CSC 261/461 – Database Systems Lecture 19

Spring 2018

CSC 261, Spring 2018, UR

Sections to Study

Chapter 18

- 18.4.1 (J3 and J4)
- 18.4.4
- Section 19.1

Chapter 19

- Very Important: 19.1.2. We have gone through the material but you must study this section for better understanding.
 If must understand each and every step in Figure 19.2 is performed. Study the last paragraph: Summary of Heuristics for Algebraic Optimization.
- 19.3.2
- 19.3.3
- 19.4 (S1 to S6)
- 19.5 (J1-J4) (Important. We cover the exact same topic using easier representation.)

External Merge Sort

Why are Sort Algorithms Important?

- Data requested from DB in sorted order is extremely common
 - e.g., find students in increasing GPA order
- Why not just use quicksort in main memory??
 - What about if we need to sort **1TB** of data with **1GB** of RAM...

A classic problem in computer science!

So how do we sort big files?

- 1. Split into chunks small enough to **sort in memory ("runs")**
- Merge pairs (or groups) of runs using the external merge algorithm
- **3. Keep merging** the resulting runs *(each time = a "pass")* until left with one sorted file!

Before we proceed..

• Question: Assume each page/block can contain 100 records. You have a file containing 80 unsorted records. What is the IO cost of sorting this file.

A. 80 * log ₂ 80 IO
B. 1 IO
C. 2 IO
D. log ₂ 80 IO

Before we proceed..

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A. 80 * log ₂ 80 IO
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EXTERNAL MERGE & SORT

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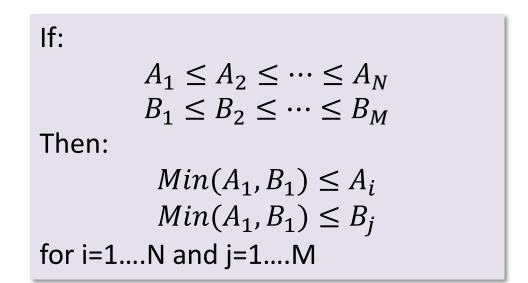
Challenge: Merging Big Files with Small Memory

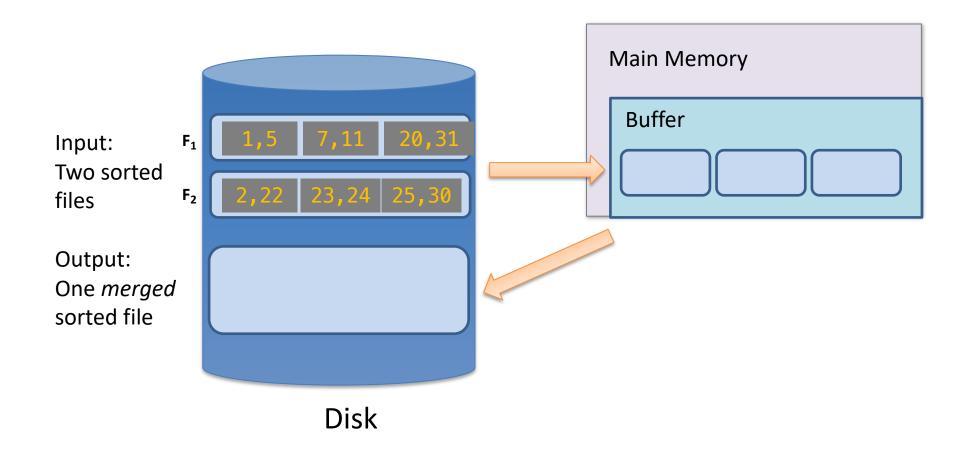
How do we *efficiently* merge two sorted files when both are much larger than our main memory buffer?

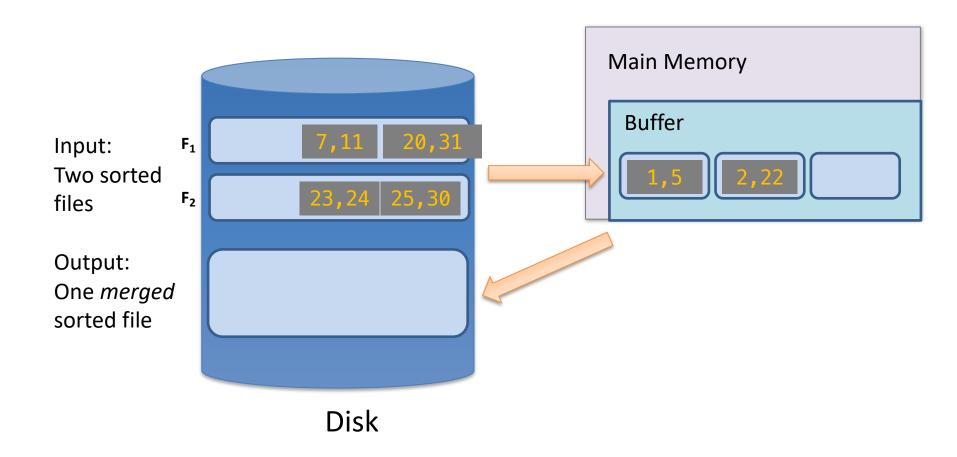
- Input: 2 sorted lists of length M and N
- **Output:** 1 sorted list of length M + N
- **Required:** At least 3 Buffer Pages
- IOs: 2(M+N)

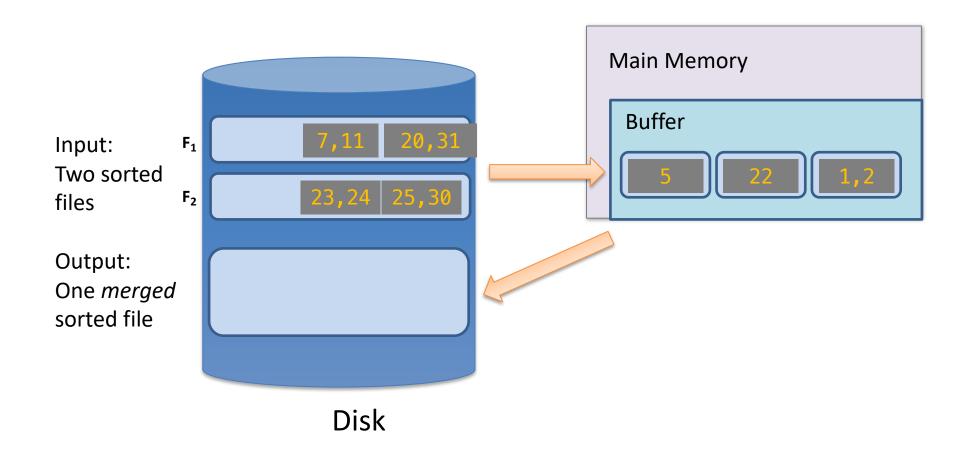
Key (Simple) Idea

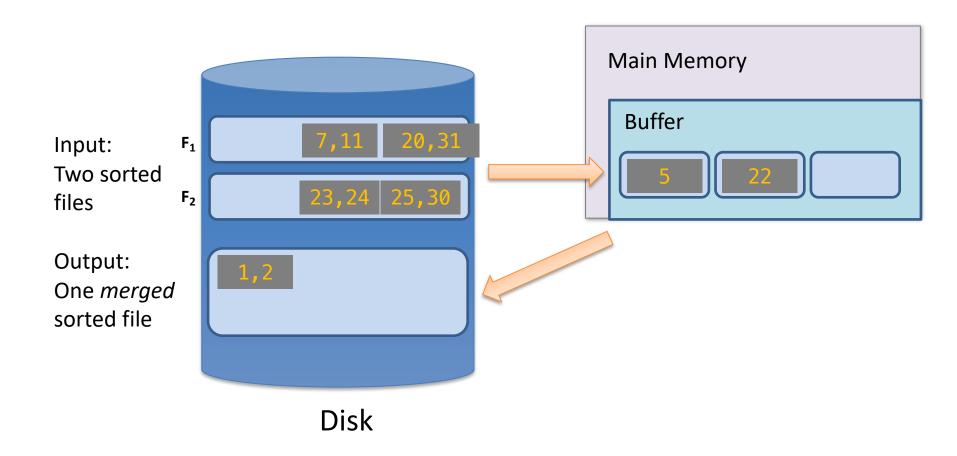
To find an element that is no larger than all elements in two lists, one only needs to compare minimum elements from each list.

