Query processing

From SQL-query to result

Let's have a look under the hood

Query processing: overview

query in SQL

↓

equivalent XRA-expression

↓

modified XRA-expression

↓

access strategy

Algebraic operators

Classical view on RA: sets

Theory of relational databases: table is a *set*

Practice (SQL): a relation is a *bag* of tuples

R

A	B
1	1
2	1
3	2
4	2

$\pi_B(R)$

B
1
2

$\pi_B(R)$

B
1
1
2
2

Bags (multisets) versus sets

Union

$\{a,b,c\} \cup \{a,a,c,d\} = \{a,a,a,b,c,c,d\}$

Intersection

$\{a,a,a,b,c,c,d\} \cap \{a,a,b,e\} = \{a,a,b\}$

Difference (minus)

$\{a,a,a,b,c,c,d\} - \{a,a,b,e\} = \{a,c,c,d\}$

New operators in XRA: projection

Extended projection

R

A	B
1	1
2	1
3	2

$\pi_{A,\ A+B}(R)$

A	AplusB
1	2
2	3
3	5

New operators in XRA: sorting

- $\tau_L(R)$ =
  list of tuples in R sorted on attributes in L

R

B	C
2	6
4	3
1	3

$\tau_{C,B\uparrow}(R)$

C	B
3	1
3	4
6	2

Grouping en aggregate functions

Trip

Company	*Destination*	*Price*
Easyjet	Barcelona	65
Ryanair	Barcelona	59
KLM	Barcelona	80
Easyjet	London	45
Lufthansa	London	58
KLM	Paris	69

$\Gamma_{destination,\ min(price)}\ (Trip)$

Destination	*MinPrice*
Barcelona	59
London	45
Paris	69

Query processing: overview

query in SQL

↓

equivalent XRA-expression

↓

modified XRA-expression

↓

access strategy

Recall: algebraic properties

- *Commutativity*
  - $a + b = b + a$
  - $a * b = b * a$
  - $a – b \neq b – a$
- *Associativity*
  - $(a + b) + c = a + (b + c)$
  - $(a * b) * c = a * (b * c)$
  - $(a - b) - c \neq a - (b - c)$
- *Distributivity*
  - $a * (b + c) = a*b + a*c$
  - $a * (b - c) = a*b - a*c$

Algebraic rewriting

cascading and commuting selections:

$\sigma_{p \wedge q}(R) \equiv \sigma_p(\sigma_q(R)) \equiv \sigma_q(\sigma_p(R))$

cascading projections:

$\pi_{L1}(\pi_{L2}(R)) \equiv \pi_{L1}(R)$ IF $L1 \subseteq L2$

commuting selections and projections:

$\pi_L(\sigma_p(R)) \equiv \sigma_p(\pi_L(R))$ IF $attr(p) \subseteq L$

Algebraic rewriting

commutativity of binary operators:

$R \bowtie_\theta S \equiv S \bowtie_\theta R$ (?!)

also for $\times, \cup, \cap$

distribution of selection over join:

$$\sigma_{p1 \wedge p2 \wedge p3}(R \bowtie S) \equiv \sigma_{p3}(\sigma_{p1}(R) \bowtie \sigma_{p2}(S))$$

IF $attr(p1) \subseteq attr(R), attr(p2) \subseteq attr(S)$

distribution of selection over union:

$$\sigma_p(R \cup S) \equiv \sigma_p(R) \cup \sigma_p(S)$$

Intermezzo

- Describe how a Selection distributes over a Minus
- Describe how a GroupBy distributes over a Union
- Rewrite the following expression for schema
  R(ABCD), S(AEFG), T(EHK)

$$\pi_{CG}(\sigma_{D>=10 \wedge E<=20 \wedge (G>0 \vee K>0)}(R \bowtie S \bowtie T))$$

Access strategies

- Focus on **selection**, **sorting** and **equijoin**
- Other operators are either simple (projection) or variants of join methods

Access strategies

- We will have a look at datastructures and algorithms to support execution of algebraic operators
- (Blok 4 INFODS) Algorithmic analysis in main memory: count the number of steps of an algorithm (= , <, +)
- Our approach: count the number of accesses to external memory (IO) and ignore data processing in CPU and main memory

How to do: duplicate elimination?

- method 1: *sorting*
  external sorting of R can be done using *merge sort*
- method 2: *hashing*
  hashing will be explained when discussing
  join methods

