



Introduction to Query Optimization

Abdu Alawini

University of Illinois at Urbana-Champaign

CS411: Database Systems



Optimization

- *So far, we talked about physical implementations. Next step: how do we use them?*
- At the heart of the database engine
- Step 1: convert the SQL query to a logical plan
- Step 2: find a better logical plan, find an associated physical plan
- (Feed the physical plan into the query processor.)



Converting from SQL to Logical Plans

Need to start someplace..

The easy cases:

Select a1, ..., an
From R1, ..., Rk
Where C

$$\pi_{a1, \dots, an} (\sigma_C (R1 \times R2 \times \dots \times Rk))$$

Select a1, ..., an, aggs
From R1, ..., Rk
Where C
Group by b1, ..., bl

Uses “extended” relational algebra, with gamma and delta

$$\pi_{a1, \dots, an} (\gamma_{b1, \dots, bl, aggs} (\sigma_C (R1 \times R2 \times \dots \times Rk)))$$

In most of these cases, the x will be a \bowtie



Optimization: Logical Query Plan

- Now we have one logical plan. Let's try to make it better.
- Ingredient 1: **Algebraic laws**: what are the ways in which an expression or tree may be rewritten without changing the meaning
- Ingredient 2: **Optimizations**: if there are multiple ways to write the same query, which one to choose.
 - Rule-based (heuristics): apply laws that seem to result in cheaper plans
 - Cost-based: estimate size and cost of intermediate results, search systematically for best plan



The three components of an optimizer

- Algebraic laws
- A cost estimator
- Optimization
 - Rule based
 - Cost based



Query Optimization: RA Equivalence Rules

Abdu Alawini

University of Illinois at Urbana-Champaign

CS411: Database Systems



Algebraic Laws

Hold independent of set or bag..

- Commutative and **Associative Laws**

- $R \cup S = S \cup R$, $R \cup (S \cup T) = (R \cup S) \cup T$

- $R \cap S = S \cap R$, $R \cap (S \cap T) = (R \cap S) \cap T$

- $R \bowtie S = S \bowtie R$, $R \bowtie (S \bowtie T) = (R \bowtie S) \bowtie T$

- **Distributive Laws**

- $R \bowtie (S \cup T) = (R \bowtie S) \cup (R \bowtie T)$



Algebraic Laws

- Laws involving selection (set semantics):
 - $\sigma_{C \text{ AND } C'}(R) = \sigma_C(\sigma_{C'}(R)) = \sigma_C(R) \cap \sigma_{C'}(R)$
 - $\sigma_{C \text{ OR } C'}(R) = \sigma_C(R) \cup \sigma_{C'}(R)$
 - $\sigma_C(R \bowtie S) = \sigma_C(R) \bowtie S$
 - When is this true?
 - Certainly true when C involves only attributes of R
 - What if it involves attributes of R and S?
 - For example: R(X, Y), S(Y, Z)
 - Say: Y = 3; X = 3 ^ Z = 5



Laws involving selection (set semantics) Cont.

- $\sigma_C(R - S) = \sigma_C(R) - S$
 - When is this true?
- $\sigma_C(R \cup S) = \sigma_C(R) \cup \sigma_C(S)$
- $\sigma_C(R \cap S) = \sigma_C(R) \cap S$



Algebraic Laws

- Example: $R(A, B, C, D), S(E, F, G)$
 - $\sigma_{F=3} (R \bowtie_{D=E} S) =$?
 - $\sigma_{A=5 \text{ AND } G=9} (R \bowtie_{D=E} S) =$?
- Simplify as much as possible by pushing down predicates
 - As close to the relations as possible



Algebraic Laws

- Example: $R(A, B, C, D), S(E, F, G)$
 - $\sigma_{F=3}(R \bowtie_{D=E} S) = R \bowtie_{D=E} (\sigma_{F=3}(S))$
 - $\sigma_{A=5 \text{ AND } G=9}(R \bowtie_{D=E} S) = (\sigma_{A=5}(R)) \bowtie_{D=E} (\sigma_{G=9}(S))$



Algebraic Laws

- Laws involving selection (set semantics):
 - $\sigma_{C \text{ AND } C'}(R) = \sigma_C(\sigma_{C'}(R)) = \sigma_C(R) \cap \sigma_{C'}(R)$
 - $\sigma_{C \text{ OR } C'}(R) = \sigma_C(R) \cup \sigma_{C'}(R)$ ← *what about this one?*
 - $\sigma_C(R \bowtie S) = \sigma_C(R) \bowtie S$
 - Only when C involves only attributes of R
 - $\sigma_C(R - S) = \sigma_C(R) - S$
 - $\sigma_C(R \cup S) = \sigma_C(R) \cup \sigma_C(S)$
 - $\sigma_C(R \cap S) = \sigma_C(R) \cap S$

*Exercise: Think about which
of these hold for bag semantics....*



Algebraic Laws

- Laws involving selection (bag semantics??):
 - $\sigma_{C \text{ OR } C'}(R) = \sigma_C(R) \cup \sigma_{C'}(R)$ \leftarrow *what about this one?*



Algebraic Laws

- Laws involving projections
 - $\Pi_M(\Pi_N(R)) = \Pi_{M \cap N}(R)$
 - $\Pi_M(R \bowtie S) = \Pi_N(\Pi_P(R) \bowtie \Pi_Q(S))$
 - Where N, P, Q are appropriate subsets of attributes of M that are “needed afterwards”
- Example $R(A,B,C,D), S(E, F, G)$
 - $\Pi_{A,B,G}(R \bowtie_{D=E} S) = \Pi_{?}(\Pi_{?}(R) \bowtie \Pi_{?}(S))$



