CSEP 544: Lecture 04

Query Execution

Announcements

Homework 2: due on Friday

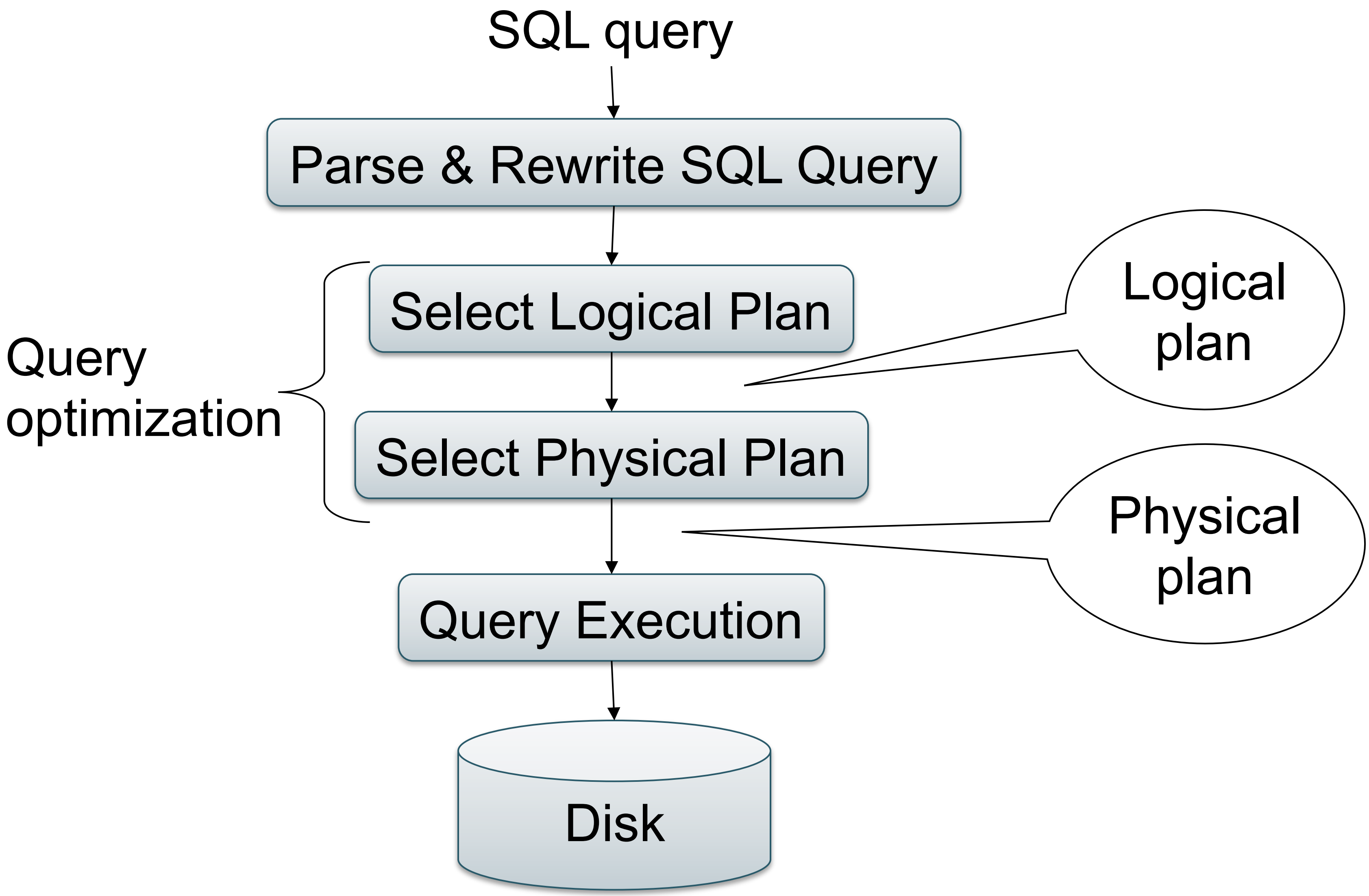
Homework 3:

- We use AWS
- You need to get an access code: https://aws.amazon.com/education/awseducate/members/

Where We Are

- We have seen:
  - Disk organization = set of blocks(pages)
  - The buffer pool
  - How records are organized in pages
  - Indexes, in particular B+ -trees
- Today: query execution, optimization

Steps of the Query Processor



Steps in Query Evaluation

- **Step 0: Admission control**
  - User connects to the db with username, password
  - User sends query in text format
- **Step 1: Query parsing**
  - Parses query into an internal format
  - Performs various checks using catalog
    - Correctness, authorization, integrity constraints
- **Step 2: Query rewrite**
  - View rewriting, flattening, etc.

Steps in Query Evaluation

- **Step 3: Query optimization**
  – Find an efficient query plan for executing the query

- **Step 4: Query execution**
  – Each operator has several implementation algorithms

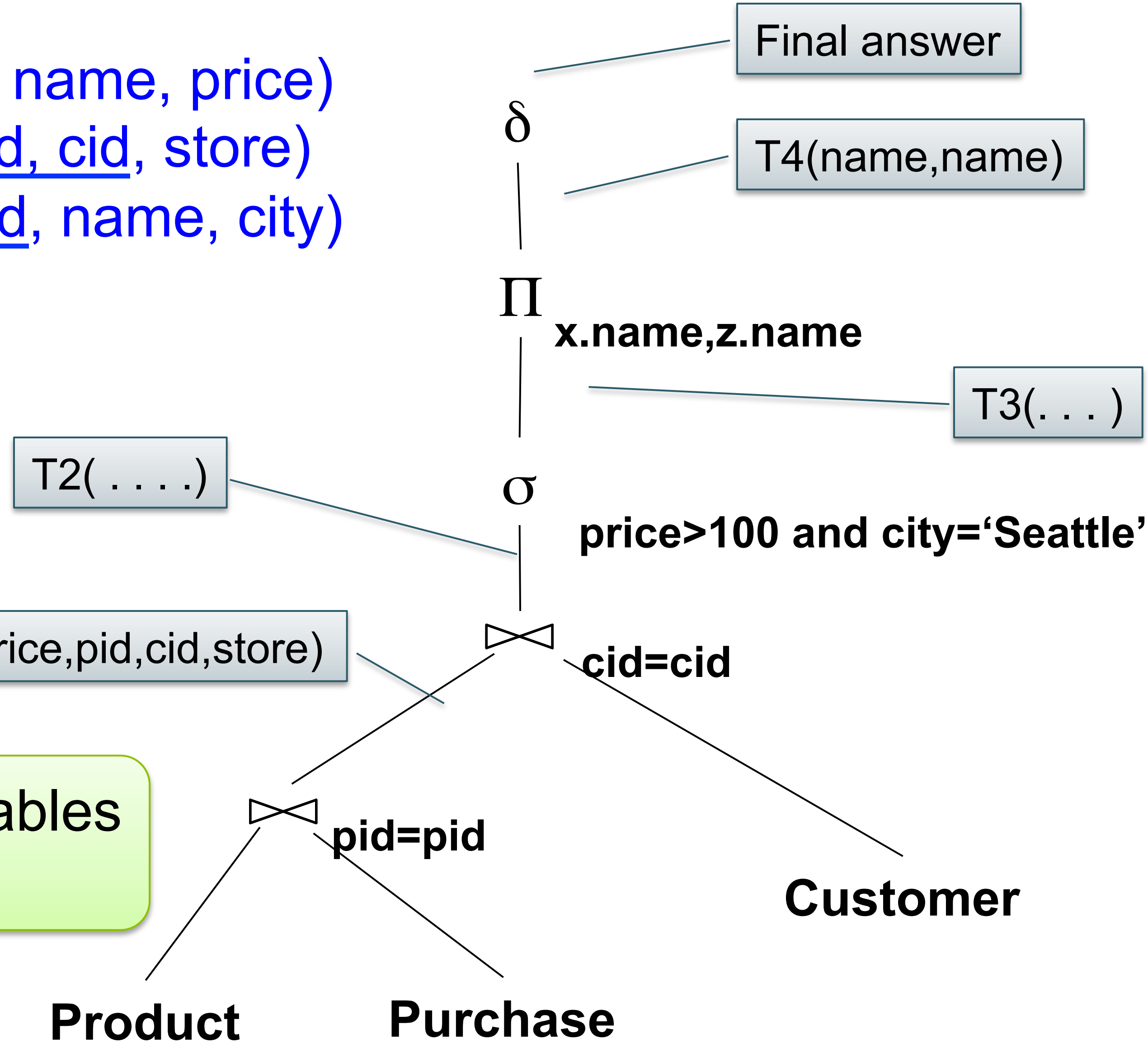
SQL Query

Product(<u>pid</u>, name, price)
Purchase(<u>pid, cid</u>, store)
Customer(<u>cid</u>, name, city)

```
SELECT DISTINCT x.name, z.name
FROM Product x, Purchase y, Customer z
WHERE x.pid = y.pid and y.cid = y.cid and
             x.price > 100 and z.city = 'Seattle'
```