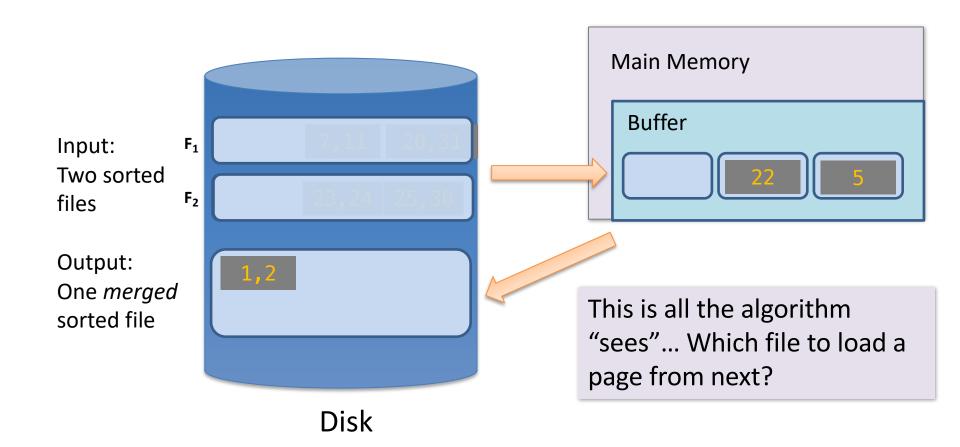


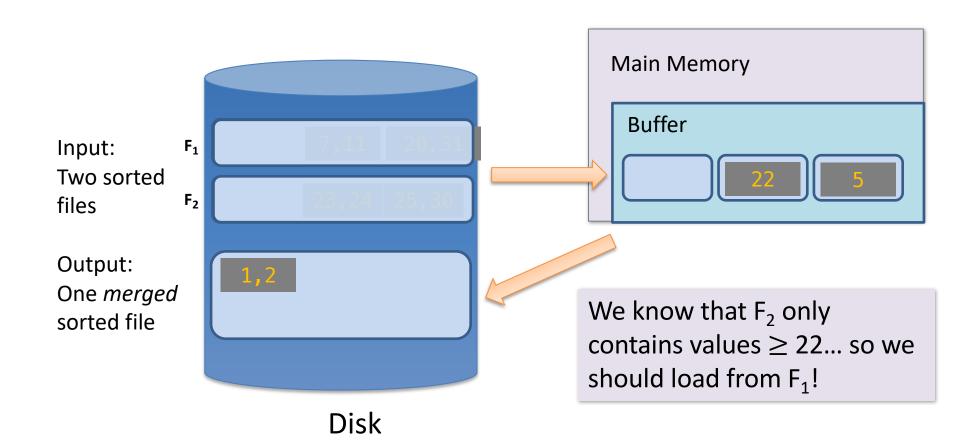


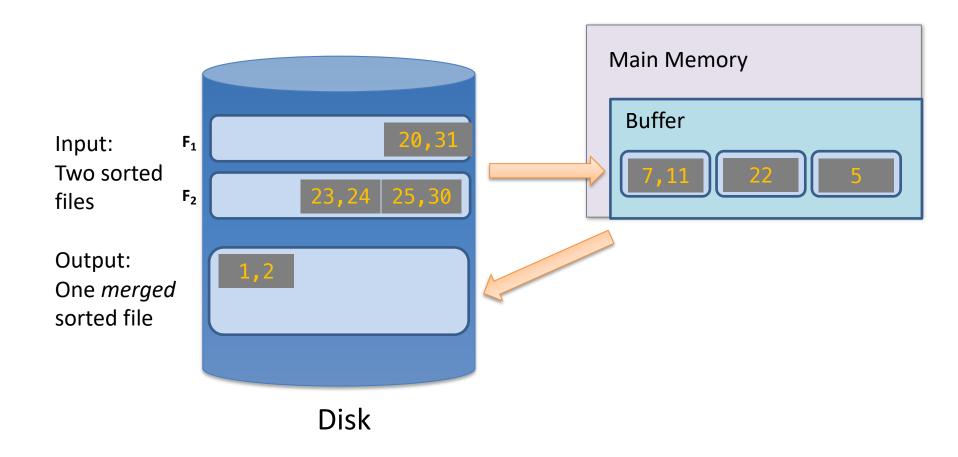


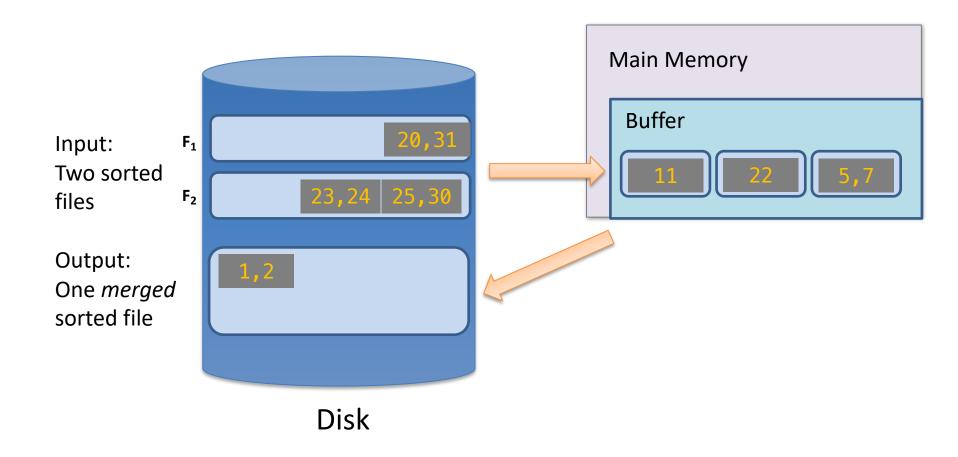


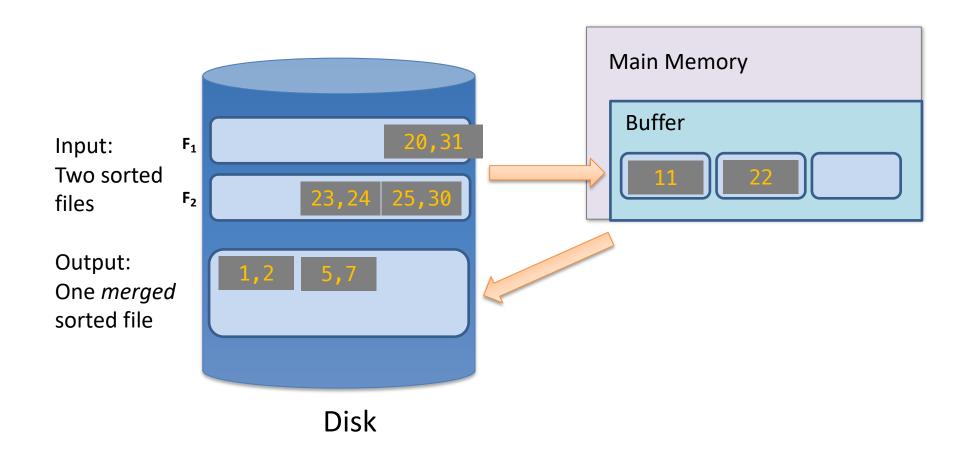


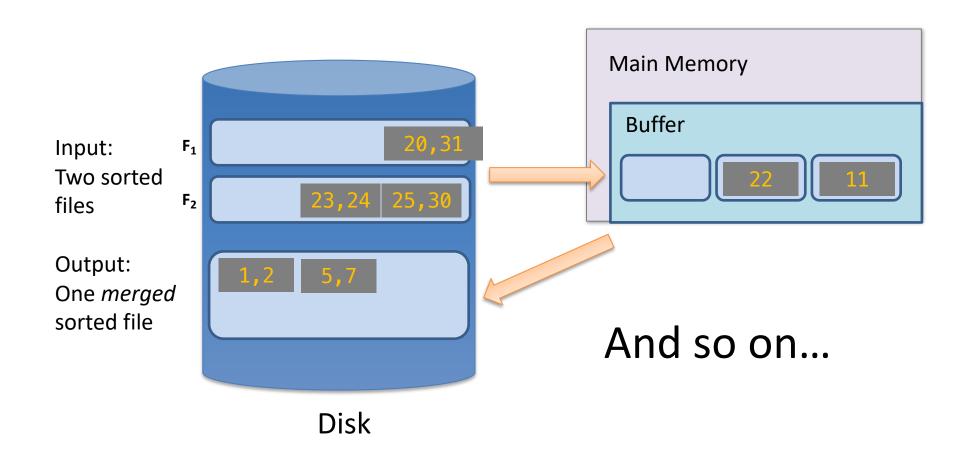






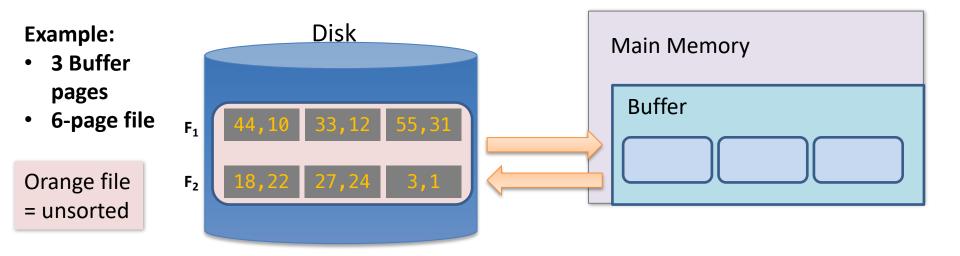




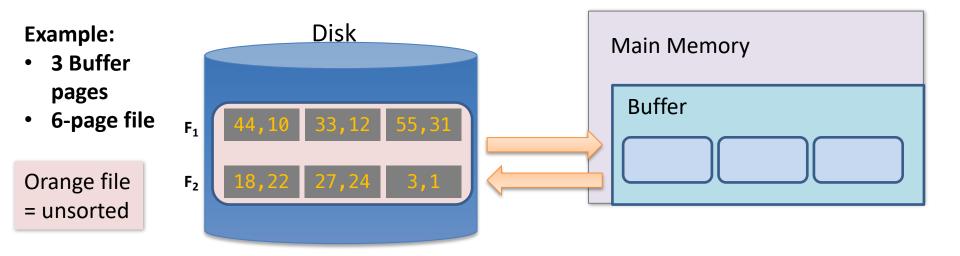


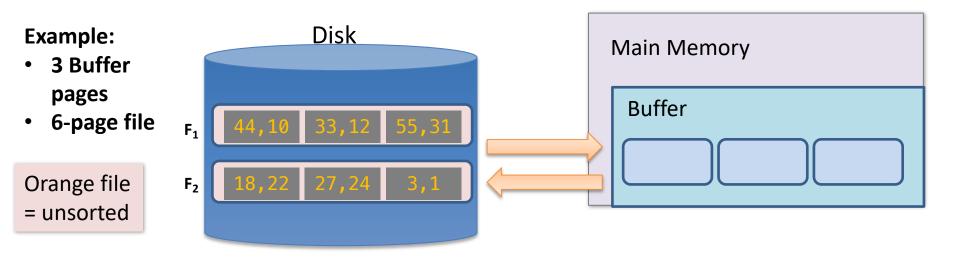
We can merge lists of **arbitrary length** with *only* 3 buffer pages.

