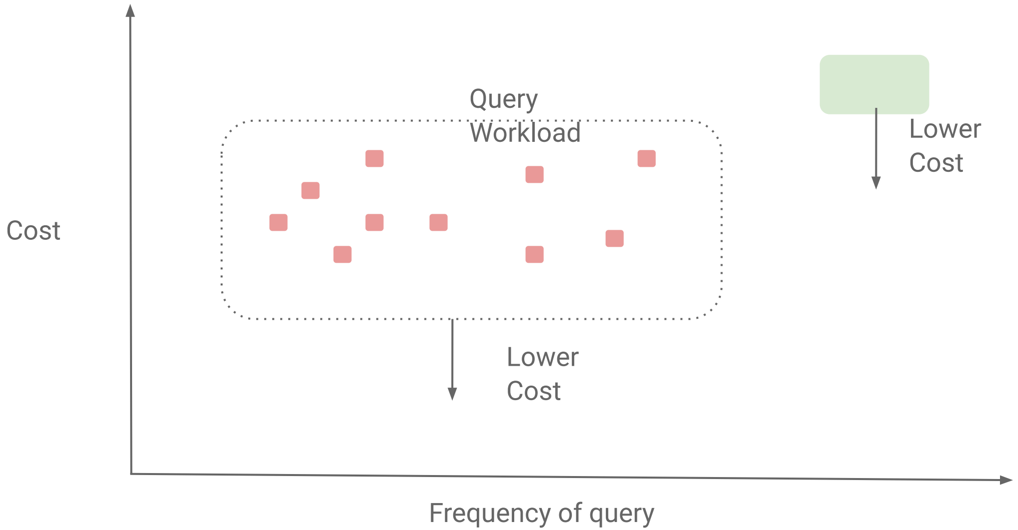
Optimization!

Optimizing

Queries and workloads



<u>Workload</u> = <Query, Frequency of query>

Example:

Basic SFW queries

Workload description

```
SELECT pname
FROM   Product
WHERE year = ? AND category =?
```

```
SELECT pname
FROM   Product
WHERE year = ? AND Category =?
AND    manufacturer = ?
```

Lower cost (query and update cost)

1. How to execute? Sort, Hash first …?
2. Maintain indexes for Year? Category? Manufacturer?
3. For query, check multiple indexes?
4. What's cost of maintaining index?
5. Use multiple machines? ...

Intuition

Manufacturers likely most **Selective.**

Many more manufacturers than Categories. Maintain index, if this query happens a lot.

Optimization

Roadmap

Build Query Plans

Analyze Plans

1. For SFW, Joins queries
    a. Sort? Hash? Count? Brute-force?
    b. Pre-build an index? B+ tree, Hash?

2. What statistics can I keep to optimize?
    a. E.g. Selectivity of columns, values

Cost in I/O, resources?
To query, maintain?

1. Nested Loop Joins

What you will learn about in this section

1. RECAP: Joins
2. Nested Loop Join (NLJ)
3. Block Nested Loop Join (BNLJ)
4. Index Nested Loop Join (INLJ)

RECAP: Joins

Joins: Example

$\mathbf{R} \bowtie \boldsymbol{S}$

```
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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S

A	D
3	7
2	2
2	3

A	B	C	D
2	3	4	2
2	3	4	3

Joins: Example

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S

A	D
3	7
2	2
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Joins: Example

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S

A	D
3	7
2	2
2	3

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

$\mathbf{R} \bowtie \boldsymbol{S}$

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

<u>Example:</u> 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

→ Cross Product → … → Filter by conditions (r.A = s.A)

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

Can we actually implement a join in this way?

Nested Loop Joins

Notes

We consider "IO aware" algorithms: *care about disk IO*

Given a relation R, let:
- T(R) = # of tuples in R
- P(R) = # of pages in R

Recall that we read / write entire pages with disk IO

We'll see lots of formulae from now
⇒ Hint: Focus on how it works. Much easier to derive from 1st principles (vs recalling formula soup)

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 $\mathrm{R} \bowtie S \ on \ A$:

```
for r in R:
  for s in S:
    if r[A] == s[A]:
      yield (r,s)
```

<u>Cost:</u>

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

```
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 ⋈ 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 bigger than P(R)*P(S)… but usually not that bad

<u>Cost:</u>

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 $\mathrm{R} \bowtie S \; on \; A$:

```
for r in R:
  for s in S:
    if r[A] == s[A]:
      yield (r,s)
```

<u>Cost:</u>

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

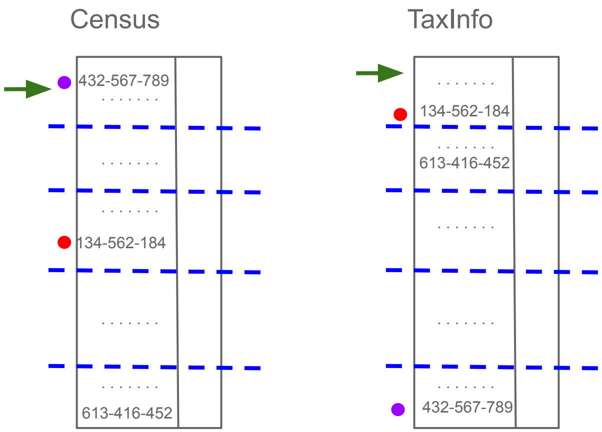
Quick Intuition

Census (SSN, Address, …)
TaxInfo (SSN, TaxPaid, …)

For 1 Billion people

Goal: Compute Census JOIN TaxInfo

Data stored in RowStores, 1000 tuples/page (million pages)



Census table
(row store)

TaxInfo table
(row store)

BNLJ
For each pair of pages
in Census and TaxInfo…

Example

Census (<u>SSN</u>, Address, ...)
TaxInfo (<u>SSN</u>, TaxPaid, ...)

For 1 Billion people

Goal: Compute Census JOIN TaxInfo

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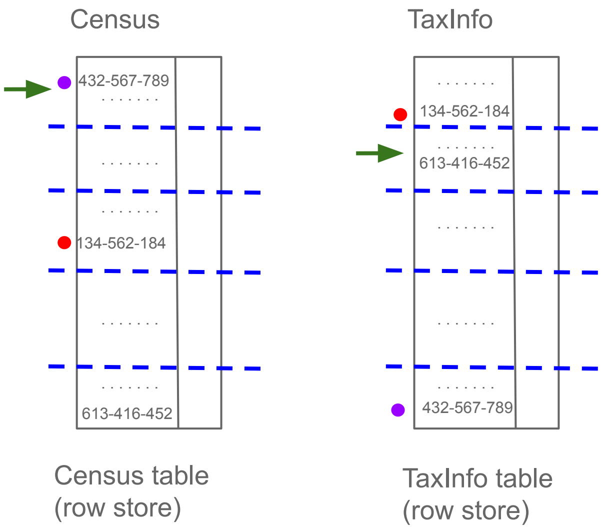


For each page in Census
-- How many pages in TaxInfo to read?
-- If you had B-1 space to cache TaxInfo?

Better?
For each pair of **pages**
in Census and TaxInfo...

Block Nested Loop Join (BNLJ)

```
Compute R ⋈ 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
(For B << P(R), P(S))

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 ⋈ 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 $\mathrm{R} \bowtie S \; on \; A$:

```
 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

<u>Cost:</u>

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

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 ⋈ 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)
```

Again, *OUT* could be bigger than P(R)*P(S)… but usually not that bad

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) + OUT

→

BNLJ

$P(R) + \frac{P(R)}{B-1} P(S)$ + 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 ~= <u>140 hours</u>**

- BNLJ: Cost = 500 + $\frac{500*1000}{10}$ **= 50 *Thousand* IOs ~= <u>0.14 hours</u>**

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

Quick Recap

Block Nested Loop Joins

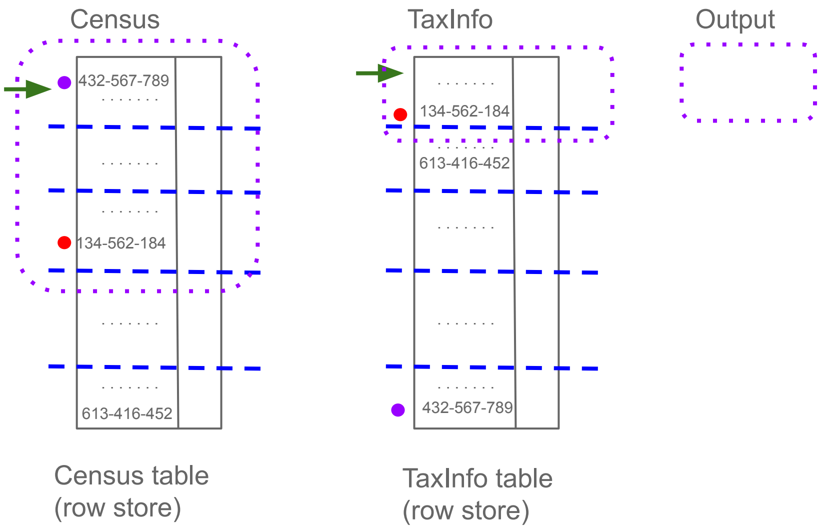
Census (<u>SSN</u>, Address, …)
TaxInfo (<u>SSN</u>, TaxPaid, …)

For 1 Billion people

Goal: Compute Census JOIN TaxInfo

Data stored in RowStores, 1000 tuples/page (million pages)

Given: B + 1 buffer space
Idea: Use **B-1** pages for Census, **1** page each for TaxInfo and output



Steps: Repeat till done
- Read B-1 pages from Census into Buffer
- Read 1 page from TaxInfo
- Partial Join into 1 output page

Block Nested Loop Join (BNLJ)

Given *B+1* pages of memory

```
Compute R ⋈ S on A:
  for each B-1 pages pr of R:
    for each page ps of S:
      for each tuple r in pr:
        for each tuple s in ps:
          if r[A] == s[A]:
            yield (r,s)
```

Cost:

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

How many R pages to read?
P(R)

How many times is each S page read?
P(R)/(B-1)

Example NLJ vs. BNLJ: Steel Cage Match

Example: P(R) = 1000, P(S) = 500,
100 tuples/page ⇒ T(R) = 1000*100, T(S)=500*100]

	B + 1 = 100 (i.e., B = 99)	**B + 1 = 20** (i.e., Buffer B = 19)
NLJ	(1000 + 1000*100*500 + OUT) ⇒ IO = ~5,001,000 +OUT	(1000 + 1000*100*500 + OUT) ⇒ IO = ~ 5,001,000 +OUT
BNLJ	(500 + 1000*500/(99-1)) ⇒ IO = ~5.6K+OUT	(500 + 1000*500/(19-1)) ⇒ IO = 28.2K IOs +OUT

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

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

But it's all about the memory.

Smarter than Cross-Products

Smarter than Cross-Products: From Quadratic to Nearly Linear

All joins computing the *full cross-product* have a 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:

- ~ $O(P(R) + P(S) + OUT)$

We get this gain by *taking advantage of structure*- moving to 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:
      s in idx(r[A]):
        yield r,s
```

Cost:

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

Where L is the IO cost to access each distinct values in index

Recall: L is usually small (e.g., 3-5)

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

Optimizing Joins

(the good stuff, multi table joins)

Message: It’s all about the IO and memory!