Query Optimization: Rule-Based Optimization

Abdu Alawini

University of Illinois at Urbana-Champaign

CS411: Database Systems



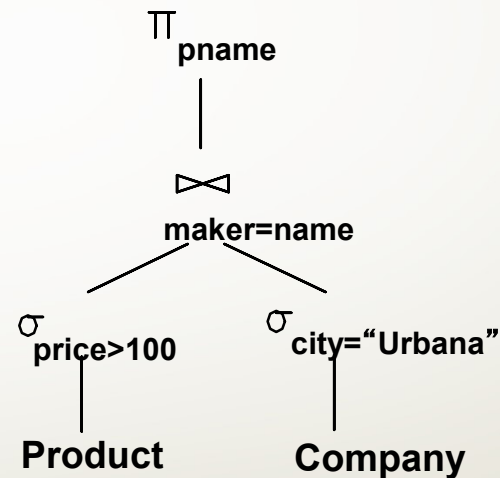
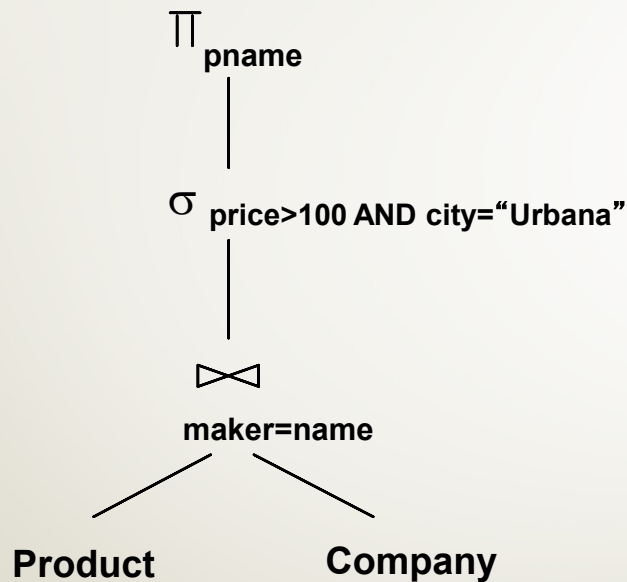
Heuristic Based Optimizations

- Rewriting of logical plan based on specific algebraic laws
- Results in better execution plans most of the time



Heuristic 1: Push selections down

$$\text{Uses } \sigma_C(R \bowtie S) = \sigma_C(R) \bowtie \sigma_C(S)$$

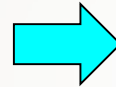


The earlier we process selections, less tuples we need to manipulate higher up in the tree



Pushing selection down: More complex Settings

```
Select y.name, Max(x.price)
From   product x, company y
Where  x.maker = y.name
GroupBy y.name
Having Max(x.price) > 100
```



```
Select y.name, Max(x.price)
From   product x, company y
Where  x.maker=y.name and
       x.price > 100
GroupBy y.name
```

- ⑩ *For each company, find the maximum price among its products.*
- ⑩ *But only display (company, maxprice) pair if maxprice > 100*
- ⑩ Advantage: the size of the join will be smaller.
- ⑩ Requires transformation rules specific to the grouping/aggregation operators.
- ⑩ *Won't work if we replace Max by Avg.*



Heuristic 2

- (In some cases) push selections up, then down
- But ultimately pushed down
- $\sigma_C(R) \bowtie S = \sigma_C(R \bowtie S) = \sigma_C(R) \bowtie \sigma_C(S)$

Typically: apply selections as close to the relations as possible so as to reduce size of intermediate results



Pushing selection up?

Bargain view: for categories with some $\text{price} < 5$, find the company that makes the cheapest product in that category, and that price

```
Select  V2.name, V2.price
From    V1, V2
Where   V1.category = V2.category and
        V1.minprice = V2.price
```

```
Create View V1 AS
Select  x.category,
        Min(x.price) AS minprice
From    product x
Where   x.price < 5
GroupBy x.category
```

```
Create View V2 AS
Select  y.name, x.category, x.price
From    product x, company y
Where   x.maker=y.name
```



Pushing selection up ...

Bargain view: for categories with some price<5, find the company that makes the cheapest product in that category, and that price

```
Select  V2.name, V2.price
From    V1, V2
Where   V1.category = V2.category and
        V1.minprice = V2.price AND V1.minprice < 5
```

```
Create View V1 AS
Select  x.category,
        Min(x.price) AS minprice
From    product x
Where   x.price < 5
GroupBy x.category
```

```
Create View V2 AS
Select  y.name, x.category, x.price
From    product x, company y
Where   x.maker=y.name
```



... and then down

Bargain view: for categories with some price<5, find the company that makes the cheapest product in that category, and that price

```
Select  V2.name, V2.price
From    V1, V2
Where   V1.category = V2.category and
        V1.minprice = V2.price AND V1.minprice < 5
```

```
Create View V1 AS
Select  x.category,
        Min(x.price) AS minprice
From    product x
Where   x.price < 5
GroupBy x.category
```

```
Create View V2 AS
Select  y.name, x.category, x.price
From    product x, company y
Where   x.maker=y.name AND x.price < 5
```