

CS 6400 A

Database Systems Concepts and Design

Lecture 11
09/30/24

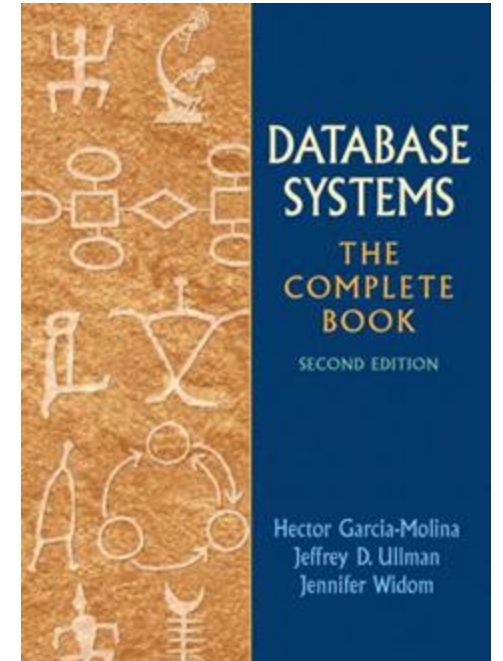
Announcement

- Project proposal due this Wednesday (Oct 2)
- Assignment 2 released today
 - Start early!!!
 - Due Oct 21
- Midterm
 - Answer will be released on canvas
 - Grades will be released on Wednesday

Reading Materials

Database Systems: The Complete Book (2nd edition)

- Chapter 15: Query Execution



Acknowledgement: The following slides have been adapted from CS145 (Intro to Big Data Systems) taught by Peter Bailis.

Agenda

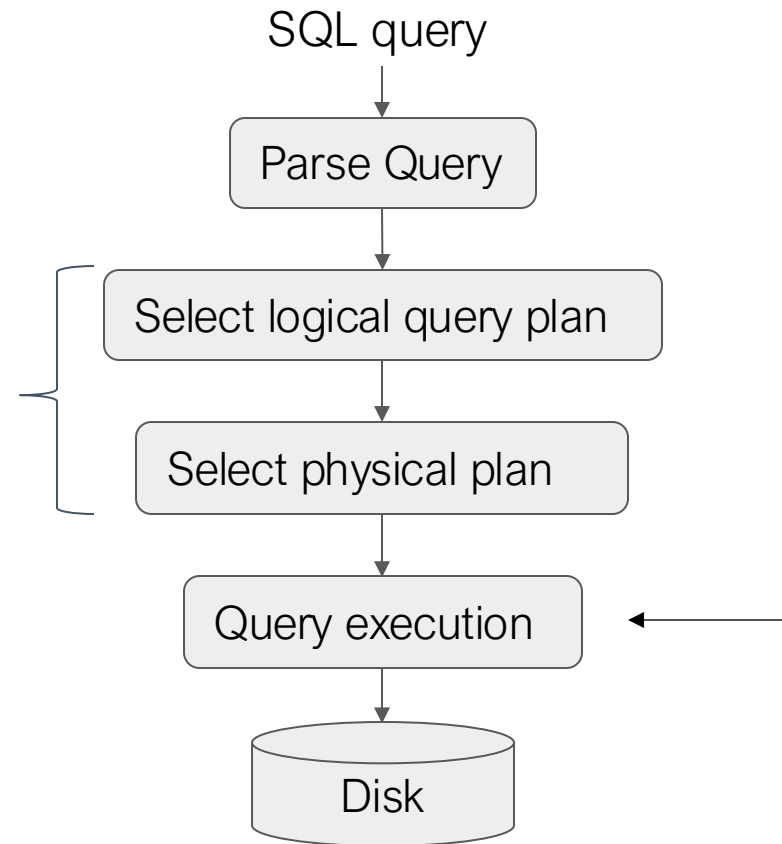
RECAP: Joins

1. Nested Loop Join (NLJ)
2. Sort-Merge Join (SMJ)
3. Hash Join (HJ)

RDBMS Architecture

How does a SQL engine work ?

Query optimization
(next 2 lectures)



Query execution (this lecture): algorithms that manipulate the data of the database

We will use JOIN algorithms as an example

- Arguable one of the most computational expensive operations in relational databases
- As we will see, different implementations of JOINS can make a huge difference in performance.

Joins: Example

R ⋈ **S**

```
SELECT R.A,B,C,D
FROM R, S
WHERE R.A = S.A
```

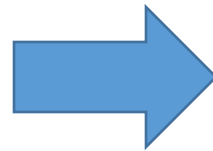
Example: Returns all pairs of tuples $r \in R, s \in S$ such that $r.A = s.A$

R

A	B	C
1	0	1
2	3	4
2	5	2
3	1	1

S

A	D
3	7
2	2
2	3



A	B	C	D
2	3	4	2

Joins: Example

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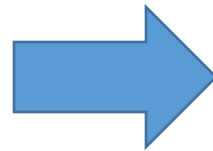
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A	B	C	D
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Joins: Example

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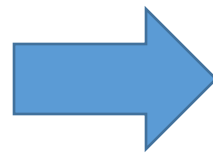
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Joins: Example

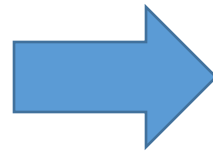
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A	D
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Joins: Example

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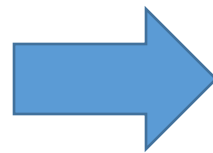
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S

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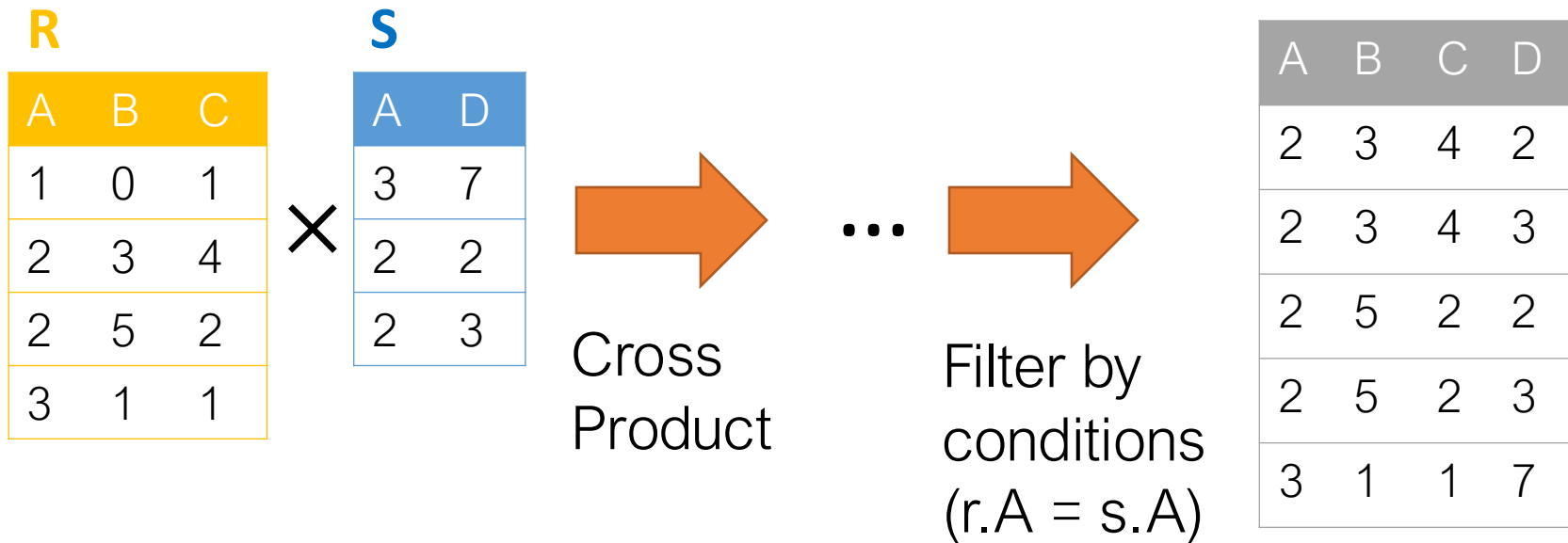
A	B	C	D
2	3	4	2
2	3	4	3
2	5	2	2
2	5	2	3
3	1	1	7

Semantically: A Subset of the Cross Product

$R \bowtie S$

```
SELECT R.A,B,C,D
FROM R, S
WHERE R.A = S.A
```

Example: Returns all pairs of tuples $r \in R, s \in S$ such that $r.A = s.A$



Can we actually implement a join in this way?

1. Nested Loop Joins

Notes

- We write $R \bowtie S$ to mean *join R and S by returning all tuple pairs where all shared attributes are equal*
- We write $R \bowtie S \text{ on } A$ to mean *join R and S by returning all tuple pairs where attribute(s) A are equal*
- For simplicity, we'll consider joins on **two tables** and with **equality constraints** (“equijoins”)

Join can involve > 2 tables, and some algorithms do support non-equality constraints!

Notes

- We are considering “IO aware” algorithms: *care about disk IO*
- Given a relation R , let:
 - $T(R)$ = # of tuples in R
 - $P(R)$ = # of pages in R
- Note also that we omit ceilings in calculations... good exercise to put back in!

Recall that we read / write entire pages with disk IO

Nested Loop Join (NLJ)

Compute $R \bowtie S$ on A :

for r in R :

for s in S :

if $r[A] == s[A]$:

yield (r,s)

Nested Loop Join (NLJ)

Compute $R \bowtie S$ on A :

for r in R :

for s in S :

if $r[A] == s[A]$:

yield (r,s)

Cost:

$P(R)$

1. Loop over the tuples in R

Note that our IO cost is based on the number of pages loaded, not the number of tuples!

Nested Loop Join (NLJ)

Compute $R \bowtie S$ on A :

for r in R :

for s in S :

if $r[A] == s[A]$:

yield (r,s)

Cost:

$$P(R) + T(R) * P(S)$$

1. Loop over the tuples in R
2. For every tuple in R , loop over all the tuples in S

Have to read all of S from disk for every tuple in R !

Nested Loop Join (NLJ)

Compute $R \bowtie S$ on A :

for r in R :

for s in S :

if $r[A] == s[A]$:

yield (r,s)

Cost:

$$P(R) + T(R) * P(S)$$

1. Loop over the tuples in R
2. For every tuple in R , loop over all the tuples in S
3. Check against join conditions

Note that NLJ can handle things other than equality constraints... just check in the if statement!

Nested Loop Join (NLJ)

Compute $R \bowtie S$ on A :

for r in R :

for s in S :

if $r[A] == s[A]$:

yield (r,s)

What would OUT be if our join condition is trivial (if TRUE)?

OUT could be $P(R)*P(S)$... but usually not that bad

Cost:

$$P(R) + T(R)*P(S) + OUT$$

1. Loop over the tuples in R
2. For every tuple in R , loop over all the tuples in S
3. Check against join conditions
4. Write out (to page, then when page full, to disk)

Nested Loop Join (NLJ)

Compute $R \bowtie S$ on A :

for r in R :

for s in S :

if $r[A] == s[A]$:

yield (r,s)

Cost:

$$P(R) + T(R) * P(S) + OUT$$

What if R (“outer”) and S (“inner”) switched?



$$P(S) + T(S) * P(R) + OUT$$

Outer vs. inner selection makes a huge difference-
DBMS needs to know which relation is smaller!

IO-Aware Approach

Block Nested Loop Join (BNLJ)

Compute $R \bowtie S$ on A :

for each $B-1$ pages pr of R :

for page ps of S :

for each tuple r in pr :

for each tuple s in ps :

if $r[A] == s[A]$:

yield (r,s)

Given $B+1$ pages of memory

Cost:

$P(R)$

1. Load in $B-1$ pages of R at a time (leaving 1 page each free for S & output)

Note: There could be some speedup here due to the fact that we're reading in multiple pages sequentially however we'll ignore this here!

Block Nested Loop Join (BNLJ)

Compute $R \bowtie S$ on A :

for each $B-1$ pages pr of R :

for page ps of S :

for each tuple r in pr :

for each tuple s in ps :

if $r[A] == s[A]$:

yield (r,s)

Given $B+1$ pages of memory

Cost:

$$P(R) + \frac{P(R)}{B-1} P(S)$$

1. Load in $B-1$ pages of R at a time (leaving 1 page each free for S & output)
2. For each $(B-1)$ -page segment of R , load each page of S

Note: Faster to iterate over the smaller relation first!

Block Nested Loop Join (BNLJ)

Compute $R \bowtie S$ on A :

for each $B-1$ pages pr of R :

for page ps of S :

for each tuple r in pr :

for each tuple s in ps :

if $r[A] == s[A]$:

yield (r,s)

Given $B+1$ pages of memory

Cost:

$$P(R) + \frac{P(R)}{B-1} P(S)$$

1. Load in $B-1$ pages of R at a time (leaving 1 page each free for S & output)
2. For each $(B-1)$ -page segment of R , load each page of S
3. Check against the join conditions

BNLJ can also handle non-equality constraints

Block Nested Loop Join (BNLJ)

Compute $R \bowtie S$ on A :

for each $B-1$ pages pr of R :

for page ps of S :

for each tuple r in pr :

for each tuple s in ps :

if $r[A] == s[A]$:

yield (r,s)

Given $B+1$ pages of memory

Cost:

$$P(R) + \frac{P(R)}{B-1} P(S) + \text{OUT}$$

1. Load in $B-1$ pages of R at a time (leaving 1 page each free for S & output)
2. For each $(B-1)$ -page segment of R , load each page of S
3. Check against the join conditions
4. Write out

BNLJ vs. NLJ: Benefits of IO Aware

In BNLJ, by loading larger chunks of R, we minimize the number of full *disk reads* of S

- We only read all of S from disk for *every (B-1)-page segment of R!*
- Still the full cross-product, but more done only *in memory*

NLJ

$$P(R) + T(R) * P(S) + \text{OUT}$$



BNLJ

$$P(R) + \frac{P(R)}{B-1} P(S) + \text{OUT}$$

BNLJ is faster by roughly $\frac{(B-1)T(R)}{P(R)}$!

BNLJ vs. NLJ: Benefits of IO Aware

Example:

- R: 500 pages
- S: 1000 pages
- 100 tuples / page
- We have 12 pages of memory ($B = 11$)

Ignoring OUT here...

NLJ: Cost = $500 + 50,000 * 1000 = 50$ Million IOs \approx 140 hours

BNLJ: Cost = $500 + \frac{500 * 1000}{10} = 50$ *Thousand* IOs \approx 0.14 hours

A very real difference from a small change
in the algorithm!

Smarter than Cross-Products

Smarter than Cross-Products: From Quadratic to Nearly Linear

All joins that compute the *full cross-product* have some **quadratic** term

- For example we saw: NLJ $P(R) + T(R)P(S) + OUT$

BNLJ $P(R) + \frac{P(R)}{B-1}P(S) + OUT$

Now we'll see some (nearly) linear joins:

- $\sim O(P(R) + P(S) + OUT)$, where again *OUT* could be quadratic but is usually better

We get this gain by taking advantage of structure - equality constraints ("equijoin") only!

Index Nested Loop Join (INLJ)

Compute $R \bowtie S$ on A :

Given index idx on $S.A$:

for r in R :

if s in $idx(r[A])$:

yield r,s

Cost:

$$P(R) + T(R)*L + OUT$$

where L is the IO cost to access all the distinct values in the index; assuming these fit on one page, $L \sim 3$ is good est.

→ We can use an index (e.g. B+ Tree) to avoid doing the full cross-product!

2. Sort-Merge Join (SMJ)

Sort Merge Join (SMJ): Basic Procedure

To compute $R \bowtie S$ on A :

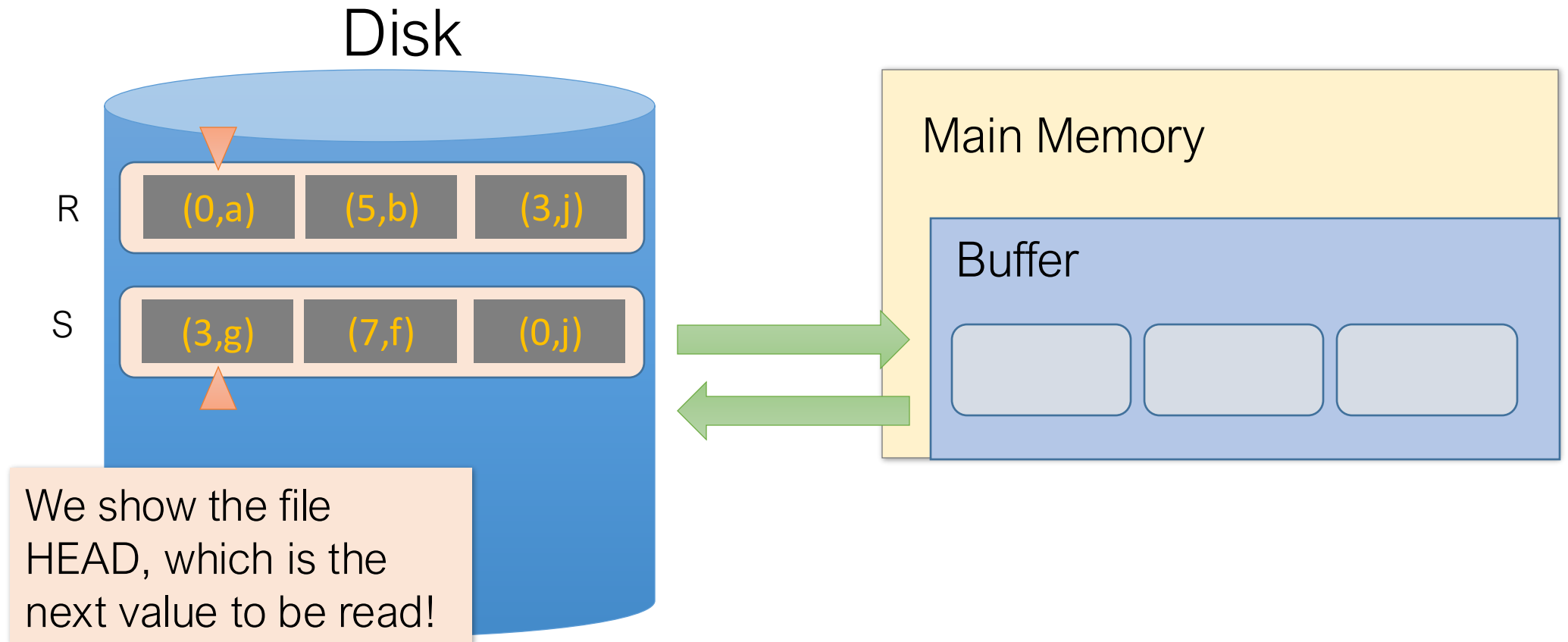
Note that we are only considering equality join conditions here

1. Sort R , S on A using *external merge sort*
2. *Scan* sorted files and “merge”
3. [*May need to “backup”- see next subsection*]

Note that if R , S are already sorted on A , SMJ will be awesome!