What you will learn about in this section

0. Intuition for smarter joins
1. Sort-Merge Join
2. HashPartion Joins

Example

Census (SSN, Address, …)
TaxInfo (SSN, TaxPaid, …)

For 1 Billion people

Goal: Compute Census JOIN TaxInfo

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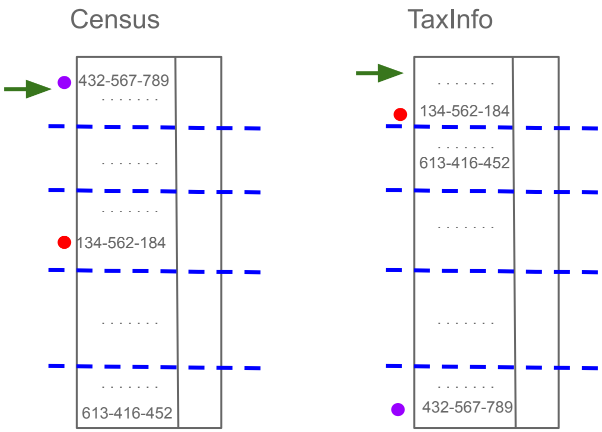

Census table
(row store)

TaxInfo table
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For each pair of pages
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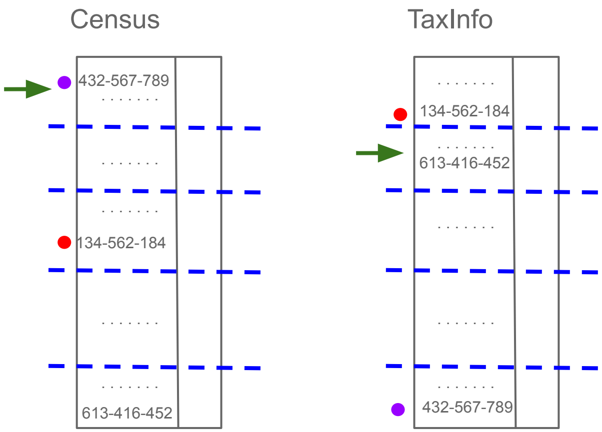


Census table
(row store)

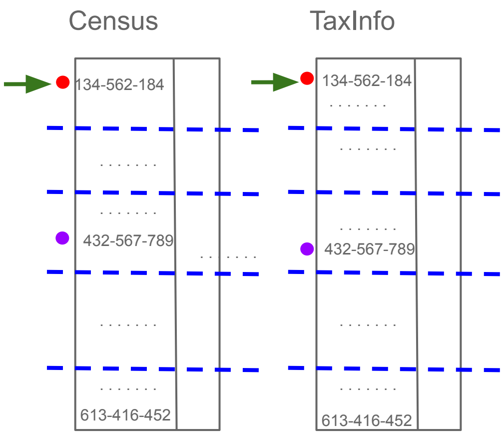
TaxInfo table
(row store)

BNLJ -- See all the extra work BNLJ is doing to JOIN for 432-567-789, ...

Pre-process data before JOINing

Preview of smarter joins

SortMergeJoin

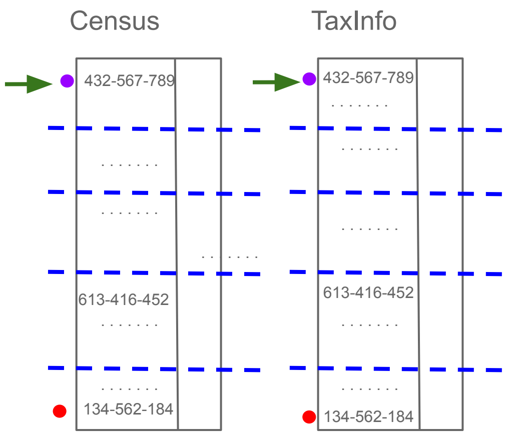


Census table (row store)

TaxInfo table (row store)

-- Sort(Census), Sort(TaxInfo) on SSN
-- Merge sorted pages

HashPartitionJoin



Census table (row store)

TaxInfo table (row store)

-- Hash(Census), Hash(TaxInfo) on SSN
-- Merge partitioned pages

Speedy Joins: With Sorting and Hashing

- ***Given enough memory***, SortMergeJoin and HashJoins cost

~3(P(R)+P(S)) + *OUT*

- Hash Joins are highly parallelizable

- Sort-Merge less sensitive to data skew and result is sorted

⇒ <u>Big takeaway</u>: IO-aware join algorithms
- Massive difference vs brute-force
- Nearly linear vs quadratic (or worse)

What you will learn about in this section

0. Intuition for smarter joins

1. Sort-Merge Join

2. HashPartion Joins

Sort-Merge Join (SMJ)

What you will learn about in this section

1. Sort-Merge Join
2. “Backup” & Total Cost
3. Optimizations

Sort Merge Join (SMJ)

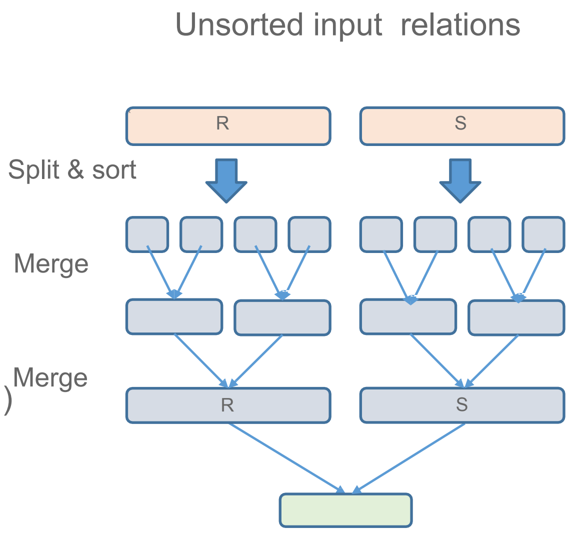
Goal: Execute R ⋈ S on A

Key Idea:

We can sort R and S [with external sort]
Then just merge-scan over them!

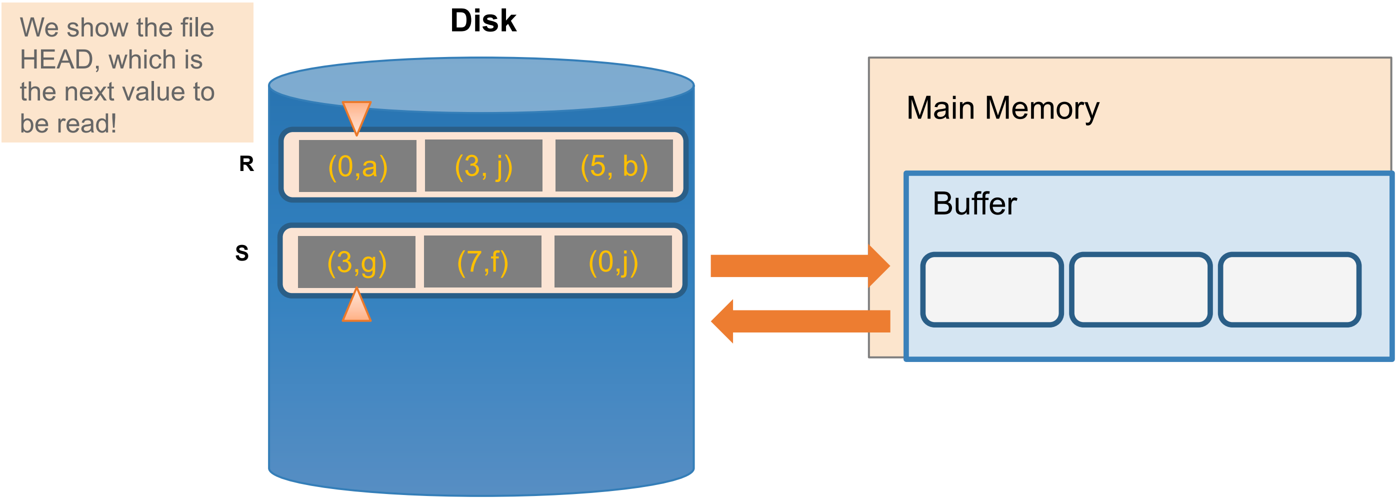
IO Cost:

- *Sort phase:* Sort(R) + Sort(S) (~2 (P(R) + P(S))
- *Merge / join phase:* ~ P(R) + P(S) + OUT

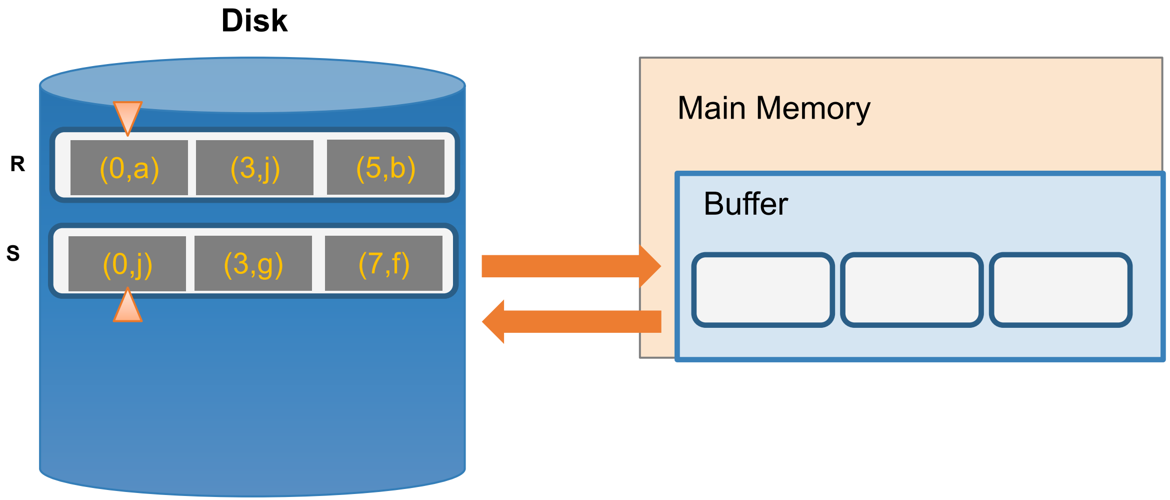


SMJ Example: $R \bowtie S$ with 3 page buffer

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

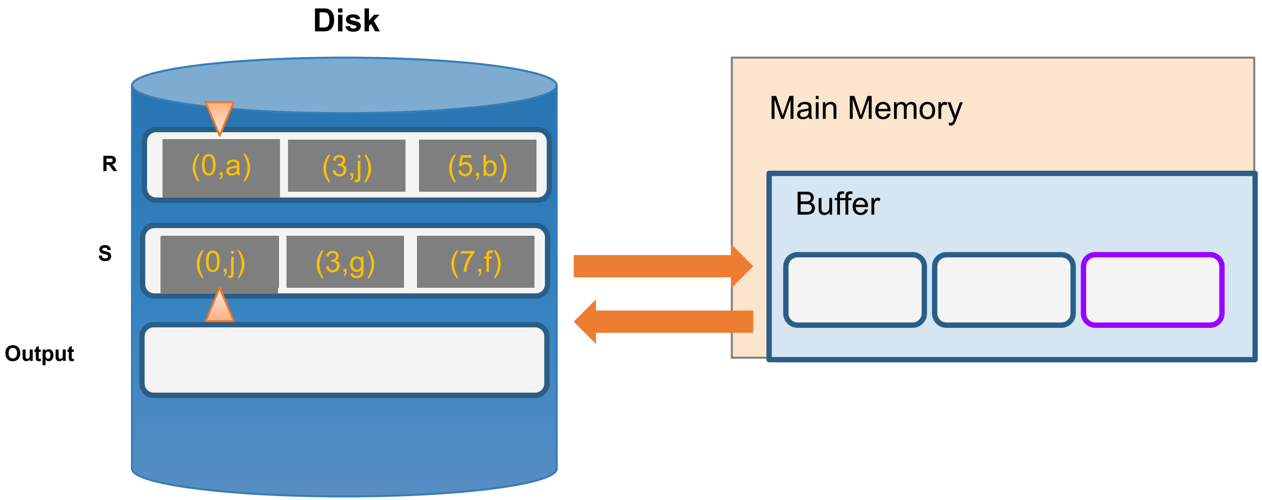


SMJ Example: R$\bowtie S$ with 3 page buffer



SMJ Example: R⋈S with 3 page buffer

2. Scan and “merge” on join key!



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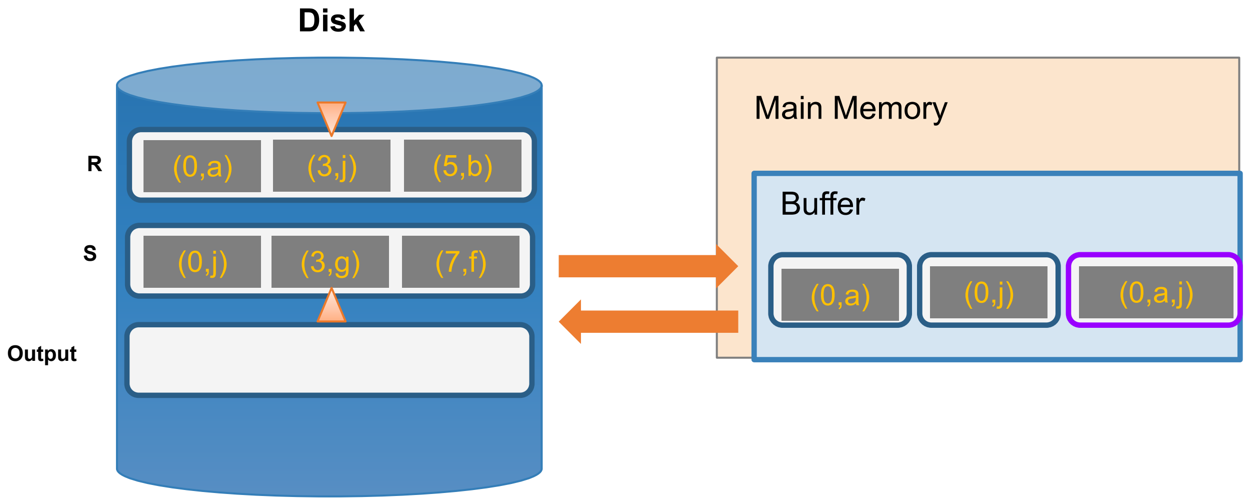

