Week 07 Lectures

Signature-based Selection

Indexing with Signatures

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

File organisation for signature indexing (two files)

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

Record placement is independent of signatures ⇒ can use with other indexing.

Signatures

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

A tuple consists of *N* attribute values A_1 .. A_n

A *codeword* $cw(A_i)$ is

- 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

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)

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 $j \le nk$ bits are set to 1
- $desc(r) = cw(A_1)$ OR $cw(A_2)$ OR ... 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

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

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, ?, ?, ?)`.

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

... SIMC Queries

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 ∪ 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 Que

Consider the query and the e

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

False match probablity 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 ≅ 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

How to determine "optimal" m and k?

1. start by choosing acceptable p_F
   (e.g. $p_F \le 10^{-5}$ 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:

$$k = 1/\log_e 2 \,.\, \log_e (1/p_F)$$

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

Query Cost for SIMC

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

$b_D = ceil(r/c_D)$ and $c_D = floor(B/ceil(m/8))$

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

b_q includes pages with r_q mat

Expected false matches = r_F $_q$ $_F$ $_F$ $_q$

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

Exercise 1: SIMC Query Cost

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

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):

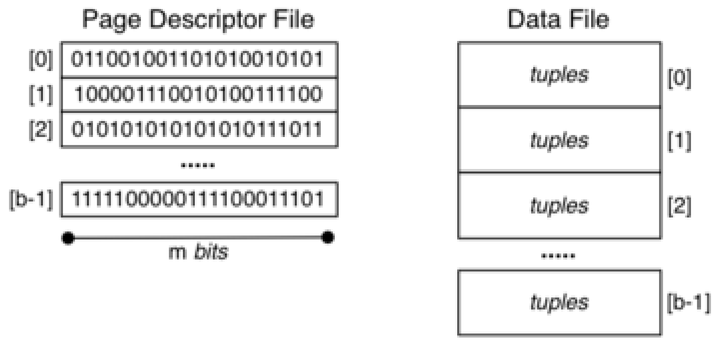
- use above formulae but with $c.n$ "attributes"

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

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

Page-Level SIMC Files

File organisation for page-level superimposed codeword index



Exercise 2: Page-level SIMC Query Cost

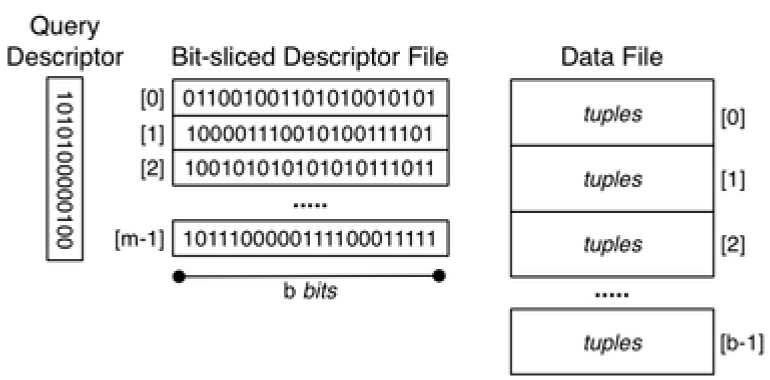
Consider a SIMC-indexed database with the following properties

- 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
- 10% of false matches

Calculate the total number of

... Page-Level SIMC Files

Improvement: store b m-bit page descriptors as m b-bit "bit-slice



... Page-Level SIMC Files

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

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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

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

Similarity Retrieval

Similarity Selection

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Relational selection is based on a boolean condition *C*

- evaluate *C* for each tup
- if *C(t)* is true, add *t* to r
- if *C(t)* is false, *t* is not p
- result is a set of tuples $\{ t_1, t_2, ..., t_n \}$ all of which satisfy *C*

Uses for relational selection:

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

... Similarity Selection

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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 $[(t_1,d_1), (t_2,d_2), ..., (t_n,d_n)]$ (ordered by d_i)