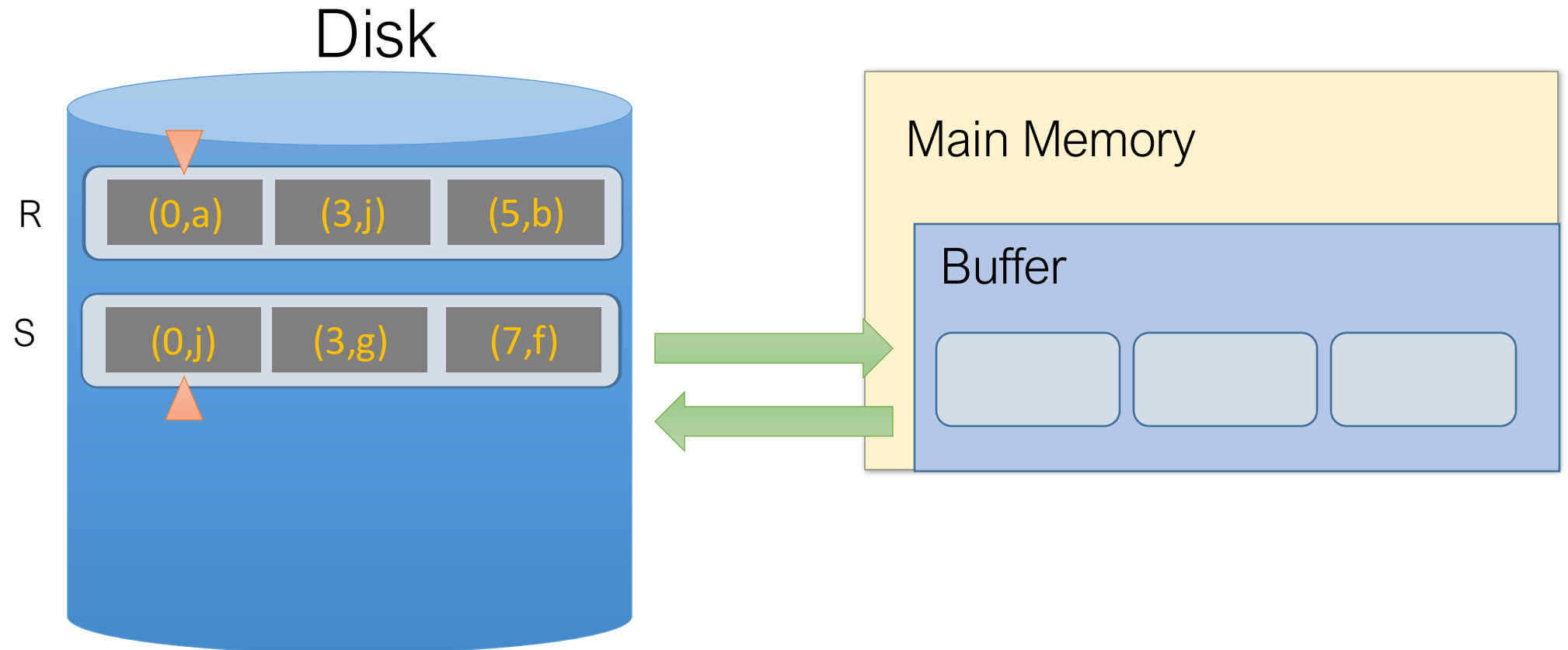
SMJ Example: $R \bowtie S$ on A with 3 page buffer

- For simplicity: Let each page be *one tuple*, and let the first value be A



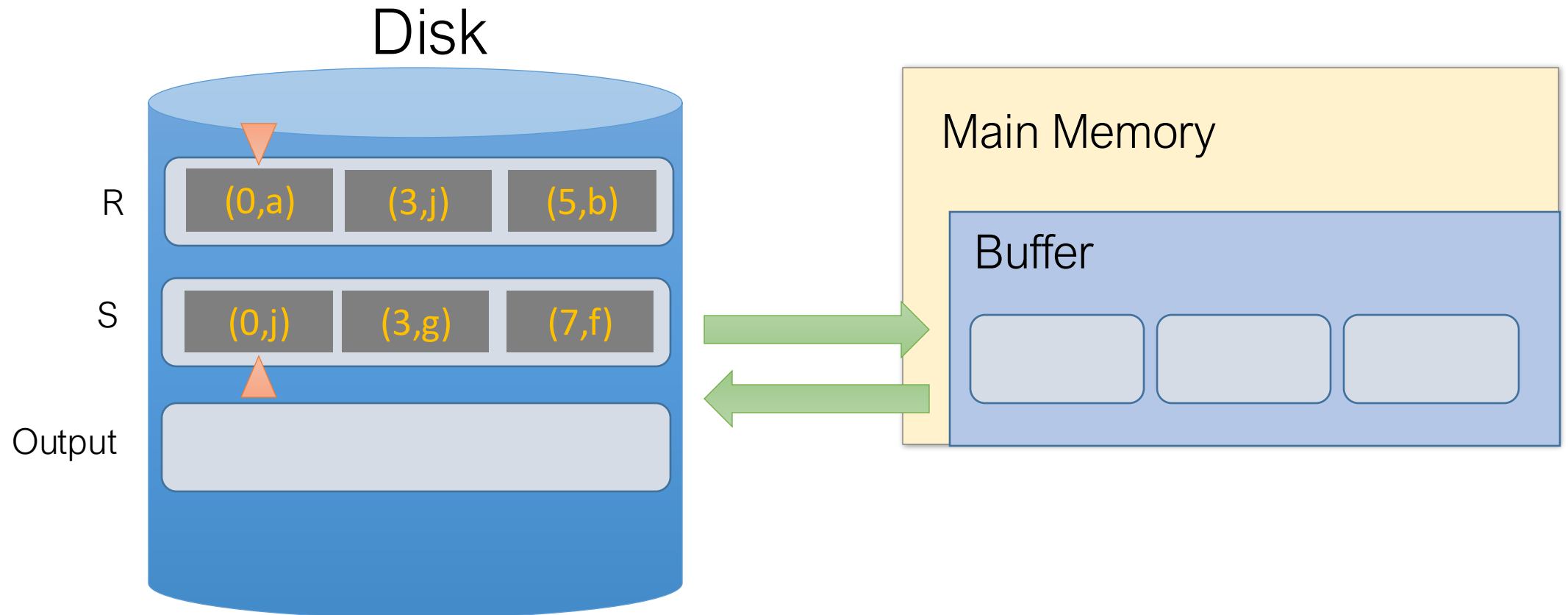
SMJ Example: $R \bowtie S$ on A with 3 page buffer

1. Sort the relations R , S on the join key (first value)



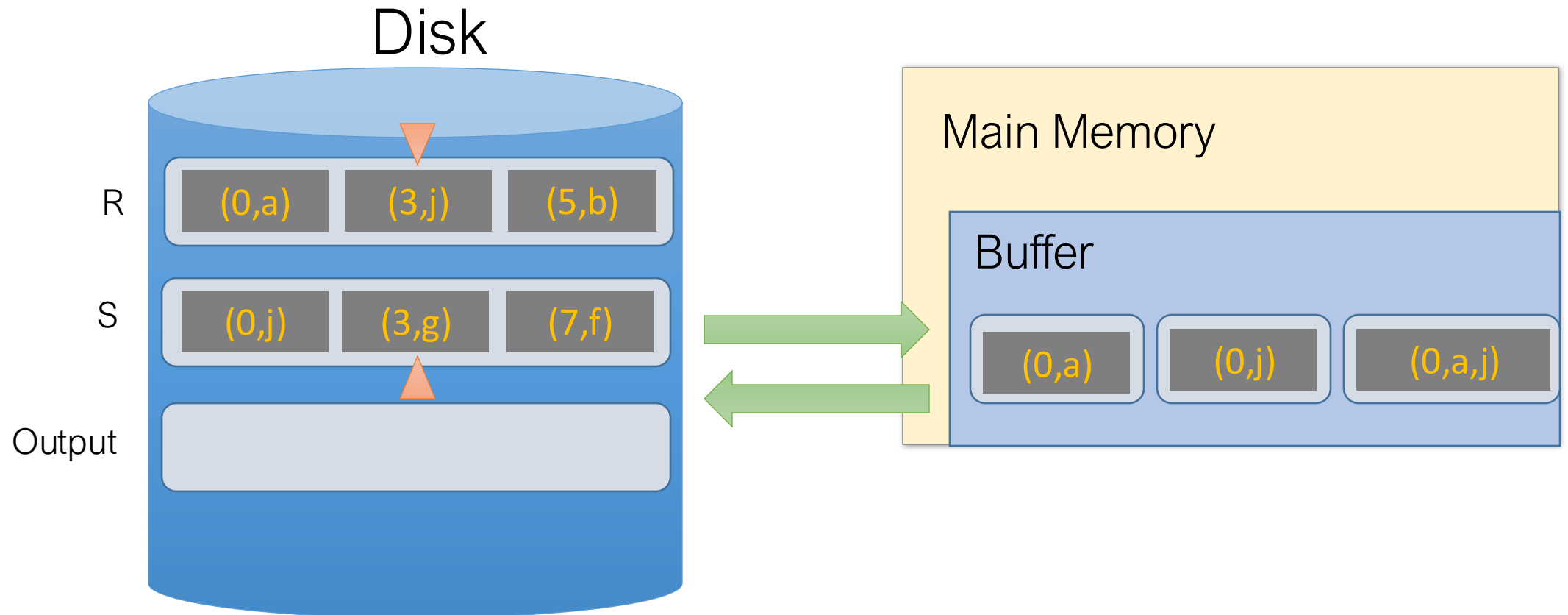
SMJ Example: $R \bowtie S$ on A with 3 page buffer

2. Scan and “merge” on join key!



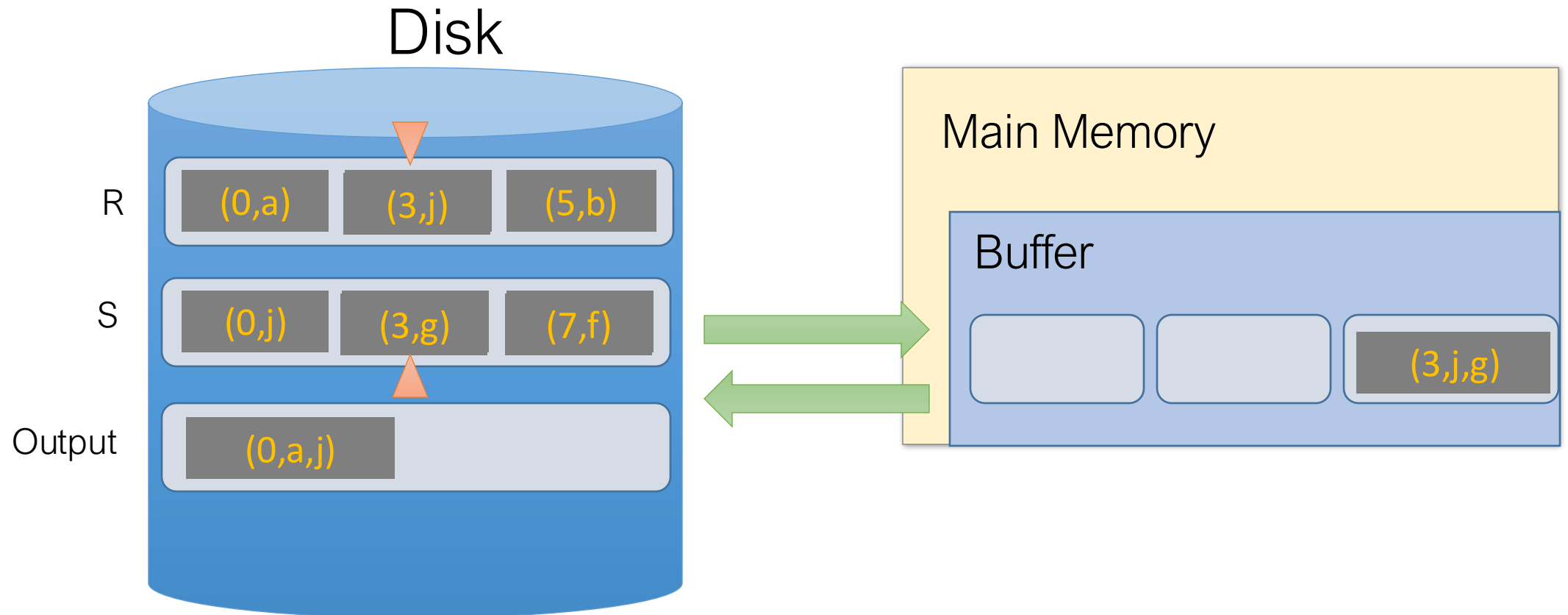
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2. Scan and “merge” on join key!



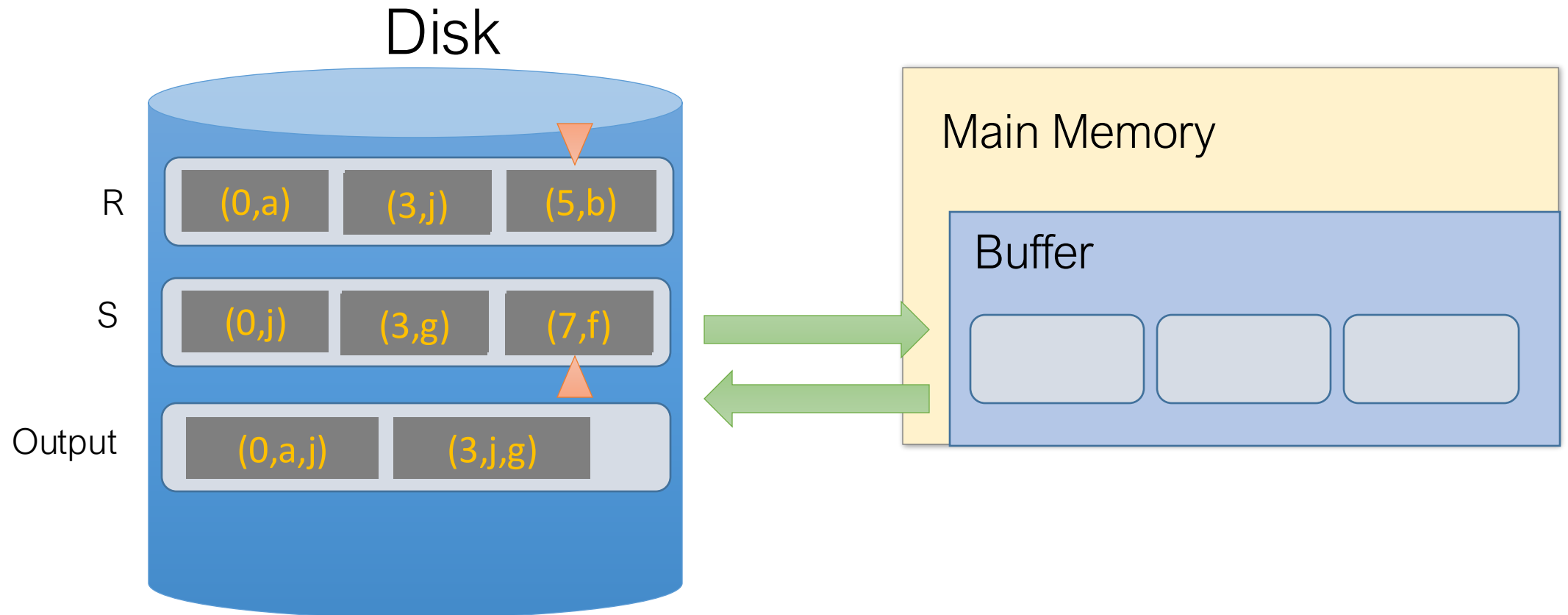
SMJ Example: $R \bowtie S$ on A with 3 page buffer

2. Scan and “merge” on join key!



SMJ Example: $R \bowtie S$ on A with 3 page buffer

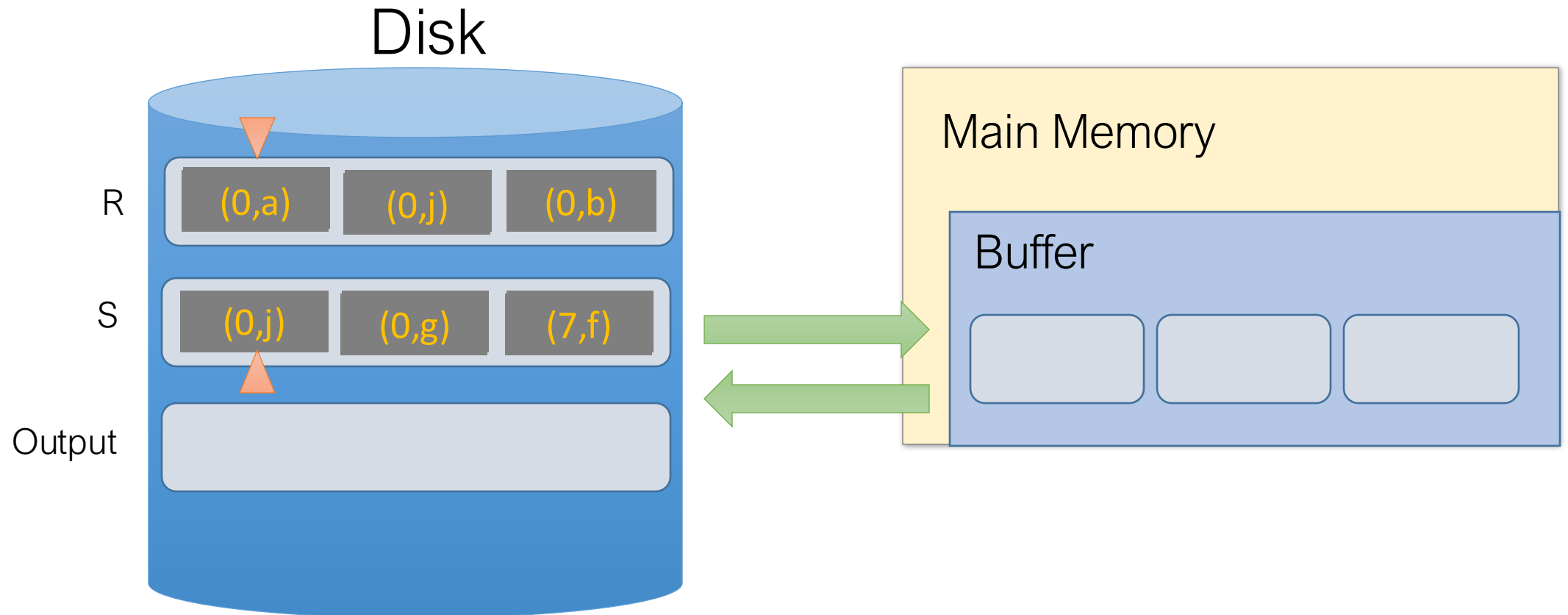
2. Done!



