

# **CS4224/CS5424 Lecture 3**

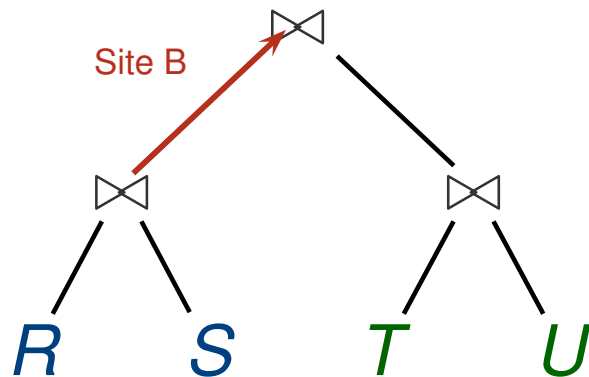
## **Distributed Query Processing**

# Query Processing

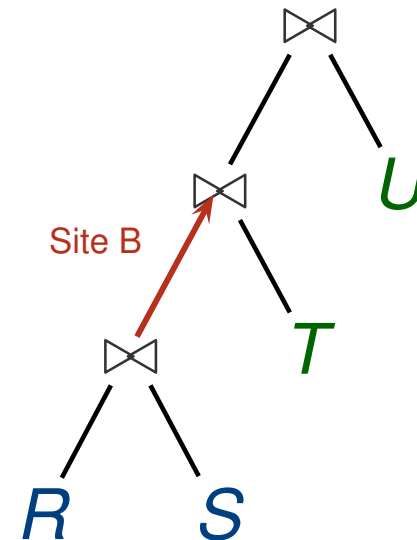
- Translates query into a query plan that minimizes some cost function
  - ▶ Minimize total cost
    - ★ CPU cost, I/O cost, & communication cost
  - ▶ Minimize response time
    - ★ Time elapsed for query execution

# Example

- **Site A:** Relations  $R(a, c, \dots)$  &  $S(a, \dots)$
- **Site B:** Relations  $T(b, c, \dots)$  &  $U(b, \dots)$
- **Query at Site B:**  
SELECT \* FROM R, S, T, U  
WHERE R.a = S.a AND T.b = U.b AND R.c = T.c
- **Query Plans:**



Plan 1

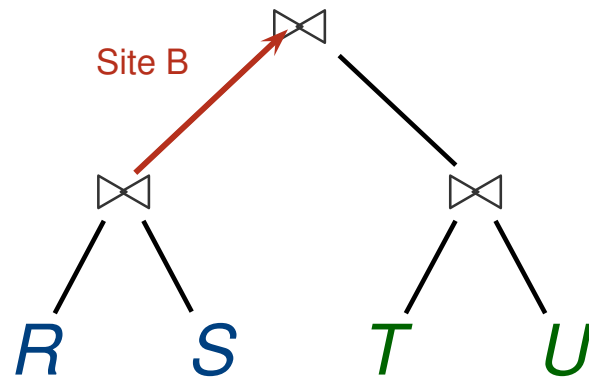


Plan 2

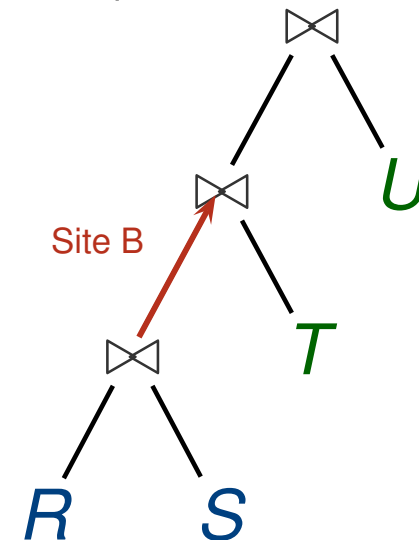
# Example (cont.)

- **Cost model:**

- ▶  $JC(X, Y)$  = CPU & I/O cost of joining relations  $X$  &  $Y$
- ▶  $CC(X)$  = Communication cost of sending relation  $X$  from one site to another site
- ▶  $JC(R, S) = 2000$ ,  $JC(T, U) = 2000$
- ▶  $JC(R \bowtie S, T) = 1000$ ,  $JC(R \bowtie S \bowtie T, U) = 600$
- ▶  $JC(R \bowtie S, T \bowtie U) = 100$ ,  $CC(R \bowtie S) = 200$



Plan 1

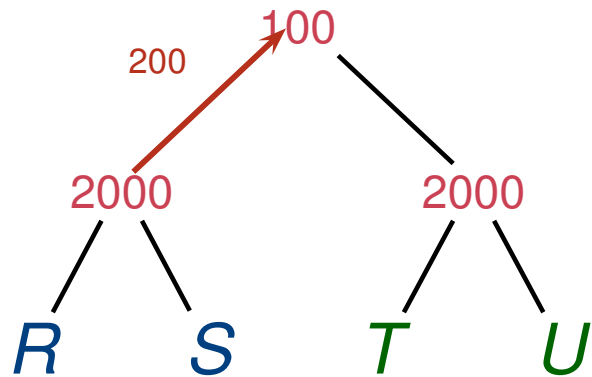


Plan 2

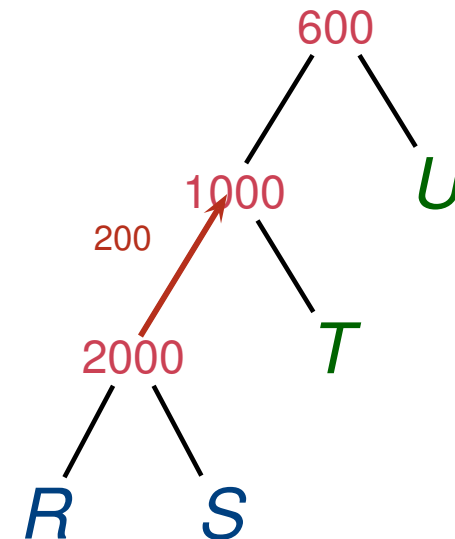
# Example (cont.)

- **Cost model:**

- ▶  $JC(X, Y)$  = CPU & I/O cost of joining relations X & Y
- ▶  $CC(X)$  = Communication cost of sending relation X from one site to another site
- ▶  $JC(R, S) = 2000$ ,  $JC(T, U) = 2000$
- ▶  $JC(R \bowtie S, T) = 1000$ ,  $JC(R \bowtie S \bowtie T, U) = 600$
- ▶  $JC(R \bowtie S, T \bowtie U) = 100$ ,  $CC(R \bowtie S) = 200$



Plan 1: Total Cost = 4300

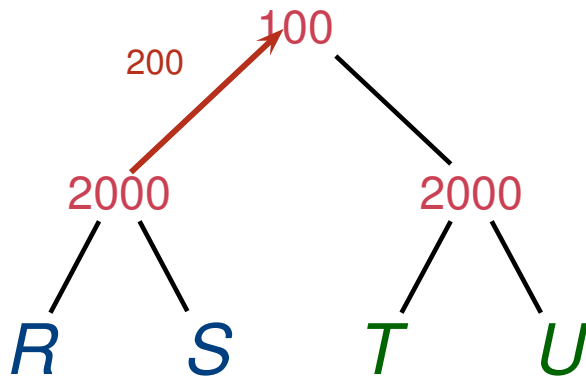


Plan 2: Total Cost = 3800

# Example (cont.)

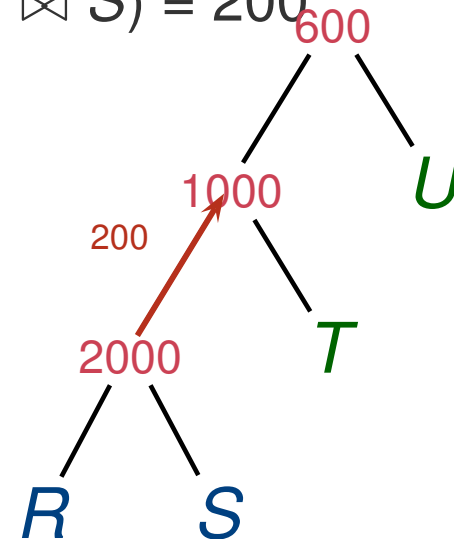
- **Cost model:**

- ▶  $JC(X, Y)$  = CPU & I/O cost of joining relations  $X$  &  $Y$
- ▶  $CC(X)$  = Communication cost of sending relation  $X$  from one site to another site
- ▶  $JC(R, S) = 2000$ ,  $JC(T, U) = 2000$
- ▶  $JC(R \bowtie S, T) = 1000$ ,  $JC(R \bowtie S \bowtie T, U) = 600$
- ▶  $JC(R \bowtie S, T \bowtie U) = 100$ ,  $CC(R \bowtie S) = 200$



Plan 1:

Response Time = 2300



Plan 2:

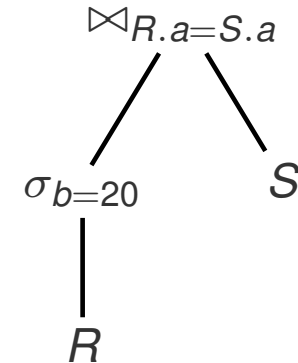
Response Time = 3800

# Query Processing Steps

- **Query rewriting**
  - ▶ Query decomposition
    - ★ Translates query into relational algebra query
  - ▶ Data localization
    - ★ Rewrites distributed query into a fragment query
- **Global query optimization**
  - ▶ Finds an optimal execution plan for query
- **Distributed query execution**
  - ▶ Executes query plan to compute query result

# Query Decomposition

SELECT \*  
FROM R, S  
WHERE R.a = S.a  
AND R.b = 20



- **Normalization**

- ▶ Rewrites query into some normal form

- **Semantic Analysis**

- ▶ Checks that query is semantically correct

- **Simplification & Restructuring**

- ▶ Rewrites query into simpler form (e.g., eliminates redundancy)



# Normalization

- A **simple predicate** defined on a relation  $R$  is of the form “ $A_i \text{ op } v$ ” where  $A_i$  is an attribute of  $R$ ,  $\text{op} \in \{=, \neq, <, \leq, >, \geq\}$  and  $v \in \text{Domain}(A_i)$

- **Conjunctive Normal Form (CNF)**

$$(p_{11} \vee p_{12} \cdots \vee p_{1n_1}) \wedge \cdots \wedge (p_{m1} \vee p_{m2} \cdots \vee p_{mn_m})$$

- **Disjunctive Normal Form (DNF)**

$$(p_{11} \wedge p_{12} \cdots \wedge p_{1n_1}) \vee \cdots \vee (p_{m1} \wedge p_{m2} \cdots \wedge p_{mn_m})$$

- Each  $p_{ij}$  is a simple predicate

# Review of RA Equivalence Rules

$\text{attributes}(R)$  = Set of attributes in schema of relation  $R$

$\text{attributes}(p)$  = Set of attributes in predicate  $p$

## 1. Commutativity of binary operators

$$1.1 \quad R \times S \equiv S \times R$$

$$1.2 \quad R \bowtie S \equiv S \bowtie R$$

## 2. Associativity of binary operators

$$2.1 \quad (R \times S) \times T \equiv R \times (S \times T)$$

$$2.2 \quad (R \bowtie S) \bowtie T \equiv R \bowtie (S \bowtie T)$$

## 3. Idempotence of unary operators

$$3.1 \quad \pi_{L'}(\pi_L(R)) \equiv \pi_{L'}(R) \\ \text{if } L' \subseteq L \subseteq \text{attributes}(R)$$

$$3.2 \quad \sigma_{p_1}(\sigma_{p_2}(R)) \equiv \sigma_{p_1 \wedge p_2}(R)$$

# Review of RA Equivalence Rules (cont.)

## 4. Commutating selection with projection

$$4.1 \quad \pi_L(\sigma_p(R)) \equiv \pi_L(\sigma_p(\pi_{L \cup \text{attributes}(p)}(R)))$$