Uses for similarity matching:

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

Similarity-based Retrieval

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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 $dist(t,q) \le d_{max}$)
- *count k* (*k* closest objects (*k* nearest neighbours))

... Similarity-based Retrieval

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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*)

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

Distance calculation often requires substantial computational effort

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... Similarity-based Retrieval

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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
    if (knn > 0 && ++n
    insert (i,d) into Results  // sorted on d
}
return Results;
```


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

---

... Similarity-based Retrieval

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

⇒ 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

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... Similarity-based Retrieval

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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

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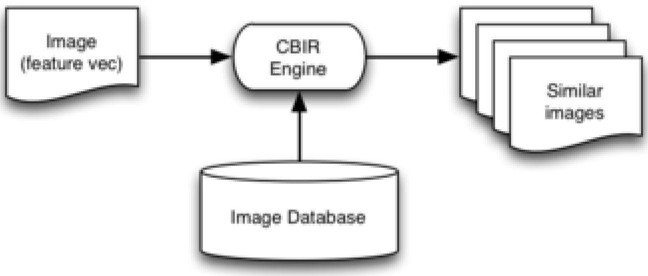
User supplies a description or sample of desired image (features).

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



... Example: Content-based Image Retrieval

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

```
// relational matching
create view Sunset as
select image from MyPh
where  title = 'Pittwa
       and taken = '20
// similarity matching
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

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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

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

... Example: Content-based Image Retrieval

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Inputs to content-based similarity-retrieval:

- a database of *r* objects $(obj_1, obj_2, \ldots, obj_r)$ plus associated ...
- $r \times n$-dimensional feature vectors $(v_{obj_1}, v_{obj_2}, \ldots, v_{obj_r})$
- 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 $[a_1, \; a_2, \; \ldots \; a_k]$
- ordered by distance $D(v_{a_1},v_q) \le D(v_{a_2},v_q) \le \ldots \le D(v_{a_k},v_q)$

Approaches to *k*NN Retrieval

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*

Approximation-based

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

... Approaches to *k*NN Retrieval

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

Similarity Retrieval

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

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

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

Join (⋈) 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 soted on join attributes
- *hash-based* ... requires good hash function and sufficient buffering

Join Example

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Consider a university database with the schema:

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


... Join Example

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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

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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

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Out = *Student* ⋈ *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 Joi

Nested Loop Join

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Basic strategy (R.a ⋈ 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 tR,tS
                       from pageR,pageS {
         if (tR.a == tS.b)
            Result = Result ∪ (tR:tS)
}  }  }
```

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

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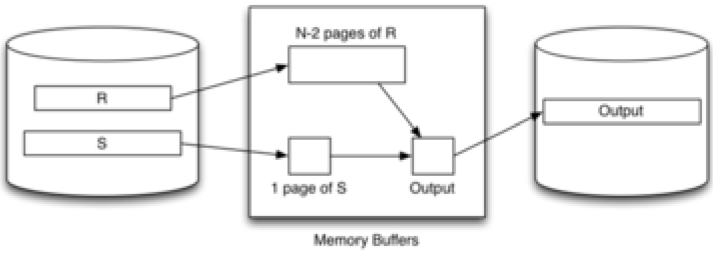
Method (for N memory buffers):

- 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*



... Block Nested Loop Join

Best-case scenario: $b_R \leq N\text{-}2$

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

Cost = $b_R + b_S$

Typical-case scenario: $b_R > N\text{-}2$

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

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

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

Exercise 4: Nested

Compute the cost (# pages fe

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)

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?

Compute the cost (# pages fetched, # pages written) for $N = 22$

... Block Nested Loop Join

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 ⇒ 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 r
}   }
```

