Understanding the Execution of Analytics Queries & Applications

MAS DSE 201

SQL as declarative programming

- SQL is a **declarative** programming language:
  - The developer's / analyst's query only describes **what** result she wants from the database
  - The developer does not describe the algorithm that the database will use in order to compute the result
- The database's optimizer automatically decides what is the most performant algorithm that computes the result of your SQL query
- "Declarative" and "automatic" have been the reason for the success and ubiquitous presence of database systems behind applications
  - Imagine trying to come up yourself with the algorithms that efficiently execute complex queries. (Not easy.)

What do you have to do to increase the performance of your db-backed app?

- Does declarative programming mean the developer does not have to think about performance?
  - After all, the database will automatically select the most performant algorithms for the developer's SQL queries

- **No, challenging cases force the A+ SQL developer / analyst to think and make choices, because...**
  - Developer decides which indices to build
  - Database may miss the best plan: Developer has to understand what plan was chosen and work around

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Diagnostics

- You need to understand a few things about the performance of your query:
1. Will it benefit from indices? If yes, which are the useful indices?
2. Has the database chosen a hugely suboptimal plan?
3. How can I hack it towards the efficient way?

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Boosting performance with indices
(a short conceptual summary)

How/when does an index help? Running selection queries without an index

Consider a table R with n tuples and the selection query

SELECT *
FROM R
WHERE R.A = ?

In the absence of an index the *Big-O* cost of evaluating an instance of this query is *O(n)* because the database will need to access the n tuples and check the condition
R.A = *<provided value>*

R

...	A	...
	5	
	22	
	3	
	8	

...

	22	
	42	
	5	
	2	

⎯ n tuples

How/when does an index help?
Running selection queries with an index

Consider a table R with *n* tuples, an index on R.A
and assume that R.A has *m* distinct values.
We issue the same query and assume the database uses the index.

SELECT *
FROM R
WHERE R.A = ?

Example request: Return pointers to tuples with R.A = 5

Index on R.A

R

...	A	...
	5	
	22	
	3	
	8	
	...	
	22	
	42	
	5	
	2	

n tupl

An index on R.A is a data structure
that answers very efficiently the request
"find the tuples with R.A = *c"*
Then a query is answered in time *O(k)*
where k is the number of tuples with R.A = c.
Therefore the expected time to answer a selection query is *O(n/m)*

The mechanics of indices:
How to create an index

How to create an index on R.A ?

After you have created table **R**, issue command
CREATE INDEX myIndexOnRA ON R(A)

How to remove the index you previously created ?

DROP INDEX myIndexOnRA

Exercise: Create and then drop an index on
Students.first_name of the enrollment example

After you have created table **students**, issue command
CREATE INDEX students_first_name ON students(first_name)

DROP INDEX students_first_name

Primary keys get an index automatically

The mechanics of indices:
How to use an index in a query

- You do **not** have to change your SQL queries in order to direct the database to use (or not use) the indices you created.
  - All you need to do is to create the index! That's easy...
- The database will decide automatically whether to use (or not use) a created index to answer your query.
- It is possible that you create an index x but the database may not use it if it judges that there is a better plan (algorithm) for answering your query, without using the index x.

Indexing will help any query step when the problem is...

Given condition on attribute find qualified records

Attr = value — (?) → Qualified records
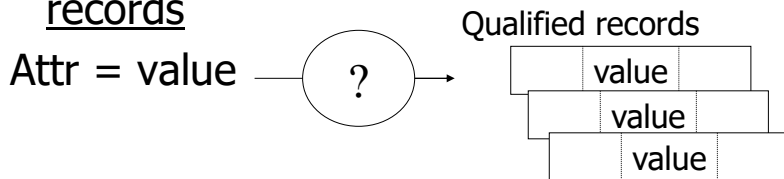
	value	
	value	
		value

Condition may also be
- Attr>value
- Attr>=value

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Indexing

- Data Stuctures used for quickly locating tuples that meet a specific type of condition
  - *Equality* condition: find Movie tuples where Director=*X*
  - Other conditions possible, eg, *range* conditions: find Employee tuples where Salary>40 AND Salary<50
- Many types of indexes. Evaluate them on
  - *Access* time
  - *Insertion* time
  - *Deletion* time
 - *Space* needed (esp. as it effects access time and or ability to fit in memory)

Should I build an index? In the presence of updates, the benefit of an index has to take maintenance cost into account

New tuples

Index on R.A

R

...	A	...
	5	
	22	
	3	
	8	
	...	
	22	
	42	
	5	
	2	
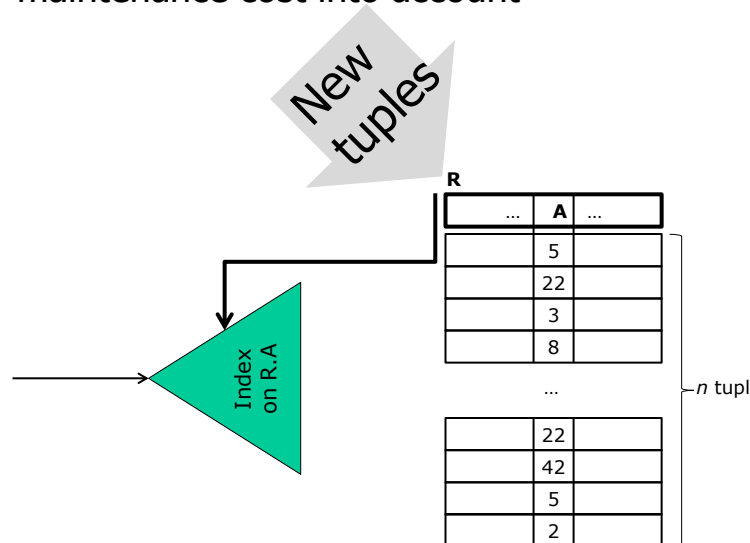
—*n* tupl

In OLAP it seems beneficial to create an index on R.A whenever m>1

Recall: Table R with n tuples, an index on R.A
and assume that R.A has m distinct values

SELECT *
FROM R
WHERE R.A = ?

Index on R.A

R

...	A	...
	5	
	22	
	3	
	8	
	...	
	22	
	42	
	5	
	2	
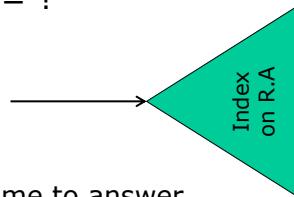
←n tupl

The expected time to answer
the selection query without index is $O(n)$
and with index is $O(n/m)$
It appears that an index is beneficial if $m>1$
but if database stored in secondary storage you will need $m>>1$
because **the cost is blocks**!

To Index or Not to Index

- Which queries can use indices and how?
- What will they do without an index?
  - Some surprisingly efficient algorithms that do not use indices

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Understanding Storage and Memory

Memory Hierarchy

- Cache memory
  - On-chip and L2
  - Increasingly important
- RAM (controlled by db system)
  - Addressable space includes virtual memory but DB systems avoid it
- SSDs
  - Block-based storage
- Disk
  - Block
  - Preference to sequential access
- Tertiary storage for archiving
  - Tapes, jukeboxes, DVDs
  - Does not matter any more

Cost per byte

Capacity

Access Speed

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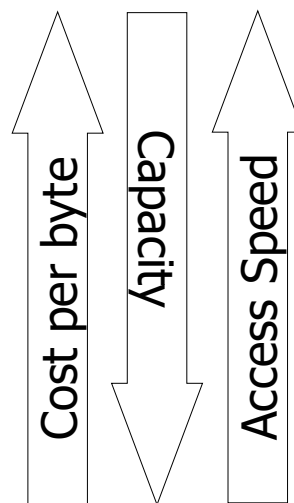
Non-Volatile Storage is important to OLTP even when RAM is large

- Persistence important for transaction atomicity and durability
- Even if database fits in main memory changes have to be written in non-volatile storage
- Hard disk
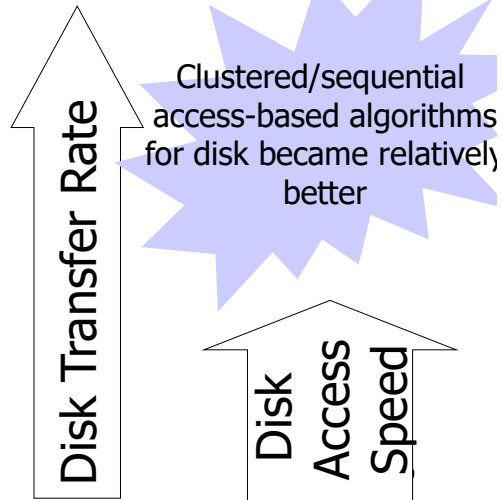- RAM disks w/ battery
- Flash memory

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Peculiarities of storage mediums affect algorithm choice

- Block-based access:
  - Access performance: How many blocks were accessed
  - ~~How many objects~~
  - Flash is different on reading Vs writing
- Clustering for sequential access:
  - Accessing consecutive blocks costs less on disk-based systems
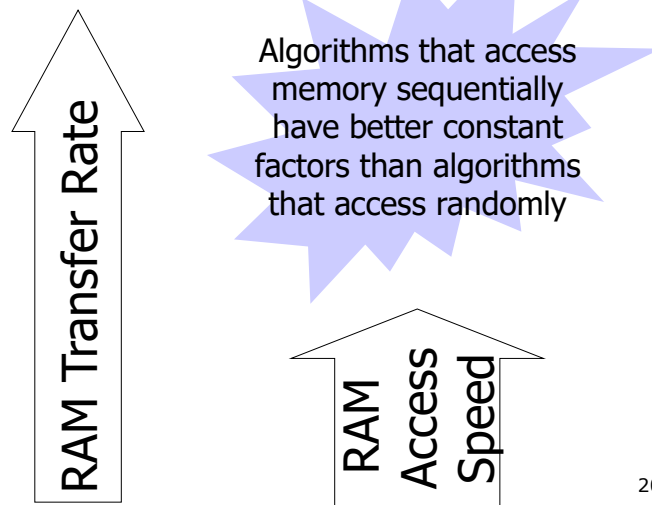- We will only consider the effects of block access

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Moore's Law: Different Rates of Improvement Lead to Algorithm & System Reconsiderations

- Processor speed
- Main memory bit/$
- Disk bit/$
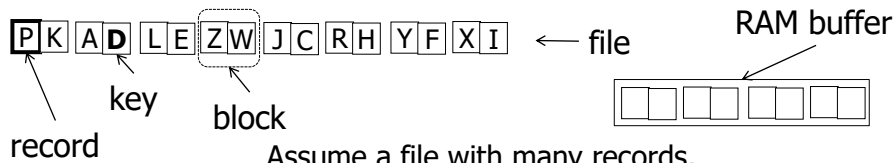- RAM access speed
- Disk access speed
- Disk transfer rate

Disk Transfer Rate

Disk Access Speed

Clustered/sequential access-based algorithms for disk became relatively better

Moore's Law: Same Phenomenon Applies to RAM

RAM Transfer Rate

RAM Access Speed

Algorithms that access memory sequentially have better constant factors than algorithms that access randomly

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2-Phase Merge Sort: An algorithm tuned for blocks (and sequential access)

P K A **D** L E Z W J C R H Y F X I ← file
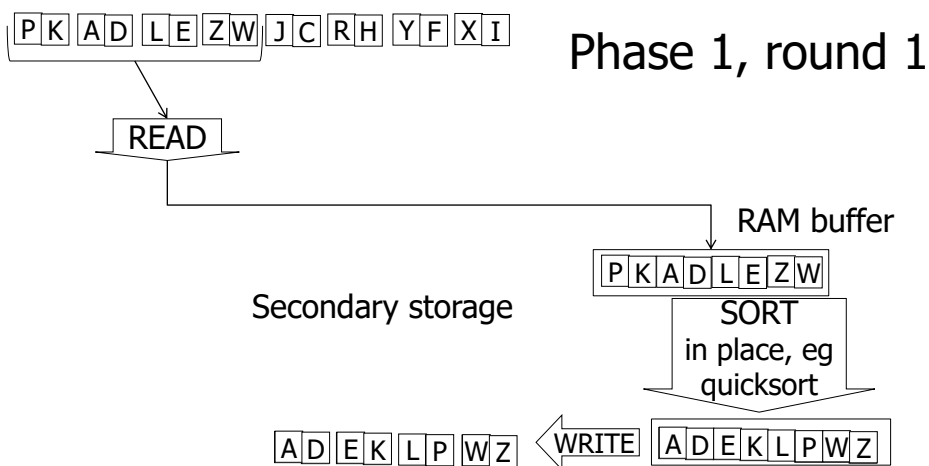
key

block

record

RAM buffer

Assume a file with many records.
Each record has a key and other data.
For ppt brevity, the slide shows only the
key of each record and not its data.
Assume each block has 2 records.
Assume RAM buffer fits 4 blocks (8 records)
In practice, expect many more records
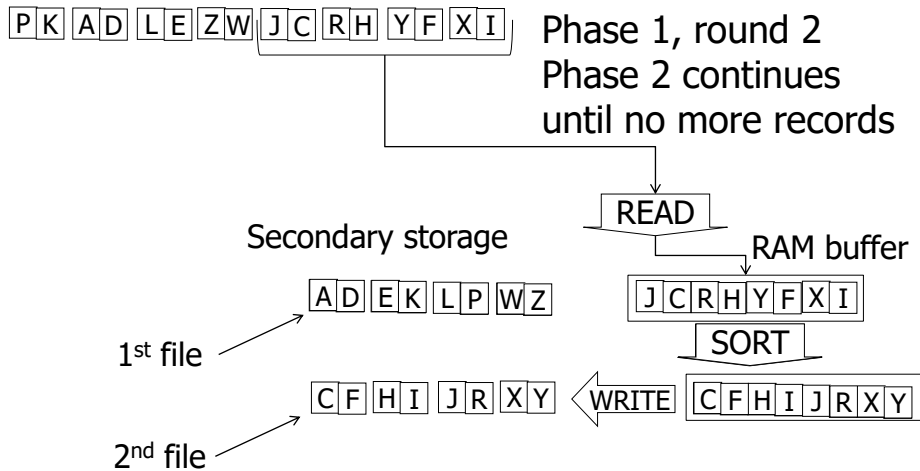per block and many more records fitting in buffer.

Problem: Sort the records according to the key.
Morale: What you learnt in algorithms and data
structures is not always the best when we
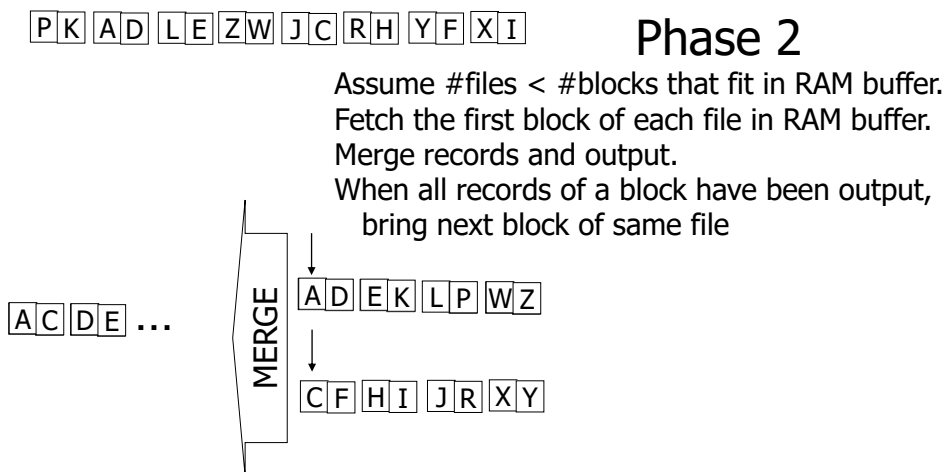consider block-based storage

2-Phase Merge Sort

P K A D L E Z W J C R H Y F X I

Phase 1, round 1

READ

RAM buffer

Secondary storage

P K A D L E Z W

SORT
in place, eg
quicksort

A D E K L P W Z WRITE A D E K L P W Z

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2-Phase Merge Sort

P K A D L E Z W J C R H Y F X I   Phase 1, round 2
Phase 2 continues
until no more records

READ

Secondary storage   RAM buffer

A D E K L P W Z   J C R H Y F X I

1st file

SORT

C F H I J R X Y   ◁ WRITE C F H I J R X Y

2nd file

In practice, probably many more Phase 1 rounds and
many respective output files   23

2-Phase Merge Sort

P K A D L E Z W J C R H Y F X I   Phase 2

Assume #files < #blocks that fit in RAM buffer.
Fetch the first block of each file in RAM buffer.
Merge records and output.
When all records of a block have been output,
   bring next block of same file

A C D E ...   MERGE   A D E K L P W Z

C F H I J R X Y

Improvement: Bring max number of blocks in memory.   24

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2-Phase Merge Sort: Most files can be sorted in just 2 passes!

Assume
- M bytes of RAM buffer (eg, 8GB)
- B bytes per block (eg, 64KB for disk, 4KB for SSD)

Calculation:
- The assumption of Phase 2 holds when *#files < M/B*

=> there can be up to M/B Phase 1 rounds
- Each round can process up to M bytes of input data

=> 2-Phase Merge Sort can sort **M^2/B** bytes
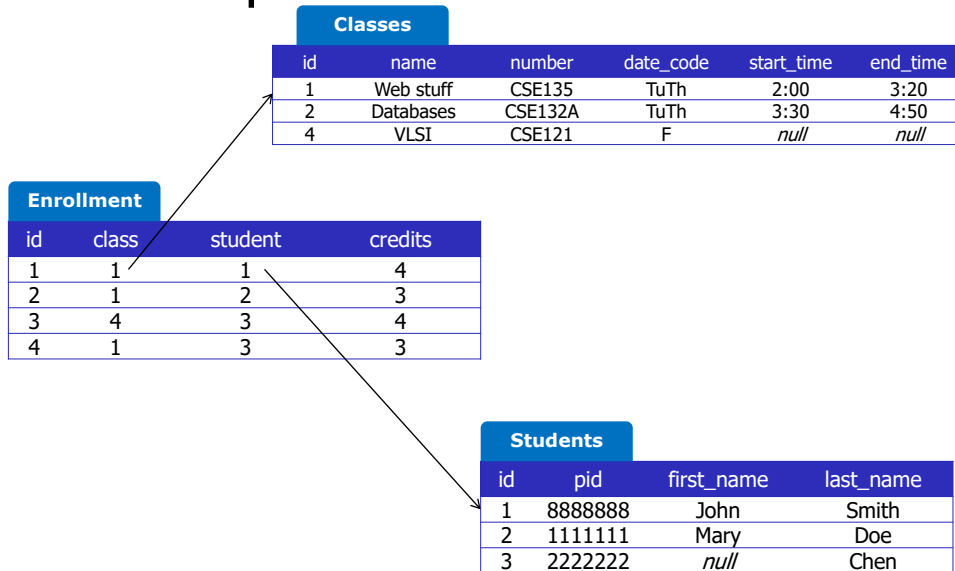 - eg $(8GB)^2/64KB = (2^{33}B)^2 / 2^{16}B = 2^{50}B = 1PB$

Horizontal placement of SQL data in blocks
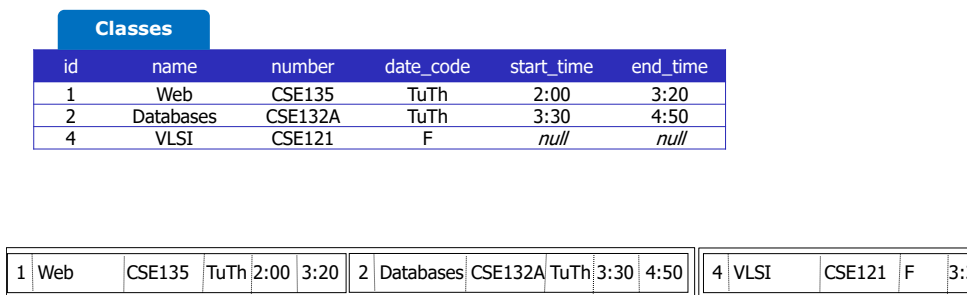
Relations:
- Pack as many tuples per block
  - improves scan time
- Do not reclaim deleted records
- Utilize overflow records if relation must be sorted on primary key
- A novel generation of databases features column storage
  - to be discussed late in class