## 5. Commutating selection with binary operators

$$5.1 \quad \sigma_p(R \times S) \equiv \sigma_p(R) \times S$$

if  $\text{attributes}(p) \subseteq \text{attributes}(R)$

$$5.2 \quad \sigma_p(R \bowtie_{p'} S) \equiv \sigma_p(R) \bowtie_{p'} S$$

if  $\text{attributes}(p) \subseteq \text{attributes}(R)$

$$5.3 \quad \sigma_p(R \cup S) \equiv \sigma_p(R) \cup \sigma_p(S)$$

# Review of RA Equivalence Rules (cont.)

## 6. Commutating projection with binary operators

Let  $L = L_R \cup L_S$ , where  $L_R \subseteq \text{attributes}(R)$  and  $L_S \subseteq \text{attributes}(S)$

$$6.1 \quad \pi_L(R \times S) \equiv \pi_{L_R}(R) \times \pi_{L_S}(S)$$

$$6.2 \quad \pi_L(R \bowtie_p S) \equiv \pi_{L_R}(R) \bowtie_p \pi_{L_S}(S)$$

if  $\text{attributes}(p) \cap \text{attributes}(R) \subseteq L_R$  and  
 $\text{attributes}(p) \cap \text{attributes}(S) \subseteq L_S$

$$6.3 \quad \pi_L(R \cup S) \equiv \pi_L(R) \cup \pi_L(S)$$

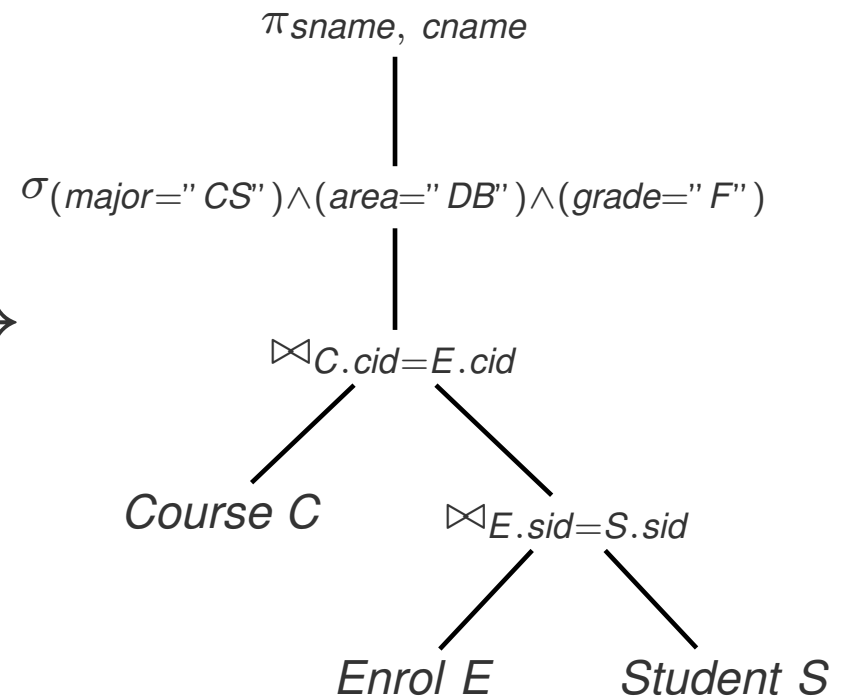
# Example

Student (sid, sname, major)

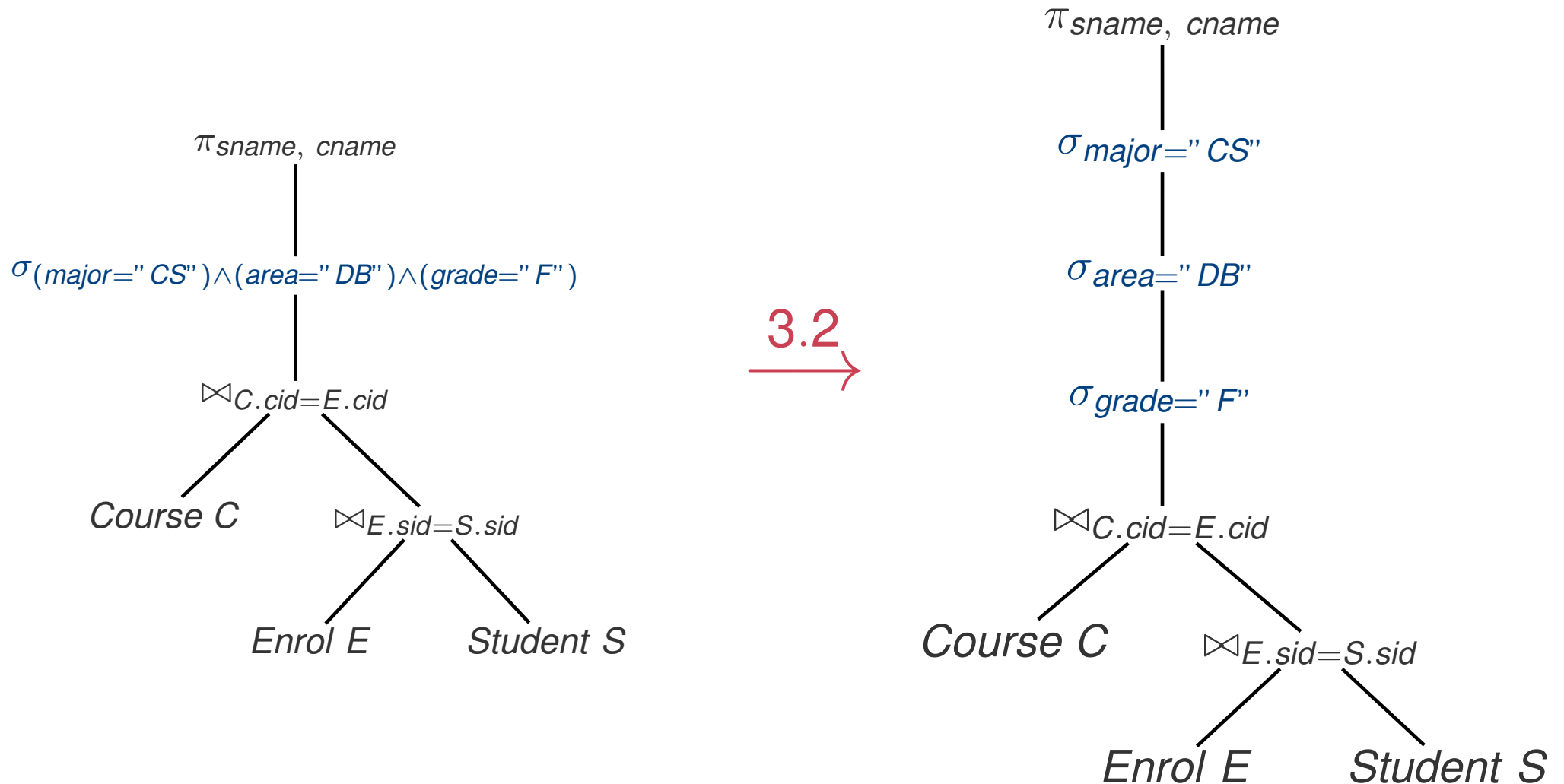
Course (cid, cname, area)

Enrol (sid, cid, grade)

SELECT sname, cname  
FROM Student S, Course C, Enrol E  
WHERE E.sid = S.sid  
AND E.cid = C.cid  
AND major = "CS"  
AND area = "DB"  
AND grade = "F"