Logical Plan

Product(pid, name, price)
Purchase(pid, cid, store)
Customer(cid, name, city)



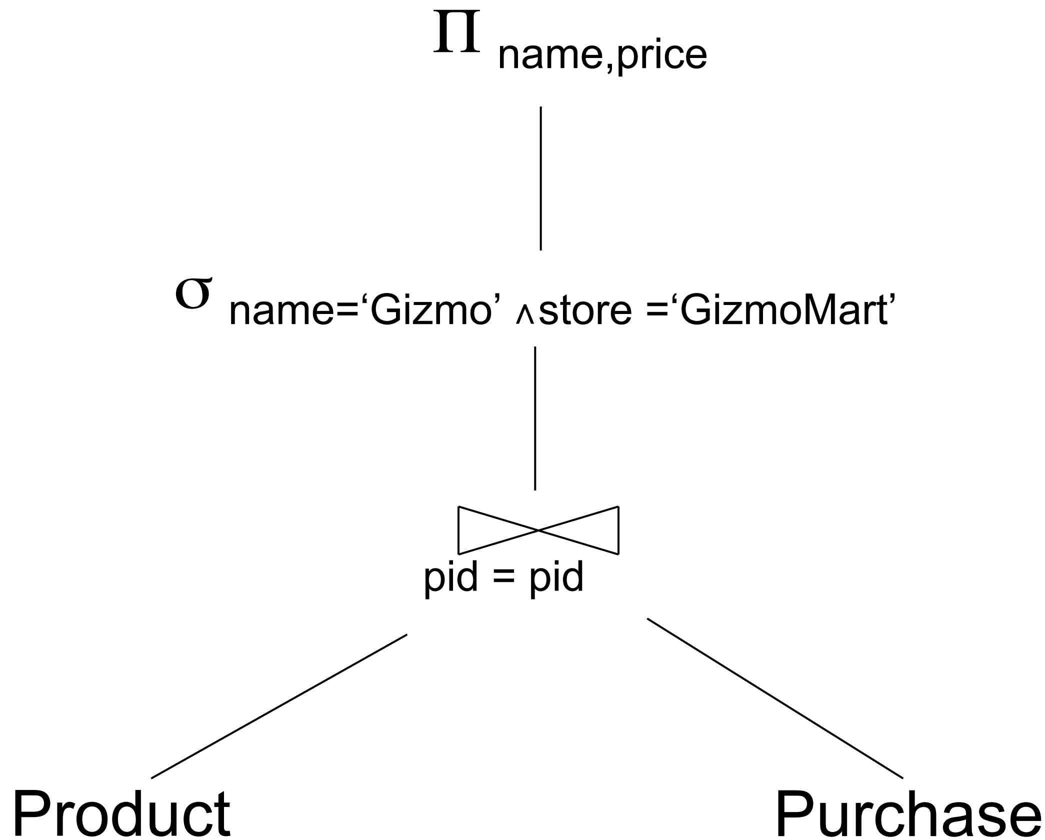
Temporary tables
T1, T2, . . .

Logical v.s. Physical Plan

- Physical plan = Logical plan plus annotations
- Access path selection for each relation
  - Use a file scan or use an index
- Implementation choice for each operator
- Scheduling decisions for operators

Product(pid, name, price)
Purchase(pid, cid, store)
Customer(cid, name, city)

Logical Query Plan



Product(pid, name, price)
Purchase(pid, cid, store)
Customer(cid, name, city)

Physical Query Plan

(On the fly) $\Pi_{\text{name,price}}$

(On the fly) $\sigma_{\text{name='Gizmo'} \wedge \text{store ='GizmoMart'}}$

(Nested loop) $\bowtie_{\text{pid = pid}}$

Product (File scan)

Purchase (File scan)

Outline of the Lecture

- Physical operators: join, group-by
- Query execution: pipeline, iterator model
- Database statistics

Extended Algebra Operators

- Union $\cup$, difference $-$
- Selection σ
- Projection Π
- Join $\bowtie$ -- also: semi-join, anti-semi-join
- Rename ρ
- Duplicate elimination δ
- Grouping and aggregation γ
- Sorting τ

Basic RA

ExtendedRA

Sets v.s. Bags

- Sets: {a,b,c}, {a,d,e,f}, { }, . . .
- Bags: {a, a, b, c}, {b, b, b, b, b}, . . .

Relational Algebra has two semantics:

- Set semantics (paper “Three languages…”)
- Bag semantics

Physical Operators

Each of the logical operators may have one or more implementations = physical operators

Will discuss several basic physical operators, with a focus on join

Main Memory Algorithms

Logical operator:

Product(pid, name, price) $\bowtie_{pid=pid}$ Purchase(pid, cid, store)

Propose three physical operators for the join, assuming the tables are in main memory:

1.
2.
3.

Product(pid, name, price)
Purchase(pid, cid, store)
Customer(cid, name, city)

Main Memory Algorithms

Logical operator:

Product(pid, name, price) $\bowtie_{pid=pid}$ Purchase(pid, cid, store)

Propose three physical operators for the join, assuming the tables are in main memory:

1. Nested Loop Join O(??)
2. Merge join O(??)
3. Hash join O(??)

Main Memory Algorithms

Logical operator:

Product(pid, name, price) $\bowtie_{pid=pid}$ Purchase(pid, cid, store)

Propose three physical operators for the join, assuming the tables are in main memory:

1. Nested Loop Join — $O(n^2)$
2. Merge join — $O(n \log n)$
3. Hash join — $O(n) \ldots O(n^2)$

BRIEF Review of Hash Tables

A (naïve) hash function:

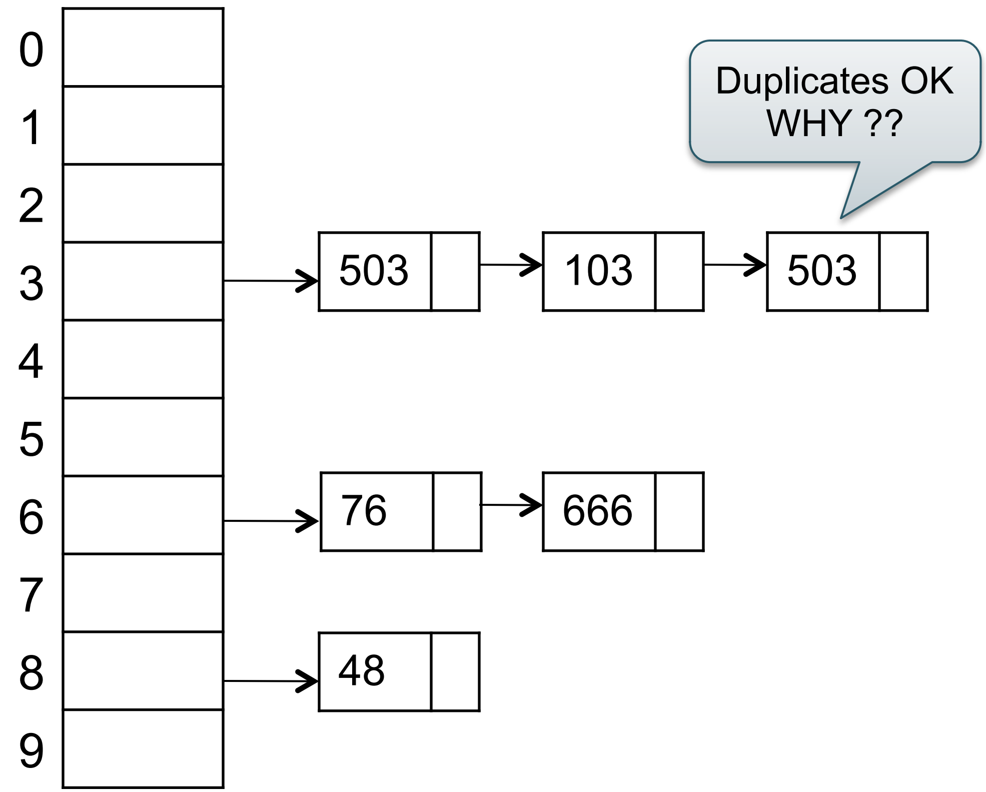
$h(x) = x \bmod 10$

Operations:

find(103) = ??

insert(488) = ??

Separate chaining:



BRIEF Review of Hash Tables

- insert(k, v) = inserts a key k with value v
- Many values for one key
  - Hence, duplicate k's are OK
- find(k) = returns the ***list*** of all values v associated to the key k

External Memory Algorithms

The *cost* of an operation = total number of I/Os

Cost parameters (used both in the book and by Shapiro):

- $B(R)$ = number of blocks for relation R (Shapiro: $|R|$)
- $T(R)$ = number of tuples in relation R
- $V(R, a)$ = number of distinct values of attribute a
- M = size of main memory buffer pool, in blocks

Facts: (1) $B(R) \ll T(R)$:
(2) When a is a key, $V(R,a) = T(R)$
When a is not a key, $V(R,a) \ll T(R)$

Cost of an Operator

Assumption: runtime dominated by # of disk I/O’s; will ignore the main memory part of the runtime

- If R (and S) fit in main memory, then we use a main-memory algorithm
- If R (or S) does not fit in main memory, then we use an external memory algorithm

Ad-hoc Convention

- The operator *reads* the data from disk
  - Note: different from Shapiro
- The operator *does not write* the data back to disk (e.g.: pipelining)
- Thus:

Any main memory join algorithms for R $\bowtie$ S: Cost = B(R)+B(S)

Any main memory grouping γ(R): Cost = B(R)

Nested Loop Joins

- Tuple-based nested loop R ⋈ S

```
for each tuple r in R do
   for each tuple s in S do
      if r and s join then output (r,s)
```

R=outer relation
S=inner relation

- Cost: T(R) B(S)

Examples

M = 4

- Example 1:
  - B(R) = 1000, T(R) = 10000
  - B(S) = 2, T(S) = 20
  - Cost = ?