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Sample relational database

Classes

id	name	number	date_code	start_time	end_time
1	Web stuff	CSE135	TuTh	2:00	3:20
2	Databases	CSE132A	TuTh	3:30	4:50
4	VLSI	CSE121	F	*null*	*null*

Enrollment

id	class	student	credits
1	1	1	4
2	1	2	3
3	4	3	4
4	1	3	3

Students

id	pid	first_name	last_name
1	8888888	John	Smith
2	1111111	Mary	Doe
3	2222222	*null*	Chen

Pack maximum #records per block

Classes

id	name	number	date_code	start_time	end_time
1	Web	CSE135	TuTh	2:00	3:20
2	Databases	CSE132A	TuTh	3:30	4:50
4	VLSI	CSE121	F	*null*	*null*

| 1 | Web | CSE135 | TuTh | 2:00 | 3:20 | 2 | Databases | CSE132A | TuTh | 3:30 | 4:50 | 4 | VLSI | CSE121 | F | 3: |

"pack" each block with maximum # records

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Utilize overflow blocks for insertions with "out of order" primary keys

Classes					
id	name	number	date_code	start_time	end_time
1	Web	CSE135	TuTh	2:00	3:20
2	Databases	CSE132A	TuTh	3:30	4:50
3	**PL**	**CSE130**	**TuTh**	**9:00**	**9:50**
4	VLSI	CSE121	F	*null*	*null*

← just inserted tuple

| 1 | Web | | CSE135 | TuTh | 2:00 | 3:20 | 2 | Databases | CSE132A | TuTh | 3:30 | 4:50 | — | 4 | VLSI | | CSE121 | F |

| 3 | PL | | CSE130 | TuTh | 9:00 | 9:50 | | |

Overflow block
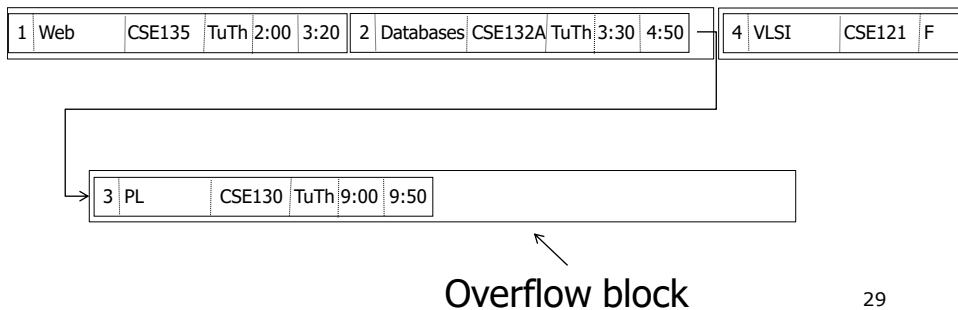
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... back to Indices, with secondary storage in mind

- Conventional indexes
  - As a thought experiment
- B-trees
  - The workhorse of most db systems
- Hashing schemes
  - Briefly covered
- Bitmaps
  - An analytics favorite

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Terms and Distinctions

- *Primary* index
  - the index on the attribute (a.k.a. search key) that determines the sequencing of the table
- *Secondary* index
  - index on any other attribute
- *Dense* index
  - every value of the indexed attribute appears in the index
- *Sparse* index
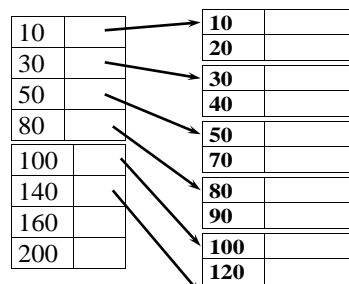 - many values do not appear

A Dense Primary Index

10	
20	
30	
40	
50	
70	
80	
90	
100	
120	
140	
150	

10	
20	
30	
40	
50	
70	
80	
90	
100	
120	

Sequential File
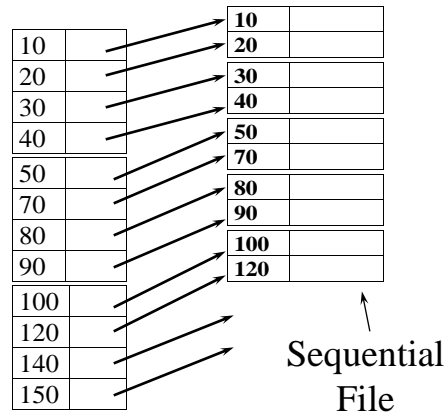
Dense and Sparse Primary Indexes

Dense Primary Index

10	
20	
30	
40	
50	
70	
80	
90	
100	
120	
140	
150	

10	
20	
30	
40	
50	
70	
80	
90	
100	
120	

Sparse Primary Index

10	
30	
50	
80	
100	
140	
160	
200	

10	
20	
30	
40	
50	
70	
80	
90	
100	
120	
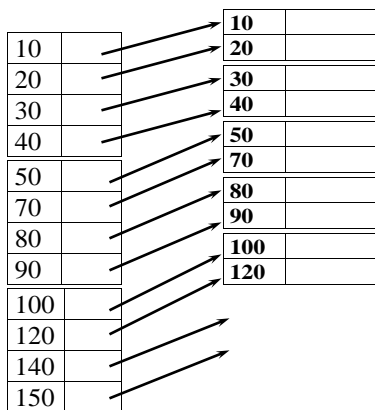
Find the index record with largest value that is less or equal to the value we are looking.

+ can tell if a value exists without accessing file (consider projection)
+ better access to overflow records

+ less index space

more + and - in a while

Sparse vs. Dense Tradeoff

- Sparse: Less index space per record
  can keep more of index in memory
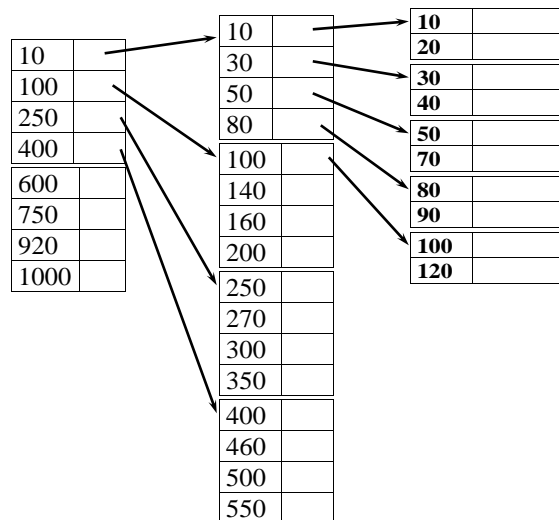- Dense: Can tell if any record exists
  without accessing file

(Later:
- sparse better for insertions
- dense needed for secondary indexes)

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Multi-Level Indexes

- Treat the index as a file and build an index on it
- "Two levels are usually sufficient. More than three levels are rare."
- Q: Can we build a dense second level index for a dense index ?

10	
100	
250	
400	
600	
750	
920	
1000	

10	
30	
50	
80	
100	
140	
160	
200	
250	
270	
300	
350	
400	
460	
500	
550	

10	
20	
30	
40	
50	
70	
80	
90	
100	
120	

A Note on Pointers

- *Record pointers* consist of *block pointer* and position of record in the block
- Using the block pointer only, saves space at no extra accesses cost
- But a block pointer cannot serve as record identifier

Representation of Duplicate Values in Primary Indexes

- Index may point to first instance of each value only

10	
40	
70	
100	

10	
10	
10	
40	
40	
70	
70	
70	
100	
120	
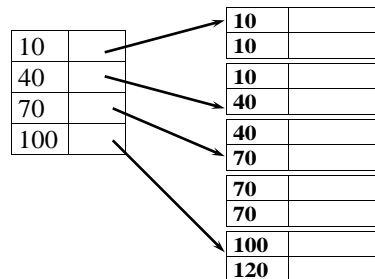
Deletion from Dense Index

Delete 40, 80

- Deletion from dense primary index file with no duplicate values is handled in the same way with deletion from a sequential file
- Q: What about deletion from dense primary index with duplicates
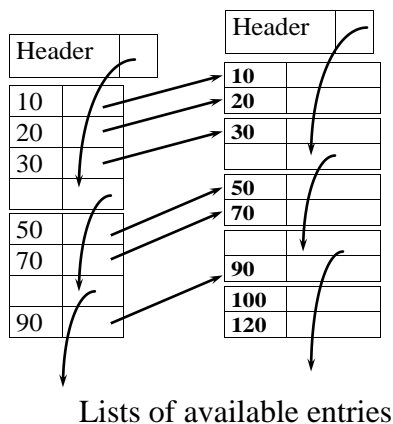
Header	
10	
20	
30	
50	
70	
90	

Header	
10	
20	
30	
50	
70	
90	
100	
120	

Lists of available entries

Deletion from Sparse Index

Delete 40

- if the deleted entry does not appear in the index do nothing

10	
30	
50	
80	
100	
140	
160	
200	

Header	
10	
20	
30	
50	
70	
80	
90	
100	
120	
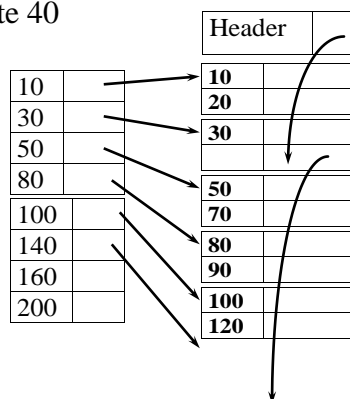
Deletion from Sparse Index (cont'd)

Delete 30

- if the deleted entry does not appear in the index do nothing
- if the deleted entry appears in the index replace it with the next search-key value
  - comment: we could leave the deleted value in the index assuming that no part of the system may assume it still exists without checking the block
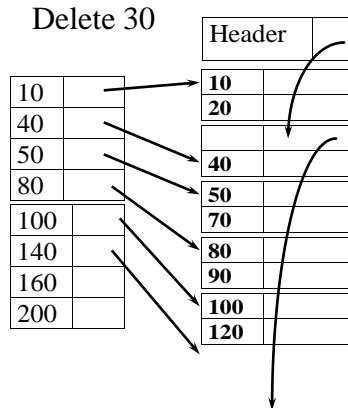
Deletion from Sparse Index (cont'd)

Delete 40, then 30

- if the deleted entry does not appear in the index do nothing
- if the deleted entry appears in the index replace it with the next search-key value
- unless the next search key value has its own index entry. In this case delete the entry
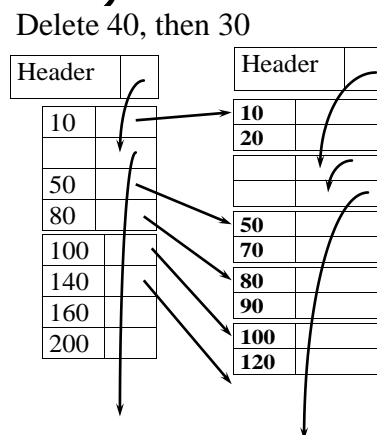
Insertion in Sparse Index

Insert 35

- if no new block is created then do nothing

10	
30	
50	
80	
100	
140	
160	
200	

Header	
10	
20	
30	
35	
50	
70	
80	
90	
100	
120	
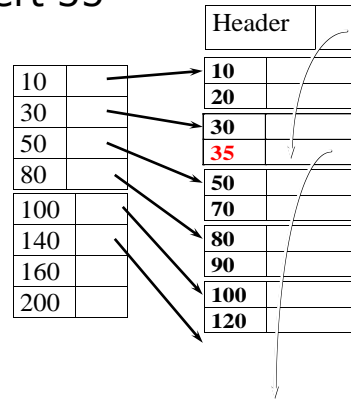
Insertion in Sparse Index

Insert 15

- if no new block is created then do nothing
- else create overflow record
  - Reorganize periodically
  - Could we claim space of next block?
  - How often do we reorganize and how much expensive it is?
  - B-trees offer convincing answers

10	
30	
50	
80	
100	
140	
160	
200	

Header	
10	
20	
30	
50	
70	
80	
90	
100	
120	

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Sequence
field

```
┌──┬──────────────┐
│30│              │
│50│              │
└──┴──────────────┘

┌──┬──────────────┐
│20│              │
│70│              │
└──┴──────────────┘

┌──┬──────────────┐
│80│              │
│40│              │
└──┴──────────────┘

┌───┬─────────────┐
│100│             │
│10 │             │
└───┴─────────────┘

┌──┬──────────────┐
│90│              │
│60│              │
└──┴──────────────┘
```
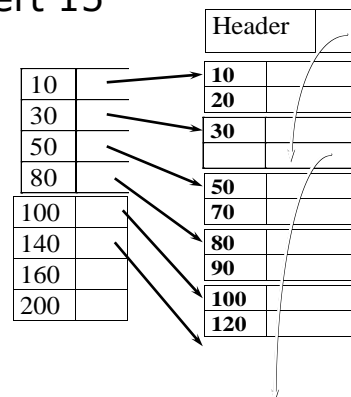
File not sorted on
secondary search key

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Sequence
field

• Sparse index

```
┌────┬──┐
│ 30 │  │
│ 20 │  │
│ 80 │  │
│100 │  │
├────┼──┤
│ 90 │  │
│ ...│  │
│    │  │
│    │  │
└────┴──┘
```

does not make sense!

```
┌───┬─────────────┐
│30 │             │
│50 │             │
└───┴─────────────┘

┌───┬─────────────┐
│20 │             │
│70 │             │
└───┴─────────────┘

┌───┬─────────────┐
│80 │             │
│40 │             │
└───┴─────────────┘

┌───┬─────────────┐
│100│             │
│10 │             │
└───┴─────────────┘

┌───┬─────────────┐
│90 │             │
│60 │             │
└───┴─────────────┘
```

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22

• Dense index

Sequence
field

```
          10                30
          20                50
  10      30
  50      40                20
  90                        70
  ...
                            80
          50                40
sparse    60
high      70                100
level     ...               10

                            90
                            60
```
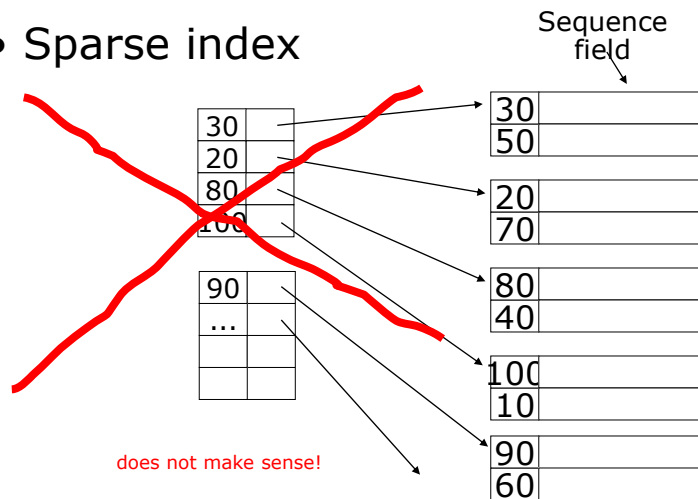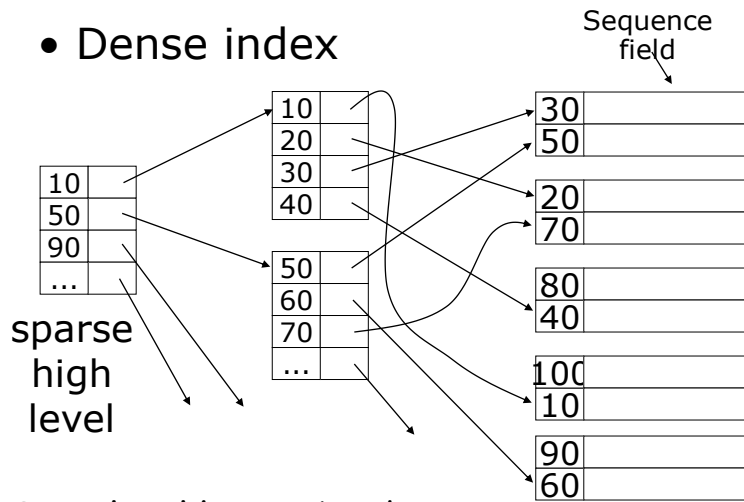
First level has to be dense,
next levels are sparse (as usual)

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Duplicate values & secondary indexes

```
20
10

20
40

10
40

10
40

30
40
```

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Duplicate values & secondary indexes

one option...

Problem:
excess overhead!
- disk space
- search time
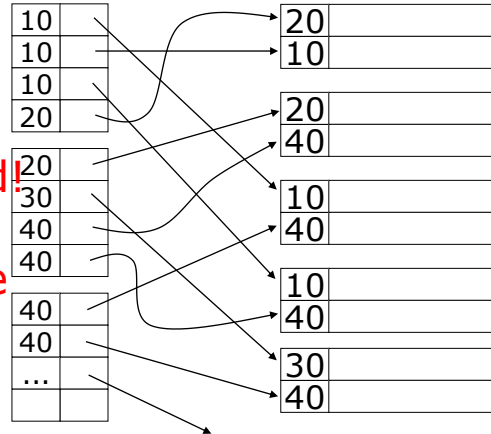
Duplicate values & secondary indexes

another option: lists of pointers

Problem:
variable size
records in
index!

Duplicate values & secondary indexes

Yet another idea :
Chain records with same key?
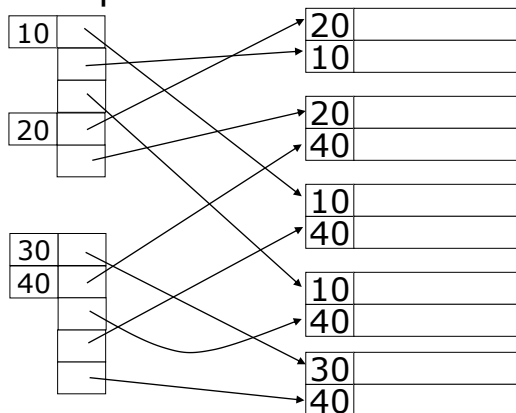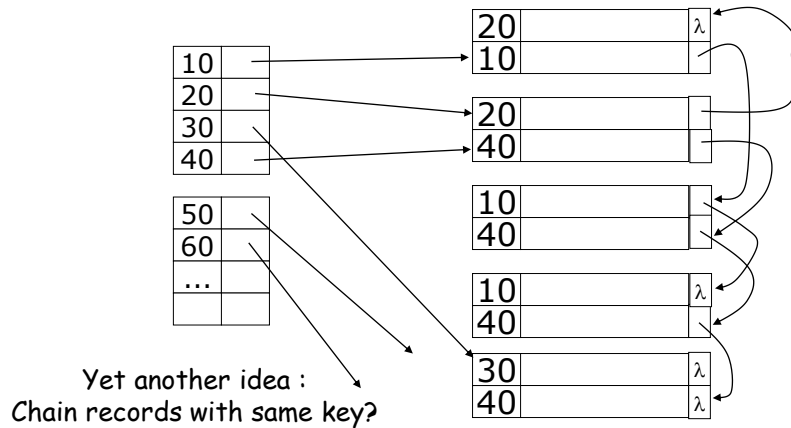
Problems:
• Need to add fields to records, messes up maintenance
• Need to follow chain to know records

49

Duplicate values & secondary indexes
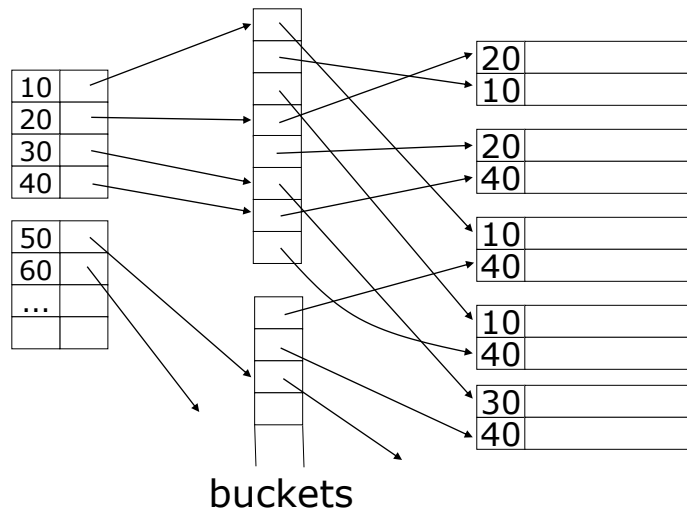
buckets

50

Why "bucket" + record pointers is useful

- Enables the processing of queries working with pointers only.
- Very common technique in Information Retrieval

Indexes	Records
Name: primary	EMP (name,dept,year,...)
Dept: secondary	
Year: secondary	

Advantage of Buckets: Process Queries Using Pointers Only

Find employees of the Toys dept with 4 years in the company

```
SELECT Name FROM Employee
WHERE Dept="Toys" AND Year=4
```


Dept Index

| Toys |
| PCs |
| Pens |
| Suits |

Aaron	Suits	4
Helen	Pens	3
Jack	PCs	4
Jim	Toys	4
Joe	Toys	3
Nick	PCs	2
Walt	Toys	5
Yannis	Pens	1

Year Index

| 1 |
| 2 |
| 3 |
| 4 |

Intersect toy bucket and 2nd Floor bucket to get set of matching EMP's
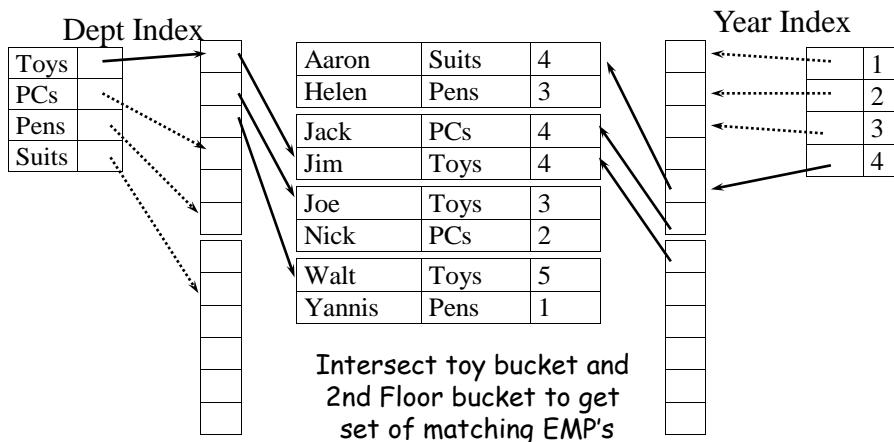
This idea used in
   text information retrieval

Documents

| cat | |
| dog | |

...the **cat** is fat ...