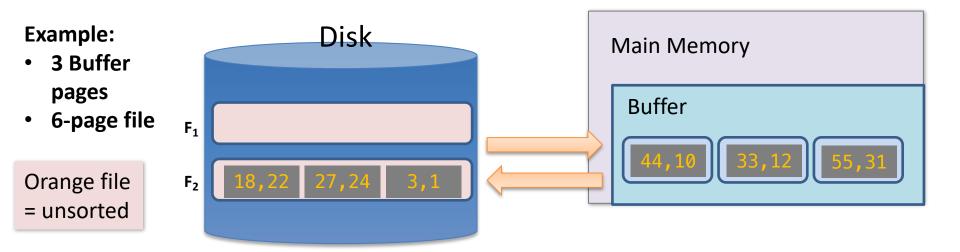
If lists of size M and N, then **Cost:** 2(M+N) IOs Each page is read once, written once

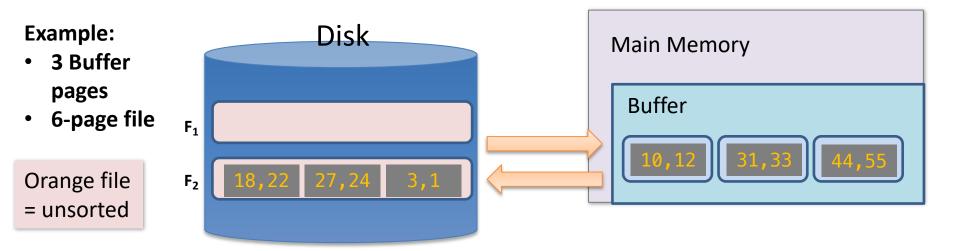


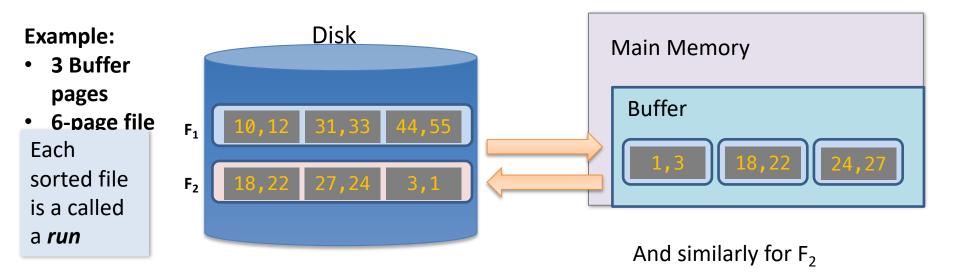
EXTERNAL MERGE SORT (BEFORE MERGE)

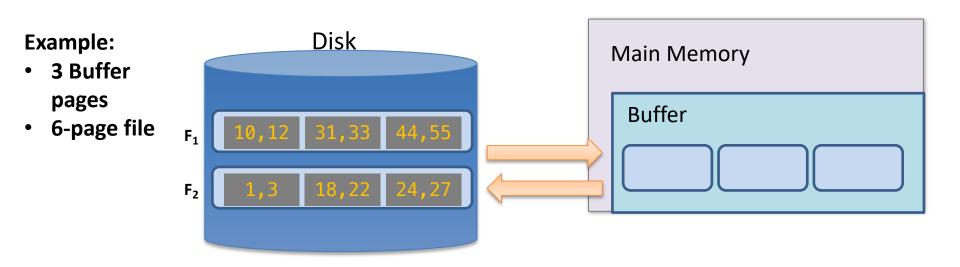












2. Now just run the **external merge** algorithm & we're done!

Calculating IO Cost

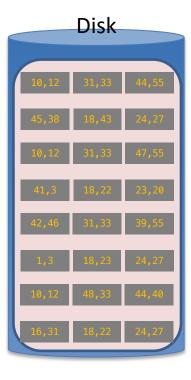
For 3 buffer pages, 6 page file:

- 1. Split into **two 3-page files** and **sort in memory**
 - 1. = 1 R + 1 W for each file = $2^{*}(3 + 3) = 12$ IO operations
- Merge each pair of sorted chunks using the external merge algorithm
 - 1. = 2*(3 + 3) = 12 IO operations

(if this explanation makes more sense: Reading contents of all pages only once writing them only once --- so, 6 + 6 = 12 IO)

3. Total cost = 24 IO

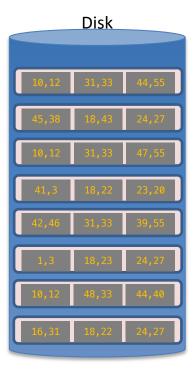
Running External Merge Sort on Larger Files



Assume we still only have 3 buffer pages (Buffer not pictured)

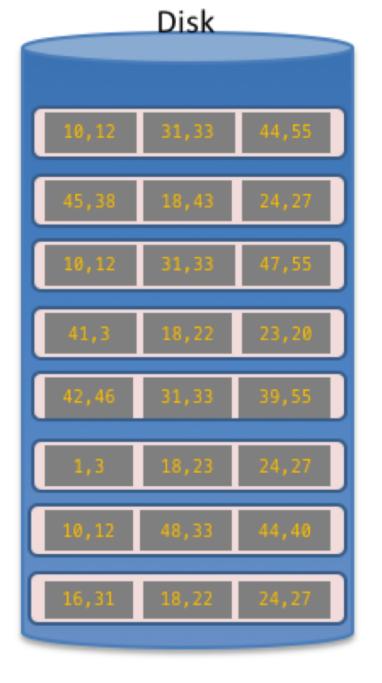
Disk		
10,12	31,33	44,55
45,38	18,43	24,27
10,12	31,33	47,55
41,3	18,22	23,20
42,46	31,33	39,55
1,3	18,23	24,27
10,12	48,33	44,40
16,31	18,22	24,27

Running External Merge Sort on Larger Files

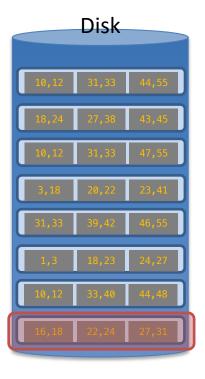


1. Split into files small enough to sort in buffer...

Assume we still only have 3 buffer pages (Buffer not pictured)



Running External Merge Sort on Larger Files

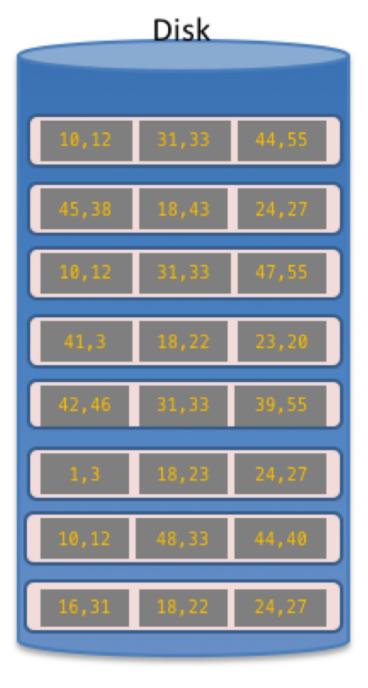


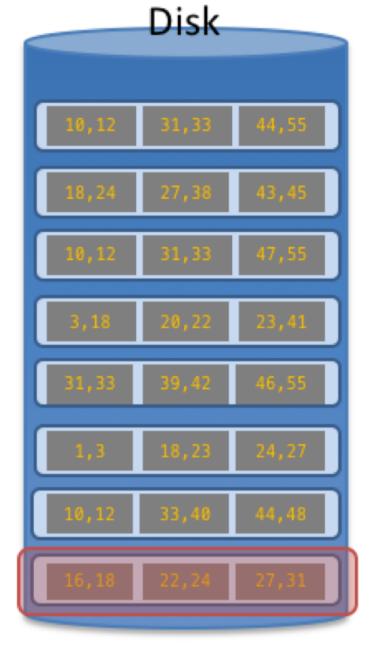
1. Split into files small enough to sort in buffer... and sort

Assume we still only have 3 buffer pages (Buffer not pictured)

Call each of these sorted files a *run*

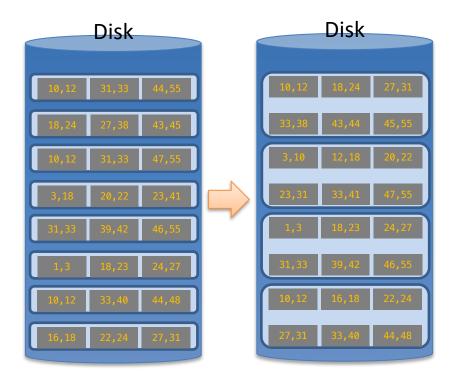
From





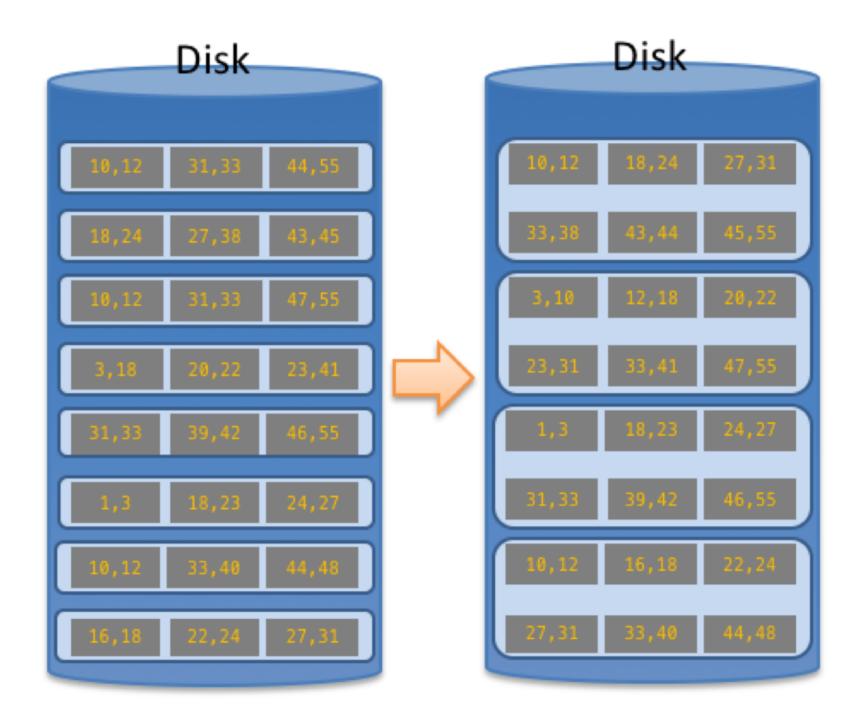
То

Running External Merge Sort on Larger Files

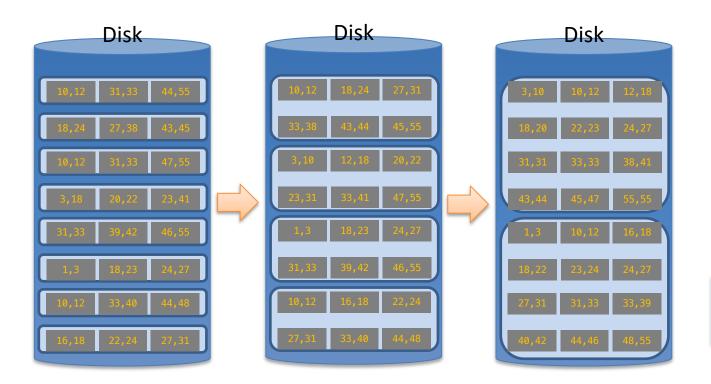


Assume we still only have 3 buffer pages (Buffer not pictured)

