Implementation of Relational Operations

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Relational Operations

- We will consider how to implement:
  - <u>*Selection*</u> (σ) Selects a subset of rows from relation.
  - <u>*Projection*</u> (π) Deletes unwanted columns from relation.
  - <u>*Join*</u> ($\bowtie$) Allows us to combine two relations.
- Since each op returns a relation, ops can be *composed*! After we cover the operations, we will discuss how to *optimize* queries formed by composing them.

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Schema for Examples

Sailors (<u>*sid*: integer</u>, *sname*: string, *rating*: integer, *age*: real)
Reserves (<u>*sid*: integer, *bid*: integer, *day*: dates</u>, *rname*: string)

- Similar to old schema; *rname* added for variations.
- Reserves:
  - Each tuple is 40 bytes long, 100 tuples per page, 1000 pages.
- Sailors:
  - Each tuple is 50 bytes long, 80 tuples per page, 500 pages.

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Simple Selections

```
SELECT  *
FROM    Reserves R
WHERE   R.rname < 'C%'
```

- Of the form $\sigma_{R.attr\ op\ value}(R)$
- Size of result approximated as *size of R * reduction factor*; we will consider how to estimate reduction factors later.
- With no index, unsorted: Must essentially scan the whole relation; cost is M (#pages in R).
- With an index on selection attribute: Use index to find qualifying data entries, then retrieve corresponding data records. (Hash index useful only for equality selections.)

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Using an Index for Selections

- Cost depends on #qualifying tuples and clustering.
  - Cost of finding qualifying data entries (typically small) plus cost of retrieving records (could be large w/o clustering).
  - In example, assuming uniform distribution of names, about 10% of tuples qualify (100 pages, 10000 tuples). With a clustered index, cost is little more than 100 I/Os; if unclustered, up to 10000 I/Os!
- *Important refinement for unclustered indexes*:
  1. Find qualifying data entries.
  2. Sort the *rid*s of the data records to be retrieved.
  3. Fetch *rid*s in order. This ensures that each data page is looked at just once (though # of such pages likely to be higher than with clustering).

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Projection via Hashing

```
SELECT  DISTINCT
        R.sid, R.bid
FROM    Reserves R
```

- *Partitioning phase*: Read R using one input buffer. For each tuple, discard unwanted fields, apply hash function *h1* to choose one of B-1 output buffers.
  - Result is B-1 partitions (of tuples with no unwanted fields).
  - 2 tuples from different partitions guaranteed to be distinct.
- *Duplicate elimination phase*: For each partition, read it and build an in-memory hash table, using hash fn *h2* (<> *h1*) on all fields, while discarding duplicates.
  - If partition does not fit in memory, can apply hash-based projection algorithm recursively to this partition.
- Cost: For partitioning, read R, write out each tuple, but with fewer fields. This is read in next phase.

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Discussion of Projection

- Sort-based approach features better handling of skew and result is sorted.
- Hash-based approach can be faster (locally).
- If an index on the relation contains all wanted attributes in its search key, can do *index-only* scan.
  - Apply projection techniques to data entries (much smaller!)
- If an ordered (i.e., tree) index contains all wanted attributes as *prefix* of search key, can do even better:
  - Retrieve data entries in order (index-only scan), discard unwanted fields, compare adjacent tuples to check for duplicates.

Equality Joins With One Join Column

```
SELECT *
FROM   Reserves R1, Sailors S1
WHERE  R1.sid=S1.sid
```

- In algebra: $R \bowtie S$. Common! Must be carefully optimized. $R \times S$ is large; so, $R \times S$ followed by a selection is inefficient.
- Assume: M tuples in R, p_R tuples per page, N tuples in S, p_S tuples per page.
  - In our examples, R is Reserves and S is Sailors.
- *Cost metric*: # of I/Os. We will ignore output costs.

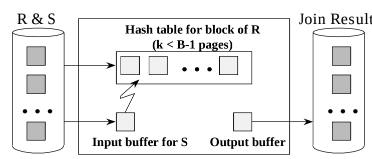
Simple Nested Loops Join

```
foreach tuple r in R do
    foreach tuple s in S do
        if ri == sj then add <r, s> to result
```

- For each tuple in the *outer* relation R, we scan the entire *inner* relation S.
  - Cost: M + p_R * M * N = 1000 + 100*1000*500 I/Os.
- Page-oriented Nested Loops join: For each *page* of R, get each *page* of S, and write out matching pairs of tuples <r, s>, where r is in R-page and S is in S-page.
  - Cost: M + M*N = 1000 + 1000*500
  - If smaller relation (S) is outer, cost = 500 + 500*1000

Block Nested Loops Join

- Use one page as an input buffer for scanning the inner S, one page as the output buffer, and use all remaining pages to hold ``block'' of outer R.
  - For each matching tuple r in R-block, s in S-page, add <r, s> to result. Then read next R-block, scan S, etc.