IO: 4 * B, with B = the number of blocks used to store R

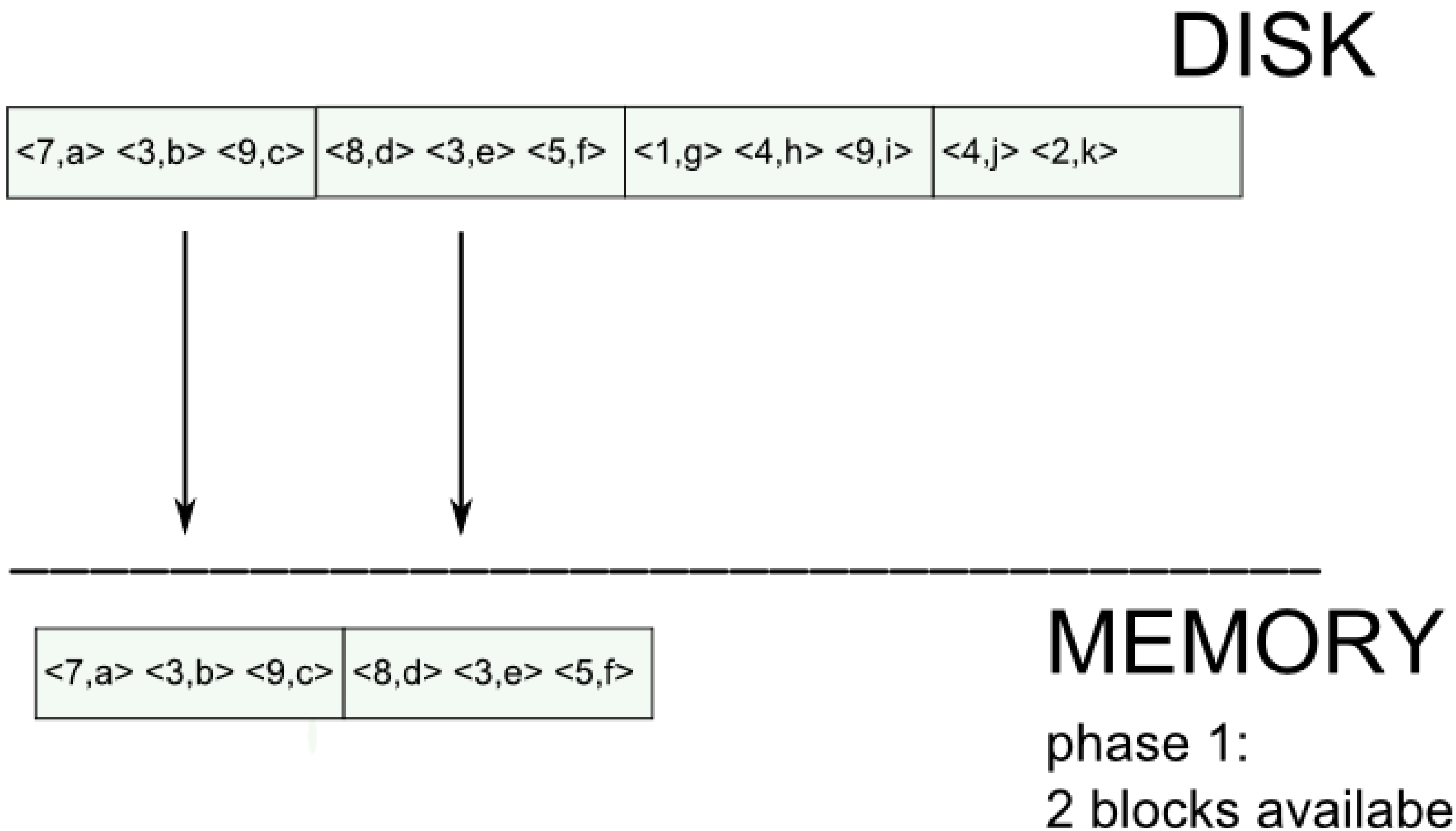
External merge sort: sort R[A,B] on A

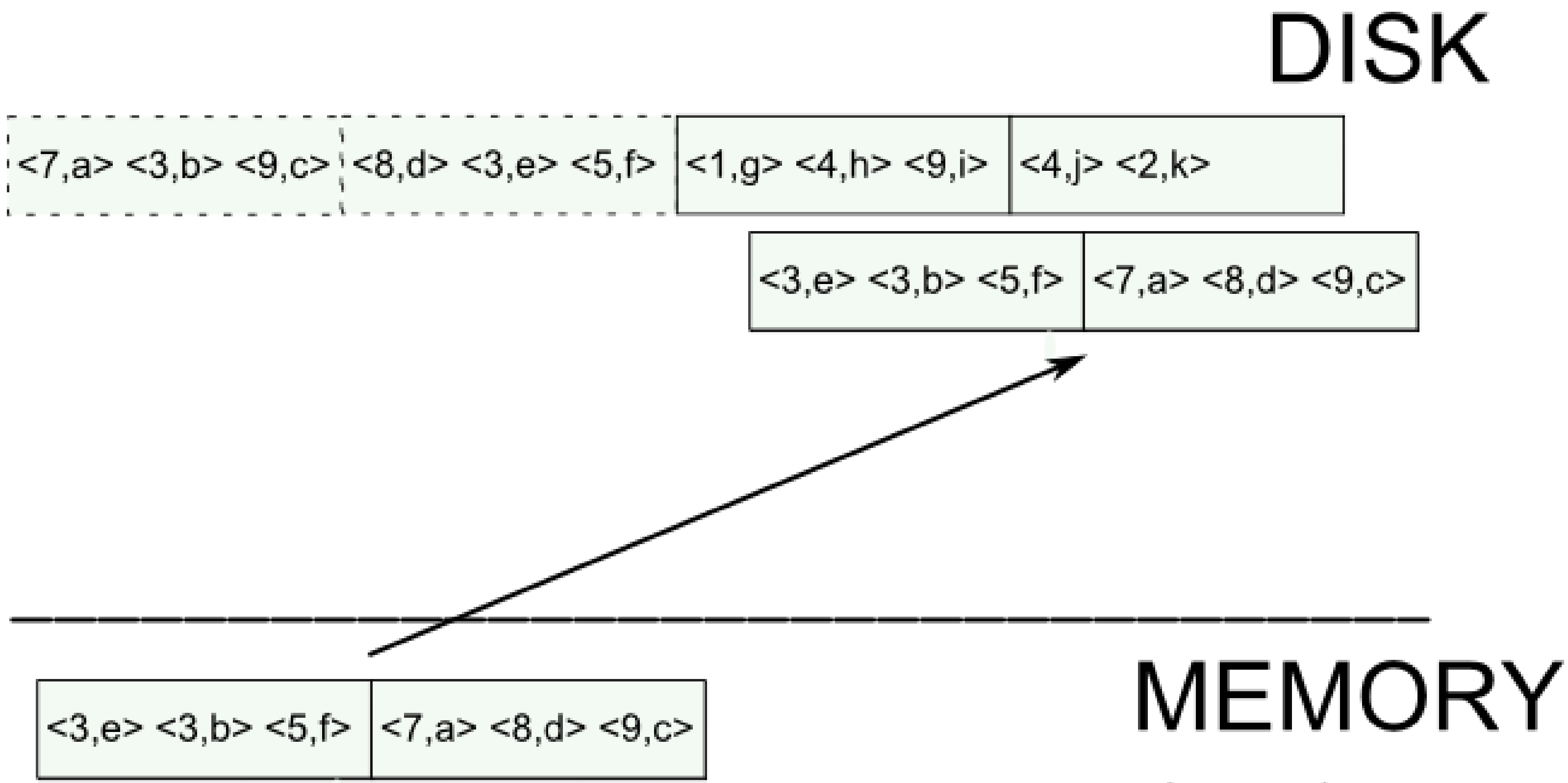
DISK

<7,a> <3,b> <9,c>	<8,d> <3,e> <5,f>	<1,g> <4,h> <9,i>	<4,j> <2,k>

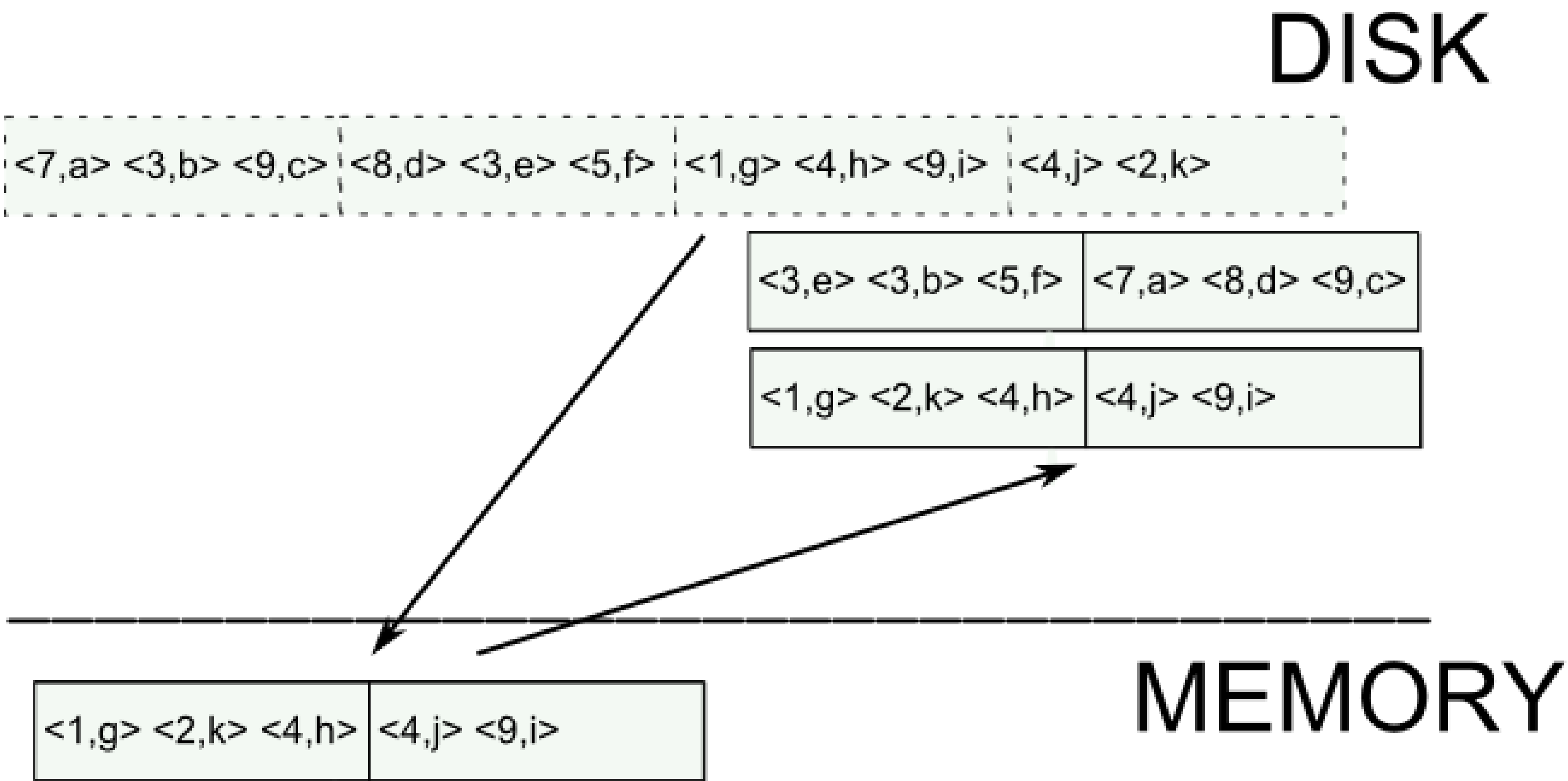
MEMORY

phase 1:
2 blocks availabe


DISK
<7,a> <3,b> <9,c>
<8,d> <3,e> <5,f>
<1,g> <4,h> <9,i>
<4,j> <2,k>
MEMORY
<7,a> <3,b> <9,c>
<8,d> <3,e> <5,f>
phase 1:
2 blocks availabe