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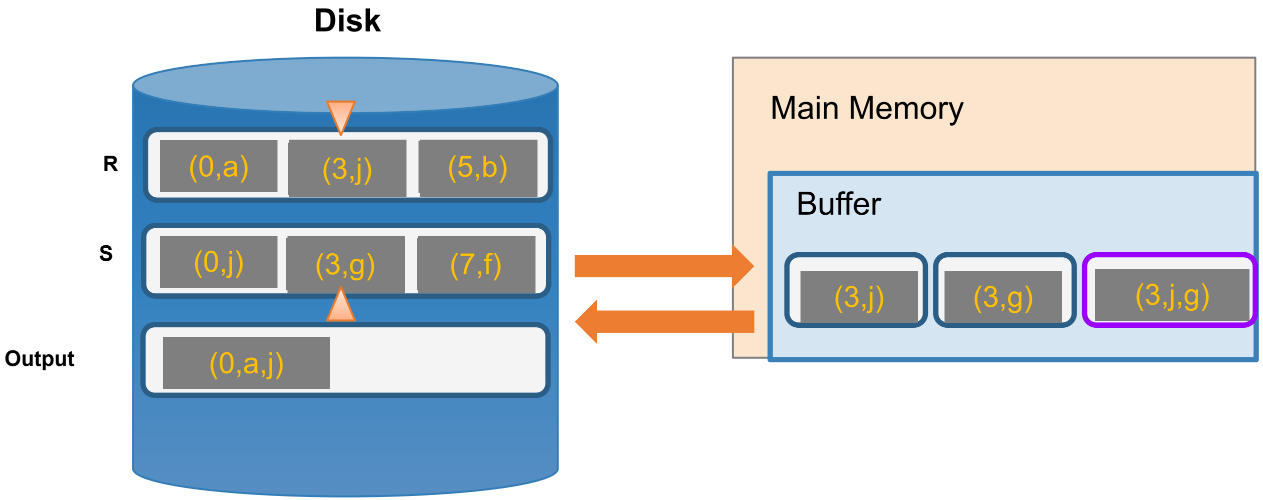
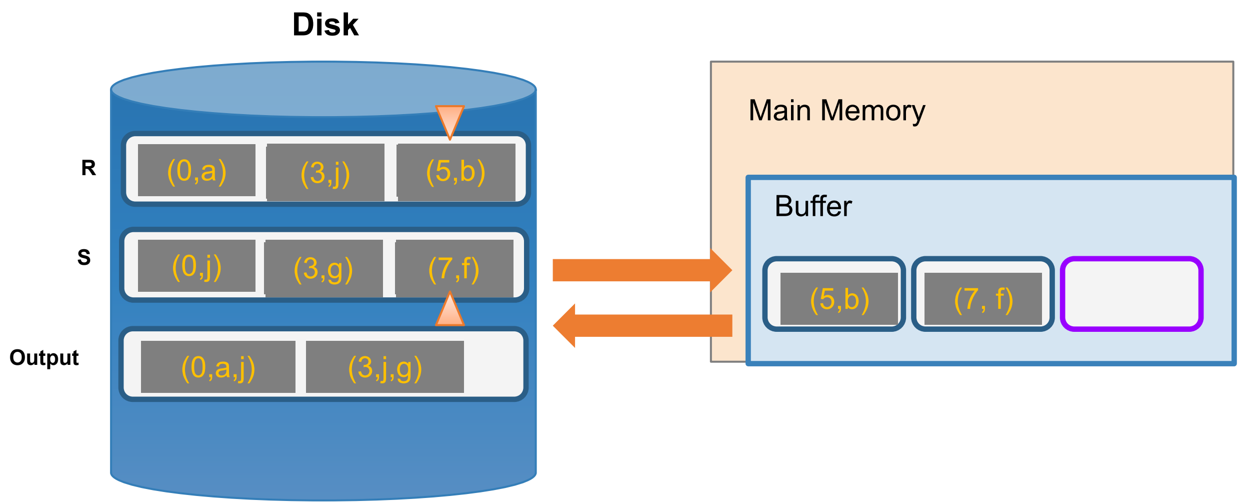


SMJ Example: R⋈S with 3 page buffer

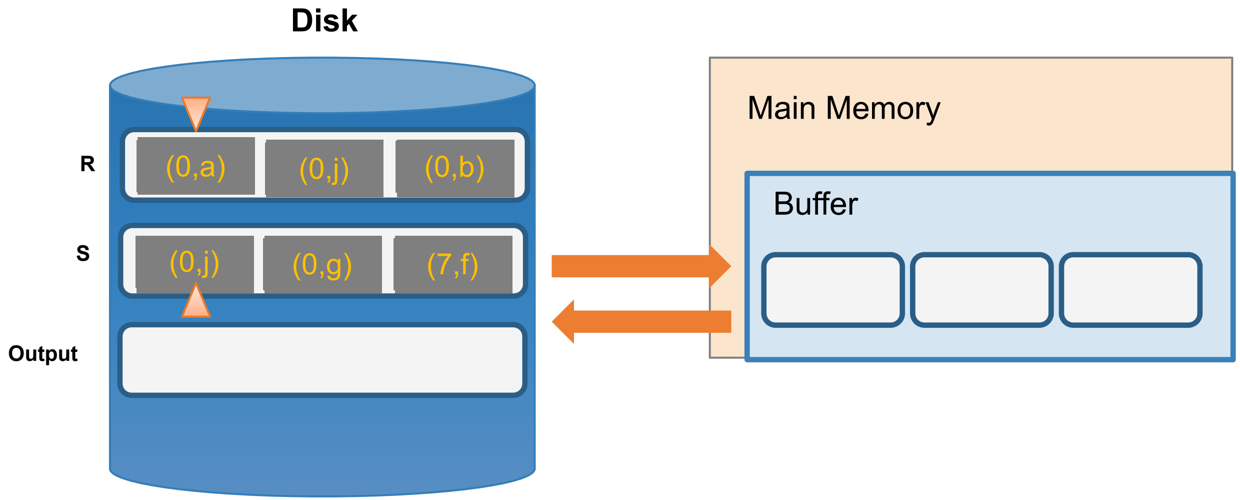
2. Done!



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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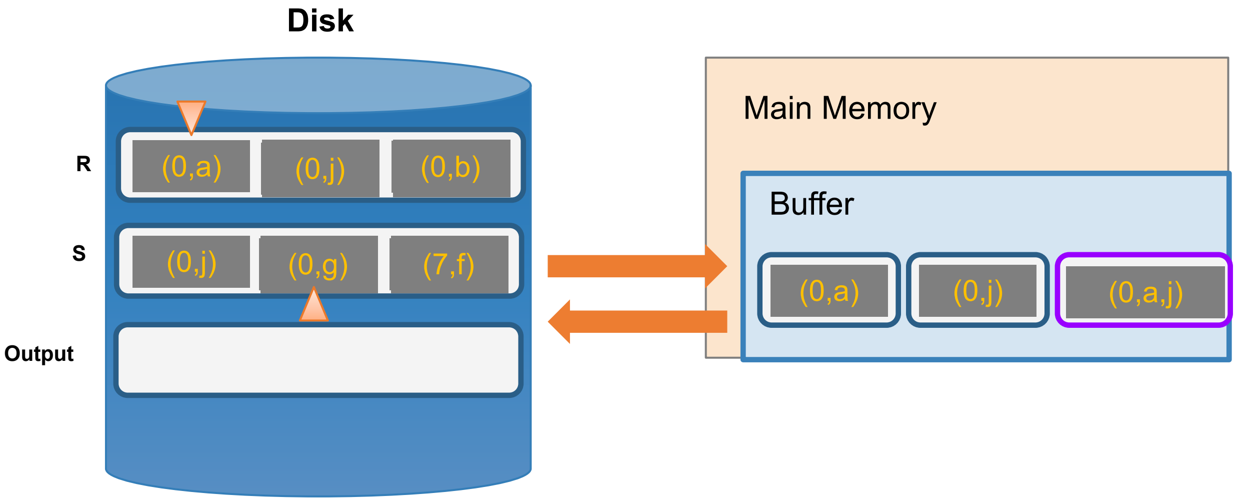

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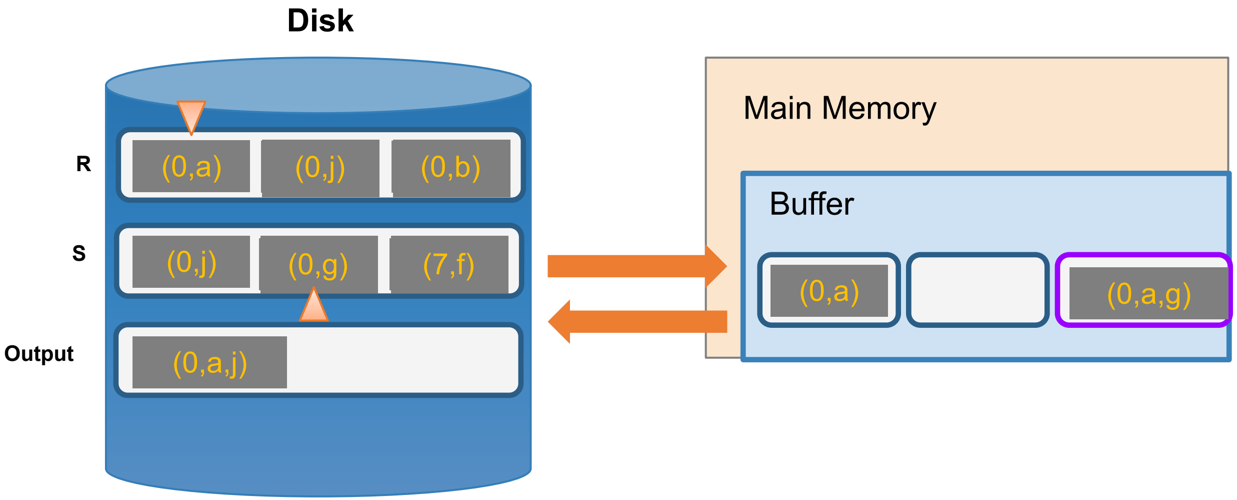
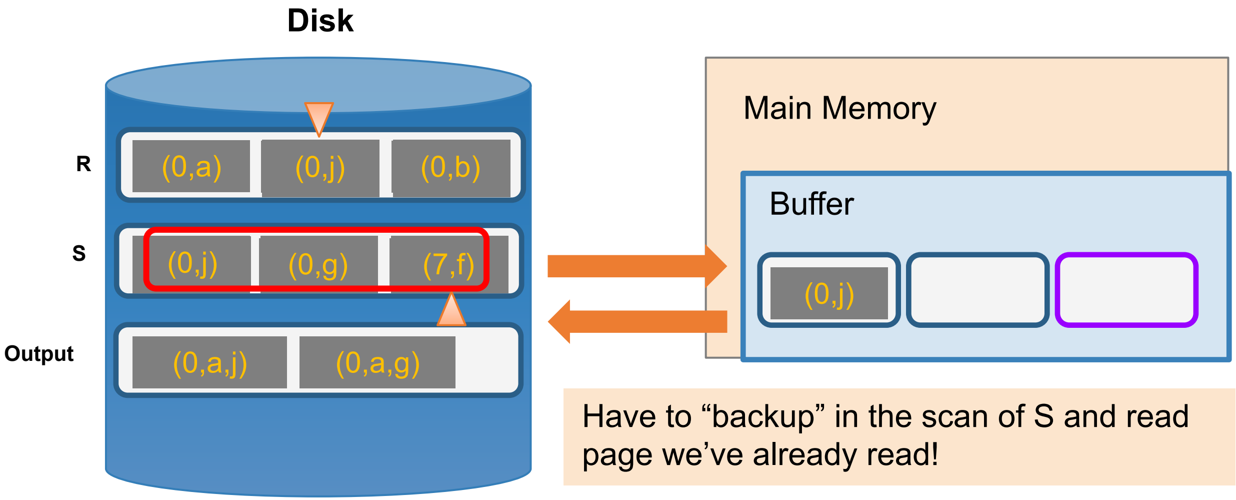