...my **cat** and my **dog** like each other...

...Fido the **dog** ...

Buckets known as

Inverted lists
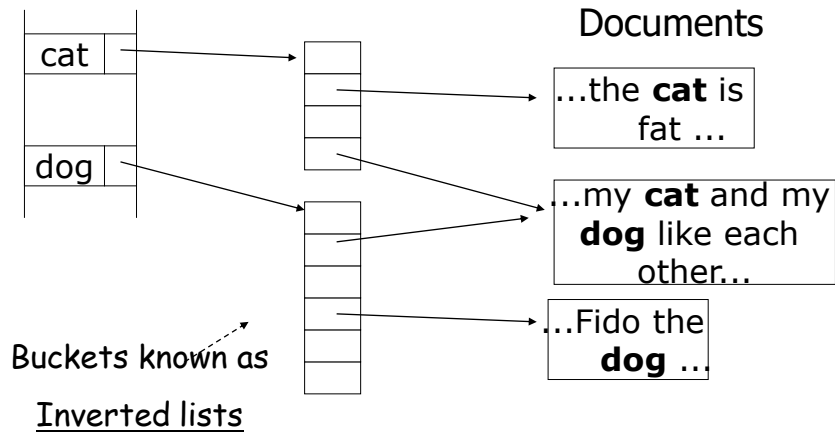
Summary of Indexing So Far

- Basic topics in conventional indexes
  - multiple levels
  - sparse/dense
  - duplicate keys and buckets
  - deletion/insertion similar to sequential files
- Advantages
  - simple algorithms
  - index is sequential file
- Disadvantages
  - eventually sequentiality is lost because of overflows, reorganizations are needed

Example   Index (sequential)

continuous

free space

overflow area
(not sequential)
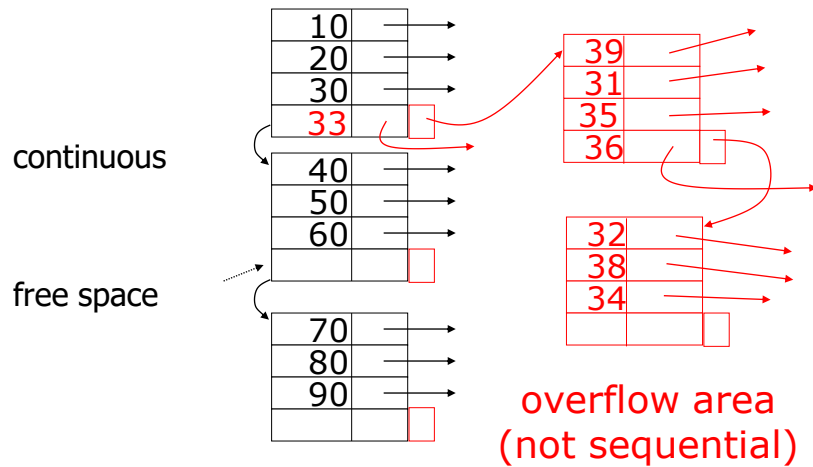
55

Outline:

- Conventional indexes
- B-Trees $\Rightarrow$ NEXT
- Hashing schemes

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- NEXT: Another type of index
  - Give up on sequentiality of index
  - Try to get "balance"

B+Tree Example   n=3

Root

Sample non-leaf

to keys   to keys   to keys   to keys

< 57   57≤ k<81   81≤k<95   ≥95

59

Sample leaf node:

From non-leaf node

to next leaf
in sequence

To record with key 57

To record with key 81

To record with key 85

60
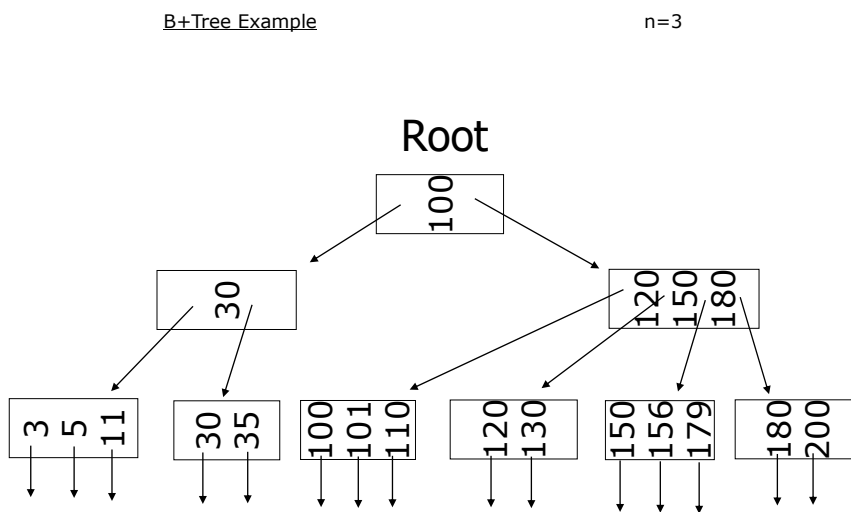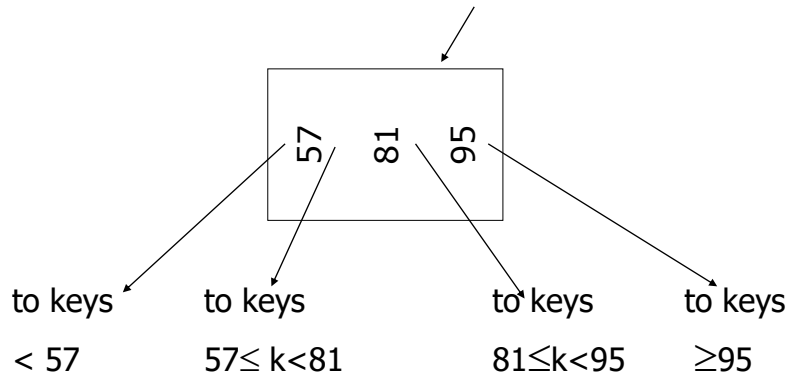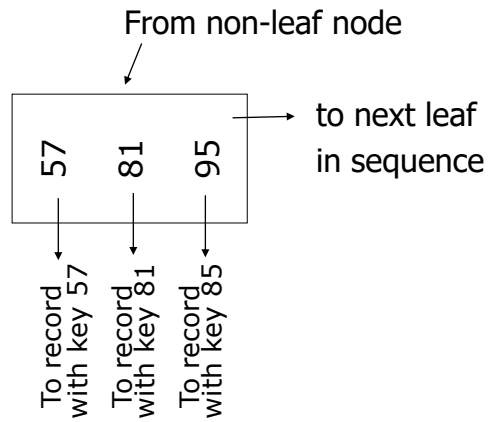
30

In textbook's notation   n=3

Leaf:
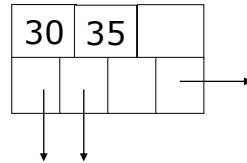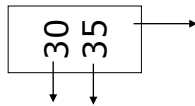
Non-leaf:
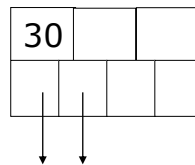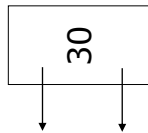
61

Size of nodes: { n+1 pointers
                    n keys   (fixed)

62

31

Non-root nodes have to be at least half-full

- Use at least

  Non-leaf: $\lceil(n+1)/2\rceil$ pointers

  Leaf: $\lfloor(n+1)/2\rfloor$ pointers to data

n=3

Full node   min. node
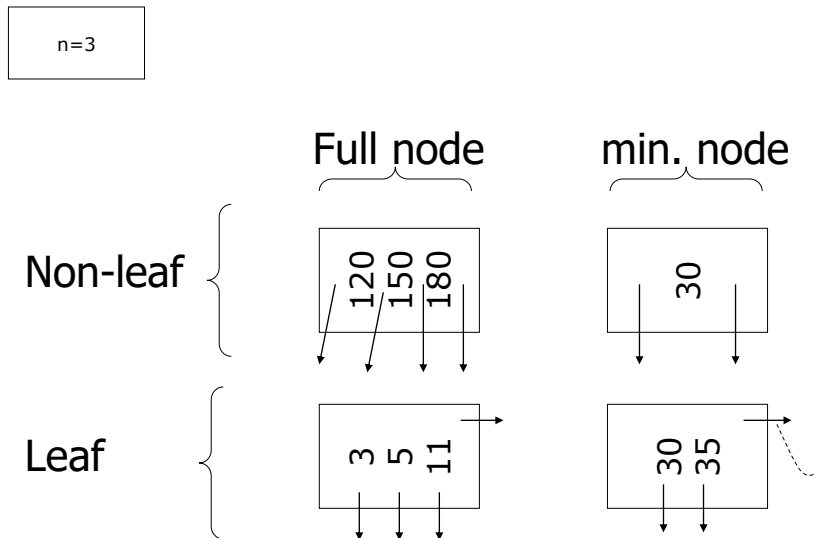
Non-leaf

Leaf

B+tree rules   tree of order n

(1) All leaves at same lowest level
       (balanced tree)
(2) Pointers in leaves point to records
       except for "sequence pointer"

(3) Number of pointers/keys for B+tree

	Max ptrs	Max keys	Min ptrs→data	Min keys
Non-leaf (non-root)	n+1	n	$\lceil(n+1)/2\rceil$	$\lceil(n+1)/2\rceil - 1$
Leaf (non-root)	n+1	n	$\lfloor(n+1)/2\rfloor$	$\lfloor(n+1)/2\rfloor$
Root	n+1	n	1	1

Insert into B+tree

(a) simple case
- space available in leaf

(b) leaf overflow

(c) non-leaf overflow

(d) new root

(a) Insert key = 32   n=3

100

30

3 5 11   30 31 32
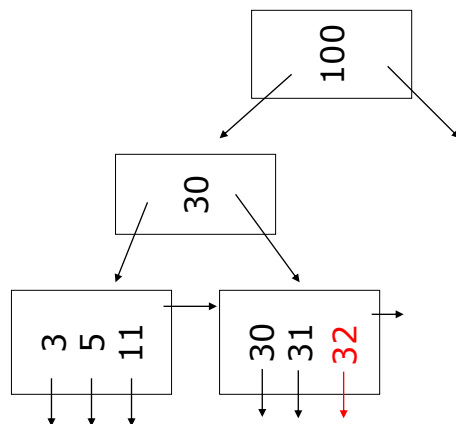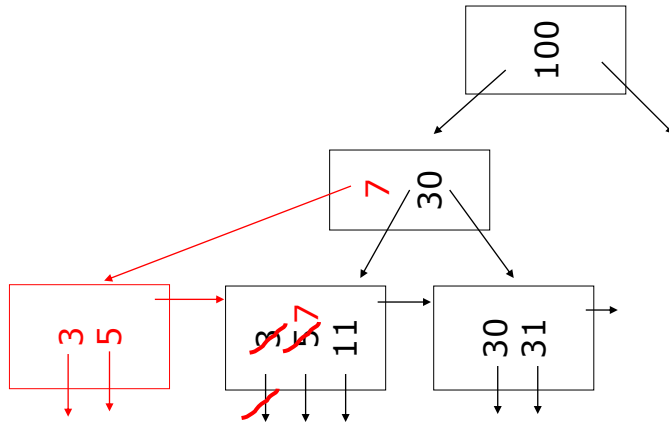
(a) Insert key = 7   n=3

69

(c) Insert key = 160   n=3

70

35

(d) New root, insert 45   n=3

new root: 30

10 20 30 | 40

1 2 3   10 12   20 25   30 32 40   40 45
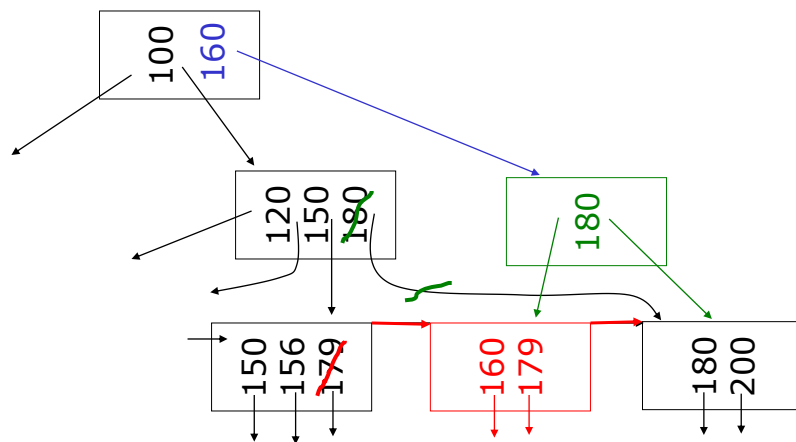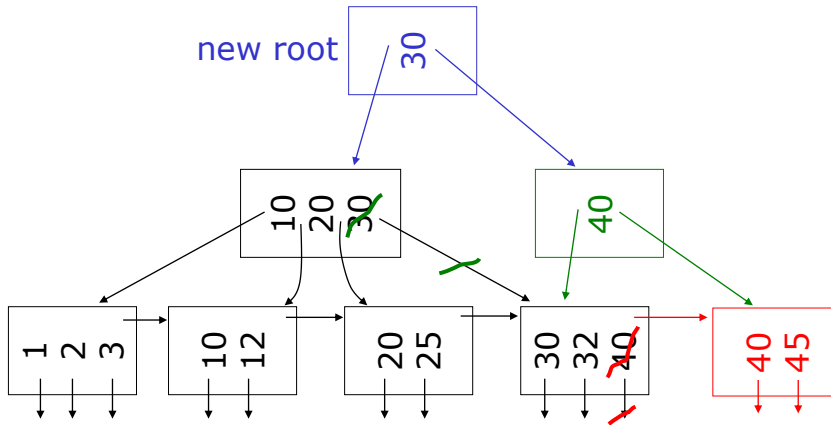
71

Deletion from B+tree

(a) Simple case - no example
(b) Coalesce with neighbor (sibling)
(c) Re-distribute keys
(d) Cases (b) or (c) at non-leaf

72

36

(b) Coalesce with sibling
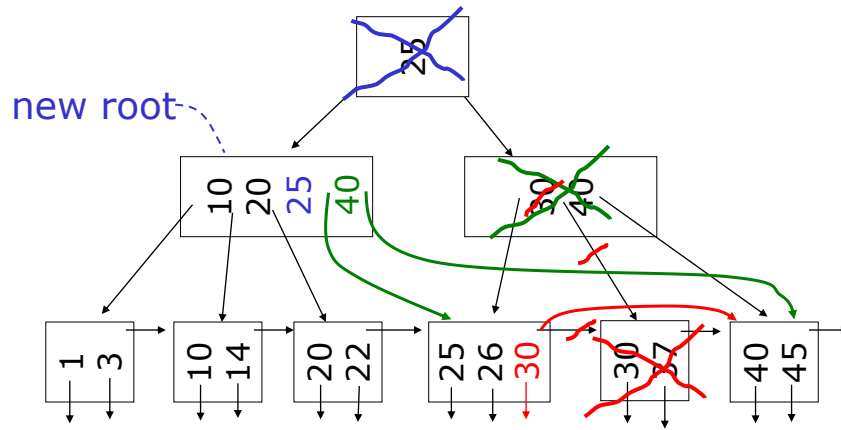– Delete 50
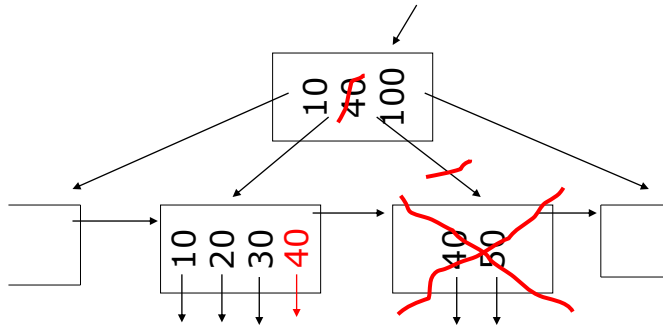
73

(c) Redistribute keys
– Delete 50

74

37

(d) Non-leaf coalese
– Delete 37

n=4

new root
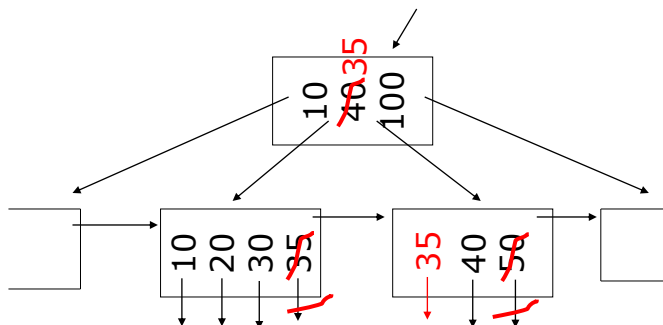
B+tree deletions in practice

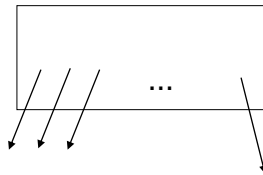– Often, coalescing is <u>not</u> implemented
  – Too hard and not worth it!

Is LRU a good policy for B+tree buffers?

$\rightarrow$ Of course not!

