

# Week 07 Lectures

## Signature-based Selection

### Indexing with Signatures

2/103

Signature-based indexing:

- designed for *pmr* queries (conjunction of equalities)
- does not try to achieve better than  $O(n)$  performance
- attempts to provide an "efficient" linear scan

Each tuple is associated with a *signature*

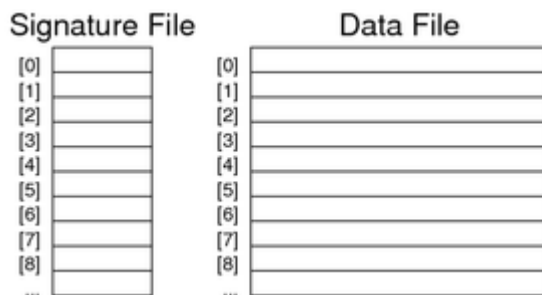
- a compact (lossy) descriptor for the tuple
- formed by combining information from multiple attributes
- stored in a signature file, parallel to data file

Instead of scanning/testing tuples, do pre-filtering via signatures.

### ... Indexing with Signatures

3/103

File organisation for signature indexing (two files)



One signature slot per tuple slot; unused signature slots are zeroed.

Record placement is independent of signatures  $\Rightarrow$  can use with other indexing.

### Signatures

4/103

A *signature* "summarises" the data in one tuple

A tuple consists of  $N$  attribute values  $A_1 \dots A_n$

A *codeword*  $cw(A_i)$  is

$m$  符号

- a bit-string,  $m$  bits long, where  $k$  bits are set to 1 ( $k \ll m$ )
- derived from the value of a single attribute  $A_i$

A *tuple descriptor* (signature) is built by combining  $cw(A_i)$ ,  $i=1..n$

- could combine by overlaying or concatenating codewords
- aim to have roughly half of the bits set to 1

### Generating Codewords

5/103

Generating a  $k$ -in- $m$  codeword for attribute  $A_i$

```
bits codeword(char *attr_value, int m, int k)
{
```

```

int  nbits = 0;    // count of set bits
bits cword = 0;   // assuming m <= 32 bits
srandom(hash(attr_value));
while (nbits < k) {
    int i = random() % m;
    if (((1 << i) & cword) == 0) {
        cword |= (1 << i);
        nbits++;
    }
}
return cword;    // m-bits with k 1-bits and m-k 0-bits
}

```

## Superimposed Codewords (SIMC)

6/103

In a superimposed codewords (simc) indexing scheme

- a tuple descriptor is formed by overlaying attribute codewords

A tuple descriptor  $desc(r)$  is

- a bit-string,  $m$  bits long, where  $j \leq nk$  bits are set to 1
- $desc(r) = cw(A_1) \text{ OR } cw(A_2) \text{ OR } \dots \text{ OR } cw(A_n)$

Method (assuming all  $n$  attributes are used in descriptor):

```

bits desc = 0
for (i = 1; i <= n; i++) {
    bits cw = codeword(A[i])
    desc = desc | cw
}

```

## SIMC Example

7/103

Consider the following tuple (from bank deposit database)

Branch	AcctNo	Name	Amount
Perryridge	102	Hayes	400

It has the following codewords/descriptor (for  $m = 12$ ,  $k = 2$ )

$A_i$	$cw(A_i)$
Perryridge	010000000001
102	000000000011
Hayes	000001000100
400	000010000100
$desc(r)$	010011000111

## SIMC Queries

8/103

To answer query  $q$  in SIMC

- first generate a query descriptor  $desc(q)$
- then use the query descriptor to search the signature file

$desc(q)$  is formed by **OR** of codewords for known attributes.

E.g. consider the query (Perryridge, ?, ?, ?).

bit manipulation

$A_i$	$cw(A_i)$
Perryridge	010000000001
?	000000000000
?	000000000000
?	000000000000
$desc(q)$	010000000001

---

### ... SIMC Queries

9/103

Once we have a query descriptor, we search the signature file:

```

pagesToCheck = {}
for each descriptor D[i] in signature file {
    if (matches(D[i], desc(q))) {
        pid = pageOf(tupleID(i))
        pagesToCheck = pagesToCheck U pid
    }
}
for each P in pagesToCheck {
    Buf = getPage(f, P)
    check tuples in Buf for answers
}
// where ...
#define matches(rdesc, qdesc)
    ((rdesc & qdesc) == qdesc)

```

---

### Example SIMC Query

10/103

Consider the query and the example database:

Signature	Deposit Record
010000000001	(Perryridge, ?, ?, ?)
100101001001	(Brighton, 217, Green, 750)
010011000111	(Perryridge, 102, Hayes, 400)
101001001001	(Downtown, 101, Johnshon, 512)
101100000011	(Mianus, 215, Smith, 700)
010101010101	(Clearview, 117, Throggs, 295)
100101010011	(Redwood, 222, Lindsay, 695)

Gives two matches: one true match, one *false match*.

---

### SIMC Parameters

11/103

False match probability  $p_F$  = likelihood of a false match

How to reduce likelihood of false matches?

- use different hash function for each attribute ( $h_i$  for  $A_i$ )
- increase descriptor size ( $m$ )
- choose  $k$  so that  $\approx$  half of bits are set

Larger  $m$  means reading more descriptor data.

Having  $k$  too high  $\Rightarrow$  increased overlapping.  
Having  $k$  too low  $\Rightarrow$  increased hash collisions.

### ... SIMC Parameters

12/103

How to determine "optimal"  $m$  and  $k$ ?

1. start by choosing acceptable  $p_F$   
(e.g.  $p_F \leq 10^{-5}$  i.e. one false match in 10,000)
2. then choose  $m$  and  $k$  to achieve no more than this  $p_F$ .

Formulae to derive  $m$  and  $k$  given  $p_F$  and  $n$ :

$$k = 1/\log_e 2 \cdot \log_e (1/p_F)$$

$$m = (1/\log_e 2)^2 \cdot n \cdot \log_e (1/p_F)$$

### Query Cost for SIMC

13/103

Cost to answer  $pmr$  query:  $Cost_{pmr} = b_D + b_q$

- read  $r$  descriptors on  $b_D$  descriptor pages
- then read  $b_q$  data pages and check for matches

$$b_D = \text{ceil}(r/c_D) \text{ and } c_D = \text{floor}(B/\text{ceil}(m/8))$$

$$\text{E.g. } m=64, B=8192, r=10^4 \Rightarrow c_D = 1024, b_D=10$$

$b_q$  includes pages with  $r_q$  matching tuples and  $r_F$  false matches

$$\text{Expected false matches} = r_F = (r - r_q) \cdot p_F \approx r \cdot p_F \text{ if } r_q \ll r$$

$$\text{E.g. Worst } b_q = r_q + r_F, \text{ Best } b_q = 1, \text{ Avg } b_q = \text{ceil}(b(r_q + r_F)/r)$$

COST

### Exercise 1: SIMC Query Cost

14/103

Consider a SIMC-indexed database with the following properties

- all pages are  $B = 8192$  bytes
- tuple descriptors have  $m = 64$  bits (= 8 bytes)
- total records  $r = 102,400$ , records/page  $c = 100$
- false match probability  $p_F = 1/1000$
- answer set has 1000 tuples from 100 pages
- 90% of false matches occur on data pages with true match
- 10% of false matches are distributed 1 per page

Calculate the total number of pages read in answering the query.