... Index Nested Loop Join

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

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

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

Exercise 6: Index Nested Loop Join Cost

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

$Cost_r$ = # pages read and $Cost_j$ = # join-condition checks

---

Sort-Merge Join

Sort-Merge Join

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

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

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


```
...
    // 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

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

Cost of sort-merge join.

Step 1: sort each relation (if n

- Cost = $2.b_R\ (1 + log_{N-1}$

  (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

Case 1: $Join_{[id=stude]}(Student,Enrolled)$

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

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

... Sort-Merge Join on Example

Case 2: $Join_{[id=stude]}(Student,Enrolled)$

- *Student* and *Enrolled* already sorted on *id#*
- memory buffers *N=4* (*S* input, 2 × *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

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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

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Basic idea:

- use hashing as a techn
- to avoid having to cons

Requires sufficent 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

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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

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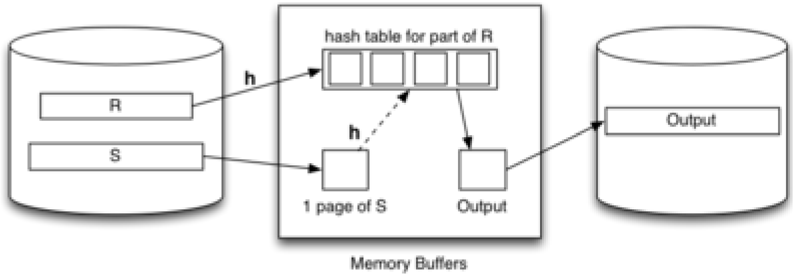
Data flow:



... Simple Hash Join

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 ≤ $r_S.c_R$ (cf. nested-loop $r_S.r_R$)

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

Exercise 8: Simple

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