$\rightarrow$ Should try to keep root in memory
at all times

(and perhaps some nodes from second level)

Hardware+ indexing problem:

For B+tree, how large should n be?


n is number of keys / node

Assumptions

- You have the right to set the block size for the disk where a B-tree will reside.
- Compute the optimum page size n assuming that
  - The items are 4 bytes long and the pointers are also 4 bytes long.
  - Time to read a node from disk is *12+.003n*
  - Time to process a block in memory is unimportant
  - B+tree is full (I.e., every page has the maximum number of items and pointers

✍Can get:
  f(n) = time to find a record

f(n)

n_{opt}

n

80
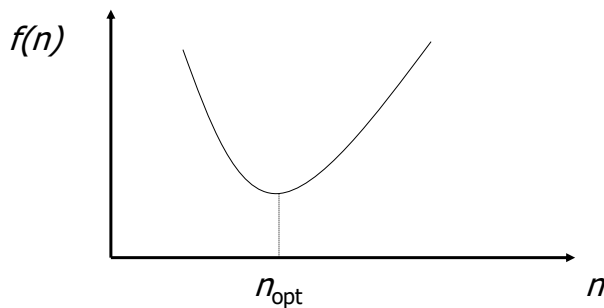
↘ FIND n_{opt} by $f'(n) = 0$

Answer should be n_{opt} = "few hundred"

↘ What happens to n_{opt} as

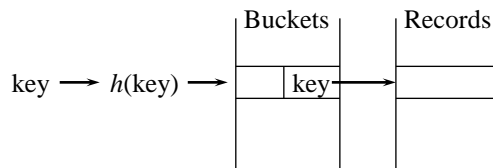- Disk gets faster?
- CPU get faster?

Outline/summary

- Conventional Indexes
    - Sparse vs. dense
    - Primary vs. secondary
- B+ trees
- Hashing schemes   -->   Next
- Bitmap indices

Hashing

- hash function h(key) returns address of bucket
- if the keys for a specific hash value do not fit into one page the bucket is a linked list of pages

```
key ⟶ h(key) ⟶
```

Buckets   Records

key

Example hash function

- Key = 'x$_1$ x$_2$ ... x$_n$' n byte character string
- Have b buckets
- h: add $x_1 + x_2 + ... x_n$
  - compute sum modulo b

⊠ This may not be best function …

⊠ Read Knuth Vol. 3 if you really
    need to select a good function.

Good hash   ☞ Expected number of
  function: keys/bucket is the
                        same for all
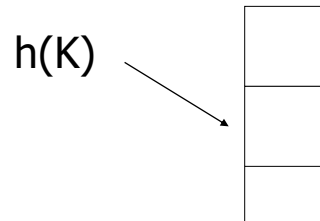   buckets

Within a bucket:

• Do we keep keys sorted?

        • Yes, if CPU time critical
          & Inserts/Deletes not too
                frequent

Next: example to illustrate
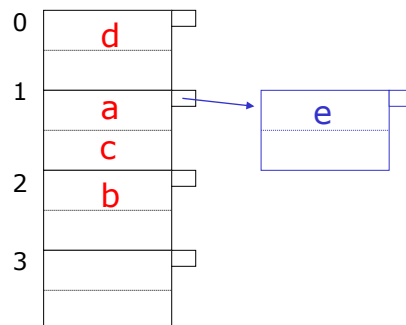inserts, overflows, deletes

h(K)

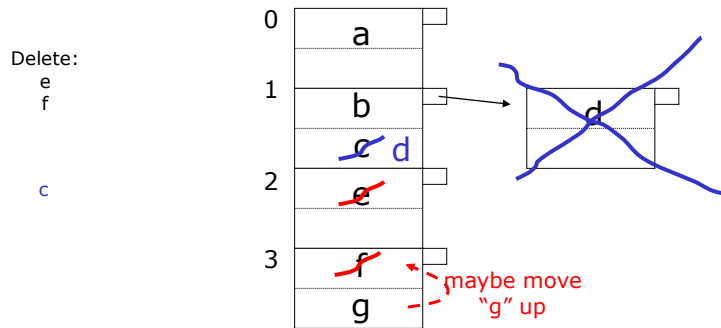EXAMPLE 2 records/bucket

INSERT:
h(a) = 1
h(b) = 2
h(c) = 1
h(d) = 0
h(e) = 1

0	d	
1	a	→ e
	c	
2	b	
3		

Delete:
  e
  f

c

0
a
1
b
  c d
2
e
3
f
g

maybe move
"g" up

Rule of thumb:

• Try to keep space utilization
  between 50% and 80%

  Utilization = $\dfrac{\text{\# keys used}}{\text{total \# keys that fit}}$

  • If < 50%, wasting space

• If > 80%, overflows significant
            depends on how good
  hash   function is & on #
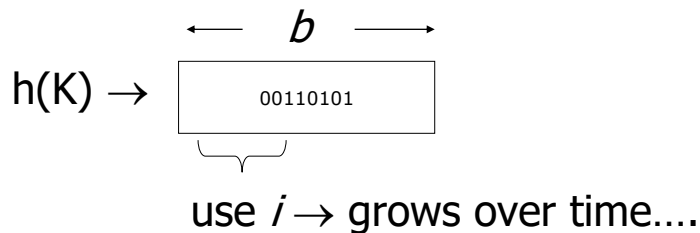   keys/bucket

How do we cope with growth?

- Overflows and reorganizations
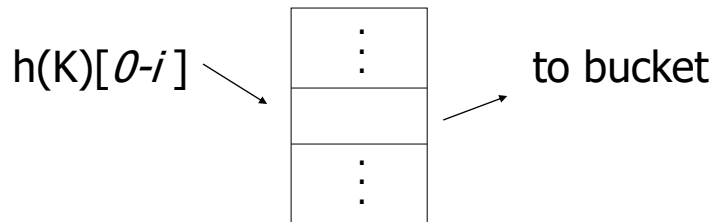- Dynamic hashing
  - Extensible
    - Linear

Extensible hashing: two ideas

(a) Use i of b bits output by hash function

$$\longleftarrow \quad b \quad \longrightarrow$$

h(K) → | 00110101 |

use $i \rightarrow$ grows over time....

(b) Use directory

h(K)[*0-i*] ⟍   ⟍ →   → to bucket

Example: h(k) is 4 bits; 2 keys/bucket

i = 1

1
0001

1
1001
1100
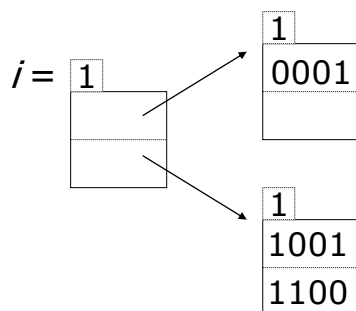
"slide" conventions:
slide shows h(k), while actual directory has key+pointer

Example: h(k) is 4 bits; 2 keys/bucket

1
0001

i = 1

~~i~~ 2
1001

1010~~1100~~

Insert
1010

~~1~~ 2
1100

i = 2

00
01
10
11

New directory

95

Example continued

i = 2

00
01
10
11

Insert:

0111

0000

2
0000
0001

~~1~~ 2
~~0001~~ 0111
~~0111~~

2
1001
1010

2
1100

96

48

Example continued

$i = 2$

00
01
10
11

Insert:
1001

$i = 3$

0000   2
0001

0111   2

1001   3
1001

1010 ~~1001~~ ~~2~~ 3
~~1010~~

1100   2

000
001
010
011
100
101
110
111
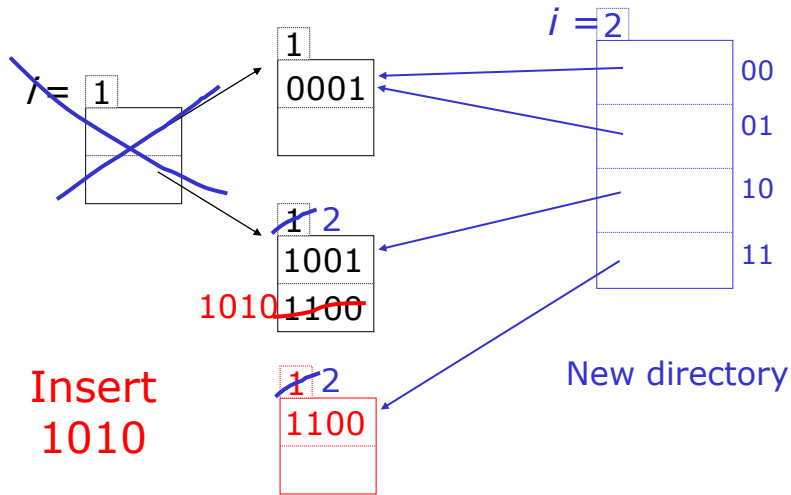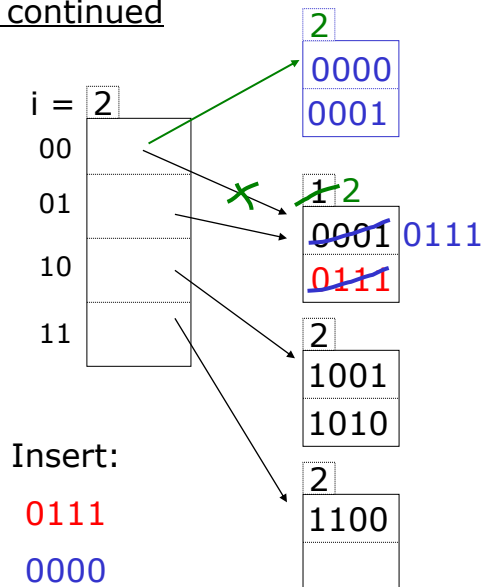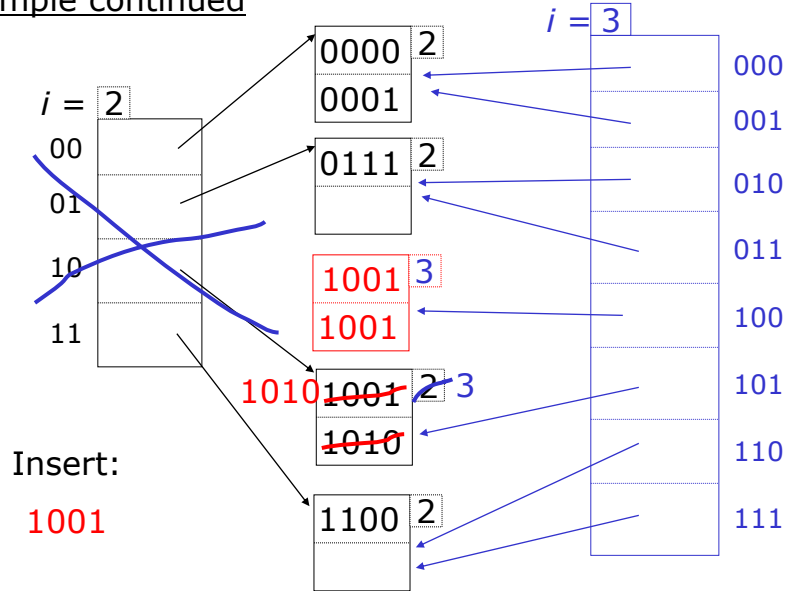
Extensible hashing: <u>deletion</u>

- No merging of blocks
- Merge blocks
   and cut directory if possible
   (Reverse insert procedure)

Deletion example:

• Run thru insert example in reverse!

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Summary

Extensible hashing

⊕ Can handle growing files

    - with less wasted space

    - with no full reorganizations

⊖   Indirection

       (Not bad if directory in
           memory)

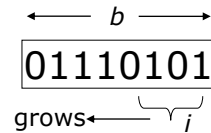⊖ Directory doubles in size

    (Now it fits, now it does not)

100

50

Linear hashing

- Another dynamic hashing scheme

Two ideas:

(a) Use i low order bits of hash

$$\overset{\longleftarrow \quad b \quad \longrightarrow}{\boxed{01110101}}$$

grows$\longleftarrow \underset{i}{\overbrace{\qquad}}$

(b) File grows linearly

Example b=4 bits, i=2, 2 keys/bucket

- insert 0101
- can have overflow chains!

| | 0101 | | |

Future growth buckets

0000	0101		
1010	1111		
00	01	10	11

m = 01 (max used block)
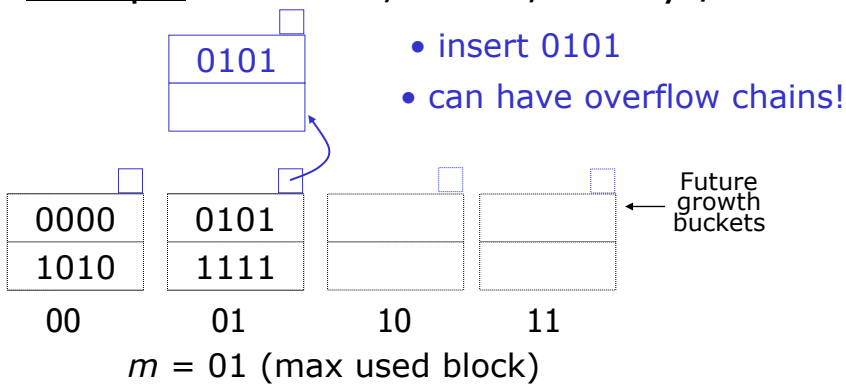
Rule   If h(k)[i] ≤ m, then
look at bucket h(k)[i]
else, look at bucket h(k)[i] -
2^{i-1}

Example $b=4$ bits, $i=2$,   2 keys/bucket

• insert 0101

	0101	

0000	0101	1010	1111
~~1010~~	0101 ~~1111~~		

← Future growth buckets

00   01   10   11

$m = $ ~~01~~ (max used block)
~~10~~
11

Example Continued: How to grow beyond this?

$i = $ ~~2~~ 3

0000	~~0101~~	1010	1111		0101
	~~0101~~				0101

000   001   010   011   100   101
~~100~~   ~~101~~   110   111   . . .

$m = $ ~~11~~ (max used block)
~~100~~
101

⊠ When do we expand file?

- Keep track of: $\dfrac{\text{\#used slots (incl. overflow)}}{\text{\#total slots in primary buckets}}$ = U

  equiv, $\dfrac{\text{\#(indexed key ptr pairs)}}{\text{\#total slots in primary buckets}}$

  - If U > threshold then increase m
    (and i, when m reaches 2^i)

Summary	Linear Hashing

⊕ Can handle growing files
 - with less wasted space
 - with no full reorganizations

⊕ No indirection like extensible hashing

⊖ Can still have overflow chains

Example: BAD CASE

Very full

Very empty

Need to move
m here…
Would waste
space…
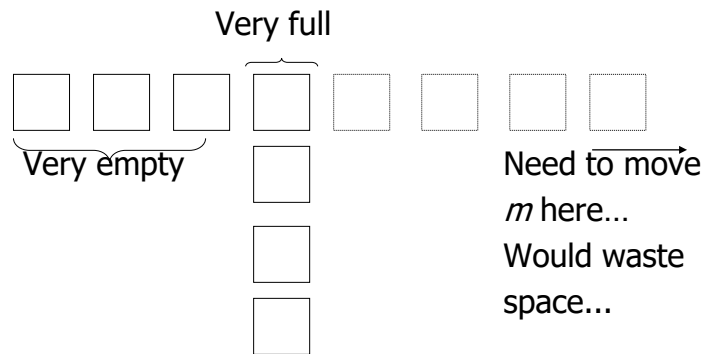
Summary

Hashing
   - How it works
      - Dynamic hashing
          - Extensible
          - Linear

Next:

- Indexing vs Hashing
- Index definition in SQL
- Multiple key access

Indexing vs Hashing

- Hashing good for probes given key

  e.g.,   SELECT ...
           FROM R
           WHERE R.A = 5

- INDEXING (Including B Trees) good for
  Range Searches:
  e.g.,   SELECT
             FROM R
             WHERE R.A > 5

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Index definition in SQL

- <u>Create</u> <u>index</u> name <u>on</u> rel (attr)
- <u>Create</u> <u>unique</u> <u>index</u> name <u>on</u> rel (attr)

  └─────→ defines candidate
                    key

  - <u>Drop</u> INDEX
    name

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| Note | CANNOT SPECIFY TYPE OF INDEX

        (e.g. B-tree, Hashing, …)

    OR PARAMETERS

        (e.g. Load Factor, Size of Hash,...)

… at least in SQL...

| Note | ATTRIBUTE <u>LIST</u> $\Rightarrow$ MULTIKEY INDEX

                           (next)

    e.g., <u>CREATE</u> <u>INDEX</u> foo <u>ON</u> R(A,B,C)

Multi-key Index

Motivation: Find records where
DEPT = "Toy" AND SAL > 50k

Strategy I:

- Use one index, say Dept.
- Get all Dept = "Toy" records
      and check their salary
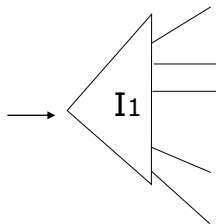
Strategy II:

- Use 2 Indexes; Manipulate Pointers

Toy → □□□□□   □□□□□□□ ← Sal
                                > 50k
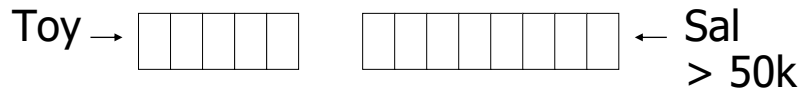
Strategy III:

- Multiple Key Index

One idea:

Example

Dept Index

Salary Index

Example Record

Name=Joe
DEPT=Sales
SAL=15k
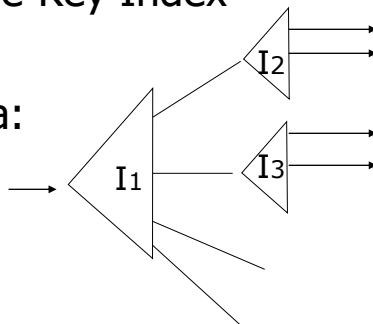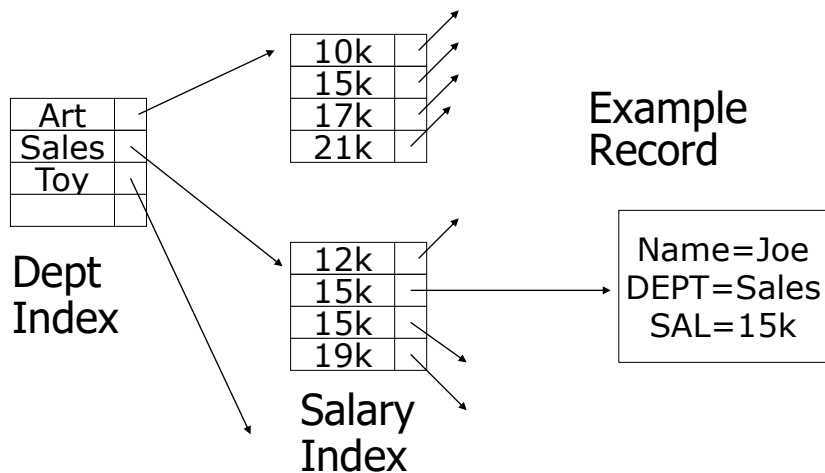
For which queries is this index good?

☐ Find RECs Dept = "Sales" ∧ SAL=20k
☐ Find RECs Dept = "Sales" ∧ SAL ≥ 20k
☐ Find RECs Dept = "Sales"
☐ Find RECs SAL = 20k

Interesting application:

- Geographic Data
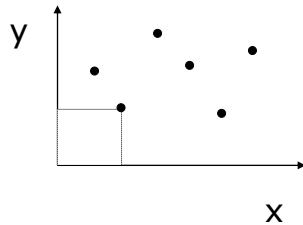
DATA:
   <X_1, Y_1, Attributes>
   <X_2, Y_2, Attributes>
      ⋮

Queries:

- What city is at <X_i, Y_i>?
- What is within 5 miles from <X_i, Y_i>?
- Which is closest point to <X_i, Y_i>?