### Page-level SIMC

15/103

SIMC has one descriptor per tuple ... potentially inefficient.

Alternative approach: one descriptor for each data page.

Every attribute of every tuple in page contributes to descriptor.

Size of page descriptor (PD) (clearly larger than tuple descriptor):

- use above formulae but with  $c \cdot n$  "attributes"

$$\text{E.g. } n = 4, c = 128, p_F = 10^{-3} \Rightarrow m \approx 7000 \text{ bits} \approx 900 \text{ bytes}$$

dense

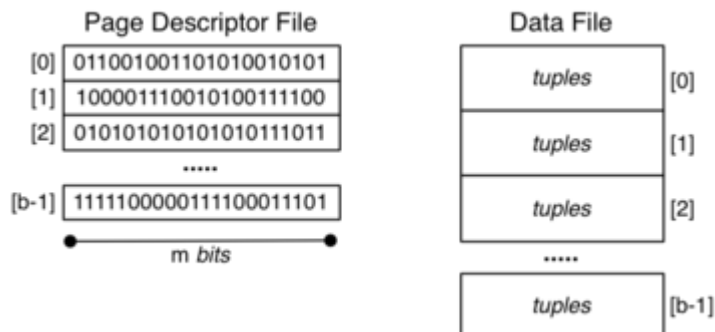
sparse

Typically, pages are 1..8KB  $\Rightarrow$  8..64 PD/page ( $N_{PD}$ ).

## Page-Level SIMC Files

16/103

File organisation for page-level superimposed codeword index



## Exercise 2: Page-level SIMC Query Cost

17/103

Consider a SIMC-indexed database with the following properties

- all pages are  $B = 8192$  bytes
- page descriptors have  $m = 4096$  bits (= 512 bytes)
- total records  $r = 102,400$ , records/page  $c = 100$
- false match probability  $p_F = 1/1000$
- answer set has 1000 tuples from 100 pages
- 90% of false matches occur on data pages with true match
- 10% of false matches are distributed 1 per page

跟exercise 1 做比较  
到时候再做一遍

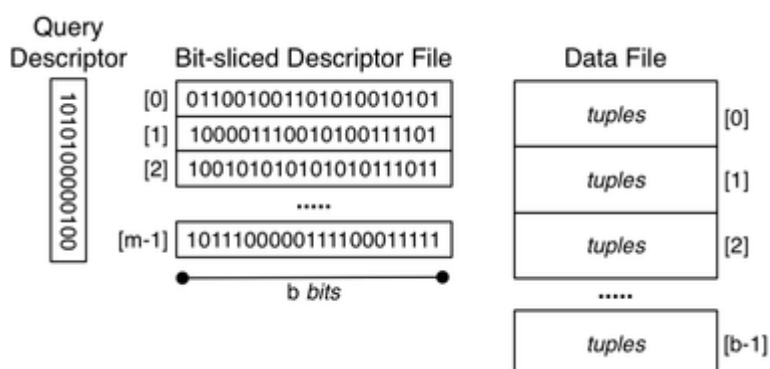
Calculate the total number of pages read in answering the query.

## ... Page-Level SIMC Files

18/103

Improvement: store  $b$   $m$ -bit page descriptors as  $m$   $b$ -bit "bit-slices"

第二次提升



## ... Page-Level SIMC Files

19/103

At query time

```
matches = ~0 //all ones
for each bit i set to 1 in desc(q) {
    slice = fetch bit-slice i
    matches = matches & slice
}
for each bit i set to 1 in matches {
    fetch page i
}
```

```
scan page for matching records
}
```

Effective because  $desc(q)$  typically has less than half bits set to 1

### Exercise 3: Bit-sliced SIMC Query Cost

20/103

Consider a SIMC-indexed database with the following properties

- all pages are  $B = 8192$  bytes
- $r = 102,400$ ,  $c = 100$ ,  $b = 1024$
- page descriptors have  $m = 4096$  bits (= 512 bytes)
- bit-slices have  $b = 1024$  bits (= 128 bytes)
- false match probability  $p_F = 1/1000$
- query descriptor has  $k = 10$  bits set to 1
- answer set has 1000 tuples from 100 pages
- 90% of false matches occur on data pages with true match
- 10% of false matches are distributed 1 per page

它说因为每个  
attribute contribute  
k bits. 只有一个  
attribute in query  
所以是 10个 page

E.g. consider the query (Perryridge, ?, ?, ?).

Calculate the total number of pages read in answering the query.

## Similarity Retrieval

### Similarity Selection

22/103

*Relational selection* is based on a boolean condition  $C$

- evaluate  $C$  for each tuple  $t$
- if  $C(t)$  is true, add  $t$  to result set
- if  $C(t)$  is false,  $t$  is not part of solution
- result is a set of tuples  $\{t_1, t_2, \dots, t_n\}$  all of which satisfy  $C$

Uses for relational selection:

- precise matching on structured data
- using individual attributes with known, exact values

### ... Similarity Selection

23/103

*Similarity selection* is used in contexts where

- cannot define a precise matching condition
- can define a measure  $d$  of "distance" between tuples
- $d=0$  is an exact match,  $d>0$  is less accurate match
- result is a list of pairs  $[(t_1, d_1), (t_2, d_2), \dots, (t_n, d_n)]$  (ordered by  $d_i$ )

Uses for similarity matching:

- text or multimedia (image/music) retrieval
- ranked queries in conventional databases

## Similarity-based Retrieval

24/103

Similarity-based retrieval typically works as follows:

- query is given as a query object  $q$  (e.g. sample image)
- system finds objects that are like  $q$  (i.e. small distance)

The system can measure distance between any object and  $q$  ...

How to restrict solution set to only the "most similar" objects:

- threshold  $d_{max}$  (only objects  $t$  such that  $dist(t,q) \leq d_{max}$ )
- count  $k$  ( $k$  closest objects ( $k$  nearest neighbours))



### ... Similarity-based Retrieval

25/103

Tuple structure for storing such data typically contains

- id to uniquely identify object (e.g. PostgreSQL oid)
- metadata (e.g. artist, title, genre, date taken, ...)
- value of object itself (e.g. PostgreSQL BLOB or bytea)



Properties of typical distance functions (on objects  $x, y, z$ )

- $dist(x, y) \geq 0$ ,  $dist(x, x) = 0$ ,  $dist(x, y) = dist(y, x)$
- $dist(x, z) < dist(x, y) + dist(y, z)$  (triangle inequality)



Distance calculation often requires substantial computational effort

### ... Similarity-based Retrieval

26/103

Naive approach to similarity-based retrieval

```
q = ... // query object
dmax = ... // dmax > 0 => using threshold
knn = ... // knn > 0 => using nearest-neighbours
Dists = [] // empty list
foreach tuple t in R {
    d = dist(t.val, q)
    insert (t.oid, d) into Dists // sorted on d
}
n = 0; Results = []
foreach (i, d) in Dists {
    if (dmax > 0 && d > dmax) break;
    if (knn > 0 && ++n > knn) break;
    insert (i, d) into Results // sorted on d
}
return Results;
```

Cost = read all  $r$  feature vectors + compute  $distance()$  for each

### ... Similarity-based Retrieval

27/103

For some applications,  $Cost(dist(x, y))$  is comparable to  $T_r$

$\Rightarrow$  computing  $dist(t.val, q)$  for every tuple  $t$  is infeasible.