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 ($O(b_R + b_S)$):

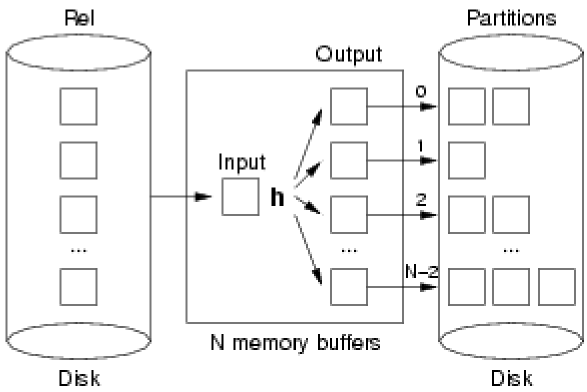
- need ≥ $\sqrt{b_R}$ buffers to hold largest partition of outer relation

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

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

... Grace Hash Join

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



... Grace Hash Join

Probe/join phase:

The second hash function (`h2`) simply speeds up the matching process.
Without it, would need to scan entire *R* partition for each record in *S* partition.

... Grace Hash Join

Cost of grace hash join:

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

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

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

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

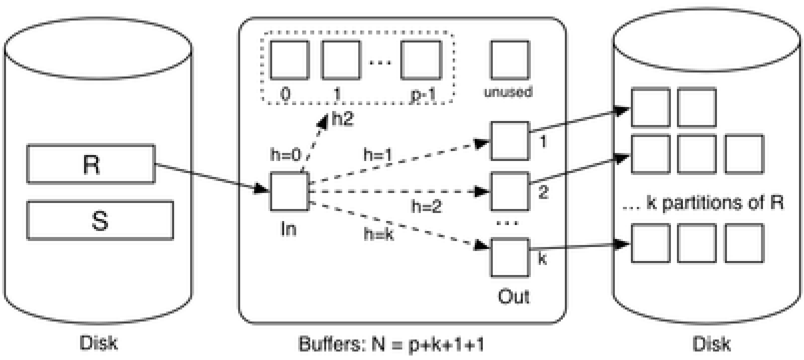
Final phase is same as grace join

Comparison:

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

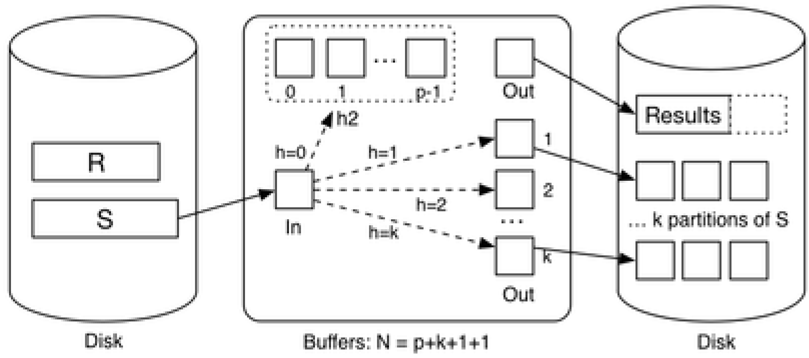
... Hybrid Hash Join

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



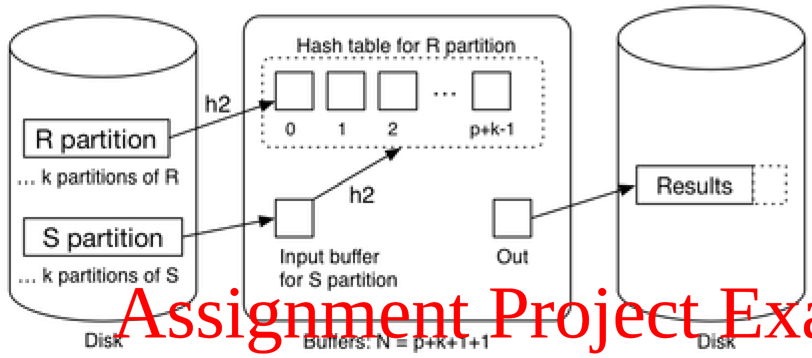
... Hybrid Hash Join

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



... Hybrid Hash Join

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



... Hybrid Hash Join

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:

- $m = 1$, $k \cong \lceil b_R/N \rceil$ (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

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

Join Summary

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. $Join_{[id=stude]}(Student,Enrolled)$:   3,000 ... 2,000,000

Join in PostgreSQL

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

PostgreSQL suports 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

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

How would the algorithms above adapt to outer join?

Consider the following ...

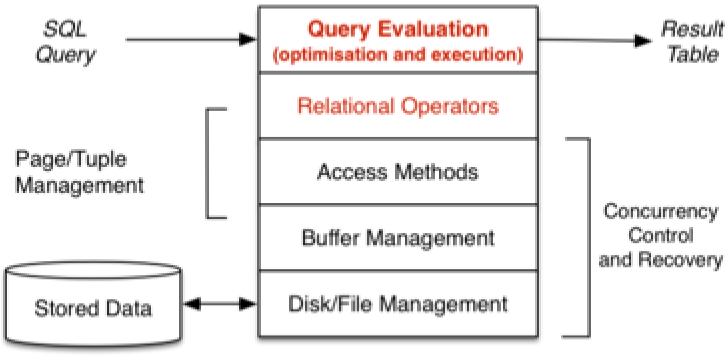
```
select *
from   R left outer join S on (R.i = S.j)