Example

- Search points near f
- Search points near b
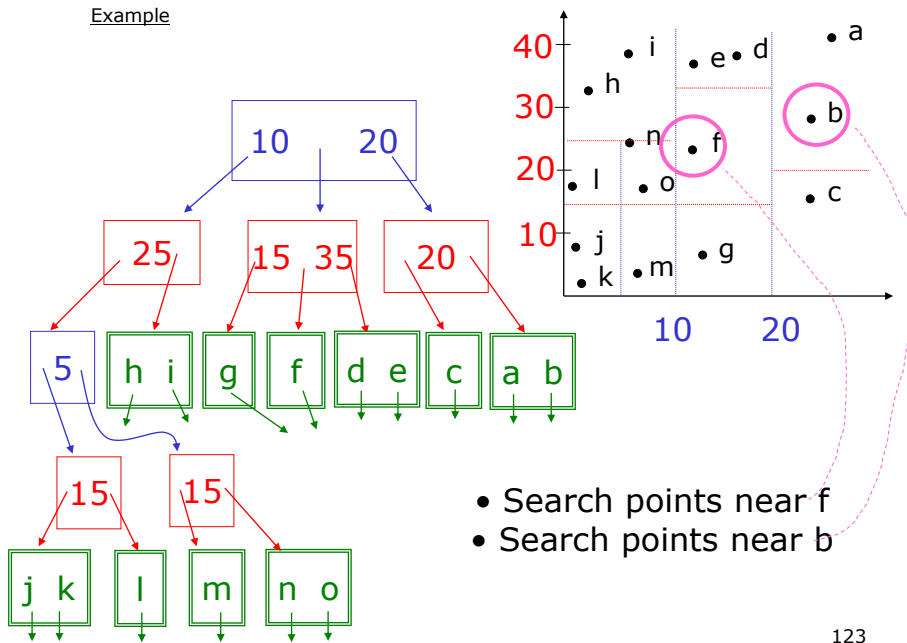
123

Queries

- Find points with Y_i > 20
- Find points with X_i < 5
- Find points "close" to i = <12,38>
- Find points "close" to b = <7,24>

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- Many types of geographic index structures have been suggested
  - Quad Trees
  - R Trees

Outline/summary

- Conventional Indexes
  - Sparse vs. dense
  - Primary vs. secondary
- B+ trees
- Hashing schemes
- Bitmap indices   -->   Next

Revisit: Processing queries without accessing records until last step

Find employees of the Toys dept with 4 years in the company
SELECT Name FROM Employee
WHERE Dept="Toys" AND Year=4

Dept Index				Year Index

Aaron	Suits	4
Helen	Pens	3
Jack	PCs	4
Jim	Toys	4
Joe	Toys	3
Nick	PCs	2
Walt	Toys	5
Yannis	Pens	1

Dept Index: Toys, PCs, Pens, Suits

Year Index: 1, 2, 3, 4
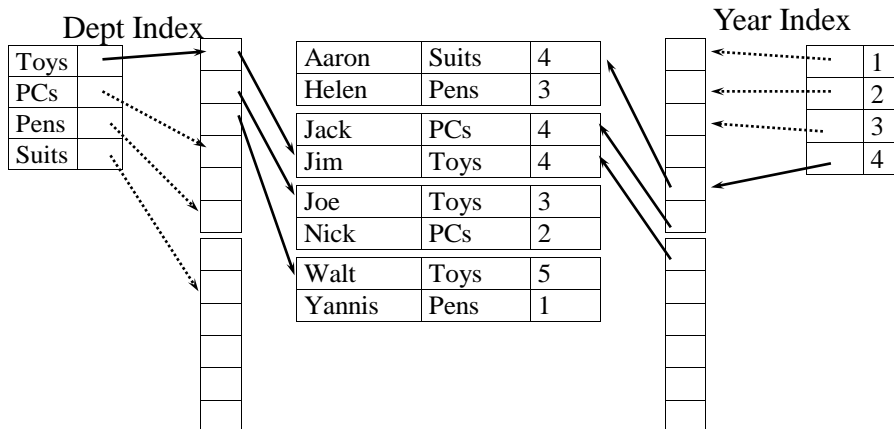
Bitmap indices: Alternate structure, heavily used in OLAP

Assume the tuples of the Employees table are ordered.
Conceptually only!

Dept Index

Toys	00011010
PCs	00100100
Pens	01000001
Suits	10000000

Aaron	Suits	4
Helen	Pens	3
Jack	PCs	4
Jim	Toys	4
Joe	Toys	3
Nick	PCs	2
Walt	Toys	1
Yannis	Pens	1

Year Index

00000011	1
00000100	2
01001000	3
10110000	4
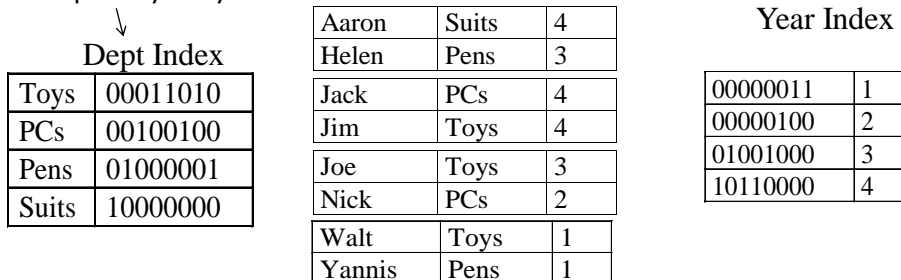
+ Find even more quickly intersections and unions
(e.g., Dept="Toys" AND Year=4)
? Seems it needs too much space -> We'll do compression
? How do we deal with insertions and deletions -> Easier than you think

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Compression, with Run-Length Encoding

- Naive solution needs mn bits, where m is #distinct values and n is #tuples
- But there is just n 1's=> let's utilize this
- Encode sequence of **runs** (e.g. [3,0,1])

Toys: 00011010

3   0   1

First run says:
The first ace appears after 3 zeros

Second run says:
The 2nd ace appears immediately after the 1st

Third run says:
The 3rd ace appears after 1 zero after the 2nd
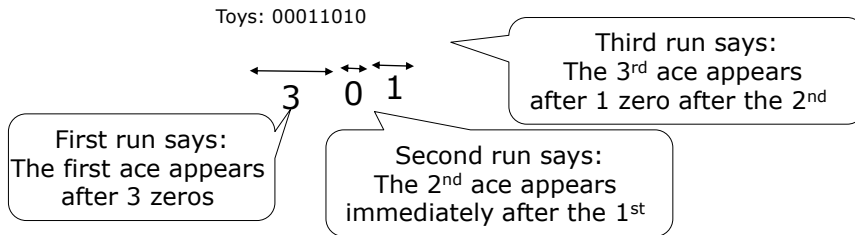
Byte-Aligned Run Length Encoding

Next key intuition: Spend fewer bits for smaller numbers

Consider the run
5, 200, 17
In binary it is
101, 11000100, 10001

A binary number of up to 7 bits => 1 byte
A binary number of up to 14 bits => 2 bytes
…
Use the first bit of each byte to denote if it is the last one of a number
0**0000101**, 1**0000001**, 0**1000100**, 0**0010001** 130

Bit-aligned 2nlog*m*
Compression (simple version)

Toys: 00011010

3   0   1

Third run says:
The 3rd ace appears
after 1 zero after the 2nd

First run says:
The first ace appears
after 3 zeros

Second run says:
The 2nd ace appears
immediately after the 1st

*10***11** *00* *0* **1**

10 says: The binary encoding of the first number
needs 1+1 digits.
11 says: The first number is 3
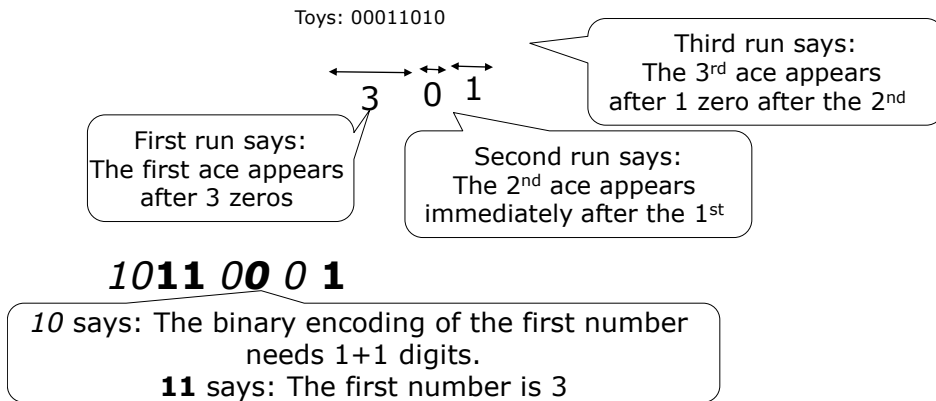
2nlog m compression

- Example
- Pens: 01000001
- Sequence [1,5]
- Encoding: *0***1** *110***101**

Insertions and deletions & miscellaneous engineering

- Assume tuples are inserted in order
- Deletions: Do nothing
- Insertions: If tuple t with value v is inserted, add one more run in v's sequence (compact bitmap)

Summing Up...

We discussed how the database stores data + basic algorithms
- Sorting
- Indexing
How are they used in query processing?

Query Processing Notes

What happens when a query is
processed and how to find out

Query Processing

- The query processor turns user queries and
  data modification commands into a query
  plan - a sequence of operations (or algorithm)
  on the database
  - from high level queries to low level commands
- Decisions taken by the query processor
  - Which of the algebraically equivalent forms of a
    query will lead to the most efficient algorithm?
  - For each algebraic operator what algorithm should
    we use to run the operator?
  - How should the operators pass data from one to
    the other? (eg, main memory buffers, disk buffers)

The differences between good plans and plans can be huge
Example

Select B,D
From R,S
Where R.A = "c" $\land$ S.E = 2 $\land$ R.C=S.C

R	A	B	C
	a	1	10
	b	1	20
	c	2	10
	d	2	35
	e	3	45

S	C	D	E
	10	x	2
	20	y	2
	30	z	2
	40	x	1
	50	y	3

Answer

B	D
2	x

• How do we execute query eventually?

One idea >

- Scan relations
- Do Cartesian product
  (literally produce all
  combinations of
  FROM clause tuples)
- Select tuples (WHERE)
- Do projection (SELECT)

RxS	R.A	R.B	R.C	S.C	S.D	S.E
	a	1	10	10	x	2
	a	1	10	20	y	2
	.					
	.					
Bingo! →	C	2	10	10	x	2
Got one...	.					
	.					

Relational Plan:

Ex: Plan I

$$\Pi_{B,D}^{FLY}$$

1. Scan R
2. For each tuple r of R scan S
3. For each (r,s), where s in S
        select and project on the fly

$$\sigma_{R.A="c" \wedge S.E=2 \wedge R.C=S.C}^{FLY}$$

X

R^{SCAN} S^{SCAN}
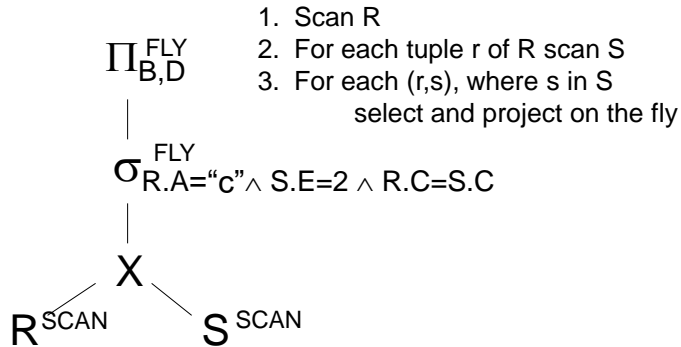
OR: $\Pi_{B,D}^{FLY} [\sigma_{R.A="c" \wedge S.E=2 \wedge R.C = S.C}^{FLY} (R^{SCAN} X\ S^{SCAN})]$

"FLY" and "SCAN" are the defaults

Ex: Plan I

$$\Pi_{B,D}$$

$$\sigma_{R.A="c" \wedge S.E=2 \wedge R.C=S.C}$$

X

R   S

Another idea:

Plan II

$$\Pi_{B,D}$$

$$\bowtie^{\text{HASH}}$$

$$\sigma_{R.A = \text{"c"}} \qquad \sigma_{S.E = 2}$$

R   S

$$\bowtie$$

natural join
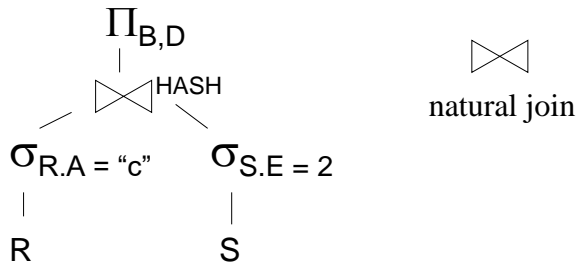
Scan R and S, perform on the fly selections,
do join using a hash structure, project

R

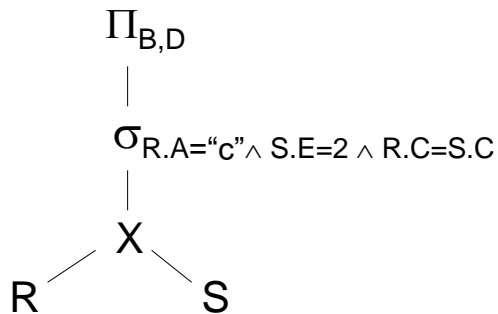| A	B	C
a	1	10
b	1	20
c	2	10
d	2	35
e	3	45

σ (R)

A	B	C
c	2	10

σ(S)

C	D	E
10	x	2
20	y	2
30	z	2

S

C	D	E
10	x	2
20	y	2
30	z	2
40	x	1
50	y	3

$$\bowtie$$

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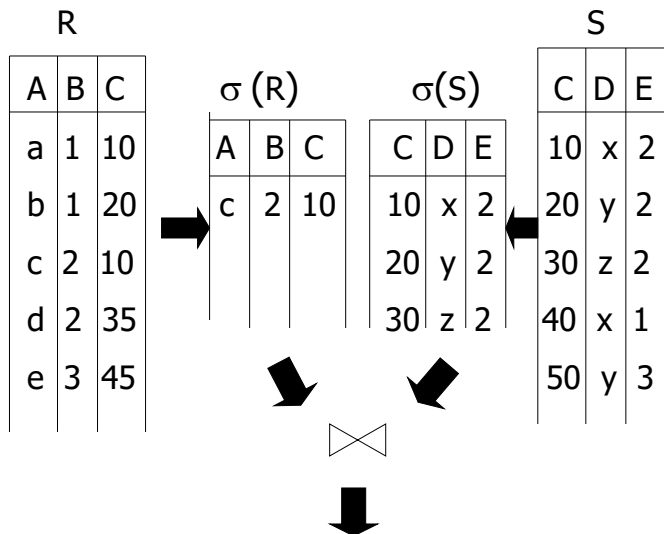
Plan III

Use R.A and S.C Indexes

(1) Use R.A index to select R tuples
with R.A = "c"

(2) For each R.C value found, use S.C
index to find matching join tuples

(3) Eliminate join tuples $S.E \neq 2$

(4) Project B,D attributes

R   S

A	B	C
a	1	10
b	1	20
c	2	10
d	2	35
e	3	45

A="c"   C

I₁   I₂

<c,2,10>   <10,x,2>

check=2?

output: <2,x>

next tuple:
<c,7,15>

C	D	E
10	x	2
20	y	2
30	z	2
40	x	1
50	y	3

Algebraic Form of Plan

$$\pi \text{ R.B, S.D}$$
$$\sigma \text{ S.E=2}$$

Right Index Join

$$\bowtie \text{ RI}$$

$$\sigma^{\text{INDEX}}_{\text{R.a=“c”}}$$

$$S$$

$$R$$
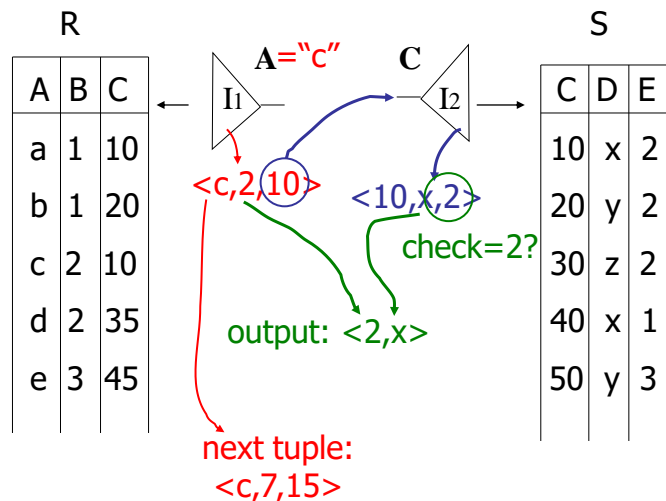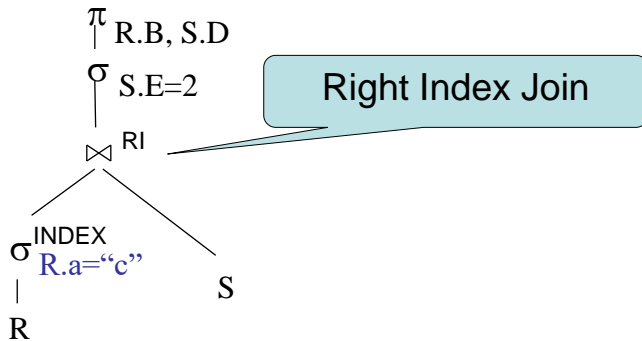
From Query To Optimal Plan

- Complex process
- Algebra-based logical and physical plans
- Transformations
- Evaluation of multiple alternatives
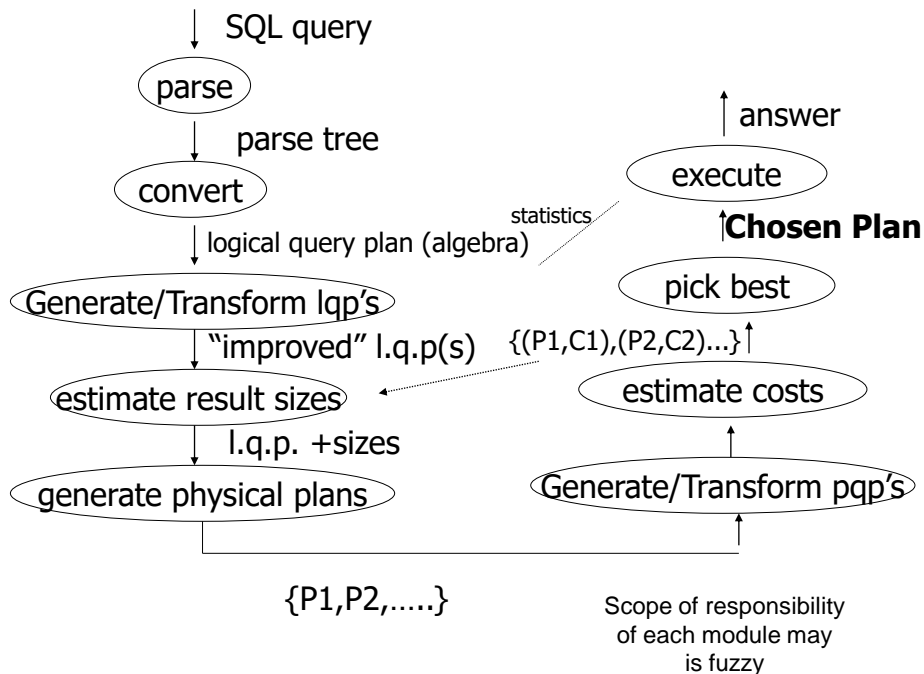
Issues in Query Processing and Optimization

- Generate Plans
  - employ efficient execution primitives for computing relational algebra operations
  - systematically transform expressions to achieve more efficient combinations of operators
- Estimate Cost of Generated Plans
  - Statistics, which are reported

$\downarrow$ SQL query

(parse)

$\downarrow$ parse tree

(convert)

$\downarrow$ logical query plan (algebra)

(Generate/Transform lqp's)

$\downarrow$ "improved" l.q.p(s)

(estimate result sizes)

$\downarrow$ l.q.p. +sizes

(generate physical plans)

{P1,P2,.....}

$\uparrow$ answer

(execute)

Chosen Plan

(pick best)

{(P1,C1),(P2,C2)...} $\uparrow$

(estimate costs)

$\uparrow$

(Generate/Transform pqp's)

$\uparrow$

statistics

Scope of responsibility of each module may is fuzzy

Algebraic Operators: A Bag version

- *Union of R and S*: a tuple t is in the result as many times as the sum of the number of times it is in R plus the times it is in S
- *Intersection of R and S*: a tuple t is in the result the minimum of the number of times it is in R and S
- *Difference of R and S*: a tuple t is in the result the number of times it is in R minus the number of times it is in S
- $\delta(R)$ converts the bag *R* into a set
  - SQL's *R UNION S* is really $\delta(R \cup S)$
- **Example:** Let *R={A,B,B}* and *S={C,A,B,C}*.Describe the union, intersection and difference...