phase 1:
internal sort;
first list to disk



phase 1:
internal sort;
second list to disk

DISK

<7,a> <3,b> <9,c>	<8,d> <3,e> <5,f>	<1,g> <4,h> <9,i>	<4,j> <2,k>

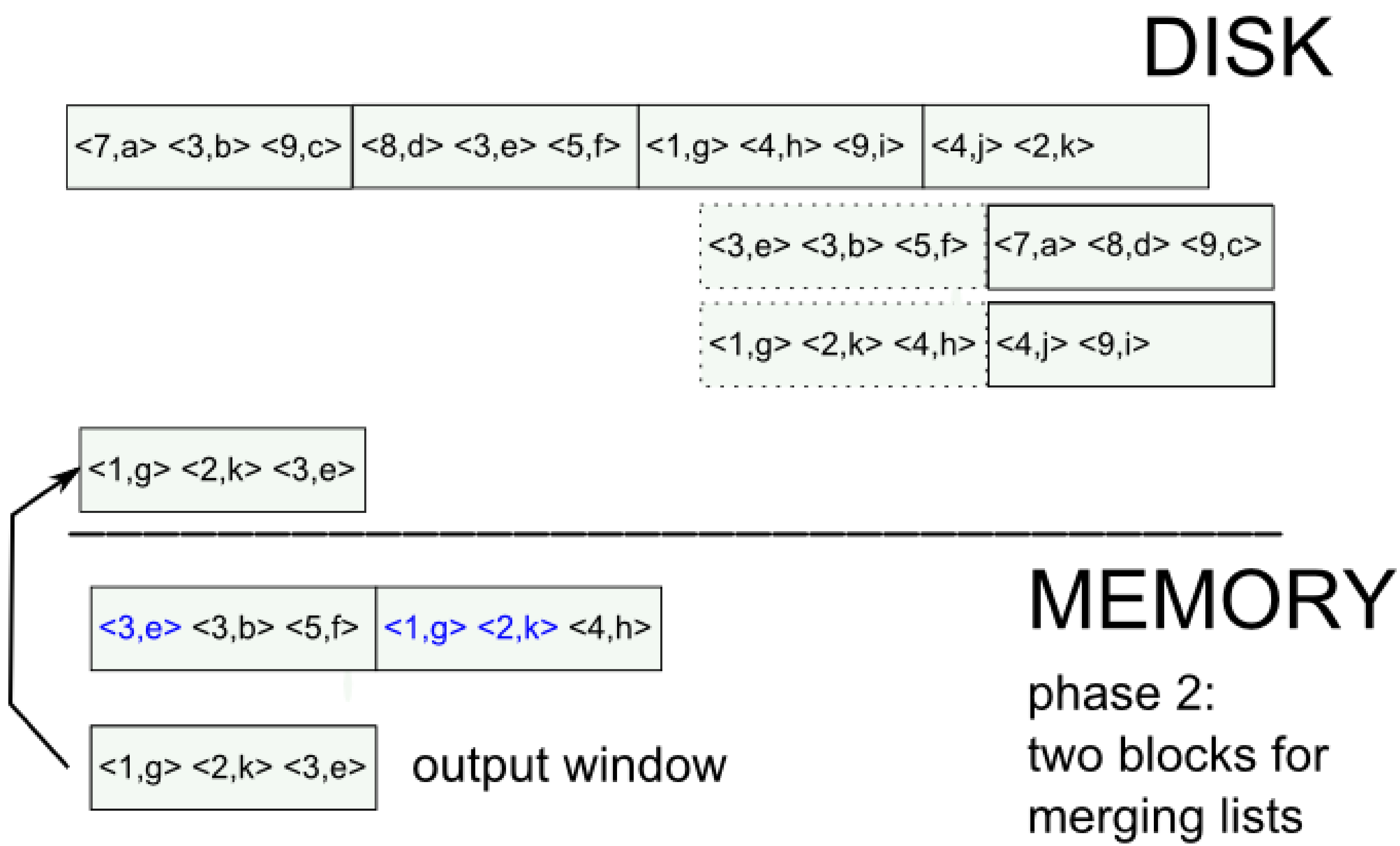
<3,e> <3,b> <5,f>	<7,a> <8,d> <9,c>
<1,g> <2,k> <4,h>	<4,j> <9,i>

MEMORY

<3,e> <3,b> <5,f>	<1,g> <2,k> <4,h>

output window

phase 2:
two blocks for
merging lists


DISK
<7,a> <3,b> <9,c>
<8,d> <3,e> <5,f>
<1,g> <4,h> <9,i>
<4,j> <2,k>
<3,e> <3,b> <5,f>
<7,a> <8,d> <9,c>
<1,g> <2,k> <4,h>
<4,j> <9,i>
<1,g> <2,k> <3,e>
MEMORY
<3,e> <3,b> <5,f>
<1,g> <2,k> <4,h>
<1,g> <2,k> <3,e>
output window
phase 2:
two blocks for
merging lists