Can you do better with nested loops?

- Example 2:
  - B(R) = 1000, T(R) = 10000
  - B(S) = 4, T(S) = 40
  - Cost = ?

Block-Based Nested-loop Join

```
for each (M-2) blocks bs of S do
   for each block br of R do
      for each tuple s in bs
         for each tuple r in br do
            if "r and s join" then output(r,s)
```

Terminology alert: sometimes S is called S the *inner* relation

Block-Based Nested-loop Join

Why not M ?

```
for each (M-2) blocks bs of S do
    for each block br of R do
        for each tuple s in bs
            for each tuple r in br do
                if "r and s join" then output(r,s)
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Terminology alert: sometimes S is called S the *inner* relation

Block-Based Nested-loop Join

Why not M ?

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for each (M-2) blocks bs of S do
   for each block br of R do
      for each tuple s in bs
         for each tuple r in br do
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```
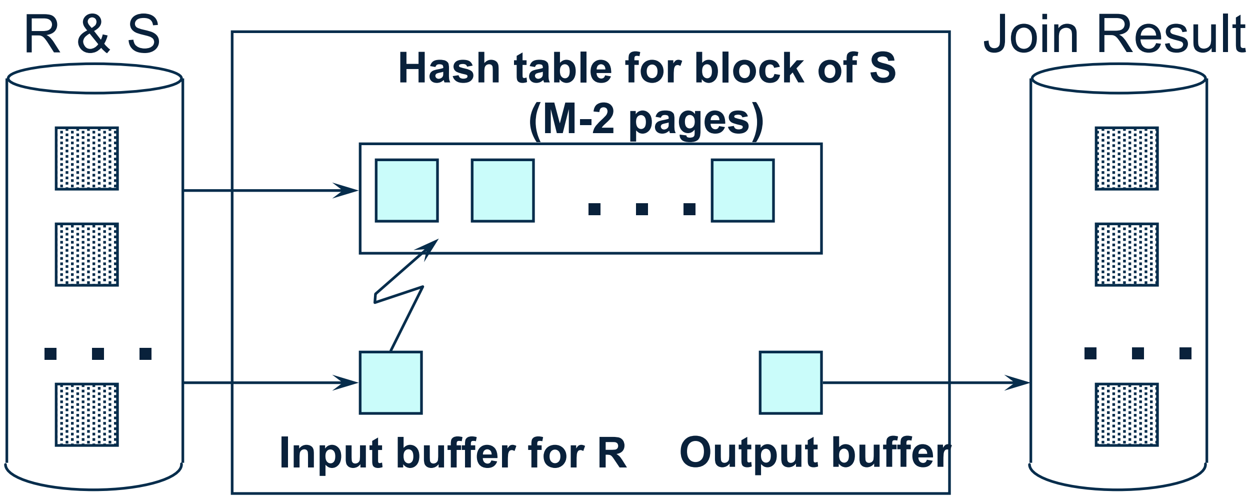

Better: main memory hash join

Terminology alert: sometimes S is called S the *inner* relation

Block Nested-loop Join



Examples

M = 4

- Example 1:
  - B(R) = 1000, T(R) = 10000
  - B(S) = 2, T(S) = 20
  - Cost = B(S) + B(R) = 1002

- Example 2:
  - B(R) = 1000, T(R) = 10000
  - B(S) = 4, T(S) = 40
  - Cost = B(S) + 2B(R) = 2004

Note: T(R) and T(S) are irrelevant here.

Cost of Block Nested-loop Join

- Read S once: cost B(S)
- Outer loop runs B(S)/(M-2) times, and each time need to read R: costs B(S)B(R)/(M-2)

Cost = B(S) + B(S)B(R)/(M-2)

Index Based Selection

Recall IMDB; assume indexes on Movie.id, Movie.year

```
SELET *
FROM Movie
WHERE id = '12345'
```

```
SELET *
FROM Movie
WHERE year = '1995'
```

B(Movie) = 10k
T(Movie) = 1M

What is your estimate of the I/O cost ?

Index Based Selection

Selection on equality: $\sigma_{a=v}(R)$

- Clustered index on a: cost ?
- Unclustered index : cost ?

Index Based Selection

Selection on equality: $\sigma_{a=v}(R)$

- Clustered index on a: cost B(R)/V(R,a)
- Unclustered index : cost T(R)/V(R,a)

Index Based Selection

Selection on equality: $\sigma_{a=v}(R)$

- Clustered index on a: cost B(R)/V(R,a)
- Unclustered index : cost T(R)/V(R,a)

Note: we assume that the cost of reading the index = 0
Why?

Index Based Selection

- Example:

$B(R) = 10k$
$T(R) = 1M$
$V(R, a) = 100$

cost of $\sigma_{a=v}(R) = ?$

- Table scan:
  - $B(R) = 10k$ I/Os
- Index based selection:
  - If index is clustered: $B(R)/V(R,a) = 100$ I/Os
  - If index is unclustered: $T(R)/V(R,a) = 10000$ I/Os

Rule of thumb:
don't build unclustered indexes when $V(R,a)$ is small !

Index Based Join

- R $\bowtie$ S
- Assume S has an index on the join attribute