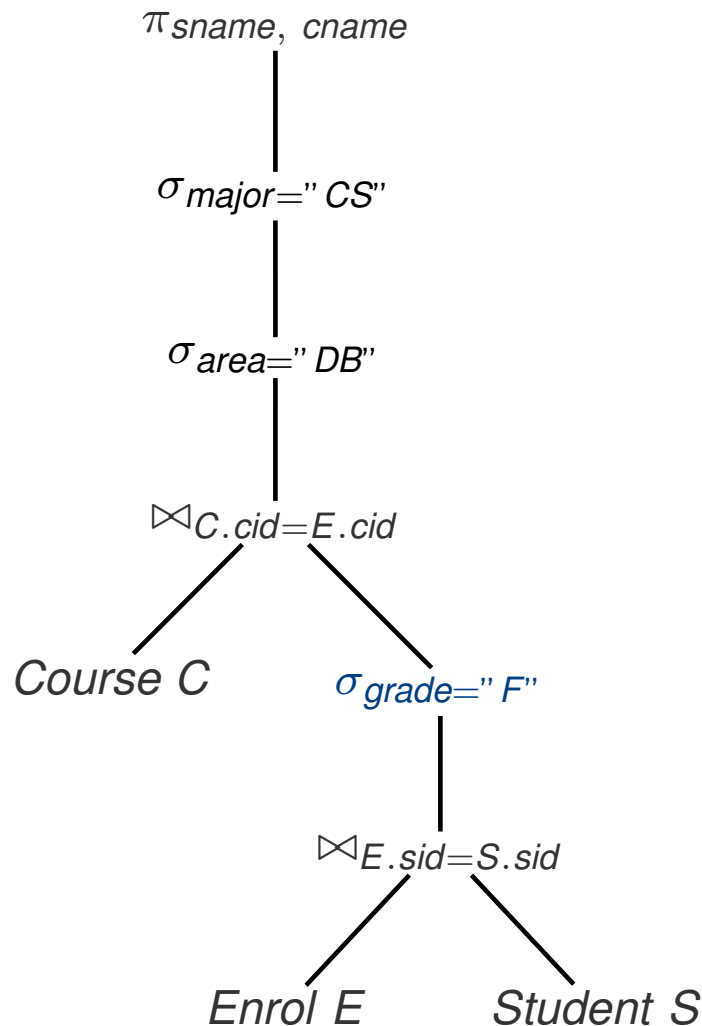


# Example (cont.)

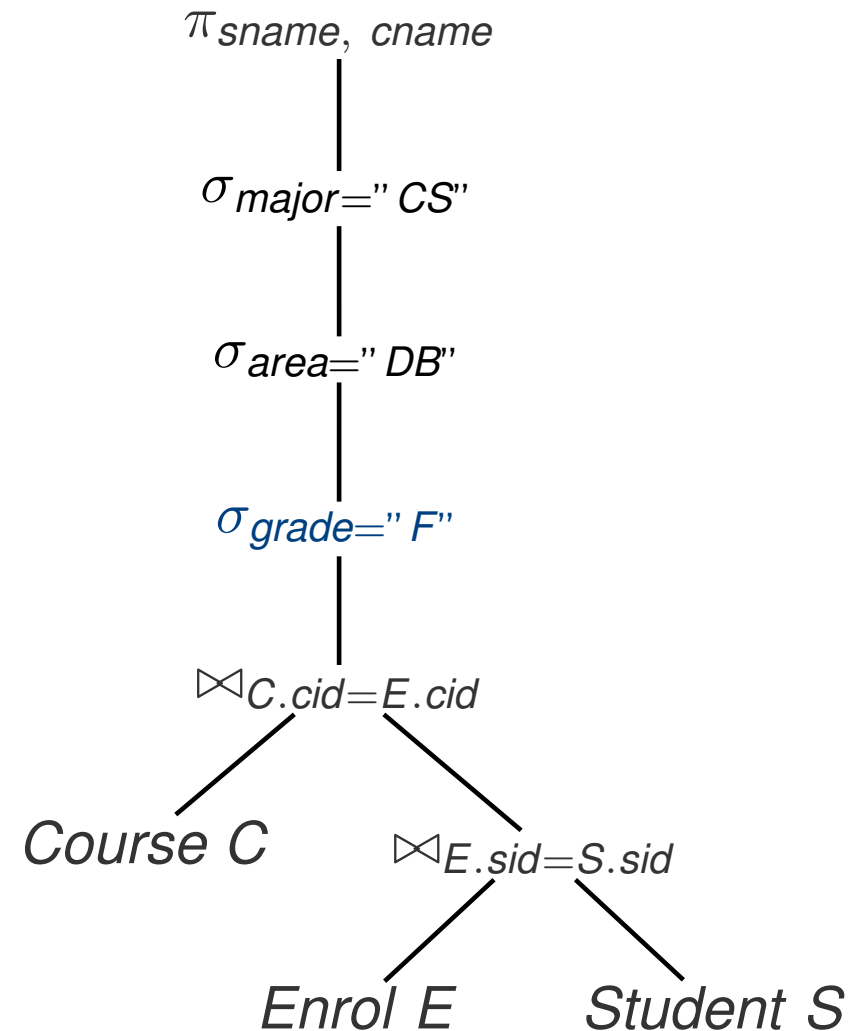


$$\sigma_{p_1}(\sigma_{p_2}(R)) \equiv \sigma_{p_1 \wedge p_2}(R)$$

# Example (cont.)

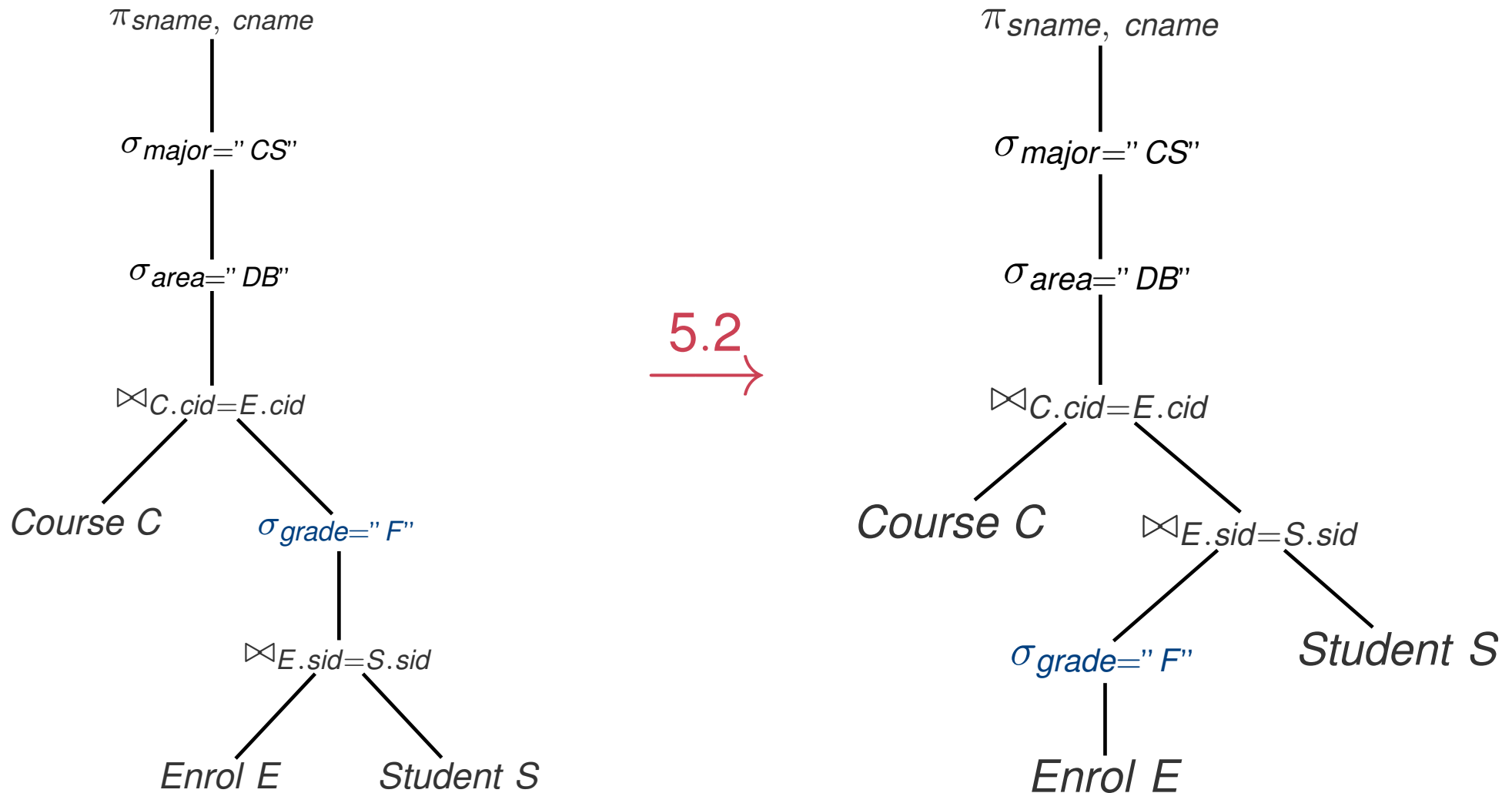


5.2



$$\sigma_p(R \bowtie_{p'} S) \equiv \sigma_p(R) \bowtie_{p'} S \text{ if } attributes(p) \subseteq attributes(R)$$

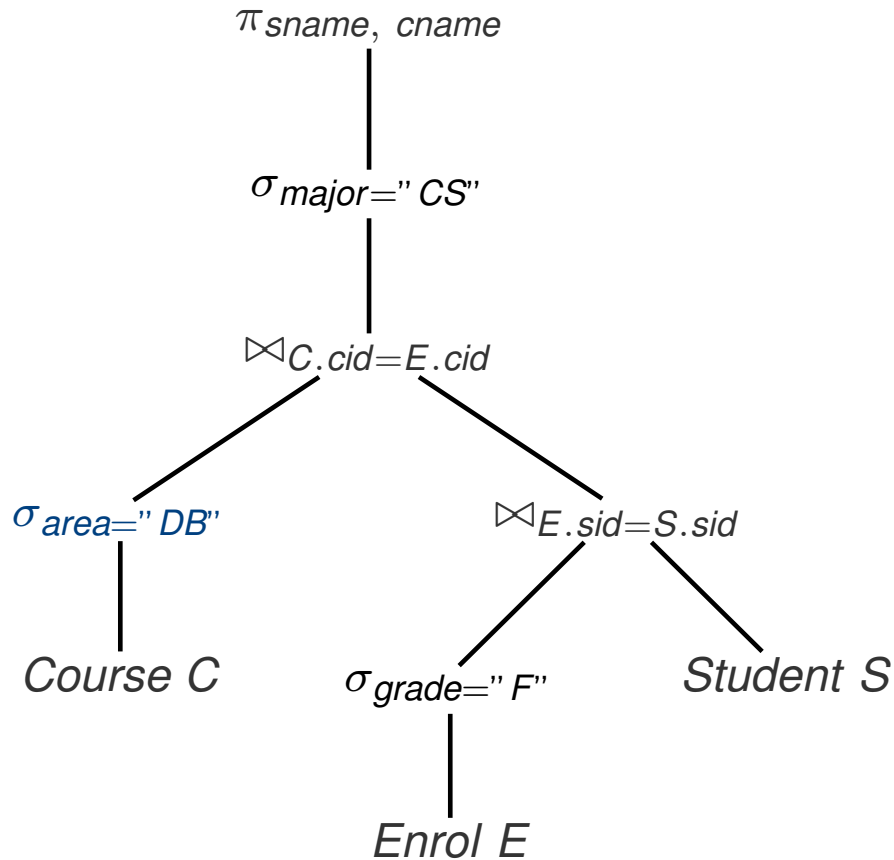
# Example (cont.)



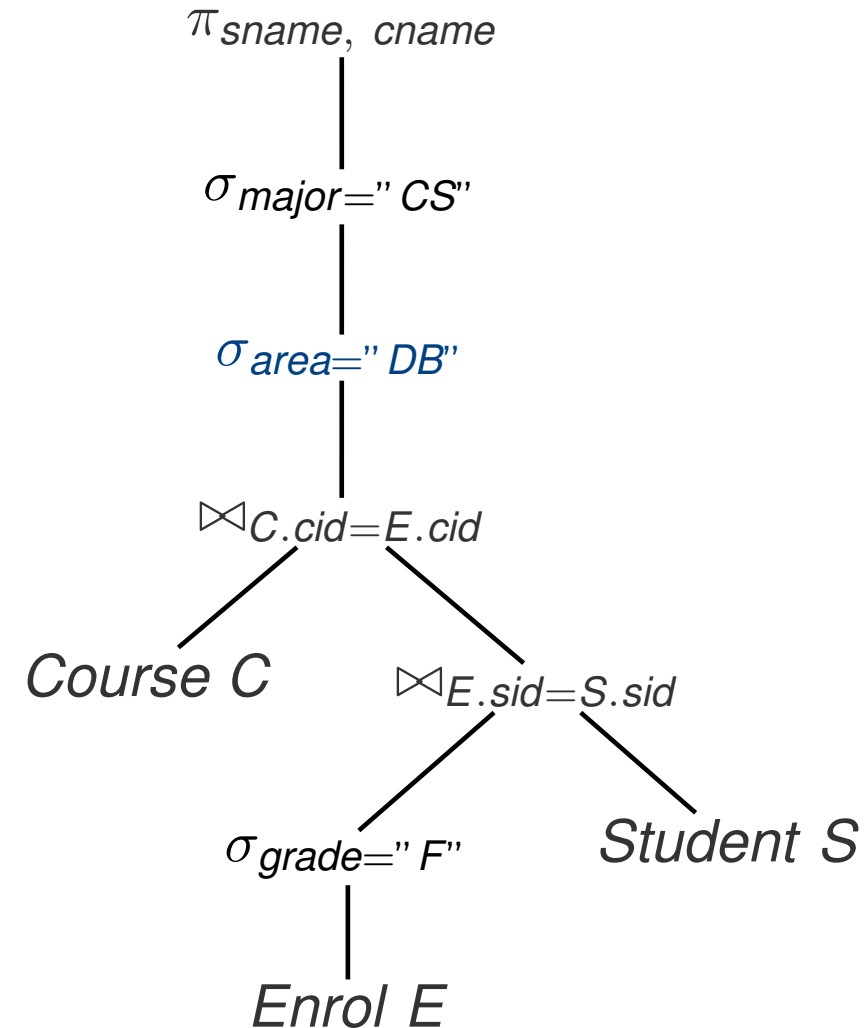
$$\sigma_p(R \bowtie_{p'} S) \equiv \sigma_p(R) \bowtie_{p'} S \text{ if } attributes(p) \subseteq attributes(R)$$



# Example (cont.)

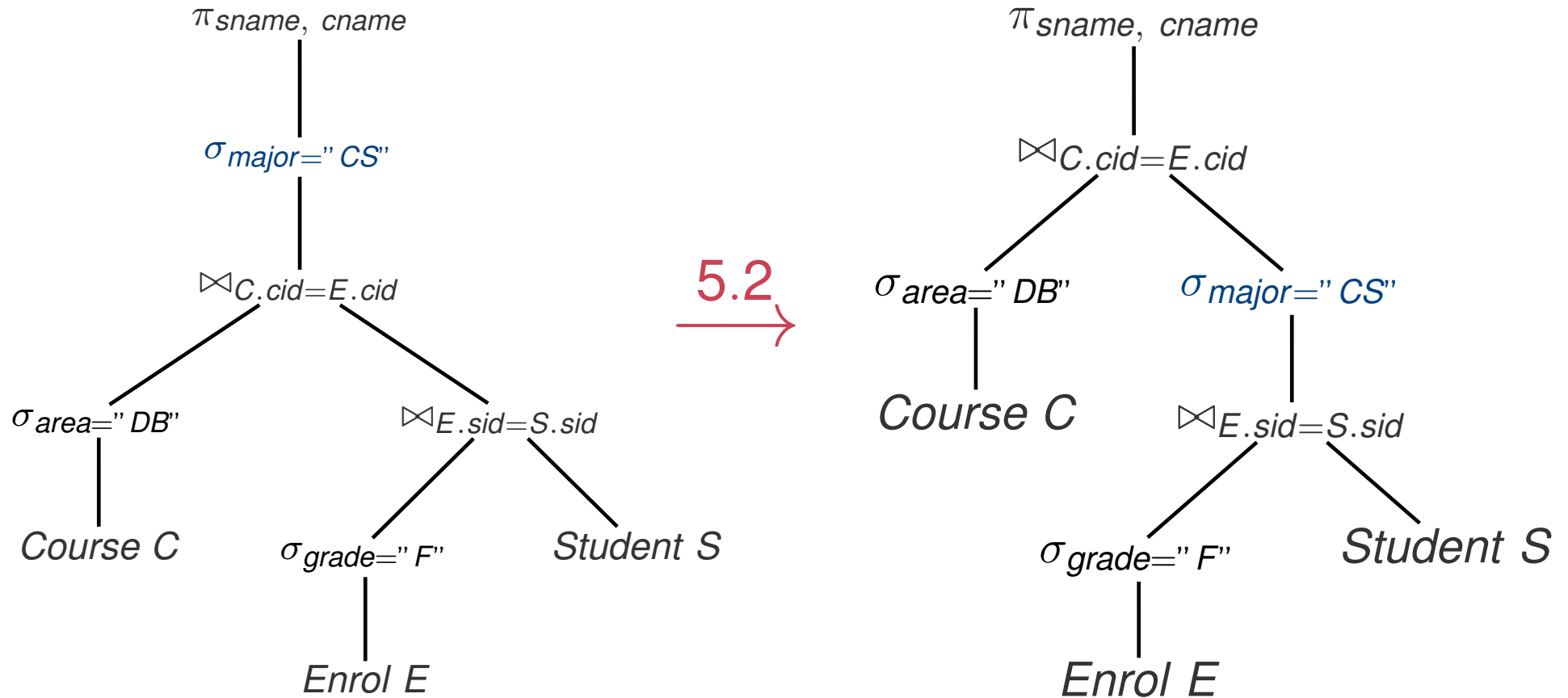


5.2



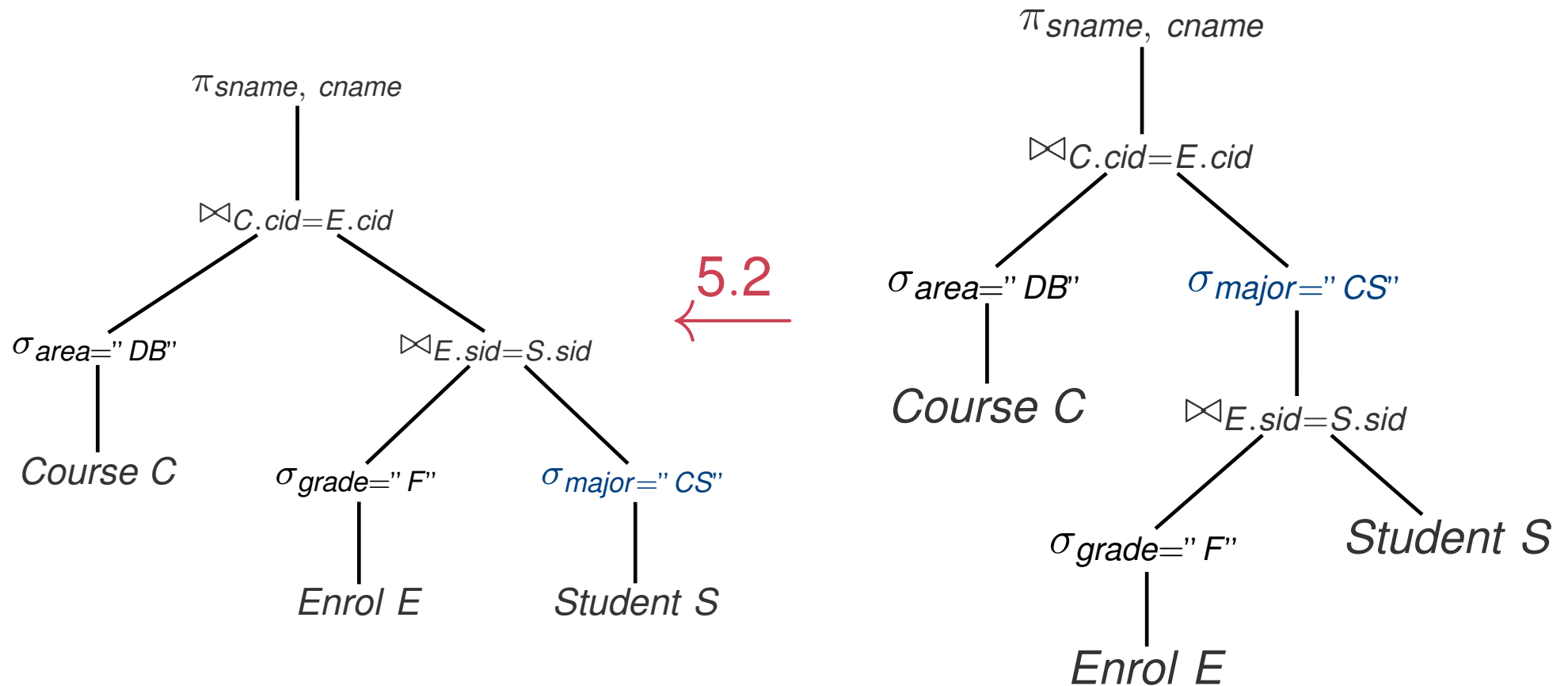
$$\sigma_p(R \bowtie_{p'} S) \equiv \sigma_p(R) \bowtie_{p'} S \text{ if } attributes(p) \subseteq attributes(R)$$