What happens with duplicate
join keys?

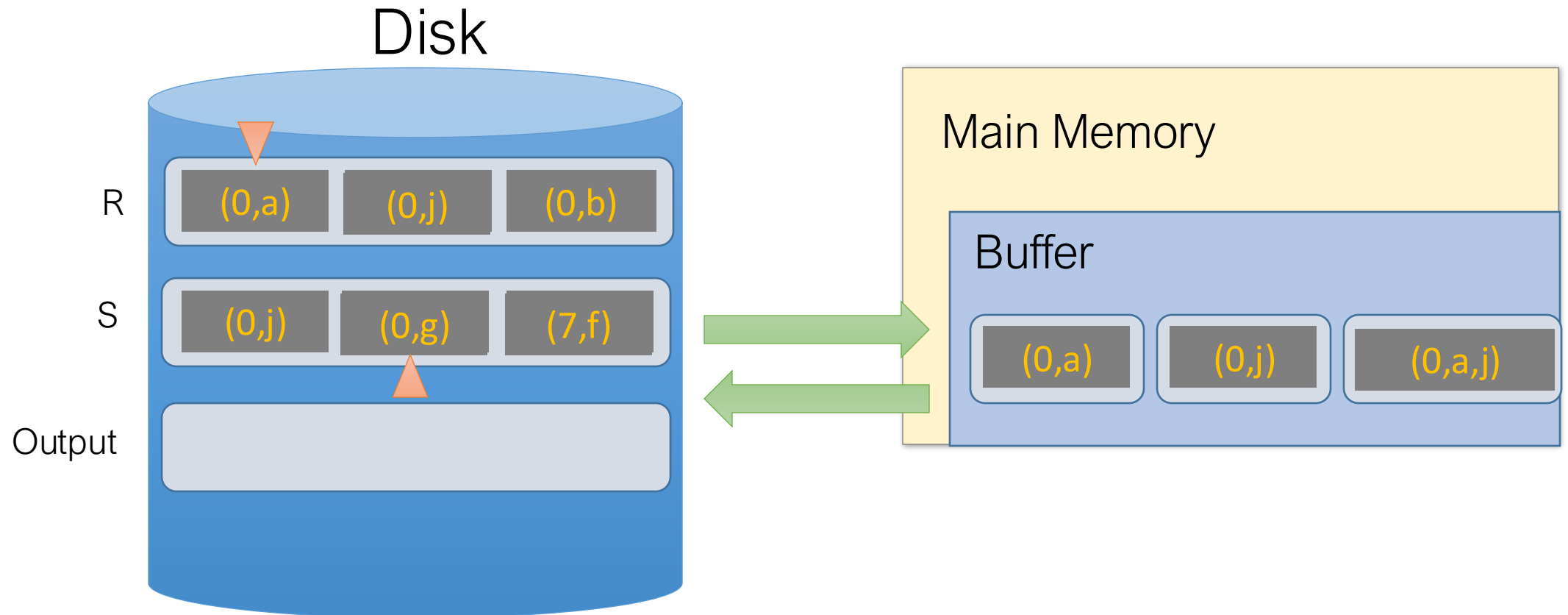
Multiple tuples with Same Join Key: “Backup”

1. Start with sorted relations, and begin scan / merge...



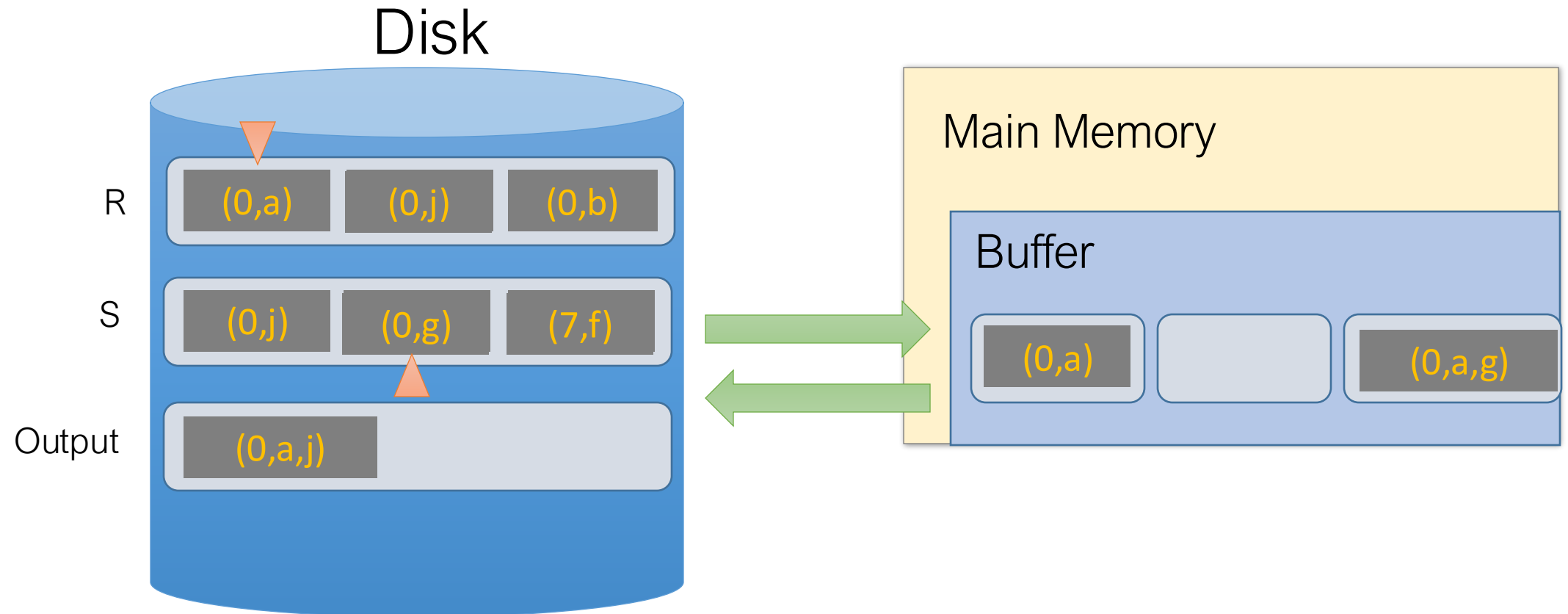
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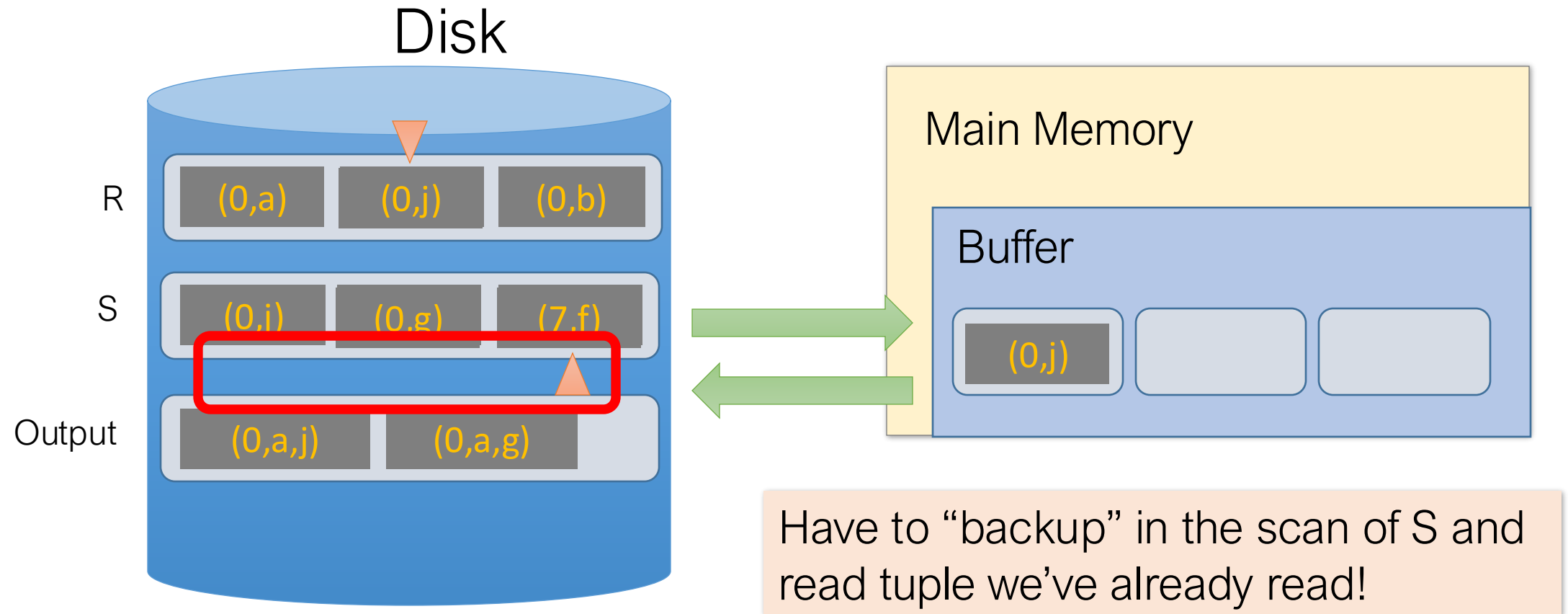
Multiple tuples with Same Join Key: “Backup”

1. Start with sorted relations, and begin scan / merge...



Multiple tuples with Same Join Key: “Backup”

1. Start with sorted relations, and begin scan / merge...



Backup

At best, no backup \rightarrow scan takes $P(R) + P(S)$ reads

- For ex: if no duplicate values in join attribute

At worst (e.g. full backup each time), scan could take $P(R) * P(S)$ reads!

- For ex: if *all* duplicate values in join attribute, i.e. all tuples in R and S have the same value for the join attribute
- Roughly: For each page of R, we'll have to *back up* and read each page of S...

Often not that bad however, plus we can:

- Leave more data in buffer (for larger buffers)

SMJ: Total cost

Cost of SMJ is **cost of sorting** R and S...

What's the cost of sorting?

Plus the **cost of scanning**: $\sim P(R) + P(S)$

- Because of *backup*: in worst case $P(R) * P(S)$; but this would be very unlikely

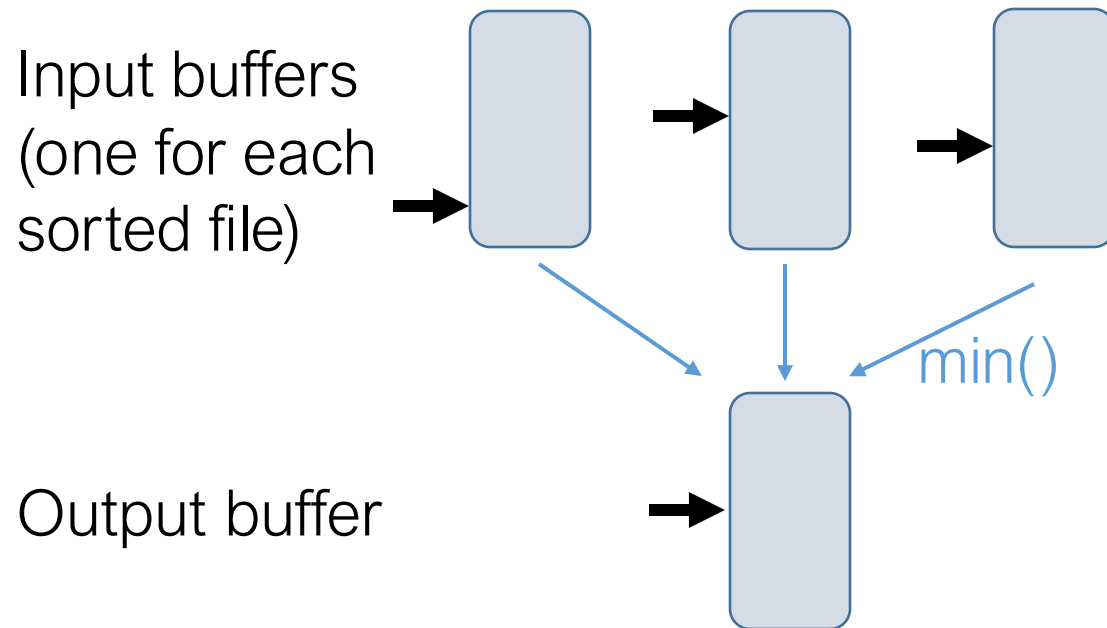
Plus the **cost of writing out**

$\sim \text{Sort}(P(R)) + \text{Sort}(P(S)) + P(R) + P(S) + \text{OUT}$

External Merge Sort

Phase 1. Split R into files small enough to sort in memory. Write sorted files to disk.

Phase 2. B-way merge of sorted files



Given $B+1$ buffer page

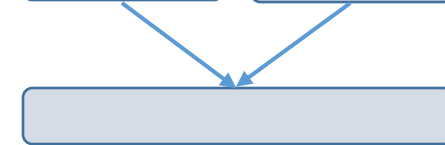
Unsorted input file



Split & sort



Merge



Merge

Sorted!

External Merge Sort

Phase 1. Split R into files small enough to sort in memory. Write sorted files to disk.

Phase 2. B-way merge of sorted files

IO costs:

- Phase 1: 1 Read and 1 Write per page = $2N$ IOs
- Phase 2: 1 Read per page = N IOs

Given $B+1$ buffer page

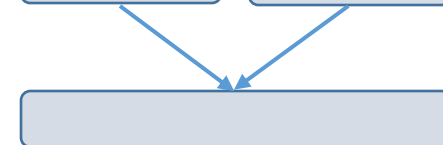
Unsorted input file



Split & sort



Merge



Merge

Sorted!

SMJ vs. BNLJ

If we have 100 buffer pages, $P(R) = 1000$ pages and $P(S) = 500$ pages:

- Sort both in two passes: $2 * 2 * (1000 + 500) = 6,000$ IOs
- Merge phase $1000 + 500 = 1,500$ IOs
- $= 7,500$ IOs + OUT

What is BNLJ?

- $500 + 1000 * \left\lceil \frac{500}{98} \right\rceil = \underline{6,500 \text{ IOs} + \text{OUT}}$

But, if we have 35 buffer pages?

- Sort Merge has same behavior (still 2 passes)
- BNLJ? $15,500$ IOs + OUT!

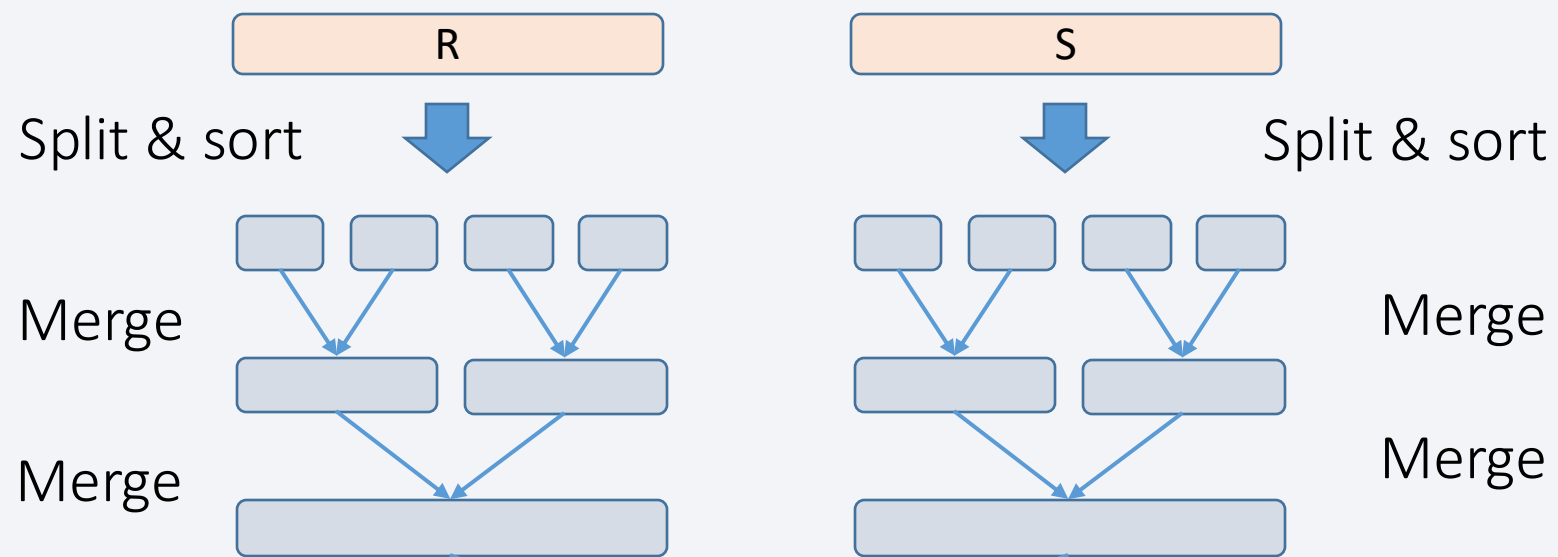
SMJ is ~ linear vs. BNLJ is quadratic...
But it's all about the memory.

Un-Optimized SMJ

Given $B+1$ buffer pages

Unsorted input relations

Sort Phase
(Ext. Merge Sort)



Merge / Join Phase

Joined output
file created!

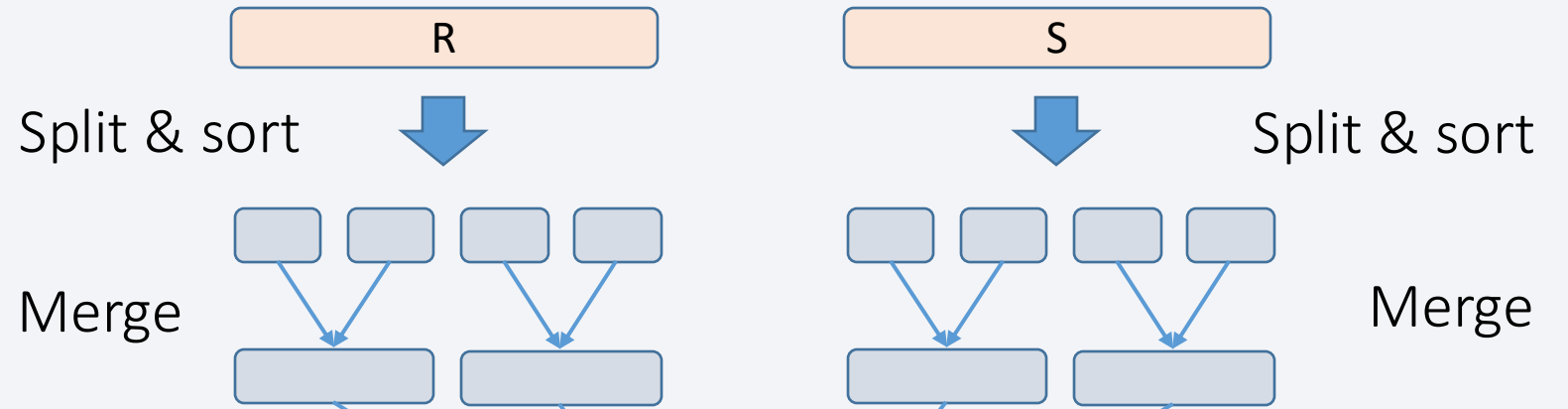
Simple SMJ Optimization

Given $B+1$ buffer pages

Unsorted input relations

Sort Phase
(Ext. Merge Sort)

$\leq B$ total sorted files



Merge / Join Phase

B-Way Merge / Join

Joined output
file created!