Multiple tuples with Same Join Key: “Backup”

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



Have to “backup” in the scan of S and read page we’ve already read!

Backup

- At best, no backup → 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 *back up* and read each page of S…
- Often not that bad however, plus we can:
  - Leave more data in buffer (for larger buffers)
  - Can try other algorithms

SMJ: Total cost

- Cost of SMJ is **cost of sorting** R and S…
- Plus the **cost of scanning**: ~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**: OUT

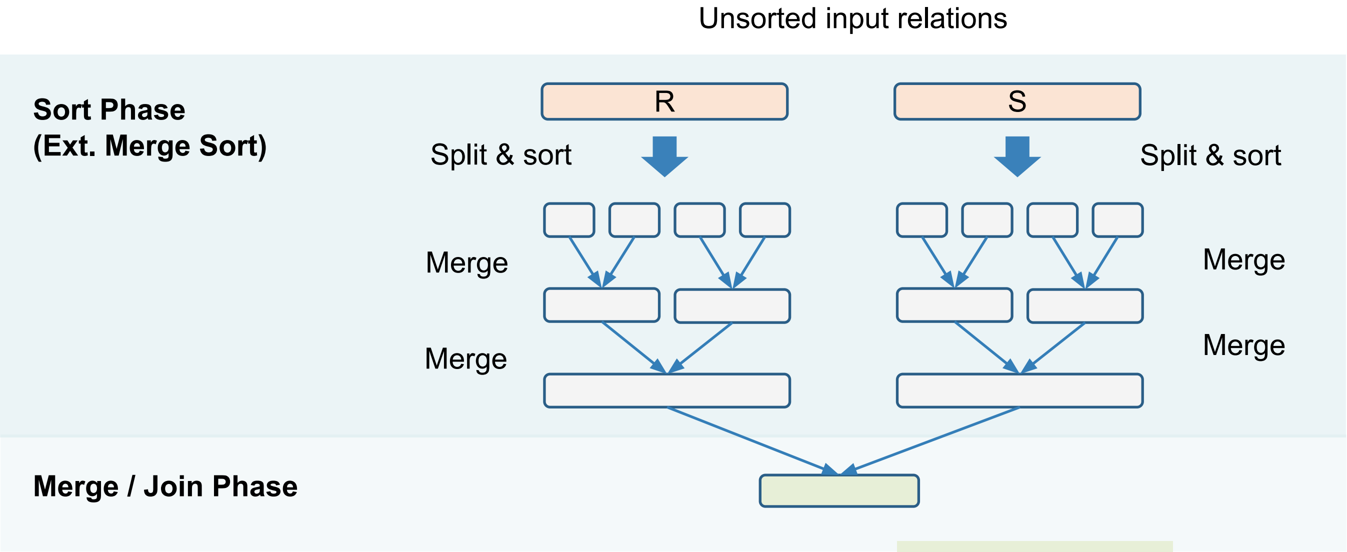
~ Sort(P(R)) + Sort(P(S)) + P(R) + P(S) + OUT

Recall: Sort(N) $\approx 2N\left(\overbrace{\left\lceil \log_B \frac{N}{2(B+1)} \right\rceil + 1}^{\text{Num passes}}\right)$

Note: this is using repacking, where we estimate that we can create initial runs of length ~2(B+1)

Un-Optimized SMJ

Given ***B+1*** buffer pages

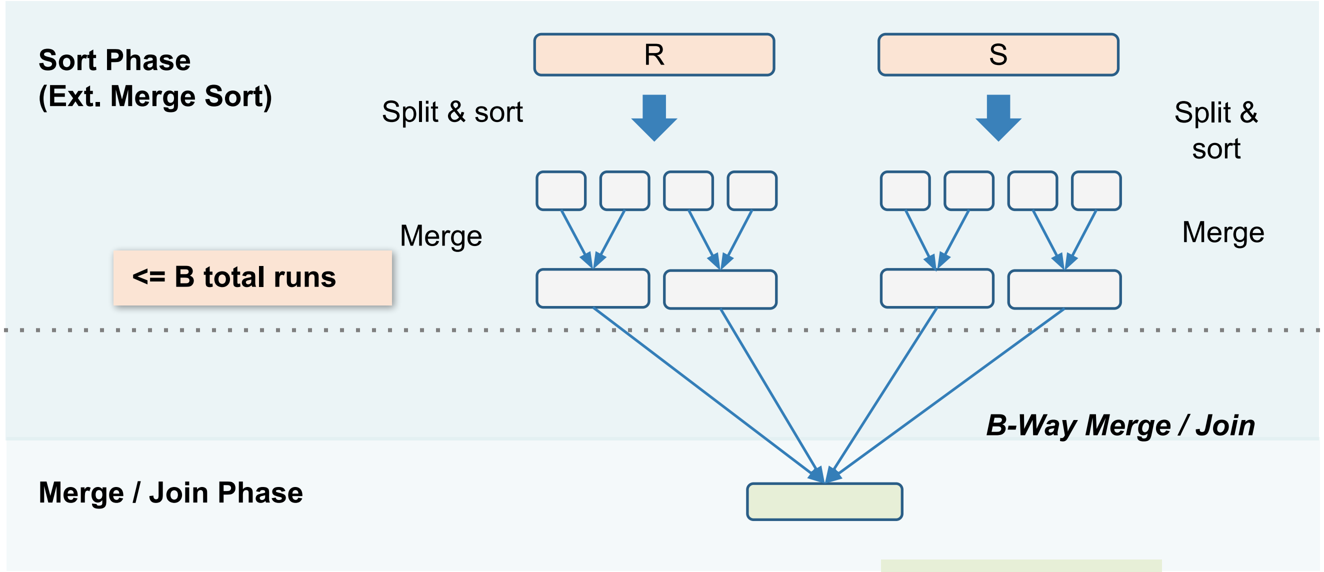


Joined output file created!

Simple SMJ Optimization

Given ***B+1*** buffer pages

Unsorted input relations



Joined output file created!

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

Example SMJ Number of passes

Consider P(R) = 1000, P(S) = 500

Recall: $\text{Sort}(N) \approx 2N\left(\left\lceil \log_B \frac{N}{2(B+1)} \right\rceil + 1\right)$

Note: this is using repacking, where we estimate that we can create initial runs of length ~2(B+1)

Num passes for R (for B+ 1 = 100) =

$K = \lceil \log_{99} 1000/(2*99) \rceil + 1) = 2$

Num passes for R (for B+ 1 = 20)

$K = \lceil \log_{19} 1000/(2*19) \rceil + 1) = 3$

(Repeat for S, and you get k = 2 and 3)

Reminder: More Buffer? Fewer passes for Sorting

Example SMJ vs. BNLJ: Steel Cage Match

Consider P(R) = 1000, P(S) = 500

~ Sort(P(R)) + Sort(P(S)) + P(R) + P(S) + OUT

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

	Buffer = 100 (i.e., B+1=100)	**Buffer = 20** (i.e., B+1=20)
SMJ	(Sort R and S in **2** passes: 2* (k* 1000 + k* 500) = 6000 Merge: 1000 + 500 = 1500 IOs) ⇒ IO = 7500 IOs + OUT	(Sort R and S in **3** passes: 2* (k* 1000 + k* 500) = 9000 Merge: 1000 + 500: 1500 IOs) ⇒ IO = 10,500 IOs + OUT
BNLJ	(500 + 1000*500/(99-1)) ⇒ IO = ~5.6K+OUT	(500 + 1000*500/(19-1)) ⇒ IO = 28.2K IOs +OUT

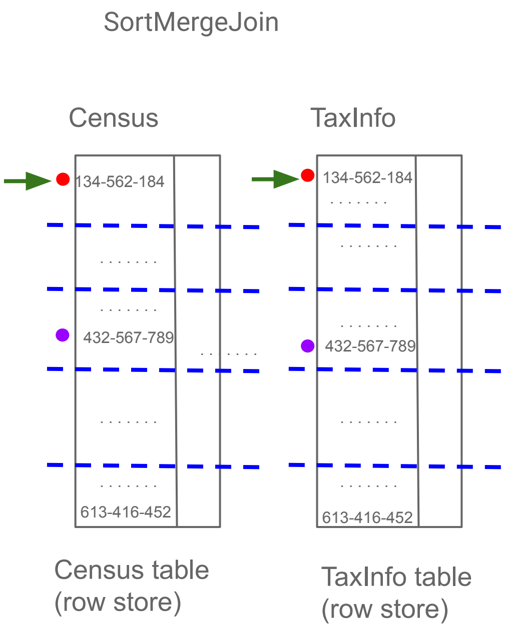
SMJ is ~ linear vs. BNLJ is quadratic…
But it's all about the memory.

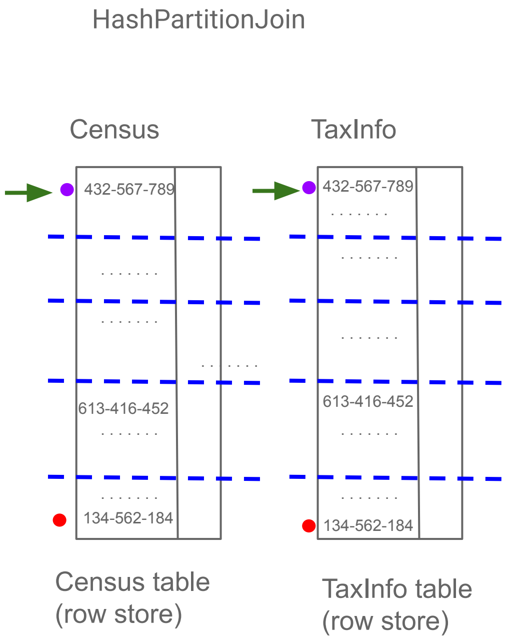
What you will learn about in this section

0. Intuition for smarter joins
1. Sort-Merge Join
2. HashPartion Joins

Preview of smarter joins

Pre-process data before JOINing





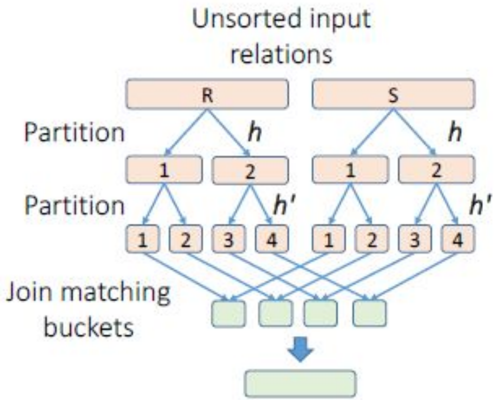
-- Sort(Census), Sort(TaxInfo) on SSN
-- Merge sorted pages

-- Hash(Census), Hash(TaxInfo) on SSN
-- Merge partitioned pages

Hash Join (HJ) or
Hash Partition Join (HPJ)

Hash Join

- ***Goal:*** Execute R ⋈ S on A
- ***Key Idea:*** We can partition R and S into buckets by hashing the join attribute-then just join the pairs of (small) matching buckets!