DISK

<7,a> <3,b> <9,c> | <8,d> <3,e> <5,f> | <1,g> <4,h> <9,i> | <4,j> <2,k>

<3,e> <3,b> <5,f> | <7,a> <8,d> <9,c>

<1,g> <2,k> <4,h> | <4,j> <9,i>

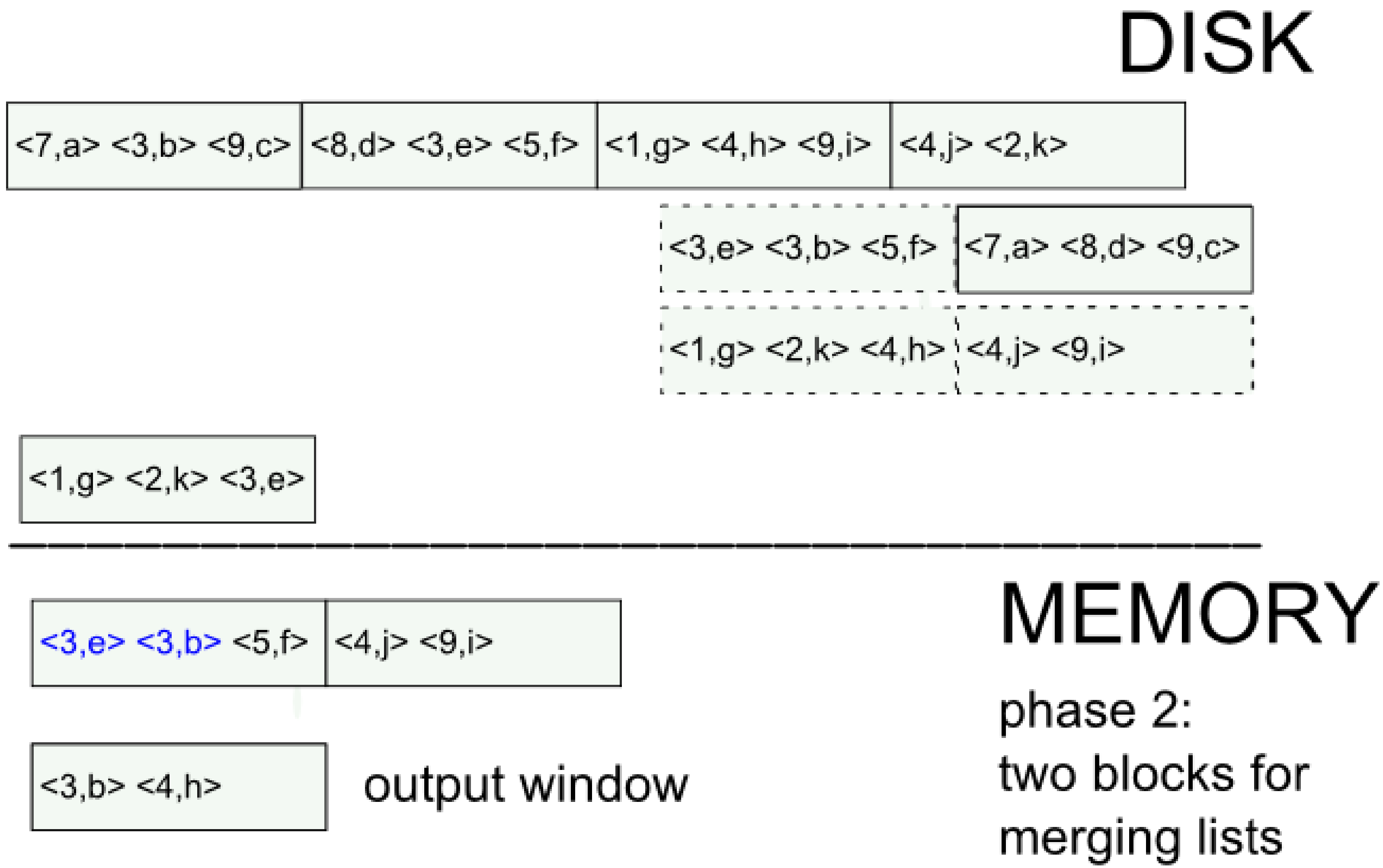
<1,g> <2,k> <3,e>

MEMORY

<3,e> <3,b> <5,f> | <1,g> <2,k> <4,h>

<3,b> <4,h> output window

phase 2:
two blocks for
merging lists


DISK