Simple SMJ Optimization

Given $B+1$ buffer pages

On this last pass, we only do $P(R) + P(S)$ IOs to complete the join!

We are saving two disk I/O's per block by combining the second phase of the sorts with the join itself. $3(P(R) + P(S)) + OUT$ for SMJ!

- 2 R/W per page to sort runs in memory, 1 R per page to B-way merge / join!

How much memory for this to happen?

- $\frac{P(R)+P(S)}{B} \leq B$
- Thus, $\max\{P(R), P(S)\} \leq B^2$ is an approximate sufficient condition

If the larger of R,S has $\leq B^2$ pages, then SMJ costs $3(P(R)+P(S)) + OUT!$

Takeaway points from SMJ

If input already sorted on join key, skip the sorts.

- SMJ is basically linear.
- Nasty but unlikely case: Many duplicate join keys.

SMJ needs to sort **both** relations

- If $\max \{ P(R), P(S) \} < B^2$ then cost is $3(P(R)+P(S)) + OUT$

3. Hash Join (HJ)

Recall: Hashing

- **Magic of hashing:**
 - A hash function h_B maps into $[0, B-1]$
 - And maps nearly uniformly
- A hash **collision** is when $x \neq y$ but $h_B(x) = h_B(y)$
 - Note however that it will never occur that $x = y$ but $h_B(x) \neq h_B(y)$
- We hash on an attribute A , so our hash function is $h_B(t)$ has the form $h_B(t.A)$.
 - **Collisions** may be more frequent.

Hash Join: High-level procedure

Given $B+1$ buffer pages

To compute $R \bowtie S$ on A :

1. **Partition Phase:** Using one (shared) hash function h_B per pass partition R and S into B buckets.
 - Each phase creates B more buckets that are a factor of B smaller.
 - Repeatedly partition with a new hash function
 - Stop when all buckets for one relation are smaller than $B-1$ pages

Each pass takes $2(P(R) + P(S))$

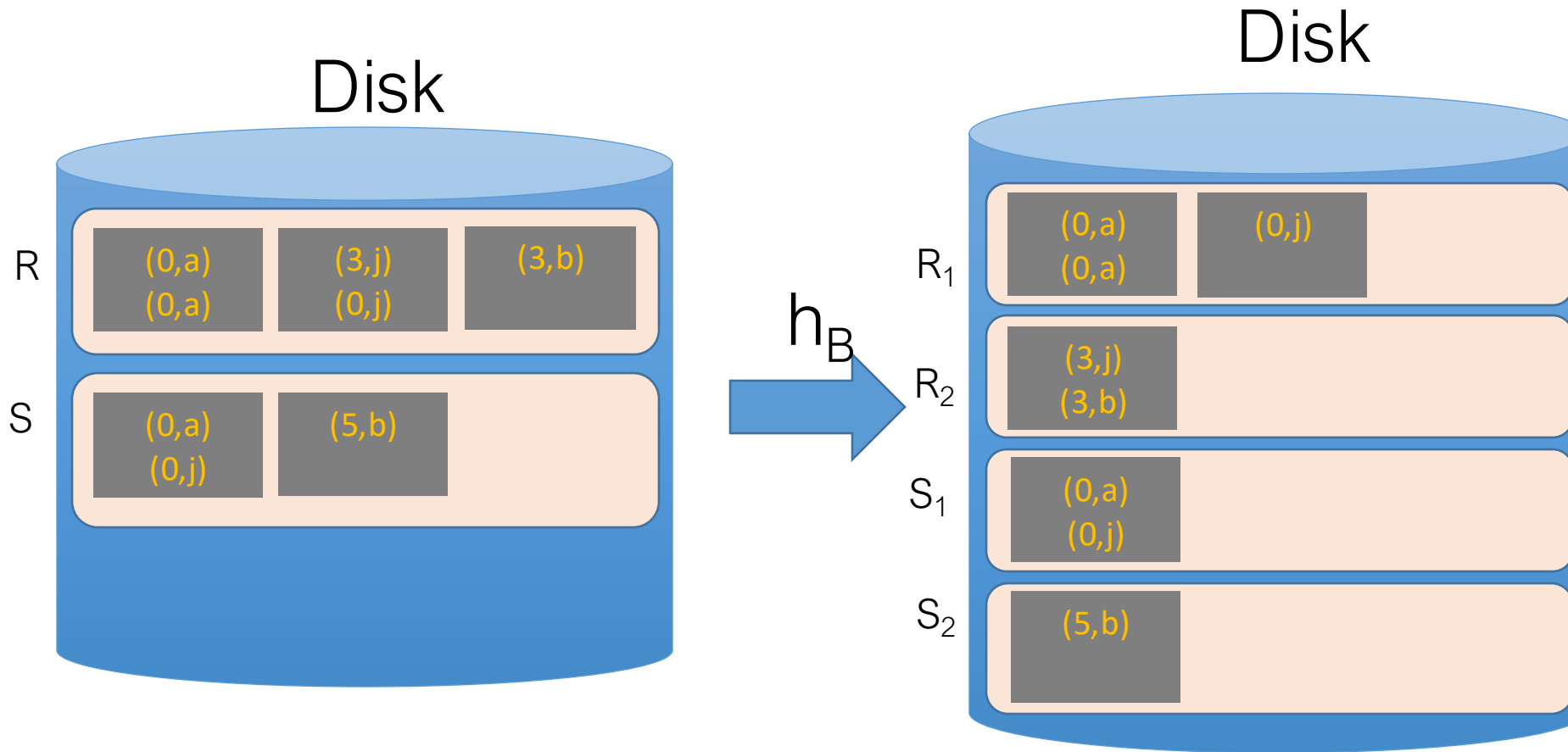
2. **Matching Phase:** Take pairs of buckets whose tuples have the same values for h , and join these
 - Use BNLJ here for each matching pair.

$P(R) + P(S) + OUT$

We *decompose* the problem using h_B , then complete the join

Hash Join: High-level procedure

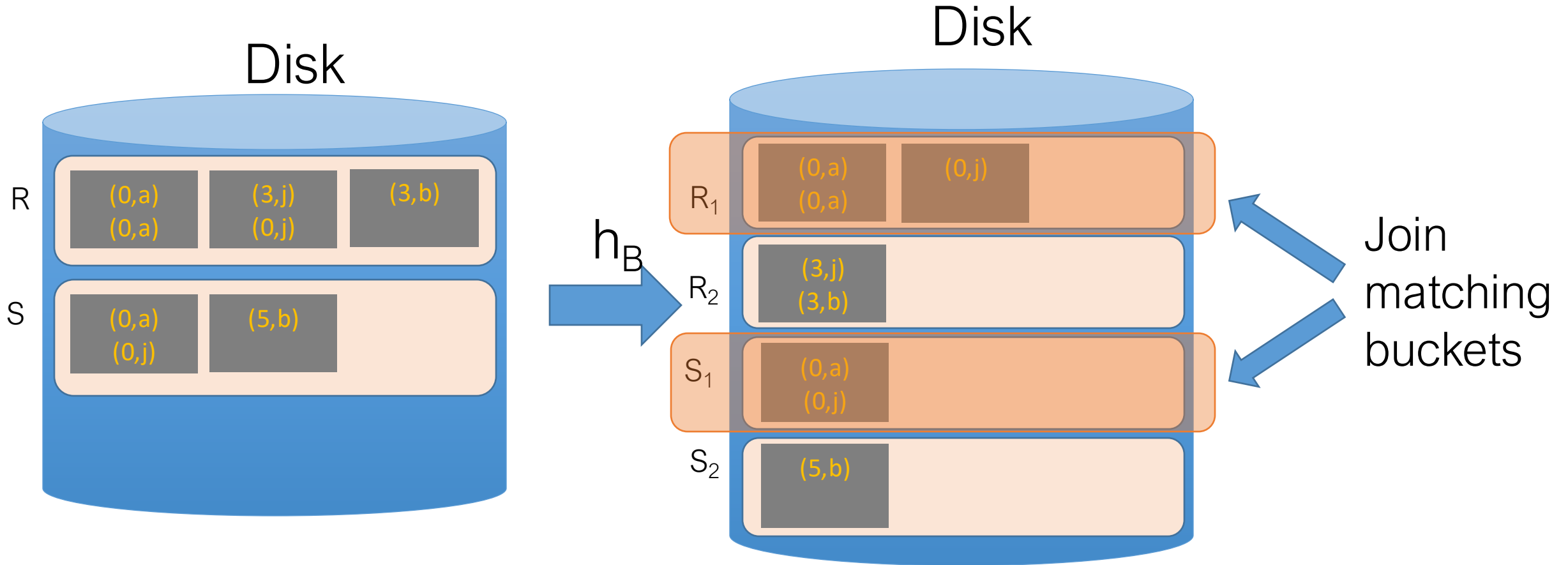
1. **Partition Phase:** Using one (shared) hash function h_B , partition R and S into B buckets



Suppose each pages has two tuples (one per row)

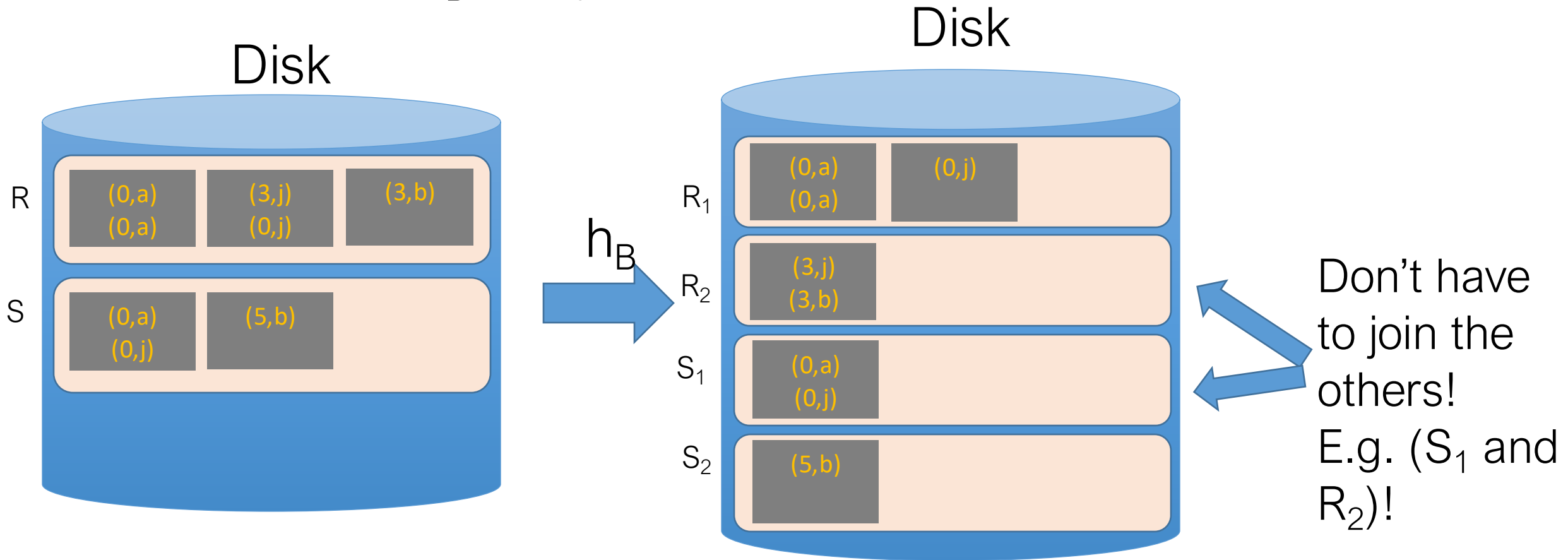
Hash Join: High-level procedure

2. Matching Phase: Take pairs of buckets whose tuples have the same values for h_B , and join these



Hash Join: High-level procedure

2. Matching Phase: Take pairs of buckets whose tuples have the same values for h_B , and join these

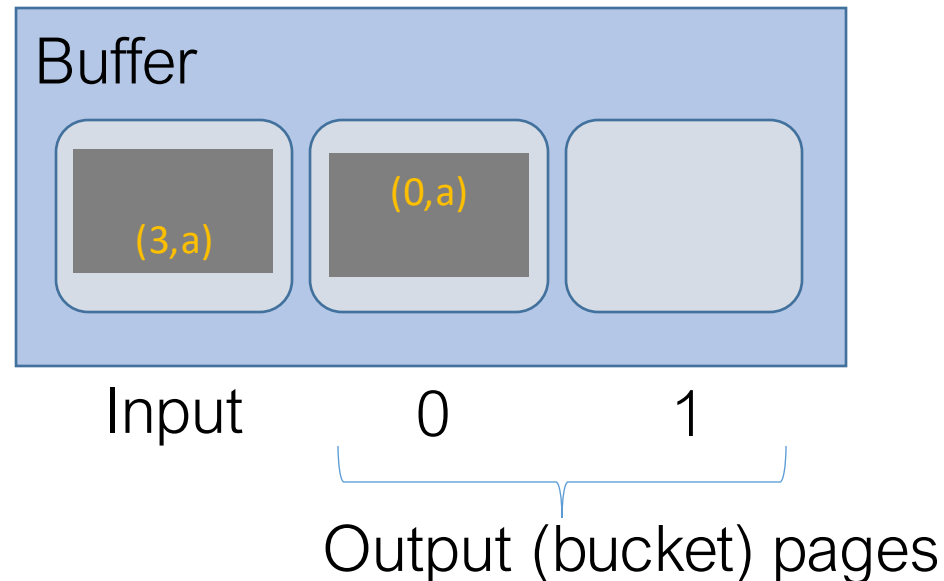


Hash Join Phase 1: Partitioning

Goal: For each relation, partition relation into **buckets** such that if $h_B(t.A) = h_B(t'.A)$ they are in the same bucket

Given $B+1$ buffer pages, we partition into B buckets:

- We use B buffer pages for output (one for each bucket), and 1 for input



How big *do we want* the resulting buckets?

Given $B+1$ buffer pages

Ideally, our buckets would be of size $\leq \mathbf{B - 1}$ pages

Recall: If we want to join a bucket from R and one from S , we can do BNLJ **in linear time** if for *one of them* (*wlog say R*), $\mathbf{P(R) \leq B - 1!}$

Recall for BNLJ:

$$P(R) + \frac{P(R)P(S)}{B - 1}$$

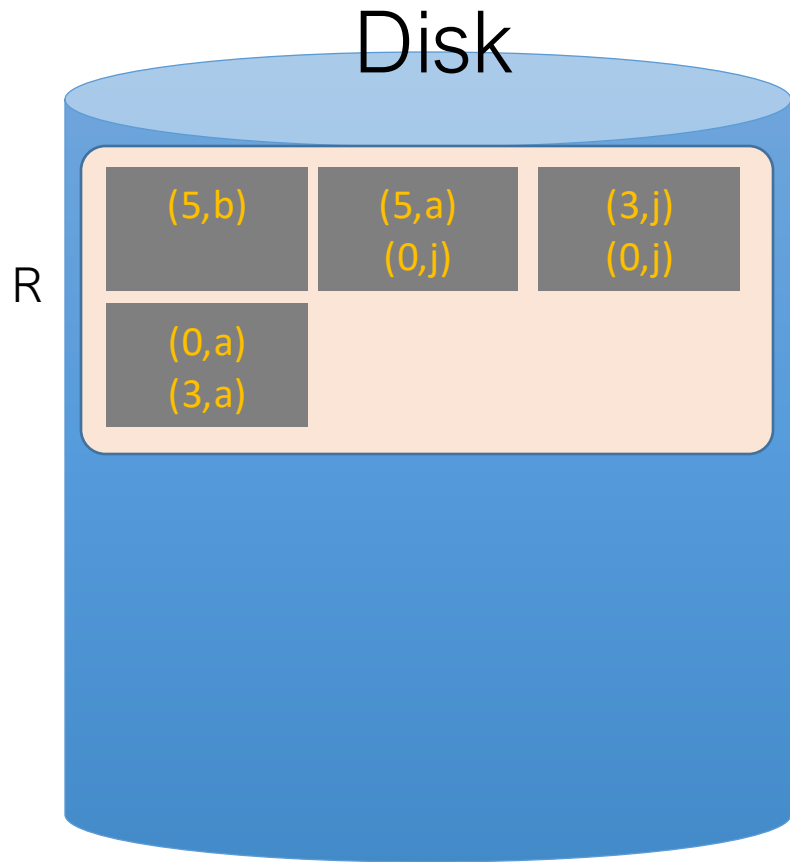
- And more generally, being able to fit bucket in memory is advantageous
- We can keep partitioning buckets until they are $\leq \mathbf{B - 1}$ pages
 - Using a new hash key which will split them...

We'll call each of these a "pass" again...