Hash Partition Join: High-level

To compute R ⋈ S on A:

Note again that we are only considering equality constraints here

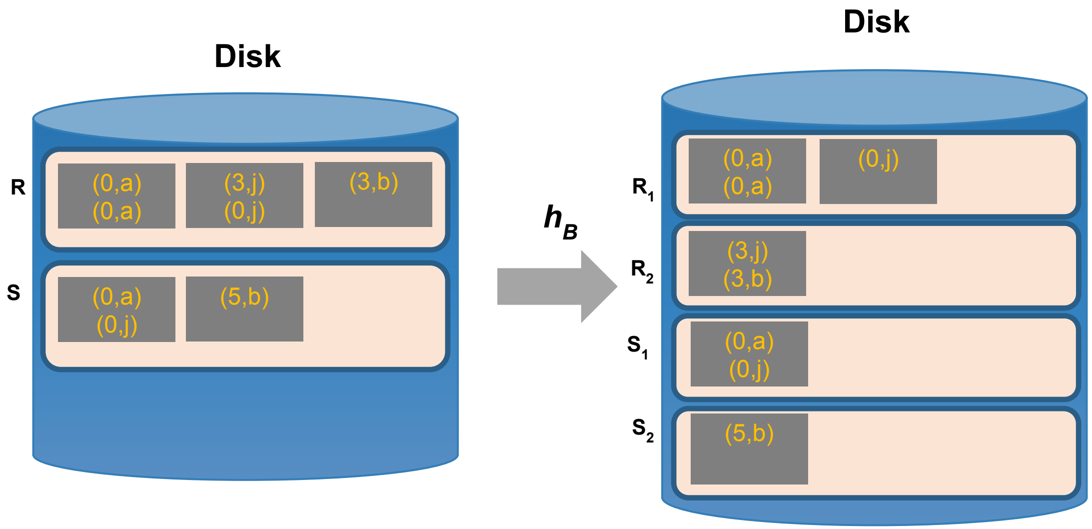
1. Hash Partition: Split R, S into B buckets, using h_B on A

2. Per-Partition Join: JOIN tuples in same partition (i.e, same hash value)

We ***decompose*** the problem using $\boldsymbol{h_B}$, then complete the join

HPJ: High-level procedure

1. Hash Partition: Split R, S into B buckets, using h_B on A

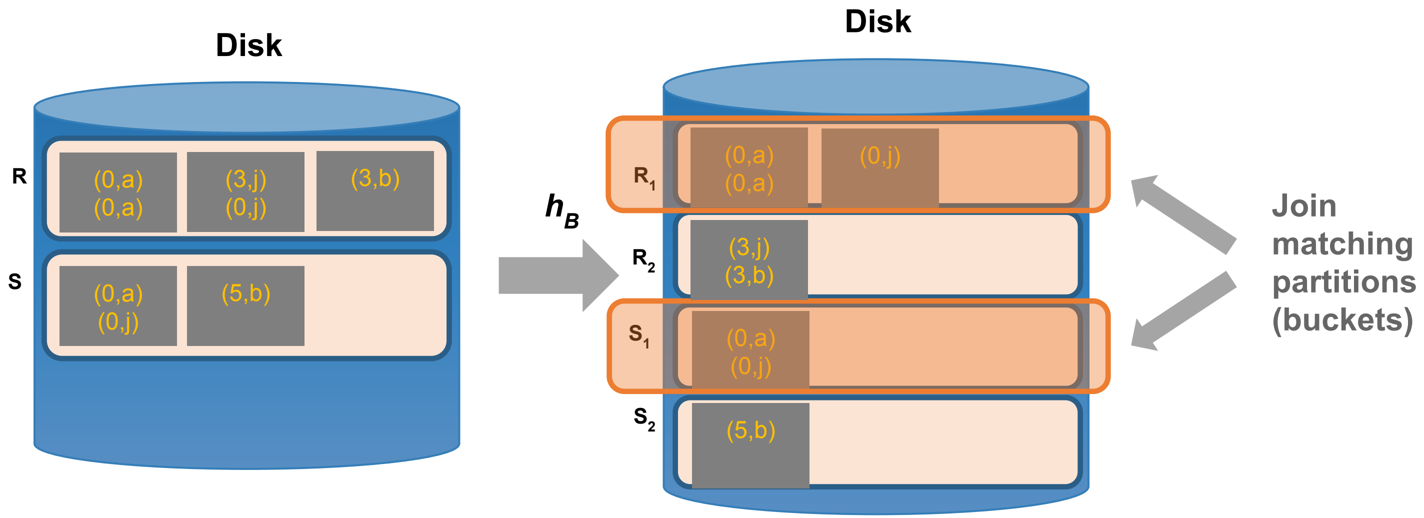


*Note our new convention: pages each have **two** tuples (one per row)*

More detail in a second…

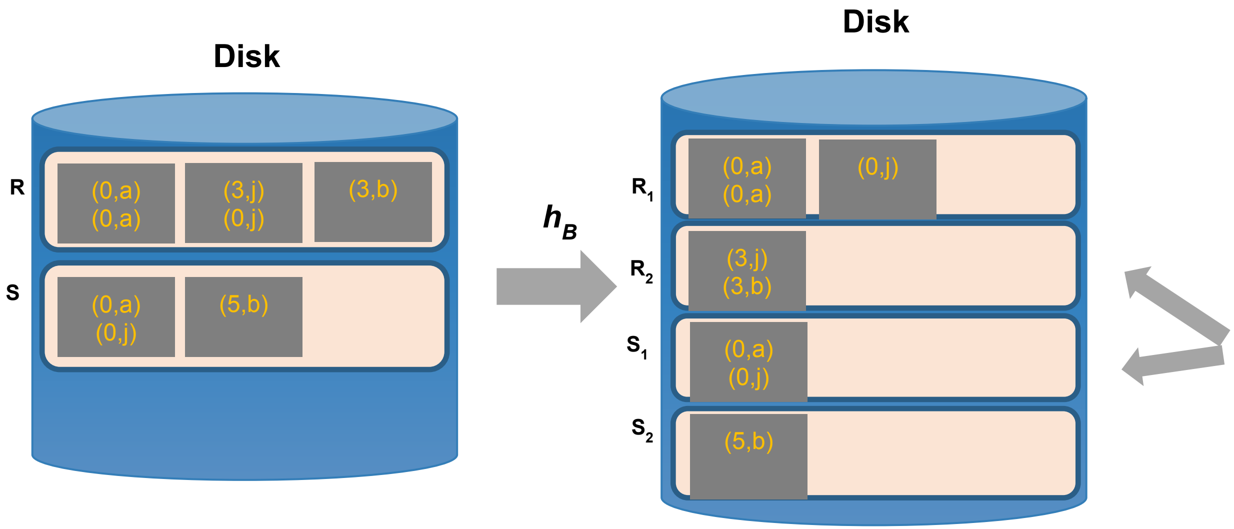
HPJ: High-level procedure

2. Per-Partition Join: JOIN tuples in same partitions



HPJ: High-level procedure

2. Per-Partition Join: JOIN tuples in same partition



Don't have to join the others! E.g. (S_1 and R_2)!

HPJ Phase 1: Hash 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

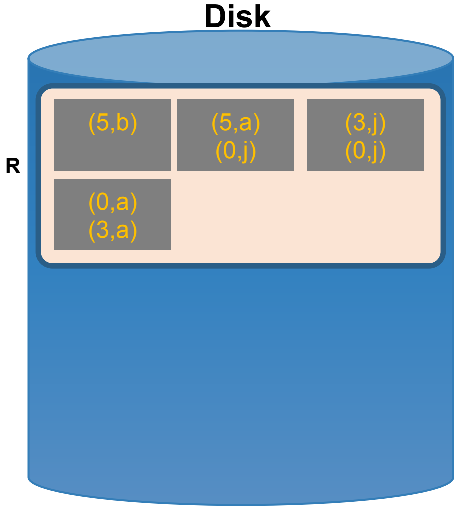
Given B+1 buffer pages, we partition into B buckets:

- We use B buffer pages for output (one for each bucket), and 1 for input
  - For each tuple t in input, copy to buffer page for $h_B(t.A)$
  - When page fills up, flush to disk.

HPJ Phase 1: Partitioning

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)

Given ***B+1* = 3** buffer pages

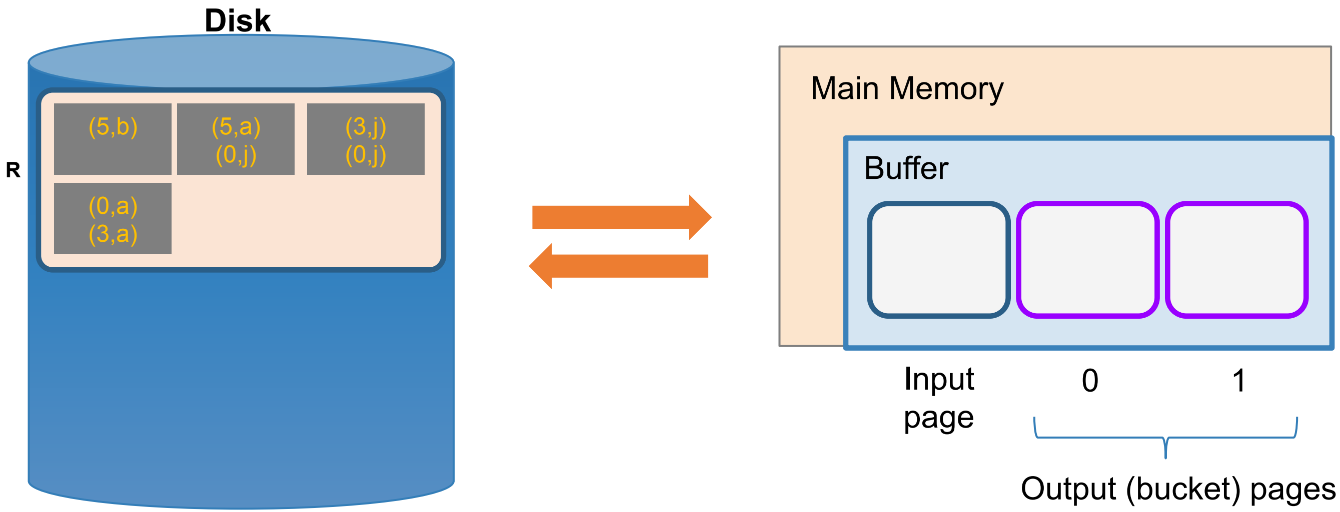


For simplicity, we'll look at partitioning one of the two relations- we just do the same for the other relation!