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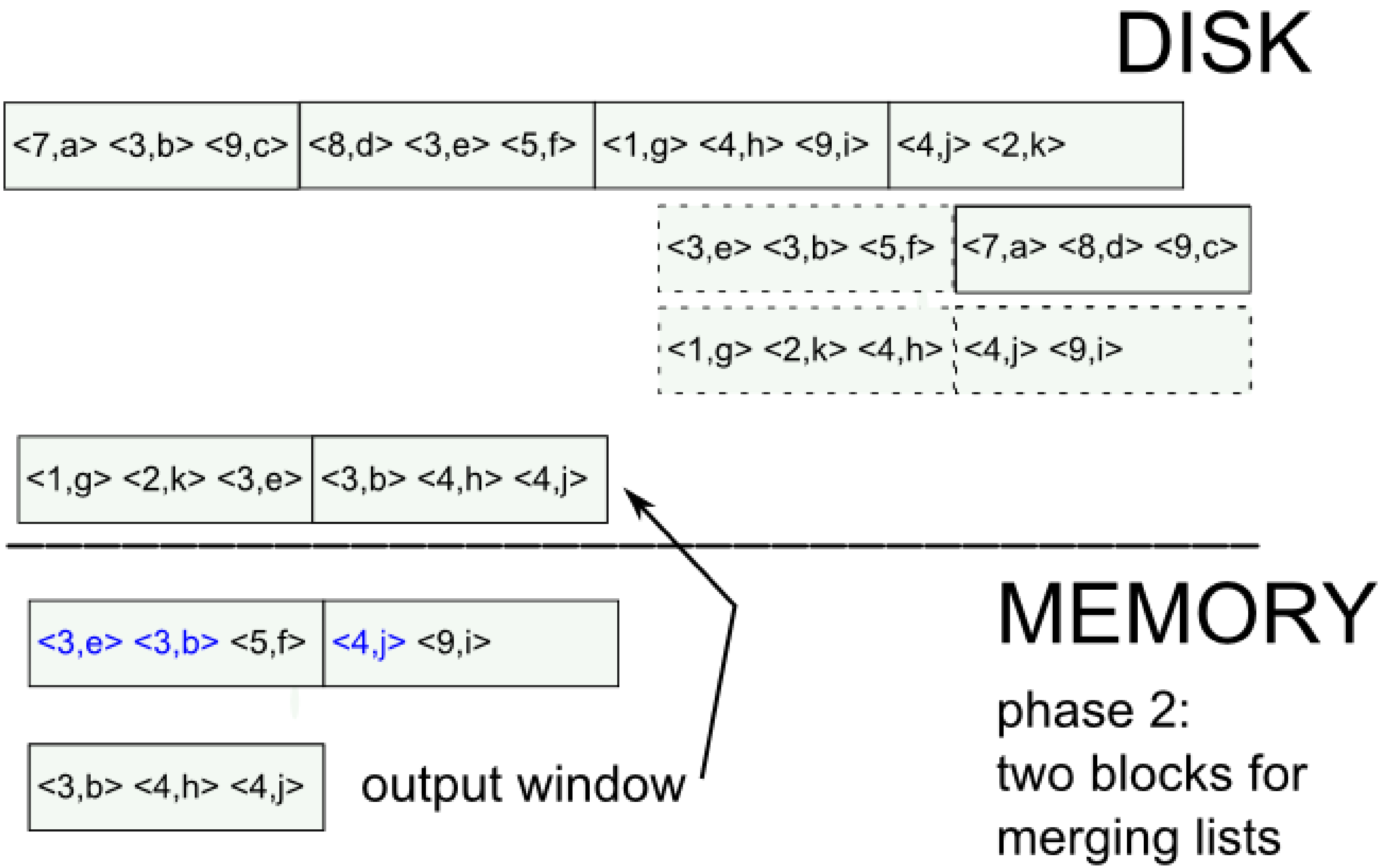
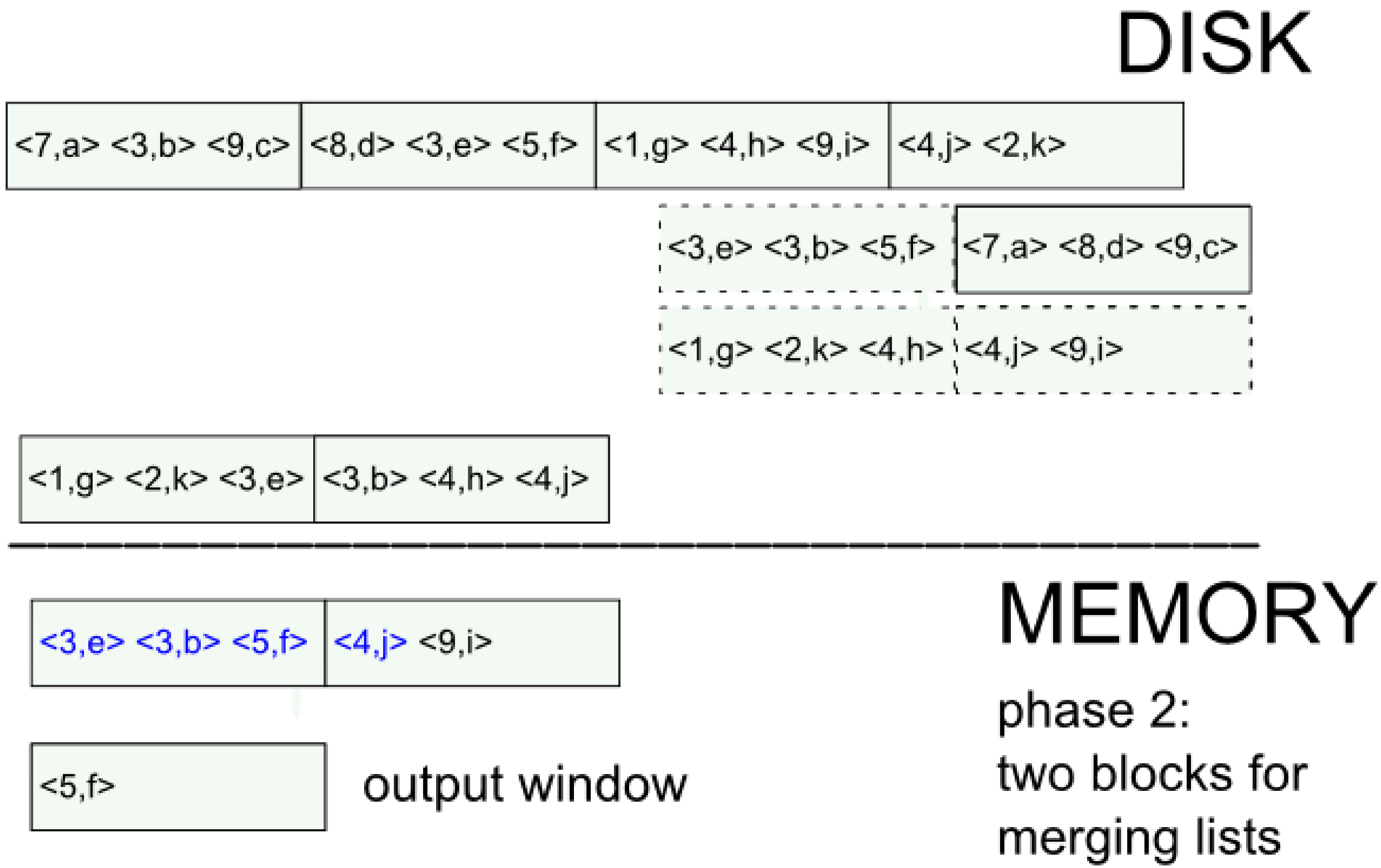
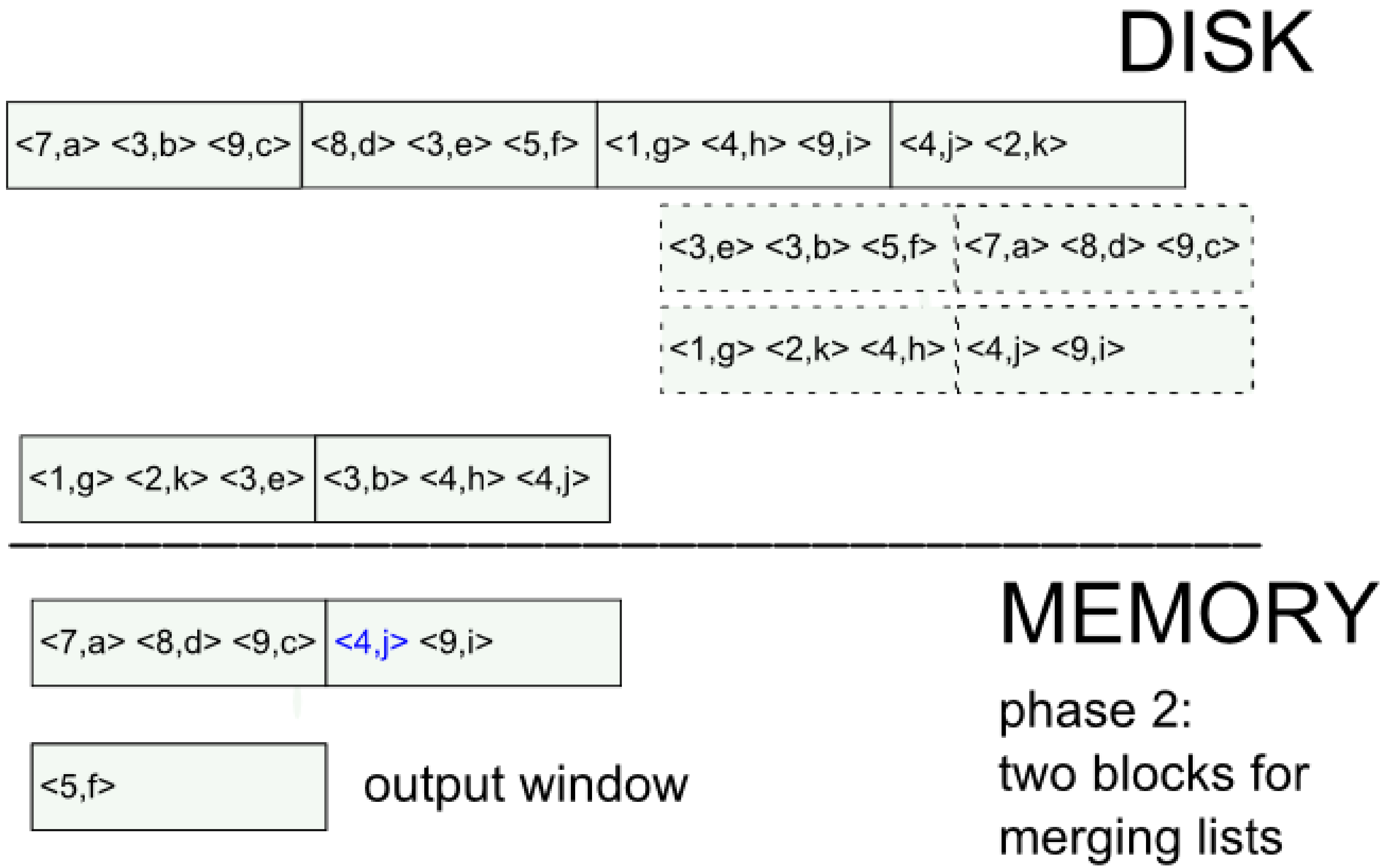
<8,d> <3,e> <5,f>
<1,g> <4,h> <9,i>
<4,j> <2,k>
<3,e> <3,b> <5,f>
<7,a> <8,d> <9,c>
<1,g> <2,k> <4,h>
<4,j> <9,i>
<1,g> <2,k> <3,e>
MEMORY
<3,e> <3,b> <5,f>
<4,j> <9,i>
<3,b> <4,h>
output window
phase 2:
two blocks for
merging lists