Hash Join Phase 1: Partitioning

Given $B+1 = 3$ buffer pages

We partition into $B = 2$ buckets using hash function h_2 so that we can have one buffer page for each partition (and one for input)



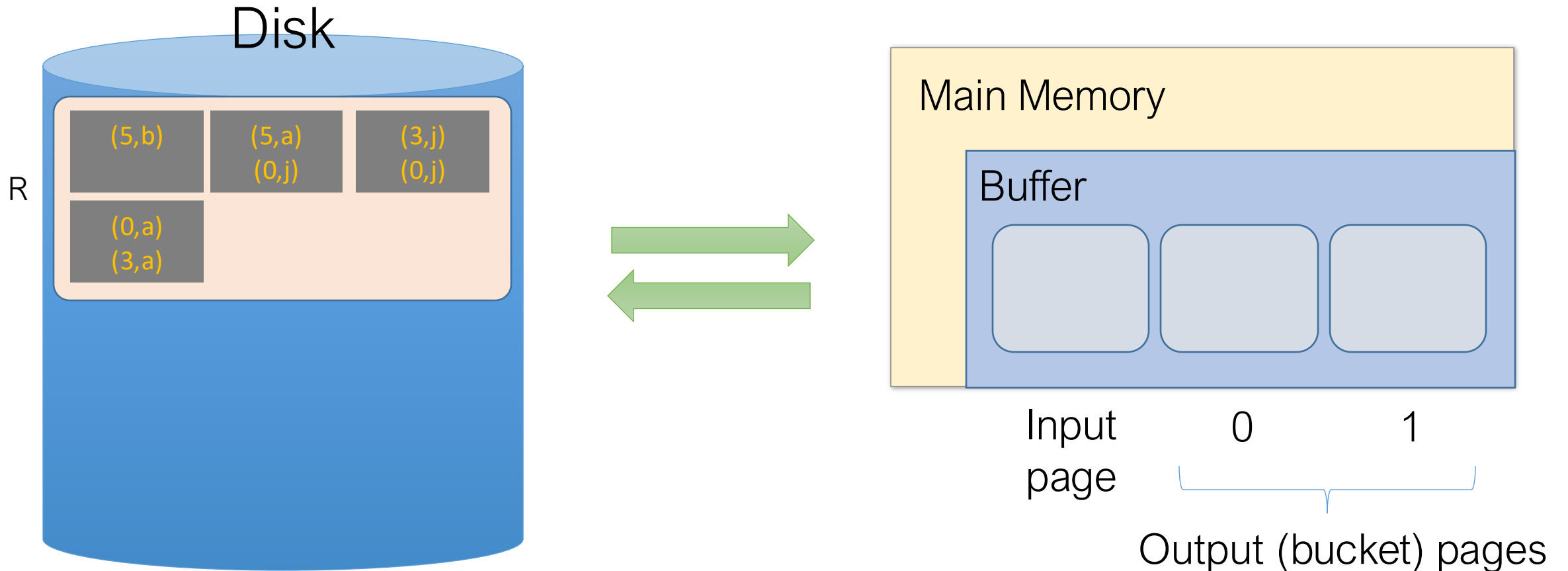
For simplicity, we'll look at partitioning one of the two relations- we just do the same for the other relation!

Recall: our goal will be to get $B = 2$ buckets of size $\leq B-1 \rightarrow 1$ page each

Hash Join Phase 1: Partitioning

Given $B+1 = 3$ buffer pages

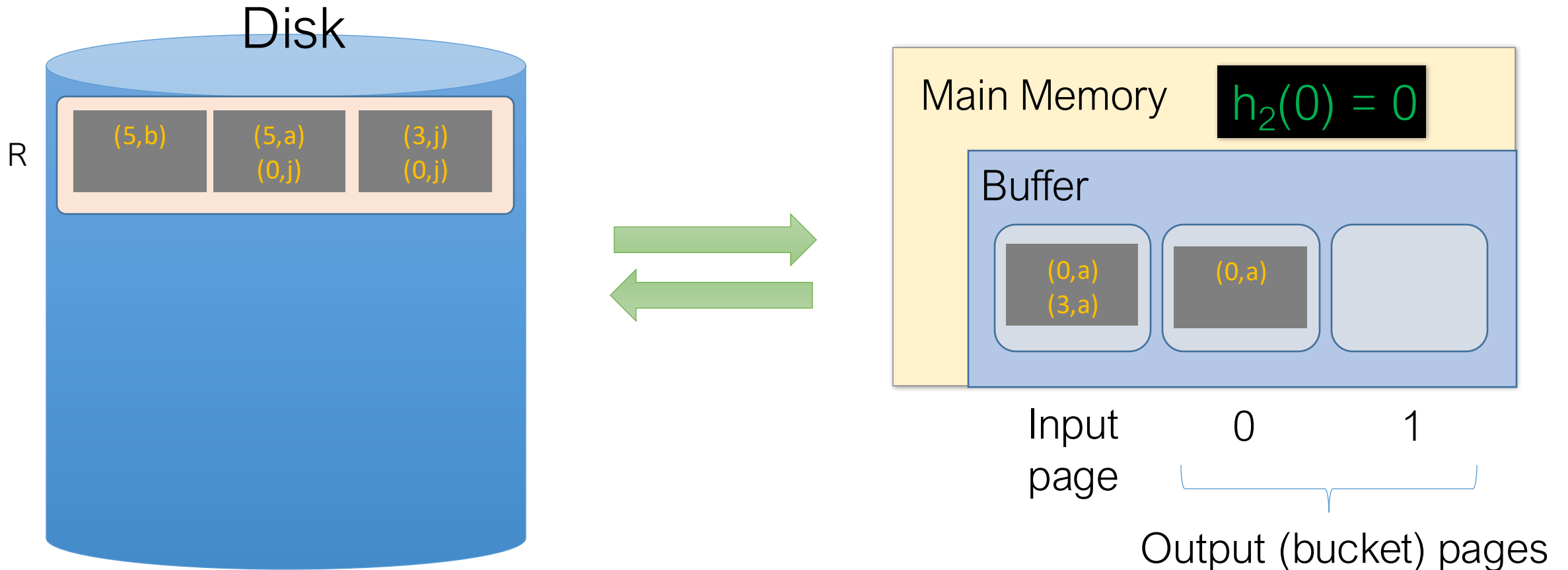
1. We read pages from R into the “input” page of the buffer...



Hash Join Phase 1: Partitioning

Given $B+1 = 3$ buffer pages

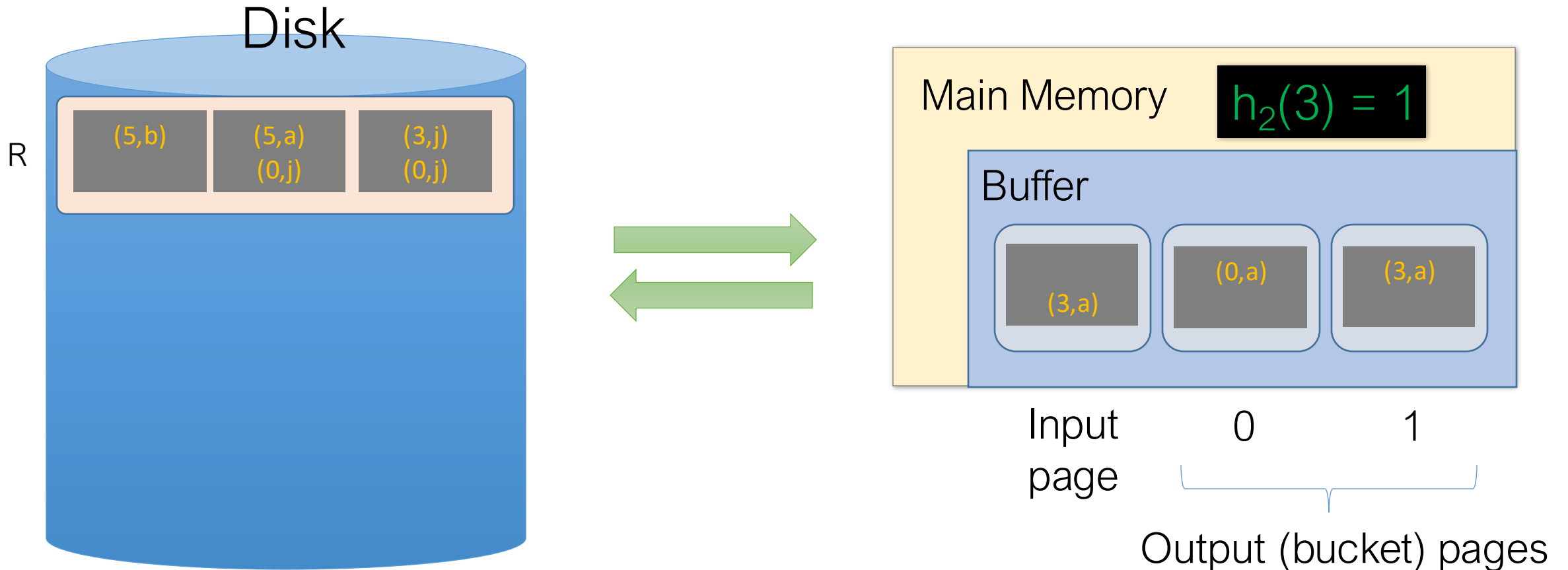
2. Then we use **hash function** h_2 to sort into the buckets, which each have one page in the buffer



Hash Join Phase 1: Partitioning

Given $B+1 = 3$ buffer pages

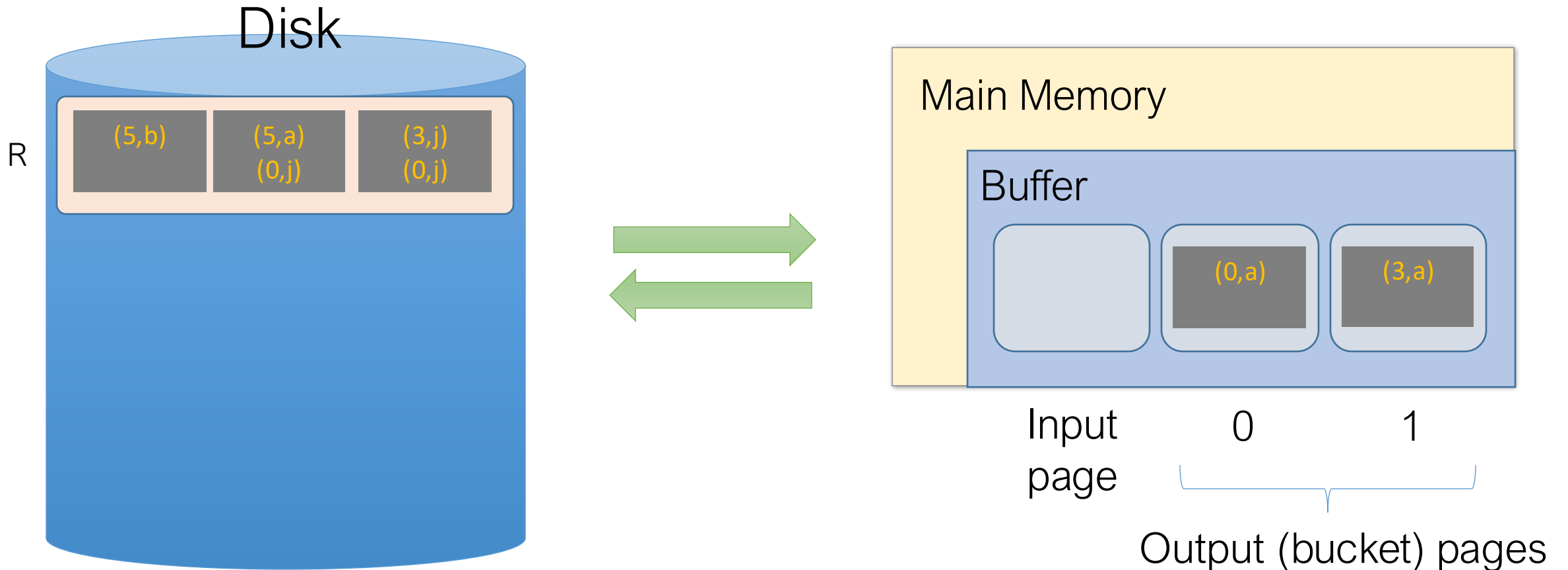
2. Then we use hash function h_2 to sort into the buckets, which each have one page in the buffer



Hash Join Phase 1: Partitioning

Given $B+1 = 3$ buffer pages

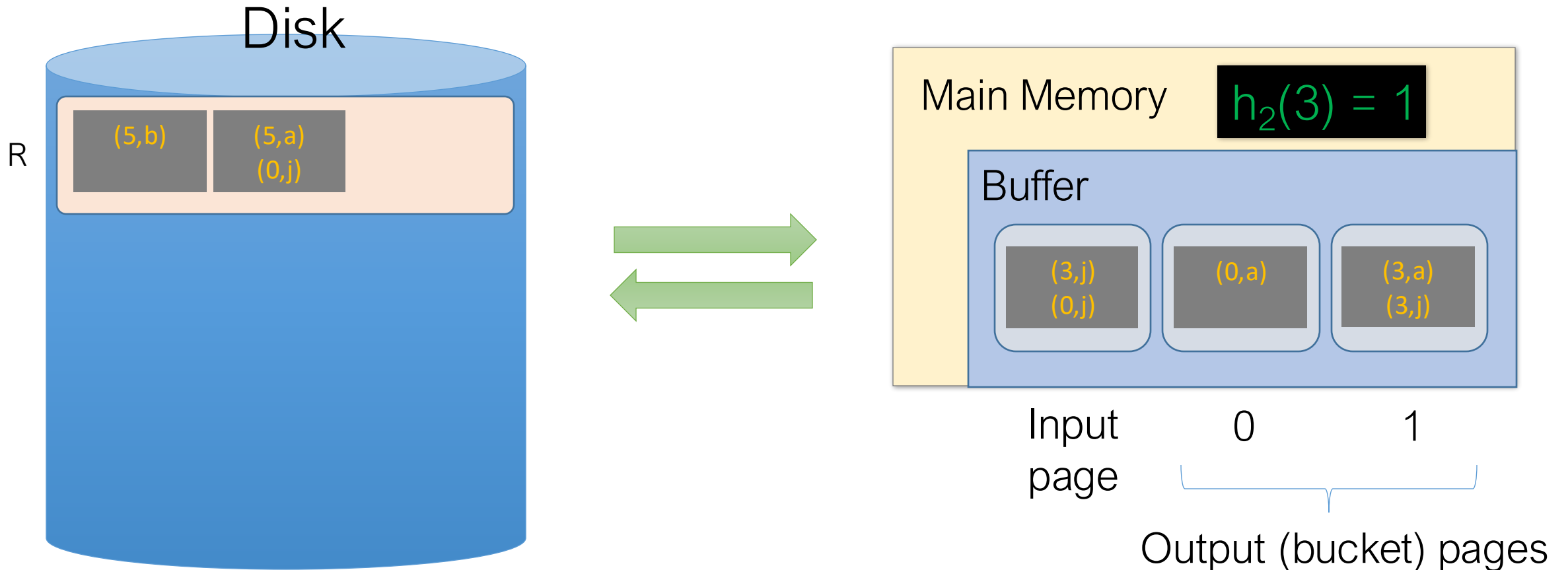
3. We repeat until the buffer bucket pages are full...



Hash Join Phase 1: Partitioning

Given $B+1 = 3$ buffer pages

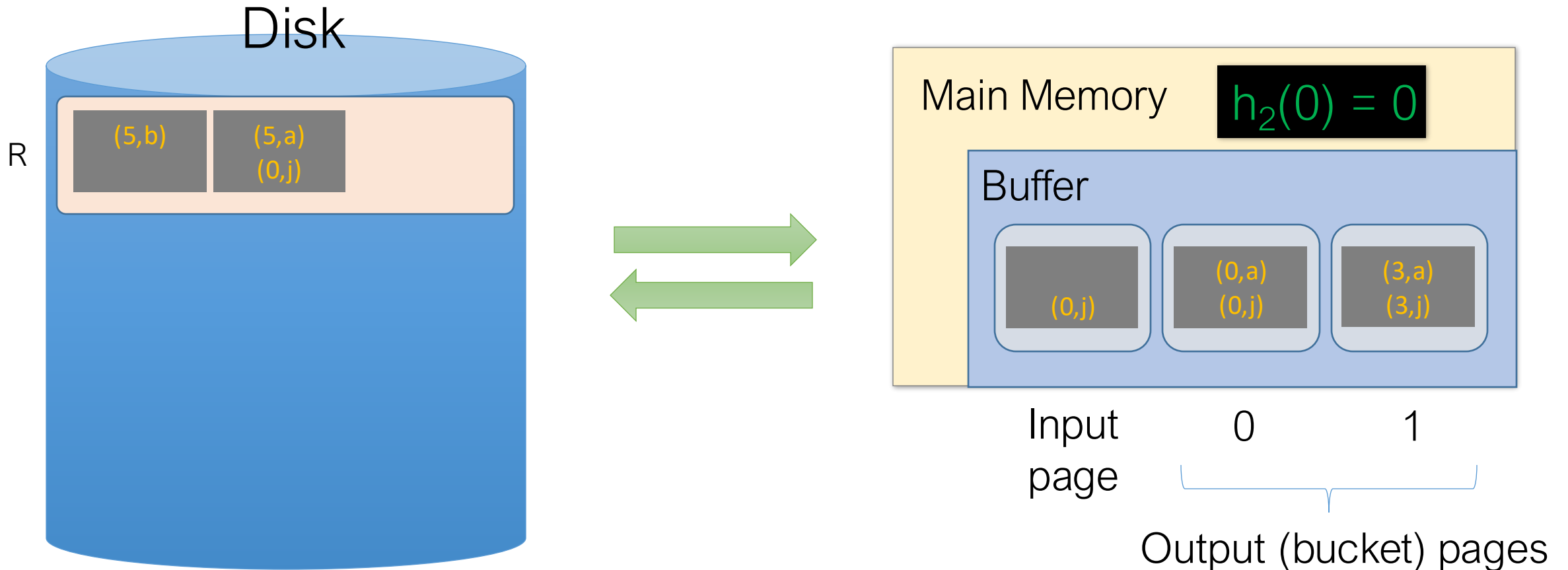
3. We repeat until the buffer bucket pages are full...



Hash Join Phase 1: Partitioning

Given $B+1 = 3$ buffer pages

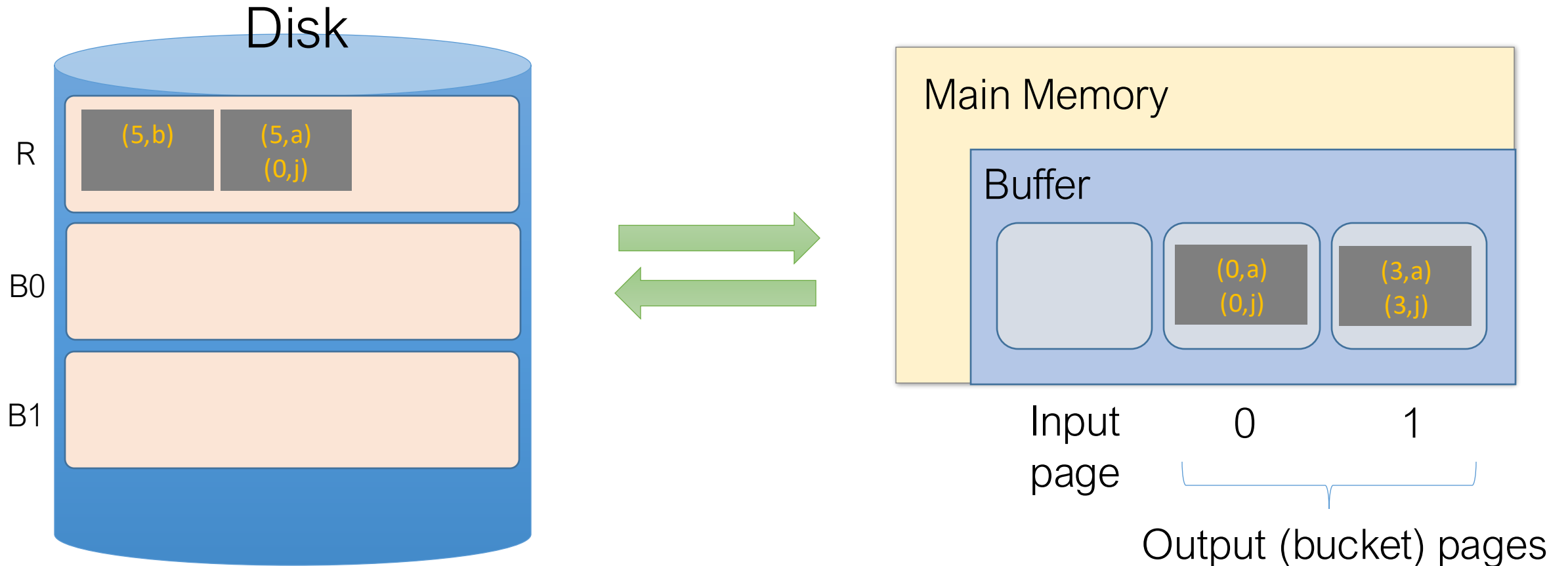
3. We repeat until the buffer bucket pages are full...