HPJ Phase 1: Partitioning

1. We read pages from R into the "input" page of the buffer…

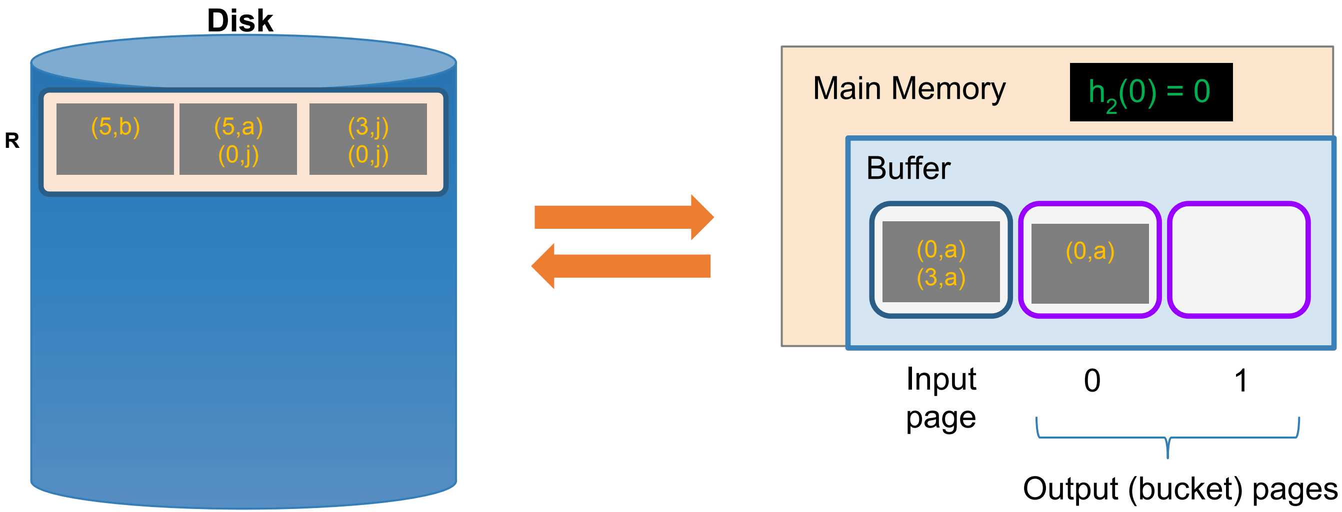
Given ***B+1 = 3*** buffer pages



HPJ Phase 1: Partitioning

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

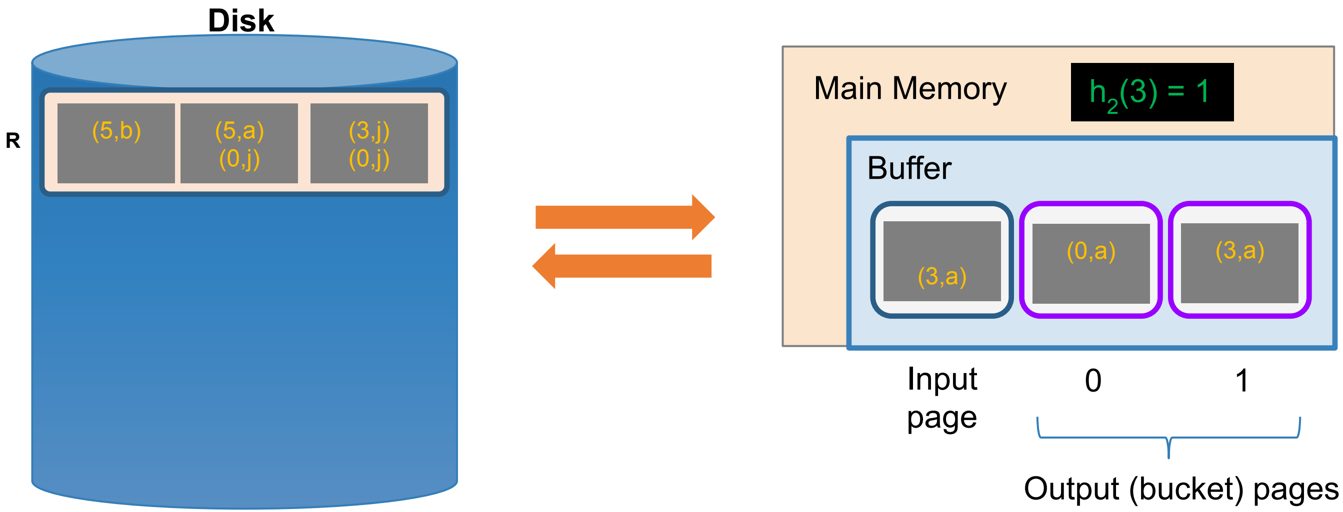
Given ***B+1 = 3*** buffer pages



HPJ Phase 1: Partitioning

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

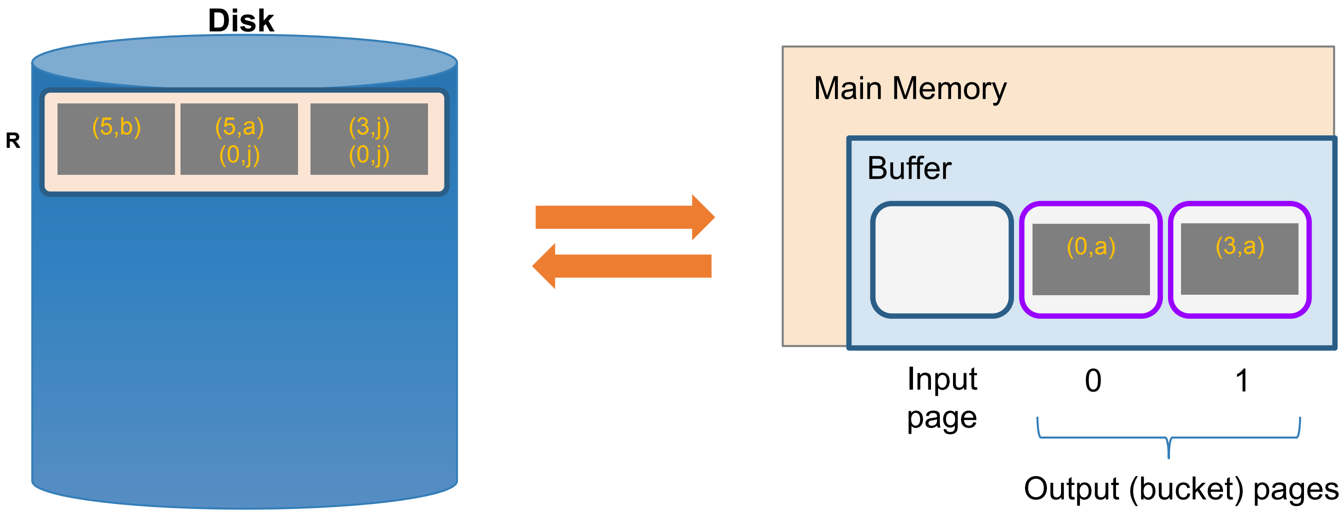
Given ***B+1* = *3*** buffer pages



HPJ Phase 1: Partitioning

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

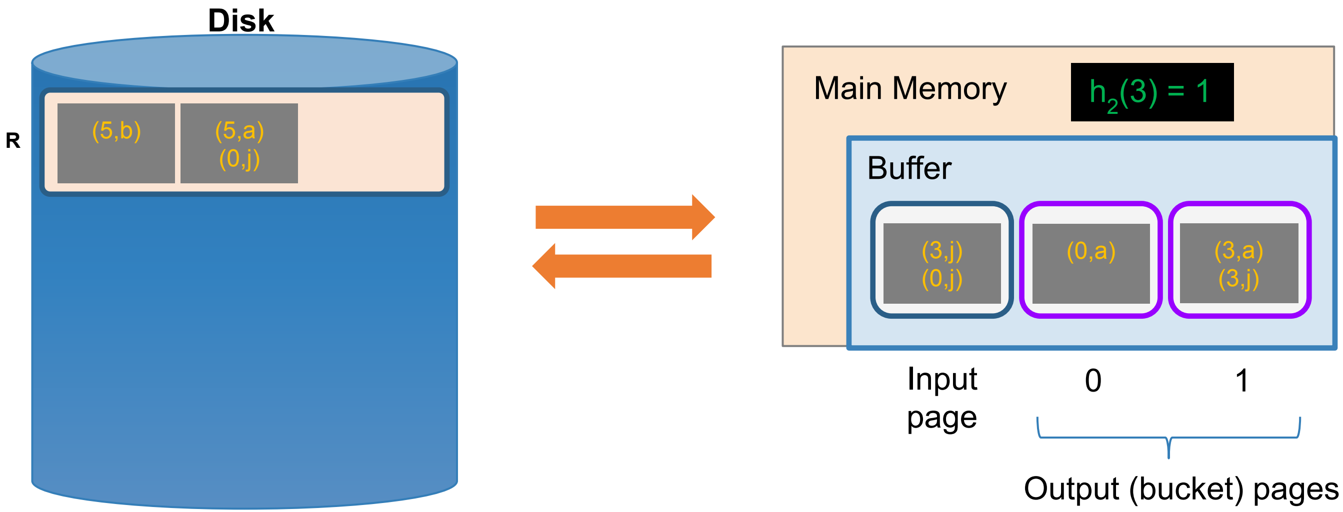
Given ***B+1 = 3*** buffer pages



HPJ Phase 1: Partitioning

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