2. Now merge pairs of (sorted) files... the resulting files will be sorted!



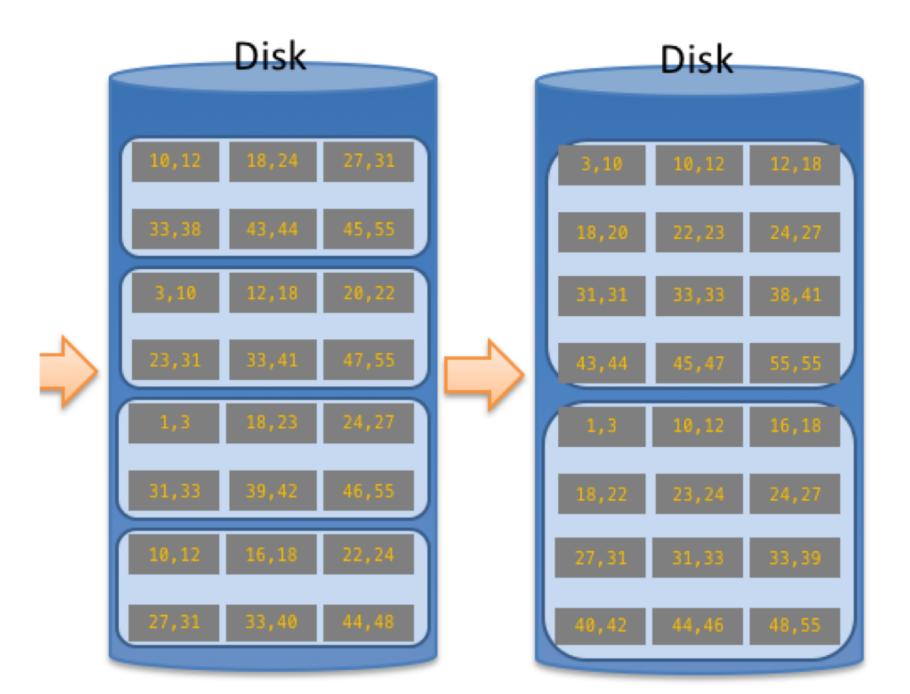
Running External Merge Sort on Larger Files



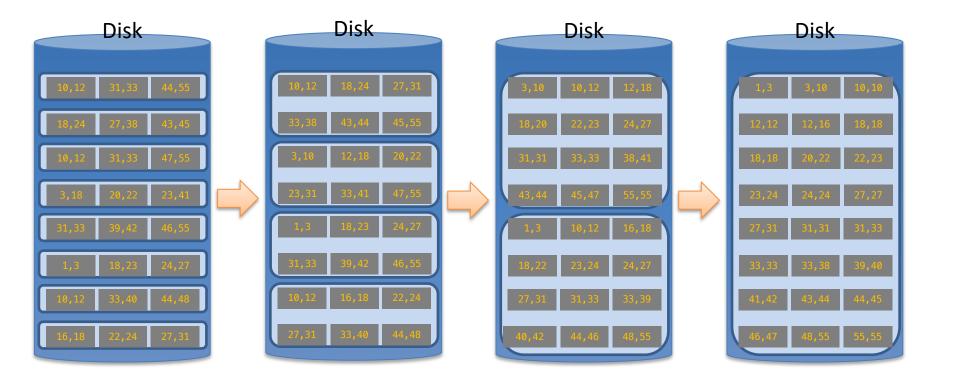
Assume we still only have 3 buffer pages (Buffer not pictured)

3. And repeat...

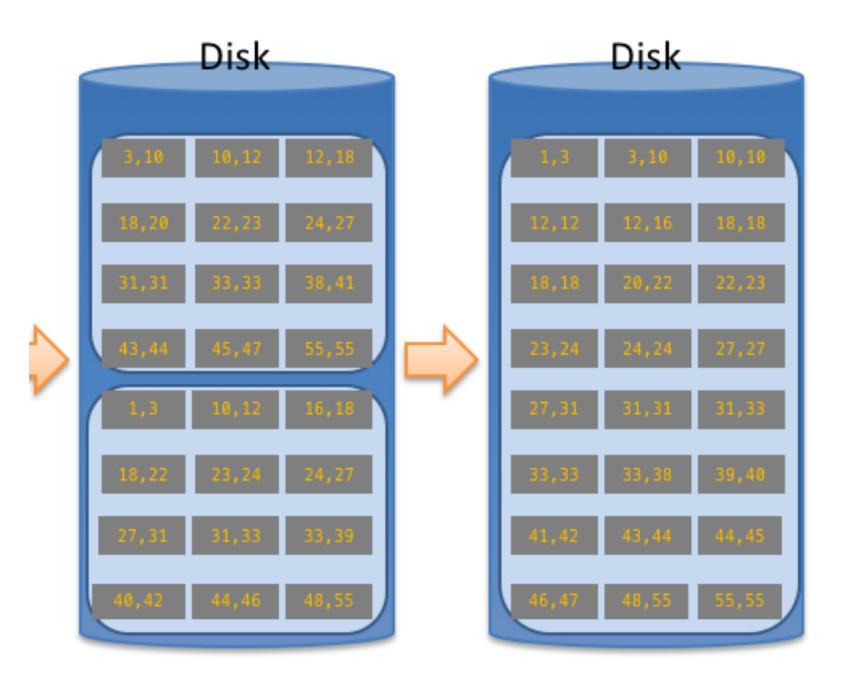
Call each of these steps a *pass*



Running External Merge Sort on Larger Files



4. And repeat!

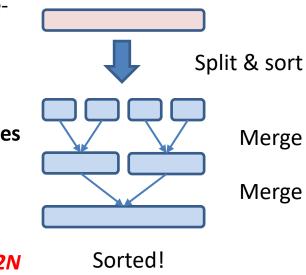


Simplified 3-page Buffer Version

Assume for simplicity that we split an N-page file into N singlepage *runs* and sort these; then:

- First pass: Merge N/2 *pairs* of runs each of length 1 page
- Second pass: Merge N/4 pairs of runs each of length 2 pages
- In general, for N pages, we do [log₂ N] passes
 +1 for the initial split & sort
- Each pass involves reading in & writing out all the pages = 2N
 IO

$\rightarrow 2N^*([log_2 N]+1)$ total IO cost!



Unsorted input file

Using B+1 buffer pages to reduce # of passes

Suppose we have B+1 buffer pages now; we can:

Increase length of initial runs. Sort B+1 at a time!
 At the beginning, we can split the N pages into runs of length B+1 and sort these in memory

IO Cost:

$$2N(\lceil \log_2 N \rceil + 1) \implies 2N(\left\lceil \log_2 \frac{N}{B+1} \right\rceil + 1)$$

Starting with runs of length 1

Starting with runs of length **B+1**

Using B+1 buffer pages to reduce # of passes

Suppose we have B+1 buffer pages now; we can:

2. Perform a B-way merge.

On each pass, we can merge groups of **B** runs at a time (vs. merging pairs of runs)!

IO Cost:

$$2N(\lceil \log_2 N \rceil + 1) \implies 2N(\lceil \log_2 \frac{N}{B+1} \rceil + 1) \implies 2N(\lceil \log_B \frac{N}{B+1} \rceil + 1)$$

Starting with runs of of length 1 Starting with runs of length **B+1** Performing **B**-way merges

What Next!

- Query Processing (Chapter 18)
- Query Optimization (Chapter 19)

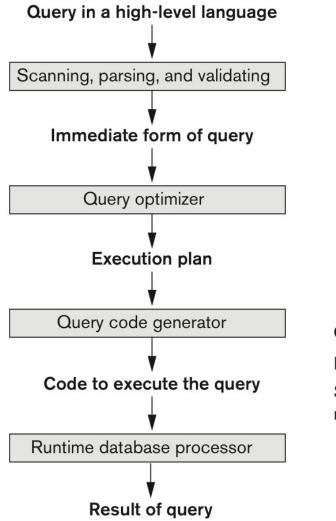
QUERY PROCESSING

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Steps in Query Processing

- Scanning
- Parsing
- Validation
- Query Tree Creation
- Query Optimization (Query planning)
- Code generation (to execute the plan)
- Running the query code

Steps in Query Processing



Code can be:

Executed directly (interpreted mode)

Stored and executed later whenever needed (compiled mode)

SQL Queries

- SQL Queries are decomposed into Query blocks:
 Select...From...Where...Group By...Having
- Translate Query blocks into Relational Algebraic expression
- Remember, SQL includes aggregate operators:
 - MIN, MAX, SUM, COUNT etc.
 - Part of the extended algebra
 - Let's go back to Chapter 8 (Section 8.4.2)

Aggregate Functions and Grouping (Relational Algebra)

- Aggregate function: \Im
- $_{< grouping attributes >} \Im_{< function list >}$ (R)

Dno \Im COUNT Ssn, AVERAGE Salary (EMPLOYEE).