Examples of Block Nested Loops

- Cost: Scan of outer + #outer blocks * scan of inner
  - #outer blocks = $\lceil \# \textit{ of pages of outer} / \textit{blocksize} \rceil$
- With Reserves (R) as outer, and 100 pages of R:
  - Cost of scanning R is 1000 I/Os; a total of 10 *blocks*.
  - Per block of R, we scan Sailors (S); 10*500 I/Os.
  - If space for just 90 pages of R, we would scan S 12 times.
- With 100-page block of Sailors as outer:
  - Cost of scanning S is 500 I/Os; a total of 5 blocks.
  - Per block of S, we scan Reserves; 5*1000 I/Os.
- With *sequential reads* considered, analysis changes: may be best to divide buffers evenly between R and S.

Index Nested Loops Join

```
foreach tuple r in R do
    foreach tuple s in S where ri == sj do
        add <r, s> to result
```

- If there is an index on the join column of one relation (say S), can make it the inner and exploit the index.
  - Cost: M + ((M*p_R) * cost of finding matching S tuples)
- For each R tuple, cost of probing S index is about 1.2 for hash index, 2-4 for B+ tree. Cost of then finding S tuples (assuming Alt. (2) or (3) for data entries) depends on clustering.
  - Clustered index: 1 I/O (typical), unclustered: up to 1 I/O per matching S tuple.

Examples of Index Nested Loops

- Hash-index (Alt. 2) on *sid* of Sailors (as inner):
  - Scan Reserves: 1000 page I/Os, 100*1000 tuples.
  - For each Reserves tuple: 1.2 I/Os to get data entry in index, plus 1 I/O to get (the exactly one) matching Sailors tuple. Total: 220,000 I/Os.
- Hash-index (Alt. 2) on *sid* of Reserves (as inner):
  - Scan Sailors: 500 page I/Os, 80*500 tuples.
  - For each Sailors tuple: 1.2 I/Os to find index page with data entries, plus cost of retrieving matching Reserves tuples. Assuming uniform distribution, 2.5 reservations per sailor (100,000 / 40,000). Cost of retrieving them is 1 or 2.5 I/Os depending on whether the index is clustered.

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Sort-Merge Join $(R \bowtie_{i=j} S)$

- Sort R and S on the join column, then scan them to do a ``merge'' (on join col.), and output result tuples.
  - Advance scan of R until current R-tuple >= current S tuple, then advance scan of S until current S-tuple >= current R tuple; do this until current R tuple = current S tuple.
  - At this point, all R tuples with same value in Ri (*current R group*) and all S tuples with same value in Sj (*current S group*) match; output <r, s> for all pairs of such tuples.
  - Then resume scanning R and S.
- R is scanned once; each S group is scanned once per matching R tuple. (Multiple scans of an S group are likely to find needed pages in buffer.)

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Example of Sort-Merge Join

sid	sname	rating	age
22	dustin	7	45.0
28	yuppy	9	35.0
31	lubber	8	55.5
44	guppy	5	35.0
58	rusty	10	35.0

sid	bid	day	rname
28	103	12/4/96	guppy
28	103	11/3/96	yuppy
31	101	10/10/96	dustin
31	102	10/12/96	lubber
31	101	10/11/96	lubber
58	103	11/12/96	dustin

- Cost: M log M + N log N + (M+N)
  - The cost of scanning, M+N, could be M*N (very unlikely!)
- With 35, 100 or 300 buffer pages, both Reserves and Sailors can be sorted in 2 passes; total join cost: 7500.

(*BNL cost: 2500 to 15000 I/Os*)

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Set Operations

- Intersection and cross-product special cases of join.
- Union (Distinct) and Except similar; we'll do union.
- Sorting based approach to union:
  - Sort both relations (on combination of all attributes).
  - Scan sorted relations and merge them.
- Hash-based approach to union:
  - Partition R and S using hash function *h*.
  - For each S-partition, build in-memory hash table (using *h2*), scan corresponding R-partition and add tuples to table while discarding duplicates.

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Impact of Buffering

- If several operations are executing concurrently, estimating the number of available buffer pages is guesswork.
- Repeated access patterns interact with buffer replacement policy.
  - e.g., Inner relation is scanned repeatedly in Simple Nested Loop Join. With enough buffer pages to hold inner, replacement policy does not matter. Otherwise, MRU is best, LRU is worst (*sequential flooding*).
  - Does replacement policy matter for Block Nested Loops?
  - What about Index Nested Loops? Sort-Merge Join?

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Summary

- A virtue of relational DBMSs: *queries are composed of a few basic operators*; the implementation of these operators can be carefully tuned (and it is important to do this!).
- Many alternative implementation techniques for each operator; no universally superior technique for most operators.
- Must consider available alternatives for each operation in a query and choose best one based on system statistics, etc. This is part of the broader task of optimizing a query composed of several ops.

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State of the Art (impl. algorithms)

- Approximate answers (data warehousing)
  - Too much data to find exact answer quickly
  - No need for an exact answer
- Top-K queries (K “best” matches)
  - Multimedia (fuzzy criteria); decision support
  - Approximate or exact
- Extensibility:
  - User-defined data types
  - User-defined functionality
- Improve time-to-first-result-tuple
  - Ripple Join *(impl. project, part 2)*

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