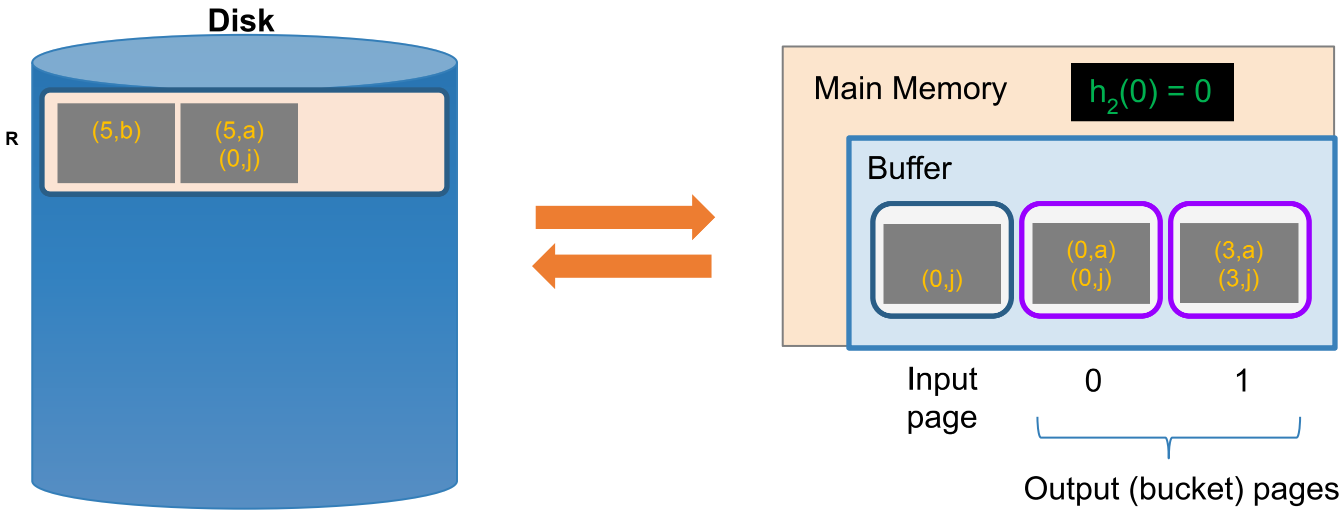
Given ***B+1 = 3*** buffer pages



HPJ Phase 1: Partitioning

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

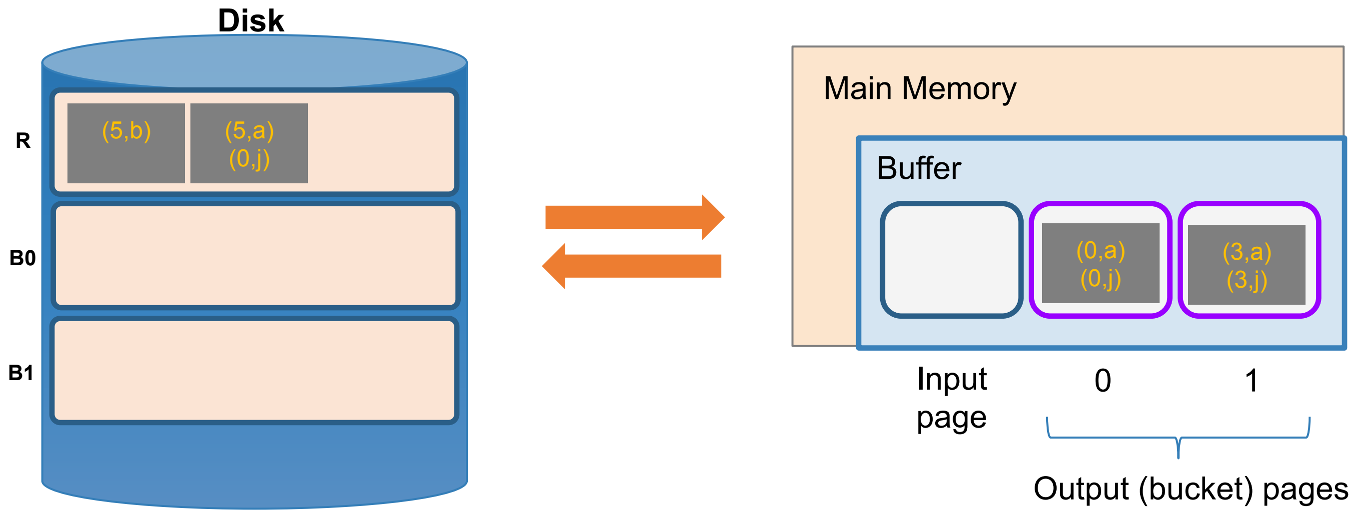
Given ***B+1 = 3*** buffer pages



HPJ Phase 1: Partitioning

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

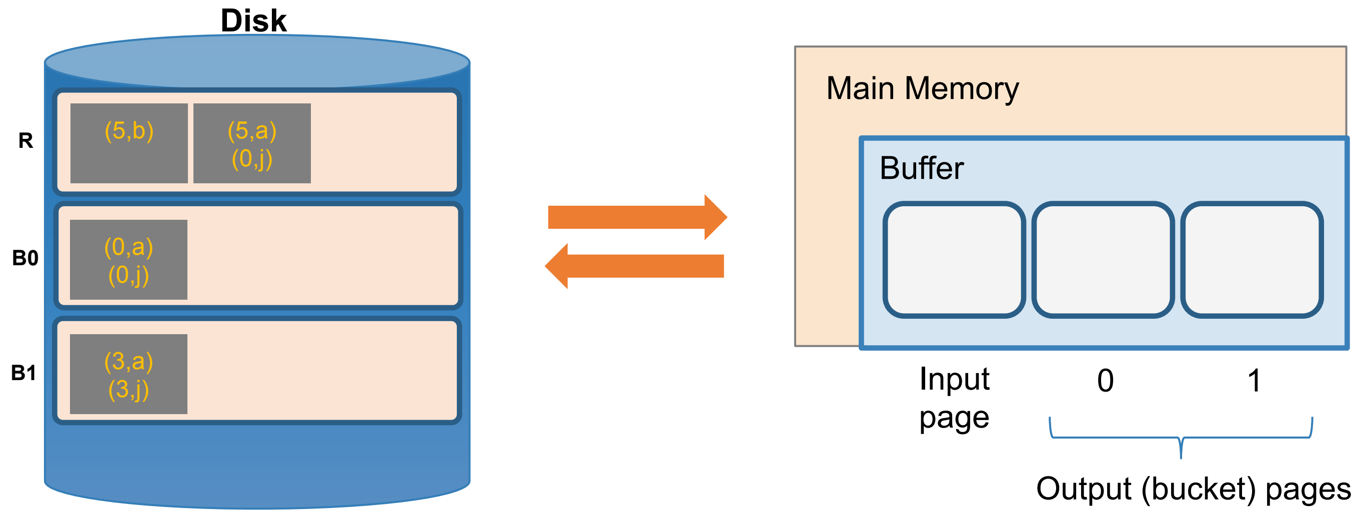
Given ***B+1 = 3*** buffer pages



HPJ Phase 1: Partitioning

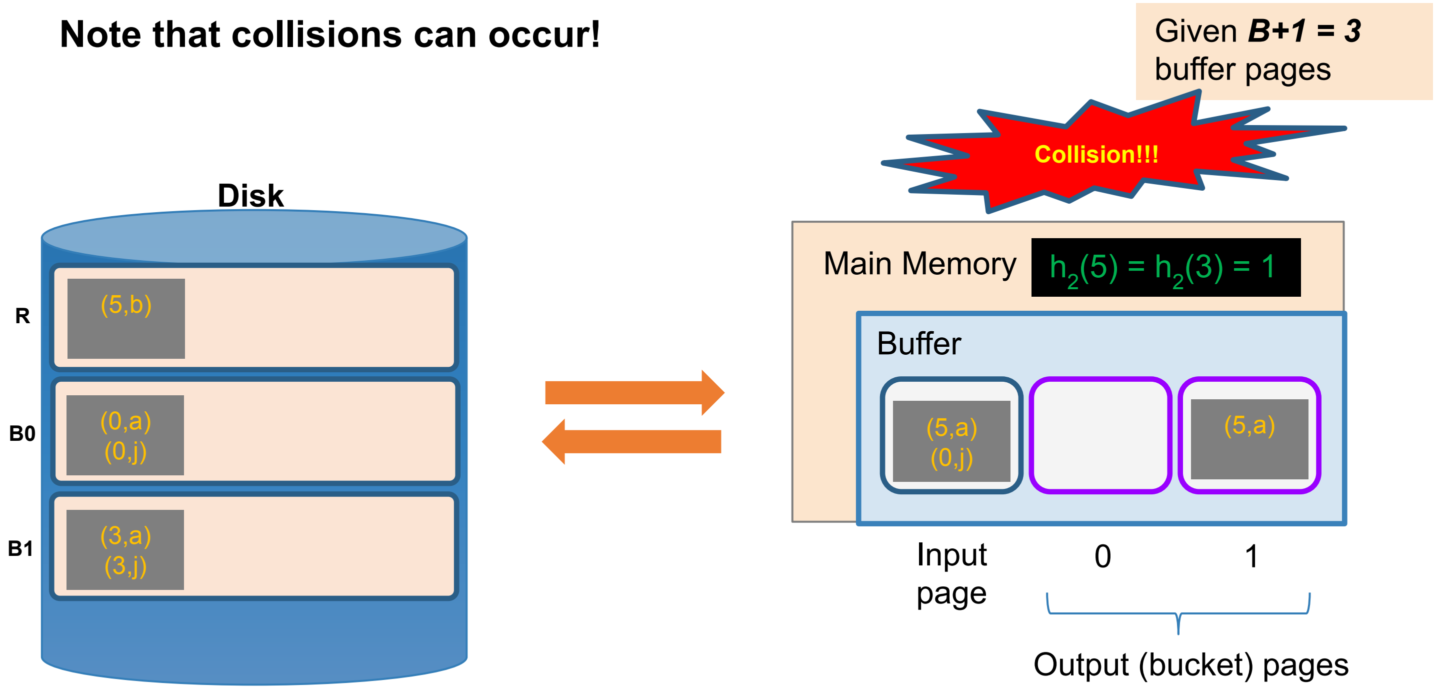
3. We repeat until the buffer bucket pages are full… then flush to disk

Given ***B+1 = 3*** buffer pages



HPJ Phase 1: Partitioning

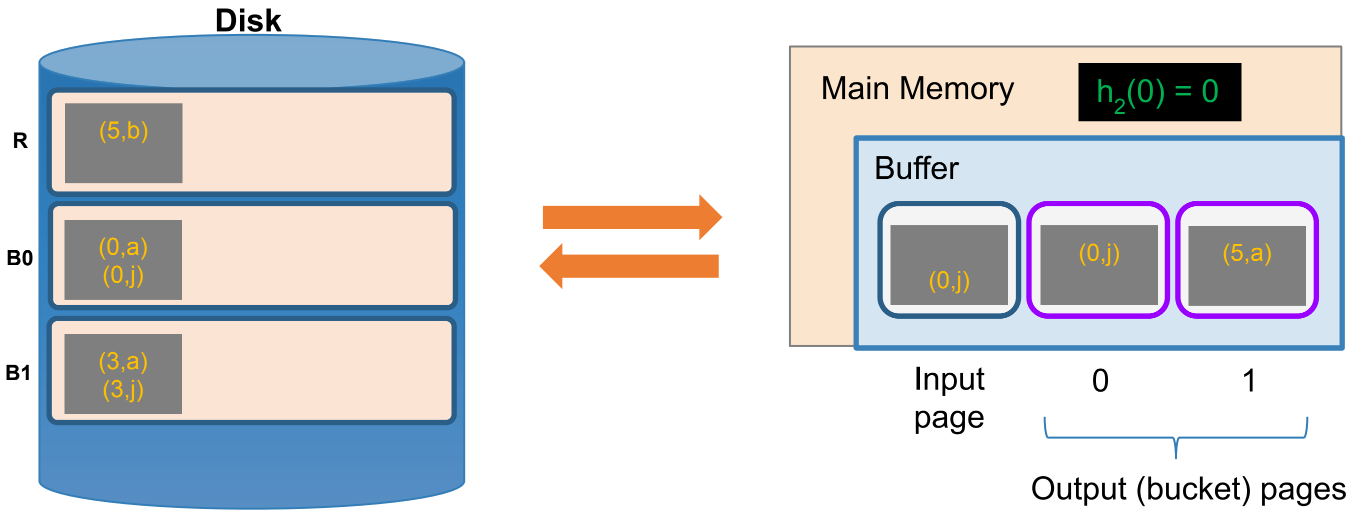
Note that collisions can occur!