# Example (cont.)



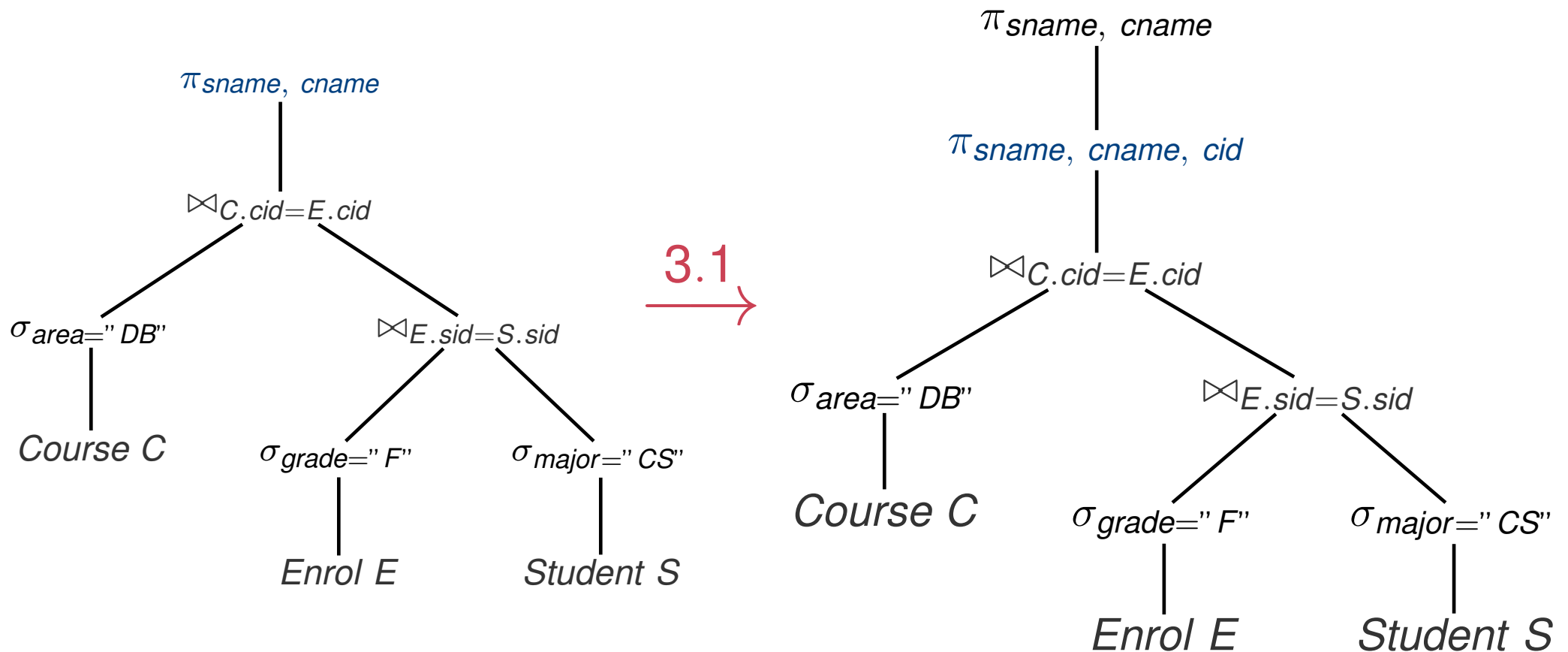
$$\sigma_p(R \bowtie_{p'} S) \equiv \sigma_p(R) \bowtie_{p'} S \text{ if } attributes(p) \subseteq attributes(R)$$

# Example (cont.)



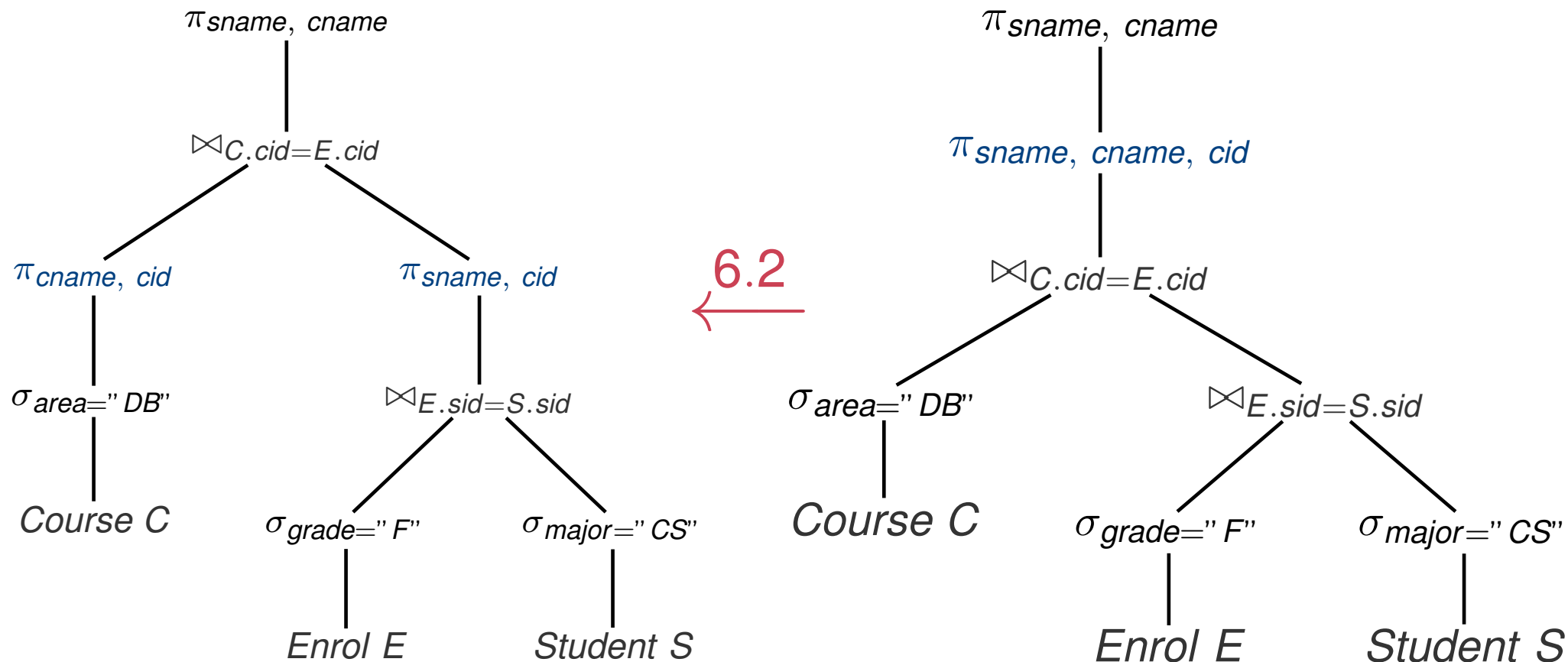
$$\sigma_p(R \bowtie_{p'} S) \equiv \sigma_p(R) \bowtie_{p'} S \text{ if } attributes(p) \subseteq attributes(R)$$

# Example (cont.)



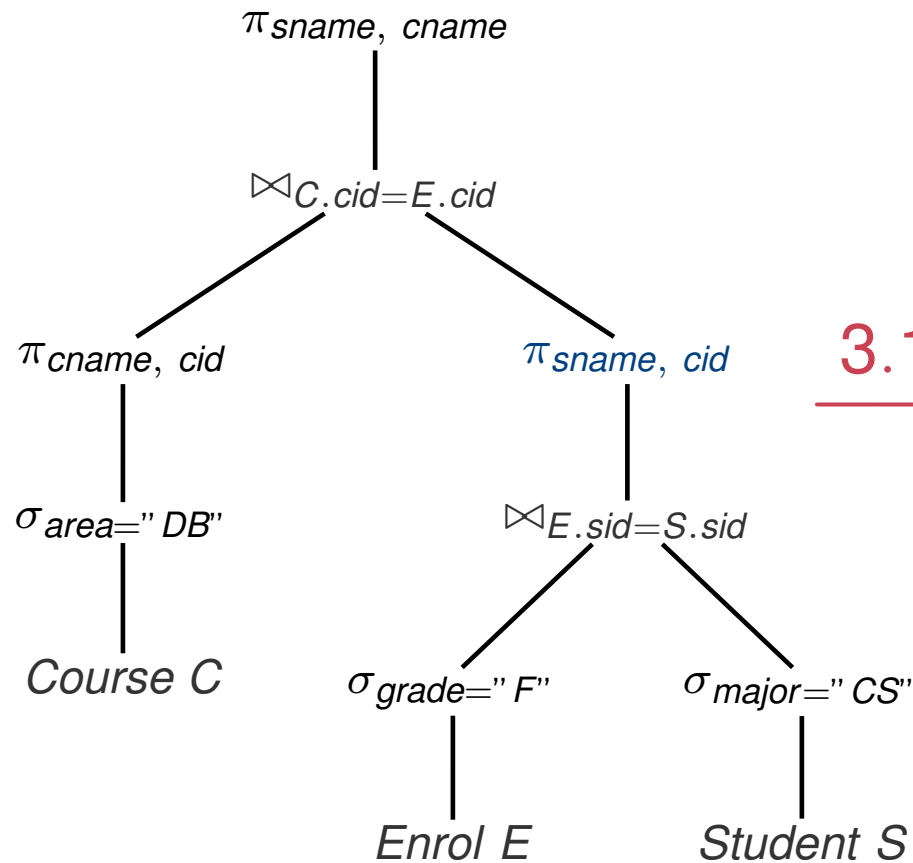
$$\pi_{L'}(\pi_L(R)) \equiv \pi_{L'}(R) \text{ if } L' \subseteq L \subseteq \text{attributes}(R)$$

