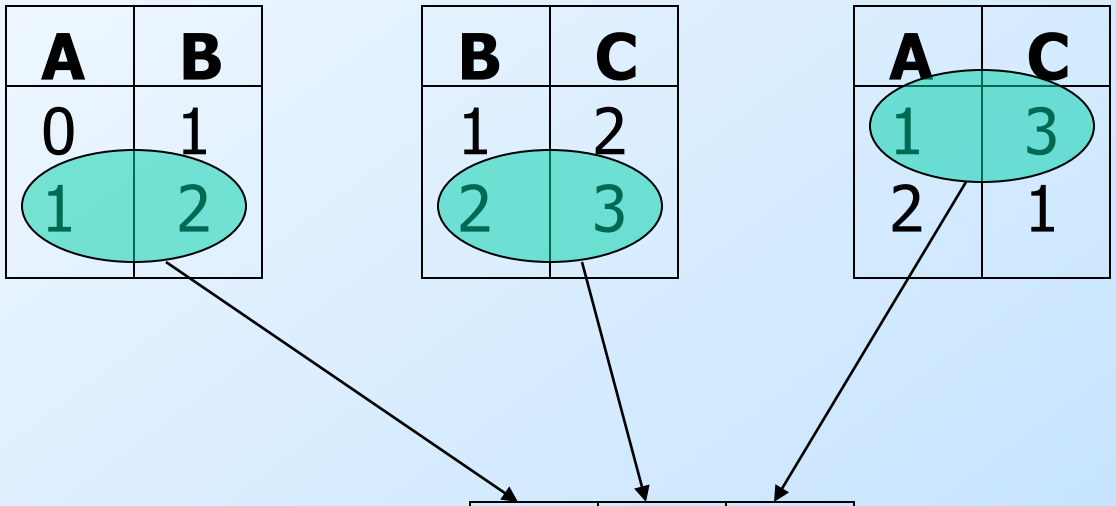
Joining by Map-Reduce

3-Way Joins

Natural Join of Relations

- Given: a collection of relations, each with attributes labeling their columns.
- Find: Those tuples over all the attributes such that when restricted to the attributes of any relation *R*, that tuple is in *R*.

Example: Natural Join



The join:

A	B	C
1	2	3

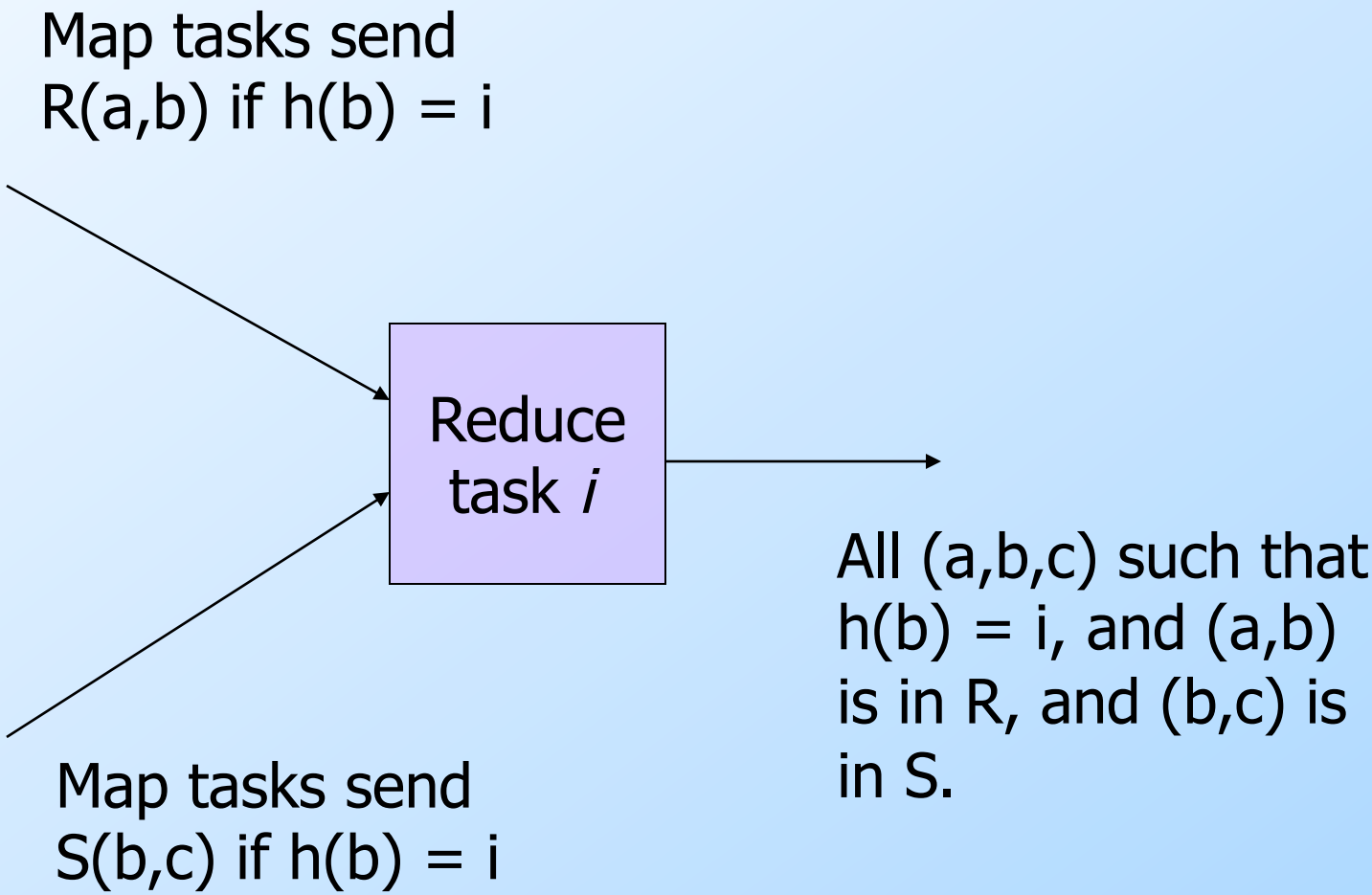
Joining by Map-Reduce

- Suppose we want to compute R(A,B) JOIN S(B,C), using *k* Reduce tasks.
  - I.e., find tuples with matching B-values.
- *R* and *S* are each stored in a chunked file.

Joining by Map-Reduce – (2)

- Use a hash function *h* from B-values to *k* buckets.
  - Bucket = Reduce task.
- The Map tasks take chunks from R and S, and send:
  - Tuple R(a,b) to Reduce task h(b).
    - Key = b value = R(a,b).
  - Tuple S(b,c) to Reduce task h(b).
    - Key = b; value = S(b,c).

Joining by Map-Reduce – (3)



Joining by Map-Reduce – (4)

- Key point: If R(a,b) joins with S(b,c), then both tuples are sent to Reduce task h(b).
- Thus, their join (a,b,c) will be produced there and shipped to the output file.

3-Way Join

- Consider a chain of three relations:

  R(A, B) JOIN S(B, C) JOIN T(C, D)

- Example: R, S, and T are "friends" relations.
- We could join any two by the 2-way map-reduce algorithm shown, then join the third with the resulting relation.
- But intermediate joins are large.