```
for each tuple r in R do
    lookup the tuple(s) s in S using the index
    output (r,s)
```

Index Based Join

Cost:

- If index is clustered:
- If unclustered:

Index Based Join

Cost:

- If index is clustered: B(R) + T(R)B(S)/V(S,a)
- If unclustered: B(R) + T(R)T(S)/V(S,a)

Operations on Very Large Tables

- Compute $R \bowtie S$ when each is larger than main memory
- Two methods:
  - Partitioned hash join (many variants)
  - Merge-join
- Similar for grouping

External Sorting

- Problem:
- Sort a file of size B with memory M
- Where we need this:
  - ORDER BY in SQL queries
  - Several physical operators
  - Bulk loading of B+-tree indexes.
- Will discuss only 2-pass sorting, when $B < M^2$

Basic Terminology

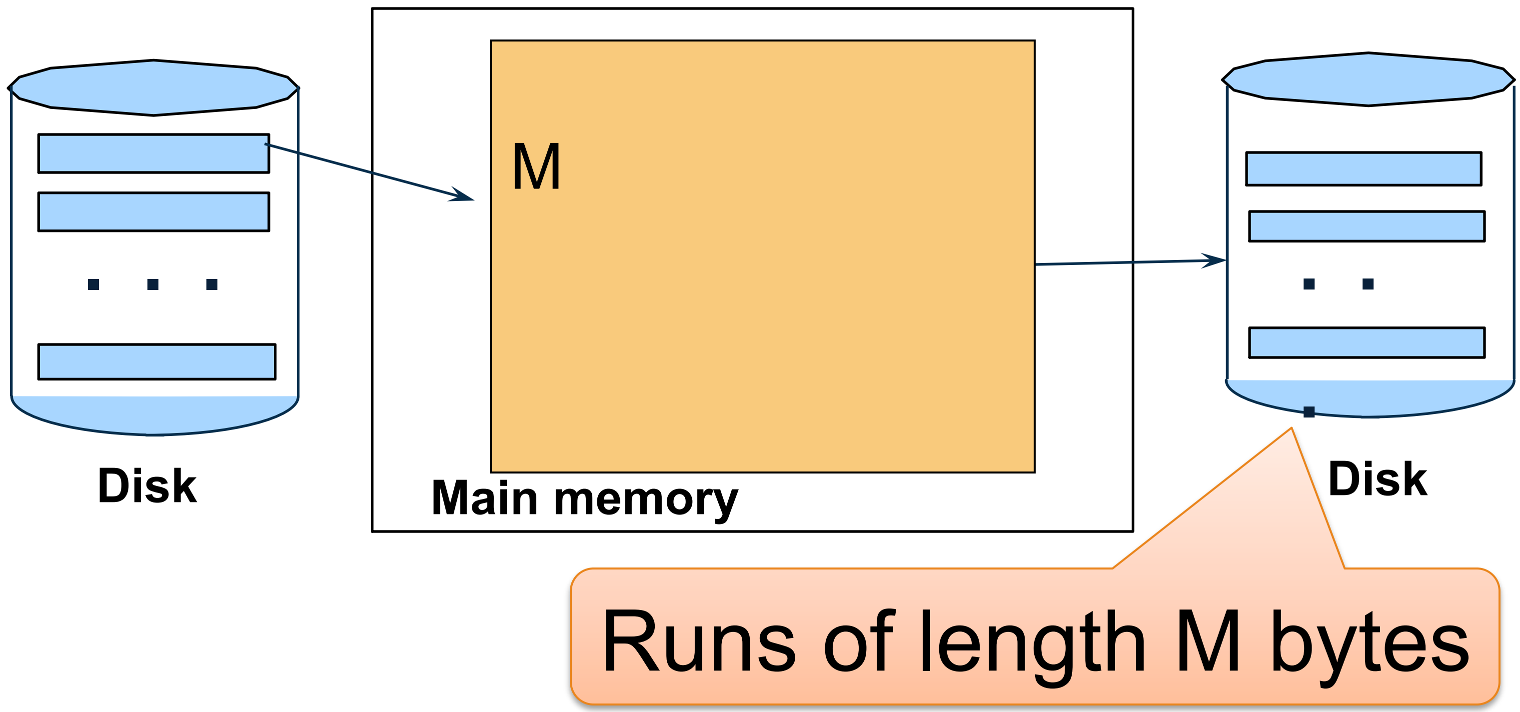
- A run in a sequence is an increasing subsequence

- What are the runs?

  2, 4, 99, 103, 88, 77, 3, 79, 100, 2, 50

External Merge-Sort: Step 1

- Phase one: load M bytes in memory, sort



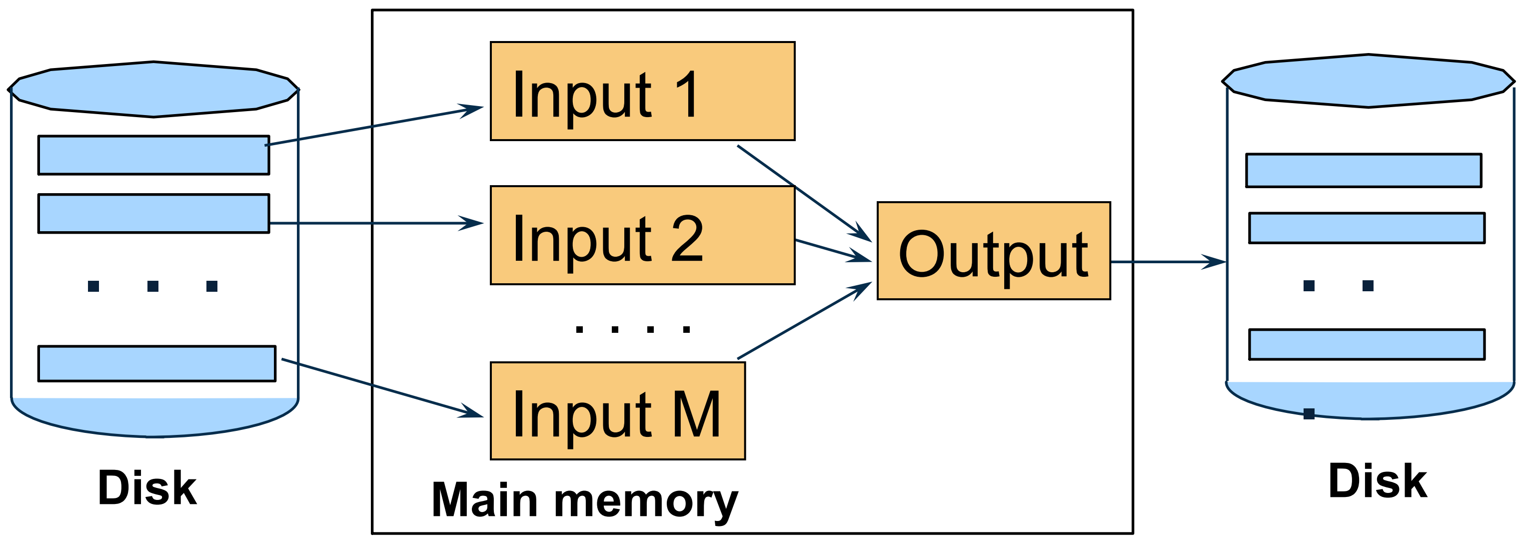
Basic Terminology

- Merging multiple runs to produce a longer run:
  0, **14, 33, 88, 92, 192, 322**
  2, 4, 7, **43, 78, 103, 523**
  1, 6, **9, 12, 33, 52, 88, 320**

  Output:
  0, 1, 2, 4, 6, 7, ?

External Merge-Sort: Step 2

- Merge M – 1 runs into a new run
- Result: runs of length M (M – 1)≈ M^2



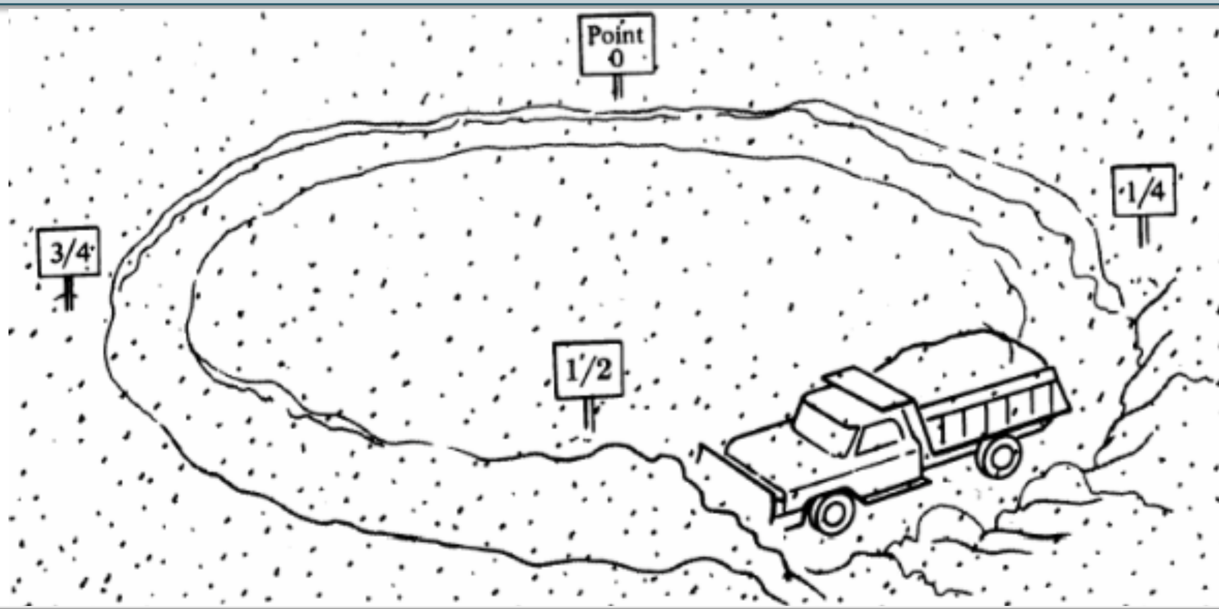
If B <= M^2 then we are done

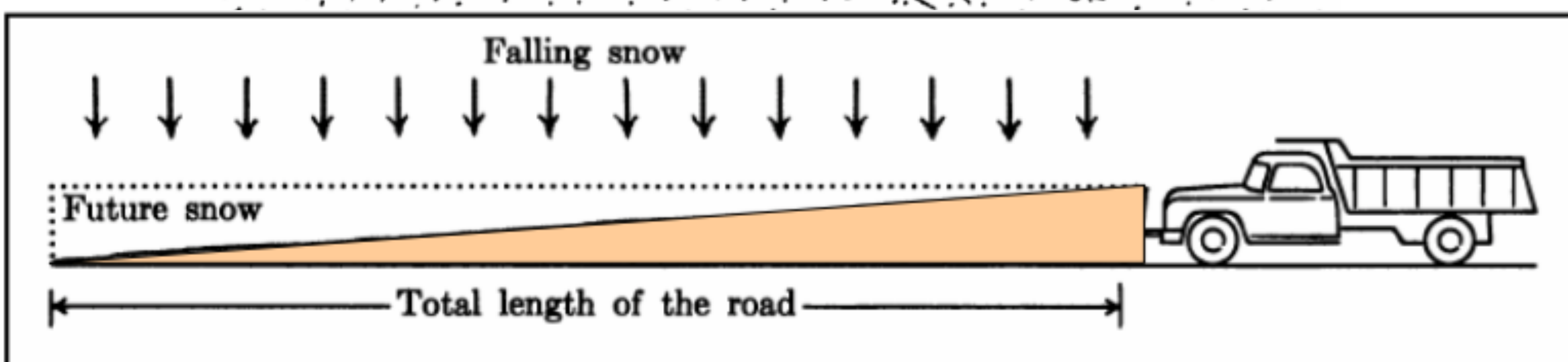
Cost of External Merge Sort

- Read+write+read = 3B(R)
- Assumption: $B(R) <= M^2$

External Merge-Sort

Can increase to length 2M using “replacement selection”





Group-by

Group-by: $\gamma_{a,\ sum(b)}$ (R)

- Idea: do a two step merge sort, but change one of the steps
- Question in class: which step needs to be changed and how ?

Cost = 3B(R)
Assumption: $B(\delta(R)) <= M^2$

Merge-Join

Join R ⋈ S

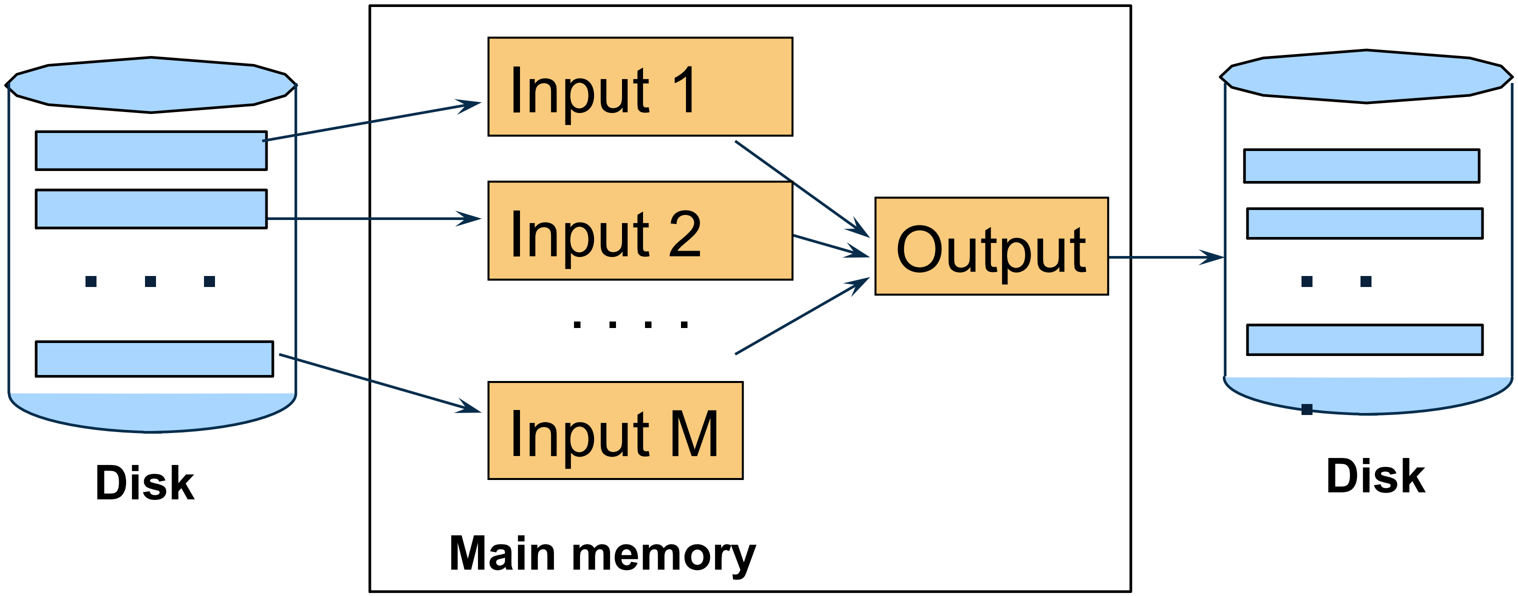
- How?....

Merge-Join

Join R ⋈ S