To improve this aspect:

- compute *feature vector* which captures "critical" object properties
- store feature vectors "in parallel" with objects (cf. signatures)
- compute distance using feature vectors (not objects)



i.e. replace  $dist(t, t_q)$  by  $dist'(vec(t), vec(t_q))$  in previous algorithm.

Further optimisation: dimension-reduction to make vectors smaller

### ... Similarity-based Retrieval

28/103

Content of feature vectors depends on application ...

- image ... colour histogram (e.g. 100's of values/dimensions)
- music ... loudness/pitch/tone (e.g. 100's of values/dimensions)
- text ... term frequencies (e.g. 1000's of values/dimensions)

Typically use multiple features, concatenated into single vector.

Feature vectors represent points in a *very* high-dimensional space.

Query: feature vector representing one point in vh-dim space.

Answer: list of objects "near to" query object in this space.

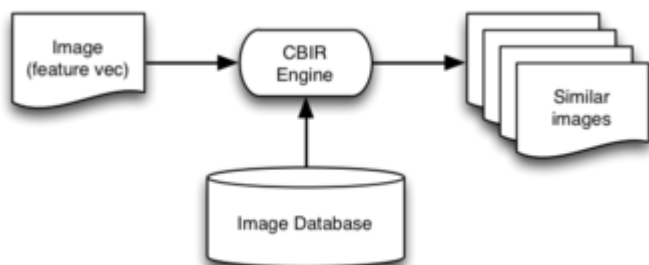
---

## Example: Content-based Image Retrieval

29/103

User supplies a description or sample of desired image (features).

System returns a ranked list of "matching" images from database.



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### ... Example: Content-based Image Retrieval

30/103

At the SQL level, this might appear as ...

```
// relational matching
create view Sunset as
select image from MyPhotos
where title = 'Pittwater Sunset'
      and taken = '2012-01-01';
// similarity matching with threshold
create view SimilarSunsets as
select title, image
from MyPhotos
where (image ~~ (select * from Sunset)) < 0.05
order by (image ~~ (select * from Sunset));
```

where the (imaginary) `~~` operator measures distance between images.

---

### ... Example: Content-based Image Retrieval

31/103

Implementing content-based retrieval requires ...

- a collection of "pertinent" image features
  - e.g. colour, texture, shape, keywords, ...
- some way of describing/representing image features
  - typically via a vector of numeric values
- a distance/similarity measure based on features
  - e.g. Euclidean distance between two vectors

$$\text{dist}(x,y) = \sqrt{(x_1-y_1)^2 + (x_2-y_2)^2 + \dots (x_n-y_n)^2}$$

---

### ... Example: Content-based Image Retrieval

32/103

**Inputs** to content-based similarity-retrieval:

- a database of  $r$  objects  $(obj_1, obj_2, \dots, obj_r)$  plus associated ...
- $r \times n$ -dimensional feature vectors  $(v_{obj_1}, v_{obj_2}, \dots, v_{obj_r})$
- a query image  $q$  with associated  $n$ -dimensional vector  $(v_q)$
- a distance measure  $D(v_i, v_j) : [0..1)$  ( $D=0 \rightarrow v_i=v_j$ )



**Outputs** from content-based similarity-retrieval:

- a list of the  $k$  nearest objects in the database  $[a_1, a_2, \dots, a_k]$
- ordered by distance  $D(v_{a_1}, v_q) \leq D(v_{a_2}, v_q) \leq \dots \leq D(v_{a_k}, v_q)$

## Approaches to $k$ NN Retrieval

33/103

### ① Partition-based

- use auxiliary data structure to identify candidates
- space/data-partitioning methods: e.g. k-d-B-tree, R-tree, ...
- unfortunately, such methods "fail" when  $\#dims > 10..20$
- absolute upper bound on  $d$  before linear scan is best  $d = 610$

### ② Approximation-based

- use approximating data structure to identify candidates
- signatures: VA-files
- projections: iDistance, LSH, MedRank, CurveIX, Pyramid

## ... Approaches to $k$ NN Retrieval

34/103

Above approaches mostly try to reduce number of objects considered.

Other optimisations to make  $k$ NN retrieval faster

- reduce I/O by reducing size of vectors (compression,  $d$ -reduction)
- reduce I/O by placing "similar" records together (clustering)
- reduce I/O by remembering previous pages (caching)
- reduce cpu by making distance computation faster

估计

## Similarity Retrieval in PostgreSQL

35/103

PostgreSQL has always supported simple "similarity" on strings

```
select * from Students where name like '%oo%';
select * from Students where name ~ '[Ss]mit';
```

Also provides support for ranked similarity on text values

- using tsvector data type (stemmed, stopped feature vector for text)
- using tsquery data type (stemmed, stopped feature vector for strings)
- using @@ similarity operator

## ... Similarity Retrieval in PostgreSQL

36/103

Example of PostgreSQL text retrieval:

```
create table Docs
( id integer, title text, body text );
// add column to hold document feature vectors
alter table Docs add column features tsvector;
update Docs set features =
    to_tsvector('english', title || ' ' || body);
// ask query and get results in ranked order
select title, ts_rank(d.features, query) as rank
from Docs d,
    to_tsquery('potter|(roger&rabbit)') as query
where query @@ d.features
order by rank desc
limit 10;
```

For more details, see PostgreSQL documentation, Chapter 12.

# Implementing Join

## Join

38/103

DBMSs are engines to *store*, *combine* and *filter* information.

*Join* ( $\bowtie$ ) is the primary means of *combining* information.

*Join* is important and potentially expensive

Most common join condition: equijoin, e.g.  $(R.pk = S.fk)$

Join varieties (natural, inner, outer, semi, anti) all behave similarly.

We consider three strategies for implementing join

- *nested loop* ... simple, widely applicable, inefficient without buffering
- *sort-merge* ... works best if tables are sorted on join attributes
- *hash-based* ... requires good hash function and sufficient buffering

## Join Example

39/103

Consider a university database with the schema:

```
create table Student(  
    id      integer primary key,  
    name    text, ...  
);  
create table Enrolled(  
    stude   integer references Student(id),  
    subj    text references Subject(code), ...  
);  
create table Subject(  
    code    text primary key,  
    title   text, ...  
);
```

## ... Join Example

40/103

List names of students in all subjects, arranged by subject.

SQL query to provide this information:

```
select E.subj, S.name  
from   Student S, Enrolled E  
where  S.id = E.stude  
order  by E.subj, S.name;
```

And its relational algebra equivalent:

$Sort_{[subj]} ( Project_{[subj, name]} ( Join_{[id=stude]} (Student, Enrolled) ) )$

To simplify formulae, we denote *Student* by *S* and *Enrolled* by *E*

## ... Join Example

41/103

Some database statistics:

Sym	Meaning	Value
$r_S$	# student records	20,000
$r_E$	# enrollment records	80,000

$c_S$	Student records/page	20
$c_E$	Enrolled records/page	40
$b_S$	# data pages in Student	1,000
$b_E$	# data pages in Enrolled	2,000

Also, in cost analyses below,  $N$  = number of memory buffers.