DISK
<7,a> <3,b> <9,c>
<8,d> <3,e> <5,f>
<1,g> <4,h> <9,i>
<4,j> <2,k>
<3,e> <3,b> <5,f>
<7,a> <8,d> <9,c>
<1,g> <2,k> <4,h>
<4,j> <9,i>
<1,g> <2,k> <3,e>
<3,b> <4,h> <4,j>
MEMORY
<3,e> <3,b> <5,f>
<4,j> <9,i>
<3,b> <4,h> <4,j>
output window
phase 2:
two blocks for
merging lists


DISK
<7,a> <3,b> <9,c>
<8,d> <3,e> <5,f>
<1,g> <4,h> <9,i>
<4,j> <2,k>
<3,e> <3,b> <5,f>
<7,a> <8,d> <9,c>
<1,g> <2,k> <4,h>
<4,j> <9,i>
<1,g> <2,k> <3,e>
<3,b> <4,h> <4,j>
MEMORY
<3,e> <3,b> <5,f>
<4,j> <9,i>
<5,f>
output window
phase 2:
two blocks for
merging lists


DISK
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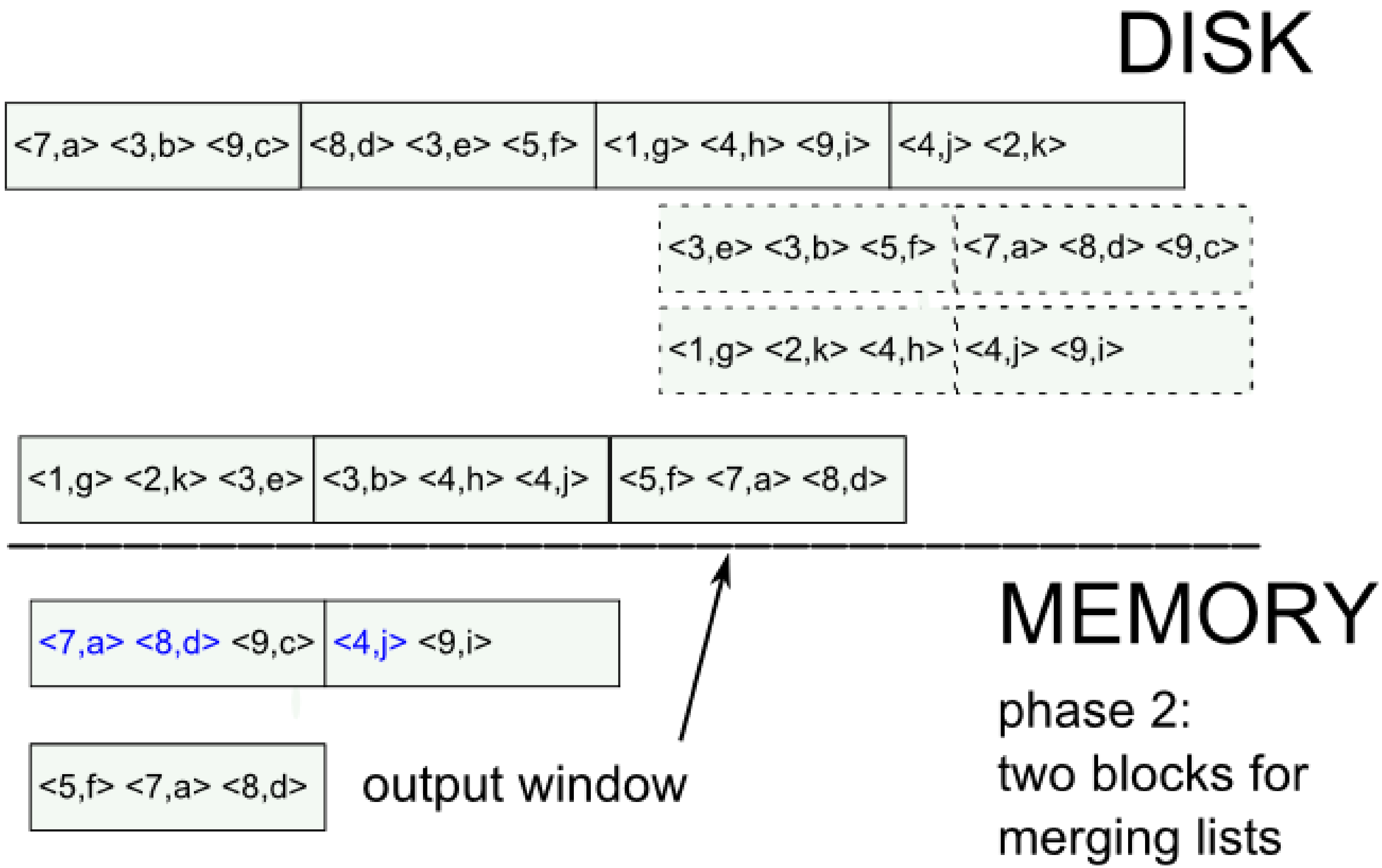
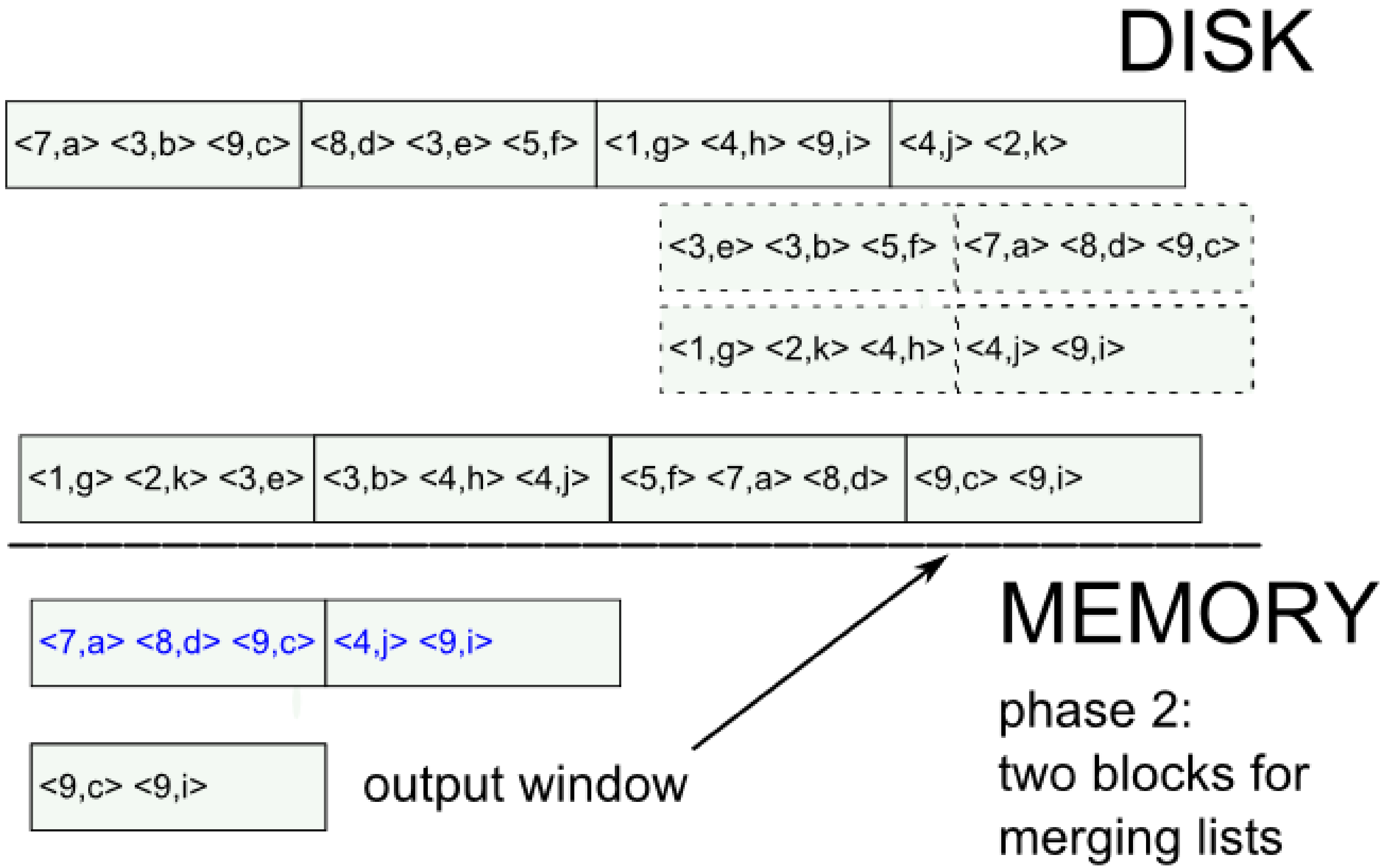
<8,d> <3,e> <5,f>
<1,g> <4,h> <9,i>
<4,j> <2,k>
<3,e> <3,b> <5,f>
<7,a> <8,d> <9,c>
<1,g> <2,k> <4,h>
<4,j> <9,i>
<1,g> <2,k> <3,e>
<3,b> <4,h> <4,j>
MEMORY
<7,a> <8,d> <9,c>
<4,j> <9,i>
<5,f>
output window
phase 2:
two blocks for
merging lists


DISK
<7,a> <3,b> <9,c>
<8,d> <3,e> <5,f>
<1,g> <4,h> <9,i>
<4,j> <2,k>
<3,e> <3,b> <5,f>
<7,a> <8,d> <9,c>
<1,g> <2,k> <4,h>
<4,j> <9,i>
<1,g> <2,k> <3,e>
<3,b> <4,h> <4,j>
<5,f> <7,a> <8,d>
MEMORY
<7,a> <8,d> <9,c>
<4,j> <9,i>
<5,f> <7,a> <8,d>
output window
phase 2:
two blocks for
merging lists


DISK
<7,a> <3,b> <9,c>
<8,d> <3,e> <5,f>
<1,g> <4,h> <9,i>
<4,j> <2,k>
<3,e> <3,b> <5,f>
<7,a> <8,d> <9,c>
<1,g> <2,k> <4,h>
<4,j> <9,i>
<1,g> <2,k> <3,e>
<3,b> <4,h> <4,j>
<5,f> <7,a> <8,d>
<9,c> <9,i>
MEMORY
<7,a> <8,d> <9,c>
<4,j> <9,i>
<9,c> <9,i>
output window
phase 2:
two blocks for
merging lists

External sorting: analysis

- R fits in B(R) blocks
- Scanning R initially requires B(R) disk accesses
- Writing sorted sublists
  (using window block for each bucket)
  requires roughly B(R) disk accesses
- Scanning each sublist for merging requires
  (roughly) B(R) disk accesses
- Writing results requires again (roughly)
  B(R) disk accesses

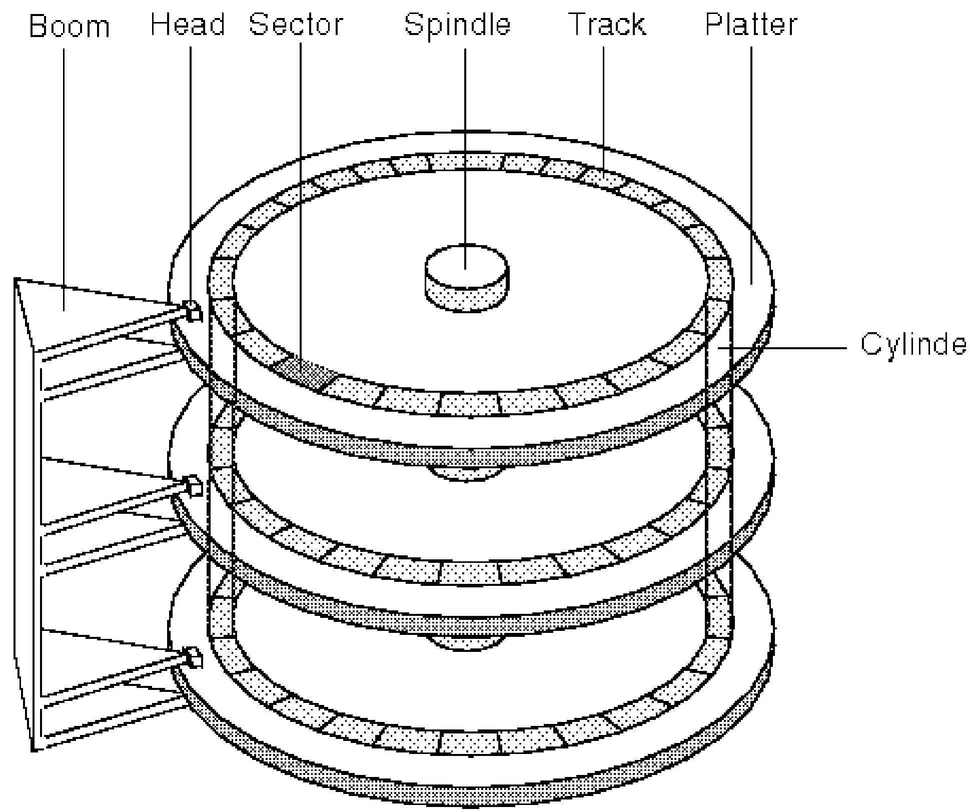
IO = 4 * B(R)

External sorting: example calculation

- IO = 4 * B(R)
- R contains one million tuples
- A tuple contains 400 bytes
- File containing R is 400 MB
- Disk block size is 32 kB
- Number of blocks is 12.500
- Number of IO’s is 50.000
- Suppose one IO takes 5 msec
- Sorting requires 250 sec

External sorting: clustering

- Sorting requires 250 sec, but …
- Assumption: file is *clustered*
- For instance: several blocks on one cylinder…
- … requires 1 x disk arm positioning …
- … *and* less rotation latency



How to do: a selection?