- Step 1a: initial runs for R
- Step 1b: initial runs for S
- Step 2: merge and join

Merge-Join



$M_1 = B(R)/M$ runs for R

$M_2 = B(S)/M$ runs for S

Merge-join $M_1 + M_2$ runs;

need $M_1 + M_2 <= M$

Partitioned Hash Algorithms

Idea:

- If $B(R) > M$, then partition it into smaller files:
  R1, R2, R3, …, Rk

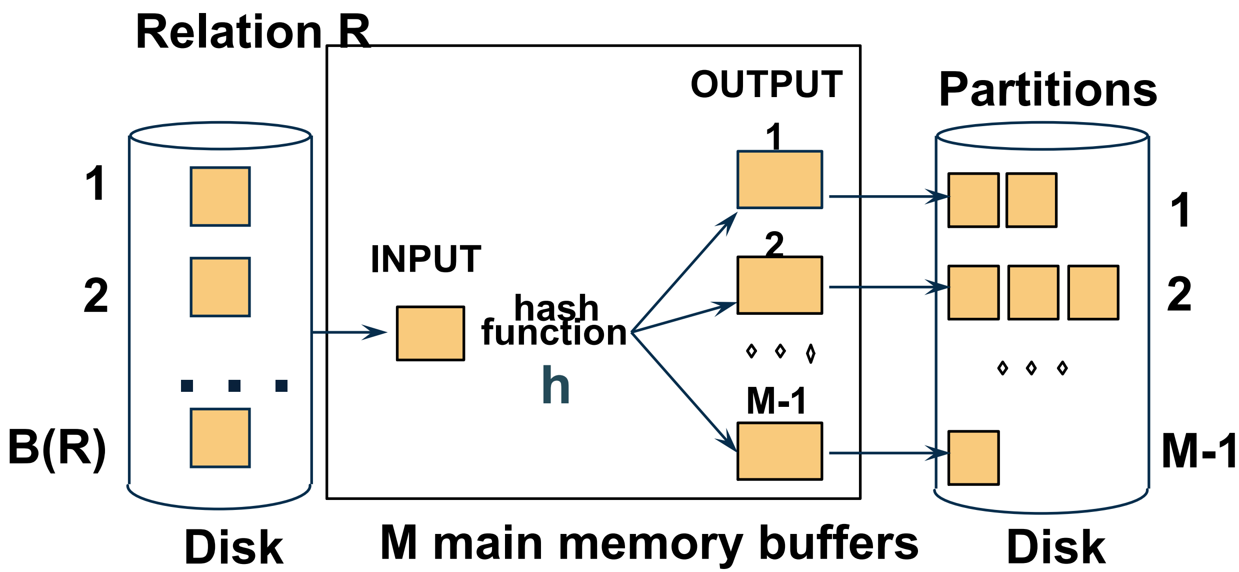
- Assuming $B(R1)=B(R2)=\ldots= B(Rk)$, we have
  $B(Ri) = B(R)/k$

- Goal: each Ri should fit in main memory:
  $B(Ri) \leq M$

How big can k be ?

Partitioned Hash Algorithms

- Idea: partition a relation R into M-1 buckets, on disk
- Each bucket has size approx. B(R)/(M-1) ≈ B(R)/M



Assumption: B(R)/M ≤ M, i.e. $B(R) \le M^2$

Grouping

- γ(R) = grouping and aggregation
- Step 1. Partition R into buckets
- Step 2. Apply γ to each bucket (may read in main memory)

- Cost: 3B(R)
- Assumption: $B(R) \leq M^2$

Grace-Join

$R \bowtie S$

Note: grace-join is also called *partitioned hash-join*

Grace-Join

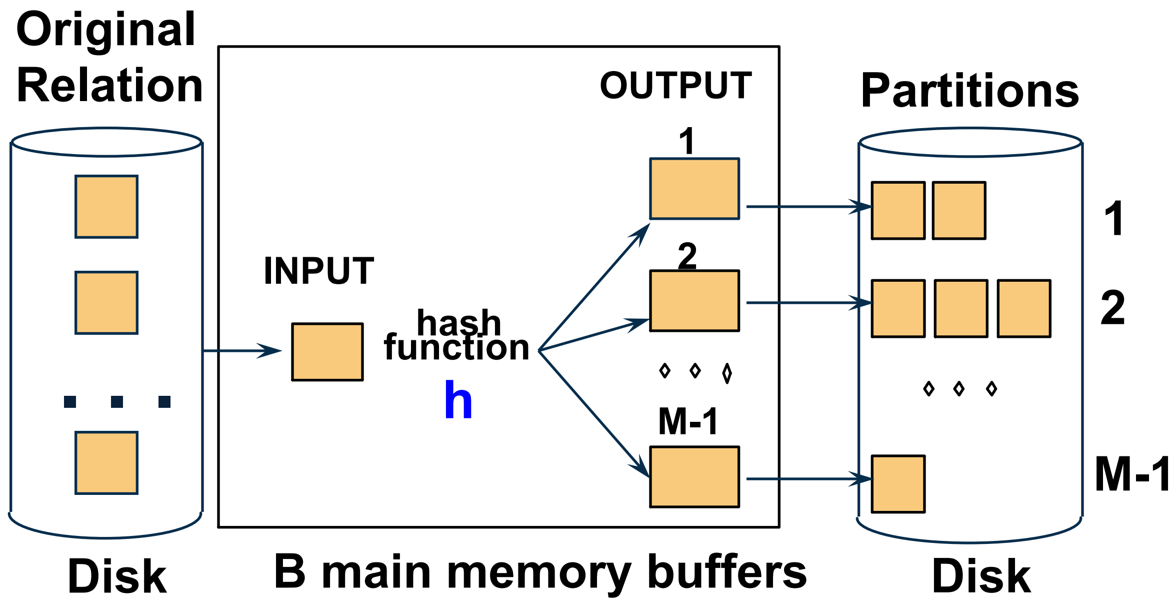
$R \bowtie S$

- Step 1:
  – Hash S into M buckets
  – send all buckets to disk
- Step 2
  – Hash R into M buckets
  – Send all buckets to disk
- Step 3
  – Join every pair of buckets

Note: grace-join is also called *partitioned hash-join*

Grace-Join

- Partition both relations using hash fn **h**: R tuples in partition i will only match S tuples in partition i.



Grace-Join

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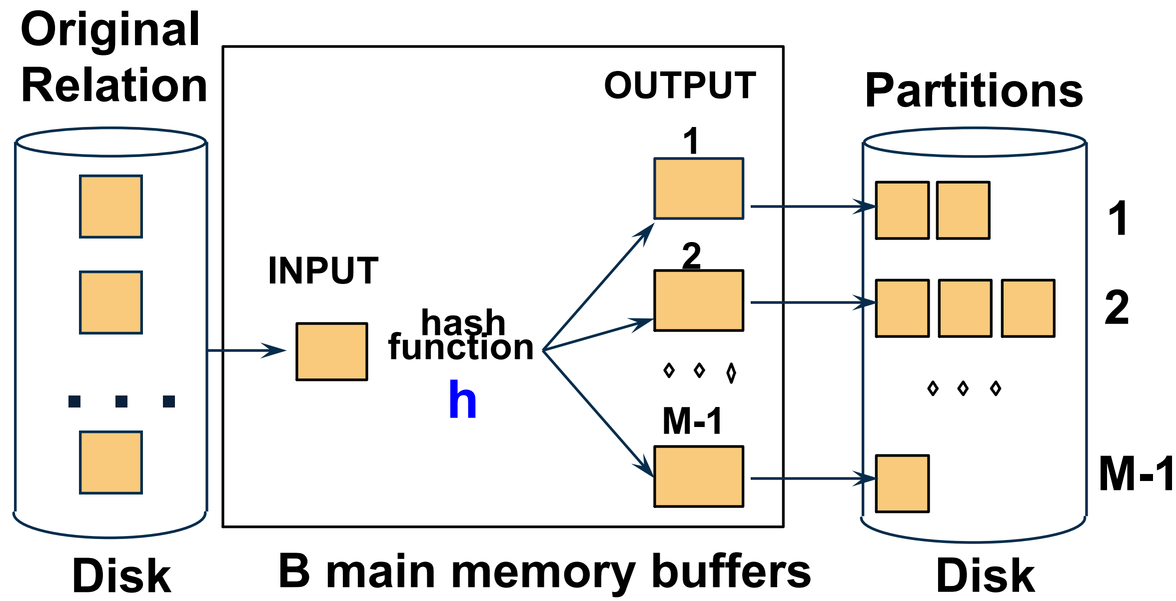
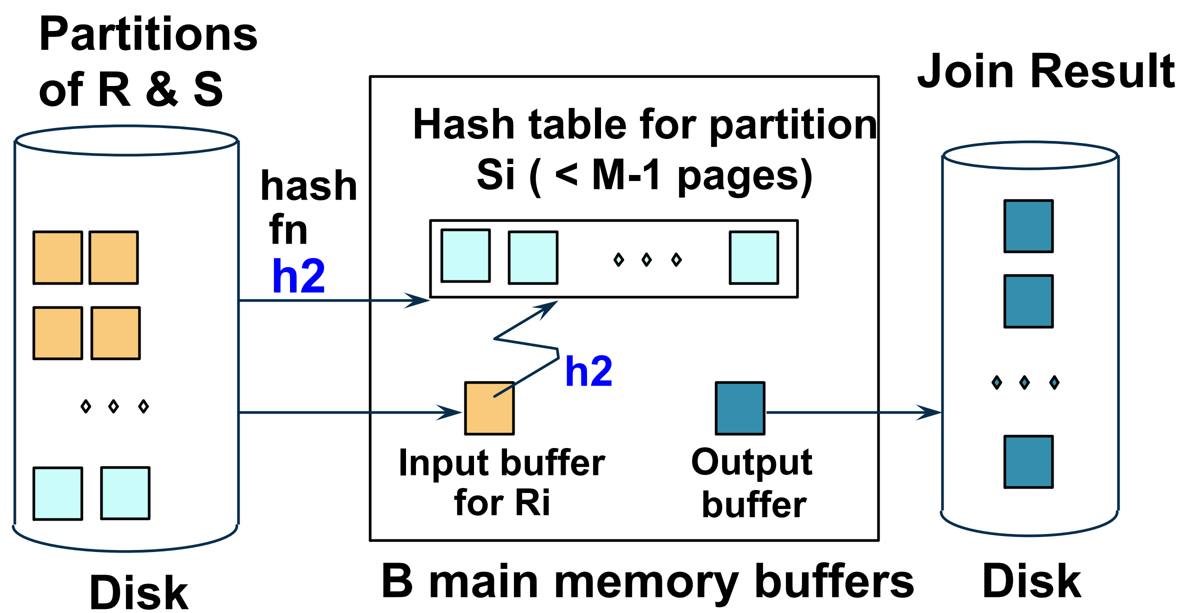


- Read in a partition of R, hash it using **h2 (<> h!)**. Scan matching partition of S, search for matches.



Grace Join

- Cost: 3B(R) + 3B(S)
- Assumption: min(B(R), B(S)) <= M^2

Hybrid Hash Join Algorithm

- Partition S into k buckets
  t buckets S_1 , …, S_t stay in memory
  k-t buckets S_{t+1}, …, S_k to disk
- Partition R into k buckets
  - First t buckets join immediately with S