### ... Join Example

42/103

Out = Student  $\bowtie$  Enrolled relation statistics:

Sym	Meaning	Value
$r_{Out}$	# tuples in result	80,000
$C_{Out}$	result records/page	80
$b_{Out}$	# data pages in result	1,000

Notes:

- $r_{Out}$  ... one result tuple for each Enrolled tuple
- $C_{Out}$  ... result tuples have only subj and name
- in analyses, ignore cost of writing result ... same in all methods

## Nested Loop Join

### Nested Loop Join

44/103

Basic strategy ( $R.a \bowtie S.b$ ):

```

Result = {}
for each page i in R {
  pageR = getPage(R,i)
  for each page j in S {
    pageS = getPage(S,j)
    for each pair of tuples  $t_R, t_S$ 
      from pageR, pageS {
        if ( $t_R.a == t_S.b$ )
          Result = Result  $\cup$  ( $t_R:t_S$ )
      }
    }
  }

```

Needs input buffers for R and S, output buffer for "joined" tuples

Terminology: R is outer relation, S is inner relation

Cost =  $b_R \cdot b_S$  ... ouch!

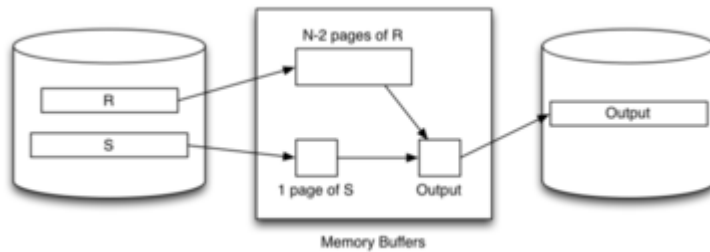
## Block Nested Loop Join

45/103

Method (for  $N$  memory buffers):

- read  $N-2$ -page chunk of  $R$  into memory buffers
- for each  $S$  page
  - check join condition on all  $(t_R, t_S)$  pairs in buffers
- repeat for all  $N-2$ -page chunks of  $R$

之前的lecture 也出现过



### ... Block Nested Loop Join

46/103

Best-case scenario:  $b_R \leq N-2$

- read  $b_R$  pages of relation  $R$  into buffers
- while  $R$  is buffered, read  $b_S$  pages of  $S$

$$\text{Cost} = b_R + b_S$$

Typical-case scenario:  $b_R > N-2$

- read  $\text{ceil}(b_R/N-2)$  chunks of pages from  $R$
- for each chunk, read  $b_S$  pages of  $S$

$$\text{Cost} = b_R + b_S \cdot \text{ceil}(b_R/N-2)$$

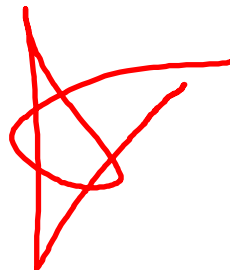
Note: always requires  $r_R \cdot r_S$  checks of the join condition

### Exercise 4: Nested Loop Join Cost

47/103

Compute the cost (# pages fetched) of  $(S \bowtie E)$

Sym	Meaning	Value
$r_S$	# student records	20,000
$r_E$	# enrollment records	80,000
$c_S$	Student records/page	20
$c_E$	Enrolled records/page	40
$b_S$	# data pages in Student	1,000
$b_E$	# data pages in Enrolled	2,000



for  $N = 22, 202, 2002$  and different inner/outer combinations

### Exercise 5: Nested Loop Join Cost (cont)

48/103

If the query in the above example was:

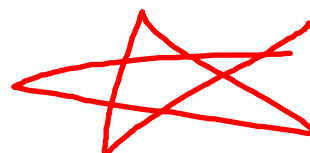
```
select j.code, j.title, s.name
from Student s
      join Enrolled e on (s.id=e.student)
      join Subject j on (e.subj=j.code)
```

how would this change the previous analysis?

What join combinations are there?

Assume 2000 subjects, with  $c_J = 10$

How large would the intermediate tuples be? What assumptions?



### ... Block Nested Loop Join

49/103

Why block nested loop join is actually useful in practice ...

Many queries have the form

`select * from R,S where r.i=s.j and r.x=k`

This would typically be evaluated as

$Join_{[i=j]}((Sel_{[r.x=k]}(R)), S)$

If  $|Sel_{[r.x=k]}(R)|$  is small  $\Rightarrow$  may fit in memory (in small #buffers)

### Index Nested Loop Join

A problem with nested-loop join:

- needs repeated scans of *entire* inner relation  $S$

If there is an index on  $S$ , we can avoid such repeated scanning.

Consider  $Join_{[R.i=S.j]}(R,S)$ :

```
for each tuple r in relation R {
  use index to select tuples
    from S where s.j = r.i
  for each selected tuple s from S {
    add (r,s) to result
  }
}
```

### ... Index Nested Loop Join

51/103

This method requires:

- one scan of  $R$  relation ( $b_R$ )
  - only one buffer needed, since we use  $R$  tuple-at-a-time
- for each *tuple* in  $R$  ( $r_R$ ), one index lookup on  $S$ 
  - cost depends on type of index and number of results
  - best case is when each  $R.i$  matches few  $S$  tuples

Cost =  $b_R + r_R \cdot Sel_S$  ( $Sel_S$  is the cost of performing a select on  $S$ ).

Typical  $Sel_S = 1-2$  (hashing) ..  $b_q$  (unclustered index)

Trade-off:  $r_R \cdot Sel_S$  vs  $b_R \cdot b_S$ , where  $b_R \ll r_R$  and  $Sel_S \ll b_S$

## Exercise 6: Index Nested Loop Join Cost

52/103

Consider executing  $Join_{[i=j]}(S,T)$  with the following parameters:

- $r_S = 1000$ ,  $b_S = 50$ ,  $r_T = 3000$ ,  $b_T = 600$
- $S.i$  is primary key, and  $T$  has index on  $T.j$
- $T$  is sorted on  $T.j$ , each  $S$  tuple joins with 2  $T$  tuples
- DBMS has  $N = 12$  buffers available for the join

Calculate the costs for evaluating the above join

- using block nested loop join
- using index nested loop join

Cost<sub>r</sub> = # pages read and Cost<sub>j</sub> = # join-condition checks

---

# Sort-Merge Join

---

## Sort-Merge Join

54/103

Basic approach:

- sort both relations on join attribute (reminder:  $Join[R.i=S.j](R,S)$ )
- scan together using *merge* to form result  $(r, s)$  tuples

Advantages:

- no need to deal with "entire"  $S$  relation for each  $r$  tuple
- deal with runs of matching  $R$  and  $S$  tuples

Disadvantages:

- cost of sorting both relations (already sorted on join key?)
- some rescanning required when long runs of  $S$  tuples

---

## ... Sort-Merge Join

55/103

Method requires several cursors to scan sorted relations:

- $r$  = current record in  $R$  relation
- $s$  = start of current run in  $S$  relation
- $ss$  = current record in current run in  $S$  relation



---

## ... Sort-Merge Join

56/103

Algorithm using query iterators/scanners:

Query  $ri, si$ ; Tuple  $r, s$ ;

```
ri = startScan("SortedR");
si = startScan("SortedS");
while ((r = nextTuple(ri)) != NULL
      && (s = nextTuple(si)) != NULL) {
    // align cursors to start of next common run
    while (r != NULL && r.i < s.j)
        r = nextTuple(ri);
    if (r == NULL) break;
    while (s != NULL && r.i > s.j)
        s = nextTuple(si);
    if (s == NULL) break;
    // must have (r.i == s.j) here
    ...
}
```

---

## ... Sort-Merge Join

57/103

```
...
// remember start of current run in S
TupleID startRun = scanCurrent(si)
```

```

// scan common run, generating result tuples
while (r != NULL && r.i == s.j) {
    while (s != NULL and s.j == r.i) {
        addTuple(outbuf, combine(r,s));
        if (isFull(outbuf)) {
            writePage(outf, outp++, outbuf);
            clearBuf(outbuf);
        }
        s = nextTuple(si);
    }
    r = nextTuple(ri);
    setScan(si, startRun);
}
}

```

### ... Sort-Merge Join

58/103

Buffer requirements:

- for sort phase:
  - as many as possible (remembering that cost is  $O(\log_N)$ )
  - if insufficient buffers, sorting cost can dominate
- for merge phase:
  - one output buffer for result
  - one input buffer for relation  $R$
  - (preferably) enough buffers for longest run in  $S$

### ... Sort-Merge Join

59/103

Cost of sort-merge join.