$S := \sigma_{A1 = C1, \ldots, An = Cn} (R)$

Several access paths

- Scan the complete table and check the conditions for each tuple
- If possible, use an index on an attribute contained in $A_1, \ldots, A_n$

How to do: a selection?

$S := \sigma_{A1 = C1, \ldots, An = Cn}(R)$

Suppose you have more than one index available

- *Option 1:* use both indices and calculate the intersection
- *Option 2:* use the most selective index

Choosing a join order

- Suppose you have to join three tables: R, S and T
- Option 1: $(R \bowtie S) \bowtie T$
- Option 2: $R \bowtie (S \bowtie T)$
- Option 3: $S \bowtie (R \bowtie T)$

- Which one is the best?

- Estimate the size of the intermediate result
- Choose the method with the smallest size
- For more than 3 relations, this is a heuristic method
- More sophisticated methods exist, but the search space grows exponentially in the number of relations

Statistics supporting estimations

T(R): the number of tuples in R

B(R): the number of blocks of R on disk

V(R,A): the number of different values of attribute A in R

Challenge: try to estimate the effect of algebraic operators on statistics of intermediate results

Statistics supporting estimations

$R' := \sigma_{A=c}(R)$

$T(R') = \ldots$

$T(R') = T(R)/V(R,A)$

Assumption: homogeneous distribution of A-values in R

Better: histograms

Disadvantage: maintenance

Alternative (very large databases): sampling

Statistics supporting estimations

$U := R \bowtie_{\theta} S$ θ: $R.A = S.A$

$T(U) = \ldots$

$T(U) = T(R)*T(S)/V(S,A)$

$T(U) = T(S)*T(R)/V(R,A)$

Choose minimum?!

How to calculate … a join?

$U := R \bowtie_{\theta} S$ θ: $R.A = S.A$

Horrible feeling: the number of IO's required to calculate the result is proportional to

T(R) * T(S)

… or at least B(R) * B(S)

How to calculate … a join?

$T := R \bowtie_{\theta} S$ $\quad\quad\quad$ $\theta: R.A = S.A$

- Block-nested loop
- Index-nested loop
- Sort-Merge
- Hash-Join

Buffer in main memory: M pages/blocks

How to calculate … a join?

Block-nested loop
S = smallest relation (nr of blocks)

```
foreach chunk of M-1 blocks of S do
    read these blocks into main memory;
    foreach block B2 of R do {
        read B2 into the free memory buffer;
        check all possible combinations
        of tuple t1 in chunk and t2 in B2;
        if (t1.A = t2.A) write the join of these
            tuples to output;
    }
```

How to calculate … a join?

Block-nested loop

S = smallest relation (nr of blocks)

IO: $B(S) + B(R) * \lceil B(S)/(M-1) \rceil$

But note that if S fits in main memory and we have at least one buffer free:

IO: $B(S) + B(R)$ *// optimal !*

How to calculate … a join?

Index-nested loop

assumption: index on S.A

```
foreach block B of R do
    foreach tuple t in B do {
        suppose t.A = a;
        use the index to find all t2 in S
        with t2.A = a;
        write the join of t with each t2 to
            output;
    }
```

How to calculate … a join?

Analysis index-nested loop

c = cost of access index (~2 for B-tree)

μ = average number of tuples found
(estimate from statistics)

IO: $B(R) + (c + \mu)\, T(R)$

$\mu \sim= T(S)/V(S,A)$

If A is superkey in S: $\mu = 1$

How to calculate … a join?

Sort-merge

1. (If necessary) sort R on A
2. (If necessary) sort S on A
3. **repeat**

    read the blocks from
    R and S containing the smallest
    common A-values;
    join the tupels in these blocks;

   until R is empty or S is empty

How to calculate … a join?

Sort-merge

A	B
a	11
b	12
a	13
c	14
c	15
a	16

A	C
b	21
a	22
c	23
b	24
c	25
a	26

1. Sort

A	B
a	11
a	13
a	16
b	12
c	14
c	15

A	C
a	22
a	26
b	21
b	24
c	23
c	25

2. Merge

A	B
a	11
a	13
a	16
b	12
c	14
c	15

A	C
a	22
a	26
b	21
b	24
c	23
c	25

buffer (mem)

A	B
a	11
a	13
a	16

A	C
a	22
a	26
b	21

2. Merge

buffer (mem)

A	B
a	11
a	13
a	16
b	12
c	14
c	15

A	C
a	22
a	26
b	21
b	24
c	23
c	25

A	B
a	11
a	13
a	16

A	C
a	22
a	26
b	21

A	B	C
a	11	22
a	11	26
a	13	22
a	13	26
a	16	22
a	16	26

2. Merge

A	B
a	11
a	13
a	16
b	12
c	14
c	15

A	C
a	22
a	26
b	21
b	24
c	23
c	25

buffer (mem)

A	B
b	12
c	14
c	15

A	C
b	21
b	24
c	23

A	B	C
a	11	22
a	11	26
a	13	22
a	13	26
a	16	22
a	16	26

2. Merge

A	B
a	11
a	13
a	16
b	12
c	14
c	15

A	C
a	22
a	26
b	21
b	24
c	23
c	25

buffer (mem)

A	B
b	12
c	14
c	15

A	C
b	21
b	24
c	23

A	B	C
…	…	…
a	16	26
b	12	21
b	12	24

2. Merge

A	B
a	11
a	13
a	16
b	12
c	14
c	15

A	C
a	22
a	26
b	21
b	24
c	23
c	25

buffer (mem)

A	B
c	14
c	15

A	C
c	23
c	25

A	B	C
…	…	…
b	12	24

2. Merge

A	B
a	11
a	13
a	16
b	12
c	14
c	15

A	C
a	22
a	26
b	21
b	24
c	23
c	25

buffer (mem)

A	B
c	14
c	15

A	C
c	23
c	25

A	B	C
…	…	…
b	12	24
c	14	23
c	14	25
c	15	23
c	15	25

Sort-merge Join on A: analysis

- R and S fit in B(R) and B(S) blocks
- Sorting R and S requires 4*(B(R) + B(S)) disk accesses (if necessary)
- Scanning the sorted sublists requires (roughly) B(R) + B(S) disk accesses
- Ignore writing resulting tuples in analysis (all methods have to do that)

$$IO = 5 * (B(R) + B(S))$$

Applying some smart tricks:

$$IO = 3 * (B(R) + B(S))$$

How to calculate … a join?

Hash Join

1. Choose the size M (nr of buckets) of the hash table
2. Choose a hash functie for the domain of A with codomain 0..M-1
3. Hash every tuple of R to the corresponding bucket
4. Hash every tuple of R to the corresponding bucket
5. Get each bucket into main-memory and construct the resulting tuples

Join R[A,B] with S[A,C]
h(a) = a DIV 10

A	B
12	a
3	b
29	c
7	d
13	e
12	f
27	g

A	C
29	h
7	i
8	j
28	k
12	l

Hash Join on A

A	B
12	a
3	b
29	c
7	d
13	e
12	f
27	g

A	C
29	h
7	i
8	j
28	k
12	l

Bucket: h(a) = 0

A	B

A	C

Bucket: h(a) = 1

A	B

A	C

Bucket: h(a) = 2

A	B

A	C

Hash Join on A

A	B
12	a
3	b
29	c
7	d
13	e
12	f
27	g

A	C
29	h
7	i
8	j
28	k
12	l

Bucket: h(a) = 0

A	B
3	b
7	d

A	C
7	i
8	j

Bucket: h(a) = 1

A	B
12	a
13	e
12	f

A	C
12	l

Bucket: h(a) = 2

A	B
29	c
27	g

A	C
29	h
28	k

Hash Join on A

Bucket:
h(a) = 0

A	B
3	b
7	d

A	C
7	i
8	j

Bucket:
h(a) = 1

A	B
12	a
13	e
12	f

A	C
12	l

Bucket:
h(a) = 2

A	B
29	c
27	g

A	C
29	h
28	k

Join each bucket in main memory:

A	B
3	b
7	d

A	C
7	i
8	j

adds:

A	B	C
7	d	i

Bucket:
h(a) = 0

A	B
3	b
7	d

A	C
7	i
8	j

Bucket:
h(a) = 1

A	B
12	a
13	e
12	f

A	C
12	l

Bucket:
h(a) = 2

A	B
29	c
27	g

A	C
29	h
28	k

Join each bucket in main memory:

A	B
12	a
13	e
12	f

A	C
12	l

adds:

A	B	C
7	d	i
12	a	l
12	f	l

Bucket:
h(a) = 0

A	B
3	b
7	d

A	C
7	i
8	j

Bucket:
h(a) = 1

A	B
12	a
13	e
12	f

A	C
12	l

Bucket:
h(a) = 2

A	B
29	c
27	g

A	C
29	h
28	k

Join each bucket in main memory:

A	B
29	c
27	g

A	C
29	h
28	k

adds:

A	B	C
7	d	i
12	a	l
12	f	l
29	c	h

Hash Join on A: analysis

- R and S fit in B(R) and B(S) blocks
- Scanning R and S to hash the tuples
  requires B(R) + B(S) disk accesses
- Writing tuples to hash table
  (using window block for each bucket)
  requires roughly B(R) + B(S) disk accesses
- Fetching each bucket for joining requires
  (roughly) B(R) + B(S) disk accesses for reading
- Ignore writing resulting tuples in analysis
  (all methods have to do that)

$$IO = 3 * (B(R) + B(S))$$

Physical tuning

- Presence of physical structures facilitates efficient query processing
- Possibilities:
  - indexes
  - keeping tables sorted on a specific attribute
  - keeping tables clustered on a specific index
  - maintaining materialized views
- Task for the DBA: monitor performance and reconsider physical database organization
- Challenge: automatic support for optimizing physical database organization

Dual architecture: OLTP vs OLAP

- OLTP = On Line Transaction Processing
- High volumes of small updating transactions, often in combination with simple queries to identify primary key values
- Typical domain: support of commercial activities
- Real time performance requirements
- High requirements with respect to transaction integrity: concurrency, recovery, constraint satisfaction
- Term: “production database”
- Relatively low number of indexes

Dual architecture: OLTP vs OLAP

- OLAP = On Line Analytical Processing
- Low volumes of massive read-only queries, often changing perspective (sales per week, month, year, article, region, …)
- Typical domain: management information systems
- No real time performance requirements, although …
- No updates, no transaction processing; periodical reloading of preprocessed snapshots from production database
- Physical organization tuned toward read queries: many indices, materialized views, precomputed aggregates, …
- Term: “data warehouse”

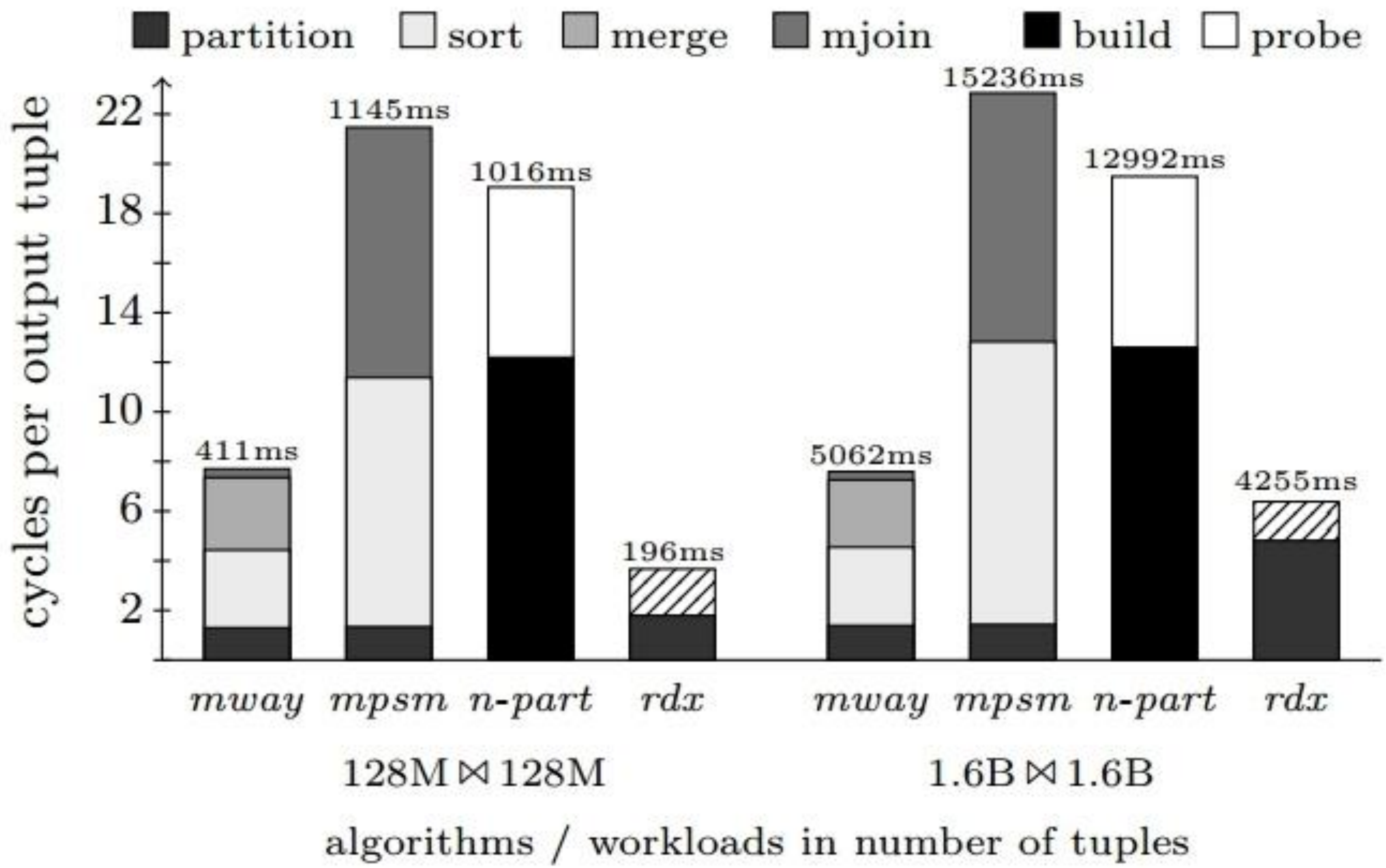
OLAP: main memory databases

- Relevant parts of database resident
- Query processing: focus on minimizing cache misses instead of minimizing IO
- Column stores instead of row stores
  - Irrelevant attributes not loaded
  - Column processing better suited for cache size
  - No overhead w.r.t. tuple management (pack/unpack)
  - But: additional joining required

OLAP: main memory databases

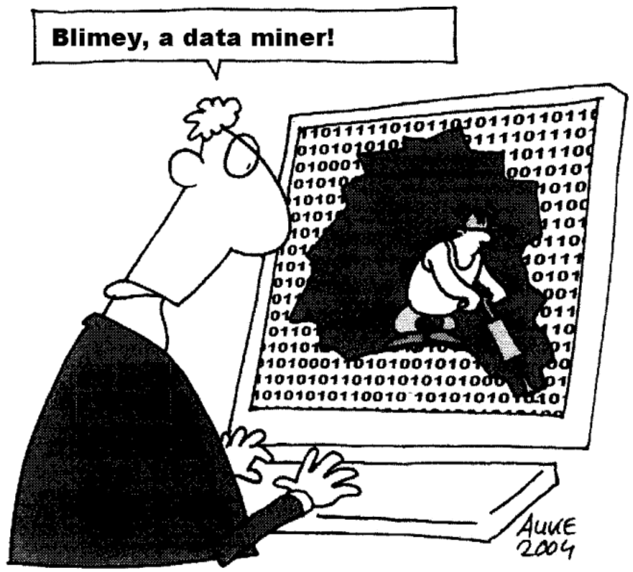
Recent research on join processing

- Intel Sandy Bridge 4*8 cores
- 32kB L1, 256 kB L2, 20 MB L3 cache



Beyond OLAP: data mining

Discovery of interesting patterns and models in data bases



Data mining example

Market basket analysis:

Find groups of products that are often bought together

Data mining example

Market basket analysis folklore: diapers & beer