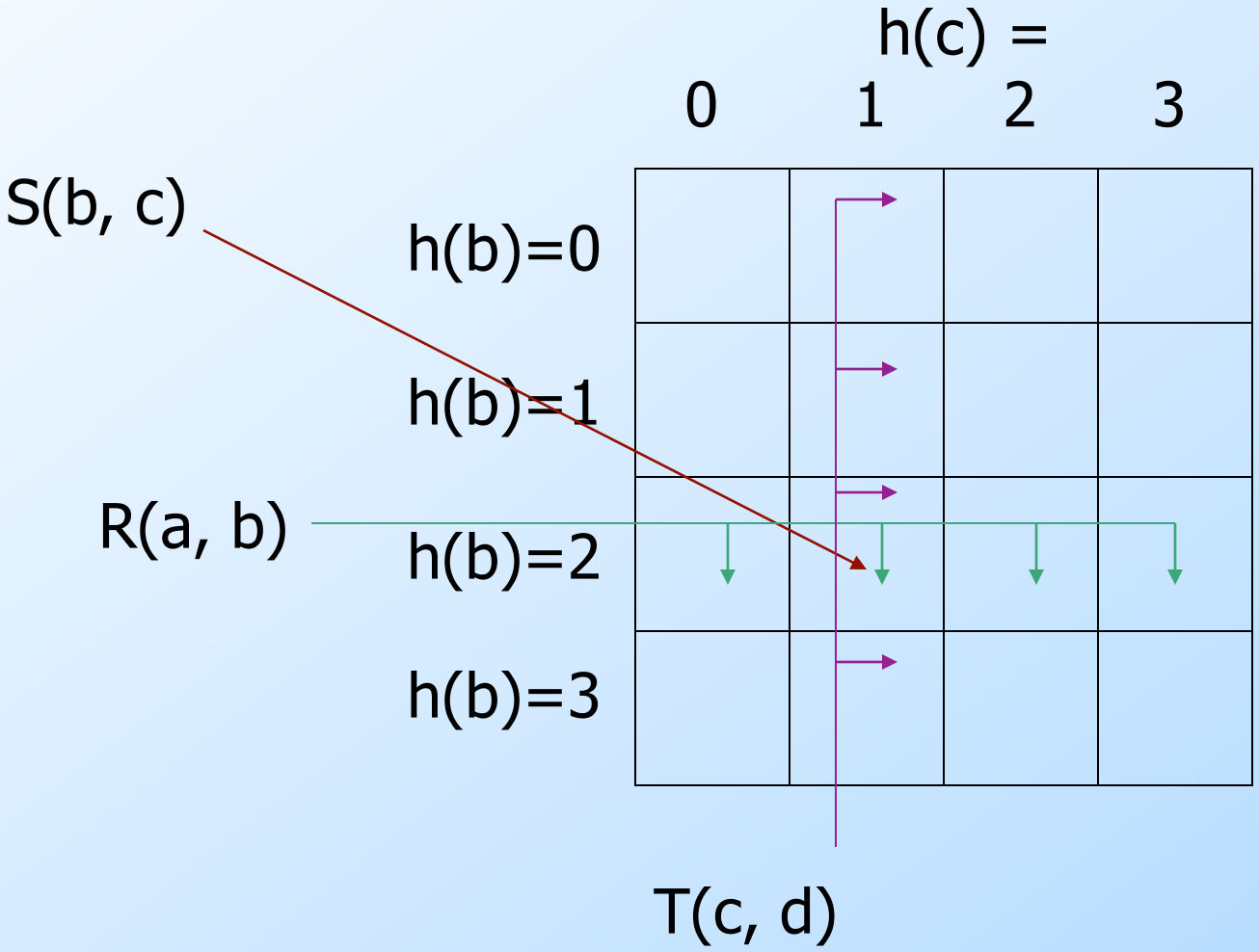
3-Way Join – (2)

- An alternative is to divide the work among $k = m^2$ Reduce tasks.
- Hash both B and C to m values.
- A Reduce task corresponds to a hashed B-value and a hashed C-value.

3-Way Join – (3)

- Each S-tuple S(b,c) is sent to one Reduce task: (h(b), h(c)).
- But each tuple R(a,b) must be sent to *m* Reduce tasks (h(b), x).
- And each tuple T(c,d) must be sent to *m* Reduce tasks (y, h(c)).

Example: m = 4; k = 16.



3-Way Join – (4)

- Thus, any joining tuples R(a,b), S(b,c), and T(c,d) will be joined at the Reduce task (h(b), h(c)).
- Data-volume cost: s + mr + mt.
  - Convention: Lower-case letter is the size of the relation whose name is the corresponding upper-case letter.
    - Example: *r* is the size of R.

Comparison of Methods

- Suppose for simplicity that:
  - Relations R, S, and T have the same size *r*.
  - The probability of two tuples joining is *p*.
- The 3-way join has cost r(2m+1).
- Two two-way joins have a cost of:
  - 3r to read the relations, plus
  - pr^2 to read the join of the first two.
  - Total = r(3+pr).

Comparison – (2)

- 3-way beats 2-way if 2m+1 < 3+pr.
- *pr* is the multiplicity of each join.
  - Thus, the 3-way chain-join is useful when the multiplicity is high.
- Example: relations are "friends"; *pr* is about 300. $m^2 = k$ can be 20,000.
- Example: relations are Web links; *pr* is about 15. $m^2 = k$ can be 64.