Hash Join Phase 1: Partitioning

Given $B+1 = 3$ buffer pages

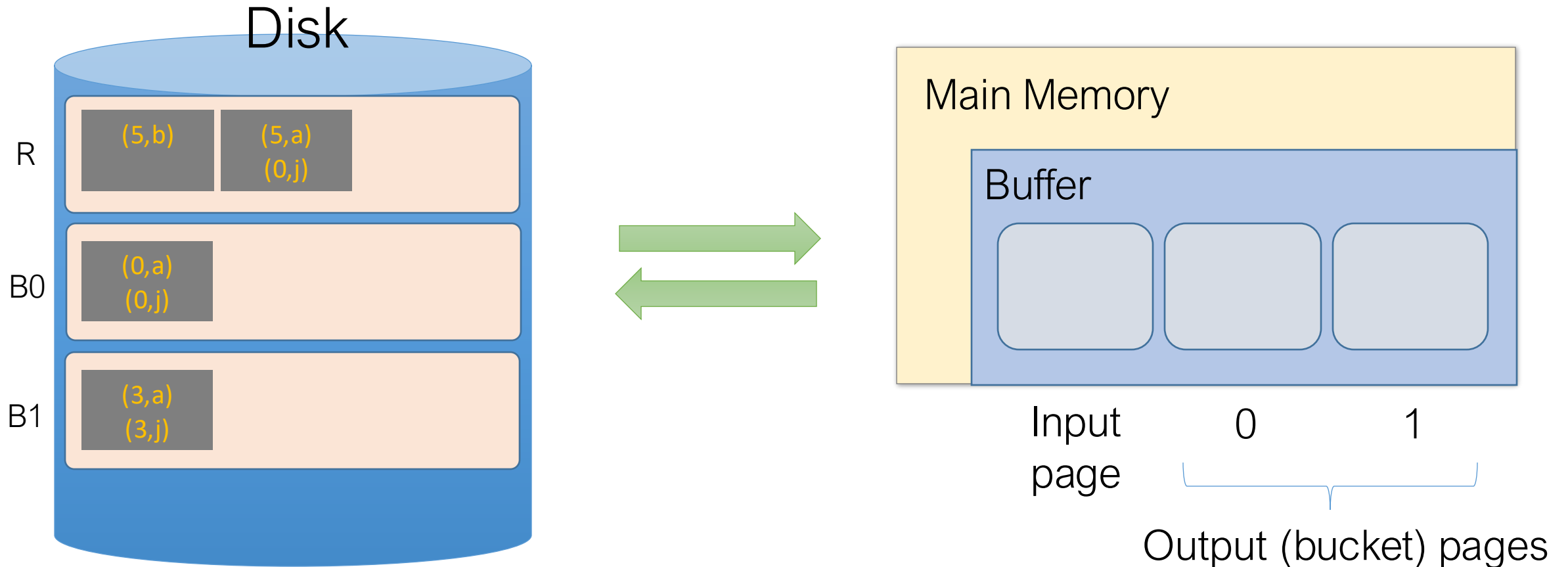
3. We repeat until the buffer bucket pages are full... then flush to disk



Hash Join Phase 1: Partitioning

Given $B+1 = 3$ buffer pages

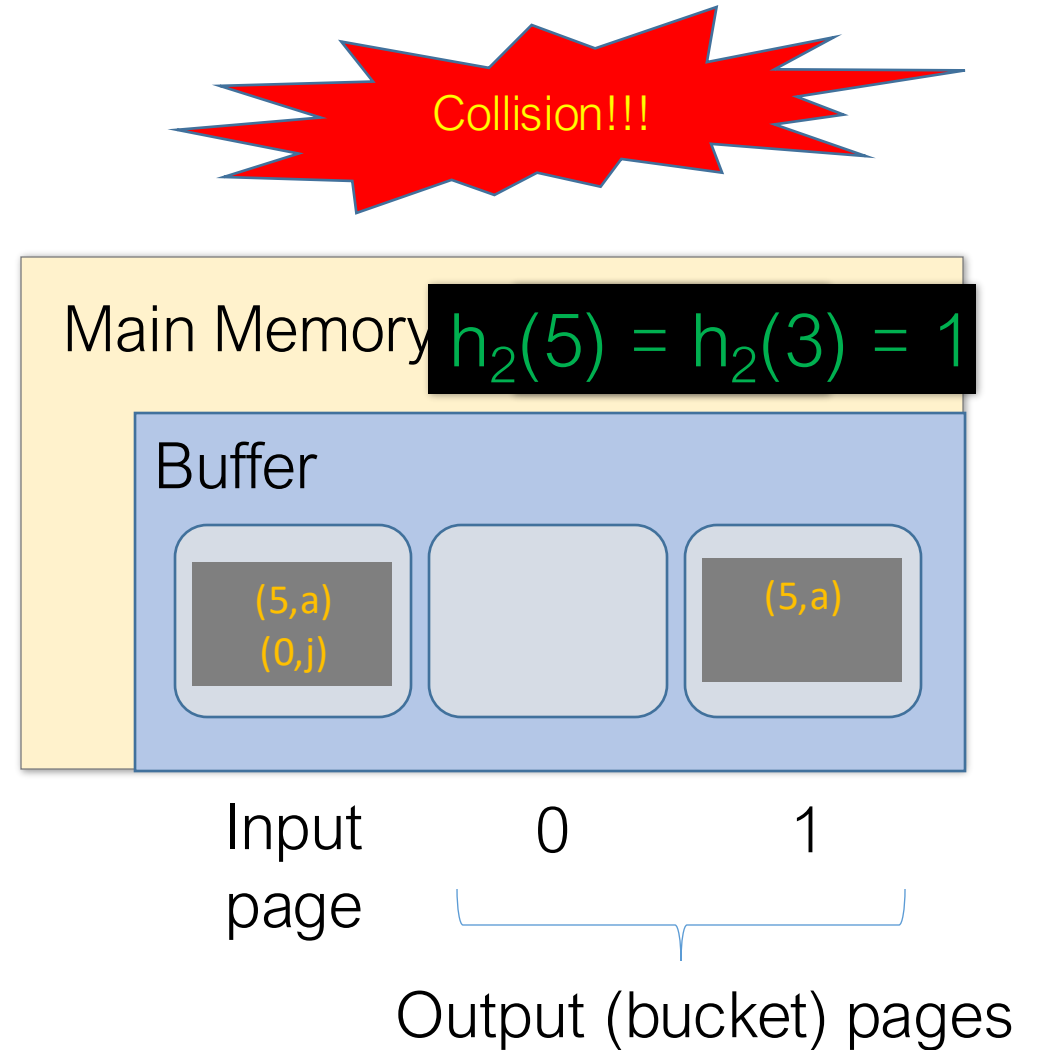
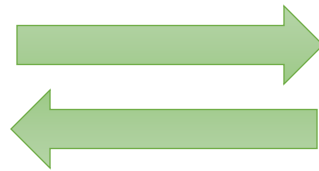
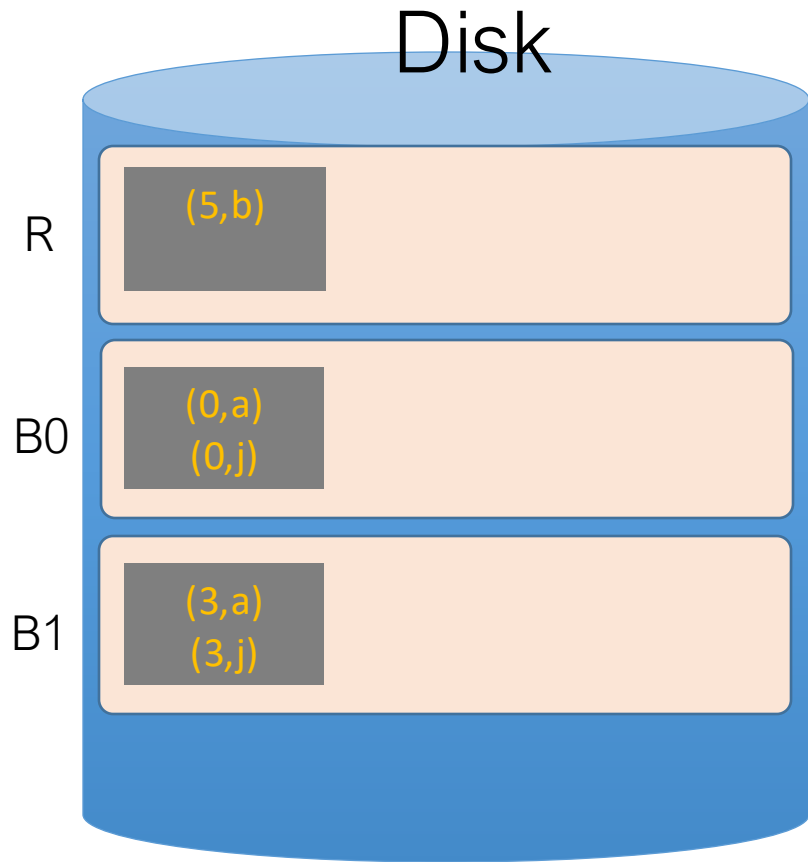
3. We repeat until the buffer bucket pages are full... then flush to disk



Hash Join Phase 1: Partitioning

Given $B+1 = 3$ buffer pages

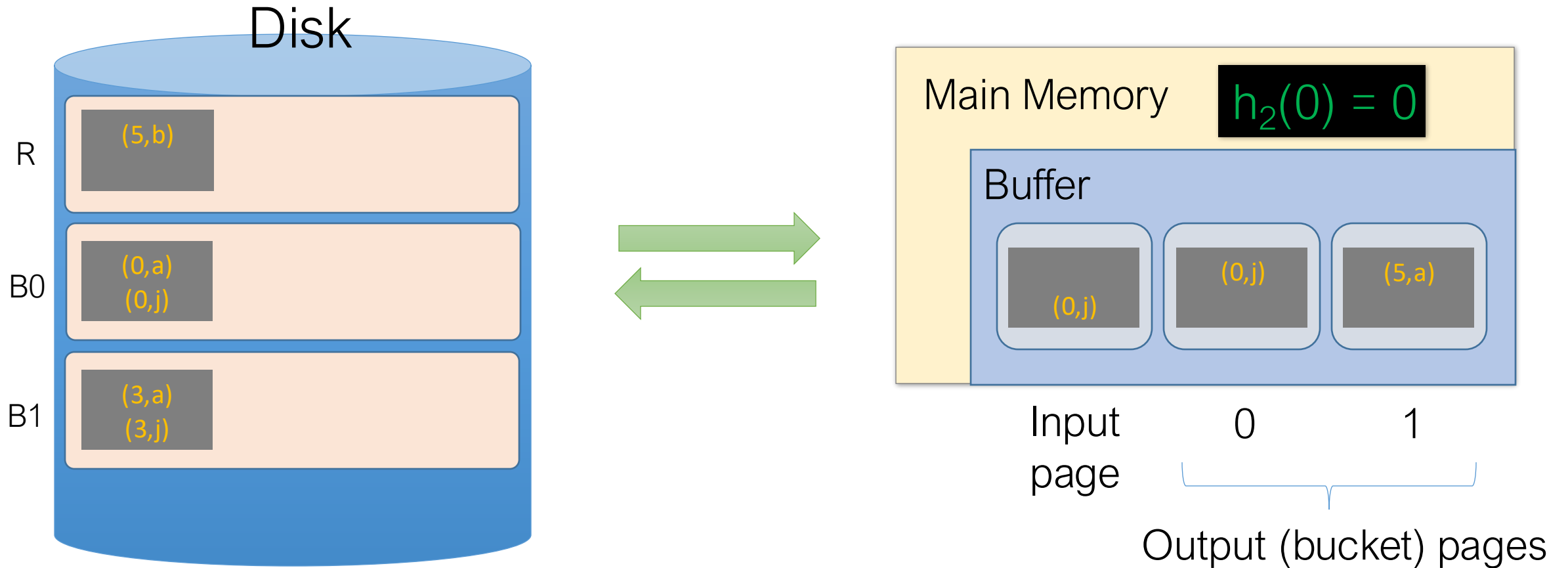
Note that collisions can occur!



Hash Join Phase 1: Partitioning

Given $B+1 = 3$ buffer pages

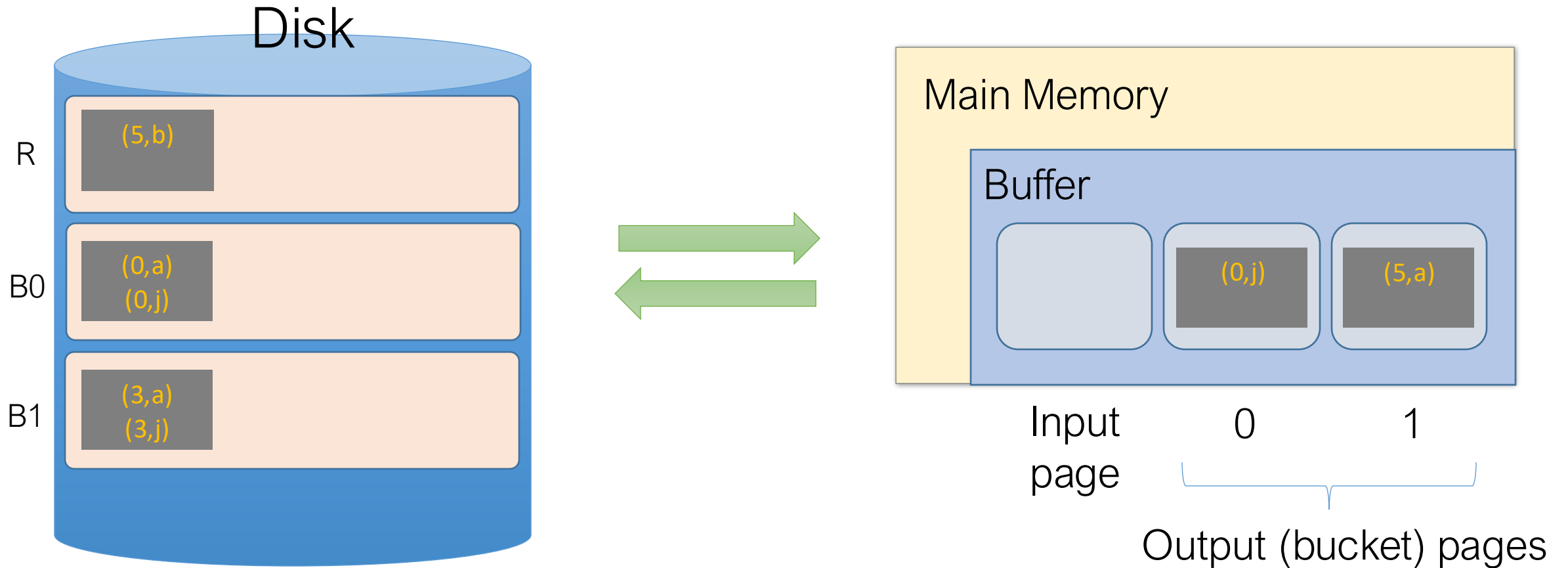
Finish this pass...