# Example (cont.)

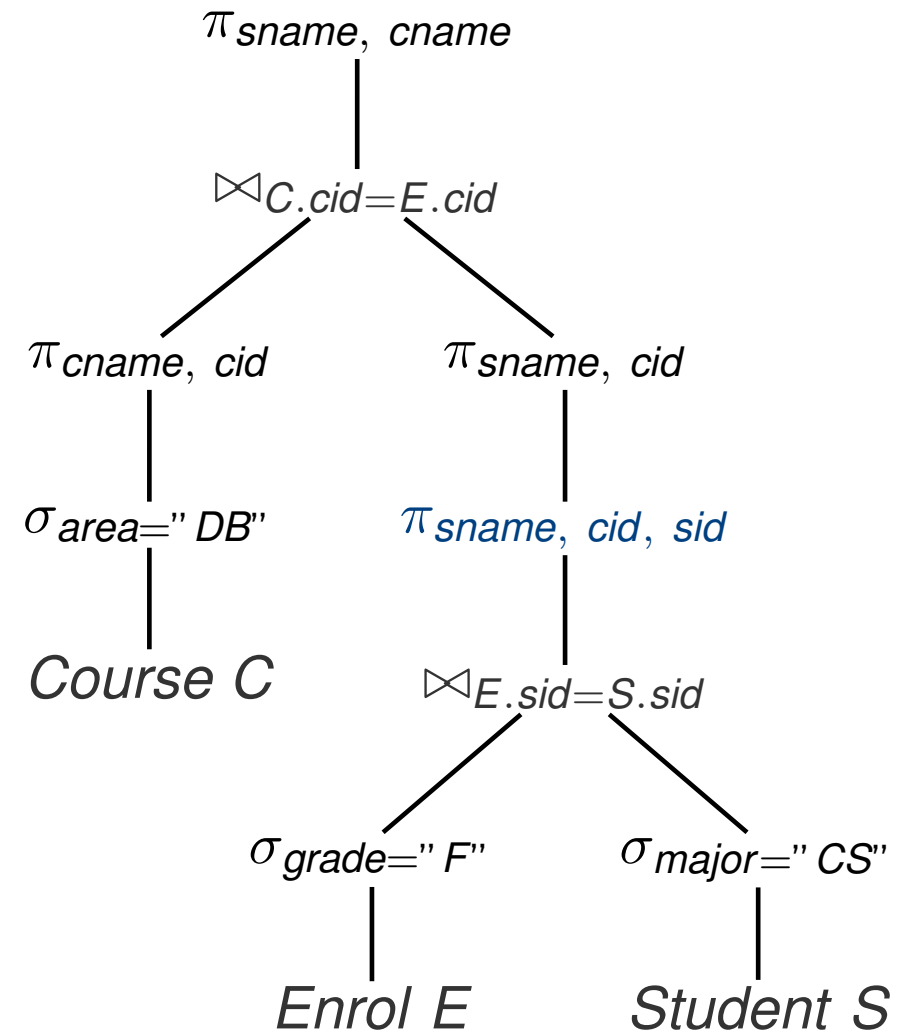


$$\pi_L(R \bowtie_p S) \equiv \pi_{L_R}(R) \bowtie_p \pi_{L_S}(S)$$

# Example (cont.)

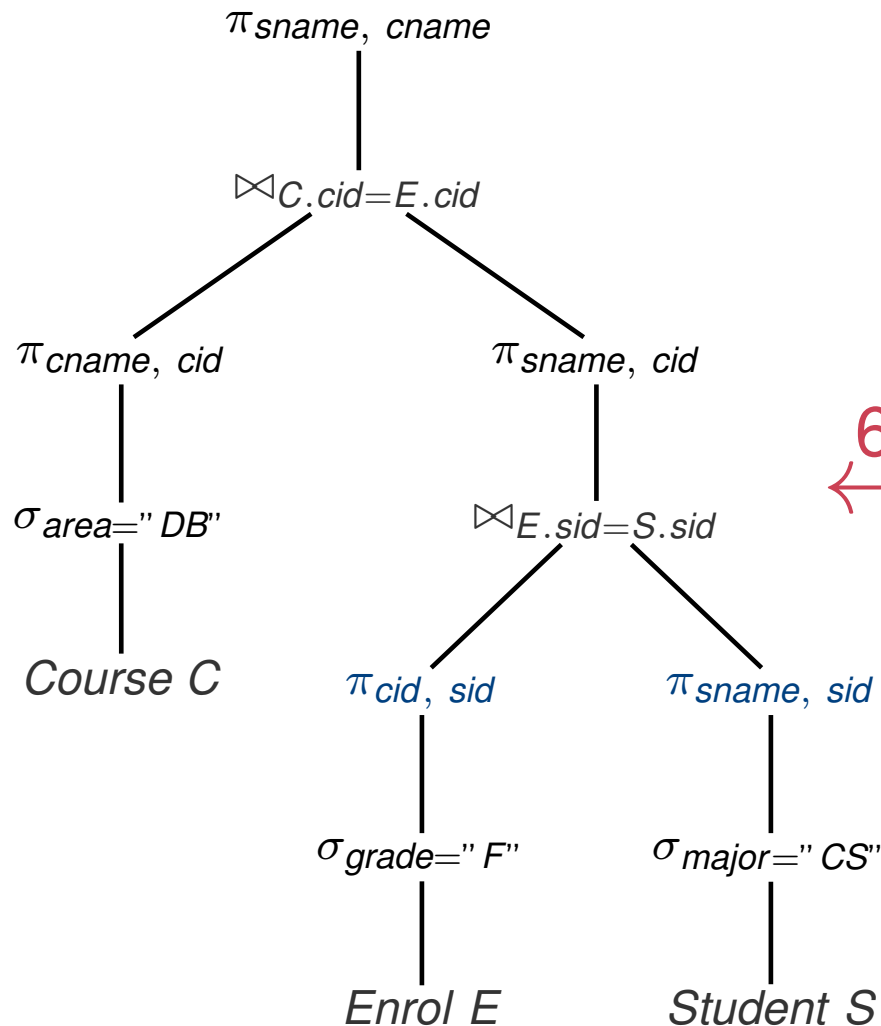


3.1  $\rightarrow$

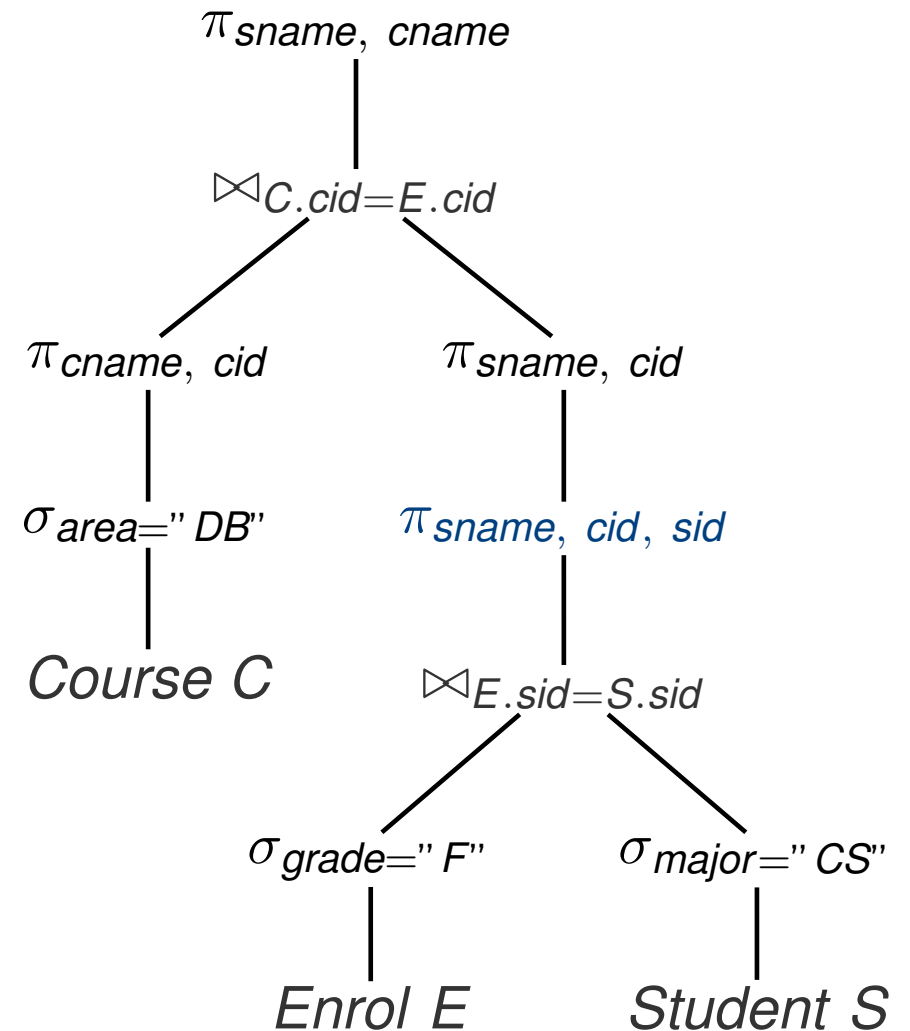


$$\pi_{L'}(\pi_L(R)) \equiv \pi_{L'}(R) \text{ if } L' \subseteq L \subseteq \text{attributes}(R)$$