Extended Projection

- project π_A , A is attribute list
  - The attribute list may include $x \rightarrow y$ in the list *A* to indicate that the attribute *x* is renamed to *y*
  - Arithmetic, string operators and scalar functions on attributes are allowed. For example,
    - $a+b \rightarrow x$ means that the sum of *a* and *b* is renamed into *x*.
    - $c||d \rightarrow y$ concatenates the result of *c* and *d* into a new attribute named *y*
- The result is computed by considering each tuple in turn and constructing a new tuple by picking the attributes names in *A* and applying renamings and arithmetic and string operators
- **Example:**

Products and Joins

- *Product of R and S (R×S)*:
  - If an attribute named *a* is found in both schemas then rename one column into *R.a* and the other into *S.a*
  - If a tuple *r* is found *n* times in *R* and a tuple *s* is found *m* times in *S* then the product contains *nm* instances of the tuple *rs*
- Joins
  - *Natural Join* $R \bowtie S = \pi_A \, \sigma_C (R \times S)$ where
    - *C* is a condition that equates all common attributes
    - *A* is the concatenated list of attributes of *R* and *S* with no duplicates
    - you may view tha above as a rewriting rule
  - *Theta Join*
    - arbitrary condition involving multiple attributes

Grouping and Aggregation

- $\gamma_{\text{GroupByList; aggrFn1} \rightarrow \text{attr1}, \ldots, \text{aggrFnN} \rightarrow \text{attrN}}$
- Conceptually, grouping leads to nested tables and is immediately followed by functions that aggregate the nested table
- Example: $\gamma_{\text{Dept; AVG(Salary)} \rightarrow \text{AvgSal} , \ldots, \text{SUM(Salary)} \rightarrow \text{SalaryExp}}$

Find the average salary for each department
SELECT Dept, AVG(Salary) AS AvgSal,
 SUM(Salary) AS SalaryExp
FROM Employee
GROUP-BY Dept

Employee

Name	Dept	Salary
Joe	Toys	45
Nick	PCs	50
Jim	Toys	35
Jack	PCs	40

Dept	Nested Table Name Salary	
Toys	Joe	45
	Jim	35
PCs	Nick	50
	Jack	40

| Dept	AvgSal	SalaryExp
Toys	40	80
PCs	45	90

Sorting and Lists

- SQL and algebra results are ordered
- Could be non-deterministic or dictated by SQL ORDER BY, algebra τ
- $\tau_{OrderByList}$
- A result of an algebraic expression o(exp) is ordered if
  - If o is a τ
  - If o retains ordering of exp and exp is ordered
    - Unfortunately this depends on implementation of o
  - If o creates ordering
  - Consider that leaf of tree may be SCAN(R)

Relational algebra optimization

- Transformation rules
  (preserve equivalence)
- A quick tour

Algebraic Rewritings:
Commutativity and Associativity

Commutativity   Associativity

Cartesian Product

Natural Join
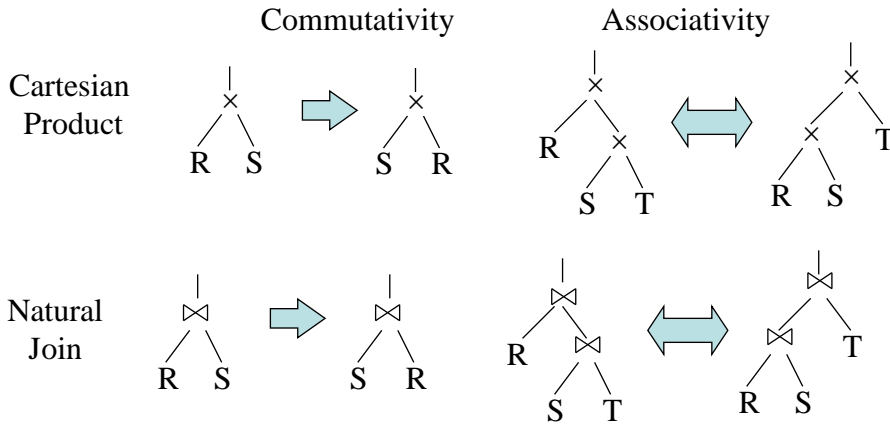
Question 1: Do the above hold for both sets and bags?
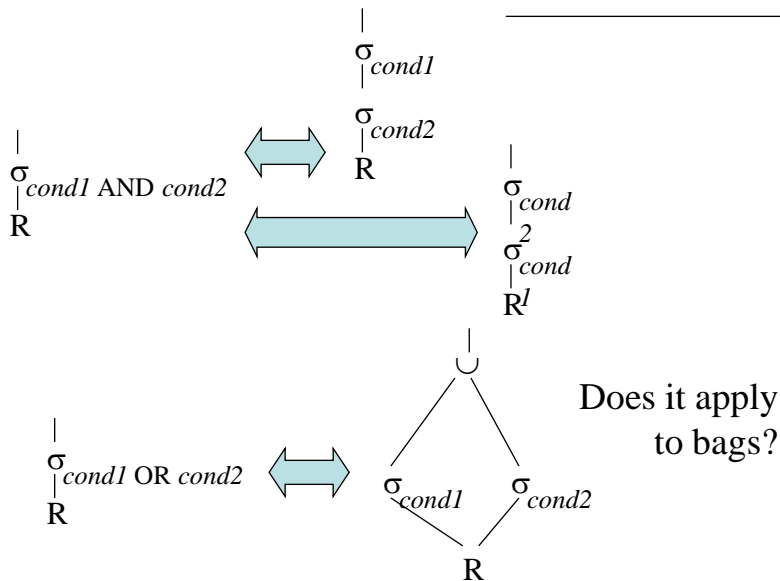**Question 2**: Do commutativity and associativity hold for arbitrary Theta Joins?

Algebraic Rewritings:
Commutativity and Associativity (2)

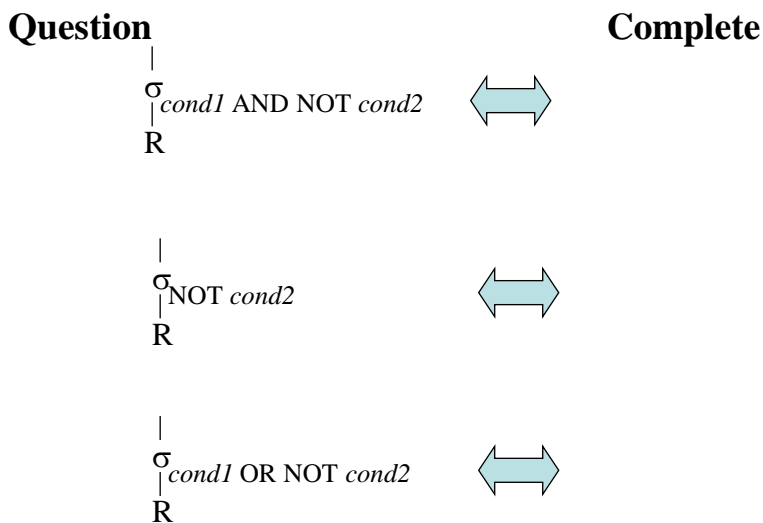Commutativity   Associativity

Union

Intersection
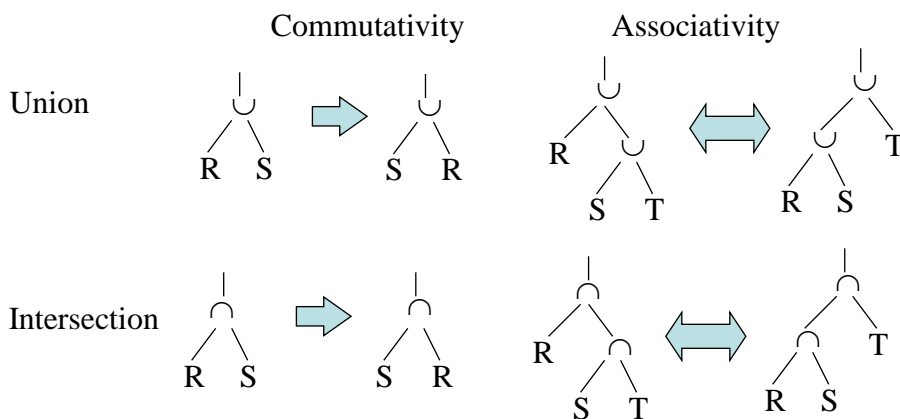
Question 1: Do the above hold for both sets and bags?
Question 2: Is difference commutative and associative?

Algebraic Rewritings for Selection: Decomposition of Logical Connectives

$$\sigma_{cond1}$$
$$\sigma_{cond2}$$
$$R$$

$$\sigma_{cond1 \text{ AND } cond2}$$
$$R$$

$$\sigma_{cond2}$$
$$\sigma_{cond1}$$
$$R$$

$$\cup$$

Does it apply to bags?

$$\sigma_{cond1 \text{ OR } cond2}$$
$$R$$

$$\sigma_{cond1} \quad \sigma_{cond2}$$
$$R$$

Algebraic Rewritings for Selection: Decomposition of Negation

Question   **Complete**

$$\sigma_{cond1 \text{ AND NOT } cond2}$$
$$R$$

$$\sigma_{\text{NOT } cond2}$$
$$R$$

$$\sigma_{cond1 \text{ OR NOT } cond2}$$
$$R$$

Pushing the Selection Thru Binary Operators: Union and Difference

Union

Difference
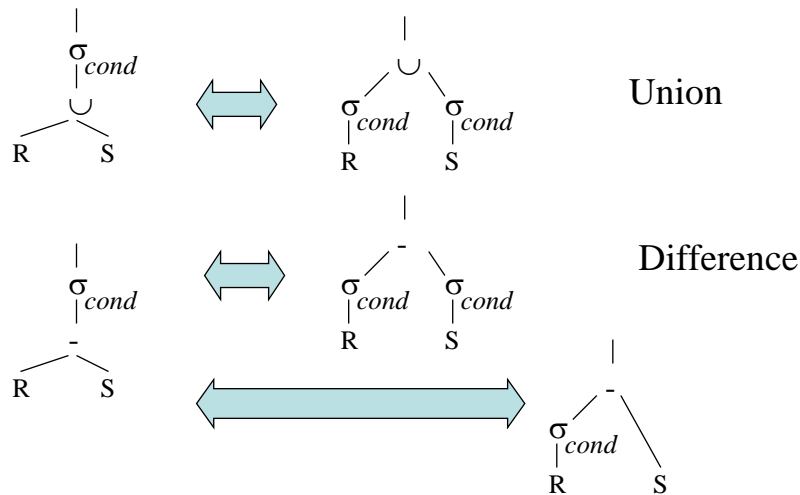
Exercise: Do the rule for intersection

Pushing Selection thru Cartesian Product and Join

The right direction requires that *cond* refers to *S* attributes only

The right direction requires that *cond* refers to *S* attributes only

The right direction requires that all *the attributes used by cond* appear in both *R and S*
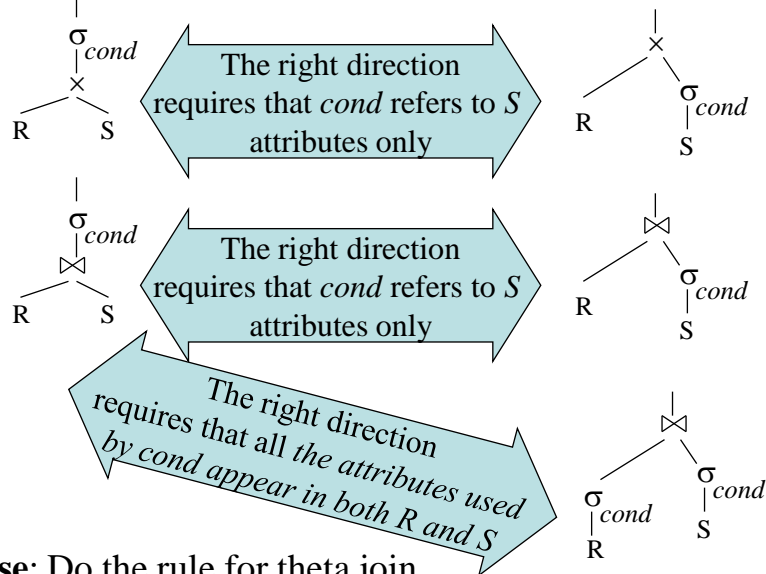
Exercise: Do the rule for theta join

<u>Rules:</u> π, σ combined
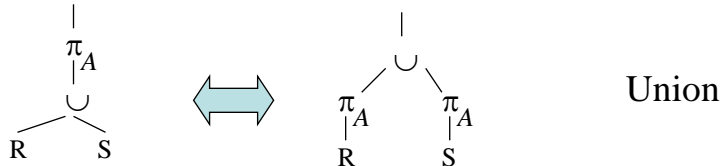
Let x = subset of R attributes
    z = attributes in predicate P
        (subset of R attributes)

$$\pi_x[\sigma_{p\,(R)}] = \pi_x \{\sigma_p[\ \overset{\pi_{xz}}{\cancel{\pi_x}}(R)\ ]\}$$

Pushing Simple Projections
Thru Binary Operators

A projection is simple if it only consists of an attribute list
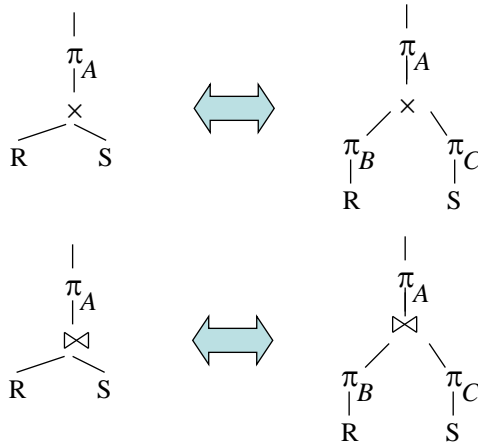

Union

Question 1: Does the above hold for both bags and sets?
Question 2: Can projection be pushed below
    intersection and difference?
    Answer for both bags and sets.

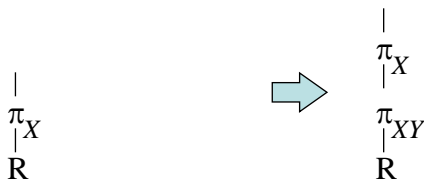## Pushing Simple Projections Thru Binary Operators: Join and Cartesian Product

π_A over $R \times S$ ⟺ π_A over ($\pi_B R$) × ($\pi_C S$)

Where B is the list of R attributes that appear in A. Similar for C.

π_A over $R \bowtie S$ ⟺ π_A over ($\pi_B R$) $\bowtie$ ($\pi_C S$)

Question: What is B and C ?

Exercise: Write the rewriting rule that pushes projection below theta join.

Projection Decomposition

$\pi_X R$ ⟹ $\pi_X (\pi_{XY} R)$

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<u>Derived Rules:</u> $\sigma + \bowtie$ combined

<u>More Rules can be Derived:</u>

$\sigma_{p \wedge q} (R \bowtie S) =$

$\sigma_{p \wedge q \wedge m} (R \bowtie S) =$

$\sigma_{p \vee q} (R \bowtie S) =$

p only at **R**, **q** only at **S**, **m** at both **R** and **S**

--> Derivation for first one:

$\sigma_{p \wedge q} (R \bowtie S) =$

$\sigma_p [\sigma_q (R \bowtie S)] =$

$\sigma_p [R \bowtie \sigma_q (S)] =$

$[\sigma_p (R)] \bowtie [\sigma_q (S)]$

Which are always "good"
transformations?

□ $\sigma_{p1 \wedge p2}(R) \rightarrow \sigma_{p1}[\sigma_{p2}(R)]$

□ $\sigma_p(R \bowtie S) \rightarrow [\sigma_p(R)] \bowtie S$

□ $R \bowtie S \rightarrow S \bowtie R$

□ $\pi_x[\sigma_p(R)] \rightarrow \pi_x\{\sigma_p[\pi_{xz}(R)]\}$

<u>In textbook:</u> more transformations

- Eliminate common sub-expressions
- Other operations: duplicate elimination

<u>Bottom line:</u>

- No transformation is <u>always</u> good at the l.q.p level
- Usually good
  - early selections
  - elimination of cartesian products
  - elimination of redundant subexpressions
- Many transformations lead to "promising" plans
  - Commuting/rearranging joins
  - In practice too "combinatorially explosive" to be handled as rewriting of l.q.p.

# Algorithms for Relational Algebra Operators

- Three primary techniques
  - Sorting
  - Hashing
  - Indexing
- Three degrees of difficulty
  - data small enough to fit in memory
  - too large to fit in main memory but small enough to be handled by a "two-pass" algorithm
  - so large that "two-pass" methods have to be generalized to "multi-pass" methods (quite unlikely nowadays)

The dominant cost of operators running on disk:

- Count # of disk blocks that must be read (or written) to execute query plan

Clustering index

Index that allows tuples to be read in an order that corresponds to a sort order

A

10	
15	
17	

19	
35	
37	

A
index
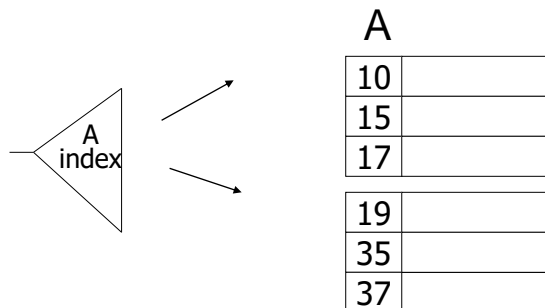
Clustering can radically change cost

- Clustered relation

| R1 R2 R3 R4 | | R5 R5 R7 R8 | ….

- Clustering index

Pipelining can radically change cost

- Interleaving of operations across multiple operators
- Smaller memory footprint, fewer object allocations
- Operators support:
  – open()
  – getNext()
  – close()
- Simple for unary
- Pipelined operation for binary discussed along with physical operators

class project
open()
{ return child.open() }

getNext()
{ return child.getNext() }

parent

open()
getNext()
close()

π

child
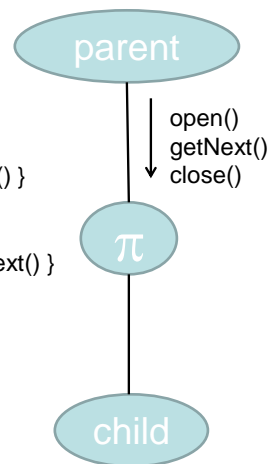
Example   R1 $\bowtie$ R2 over common attribute C

First we will see main memory-based
  implementations

- Iteration join (conceptually – without
  taking into account disk block issues)
- For each tuple of left argument, re-scan
  the right argument

     for each r $\in$ R1 do
       for each s $\in$ R2 do
         if r.C = s.C then output r,s pair

Also called "nested loop join" in some databases
(eg Postgres)

- Join with index (Conceptually)
  - alike iteration join but right relation
    accessed with index

For each r ∈ R1 do

| Assume R2.C index |

    [X ← index (R2, C, r.C)

        for each s ∈ X do

                output r,s pair]

Note: X ← index(rel, attr, value)

        then X = set of rel tuples with attr = value

- Merge join (conceptually)
  (1) if R1 and R2 not sorted, sort them
  (2) i ← 1; j ← 1;
      While (i ≤ T(R1)) ∧ (j ≤ T(R2)) do
        if R1{ i }.C = R2{ j }.C then outputTuples
        else if R1{ i }.C > R2{ j }.C then j ← j+1
        else if R1{ i }.C < R2{ j }.C then i ← i+1

Procedure Output-Tuples

While (R1{ i }.C = R2{ j }.C) ∧ (i ≤ T(R1)) do

    [jj ← j;

    while (R1{ i }.C = R2{ jj }.C) ∧ (jj ≤ T(R2)) do

             [output pair R1{ i }, R2{ jj };

                jj ← jj+1]

    i ← i+1]

Example

i	R1{i}.C	R2{j}.C	j
1	10	5	1
2	20	20	2
3	20	20	3
4	30	30	4
5	40	30	5
		50	6
		52	7

- Hash join, hashing both sides (conceptual)

  – Hash function h, range 0 → k
  – Buckets for R1: G0, G1, ... Gk
  – Buckets for R2: H0, H1, ... Hk
  <u>Algorithm</u>
  (1) Hash R1 tuples into G buckets
  (2) Hash R2 tuples into H buckets
  (3) For i = 0 to k do
       match tuples in Gi, Hi buckets

<u>Simple example</u>   hash: even/odd

R1	R2		Buckets	
2	5	Even	2 4 8	4 12 8 14
4	4		R1	R2
3	12	Odd:		
5	3		3 5 9	5 3 13 11
8	13			
9	8			
	11			
	14			

Variation: Hash one side only

Algorithm

(1) Hash R1 tuples into G buckets

(2) For each tuple r2 or R2

　　　 find i=hash(r2)

　　　 match r2 with tuples in Gi

What's the benefit in hashing both sides?
Wait till we discuss hash joins on secondary storage…

Disk-oriented Cost Model

- There are *M* main memory buffers.
  - Each buffer has the size of a disk block
- The input relation is read one block at a time.
- The cost is the number of blocks read.
- (Applicable to Hard Disks:) If *B* consecutive blocks are read the cost is *B/d*.
- The output buffers are not part of the *M* buffers mentioned above.
  - *Pipelining* allows the output buffers of an operator to be the input of the next one.
  - We do not count the cost of writing the output.