Hash Join Phase 1: Partitioning

Given $B+1 = 3$ buffer pages

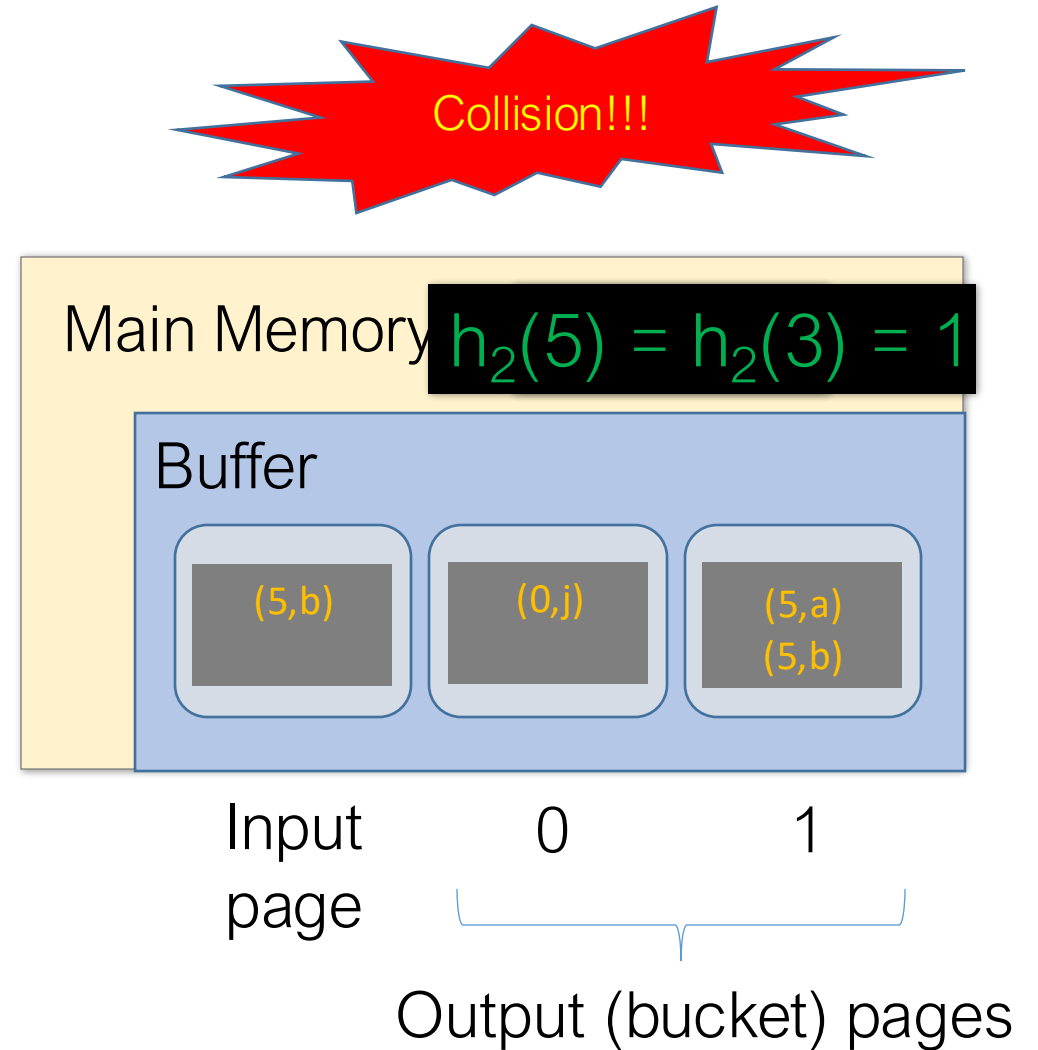
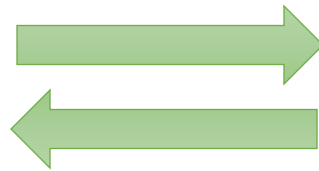
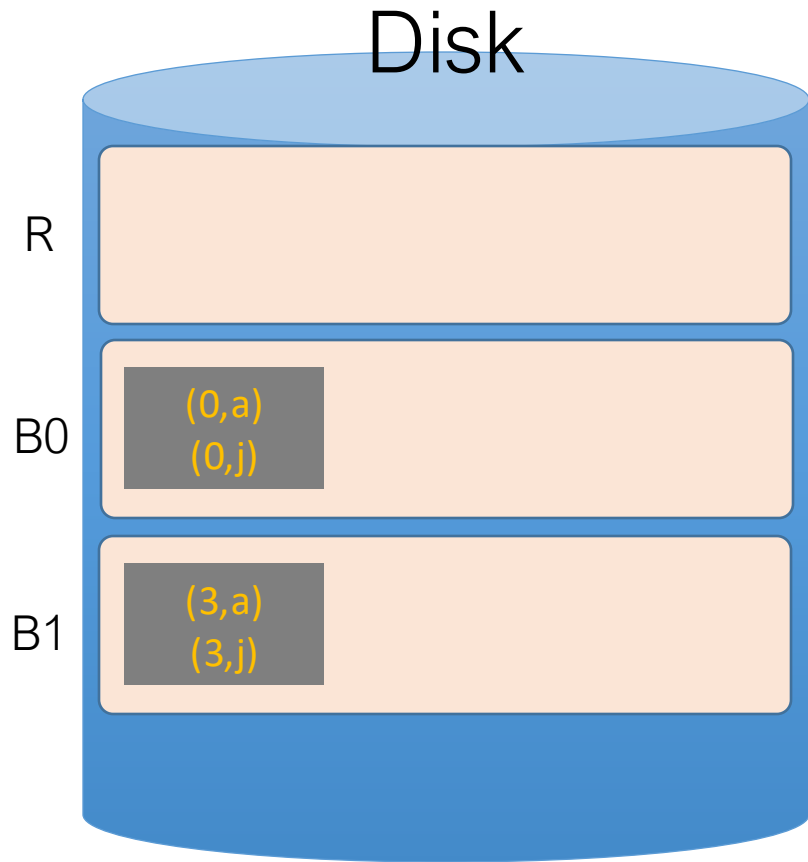
Finish this pass...



Hash Join Phase 1: Partitioning

Given $B+1 = 3$ buffer pages

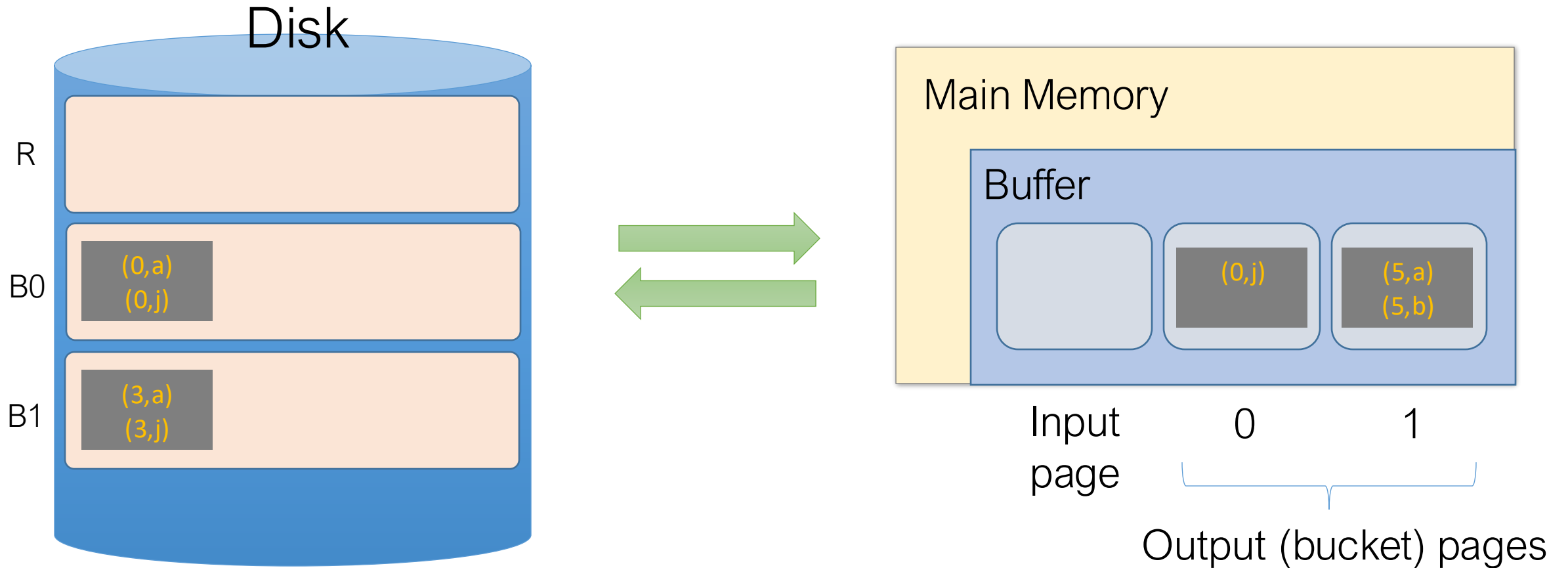
Finish this pass...



Hash Join Phase 1: Partitioning

Given $B+1 = 3$ buffer pages

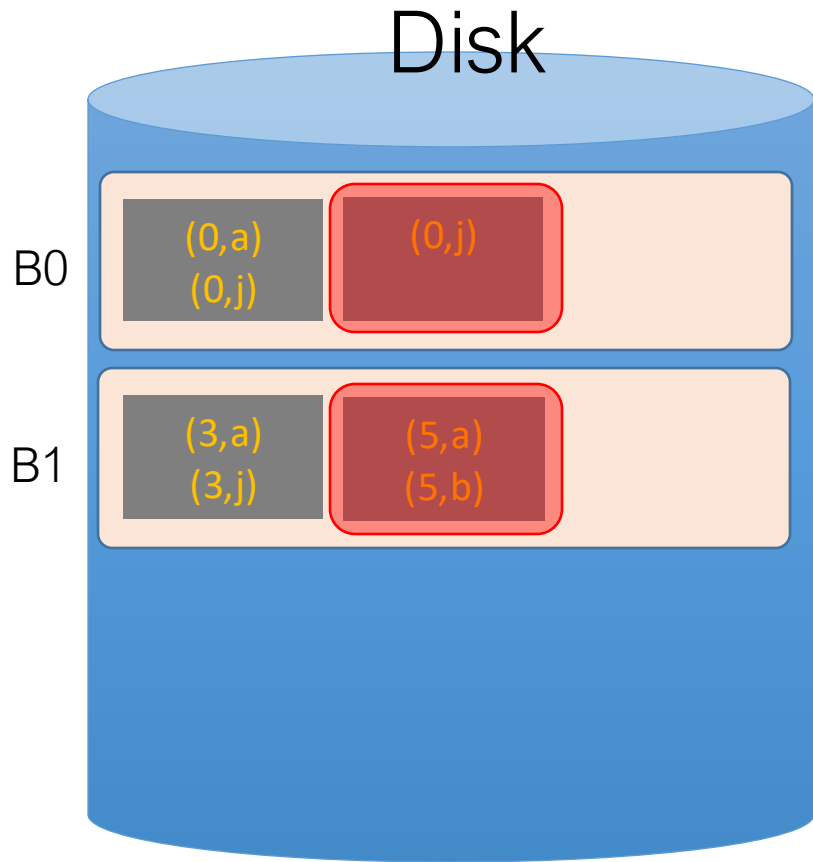
Finish this pass...



Hash Join Phase 1: Partitioning

Given $B+1 = 3$ buffer pages

We wanted buckets of size $B-1 = 1...$
however we got larger ones due to:

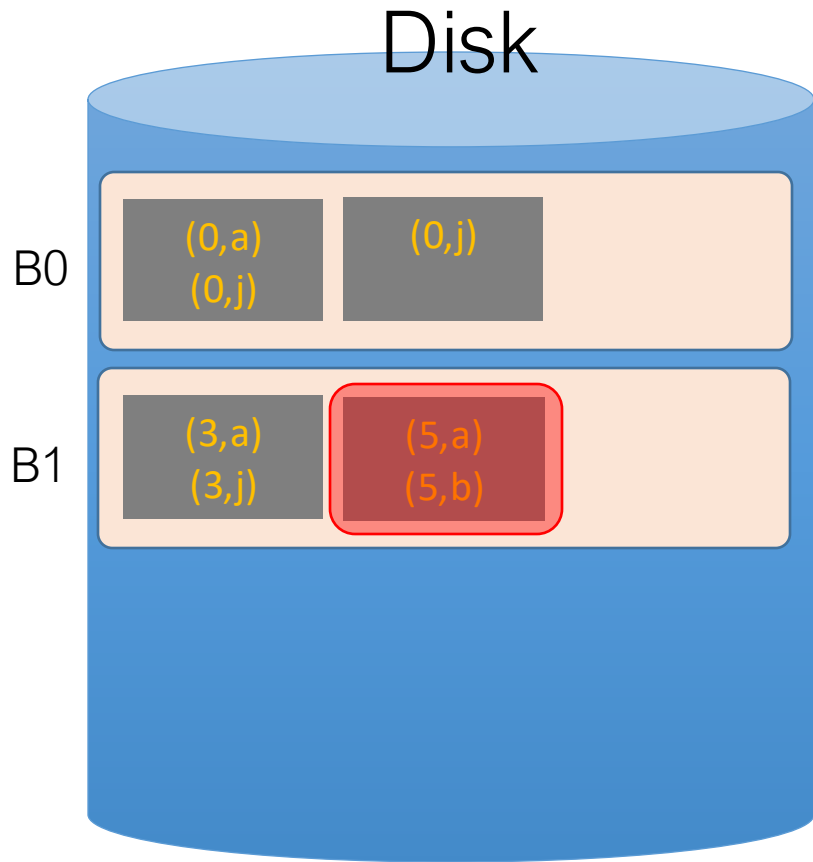


(1) Duplicate join keys

(2) Hash collisions

Hash Join Phase 1: Partitioning

Given $B+1 = 3$ buffer pages



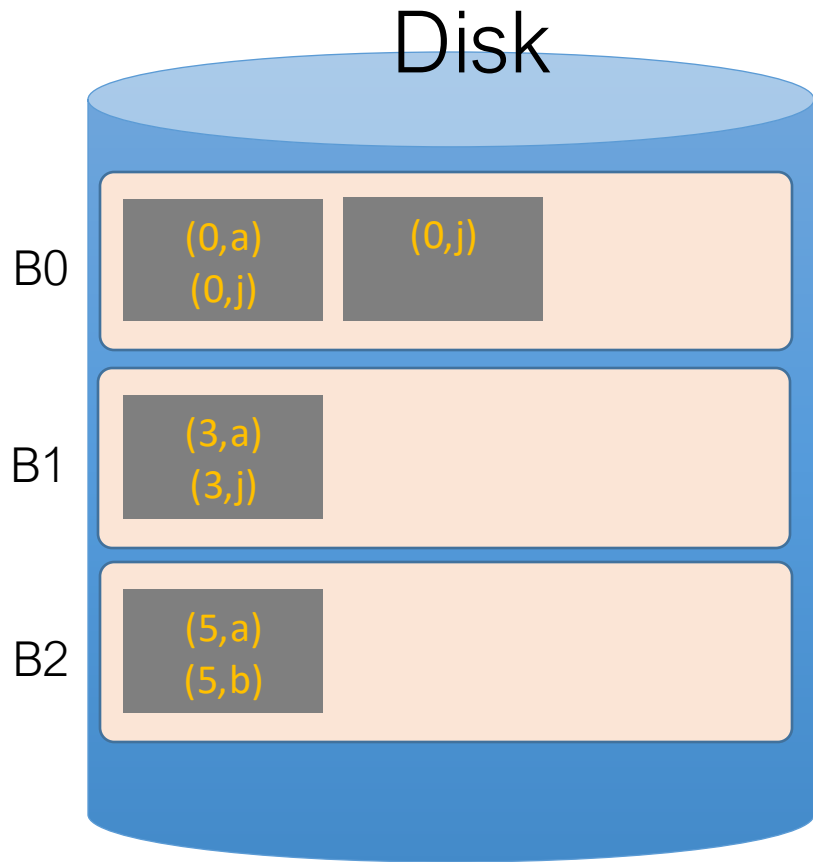
To take care of larger buckets caused by (2) hash collisions, we can just do another pass!

Do another pass with a different hash function, h'_2 , ideally such that:

$$h'_2(3) \neq h'_2(5)$$

Hash Join Phase 1: Partitioning

Given $B+1 = 3$ buffer pages



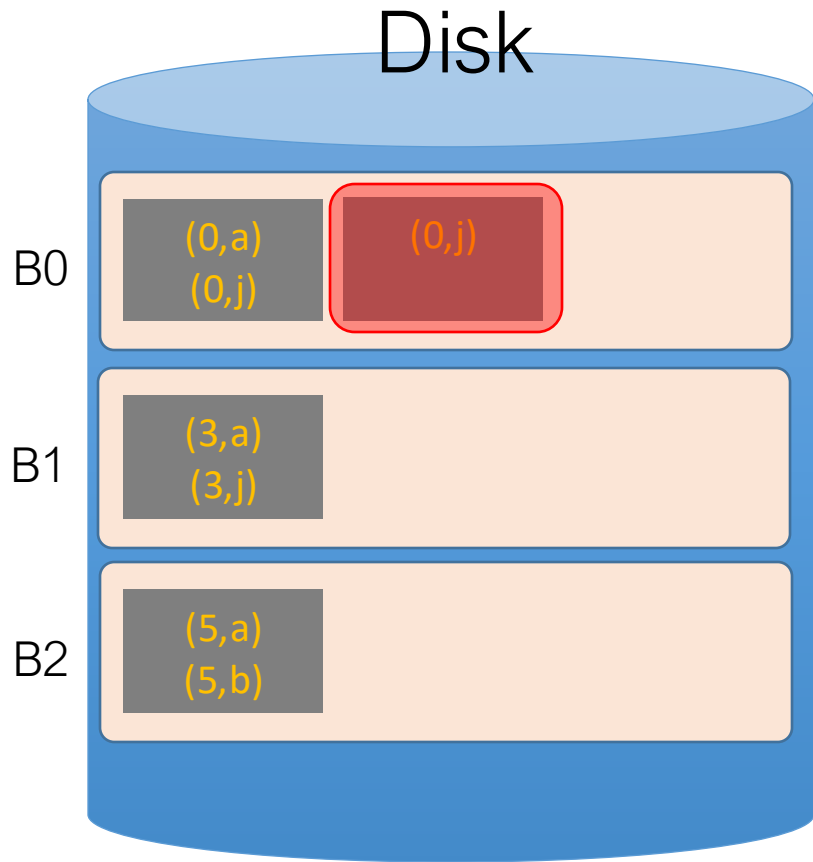
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Hash Join Phase 1: Partitioning

Given $B+1 = 3$ buffer pages



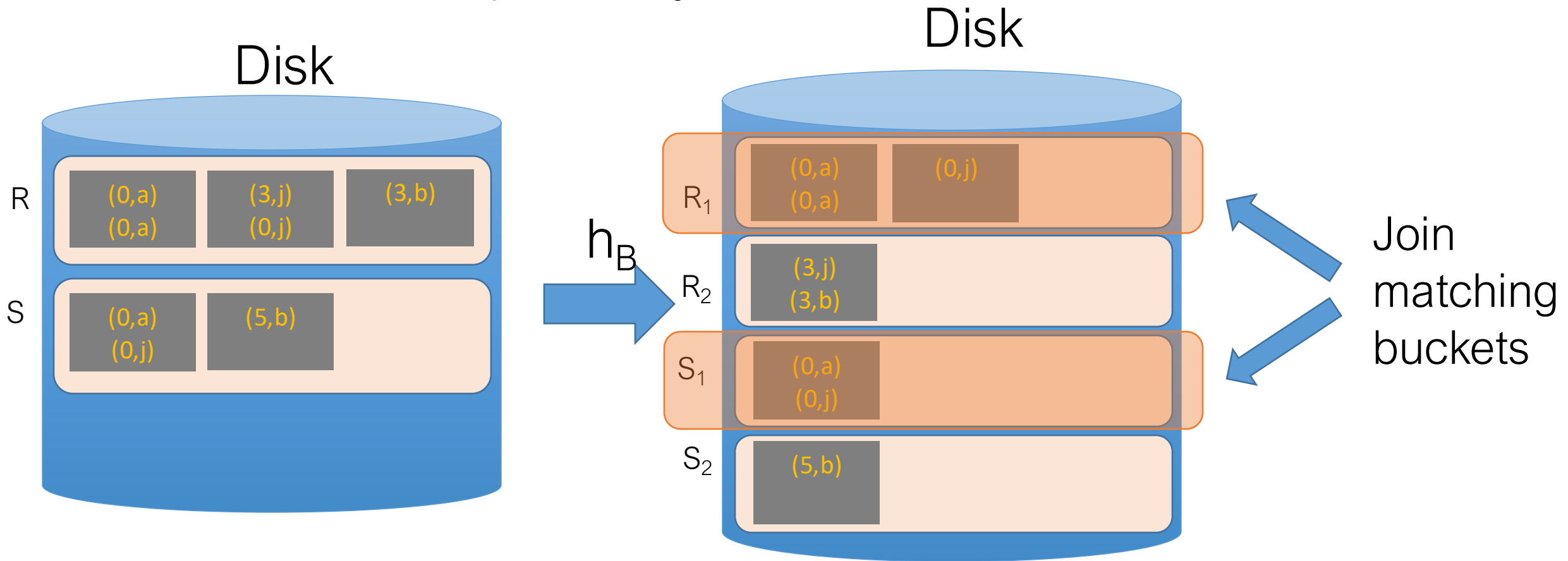
What about duplicate join keys?
Unfortunately this is a problem...
but usually not a huge one.