# Example (cont.)

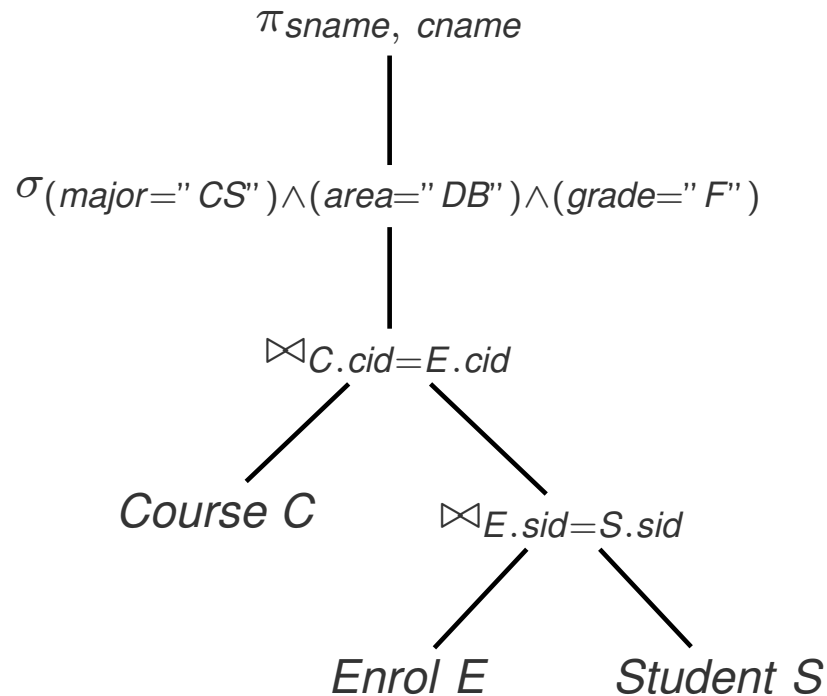


6.2

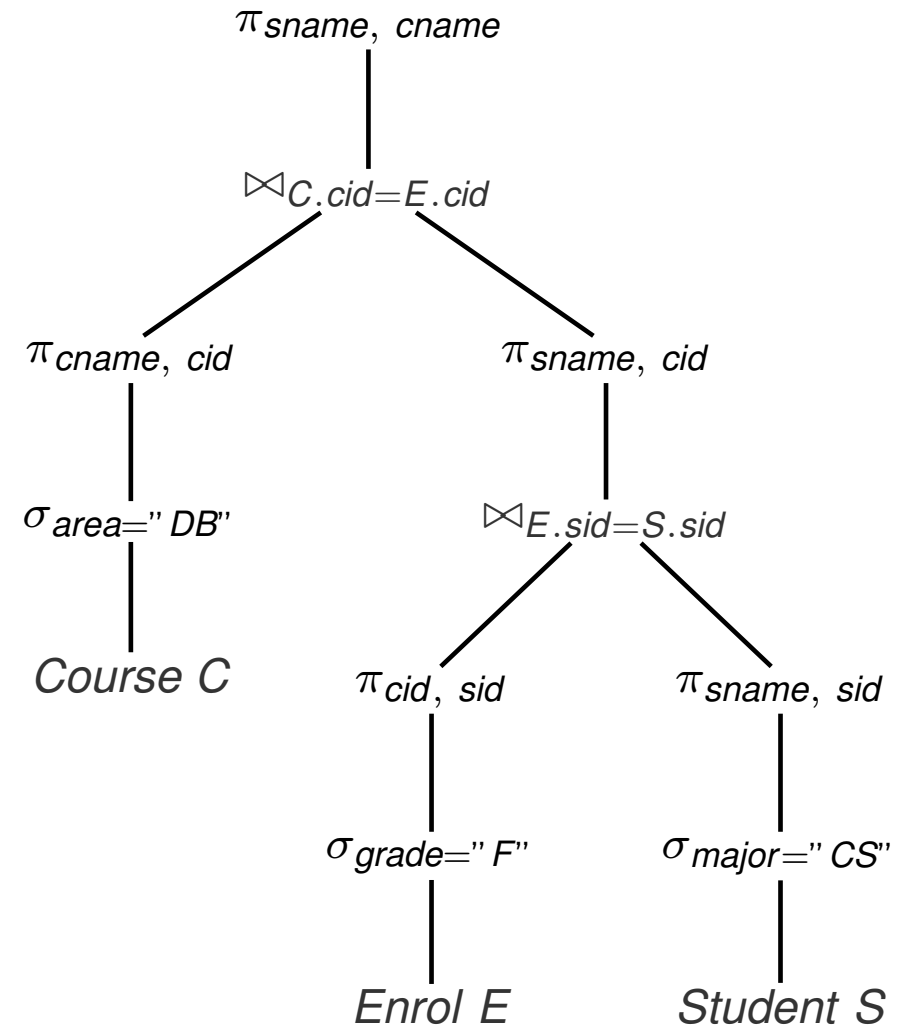


$$\pi_L(R \bowtie_p S) \equiv \pi_{L_R}(R) \bowtie_p \pi_{L_S}(S)$$

# Example (cont.)



Original Query

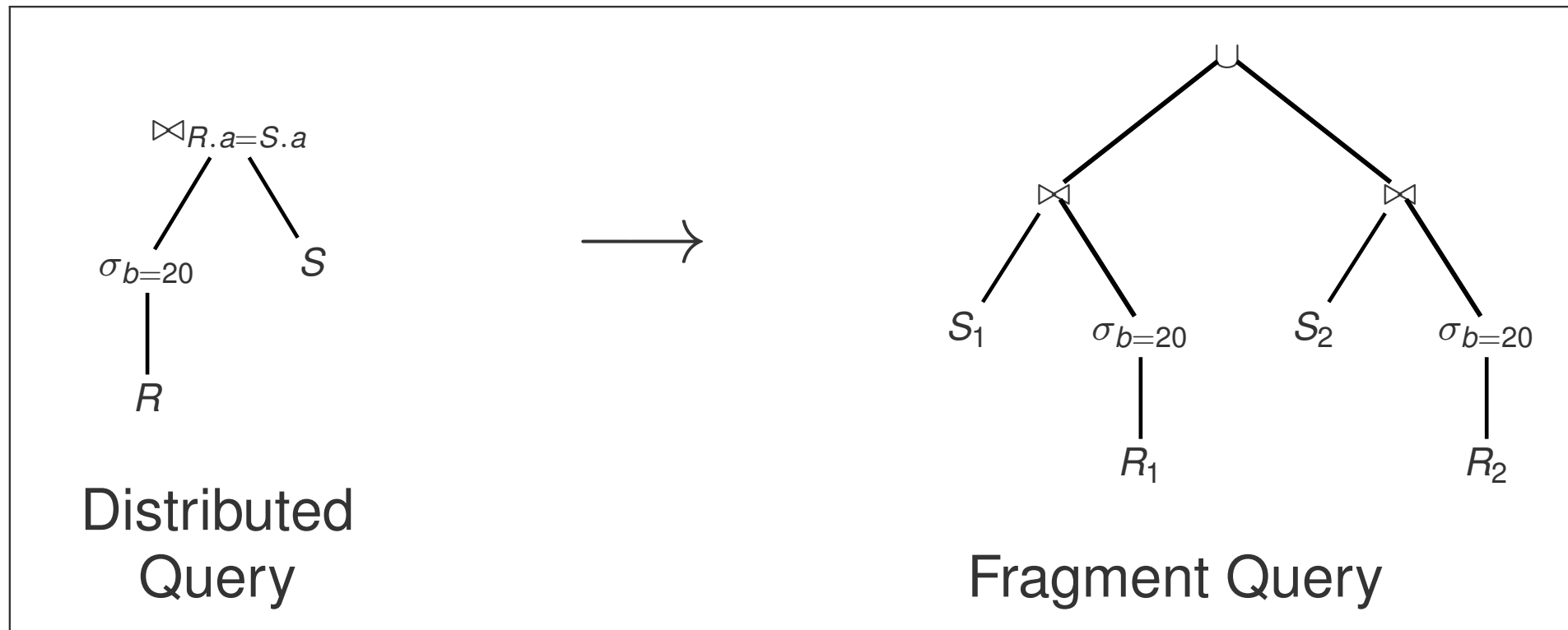


Final Query



# Query Localization

- Rewrites distributed query into a fragment query
- Uses data distribution information to determine which fragments are involved

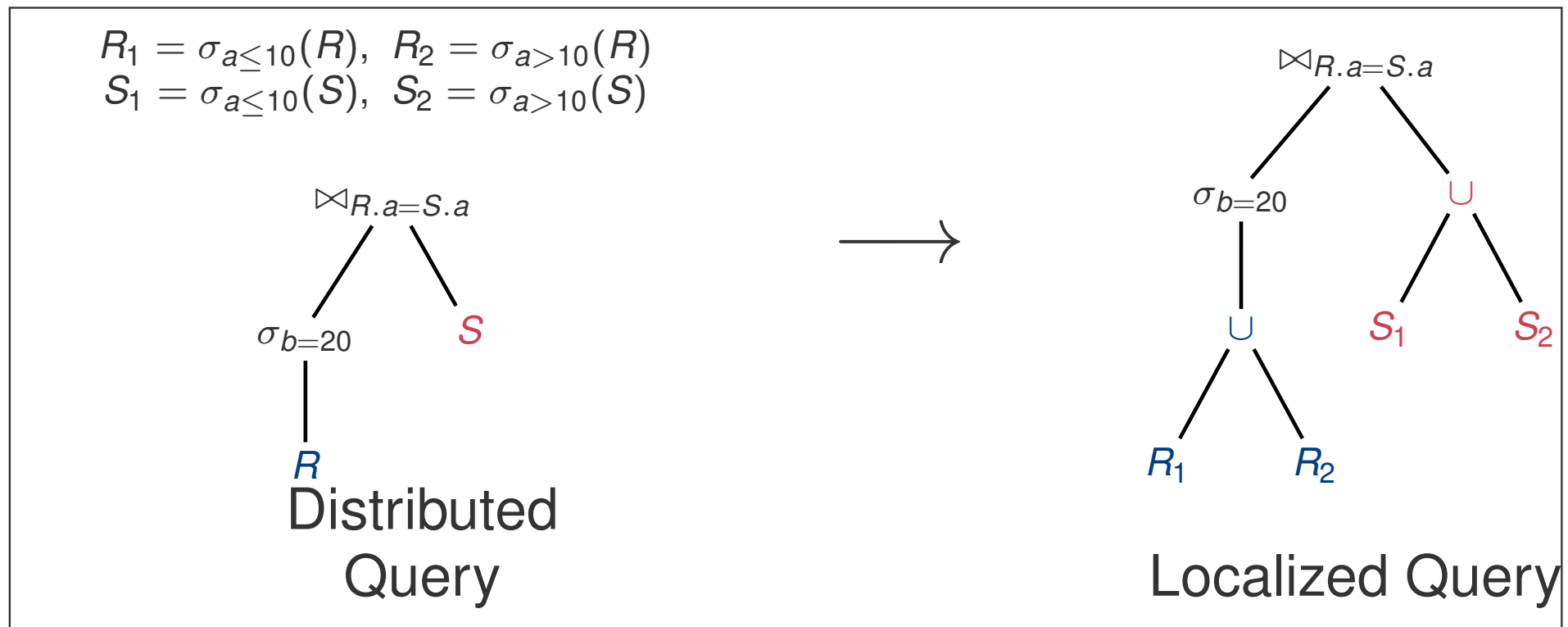


# Localization Program

- A **localization program** for a fragmented relation  $R$  is a reconstruction rule for  $R$  in terms of its fragments
- **Example:**
  - ▶ Let  $\{R_1, \dots, R_n\}$  be a complete & disjoint partitioning of  $R$
  - ▶ If each  $R_i = \sigma_{F_i}(R)$ , then localization program for  $R$  is  $R_1 \cup \dots \cup R_n$
  - ▶ If each  $R_i = \pi_{L_i}(R)$  &  $key(R) \in L_i$ , then localization program for  $R$  is  $R_1 \bowtie \dots \bowtie R_n$

# Localized Query

- **Localized query** = query with each fragmented relation replaced by its localization program



# Reduction Techniques

- **Reduction techniques** = rewriting techniques to simplify localized queries
- Identify & eliminate query expressions on fragments that do not contribute to query results
- Techniques:
  - ▶ Reduction for horizontal fragmentation
    - ★ Reduction with selection
    - ★ Reduction with join
  - ▶ Reduction for derived horizontal fragmentation
  - ▶ Reduction for vertical fragmentation
  - ▶ Reduction for hybrid fragmentation

# Reduction with Selection

**Rule 1:**  $\sigma_p(R_i) = \emptyset$  if  $R_i = \sigma_{F_i}(R)$  and  $F_i \wedge p = \text{false}$

$$R = R_1 \cup R_2 \cup R_3$$

$$R_1 = \sigma_{a < 10}(R)$$

$$R_2 = \sigma_{a \in [10, 70]}(R)$$

$$R_3 = \sigma_{a > 70}(R)$$

$$Q_1 = \sigma_{a=12}(R)$$

$$= \sigma_{a=12}(R_1 \cup R_2 \cup R_3)$$

$$= \sigma_{a=12}(R_1) \cup \sigma_{a=12}(R_2) \cup \sigma_{a=12}(R_3)$$

$$= \sigma_{a=12}(R_2)$$

# Reduction with Join

**Rule 2:**  $R_i \bowtie_a S_j = \emptyset$  if  $R_i = \sigma_{F_a \wedge F}(R)$ ,  $S_j = \sigma_{F'_a \wedge F'}(S)$ ,  $F_a \& F'_a$  are predicates on attribute  $a$ , and  $F_a \wedge F'_a = \text{false}$

$$R = R_1 \cup R_2 \cup R_3$$

$$R_1 = \sigma_{a < 10}(R)$$

$$R_2 = \sigma_{a \in [10, 70]}(R)$$

$$R_3 = \sigma_{a > 70}(R)$$

$$S = S_1 \cup S_2$$

$$S_1 = \sigma_{a < 10}(S)$$

$$S_2 = \sigma_{a \geq 10}(S)$$

$$Q = R \bowtie_a S$$

$$= (R_1 \cup R_2 \cup R_3) \bowtie_a (S_1 \cup S_2)$$

$$= (R_1 \bowtie_a S_1) \cup (R_1 \bowtie_a S_2) \cup (R_2 \bowtie_a S_1) \cup$$

$$(R_2 \bowtie_a S_2) \cup (R_3 \bowtie_a S_1) \cup (R_3 \bowtie_a S_2)$$

$$= (R_1 \bowtie_a S_1) \cup (R_2 \bowtie_a S_2) \cup (R_3 \bowtie_a S_2)$$

# Reduction for Derived Fragmentation

**Rule 3:**  $S_i \bowtie_a R_j = \emptyset$  if  $S_i = S \bowtie_a R_i$  is a derived horizontal fragmentation of  $S$  wrt  $R$ , and  $i \neq j$

Consider  $R(\underline{a}, b, c)$ ,  $S(\underline{x}, y, a)$   
where  $S.a$  is a foreign key of  $R$

- $R_1 = \sigma_{b=10}(R)$ ,  $R_2 = \sigma_{b \neq 10}(R)$
- $S_1 = S \bowtie_a R_1$ ,  $S_2 = S \bowtie_a R_2$

$$\begin{aligned} Q &= \sigma_{b=20}(R) \bowtie_a S \\ &= \sigma_{b=20}(R_1 \cup R_2) \bowtie_a (S_1 \cup S_2) \\ &= \sigma_{b=20}(R_2) \bowtie_a (S_1 \cup S_2) \\ &= (\sigma_{b=20}(R_2) \bowtie_a S_1) \cup (\sigma_{b=20}(R_2) \bowtie_a S_2) \\ &= \sigma_{b=20}(R_2) \bowtie_a S_2 \end{aligned}$$

# Reduction for Vertical Fragmentation

**Rule 4:**  $\pi_L(R_1 \bowtie R_2 \bowtie \cdots \bowtie R_n) = \pi_L(R_2 \bowtie \cdots \bowtie R_n)$   
if  $R_1, \dots, R_n$  are vertical fragments of  $R$  and  
( $attributes(R_1) - key(R)$ )  $\cap L = \emptyset$

Consider  $R(\underline{a}, b, c)$  where  $R = R_1 \bowtie_a R_2$   
 $R_1 = \pi_{a,b}(R)$   
 $R_2 = \pi_{a,c}(R)$

$$\begin{aligned} Q &= \pi_c(R) \\ &= \pi_c(R_1 \bowtie_a R_2) \\ &= \pi_c(R_2) \end{aligned}$$



# Reduction for Hybrid Fragmentation

$$\begin{aligned} R &= (R_1 \cup R_2) \bowtie_a R_3 \\ R_1 &= \pi_{a,b}(\sigma_{a < 10}(R)) \\ R_2 &= \pi_{a,b}(\sigma_{a \geq 10}(R)) \\ R_3 &= \pi_{a,c}(R) \end{aligned}$$

$$\begin{aligned} Q &= \pi_b(\sigma_{a=20}(R)) \\ &= \pi_b(\sigma_{a=20}((R_1 \cup R_2) \bowtie_a R_3)) \\ &= \pi_b(\sigma_{a=20}(R_1 \cup R_2)) \\ &= \pi_b(\sigma_{a=20}(R_1) \cup \sigma_{a=20}(R_2)) \\ &= \pi_b(\sigma_{a=20}(R_2)) \end{aligned}$$

# Distributed Join Strategies for $R \bowtie_A S$

- There are three cases to consider for  $R \bowtie_A S$ :
  - ▶ Case 1: Both  $R$  and  $S$  have been partitioned on join key
  - ▶ Case 2: Only  $R$  (but not  $S$ ) has been partitioned on join key
  - ▶ Case 3: Neither  $R$  nor  $S$  has been partitioned on join key
- Case 1: Collocated/Local join
- Case 2: Directed join
  - ▶ Dynamically repartition  $S$  on join key
- Case 3: Repartitioned join
  - ▶ Dynamically repartition  $R$  &  $S$  on join key
- Broadcast join: Replicate either  $R$  or  $S$  to all nodes
  - ▶ Applicable for cases 2 & 3

# Join Strategies: Example

- Customers (cust#, cname, city)
- Orders (order#, cust#, odate)
- Suppliers (supp#, sname, city)

Customers		
cust#	cname	city
1	Alice	Singapore
2	Bob	Penang
3	Carol	Bangkok
4	Dave	Singapore
5	Eve	Singapore
6	Fred	Penang
7	George	Bangkok

Orders		
order#	cust#	odate
302	1	June 2013
304	2	May 2013
307	3	Nov 2013
308	1	April 2013
309	5	May 2013
311	6	Dec 2013
312	3	July 2013

Suppliers		
supp#	sname	city
32	A	Bangkok
33	B	Singapore
34	C	Singapore
36	D	Bangkok
37	E	Penang
38	F	Penang
39	G	Singapore