Notation

- $B(R)$ = number of blocks that R occupies
- $T(R)$ = number of tuples of R
- $V(R,[a_1, a_2,\ldots, a_n])$ = number of distinct tuples in the projection of R on $a_1, a_2,\ldots, a_n$

One-Pass Main Memory Algorithms for Unary Operators

- Assumption: Enough memory to keep the relation
- Projection and selection:
  - Scan the input relation R and apply operator one tuple at a time
  - Incremental cost of "on the fly" operators is 0

- Duplicate elimination and aggregation
  - create one entry for each group and compute the aggregated value of the group
  - it becomes hard to assume that CPU cost is negligible
    - main memory data structures are needed

One-Pass Nested Loop Join

- Assume *B(R)* is less than *M*
- Tuples of *R* should be stored in an efficient lookup structure
- **Exercise:** Find the cost of the algorithm below

```
for each block Br of R do
  store tuples of Br in main memory
for each each block Bs of S do
  for each tuple s of Bs
    join tuples of s with matching tuples of R
```

A variation where the inner side is organized into a hash (hash join in some databases)

```
for each block Br of R do
  store tuples of Br in main memory
                hash buckets G1,…, Gn
for each each block Bs of S do
  for each tuple s of Bs
    find h=hash(s)
    join s with matching tuples in Gh
```

Generalization of Nested-Loops

```
for each chunk of M-1 blocks Br of R do
  store tuples of Br in main memory
  for each each block Bs of S do
    for each tuple s of Bs
      join tuples of s with matching tuples of R
```

Exercise: Compute cost

Simple Sort-Merge Join

- Assume natural join on *C*
- Sort *R* on *C* using the two-phase multiway merge sort
  - if not already sorted
- Sort *S* on *C*
- Merge (opposite side)
  - assume two pointers **Pr,Ps** to tuples on disk, initially pointing at the start
  - sets **R'**, **S'** in memory
- Remarks:
  - Very low average memory requirement during merging (but no guarantee on how much is needed)
  - **Cost:**

```
while Pr!=EOF and Ps!=EOF
  if *Pr[C] == *Ps[C]
    do_cart_prod(Pr,Ps)
  else if *Pr[C] > *Ps[C]
    Ps++
  else if *Ps[C] > *Pr[C]
    Pr++

function do_cart_prod(Pr,Ps)
  val=*Pr[C]
  while *Pr[C]==val
    store tuple *Pr in set R'
  while *Ps[C]==val
    store tuple *Ps in set S';
  output cartesian product
      of R' and S'
```

Efficient Sort-Merge Join

- Idea: Save two disk I/O's per block by combining the second pass of sorting with the ``merge''.
- Step 1: Create sorted sublists of size M for R and S
- Step 2: Bring the first block of each sublist to a buffer
  - assume no more than M sublists in all
- Step 3: Repeatedly find the least C value c among the first tuples of each sublist. Identify all tuples with join value c and join them.
  - When a buffer has no more tuple that has not already been considered load another block into this buffer.

Efficient Sort-Merge Join Example

R	C	RA
	1	r_1
	2	r_2
	3	r_3
	...	
	20	r_{20}

S	C	SA
	1	s_1
	...	
	5	s_5
	16	s_{16}
	...	
	20	s_{20}

Assume that after first phase of multiway sort we get 4 sublists, 2 for R and 2 for S. Also assume that each block contains two tuples.

R	3 7	8 10	11 13	14 16	17 18
	1 2	4 5	6 9	12 15	19 20

S	1 3	5 17		
	2 4	16 18	19 20	

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Sort and Merge Join are typically separate operators

- Modularity
  - The sorting needed by join is no different than the sorting needed by ORDER BY
- May be only one side or no side needs sorting

Two-Pass Hash-Based Algorithms

- General Idea: Hash the tuples of the input arguments in such a way that all tuples that must be considered together will have hashed to the same hash value.
  - If there are M buffers pick $M-1$ as the number of hash buckets
- Example: Duplicate Elimination
  - Phase 1: Hash each tuple of each input block into one of the $M-1$ bucket/buffers. When a buffer fills save to disk.
  - Phase 2: For each bucket:
    - load the bucket in main memory,
    - treat the bucket as a small relation and eliminate duplicates
    - save the bucket back to disk.
  - **Catch:** Each bucket has to be less than M.
  - **Cost:**

Hash-Join Algorithms

- Assuming natural join, use a hash function that
  - is the same for both input arguments R and S
  - uses only the join attributes
- Phase 1: Hash each tuple of R into one of the $M-1$ buckets R_i and similar each tuple of S into one of S_i
- Phase 2: For $i=1\ldots M-1$
  - load R_i and S_i in memory
  - join them and save result to disk
- **Question:** What is the maximum size of buckets?
- **Question:** Does hashing maintain sorting?

Index-Based Join: The Simplest Version

Assume that we do natural join of $R(A,B)$ and $S(B,C)$ and there's an index on S

```
for each Br in R do
  for each tuple r of Br with B value b
    use index of S to find
        tuples {s_1 ,s_2 ,...,s_n} of S with B=b
    output {rs_1 ,rs_2 ,...,rs_n}
```

Cost: Assuming R is clustered and non-sorted and the index on S is clustered on B then
$B(R)+T(R)B(S)/V(S,B)$ + some more for reading index
Question: What is the cost if R is sorted?

Reading the plan that was chosen by the database (EXPLAIN)

EXPLAIN SELECT s.pid, s.first_name, s.last_name, e.credits
FROM   students s, enrollment e
WHERE s.id = e.student
        AND e.class = 1;

Output pane

| Data Output | Explain | Messages | History |

QUERY PLAN
text

1	Hash Join (cost=1.07..2.17 rows=3 width=100)
2	Hash Cond: (e.student = s.id)
3	-> Seq Scan on enrollment e (cost=0.00..1.06 rows=3 width=8)
4	Filter: (class = 1)
5	-> Hash (cost=1.03..1.03 rows=3 width=100)
6	-> Seq Scan on students s (cost=0.00..1.03 rows=3 width=100)

Notes on physical operators of Postgres and other databases

σ_c R turns into single operator

- Sequential Scan with filter c

  Seq Scan on R

    Filter: (c)

- Index Scan

  Index Scan using <index> on R

    Index Cond: (c)

Steps of joins, aggregations broken into fine granularity operators

- No sort-merge: Separate sort and merge
- Hash join has separate operation creating hash table and separate operation doing the looping

Sorting

- Sorting may be accomplished using index
  - Rarely wins 2-phase sort if table is not clustered and is much bigger than memory

- Estimating cost of query plan

(1) Estimating <u>size</u> of results

(2) Estimating run time (often reduces to #IOs)

Both estimates can go very wrong!

```
Output pane
 Data Output   Explain   Messages   History
        QUERY PLAN
        text
  1   Hash Join  (cost=1.07..2.17 rows=3 width=100)
  2      Hash Cond: (e.student = s.id)
  3      -> Seq Scan on enrollment e  (cost=0.00..1.06 rows=3 width=8)
  4            Filter: (class = 1)
  5      -> Hash  (cost=1.03..1.03 rows=3 width=100)
  6            -> Seq Scan on students s  (cost=0.00..1.03 rows=3 width=100)
```

How does the database estimate query run time?

How does the database estimate size of such intermediate result

Estimating result size

- Keep statistics for relation R
  - T(R) : # tuples in R
  - S(R) : # of bytes in each R tuple
  - B(R): # of blocks to hold all R tuples
  - V(R, A) : # distinct values in R
    for attribute A

Example

R

A	B	C	D
cat	1	10	a
cat	1	20	b
dog	1	30	a
dog	1	40	c
bat	1	50	d

A: 20 byte string
B: 4 byte integer
C: 8 byte date
D: 5 byte string

$T(R) = 5$ $S(R) = 37$

$V(R,A) = 3$ $V(R,C) = 5$

$V(R,B) = 1$ $V(R,D) = 4$

Size estimates for W = R1 x R2

T(W) =
$$T(R1) \times T(R2)$$

S(W) =
$$S(R1) + S(R2)$$

Size estimate for W = $\sigma_{Z=val}$ (R)

S(W) = S(R)

T(W) = ?

<u>Example</u>

R

A	B	C	D
cat	1	10	a
cat	1	20	b
dog	1	30	a
dog	1	40	c
bat	1	50	d

$V(R,A)=3$

$V(R,B)=1$

$V(R,C)=5$

$V(R,D)=4$

$$W = \sigma_{z=val}(R) \quad T(W) = \frac{T(R)}{V(R,Z)}$$

What about $W = \sigma_{z \geq val}(R)$?

$T(W) = ?$

- Solution # 1:
    $T(W) = T(R)/2$

- Solution # 2:
    $T(W) = T(R)/3$

- Solution # 3:   Estimate values in range

Example R

Min=1 $V(R,Z)=10$

$W = \sigma_{z \geq 15}(R)$

Max=20

$f = \dfrac{20-15+1}{20-1+1} = \dfrac{6}{20}$ (fraction of range)

$T(W) = f \times T(R)$

Equivalently:

$f \times V(R,Z)$ = fraction of distinct values

$T(W) = [f \times V(Z,R)] \times \dfrac{T(R)}{V(Z,R)} = f \times T(R)$

Size estimate for $W = R1 \bowtie R2$

Let x = attributes of R1
  y = attributes of R2

Case 1 $X \cap Y = \varnothing$

Same as R1 x R2

Case 2 $W = R1 \bowtie R2$ $X \cap Y = A$

| R1 | A | B | C | | R2 | A | D |

Assumption:

$\Pi_A R1 \subseteq \Pi_A R2 \Rightarrow$ Every A value in R1 is in R2
                    (typically A of R1 is foreign key
                        of the primary key of A of R2)
$\Pi_A R2 \subseteq \Pi_A R1 \Rightarrow$ Every A value in R2 is in R1
"containment of value sets"   (justified by primary
  key – foreign key relationship)

Computing T(W) when A of R1 is the
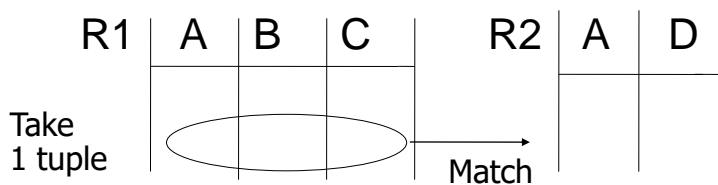
foreign key $\Pi_A R1 \subseteq \Pi_A R2$

R1 | A | B | C | R2 | A | D |
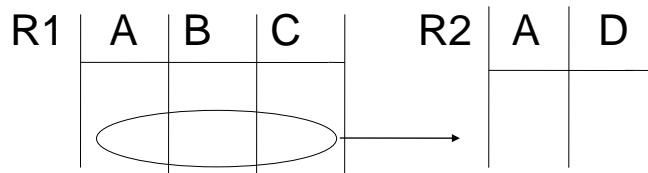
1 tuple of R1 matches with exactly 1 tuple
of R2

so   T(W) =   T(R1)

Another way to approach when

$\Pi_A R1 \subseteq \Pi_A R2$

R1 | A | B | C | R2 | A | D |

Take
1 tuple   Match

1 tuple matches with $\dfrac{T(R2)}{V(R2,A)}$ tuples...

so $T(W) = \dfrac{T(R2)}{V(R2, A)} \times T(R1)$

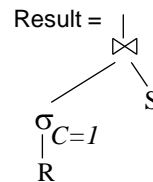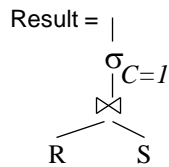- $V(R1,A) \leq V(R2,A)$ $T(W) = \dfrac{T(R2)\ T(R1)}{V(R2,A)}$

- $V(R2,A) \leq V(R1,A)$ $T(W) = \dfrac{T(R2)\ T(R1)}{V(R1,A)}$

[A is common attribute]

<u>In general</u> $W = R1 \bowtie R2$

$$T(W) = \frac{T(R2)\ T(R1)}{\max\{\ V(R1,A),\ V(R2,A)\ \}}$$
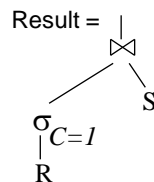
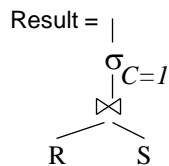# Combining estimates on subexpressions: Value preservation

Result = |
$\sigma_{C=1}$
⋈
R   S

Result = |
⋈
S
$\sigma_{C=1}$
R

R(A, C)
$T(R) = 10^3$
$V(A, R) = 10^3$
$V(C, R) = 10^2$

S(A, B)
$T(S) = 10^2$
$V(A, S) = 50$

$T(R \bowtie S) =$
$T(R) \times T(S) / \max(V(A,R), V(A, S)) = 10^2$

$V(C, R \bowtie S) = 10^2$ ← (Big) assumption:
Value preservation of C

$T(Result) = T(R \bowtie S) / V(C, R \bowtie S) = 1$

Value preservation may have to be pushed to a weird assumption (but there's logic behind it!)

Result = |
$\sigma_{C=1}$
⋈
R   S

Result = |
⋈
S
$\sigma_{C=1}$
R

Ideally, the size estimation should not depend on which of the two equivalent formulas for Result one uses. However, to achieve this we may need to push the value preservation assumption to artificial intermediate estimates…

R(A, C)
$T(R) = 10^3$
$V(A, R) = 10^3$
$V(C, R) = 10^2$

S(A, B)
$T(S) = 10^2$
$V(A, S) = 50$

$T(R \bowtie S) = 10^2$

$V(C, R \bowtie S) = 10^2$
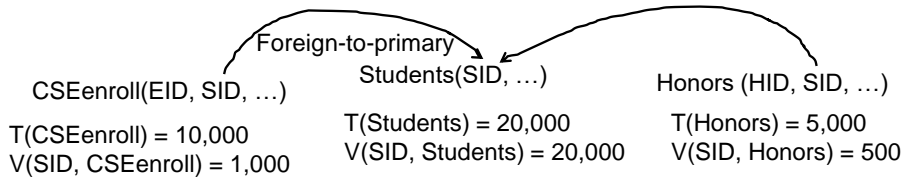
$T(Result) = 1$

$T(\sigma_{c=1}R) = T(R) / V(C, R) = 10$
$V(A, \sigma_{c=1}R) = \mathbf{10^3}$
$T(Result) =$
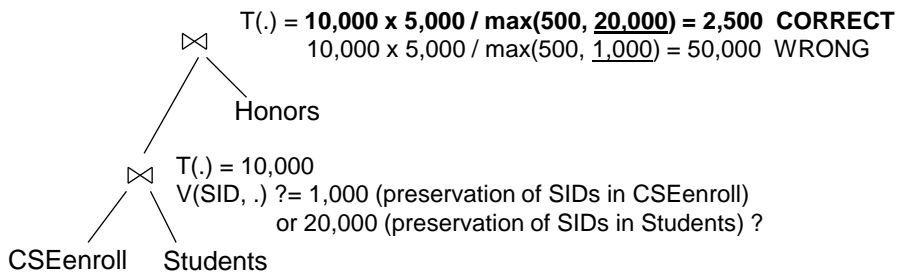$T(\sigma_{c=1}R) \times T(S) / \max(V(A, \sigma_{c=1}R), V(A, S)) = 1$

We had to extend value preservation to the weird assumption that attribute A has more values than the number of tuples in R. In this way the number of S tuples matching an R tuple stays steady
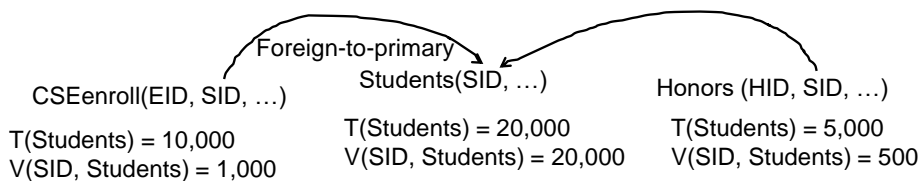
Value preservation of join attribute

Foreign-to-primary

CSEenroll(EID, SID, …)   Students(SID, …)   Honors (HID, SID, …)

T(CSEenroll) = 10,000   T(Students) = 20,000   T(Honors) = 5,000
V(SID, CSEenroll) = 1,000   V(SID, Students) = 20,000   V(SID, Honors) = 500

T(CSEenroll(EID, SID, …) $\bowtie$ Students(SID, …) $\bowtie$ Honors (HID, SID, …)) = ?

T(.) = **10,000 x 5,000 / max(500, 20,000) = 2,500 CORRECT**
10,000 x 5,000 / max(500, 1,000) = 50,000 WRONG

$\bowtie$

Honors

$\bowtie$ T(.) = 10,000
V(SID, .) ?= 1,000 (preservation of SIDs in CSEenroll)
    or 20,000 (preservation of SIDs in Students) ?

CSEenroll   Students

If in doubt, think in terms of probabilities and matching records

• A SID of Student appears in CSEEnroll with probability 1000/20000
    • i.e., 5% of students are enrolled in CSE
• A SID of Student appears in Honors with probability 500/20000
    • i.e., 2.5% of students are honors students
=> An SID of Student appears in the join result with probability 5% x 2.5%
• On the average, each SID of CSEEnroll appears in 10,000/1,000 tuples
    • i.e., each CSE-enrolled student has 10 enrollments
• On the average, each SID of Honors appears in 5,000/500 tuples
    • i.e., each honors' student has 10 honors
$\Rightarrow$ Each Student SID that is in both Honors and CSEEnroll is in 10x10 result tuples
$\Rightarrow$ T(result) = 20,000 x 5% x 2.5% x 10 x 10 = 2,500 tuples

Foreign-to-primary

CSEenroll(EID, SID, …)   Students(SID, …)   Honors (HID, SID, …)

T(Students) = 10,000   T(Students) = 20,000   T(Students) = 5,000
V(SID, Students) = 1,000   V(SID, Students) = 20,000   V(SID, Students) = 500

T(CSEenroll(EID, SID, …) $\bowtie$ Students(SID, …) $\bowtie$ Honors (HID, SID, …)) = ?