Step 1: sort each relation (if not already sorted):

- Cost =  $2 \cdot b_R (1 + \log_{N-1}(b_R/N)) + 2 \cdot b_S (1 + \log_{N-1}(b_S/N))$   
(where  $N$  = number of memory buffers)

Step 2: merge sorted relations:

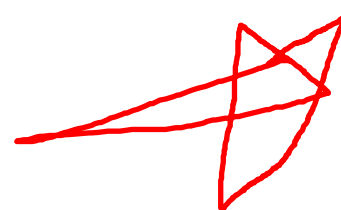
- if every run of values in  $S$  fits completely in buffers, merge requires single scan, Cost =  $b_R + b_S$
- if some runs in of values in  $S$  are larger than buffers, need to re-scan run for each corresponding value from  $R$

## Sort-Merge Join on Example

60/103

Case 1:  $Join[id=stude](Student, Enrolled)$

- relations are not sorted on  $id\#$
- memory buffers  $N=32$ ; all runs are of length  $< 30$



$$\begin{aligned}
 \text{Cost} &= \text{sort}(S) + \text{sort}(E) + b_S + b_E \\
 &= 2b_S(1 + \log_{31}(b_S/32)) + 2b_E(1 + \log_{31}(b_E/32)) + b_S + b_E \\
 &= 2 \times 1000 \times (1+2) + 2 \times 2000 \times (1+2) + 1000 + 2000 \\
 &= 6000 + 12000 + 1000 + 2000 \\
 &= 21,000
 \end{aligned}$$

### ... Sort-Merge Join on Example

61/103

Case 2:  $Join[id=stude](Student, Enrolled)$

- *Student* and *Enrolled* already sorted on *id#*
- memory buffers  $N=4$  ( $S$  input,  $2 \times E$  input, output)
- 5% of the "runs" in  $E$  span two pages
- there are no "runs" in  $S$ , since *id#* is a primary key

For the above, no re-scans of  $E$  runs are ever needed

$Cost = 2,000 + 1,000 = 3,000$  (regardless of which relation is outer)

## Exercise 7: Sort-merge Join Cost

62/103

Consider executing  $Join[i=j](S, T)$  with the following parameters:

- $r_S = 1000$ ,  $b_S = 50$ ,  $r_T = 3000$ ,  $b_T = 150$
- $S.i$  is primary key, and  $T$  has index on  $T.j$
- $T$  is sorted on  $T.j$ , each  $S$  tuple joins with 2  $T$  tuples
- DBMS has  $N = 42$  buffers available for the join

Calculate the cost for evaluating the above join

- using sort-merge join
- compute #pages read/written
- compute #join-condition checks performed

## Hash Join

### Hash Join

64/103

Basic idea:

- use hashing as a technique to partition relations
- to avoid having to consider all pairs of tuples

Requires sufficient memory buffers

- to hold substantial portions of partitions
- (preferably) to hold largest partition of outer relation

Other issues:

- works only for equijoin  $R.i = S.j$  (but this is a common case)
- susceptible to data skew (or poor hash function)

Variations: *simple*, *grace*, *hybrid*.

### Simple Hash Join

65/103

Basic approach:

- hash part of outer relation  $R$  into memory buffers (build)
- scan inner relation  $S$ , using hash to search (probe)
  - if  $R.i = S.j$ , then  $h(R.i) = h(S.j)$  (hash to same buffer)
  - only need to check one memory buffer for each  $S$  tuple
- repeat until whole of  $R$  has been processed

No overflows allowed in in-memory hash table

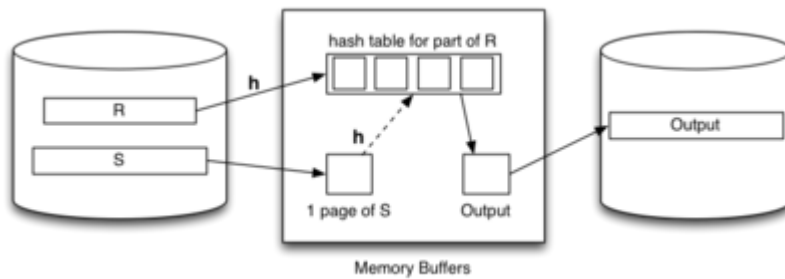
- works best with uniform hash function
- can be adversely affected by data/hash skew

### ... Simple Hash Join

66/103

Data flow:





## ... Simple Hash Join

67/103

Algorithm for simple hash join  $Join[R.i=S.j](R,S)$ :

```

for each tuple r in relation R {
  if (buffer[h(R.i)] is full) {
    for each tuple s in relation S {
      for each tuple rr in buffer[h(S.j)] {
        if ((rr,s) satisfies join condition) {
          add (rr,s) to result
        } } }
    clear all hash table buffers
  }
  insert r into buffer[h(R.i)]
}

```

# join tests  $\leq r_S \cdot c_R$  (cf. nested-loop  $r_S \cdot r_R$ )

# page reads depends on #buffers  $N$  and properties of data/hash.

## Exercise 8: Simple Hash Join Cost

68/103

Consider executing  $Join[i=j](R,S)$  with the following parameters:

- $r_R = 1000$ ,  $b_R = 50$ ,  $r_S = 3000$ ,  $b_S = 150$ ,  $c_{Res} = 30$
- $R.i$  is primary key, each  $R$  tuple joins with 2  $S$  tuples
- DBMS has  $N = 42$  buffers available for the join
- data + hash have uniform distribution

Calculate the cost for evaluating the above join

- using simple hash join
- compute #pages read/written
- compute #join-condition checks performed
- assume that hash table has  $L=0.75$  for each partition

## Grace Hash Join

69/103

Basic approach (for  $R \bowtie S$ ):

- partition both relations on join attribute using hashing ( $h1$ )
- load each partition of  $R$  into  $N$ -buffer hash table ( $h2$ )
- scan through corresponding partition of  $S$  to form results
- repeat until all partitions exhausted

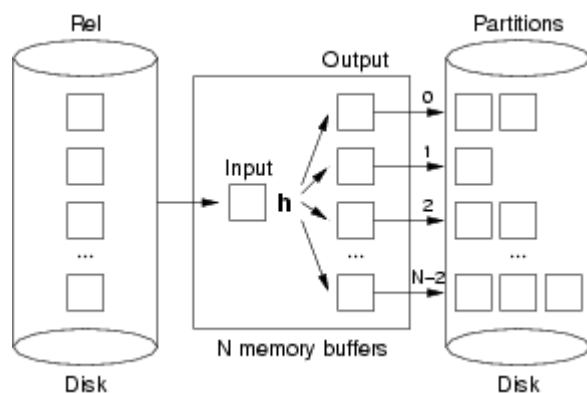
For best-case cost ( $O(b_R + b_S)$ ):