  - Rest k-t buckets go to disk
- Finally, join k-t pairs of buckets:
  (R_{t+1},S_{t+1}), (R_{t+2},S_{t+2}), …, (R_k,S_k)

Hybrid Hash Join Algorithm

- Partition S into k buckets

  t buckets S_1 , …, S_t stay in memory

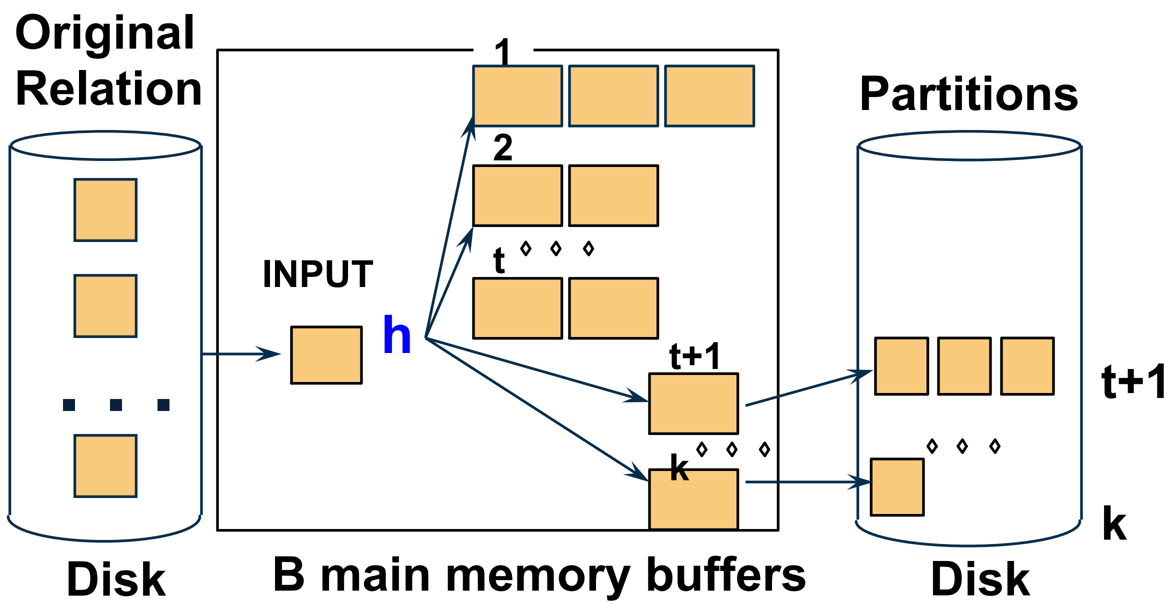
  k-t buckets S_{t+1}, …, S_k to disk

- Partition R into k buckets
  - First t buckets join immediately with S
  - Rest k-t buckets go to disk
- Finally, join k-t pairs of buckets:

  (R_{t+1},S_{t+1}), (R_{t+2},S_{t+2}), …, (R_k,S_k)

Shapiro's notation:
1/(B+1) = t/k in main memory
B/(B+1) = (k-t)/k go to disk

Hybrid Hash Join Algorithm



Hybrid Join Algorithm

- How to choose k and t ?
  - Choose k large but s.t. $k <= M$
  - Choose t/k large but s.t. $t/k * B(S) <= M$
  - Moreover: $t/k * B(S) + k\text{-}t <= M$

- Assuming $t/k * B(S) >> k\text{-}t$: $t/k = M/B(S)$

Hybrid Join Algorithm

Cost of Hybrid Join:

- Grace join: 3B(R) + 3B(S)
- Hybrid join:
  - Saves 2 I/Os for t/k fraction of buckets
  - Saves 2t/k(B(R) + B(S)) I/Os
  - Cost:
    (3-2t/k)(B(R) + B(S)) = (3-2M/B(S))(B(R) + B(S))

Hybrid Join Algorithm

- Question in class: what is the advantage of the hybrid algorithm ?

Summary of External Join Algorithms

- Block Nested Loop: B(S) + B(R)*B(S)/M
- Index Join: B(R) + T(R)B(S)/V(S,a)
- Partitioned Hash: 3B(R)+3B(S);
  - min(B(R),B(S)) <= M^2
- Merge Join: 3B(R)+3B(S)
  - B(R)+B(S) <= M^2

Outline of the Lecture

- Physical operators: join, group-by
- Query execution: pipeline, iterator model
- Database statistics

Iterator Interface

Each **operator implements this interface**

- **open()**
  - Initializes operator state
  - Sets parameters such as selection condition
- **get_next()**
  - Operator invokes get_next() recursively on its inputs
  - Performs processing and produces an output tuple
- **close()**: cleans-up state

Product(pid, name, price)
Purchase(pid, cid, store)
Customer(cid, name, city)

1. Nested Loop Join