Optimization of Multway Joins

Share Variables and Their Optimization

Special Case: Star Joins

Some Questions

- When we discussed the 3-way chain-join R(A, B) JOIN S(B, C) JOIN T(C,D), we used attributes B and C for the *map-key* (index for the Reduce tasks).
- Why not include A and/or D?
- Why use the same number of buckets for B and C?

Share Variables

- For the general problem, we use a *share variable* for each attribute.
  - The number of buckets into which values of that attribute are hashed.
- Convention: The share variable for an attribute is the corresponding lower-case letter.
  - Example: the share variable for attribute A is always *a*.

Share Variables – (2)

- The product of all the share variables is *k*, the number of Reduce tasks.
- The data-volume cost for a multiway join is the sum of: the size of each relation times the product of the share variables for the attributes that *do not* appear in the schema of that relation.

Example: Minimizing Cost

- Consider the cyclic join R
  (A, B) JOIN S(B, C) JOIN T(A, C)
- Cost function is rc + sa + tb.
- Construct the Lagrangean:
  rc + sa + tb – λ(abc – k)
- Take derivative wrt each share variable, then multiply by that variable.
  - Result is 0 at minimum.

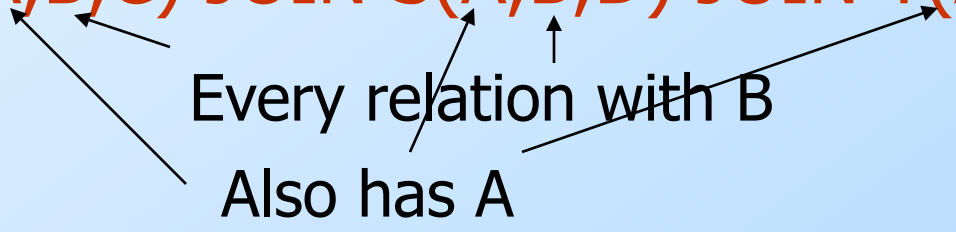
Example – Continued

- d/da of $rc + sa + tb - \lambda(abc - k)$ is $s - \lambda bc$.
- Multiply by a and set to 0: $sa - \lambda abc = 0$.
- Note: $abc = k$: $sa = \lambda k$.
- Similarly, d/db and d/dc give: $sa = tb = rc = \lambda k$.
- Solution: $a = (krt/s^2)^{1/3}$; $b = (krs/t^2)^{1/3}$; $c = (kst/r^2)^{1/3}$.
- Cost = $rc + sa + tb = 3(krst)^{1/3}$.

Dominated Attributes

- Certain attributes can't be in the map-key.
- A *dominates* B if every relation of the join with B also has A.
- Example:

R(A,B,C) JOIN S(A,B,D) JOIN T(A,E) JOIN U(C,E)



Example – (2)

R(A,B,C) JOIN S(A,B,D) JOIN T(A,E) JOIN U(C,E)

- Cost expression:

  rde + sce + tbcd + uabd

- Since *b* appears wherever *a* does, if there were a minimum-cost solution with $b > 1$, we could replace *b* by 1 and *a* by *ab*, and the cost would *lower*.

Dominated Attributes – Continued

- This rule explains why, in the discussion of the chain join

  R(A, B) JOIN S(B, C) JOIN T(C,D)

  we did not give dominated attributes A and D a share.

Solving the General Case

- Unfortunately, there are more complex cases than dominated attributes, where the equations derived from the Lagrangean imply a positive sum of several terms = 0.
- We can fix, generalizing dominated attributes, but we have to branch on which attribute needs to be eliminated from the map-key.

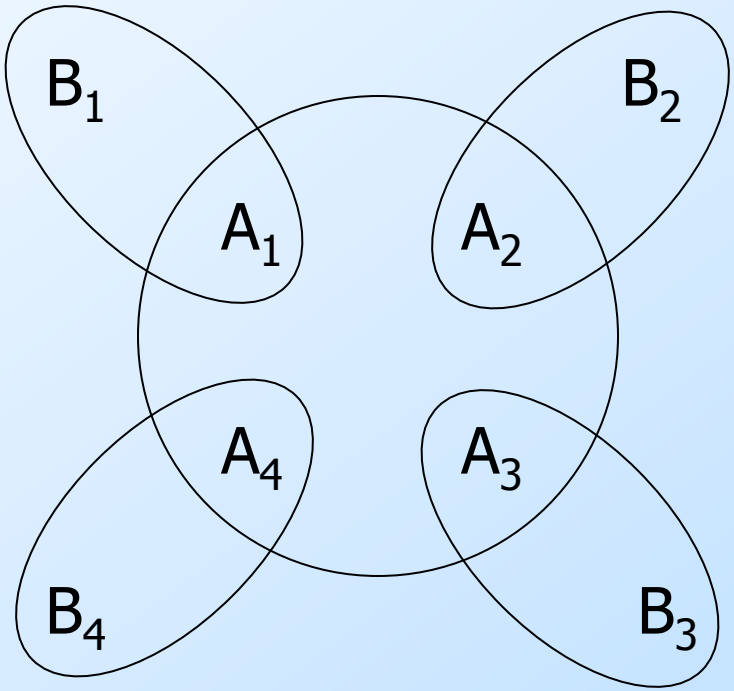
Solving – (2)