Dno	Count_ssn	Average_salary
5	4	33250
4	3	31000
1	1	55000

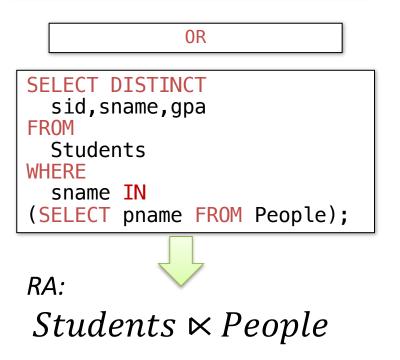
Semijoin (⋈)

- $R \ltimes S = \prod_{A1,...,An} (R \Join S)$
- Where A₁, ..., A_n are the attributes in R
- Example:

Students(sid,sname,gpa)
People(ssn,pname,address)

SQL:

SELECT DISTINCT	
sid,sname,gpa	
FROM	
Students,People	
WHERE	
sname = pname;	



Algorithm for External Sorting

• We have already covered

Algorithm fro Select Operation

- Read Section 18.3 (18.3.1, 18.3.2, 18.3.3, 18.3.4)
- Mostly covers searching:
- 1. Linear Search
- 2. Binary Search
- 3. Indexing
- 4. Hashing
- 5. B+ Tree
- (Skip bitmap index and functional index if you want)

Algorithm for Join Operation

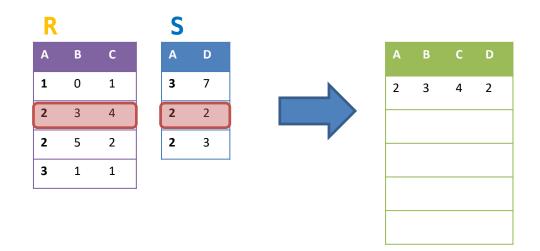
• The most time consuming operation

What you will learn about in this section

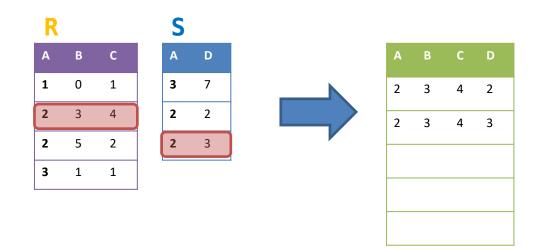
- 1. Nested Loop Join (NLJ)
- 2. Block Nested Loop Join (BNLJ)
- 3. Index Nested Loop Join (INLJ)
- 4. Sorted-Merge Join
- 5. Hash Join

RECAP: Joins

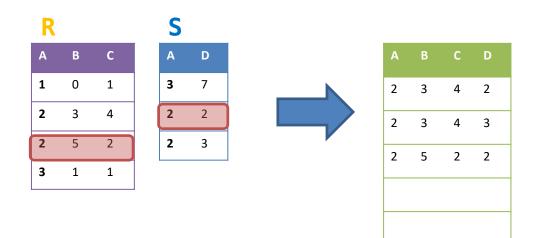
 $\mathbf{R} \bowtie S$



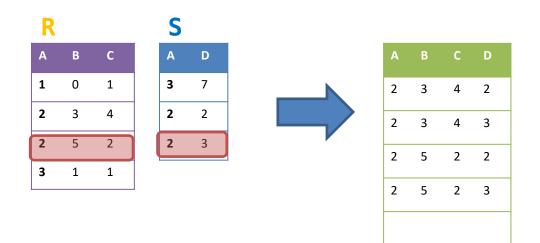
 $\begin{array}{c|c} \mathbf{R} \bowtie \boldsymbol{S} & \textbf{SELECT} \ R.A,B,C,D \\ \hline FROM & R, S \\ WHERE & R.A = S.A \end{array}$



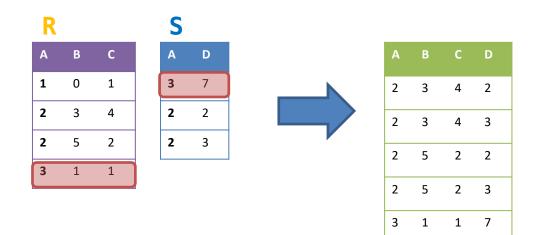
 $\begin{array}{c|c} \mathbf{R} \bowtie \boldsymbol{S} & \textbf{SELECT} \ R.A,B,C,D \\ \hline FROM & R, S \\ WHERE & R.A = S.A \end{array}$



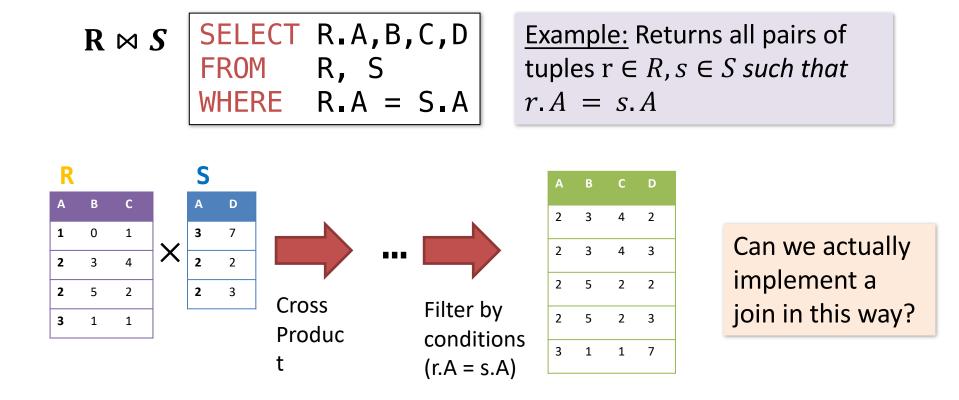
 $\begin{array}{c|c} \mathbf{R} \bowtie \boldsymbol{S} & \textbf{SELECT} \ R.A,B,C,D \\ \hline FROM & R, S \\ WHERE & R.A = S.A \end{array}$



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



Semantically: A Subset of the Cross Product



Notes

- We write **R** ⋈ *S* to mean *join R and S by returning all tuple pairs* where **all shared attributes** are equal
- We write **R** ⋈ **S** 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")

However joins *can* merge > 2 tables, and some algorithms do support non-equality constraints!