```
for x in Product do {
   for  y in Purchase do {
        if (x.pid == y.pid) output(x,y);
   }
}
```

Product = *outer relation*
Purhcase = *inner relation*
Note: sometimes terminology is switched

When is it more efficient to iterate first over Purchase, then over Product?

It's more complicated…

- Each **operator implements this interface**
- **open()**
- **get_next()**
- **close()**

Product(pid, name, price)
Purchase(pid, cid, store)
Customer(cid, name, city)

Main Memory Nested Loop Join

```
open ( ) {
  Product.open( );
  Purchase.open( );
  x = Product.get_next( );
}
```

```
close ( ) {
  Product.close ( );
  Purchase.close ( );
}
```

```
get_next( ) {
  repeat {
    y = Purchase.get_next( );
    if (y == NULL)
      { Purchase.close();
        Purchase.open( );
        x = Product.get_next( );
         if (x== NULL) return NULL;
         y = Purchase.get_next( );
       }
  until (x.pid == y.pid);
  return (x,y)
}
```

ALL operators need to be implemented this way !

Product(pid, name, price)
Purchase(pid, cid, store)
Customer(cid, name, city)

2. Hash Join (main memory)

Build phase

```
for x in Product do  insert(x.pid, x);

for y in Purchase do {
   ys = find(y.pid);
   for y in ys do { output(x,y); }
}
```

Probe phase

Product=outer
Purchase=inner

Recall: need to rewrite as open, get_next, close

Product(pid, name, price)
Purchase(pid, cid, store)
Customer(cid, name, city)

3. Merge Join (main memory)

```
Product1       = sort(Product, pid);
Purchase1      = sort(Purchase, pid);

x=Product1.get_next();
y=Purchase1.get_next();

While (x!=NULL and y!=NULL) {
    case:
      x.pid < y.pid:    x = Product1.get_next( );
      x.pid > y.pid:    y = Purchase1.get_next();
      x.pid == y.pid { output(x,y);
                       y = Purchase1.get_next();
                     }
}
```

Why ???

Product(pid, name, price)
Purchase(pid, cid, store)
Customer(cid, name, city)

Physical Query Plan

(On the fly) $\Pi_{\text{name,price}}$

(On the fly) $\sigma_{\text{name='Gizmo'} \wedge \text{store ='GizmoMart'}}$

(Nested loop) $\bowtie_{\text{pid = pid}}$

Product (File scan)

Purchase (File scan)

Pipelined Execution

- Applies parent operator to tuples directly as they are produced by child operators
- Benefits
  - No operator synchronization issues
  - Saves cost of writing intermediate data to disk
  - Saves cost of reading intermediate data from disk
  - Good resource utilizations on single processor
- This approach is used whenever possible

Product(pid, name, price)
Purchase(pid, cid, store)
Customer(cid, name, city)

Physical Query Plan

$\Pi_{\text{name,price}}$

(On the fly)

$\sigma_{\text{name='Gizmo'} \wedge \text{store ='GizmoMart'}}$

(Materialize to T1)

$\bowtie_{\text{pid = pid}}$

(Sort-merge join)

Product

(File scan)

Purchase

(File scan)

Intermediate Tuple Materialization

- Writes the results of an operator to an intermediate table on disk

- No direct benefit but
- Necessary data is larger than main memory
- Necessary when operator needs to examine the same tuples multiple times

Outline of the Lecture

- Physical operators: join, group-by
- Query execution: pipeline, iterator model
- Database statistics
  - Partially based on *Graphical Models* paper

Database Statistics

- Collect statistical summaries of stored data
- Estimate size (=cardinality), bottom-up
- Estimate cost by using the estimated size

Database Statistics

- Number of tuples = cardinality
- Indexes: number of keys in the index
- Number of physical pages, clustering info
- Statistical information on attributes
  - Min value, max value, number distinct values
  - Histograms
- Correlations between columns

Collection approach: periodic, using sampling

Size Estimation Problem

S = SELECT list
FROM R1, …, Rn
WHERE cond_1 AND cond_2 AND . . . AND cond_k

Given T(R1), T(R2), …, T(Rn)
Estimate T(S)

How can we do this ? Note: doesn't have to be exact.

Size Estimation Problem

```
S = SELECT list
     FROM    R1, …, Rn
     WHERE cond1 AND cond2 AND . . . AND condk
```

Remark: $T(S) \leq T(R1) \times T(R2) \times \ldots \times T(Rn)$

Selectivity Factor

- Each condition *cond* reduces the size by some factor called *selectivity factor*
- Assuming independence, multiply the selectivity factors

Example

R(A,B)
S(B,C)
T(C,D)

```
SELECT *
FROM R, S, T
WHERE R.B=S.B and S.C=T.C and R.A<40
```

T(R) = 30k, T(S) = 200k, T(T) = 10k

Selectivity of R.B = S.B is 1/3
Selectivity of S.C = T.C is 1/10
Selectivity of R.A < 40 is ½

What is the estimated size of the query output ?

Example

R(A,B)
S(B,C)
T(C,D)

```
SELECT *
FROM R, S, T
WHERE R.B=S.B and S.C=T.C and R.A<40
```

T(R) = 30k, T(S) = 200k, T(T) = 10k

Selectivity of R.B = S.B is 1/3
Selectivity of S.C = T.C is 1/10
Selectivity of R.A < 40 is ½

What is the estimated size of the query output ?

30k * 200k * 10k * 1/3 * 1/10 * ½
= 1TB

Discussion: Paper

What is the probability space?

S = SELECT list
FROM R_1 as x_1, …, R_k as x_k
WHERE Cond -- a conjunction of predicates

Discussion: Paper

What is the probability space?

S = SELECT list
FROM R_1 as x_1, …, R_k as x_k
WHERE Cond -- a conjunction of predicates

(x_1, x_2, …, x_k), drawn randomly, independently from R_1, ..., R_k

$\Pr(R_1.A = 40)$ = prob. that random tuple in R_1 has A=40

Descriptive attribute

Join indicator (in class…)

$\Pr(R_1.A = 40 \text{ and } J_{R1.B = R2.C} \text{ and } R_2.D = 90)$ = prob. that …

$E[\,|\text{SELECT ... WHERE Cond}|\,] = \Pr(\text{Cond}) * T(R_1) * T(R_2) * \ldots * T(R_k)$

Discussion: Paper

What is the probability space?

S = SELECT list
FROM R_1 as x_1, …, R_k as x_k
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What are the three simplifying assumptions?

Discussion: Paper

What is the probability space?

S = SELECT list
FROM R_1 as x_1, …, R_k as x_k
WHERE Cond -- a conjunction of predicates

What are the three simplifying assumptions?

Uniform:	$Pr(R_1.A = \text{'a'}) = 1/V(R_1, A)$
Attribute Indep.:	$Pr(R_1.A = \text{'a'} \text{ and } R_1.B = \text{'b'}) = Pr(R_1.A = \text{'a'})\ Pr(R_1.B = \text{'b'})$
Join Indep.:	$Pr(R_1.A = \text{'a'} \text{ and } J_{R1.B = R2.C}) = Pr(R_1.A = \text{'a'})\ Pr(J_{R1.B = R2.C})$

Rule of Thumb

- If selectivities are unknown, then:
  selectivity factor = 1/10
  [System R, 1979]

Using Data Statistics

- Condition is A = c   /* value selection on R */
  - Selectivity = $1/V(R,A)$
- Condition is A < c   /* range selection on R */
  - Selectivity = $(c - Low(R, A))/(High(R,A) - Low(R,A))T(R)$
- Condition is A = B   /* $R \bowtie_{A=B} S$ */
  - Selectivity = $1 / \max(V(R,A),V(S,A))$
  - (will explain next)

Selectivity of Join Predicates

Assumptions:

- *Containment of values*: if V(R,A) <= V(S,B), then the set of A values of R is included in the set of B values of S
  - Note: this indeed holds when A is a foreign key in R, and B is a key in S

- *Preservation of values*: for any other attribute C, $V(R \bowtie_{A=B} S, C) = V(R, C)$ (or $V(S, C)$)

Selectivity of Join Predicates

Assume V(R,A) <= V(S,B)

- Each tuple t in R joins with T(S)/V(S,B) tuple(s) in S
- Hence $T(R \bowtie_{A=B} S) = T(R)\ T(S) / V(S,B)$

In general: $T(R \bowtie_{A=B} S) = T(R)\ T(S) / \max(V(R,A),V(S,B))$

Selectivity of Join Predicates

Example:

- $T(R) = 10000$, $T(S) = 20000$
- $V(R,A) = 100$, $V(S,B) = 200$
- How large is $R \bowtie_{A=B} S$?

Histograms

- Statistics on data maintained by the RDBMS
- Makes size estimation much more accurate (hence, cost estimations are more accurate)

Histograms

Employee(ssn, name, age)

T(Employee) = 25000, V(Empolyee, age) = 50
min(age) = 19, max(age) = 68

$\sigma_{age=48}$(Empolyee) = ? $\sigma_{age>28 \text{ and } age<35}$(Empolyee) = ?

Histograms

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Age:	0..20	20..29	30-39	40-49	50-59	> 60
Tuples	200	800	5000	12000	6500	500

Histograms

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Tuples	200	800	5000	12000	6500	500

Estimate = 1200   Estimate = 1*80 + 5*500 = 2580

Types of Histograms

- How should we determine the bucket boundaries in a histogram ?

Types of Histograms

- How should we determine the bucket boundaries in a histogram ?

- Eq-Width
- Eq-Depth
- Compressed
- V-Optimal histograms

Employee(ssn, name, age)

Histograms

Eq-width:

Age:	0..20	20..29	30-39	40-49	50-59	> 60
Tuples	200	800	5000	12000	6500	500

Eq-depth:

Age:	0..20	20..29	30-39	40-49	50-59	> 60
Tuples	1800	2000	2100	2200	1900	1800

Compressed: store separately highly frequent values: (48,1900)

V-Optimal Histograms

- Defines bucket boundaries in an optimal way, to minimize the error over all point queries
- Computed rather expensively, using dynamic programming
- Modern databases systems use V-optimal histograms or some variations

Difficult Questions on Histograms

- Small number of buckets
  - Hundreds, or thousands, but not more
  - WHY ?
- *Not* updated during database update, but recomputed periodically
  - WHY ?

Multidimensional Histograms

Classical example:

SQL query:

```
SELECT …  FROM    …
WHERE  Person.city = ‘Seattle’ …
```

User “optimizes” it to:

```
SELECT …  FROM    …
WHERE  Person.city = ‘Seattle’
       and Person.state = ‘WA’
```

Big problem! (Why?)

Multidimensional Histograms

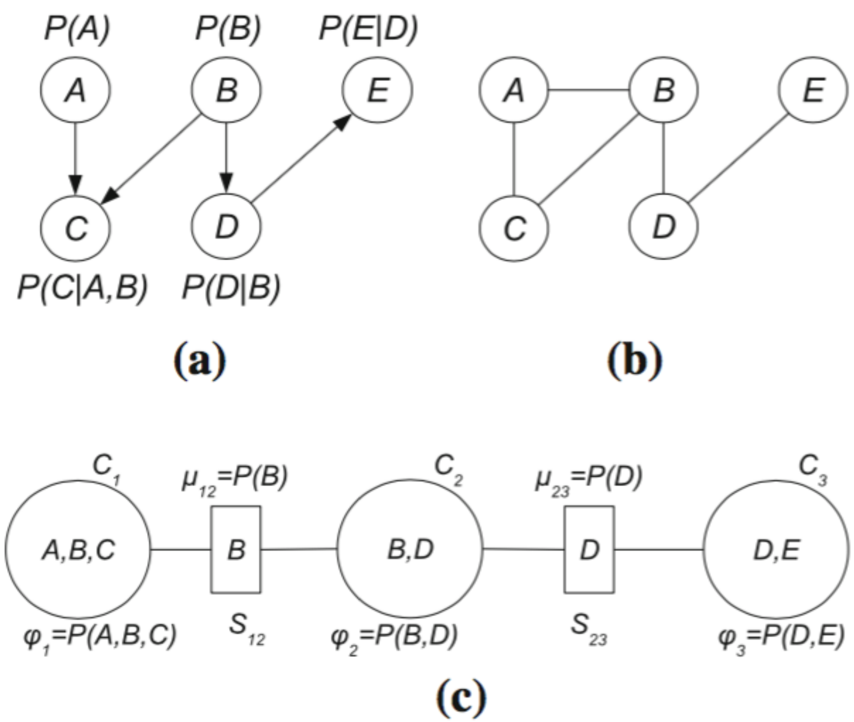
- Store distributions on two or more attributes
- Curse of dimensionality: space grows exponentially with dimension
- Paper: discusses using only two dimensional histograms

Paper: Bayesian Networks

$$P_{BN}(A, B, C, D, E) = P(E|D)P(D|B)P(C|A, B)\ P(A)P(B).$$

Paper: Bayesian Networks

$P_{BN}(A, B, C, D, E) = P(E|D)P(D|B)P(C|A, B)\ P(A)P(B).$



a	b	c	$P(a,b,c)$
a_1	b_1	c_1	0.25
a_1	b_1	c_2	0.32
a_1	b_2	c_1	0.01
a_1	b_2	c_2	0.12
a_2	b_1	c_1	0.08
a_2	b_1	c_2	0.04
a_2	b_2	c_1	0.1
a_2	b_2	c_2	0.08

b	d	$P(b,d)$
b_1	d_1	0.4
b_1	d_2	0.3
b_2	d_1	0.15
b_2	d_2	0.15

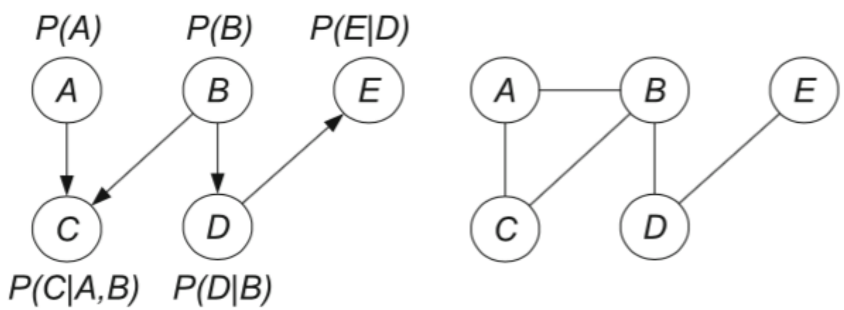
d	e	$P(d,e)$
d_1	e_1	0.7
d_1	e_2	0.1
d_2	e_1	0.05
d_2	e_2	0.15

(d)

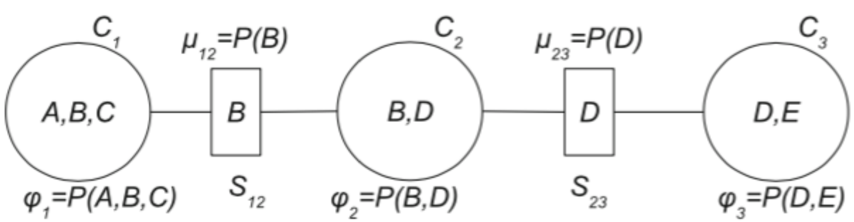
Fig. 1 A small graphical model of five binary random variables A, B, C, D, E **a** Bayesian network. **b** Moral graph. **c** Junction tree. **d** Clique potentials

Paper: Bayesian Networks

$P_{BN}(A, B, C, D, E) = P(E|D)P(D|B)P(C|A, B)\ P(A)P(B).$



(a) **(b)**



(c)

a	b	c	$P(a,b,c)$
a_1	b_1	c_1	0.25
a_1	b_1	c_2	0.32
a_1	b_2	c_1	0.01
a_1	b_2	c_2	0.12
a_2	b_1	c_1	0.08
a_2	b_1	c_2	0.04
a_2	b_2	c_1	0.1
a_2	b_2	c_2	0.08

b	d	$P(b,d)$
b_1	d_1	0.4
b_1	d_2	0.3
b_2	d_1	0.15
b_2	d_2	0.15

d	e	$P(d,e)$
d_1	e_1	0.7
d_1	e_2	0.1
d_2	e_1	0.05
d_2	e_2	0.15

(d)

Fig. 1 A small graphical model of five binary random variables A, B, C, D, E **a** Bayesian network. **b** Moral graph. **c** Junction tree. **d** Clique potentials

$$P(A, D) = \sum_{B,C} \frac{P(A, B, C)P(B, D)}{P(B)}.$$

Paper Highlights

- Universal table (what is it?)
- Acyclic v.s. Cyclic Schemas
- Within a table: tree-BN only
- Join indicator: two parents only
- Hence: acyclic schema → 2D-histograms only in the junction tree
- Simplifies construction, estimation

Next Lecture

Plan:

- Revisit Grace join after you read the paper
- Query optimization
- Latest results in optimal query processing
- Start Parallel DBs