HPJ Phase 1: Partitioning

Finish this pass…

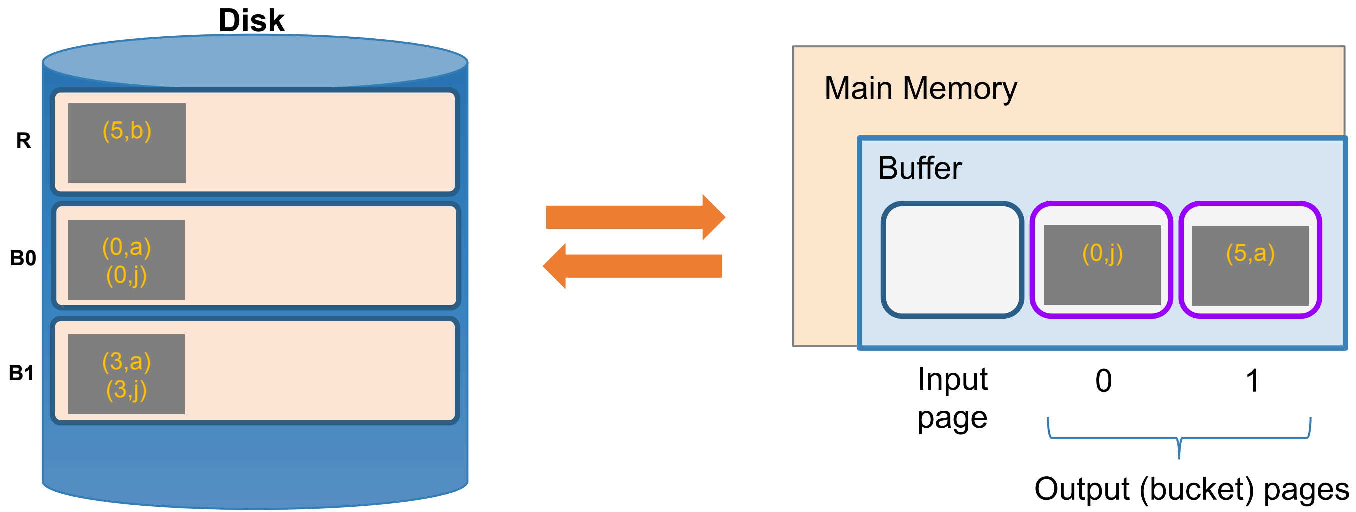
Given ***B+1 = 3*** buffer pages



HPJ Phase 1: Partitioning

Finish this pass…

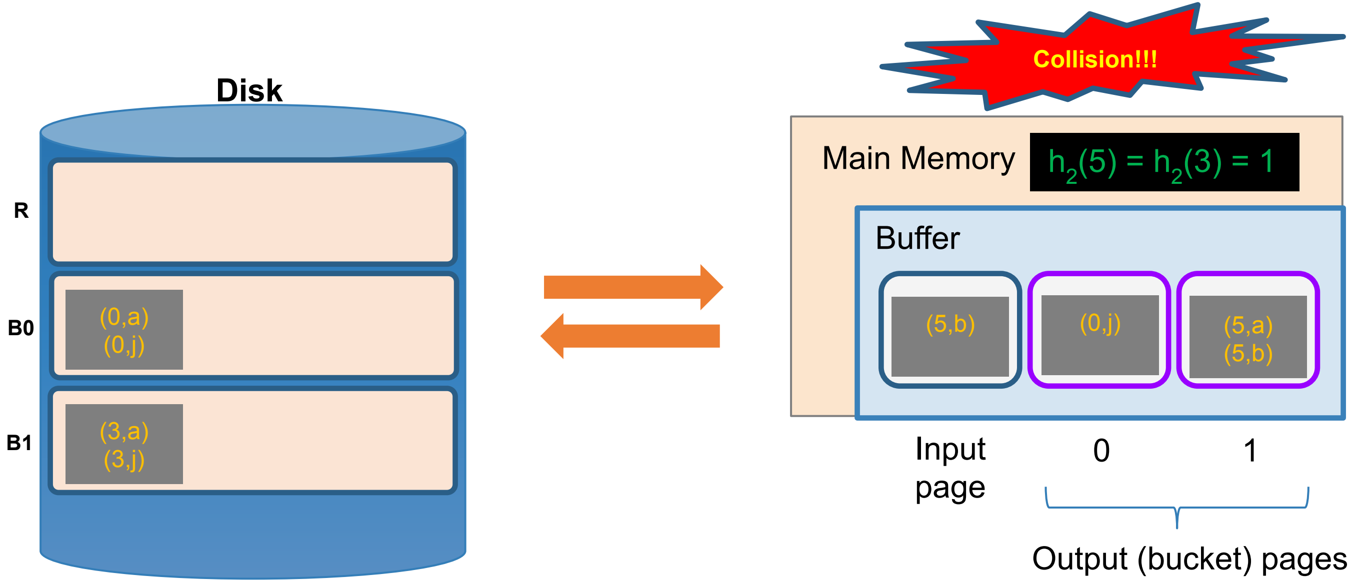
Given ***B+1 = 3*** buffer pages



HPJ Phase 1: Partitioning

Finish this pass…

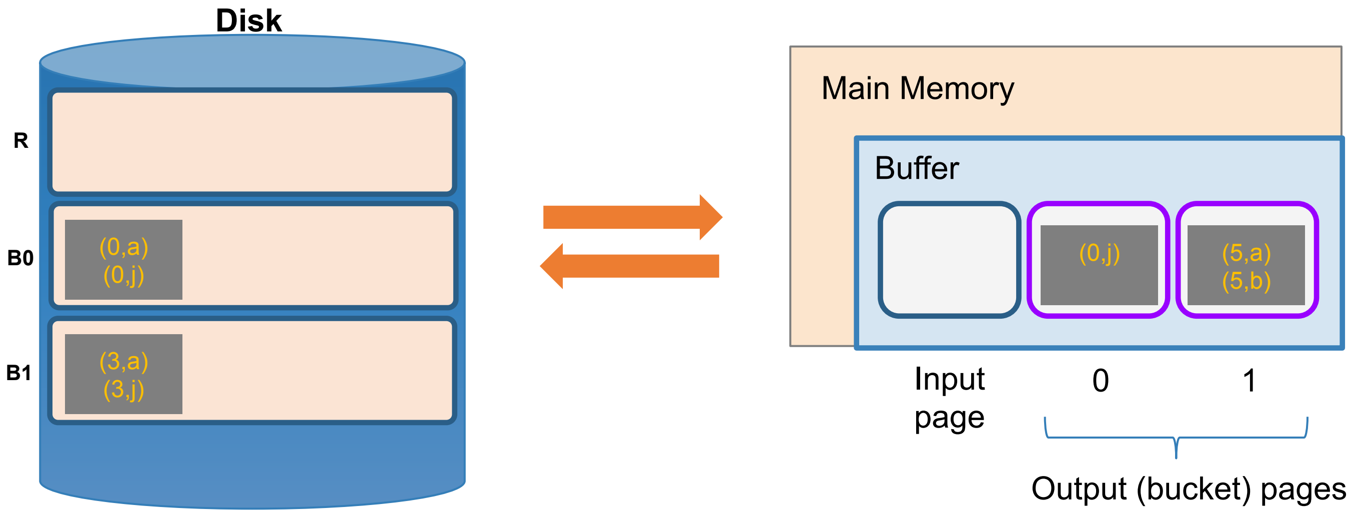
Given ***B+1 = 3*** buffer pages



HPJ Phase 1: Partitioning

Finish this pass…

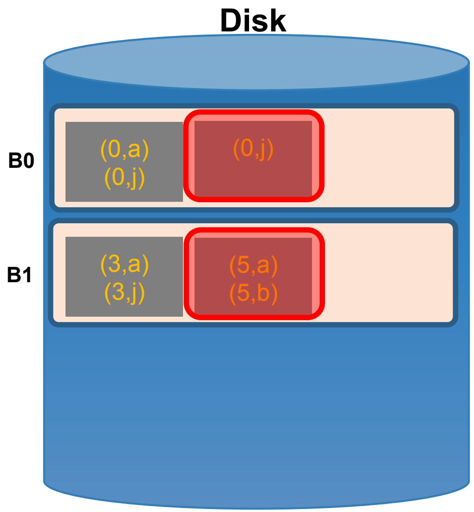
Given ***B+1 = 3*** buffer pages



HPJ Phase 1: Partitioning

Given ***B+1 = 3*** buffer pages

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

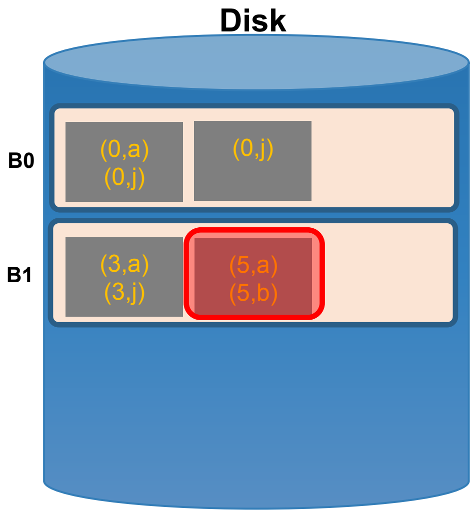


(1) Duplicate join keys

(2) Hash collisions

HPJ 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!

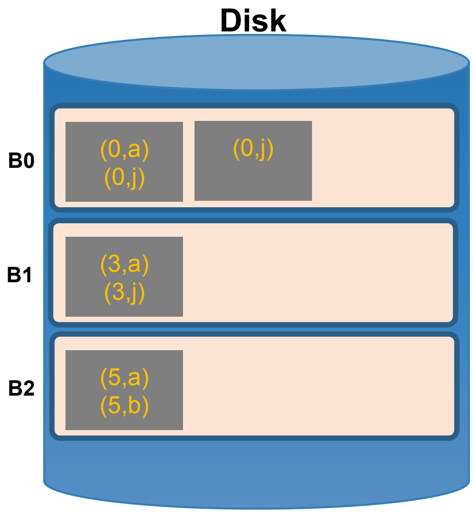
What hash function should we use?

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

$$h'_2(3) \mathrel{!=} h'_2(5)$$

HPJ Phase 1: Partitioning

Given ***B+1 = 3*** buffer pages



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What hash function should we use?

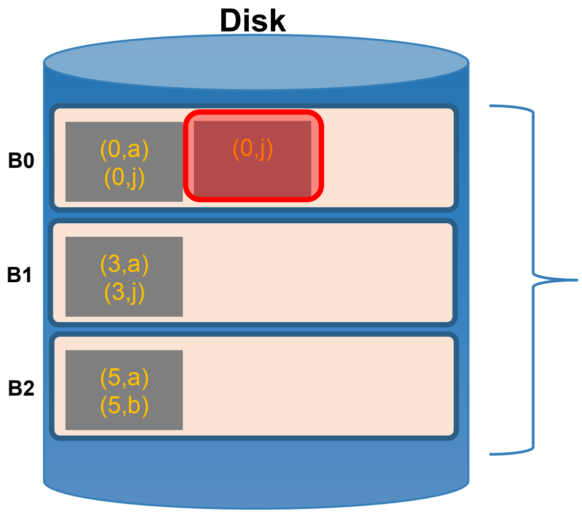
Do another pass with a different hash function, h'_2, ideally such that:

$$h'_2(3) \mathrel{!=} h'_2(5)$$

HPJ 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.

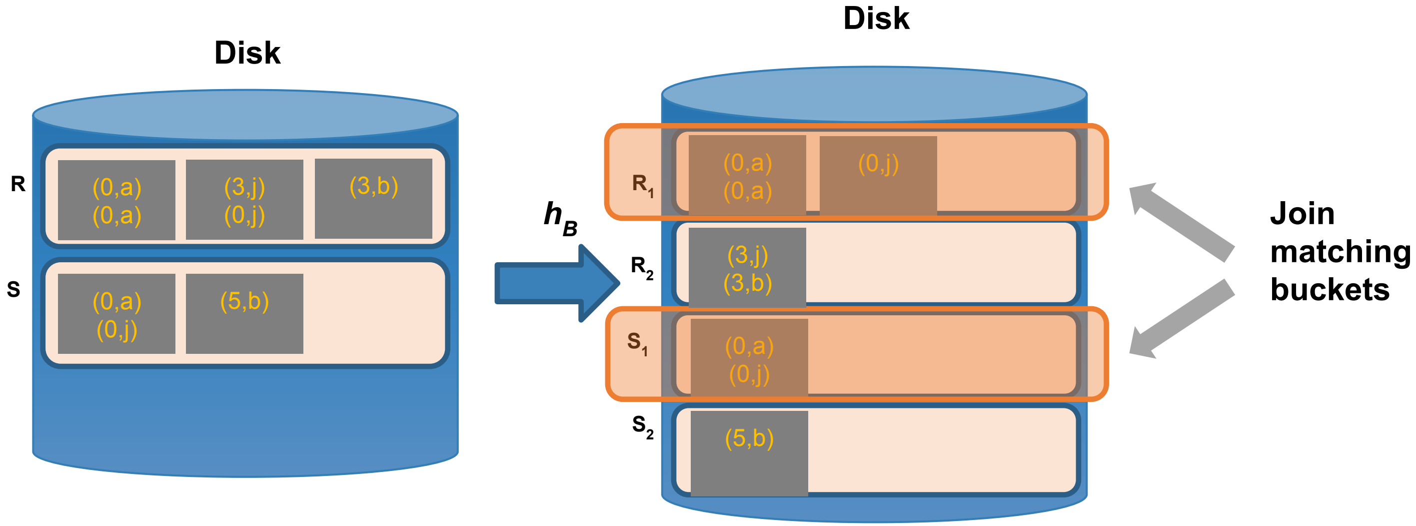


We call this unevenness in the bucket size **skew**

Now that we have partitioned R and S…

HPJ Phase 2: Partition Join

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



HPJ Summary

Given enough buffer pages…

- **Hash Partition** requires reading + writing each page of R,S
  - → 2(P(R)+P(S)) IOs
- **Partition Join** (with BNLJ) requires reading each page of R,S
  - → P(R) + P(S) IOs

HJ takes **~3(P(R)+P(S)) + *OUT*** IOs!

SMJ vs HPJ Joins Summary

- ***Given enough memory***, both SMJ and HJ have performance:

~3(P(R)+P(S)) + *OUT*

- Hash Joins are highly parallelizable

- Sort-Merge less sensitive to data skew and result is sorted

⇒ <u>Big takeaway</u>: IO-aware join algorithms
  - Massive difference vs brute-force
  - Nearly linear vs quadratic (or worse)