- Solutions not in integers:
  - Drop an attribute with a share < 1 from the map-key and re-solve.
  - Round other nonintegers, and treat *k* as a suggestion, since the product of the integers may not be *k*.

Special Case: Star Joins

- A *star join* combines a huge *fact table* $F(A_1,A_2,\ldots,A_n)$ with large but smaller *dimension tables* $D_1(A_1,B_1)$, $D_2(A_2,B_2)$, …, $D_n(A_n,B_n)$.
  - There may be other attributes not shown, each belonging to only one relation.
- Example: Facts = sales; dimensions tell about buyer, product, etc.

Star-Join Pattern



Star Joins – (2)

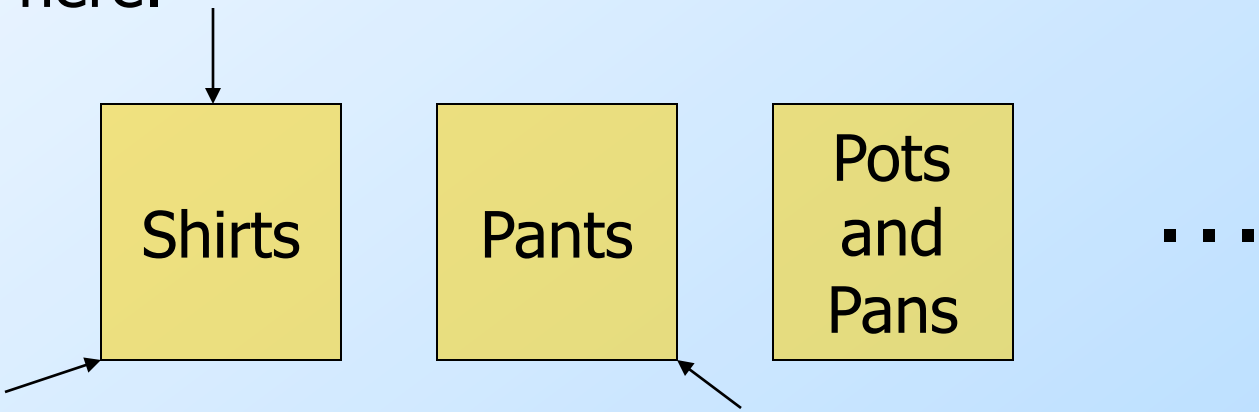
- Map-key = the A's.
  - B's are dominated.
- Solution: $d_i/a_i = \lambda k$ for all i.
  - That is, the shares are proportional to the dimension-table sizes.

Cool Application of Star Join Result

- Fact/dimension tables are often used for analytics.
- Aster Data approach: partition (*shard*) fact table among compute nodes permanently; replicate needed pieces of dimension tables.
  - They use a data-dependent way to cluster facts so replication of dimension tables is minimized.

Example: Shard by Product

But all Customer tuples for customers who bought shirts, or might buy shirts go here.



Only Item tuples for shirts go here

Only Item tuples for pants go here

Star-Join Application – (2)

- Our solution lets you partition the fact table to *k* nodes in a data-independent way.
  - Avoids the need to reshard the fact table.
- Replication of tuples in the dimension tables is minimized.

Summary

1. Multiway joins can be computed by replicating tuples and distributing them to many compute nodes.
2. Minimizing data-volume cost requires us to solve a nonlinear optimization.
3. Multiway beats 2-way joins for star queries and queries on high-fanout graphs.
4. Exact solution for star queries.