Nested Loop Joins

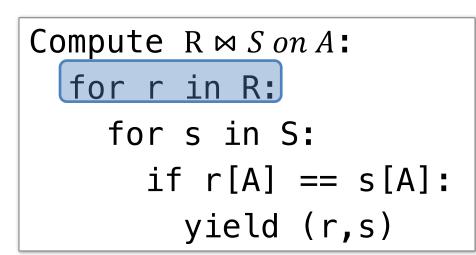
Notes

- We are again 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

Recall that we read / write entire pages with disk IO

• Note also that we omit ceilings in calculations... good exercise to put back in!

```
Compute R ⋈ 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!

<u>Cost:</u>

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!*

<u>Cost:</u>

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)

<u>Cost:</u>

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

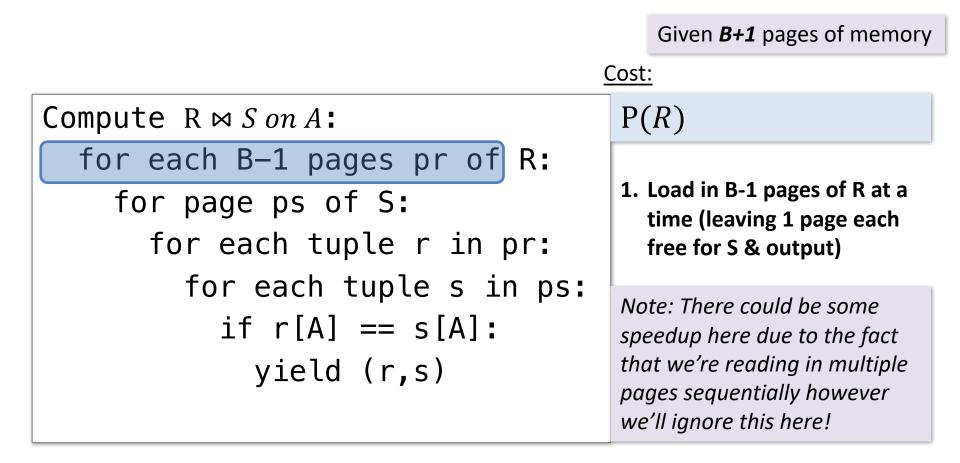
- 1. Loop over the tuples in R
- 2. For every tuple in R, loop over all the tuples in S
- 3. Check against join conditions
- 4. Write out (to page, then when page full, to disk)

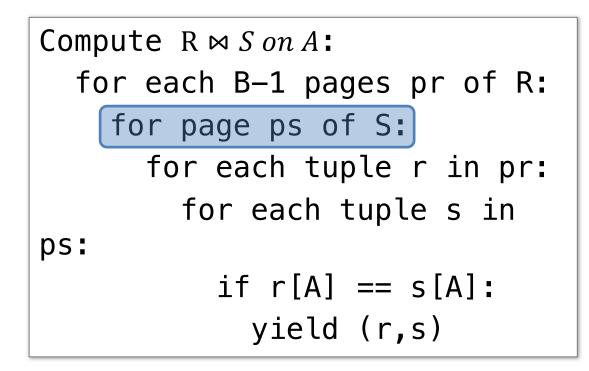
Nested Loop Join (NLJ)

Compute
$$R \bowtie S \text{ on } A$$
:
for r in R:
for s in S:
if $r[A] == s[A]$:
yield (r,s)

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

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





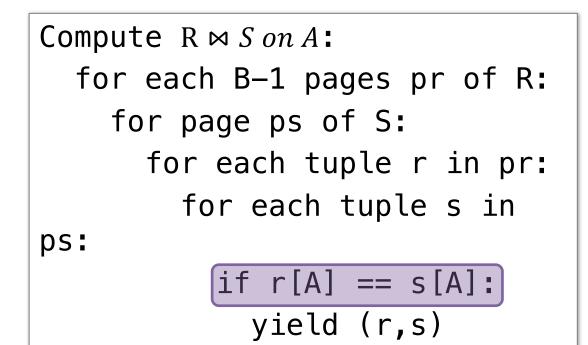
Given **B+1** pages of memory

Cost:

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

- 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!



Given **B+1** pages of memory

Cost:

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

- 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

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

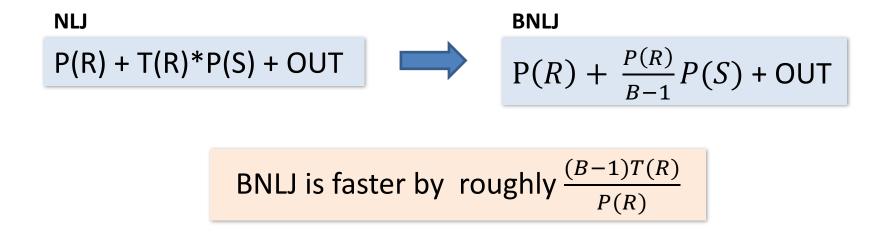
<u>Cost:</u>

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

- 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*



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 = $500 + \frac{500 \times 1000}{10} = 50$ Thousand IOs ~= <u>0.14 hours</u>

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

- For example we saw:

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*- moving to equality constraints ("equijoin") only!

Index Nested Loop Join (INLJ)

Cost:

Compute $R \bowtie S \text{ on } A$:	P(R) + T(R)* <i>L</i> + OUT
Given index idx on	
S.A:	where <i>L</i> is the IO cost to
for r in R:	access all the distinct values in
s in idx(r[A]):	the index; assuming these fit on one page, $L \sim 3$ is good
yield r,s	est.

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

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): Basic Procedure

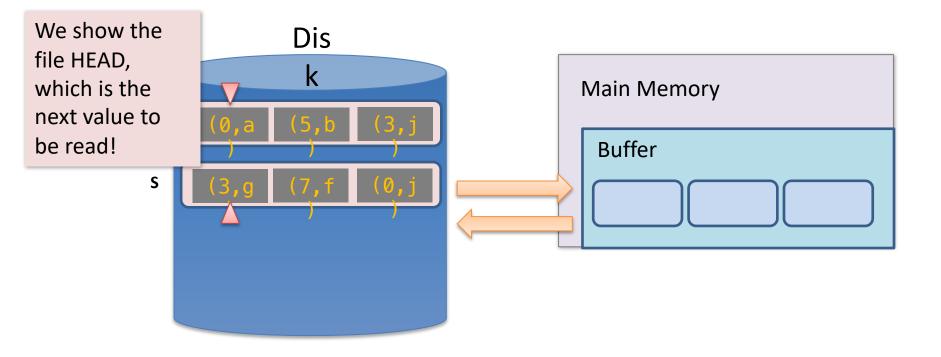
To compute $R \bowtie S$ on A:

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

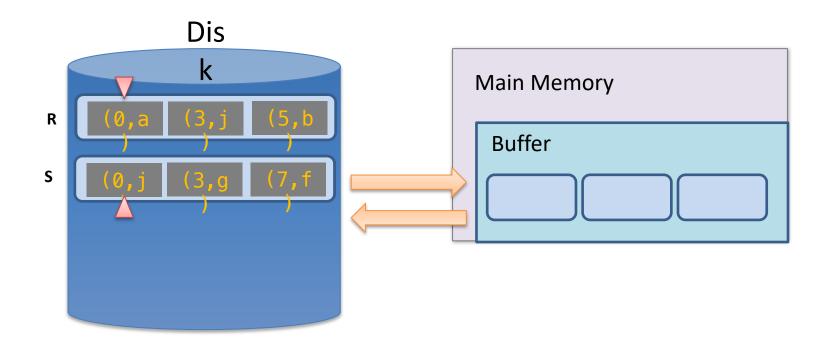
Note that if R, S are already sorted on A, SMJ will be awesome!

Note that we are only considering equality join conditions here

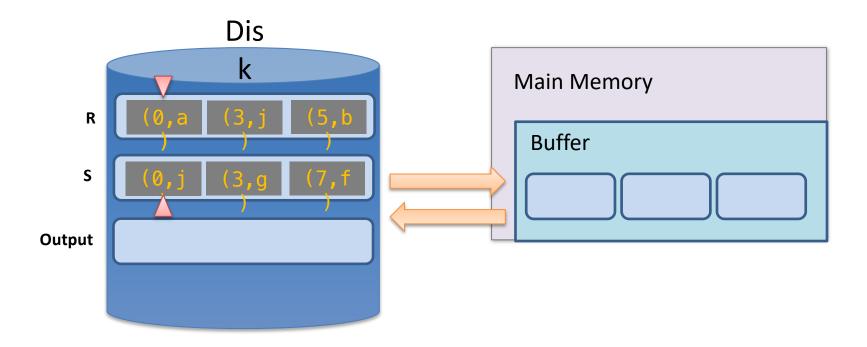
For simplicity: Let each page be *one tuple*, and let the first value be A



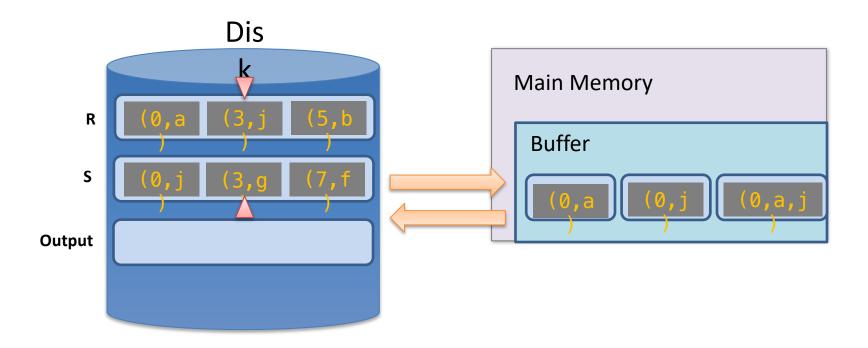
1. Sort the relations R, S on the join key (first value)



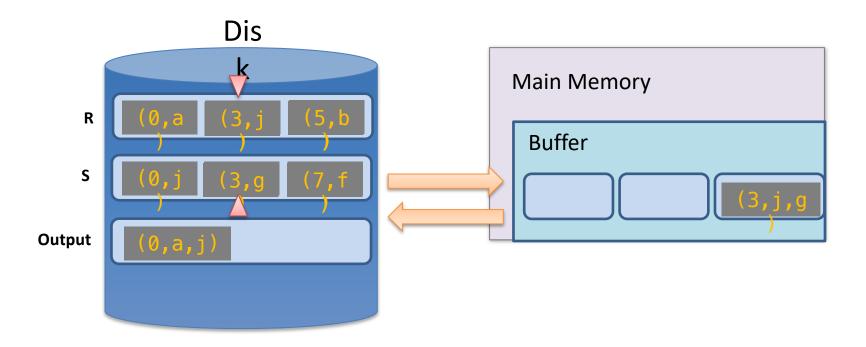
2. Scan and "merge" on join key!



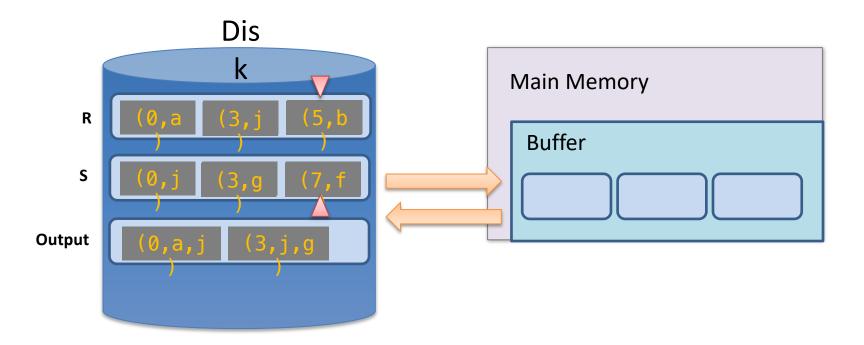
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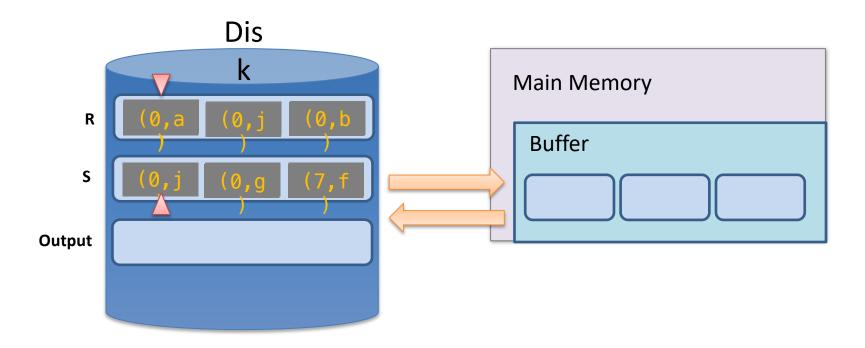
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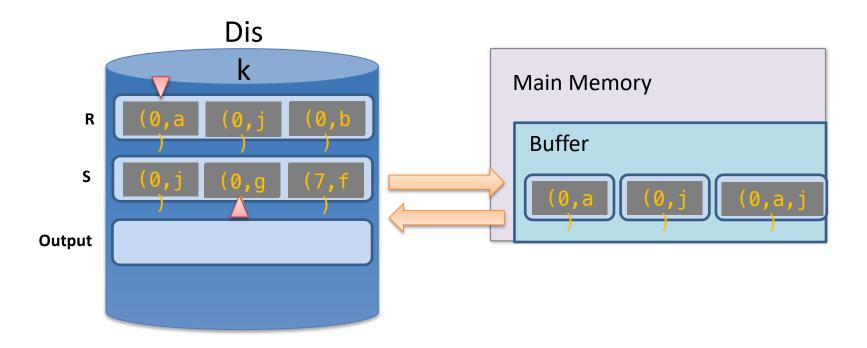


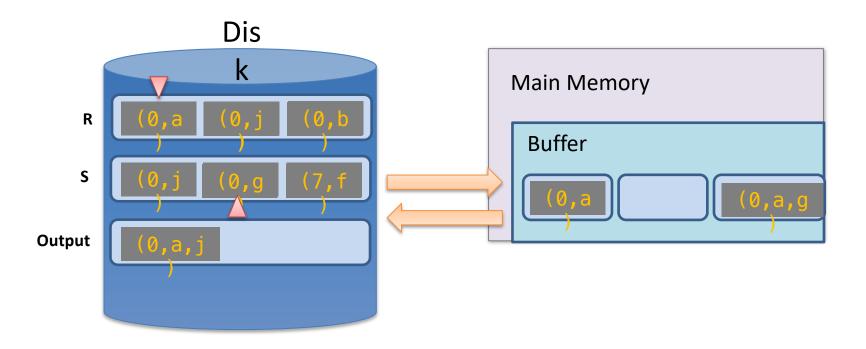
2. Done!

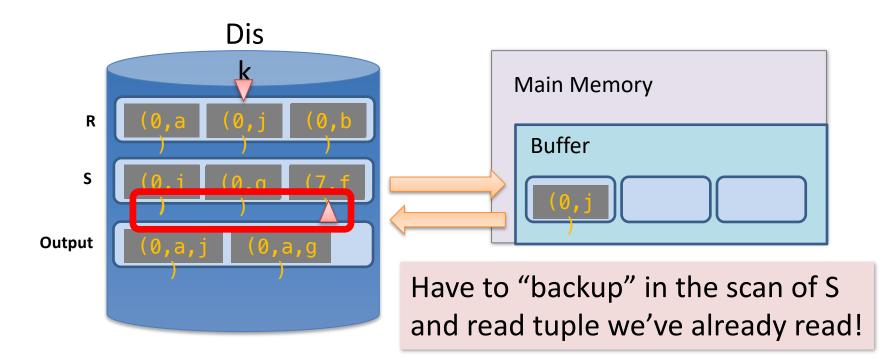


What happens with duplicate join keys?









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 have to back up and read each page of S...
- Often not that bad however

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: ~P(R)+P(S) but in worst case T(R)*T(S)