Plan Enumeration: Yet another source of suboptimalities

Not all possible equivalent plans are generated

• Possible rewritings may not happen

• Join sequences of n tables lead to #plans that is exponential in n

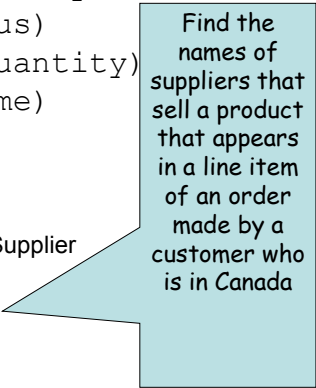 – Eg, Postgres comes with a default exhaustive search for up to 12 joins

Morale: The plan you have in mind have not been considered

Arranging the Join Order: the Wong-Youssefi algorithm (INGRES)

Sample TPC-H Schema
```
Nation(NationKey, NName)
Customer(CustKey, CName, NationKey)
Order(OrderKey, CustKey, Status)
Lineitem(OrderKey, PartKey, Quantity)
Product(SuppKey, PartKey, PName)
Supplier(SuppKey, SName)
```
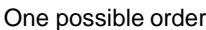
Find the names of suppliers that sell a product that appears in a line item of an order made by a customer who is in Canada

SELECT SName
FROM Nation, Customer, Order, LineItem, Product, Supplier
WHERE Nation.NationKey = Cuctomer.NationKey
        AND Customer.CustKey = Order.CustKey
        AND Order.OrderKey=LineItem.OrderKey
        AND LineItem.PartKey= Product.Partkey
        AND Product.Suppkey = Supplier.SuppKey
   AND NName = "Canada"

Challenges with Large Natural Join Expressions

For simplicity, assume that in the query
1. All joins are natural
2. whenever two tables of the FROM clause have common attributes we join on them
1. Consider Right-Index only

π_{SName}

RI

RI

One possible order

RI

RI

RI

RI

$\sigma_{NName="Canada"}^{Index}$

Nation   Customer → Order → LineItem → Product → Supplier

Multiple Possible Orders

π_{SName}

RI

RI

RI

RI

RI

$\sigma_{NName="Canada"}$

Order

LineItem   Product   Supplier   Nation   Customer
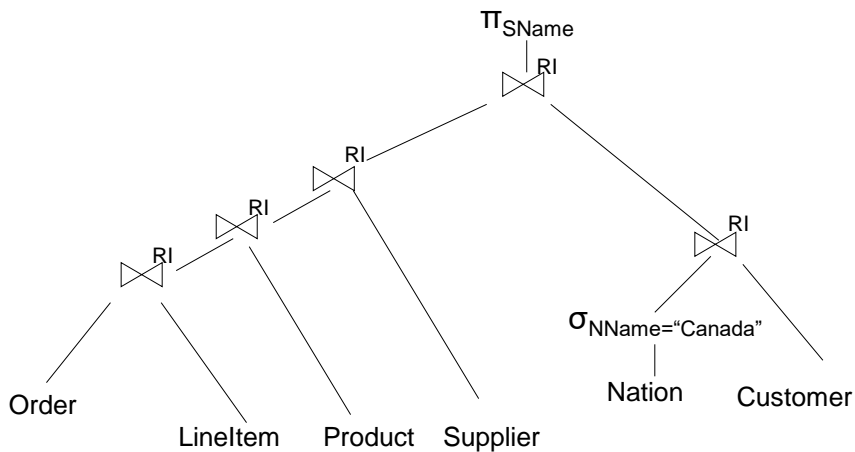
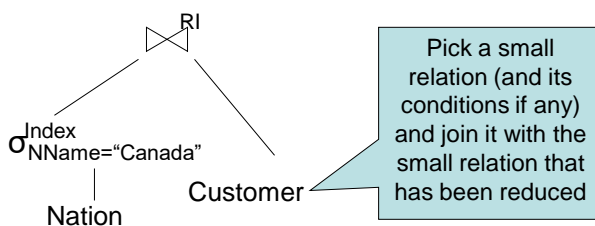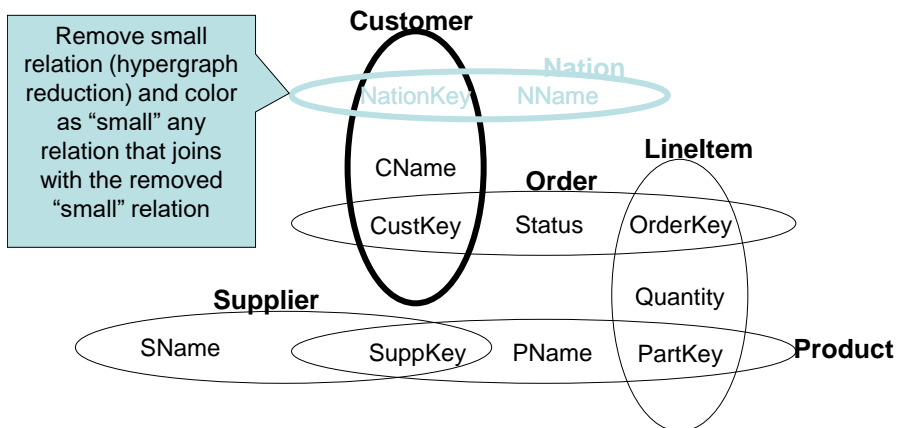# Wong-Yussefi algorithm assumptions and objectives

- Assumption 1 (weak): Indexes on all join attributes (keys and foreign keys)
- Assumption 2 (strong): At least one selection creates a *small* relation
  - A join with a small relation results in a small relation
- Objective: Create sequence of index-based joins such that all intermediate results are small

Hypergraphs
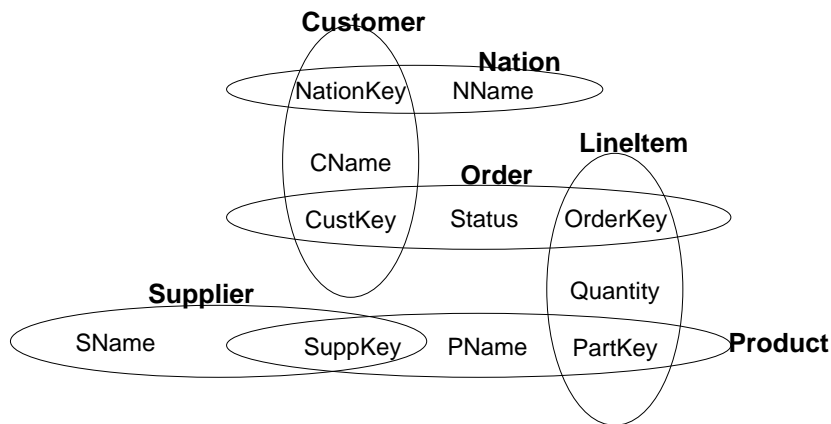
- relation hyperedges
  - two hyperedges for same relation are possible
- each node is an attribute
- can extend for non-natural equality joins by merging nodes

Small Relations/Hypergraph Reduction

Customer

Nation

NationKey   NName

"Nation" is small because it has the equality selection NName = "Canada"

CName   **Order**   **LineItem**

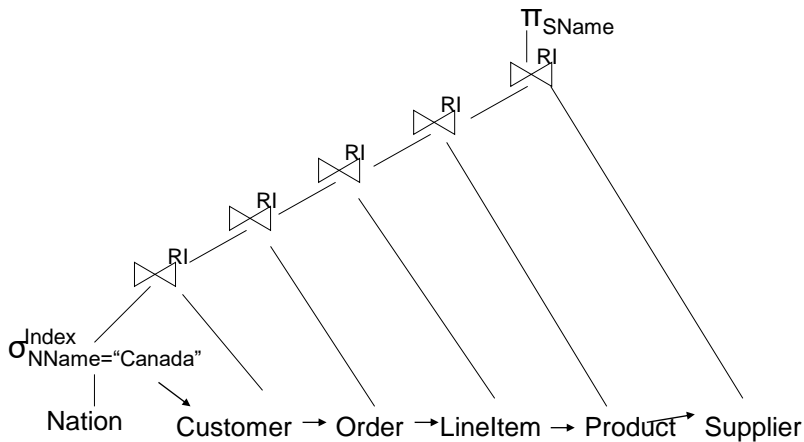CustKey   Status   OrderKey

Quantity

Supplier

SName   SuppKey   PName   PartKey   **Product**

$\sigma^{Index}_{NName="Canada"}$

|
Nation

Pick a small relation (and its conditions) to start the plan

Customer

Remove small relation (hypergraph reduction) and color as "small" any relation that joins with the removed "small" relation

Nation

NationKey   NName

CName   **LineItem**

Order

CustKey   Status   OrderKey

Quantity

Supplier

SName   SuppKey   PName   PartKey   **Product**

RI
⋈

$\sigma^{Index}_{NName="Canada"}$

|
Nation   Customer

Pick a small relation (and its conditions if any) and join it with the small relation that has been reduced

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After a bunch of steps…

$$\pi_{SName}$$

RI

RI

RI

RI

RI

RI

$$\sigma^{Index}_{NName="Canada"}$$

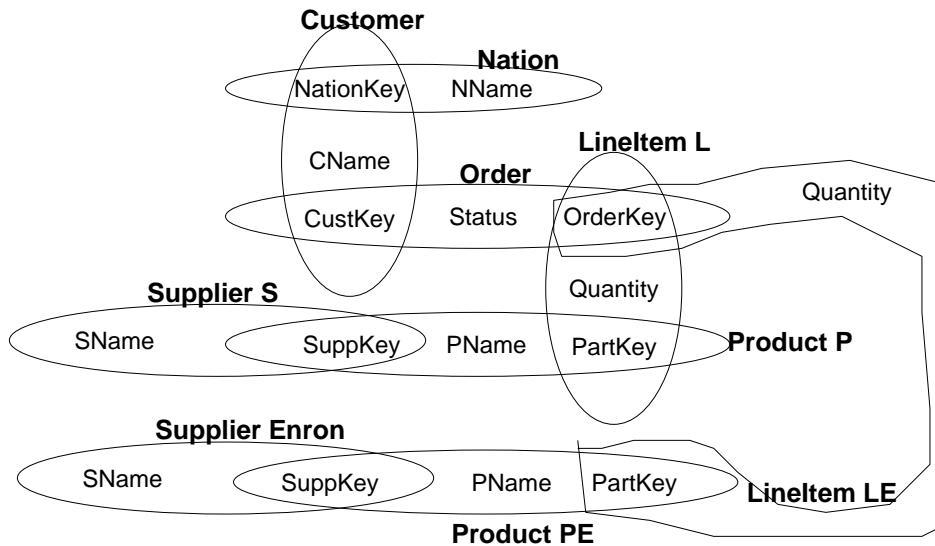Nation → Customer → Order → LineItem → Product → Supplier

Multiple Instances of Each Relation
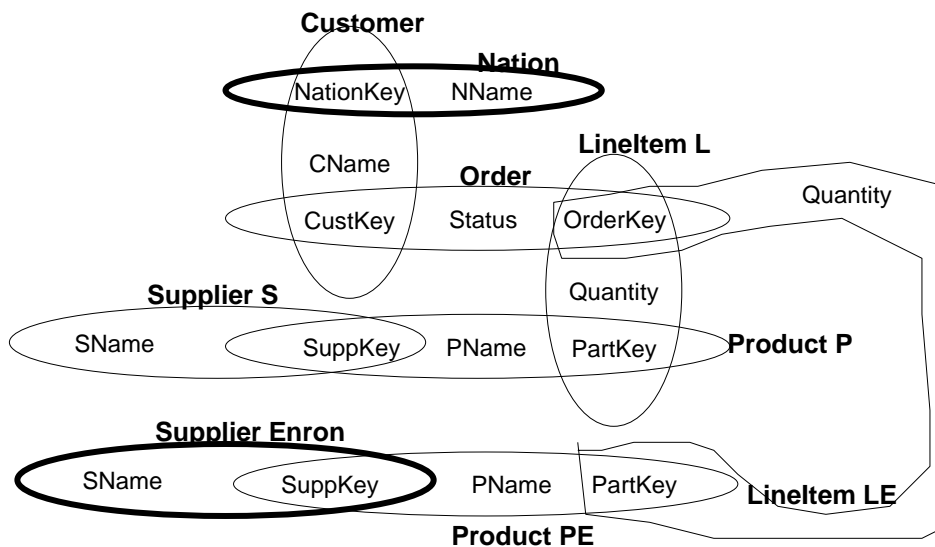
SELECT S.SName
FROM Nation, Customer, Order, LineItem L, Product P, Supplier S,
           LineItem LE, Product PE, Supplier Enron
WHERE Nation.NationKey = Cuctomer.NationKey
        AND Customer.CustKey = Order.CustKey
        AND Order.OrderKey=L.OrderKey
        AND L.PartKey= P.Partkey
        AND P.Suppkey = S.SuppKey
        AND Order.OrderKey=LE.OrderKey
        AND LE.PartKey= PE.Partkey
        AND PE.Suppkey = Enron.SuppKey
        AND Enron.Sname = "Enron"
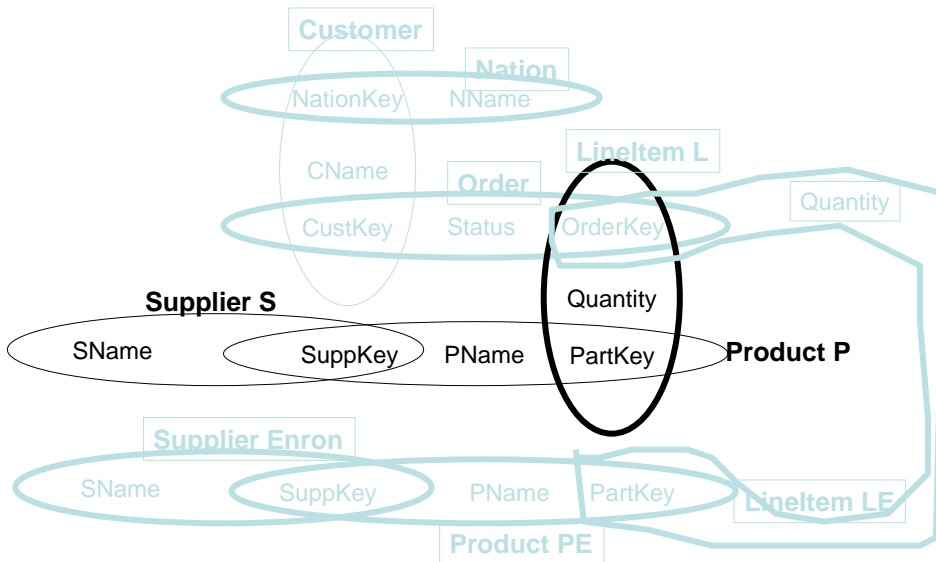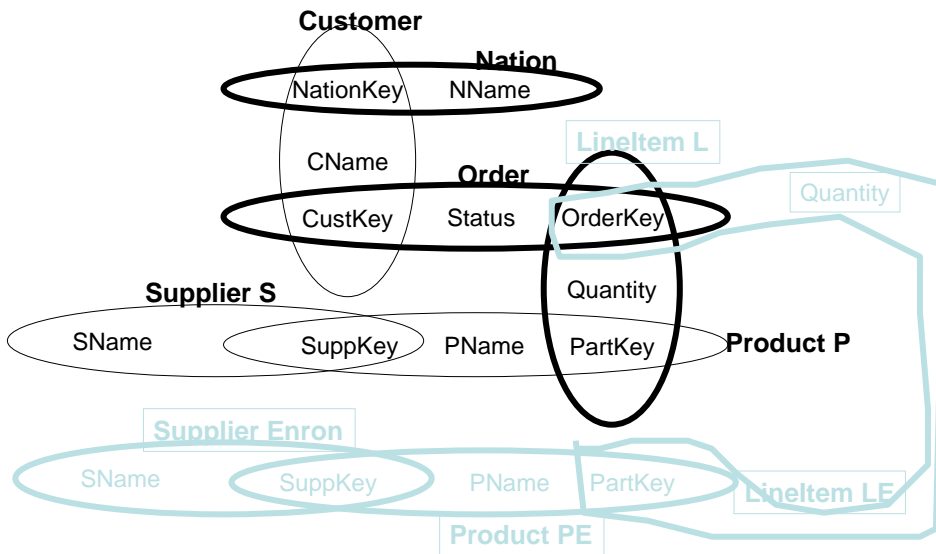   AND NName = "Cayman"

Find the names of suppliers whose products appear in an order made by a customer who is in Cayman Islands and an Enron product appears in the same order

Multiple Instances of Each Relation

Customer

Nation

NationKey NName

CName **Order**

LineItem L

CustKey Status OrderKey Quantity

Quantity

Supplier S

SName SuppKey PName PartKey **Product P**

Supplier Enron

SName SuppKey PName PartKey **LineItem LE**

Product PE

Multiple choices are possible

Customer

Nation

NationKey NName

CName **Order**

LineItem L

CustKey Status OrderKey Quantity

Quantity

Supplier S

SName SuppKey PName PartKey **Product P**

Supplier Enron

SName SuppKey PName PartKey **LineItem LE**

Product PE

RI

RI

RI

LineItem   Product   Suppli

RI

RI

RI

$\sigma_{SName="Enron"}^{Index}$

$\sigma_{NName="Cayman"}^{Index}$

Enron   PE   LE   Nation   Customer   Order
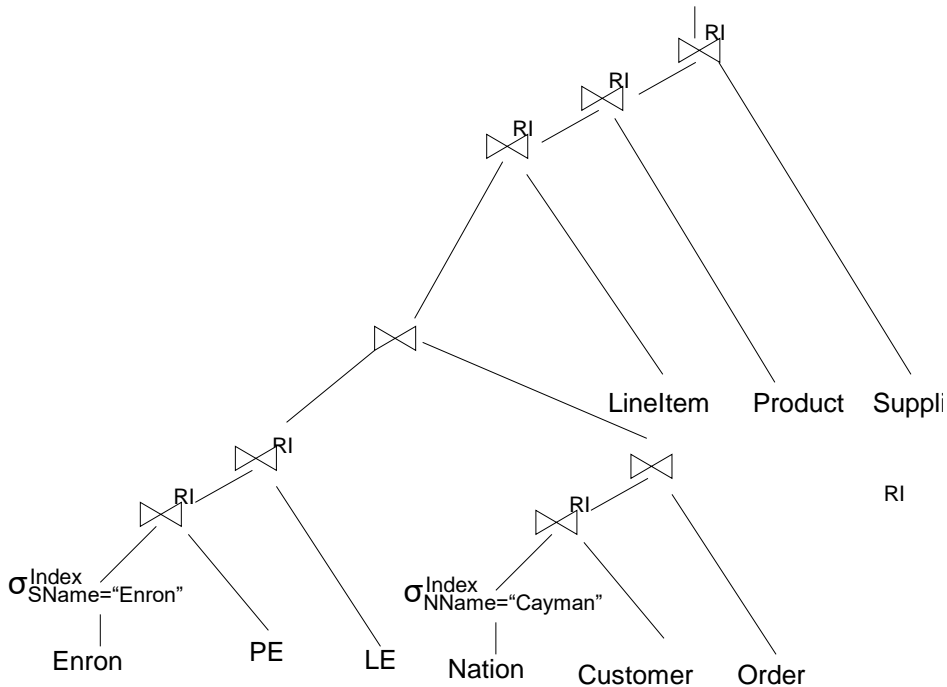
The basic dynamic programming approach to enumerating plans

for each sub-expression

$op(e_1\,e_2\,\dots\,e_n)$ of a logical plan

– (recursively) compute the best plan and cost for each subexpression e_i

– for each physical operator op^p implementing op

  • evaluate the cost of computing op using op^p and the best plan for each subexpression e_i

  • (for faster search) memo the best op^p

Local suboptimality of basic approach and the Selinger improvement

- Basic dynamic programming may lead to (globally) suboptimal solutions
- Reason: A suboptimal plan for e_1 may lead to the optimal plan for $op(e_1\ e_2\ \dots\ e_n)$
  - Eg, consider $e_1 \bowtie_A e_2$ and
  - assume that the optimal computation of e_1 produces unsorted result
  - Optimal $\bowtie$ is via sort-merge join on A
  - It could have paid off to consider the suboptimal computation of e_1 that produces result sorted on A
- Selinger improvement: memo also any plan (that computes a subexpression) and produces an order that may be of use to ancestor operators

Using dynamic programming to optimize a join expression

- Goal: Decide the join order and join methods
- Initiate with n-ary join $\bowtie_C (e_1\ e_2\ \dots\ e_n)$, where c involves only join conditions
- Bottom up: consider 2-way non-trivial joins, then 3-way non-trivial joins etc
  - "non trivial" -> no cartesian product

Summary

We learned

- how a database processes a query
- how to read the plan the database chose
  – Including size and cost estimates

Back to action:

- Choosing Indices, with our knowledge of cost with and without indices
- What if the database cannot find the best plan?