# Collocated Join: Example

- Customers hash partitioned on cust# using  $h_{cust}$
- Orders hash partitioned on cust# using  $h_{cust}$
- $h_{cust}(c) = (c \bmod 3) + 1$

Site 1	Customers <sub>1</sub>		
	<b>cust#</b>	<b>cname</b>	<b>city</b>
	3	Carol	Bangkok
	6	Fred	Penang

Orders <sub>1</sub>		
<b>order#</b>	<b>cust#</b>	<b>odate</b>
307	3	Nov 2013
311	6	Dec 2013
312	3	July 2013

Site 2	Customers <sub>2</sub>		
	<b>cust#</b>	<b>cname</b>	<b>city</b>
	1	Alice	Singapore
	4	Dave	Singapore
	7	George	Bangkok

Orders <sub>2</sub>		
<b>order#</b>	<b>cust#</b>	<b>odate</b>
302	1	June 2013
308	1	April 2013

Site 3	Customers <sub>3</sub>		
	<b>cust#</b>	<b>cname</b>	<b>city</b>
	2	Bob	Penang
	5	Eve	Singapore

Orders <sub>3</sub>		
<b>order#</b>	<b>cust#</b>	<b>odate</b>
304	2	May 2013
309	5	May 2013

# Collocated Join: Example (cont.)

- **Query 1:** Customers  $\bowtie_{cust\#}$  Orders

Site 1	Customers <sub>1</sub>			Orders <sub>1</sub>		
	<b>cust#</b>	<b>cname</b>	<b>city</b>	<b>order#</b>	<b>cust#</b>	<b>odate</b>
	3	Carol	Bangkok	307	3	Nov 2013
	6	Fred	Penang	311	6	Dec 2013
				312	3	July 2013

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Site 2	Customers <sub>2</sub>			Orders <sub>2</sub>		
	<b>cust#</b>	<b>cname</b>	<b>city</b>	<b>order#</b>	<b>cust#</b>	<b>odate</b>
	1	Alice	Singapore	302	1	June 2013
	4	Dave	Singapore	308	1	April 2013
	7	George	Bangkok			

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Site 3	Customers <sub>3</sub>			Orders <sub>3</sub>		
	<b>cust#</b>	<b>cname</b>	<b>city</b>	<b>order#</b>	<b>cust#</b>	<b>odate</b>
	2	Bob	Penang	304	2	May 2013
	5	Eve	Singapore	309	5	May 2013

$$\bigcup_{i=1}^3 (Customers_i \bowtie Orders_i)$$

# Directed Join: Example

- Customers hash partitioned on cust# using  $h_{cust}$
- Orders hash partitioned on order# using  $h_{order}$
- $h_{cust}(c) = (c \bmod 3) + 1$
- $h_{order}(o) = (o \bmod 3) + 1$

Site 1

Customers <sub>1</sub>		
cust#	cname	city
3	Carol	Bangkok
6	Fred	Penang

Orders <sub>1</sub>		
order#	cust#	odate
309	5	May 2013
312	3	July 2013

Site 2

Customers <sub>2</sub>		
cust#	cname	city
1	Alice	Singapore
4	Dave	Singapore
7	George	Bangkok

Orders <sub>2</sub>		
order#	cust#	odate
304	2	May 2013
307	3	Nov 2013

Site 3

Customers <sub>3</sub>		
cust#	cname	city
2	Bob	Penang
5	Eve	Singapore

Orders <sub>3</sub>		
order#	cust#	odate
302	1	June 2013
308	1	April 2013
311	6	Dec 2013

# Directed Join: Example (cont.)

- **Query 1:** Customers  $\bowtie_{cust\#}$  Orders

Site 1	Customers <sub>1</sub>		
	<b>cust#</b>	<b>cname</b>	<b>city</b>
	3	Carol	Bangkok
	6	Fred	Penang

Orders <sub>1</sub>		
<b>order#</b>	<b>cust#</b>	<b>odate</b>
309	5	May 2013
312	3	July 2013

Site 2	Customers <sub>2</sub>		
	<b>cust#</b>	<b>cname</b>	<b>city</b>
	1	Alice	Singapore
	4	Dave	Singapore
	7	George	Bangkok

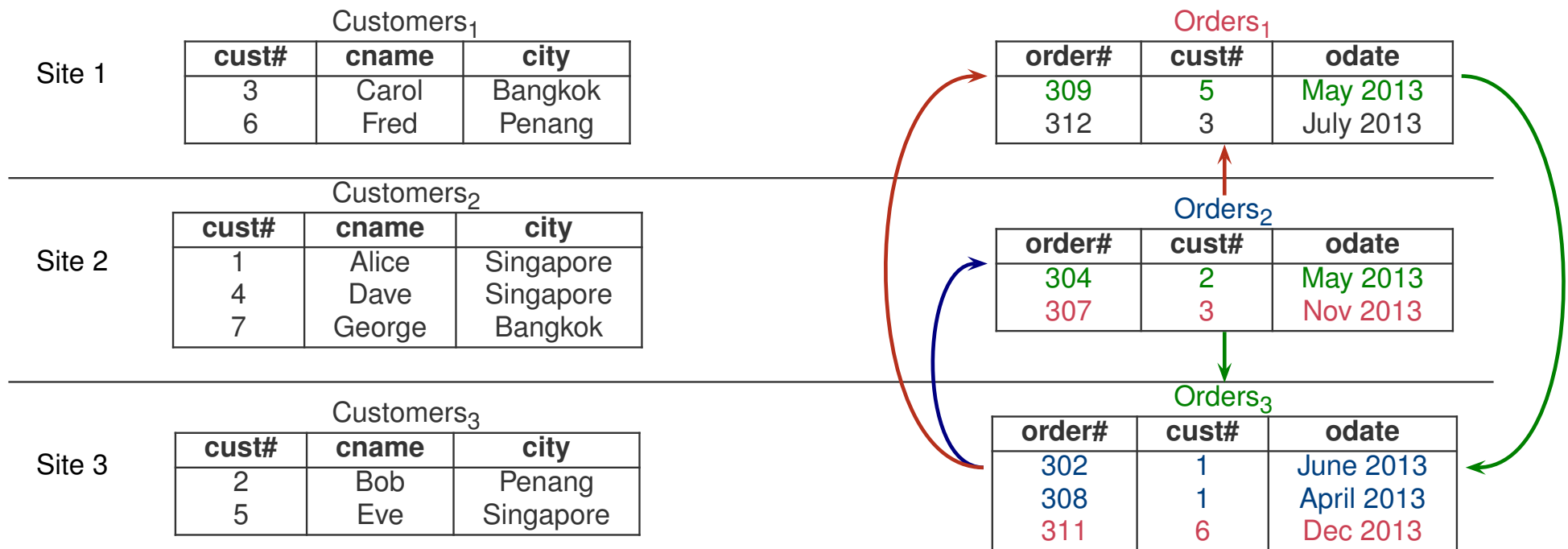
Orders <sub>2</sub>		
<b>order#</b>	<b>cust#</b>	<b>odate</b>
304	2	May 2013
307	3	Nov 2013

Site 3	Customers <sub>3</sub>		
	<b>cust#</b>	<b>cname</b>	<b>city</b>
	2	Bob	Penang
	5	Eve	Singapore

Orders <sub>3</sub>		
<b>order#</b>	<b>cust#</b>	<b>odate</b>
302	1	June 2013
308	1	April 2013
311	6	Dec 2013

# Directed Join: Example (cont.)

- Query 1: Customers  $\bowtie_{cust\#}$  Orders



Repartition Orders on cust# :  $Orders'_i = \sigma_{h_{cust}(cust\#)=i}(Orders)$

$$\bigcup_{i=1}^3 (Customers_i \bowtie Orders'_i)$$



# Repartitioned Join: Example

- Customers hash partitioned on cust# using  $h_{cust}$
- Suppliers hash partitioned on supp# using  $h_{supp}$
- $h_{cust}(c) = (c \bmod 3) + 1$
- $h_{supp}(s) = (s \bmod 3) + 1$

Site 1

cust#	cname	city
3	Carol	Bangkok
6	Fred	Penang

supp#	sname	city
33	B	Singapore
36	D	Bangkok
39	G	Singapore

Site 2

cust#	cname	city
1	Alice	Singapore
4	Dave	Singapore
7	George	Bangkok

supp#	sname	city
34	C	Singapore
37	E	Penang

Site 3

cust#	cname	city
2	Bob	Penang
5	Eve	Singapore

supp#	sname	city
32	A	Bangkok
38	F	Penang

# Repartitioned Join: Example (cont.)

- **Query 2:** Customers  $\bowtie_{city}$  Suppliers

Site 1	Customers <sub>1</sub>		
	<b>cust#</b>	<b>cname</b>	<b>city</b>
	3	Carol	Bangkok
	6	Fred	Penang

Suppliers <sub>1</sub>		
<b>supp#</b>	<b>sname</b>	<b>city</b>
33	B	Singapore
36	D	Bangkok
39	G	Singapore

Site 2	Customers <sub>2</sub>		
	<b>cust#</b>	<b>cname</b>	<b>city</b>
	1	Alice	Singapore
	4	Dave	Singapore
	7	George	Bangkok

Suppliers <sub>2</sub>		
<b>supp#</b>	<b>sname</b>	<b>city</b>
34	C	Singapore
37	E	Penang

Site 3	Customers <sub>3</sub>		
	<b>cust#</b>	<b>cname</b>	<b>city</b>
	2	Bob	Penang
	5	Eve	Singapore

Suppliers <sub>3</sub>		
<b>supp#</b>	<b>sname</b>	<b>city</b>
32	A	Bangkok
38	F	Penang

# Repartitioned Join: Example (cont.)

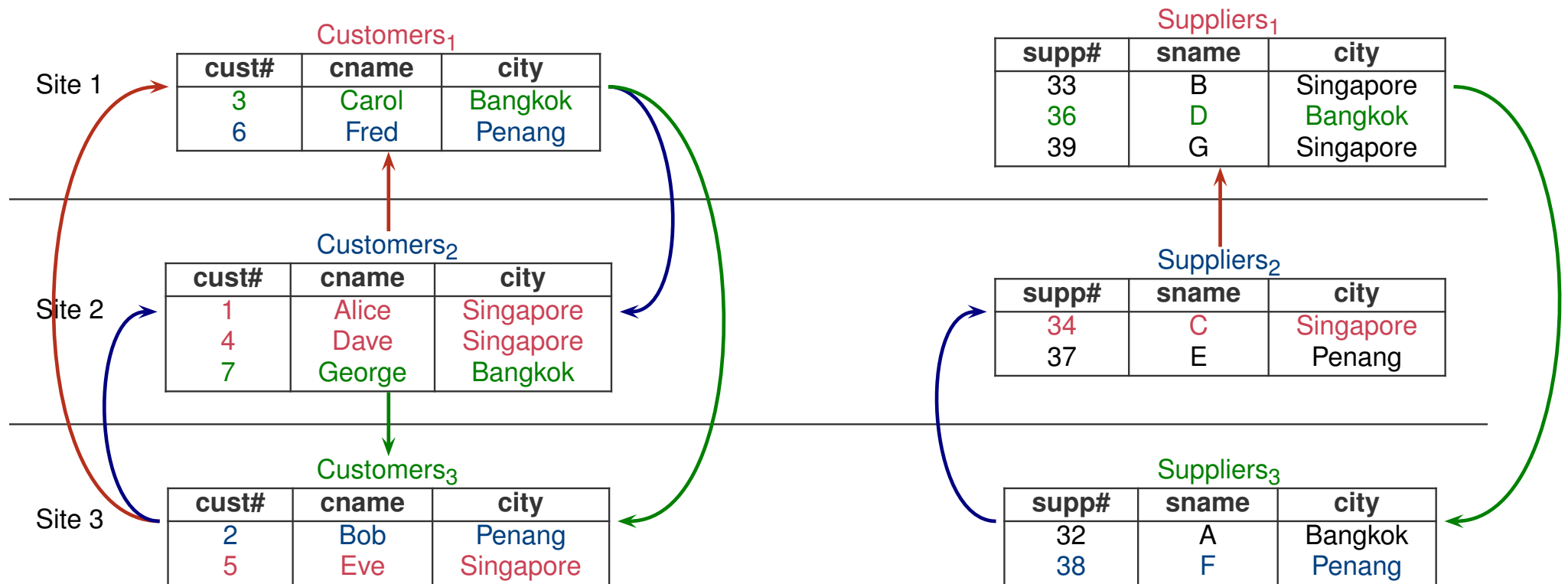
- **Query 2:** Customers  $\bowtie_{city}$  Suppliers
- Repartition both tables using  $h_{city}$

c	$h_{city}(c)$
Singapore	1
Penang	2
Bangkok	3

- $Customers'_i = \sigma_{h_{city}(city)=i}(Customers)$
- $Suppliers'_i = \sigma_{h_{city}(city)=i}(Suppliers)$

# Repartitioned Join: Example (cont.)

Query 2: Customers  $\bowtie_{city}$  Suppliers



$$\bigcup_{i=1}^3 (Customers'_i \bowtie Suppliers'_i)$$

# Broadcast Join: Example

- Customers hash partitioned on cust# using  $h_{cust}$
- Suppliers hash partitioned on supp# using  $h_{supp}$
- $h_{cust}(c) = (c \bmod 3) + 1$
- $h_{supp}(s) = (s \bmod 3) + 1$