- need  $\geq \sqrt{b_R}$  buffers to hold largest partition of outer relation

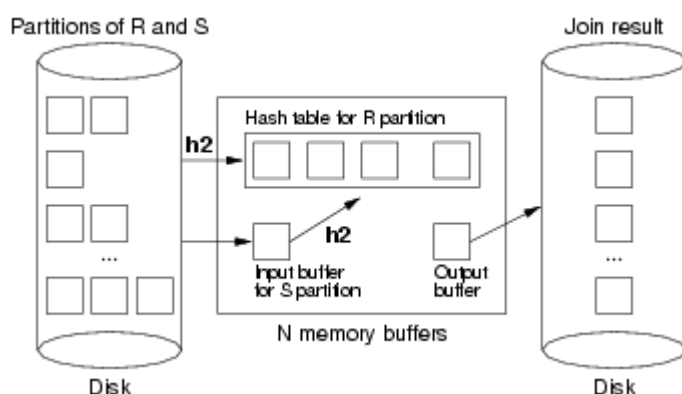
If  $< \sqrt{b_R}$  buffers or poor hash distribution

- need to scan some partitions of  $S$  multiple times

Partition phase (applied to both  $R$  and  $S$ ):



Probe/join phase:



The second hash function ( $h_2$ ) simply speeds up the matching process. Without it, would need to scan entire  $R$  partition for each record in  $S$  partition.

Cost of grace hash join:

- #pages in all partition files of  $Rel \approx b_{Rel}$  (maybe slightly more)
- partition relation  $R$  ... Cost =  $b_R \cdot T_r + b_R \cdot T_w = 2b_R$
- partition relation  $S$  ... Cost =  $b_S \cdot T_r + b_S \cdot T_w = 2b_S$
- probe/join requires one scan of each (partitioned) relation  
Cost =  $b_R + b_S$
- all hashing and comparison occurs in memory  $\Rightarrow \approx 0$  cost

$$\text{Total Cost} = 2b_R + 2b_S + b_R + b_S = 3(b_R + b_S)$$

## Exercise 9: Grace Hash Join Cost

Consider executing  $Join_{i=j}(R, S)$  with the following parameters:

- $r_R = 1000$ ,  $b_R = 50$ ,  $r_S = 3000$ ,  $b_S = 150$ ,  $c_{Res} = 30$
- $R.i$  is primary key, each  $R$  tuple joins with 2  $S$  tuples
- DBMS has  $N = 43$  buffers available for the join
- data + hash have reasonably uniform distribution

Calculate the cost for evaluating the above join

- using Grace hash join
- compute #pages read/written
- compute #join-condition checks performed

- assume that no  $R$  partition is larger than 40 pages

## Exercise 10: Grace Hash Join Cost

74/103

Consider executing  $Join_{i=j}(R,S)$  with the following parameters:

- $r_R = 1000$ ,  $b_R = 50$ ,  $r_S = 3000$ ,  $b_S = 150$ ,  $c_{Res} = 30$
- $R.i$  is primary key, each  $R$  tuple joins with 2  $S$  tuples
- DBMS has  $N = 42$  buffers available for the join
- data + hash have reasonably uniform distribution

Calculate the cost for evaluating the above join

- using Grace hash join
- compute #pages read/written
- compute #join-condition checks performed
- assume that one  $R$  partition has 50 pages, others  $< 40$  pages
- assume that the corresponding  $S$  partition has 30 pages

## Hybrid Hash Join

75/103

A variant of grace join if we have  $\sqrt{b_R} < N < b_R + 2$

- create  $k \ll N$  partitions,  $m$  in memory,  $k-m$  on disk
- buffers: 1 input,  $k-m$  output,  $p = N-(k-m)-1$  for in-memory partitions

When we come to scan and partition  $S$  relation

- any tuple with hash in range  $0..m-1$  can be resolved
- other tuples are written to one of  $k$  partition files for  $S$

Final phase is same as grace join, but with only  $k$  partitions.

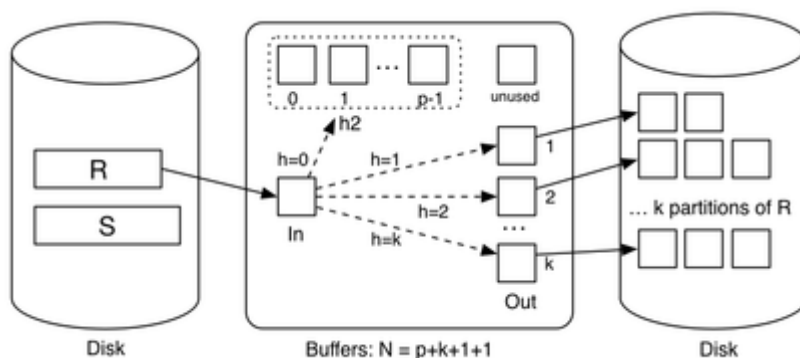
Comparison:

- grace hash join creates  $N-1$  partitions on disk
- hybrid hash join creates  $m$  (memory) +  $k$  (disk) partitions

### ... Hybrid Hash Join

76/103

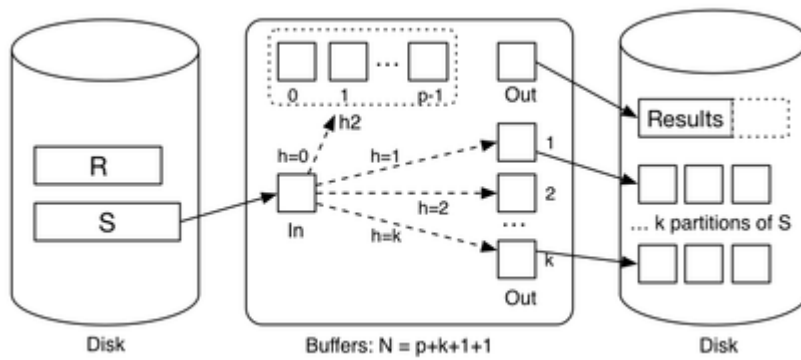
First phase of hybrid hash join with  $m=1$  (partitioning  $R$ ):



### ... Hybrid Hash Join

77/103

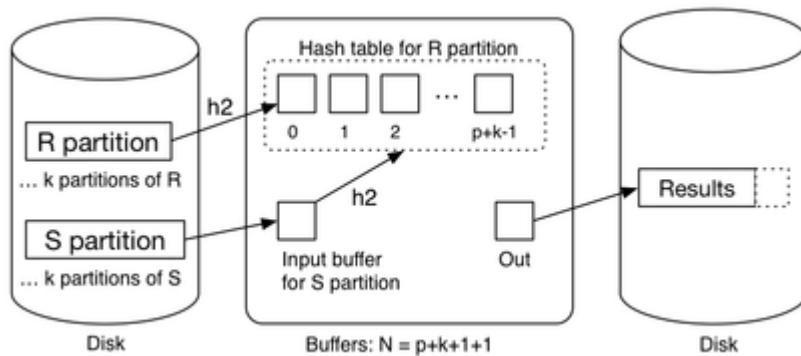
Next phase of hybrid hash join with  $m=1$  (partitioning  $S$ ):



### ... Hybrid Hash Join

78/103

Final phase of hybrid hash join with  $m=1$  (finishing join):



### ... Hybrid Hash Join

79/103

Some observations:

- with  $k$  partitions, each partition has expected size  $b_R/k$
- holding  $m$  partitions in memory needs  $\lceil mb_R/k \rceil$  buffers
- trade-off between in-memory partition space and #partitions

Best-cost scenario:

- $m = 1$ ,  $k \approx \lceil b_R/N \rceil$  (satisfying above constraint)

Other notes:

- if  $N = b_R+2$ , using block nested loop join is simpler
- cost depends on  $N$  (but less than grace hash join)

## Exercise 11: Hybrid Hash Join Cost

80/103

Consider executing  $Join_{i=j}(R,S)$  with the following parameters:

- $r_R = 1000$ ,  $b_R = 50$ ,  $r_S = 3000$ ,  $b_S = 150$ ,  $c_{Res} = 30$
- $R.i$  is primary key, each  $R$  tuple joins with 2  $S$  tuples
- DBMS has  $N = 42$  buffers available for the join
- data + hash have reasonably uniform distribution

Calculate the cost for evaluating the above join

- using hybrid hash join with  $m=1$ ,  $p=40$
- compute #pages read/written
- compute #join-condition checks performed
- assume that no  $R$  partition is larger than 40 pages

No single join algorithm is superior in some overall sense.

Which algorithm is best for a given query depends on:

- sizes of relations being joined, size of buffer pool
- any indexing on relations, whether relations are sorted
- which attributes and operations are used in the query
- number of tuples in  $S$  matching each tuple in  $R$
- distribution of data values (uniform, skew, ...)

Choosing the "best" join algorithm is critical because the cost difference between best and worst case can be very large.

E.g.  $\text{Join}_{[id=stude]}(Student, Enrolled)$ : 3,000 ... 2,000,000

---

## Join in PostgreSQL

82/103

Join implementations are under: **src/backend/executor**

PostgreSQL supports three kinds of join:

- nested loop join (**nodeNestloop.c**)
- sort-merge join (**nodeMergejoin.c**)
- hash join (**nodeHashjoin.c**) (hybrid hash join)

Query optimiser chooses appropriate join, by considering

- physical characteristics of tables being joined
- estimated selectivity (likely number of result tuples)

---

## Exercise 12: Outer Join?

83/103

Above discussion was all in terms of theta inner-join.

How would the algorithms above adapt to outer join?

Consider the following ...

```
select *  
from R left outer join S on (R.i = S.j)
```

```
select *  
from R right outer join S on (R.i = S.j)
```

```
select *  
from R full outer join S on (R.i = S.j)
```

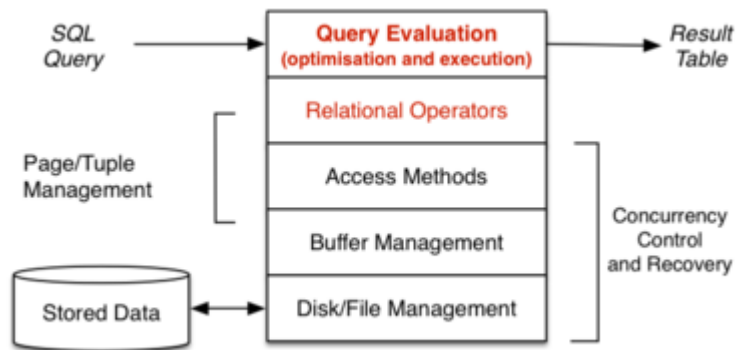


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## Query Evaluation

### Query Evaluation

85/103



### ... Query Evaluation

86/103

A *query* in SQL:

- states *what* kind of answers are required (declarative)
- does not say *how* they should be computed (procedural)

A *query evaluator/processor* :

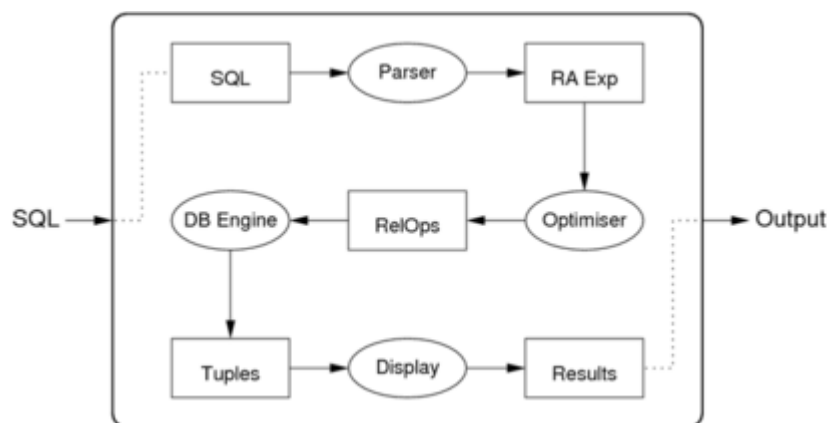
- takes declarative description of query (in SQL)
- parses query to internal representation (relational algebra)
- determines plan for answering query (expressed as DBMS ops)
- executes method via DBMS engine (to produce result tuples)

Some DBMSs can save query plans for later re-use.

### ... Query Evaluation

87/103

Internals of the query evaluation "black-box":



### ... Query Evaluation

88/103

DBMSs provide several "flavours" of each RA operation.

For example:

- several "versions" of selection ( $\sigma$ ) are available
  - each version is effective for a particular kind of selection, e.g
- ```

select * from R where id = 100  -- hashing
select * from S                 -- Btree index
where age > 18 and age < 35
select * from T                 -- MALH file
where a = 1 and b = 'a' and c = 1.4
  
```

Similarly,  $\pi$  and  $\Join$  have versions to match specific query types.

We call these specialised version of RA operations *RelOps*.

One major task of the query processor:

- given a set of RA operations to be executed
- find a combination of RelOps to do this efficiently

Requires the query translator/optimiser to consider

- information about relations (e.g. sizes, primary keys, ...)
- information about operations (e.g. selection reduces size)

RelOps are realised at execution time

- as a collection of inter-communicating *nodes*
- communicating either via pipelines or temporary relations

## Terminology Variations

90/103

Relational algebra expression of SQL query

- intermediate query representation
- logical query plan

Execution plan as collection of RelOps

- query evaluation plan
- query execution plan
- physical query plan

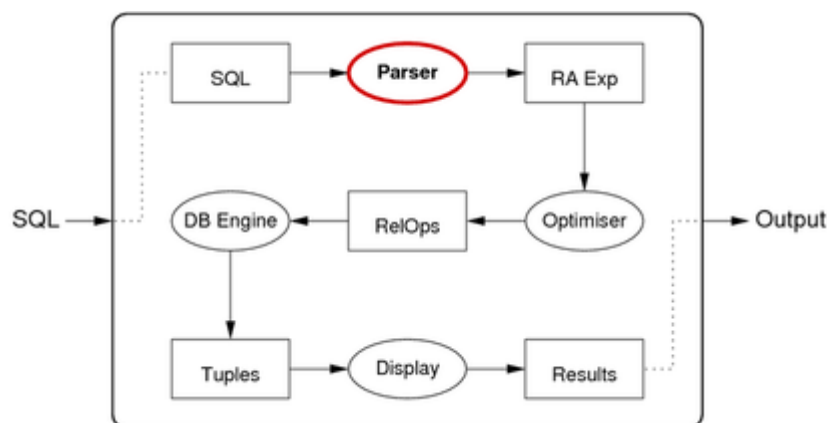
Representation of RA operators and expressions

- $\sigma = \text{Select} = \text{Sel}$ ,  $\pi = \text{Project} = \text{Proj}$
- $R \bowtie S = R \text{ Join } S = \text{Join}(R, S)$ ,  $\wedge = \&$ ,  $\vee = \mid$

## Query Translation

91/103

Query translation: SQL statement text  $\rightarrow$  RA expression



## Query Translation

92/103

Translation step: SQL text  $\rightarrow$  RA expression

Example:

SQL: select name from Students where id=7654321;  
 -- is translated to  
 RA: Proj[name](Sel[id=7654321]Students)

Processes: lexer/parser, mapping rules, rewriting rules.