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

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

Query Evaluation

Query Evaluation



... Query Evaluation

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

Internals of the query evaluati

... Query Evaluation

DBMSs provide several "flavours" of each RA operation.

For example:

- several "versions" of selection (σ) 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, π and $\bowtie$ have versions to match specific query types.

... Query Evaluation

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

Relational algebra expression of SQL query

- intermediate query representation
- logical query plan

Execution plan as collection of RelOps

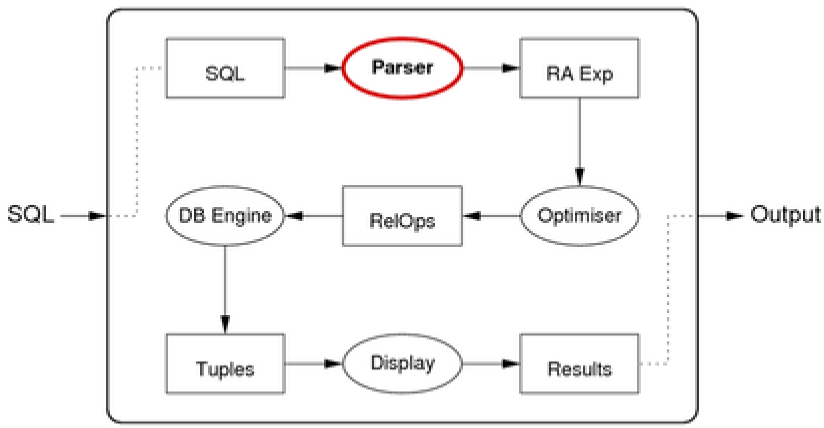
- query evaluation plan
- query execution plan
- physical query plan

Representation of RA operato

- σ = *Select* = *Sel*, π =
- $R \bowtie S$ = *R Join S* = *Joi* $\wedge$ $\vee$

Query Translation

Query translation: SQL statement text → RA expression



Query Translation

Translation step: SQL text → 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

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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

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A given SQL query typically h

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

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

... Mapping SQL to Relational Algebra

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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

$$
\begin{array}{l}
Uniq(Proj_{[code]}(\\
\quad GroupSelect_{[groupSize>100]}(\\
\quad\quad GroupBy_{[s.id]}\ (\\
\quad\quad\quad Enrolment \bowtie Course \bowtie Subjects \\
))))
\end{array}
$$

... Mapping SQL to Relational Algebra

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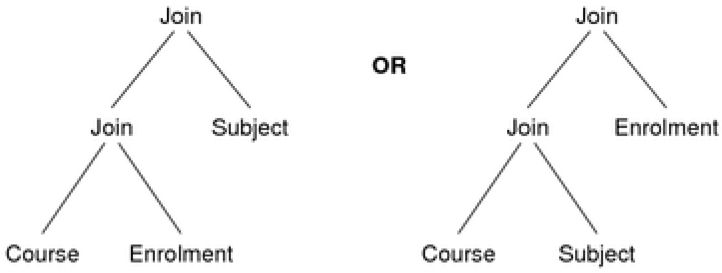
The join operations could be done in two different ways:



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

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Mapping from SQL → RA expression requires:

- a collection of *templates*, ≥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 u

... Mapping Rules

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Projection:

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

⇒ $Proj_{[x \leftarrow a+b,\ y \leftarrow c]}(R)$

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` ...

⇒ $Join_{[R.f\ op\ S.g\ ]}(R,S)$

... Mapping Rules

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Selection:

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

⇒ $Select_{[R.f\ op\ val]}(R)$

`SELECT` ... `FROM` ... *R* ... `WHERE` ... $Cond_{1,R}$ `AND` $Cond_{2,R}$ ...

⇒ $Select_{[Cond_{1,R}\ \&\ Cond_{2,R}]}(R)$

or

⇒ $Select_{[Cond_{1,R}]}(Select_{[Cond_{2,R}]}(R))$

Exercise 13: Mapping OR expressions

Possible mappings for `WHERE` expressions with `AND` are

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

$\Rightarrow$ $Select_{[X\ \&\ Y]}(R)$ or $Select_{[X]}(Select_{[Y]}(R))$

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

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

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

Sorting (`ORDER BY`):

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

Duplicate elimination (`DISTINCT`):

- add *Uniq* operator into extended RA (e.g. *Uniq(Proj(...))*)

Grouping (`GROUP BY`, `HAVIN`

- add operators into exte

... Mapping Rules

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

- $OldEmps = Select_{[birthdate<'01-01-1960']}(Employees)$
- $Proj_{name}(OldEmps)$

  $\Rightarrow$ $Proj_{name}(Select_{[birthdate<'01-01-1960']}(Employees))$

Exercise 14: Mapping Views

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;
```