Site 1

cust#	cname	city
3	Carol	Bangkok
6	Fred	Penang

supp#	sname	city
33	B	Singapore
36	D	Bangkok
39	G	Singapore

Site 2

cust#	cname	city
1	Alice	Singapore
4	Dave	Singapore
7	George	Bangkok

supp#	sname	city
34	C	Singapore
37	E	Penang

Site 3

cust#	cname	city
2	Bob	Penang
5	Eve	Singapore

supp#	sname	city
32	A	Bangkok
38	F	Penang

# Broadcast Join: Example (cont.)

- **Query 2:** Customers  $\bowtie_{city}$  Suppliers

Site 1

Customers<sub>1</sub>

cust#	cname	city
3	Carol	Bangkok
6	Fred	Penang

Suppliers<sub>1</sub>

supp#	sname	city
33	B	Singapore
36	D	Bangkok
39	G	Singapore

Site 2

Customers<sub>2</sub>

cust#	cname	city
1	Alice	Singapore
4	Dave	Singapore
7	George	Bangkok

Suppliers<sub>2</sub>

supp#	sname	city
34	C	Singapore
37	E	Penang

Site 3

Customers<sub>3</sub>

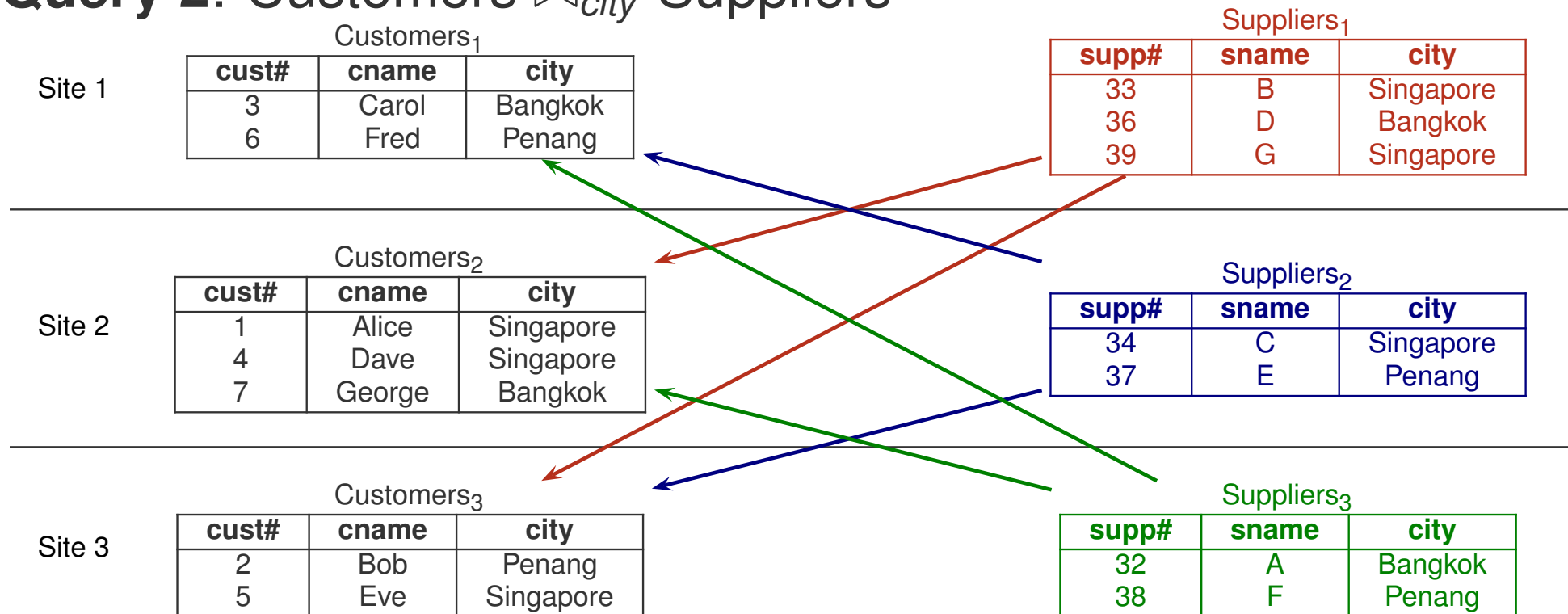
cust#	cname	city
2	Bob	Penang
5	Eve	Singapore

Suppliers<sub>3</sub>

supp#	sname	city
32	A	Bangkok
38	F	Penang

# Broadcast Join: Example (cont.)

## Query 2: Customers $\bowtie_{city}$ Suppliers

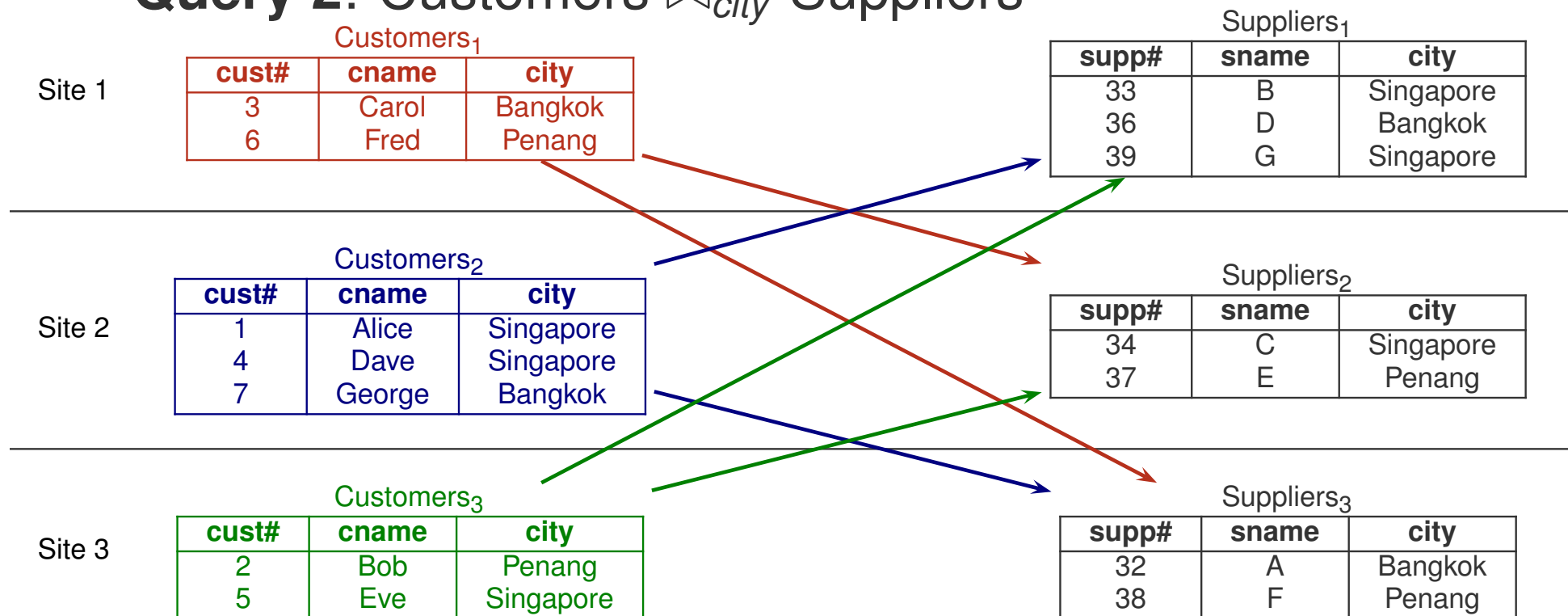


## Option 1: Broadcast Suppliers

$$\bigcup_{i=1}^3 (Customers_i \bowtie Suppliers)$$

# Broadcast Join: Example (cont.)

- Query 2: Customers  $\bowtie_{city}$  Suppliers



## Option 2: Broadcast Customers

$$\bigcup_{i=1}^3 (Customers \bowtie Suppliers_i)$$



# Comparison of join strategies for $R \bowtie S$

Let the relations be partitioned over  $n$  nodes

Join Strategy	Communication Cost
Collocated	0
Directed	$size(R)$ if $R$ is being repartitioned
Repartitioned	$size(R) + size(S)$
Broadcast	$(n - 1) \times size(R)$ if $R$ is being broadcast

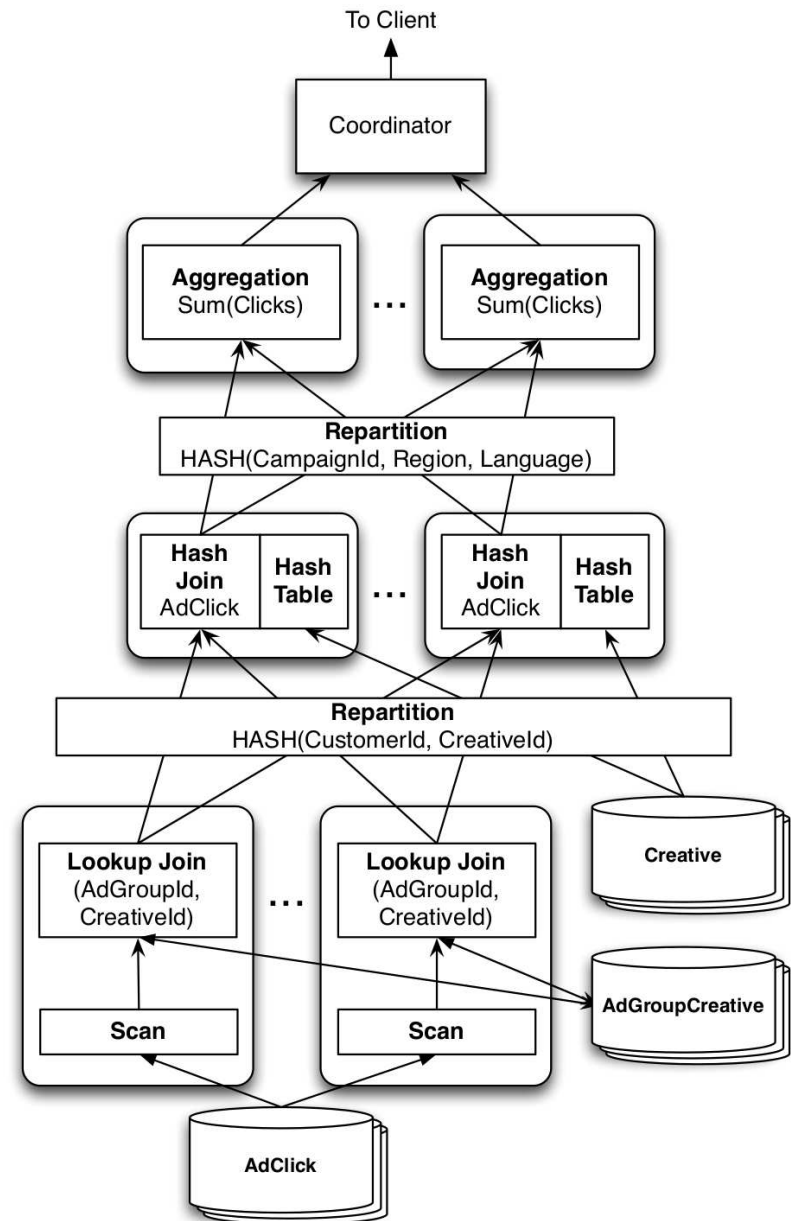
# Query Processing in Google's F1

- Google's early NewSQL system
  - ▶ Distributed relational database system
  - ▶ Hybrid of NoSQL & RDBMS
  - ▶ NoSQL: High availability, scalability
  - ▶ RDBMS: Functionality, consistency, usability (SQL, transactions)
- Used by Google's AdWords system since 2012
  - ▶ 100s of applications & 1000s of users
  - ▶ Database is over 100 TB,  $10^5$  requests/sec

# Query Processing in Google's F1

SELECT      agc.CampaignId,  
              ac.Region,  
              c.Language,  
              SUM(ac.Clicks)  
FROM        AdClick ac  
              JOIN AdGroupCreative agc  
              USING (AdGroupId, CreativeId)  
              JOIN Creative c  
              USING (CustomerId, CreativeId)  
WHERE  
GROUP BY    agc.CampaignId, ac.Region,  
              c.Language

**Creative** (CreativeId, CustomerId, Language, ...)  
**AdGroupCreative** (AdGroupId, CreativeId, CampaignId, CustomerId, ...)  
**AdClick** (AdGroupId, CreativeId, Region, Date, Clicks, ...)



(Shute, et al., 2013)

# References

- T. Özsu & P. Valdureiz, *Distributed Query Processing*, Chapter 4, Principles of Distributed Database Systems, 4<sup>th</sup> Edition, 2020
- C. Baru, et al. *DB2 Parallel Edition*, IBM Systems Journal, 34(2), 1995.
- *Google goes back to the future with SQL F1 database*, The Register, August 2013, [https://www.theregister.co.uk/2013/08/30/google\\_f1\\_deepdive/](https://www.theregister.co.uk/2013/08/30/google_f1_deepdive/)
- *F1: A Distributed SQL Database That Scales*, VLDB 2013, <https://research.google.com/pubs/pub41344.html>