We call this
unevenness in the
bucket size skew

Now that we have partitioned R and S ...

Hash Join Phase 2: Matching

- Now, we just join pairs of buckets from R and S that have the same hash value to complete the join!



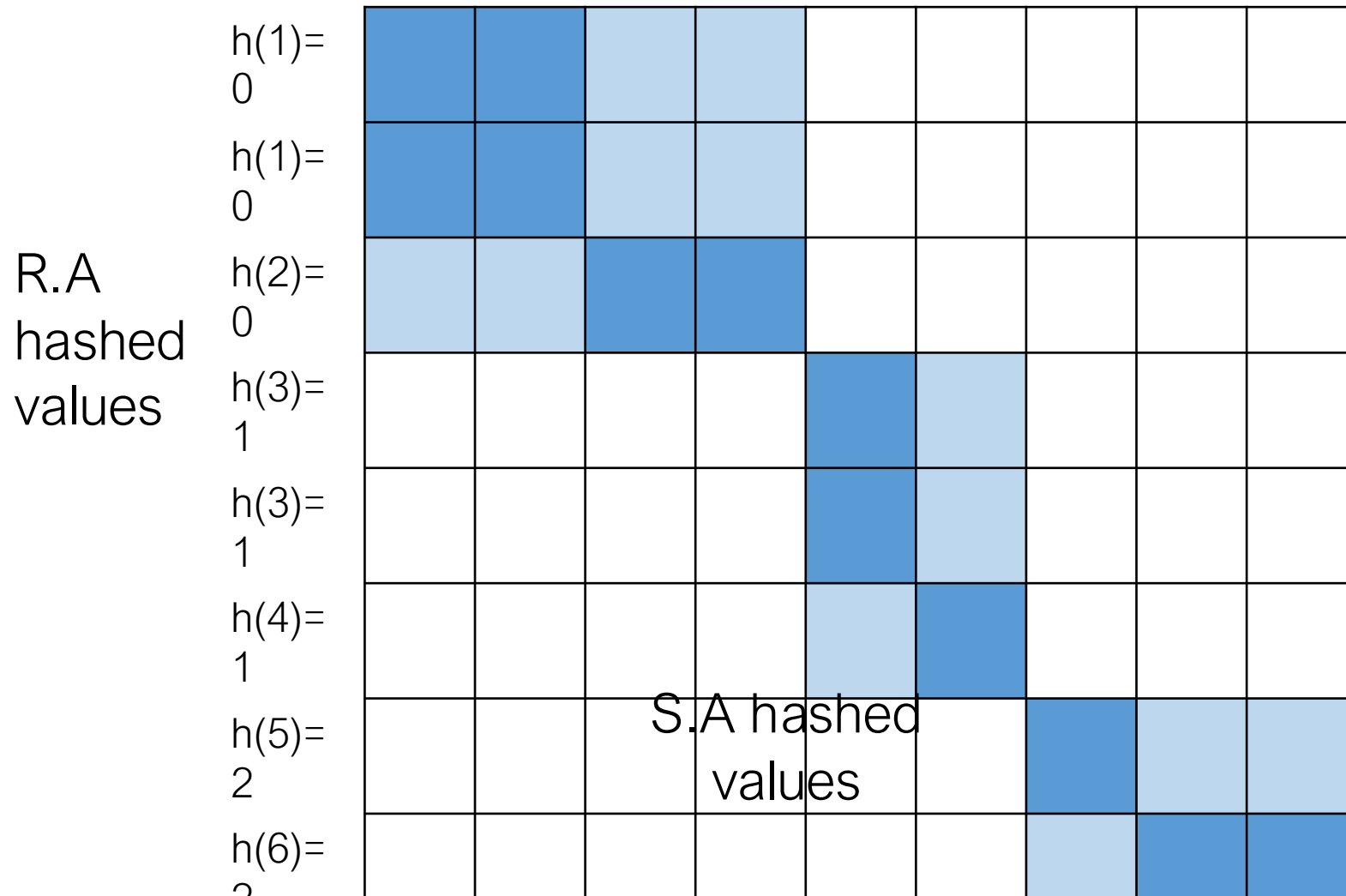
Hash Join Phase 2: Matching

- Note that since $x = y \rightarrow h(x) = h(y)$, we only need to consider pairs of buckets (one from R, one from S) that have the same hash function value
- If our buckets are $\sim \mathbf{B - 1}$ pages, can join each such pair using BNLJ *in linear time*; recall (with $P(R) = B-1$):

$$\text{BNLJ Cost: } P(R) + \frac{P(R)P(S)}{B-1} = P(R) + \frac{(B-1)P(S)}{B-1} = P(R) + P(S)$$

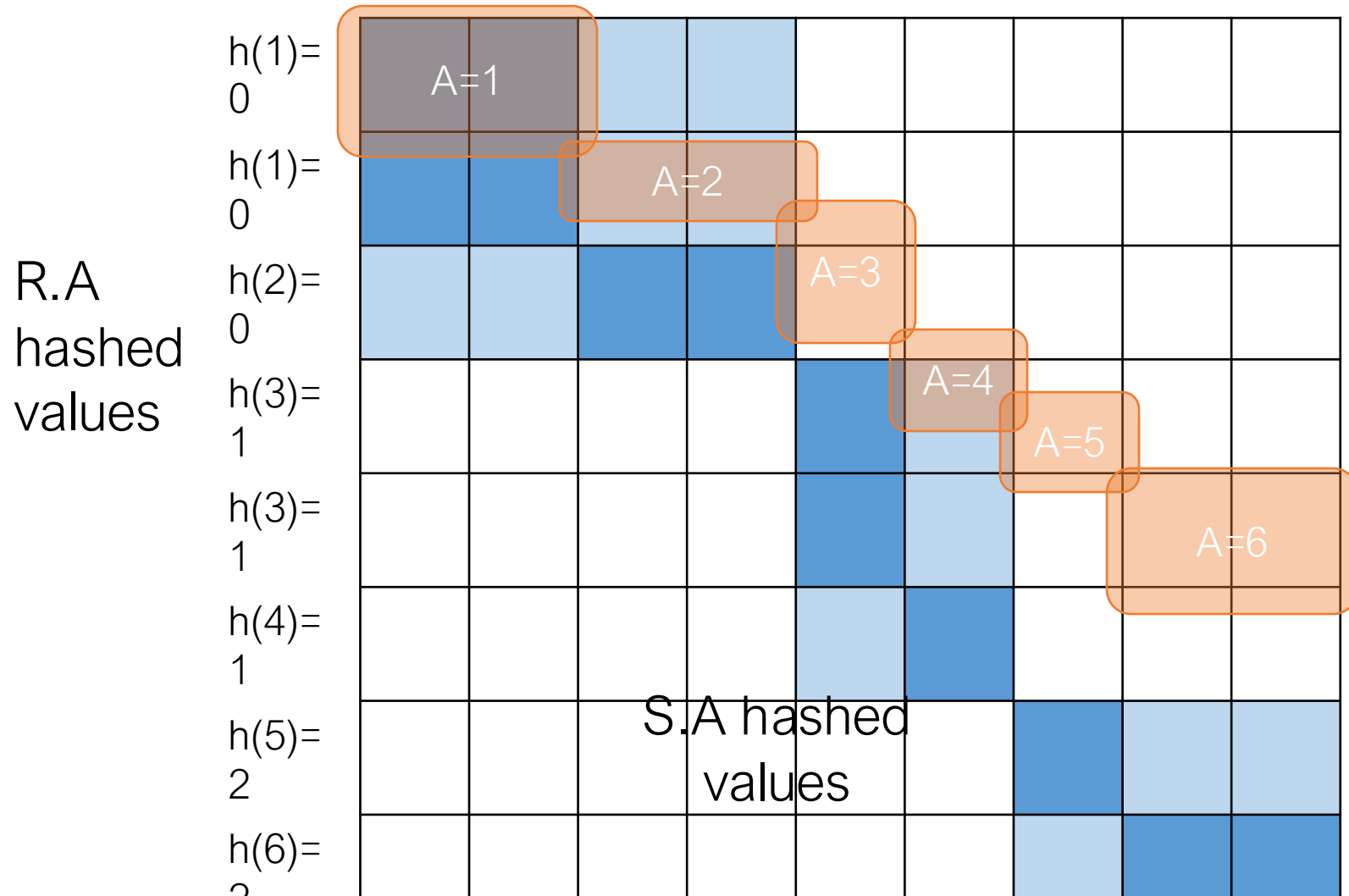
Joining the pairs of buckets is linear!
(As long as smaller bucket $\leq B-1$ pages)

Hash Join Phase 2: Matching



$R \bowtie S \text{ on } A$

Hash Join Phase 2: Matching

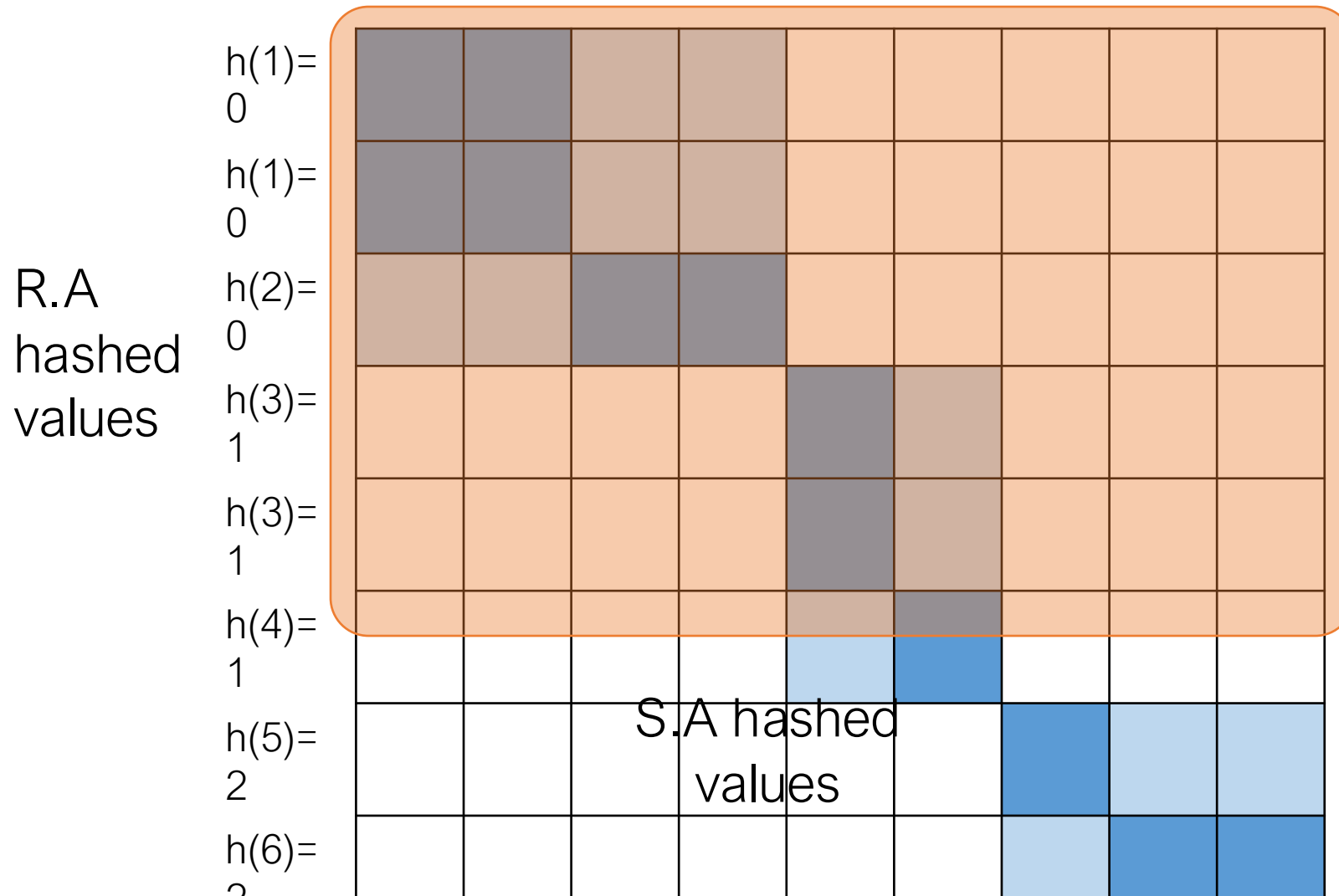


$R \bowtie S$ on A

To perform the join, we ideally just need to explore the dark blue regions

= the tuples with same values of the join key A

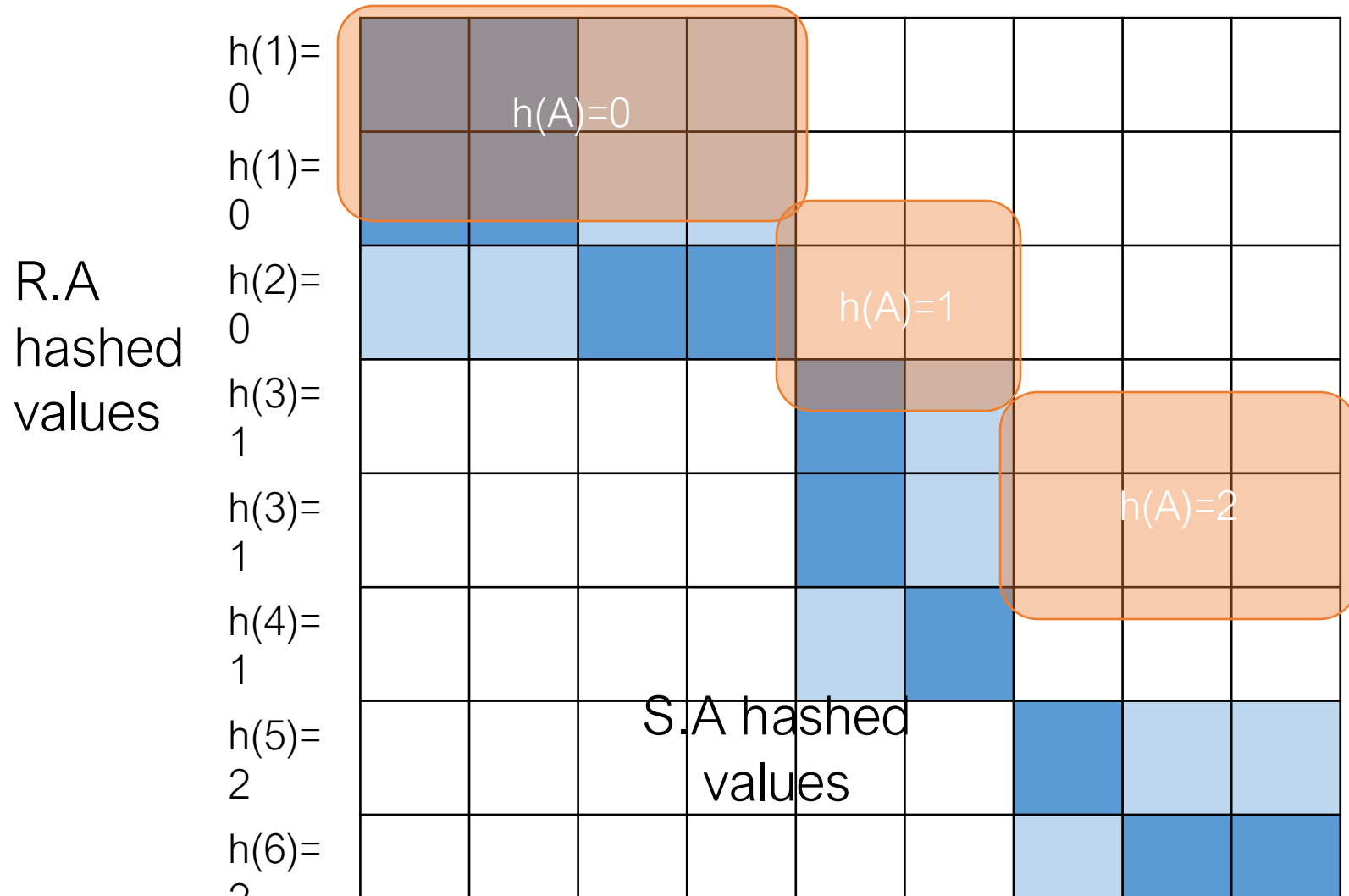
Hash Join Phase 2: Matching



$R \bowtie S \text{ on } A$

With a join algorithm like BNLJ that doesn't take advantage of equijoin structure, we'd have to explore this whole grid!

Hash Join Phase 2: Matching



$R \bowtie S$ on A

With HJ, we only explore the blue regions

= the tuples with same values of $h(A)$!

We can apply BNLJ to each of these regions

How much memory do we need for HJ?

- Given $B+1$ buffer pages + WLOG: Assume $P(R) \leq P(S)$
- Suppose (reasonably) that we can partition into B buckets in 2 passes:
 - For R , we get B buckets of size $\sim P(R)/B$
 - To join these buckets in linear time, we need these buckets to fit in $B-1$ pages, so we have:

$$B - 1 \geq \frac{P(R)}{B} \Rightarrow \sim B^2 \geq P(R)$$

Quadratic relationship
between smaller relation's
size & memory!

Hash Join Summary

- *Given enough buffer pages as on previous slide ...*
 - **Partitioning** requires reading + writing each page of R,S
 - $\rightarrow 2(P(R)+P(S))$ IOs
 - **Matching** (with BNLJ) requires reading each page of R,S
 - $\rightarrow P(R) + P(S)$ IOs
 - **Writing out results** could be as bad as $P(R)*P(S)$... but probably closer to $P(R)+P(S)$

HJ takes $\sim 3(P(R)+P(S)) + \text{OUT}$ IOs!

Sort-Merge v. Hash Join

Given enough memory, both SMJ and HJ have performance:

$$\sim 3(P(R)+P(S)) + \text{OUT}$$

“Enough” memory =

- SMJ: $B^2 > \max\{P(R), P(S)\}$
- HJ: $B^2 > \min\{P(R), P(S)\}$

Hash Join superior if relation sizes differ greatly. Why?

Further Comparisons of Hash and Sort Joins

- Hash Joins are highly parallelizable.
- Sort-Merge less sensitive to data skew and result is sorted