Mapping from SQL to RA may include some optimisations, e.g.

```
select * from Students where id = 54321 and age > 50;
-- is translated to
Sel[age>50](Sel[id=54321]Students)
-- rather than ... because of index on id
Sel[id=54321&age>50](Students)
```

---

## Parsing SQL

93/103

Parsing task is similar to that for programming languages.

Language elements:

- keywords: create, select, from, where, ...
- identifiers: Students, name, id, CourseCode, ...
- operators: +, -, =, <, >, AND, OR, NOT, IN, ...
- constants: 'abc', 123, 3.1, '01-jan-1970', ...

PostgreSQL parser ...

- implemented via lex/yacc ([src/backend/parser](#))
- maps all identifiers to lower-case (A-Z → a-z)
- needs to handle user-extendable operator set
- makes extensive use of catalog ([src/backend/catalog](#))

---

## Mapping SQL to Relational Algebra

94/103

A given SQL query typically has many translations to RA.

For example:

```
SELECT s.name, e.subj
FROM   Students s, Enrolments e
WHERE  s.id = e.sid AND e.mark < 50;
```

is equivalent to any of

- $\pi_{s.name, e.subj}(\sigma_{s.id=e.sid \wedge e.mark<50} (Students \times Enrolments))$
- $\pi_{s.name, e.subj}(\sigma_{s.id=e.sid} (\sigma_{e.mark<50} (Students \times Enrolments)))$
- $\pi_{s.name, e.subj}(\sigma_{e.mark<50} (Students \bowtie_{s.id=e.sid} Enrolments))$
- $\pi_{s.name, e.subj}(Students \bowtie_{s.id=e.sid} (\sigma_{e.mark<50} (Enrolments)))$

对曰

---

### ... Mapping SQL to Relational Algebra

95/103

More complex example:

```
select  distinct s.code
from    Course c, Subject s, Enrolment e
where   c.id = e.course and c.subject = s.id
group by s.id having count(*) > 100;
```

can be translated to the relational algebra expression

```
Uniq(Proj[code](
  GroupSelect[groupSize>100](
    GroupBy[s.id] (
      Enrolment ⋈ Course ⋈ Subjects
    )))
```

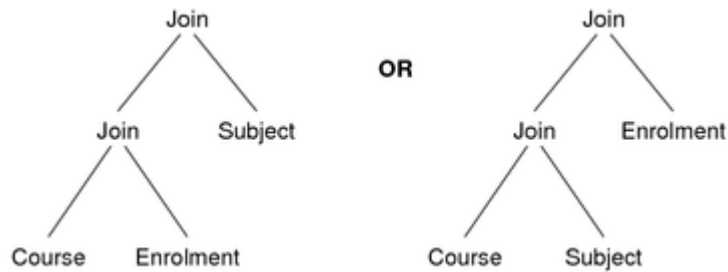
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### ... Mapping SQL to Relational Algebra

96/103



The join operations could be done in two different ways:



Note: for a join on  $n$  tables, there are potentially  $O(n!)$  possible trees

The *query optimiser* aims to find version with lowest total cost.

---

## Mapping Rules

97/103

Mapping from SQL  $\rightarrow$  RA expression requires:

- a collection of *templates*,  $\geq 1$  for each kind of query
- a process to match an SQL statement to a template
- mapping rules for translating matched query into RA

May need to apply  $>1$  templates to map whole SQL statement.

After mapping, apply rewriting rules to "improve" RA expression

- convert to equivalent, simpler, more efficient expression

Note: PostgreSQL also has user-defined mapping rules (`CREATE RULE`)

---

### ... Mapping Rules

98/103

#### Projection:

`SELECT a+b AS x, c AS y FROM R ...`

$\Rightarrow \text{Proj}_{[x \leftarrow a+b, y \leftarrow c]}(R)$

SQL projection extends RA projection with renaming and assignment

#### Join:

`SELECT ... FROM ... R, S ... WHERE ... R.f op S.g ... , or`

`SELECT ... FROM ... R JOIN S ON (R.f op S.g) ... WHERE ...`

$\Rightarrow \text{Join}_{[R.f \text{ op } S.g]}(R, S)$

---

### ... Mapping Rules

99/103

#### Selection:

`SELECT ... FROM ... R ... WHERE ... R.f op val ...`

$\Rightarrow \text{Select}_{[R.f \text{ op } val]}(R)$

`SELECT ... FROM ... R ... WHERE ... Cond1,R AND Cond2,R ...`

$\Rightarrow \text{Select}_{[Cond_{1,R} \ \& \ Cond_{2,R}]}(R)$

or

$\Rightarrow \text{Select}_{[Cond_{1,R}]}(\text{Select}_{[Cond_{2,R}]}(R))$

---

## Exercise 13: Mapping OR expressions

100/103

Possible mappings for WHERE expressions with AND are

```
SELECT ... FROM ... R ... WHERE ... X AND Y ...
```

$\Rightarrow \text{Select}_{[X \& Y]}(R)$  or  $\text{Select}_{[X]}(\text{Select}_{[Y]}(R))$

What are possible mappings for

```
SELECT ... FROM ... R ... WHERE ... X OR Y ...
```

Use these to translate:

```
select * from R where (a=1 or a=3) and b < c
```

## Mapping Rules

101/103

Aggregation operators (e.g. MAX, SUM, ...):

- add as new operators in extended RA  
e.g. `SELECT MAX(age) FROM ...`  $\Rightarrow \text{max}(\text{Proj}_{[\text{age}]}(...))$

Sorting (ORDER BY):

- add *Sort* operator into extended RA (e.g.  $\text{Sort}_{[+name, -age]}(...)$ )

Duplicate elimination (DISTINCT):

- add *Uniq* operator into extended RA (e.g.  $\text{Uniq}(\text{Proj}(...))$ )

Grouping (GROUP BY, HAVING):

- add operators into extended RA (e.g. *GroupBy*, *GroupSelect*)

## ... Mapping Rules

102/103

View example: assuming *Employee(id,name,birthdate,salary)*

```
-- view definition
create view OldEmps as
select * from Employees
where birthdate < '01-01-1960';
-- view usage
select name from OldEmps;
```

yields

- $\text{OldEmps} = \text{Select}_{[\text{birthdate} < '01-01-1960']}(Employees)$
- $\text{Proj}_{\text{name}}(\text{OldEmps})$   
 $\Rightarrow \text{Proj}_{\text{name}}(\text{Select}_{[\text{birthdate} < '01-01-1960']}(Employees))$

## Exercise 14: Mapping Views

103/103

Given the following definitions:

```
create table R(a integer, b integer, c integer);
```

```
create view RR(f,g,h) as
select * from R where a > 5 and b = c;
```

Show how the following might be mapped to RA:

```
select * from RR where f > 10;
```