```
\sim Sort(P(R)) + Sort(P(S))
+ P(R) + P(S) + OUT
```

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 + 2 * 2 * 500 = 6,000 IOs
 - Merge phase 1000 + 500 = 1,500 IOs

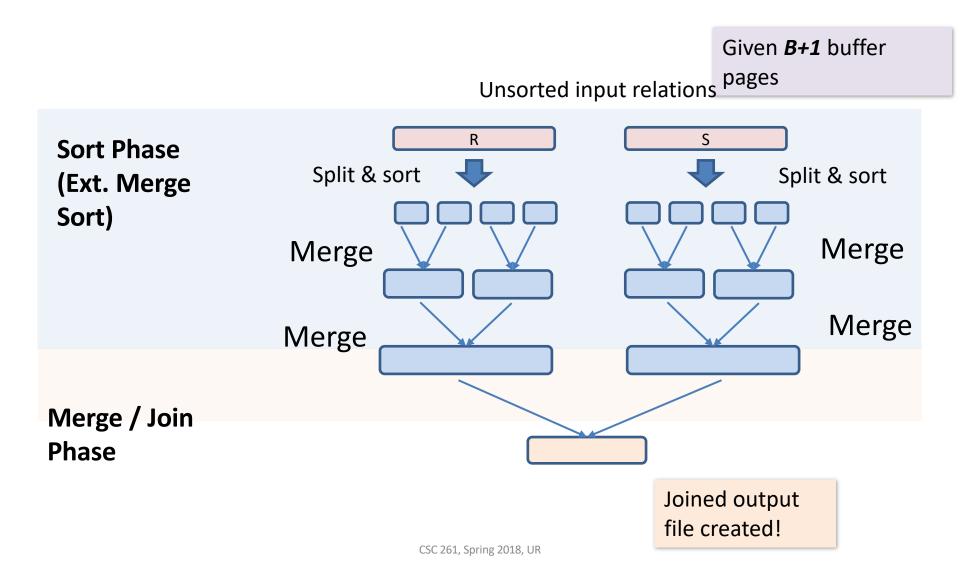
- <u>= 7,500 IOs + OUT</u>

What is BNLJ?

$$-500 + 1000* \left[\frac{500}{98} \right] = \frac{6,500 \text{ IOs} + \text{OUT}}{6,500 \text{ IOs} + \text{OUT}}$$

- But, if we have 35 buffer pages?
 - Sort Merge has same behavior (still 2 passes)
 - BNLJ? 15,500 IOs + OUT!

Basic SMJ



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.

4. HASH JOIN (HJ)

CSC 261, Spring 2018, UR

What you will learn about in this section

- 1. Hash Join
- 2. Memory requirements

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 = y but $h_B(x) = h_B(y)$
 - Note however that it will <u>**never**</u> occur that x = y but $h_B(x) != h_B(y)$

Hash Join: High-level procedure

To compute $R \bowtie S$ on A:

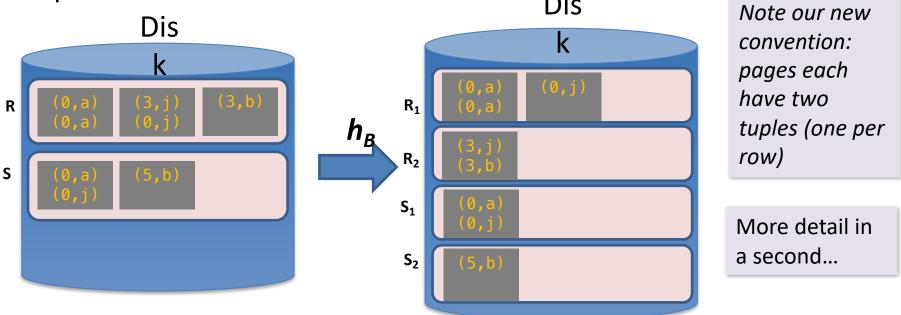
Note again that we are only considering equality constraints here

- Partition Phase: Using one (shared) hash function h_B, partition R and S into B buckets
- 2. Matching Phase: Take pairs of buckets whose tuples have the same values for *h*, and join these
 - 1. Use BNLJ here; or hash again → either way, operating on small partitions so fast!

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

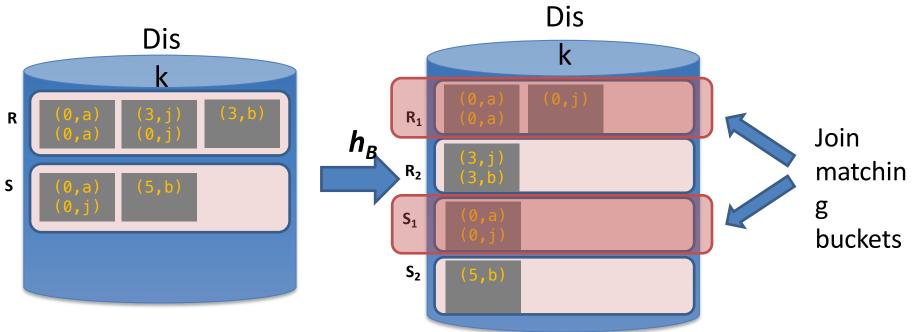
Hash Join: High-level procedure

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



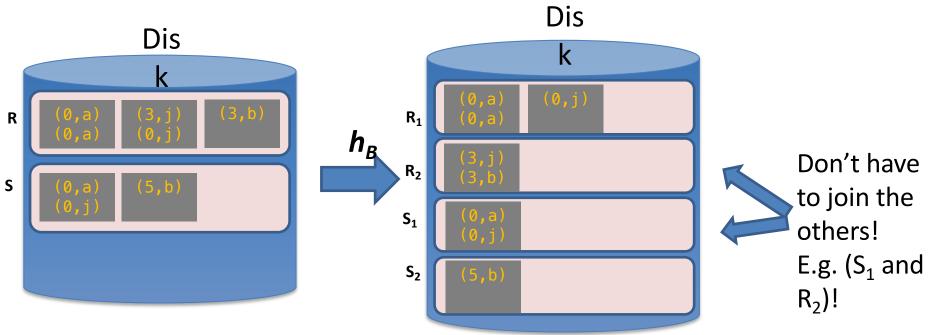
Hash Join: High-level procedure

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



Goal: For each relation, partition relation into buckets such that if $h_B(t_i.A) = h_B(t_i.A)$ 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.

How big are the resulting buckets?

Given **B+1** buffer

pages

- Given N input pages, we partition into B buckets:
 - \rightarrow Ideally our buckets are each of size ~ N/B pages

How big do we want the resulting buckets?

Ideally, our buckets would be of size ≤ B − 1 pages
 − 1 for input page, 1 for output page, B-1 for each bucket

Given **B+1** buffer 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),* $P(R) \leq B 1!$
 - And more generally, being able to fit bucket in memory is advantageous
- We can keep partitioning buckets that are > B-1 pages, until they are ≤ B − 1 pages

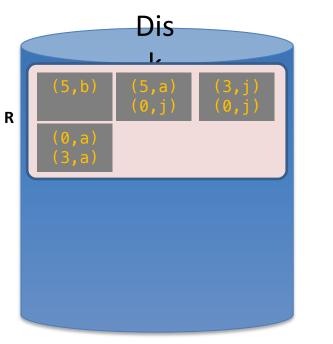
- Using a new hash key which will split them...

Recall for BNLJ: P(R) $+ \frac{P(R)P(S)}{B-1}$

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

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)

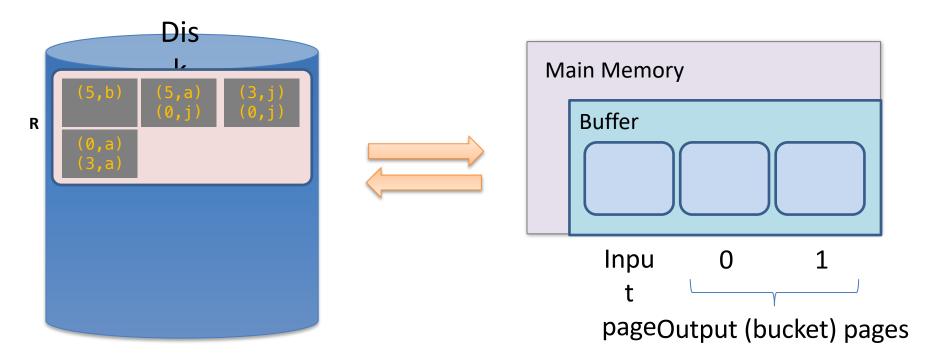


For simplicity, we'll look at partitioning one of the two relations- we just do the same for the other relation!

Recall: our goal will be to get *B* = 2 buckets of size <= *B*-1 → 1 page each

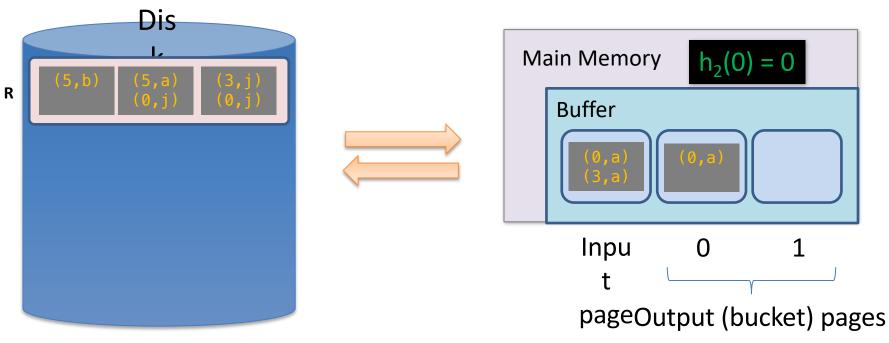
Given *B***+1** = *3* buffer pages

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



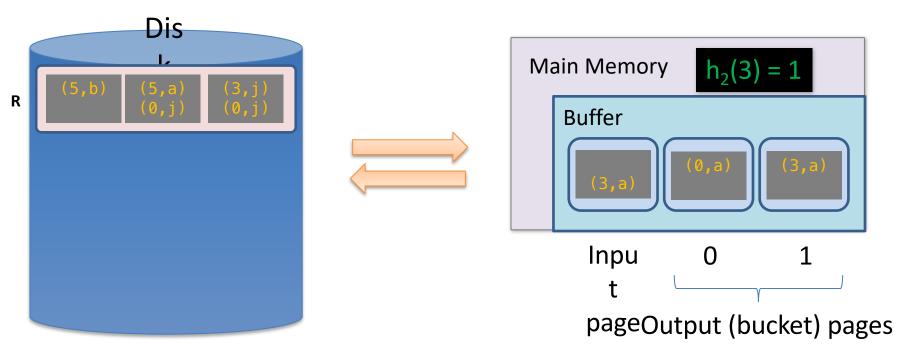
Given *B***+1** = *3* buffer pages

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



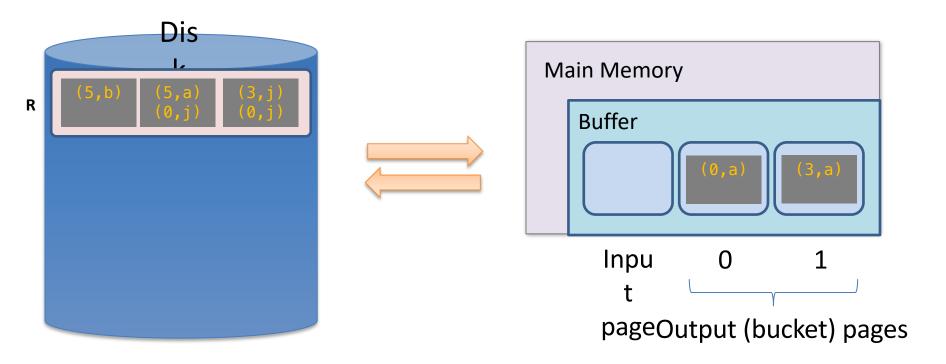
Given *B***+1 = 3** buffer pages

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



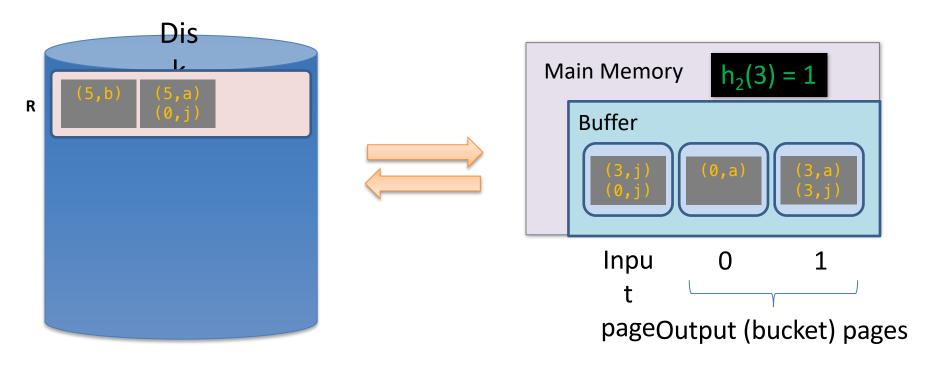
Given *B***+1 = 3** buffer pages

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



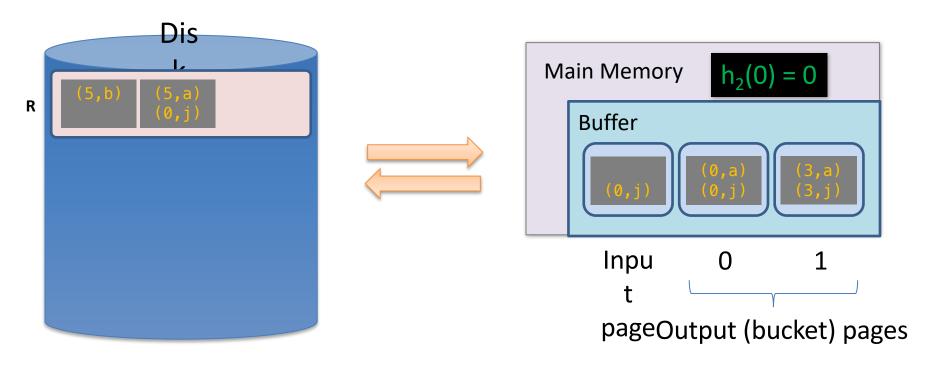
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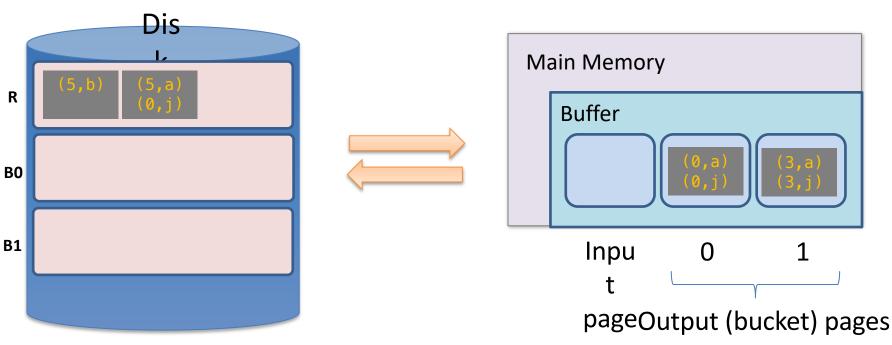
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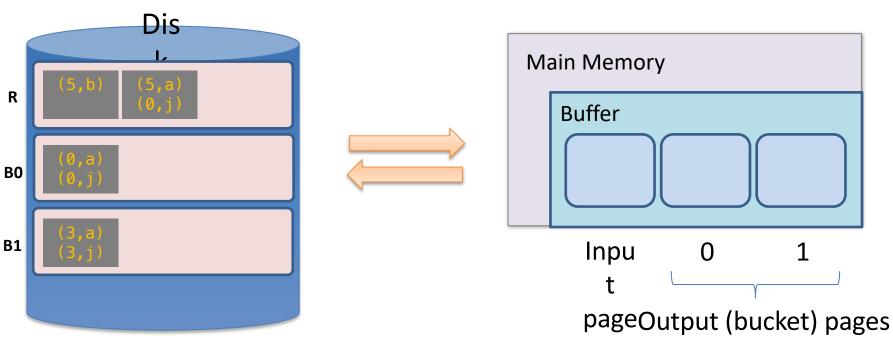
Given *B***+1 = 3** buffer pages

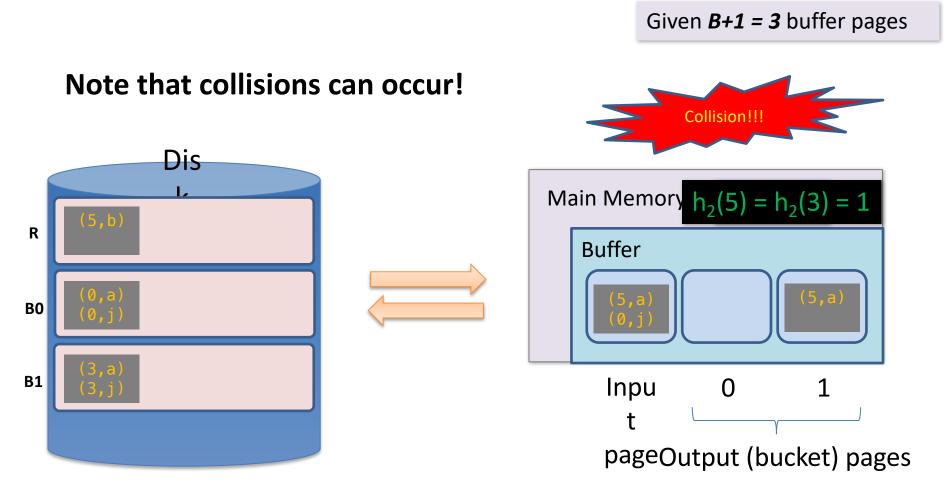
3. We repeat until the buffer bucket pages are full... then flush to disk



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

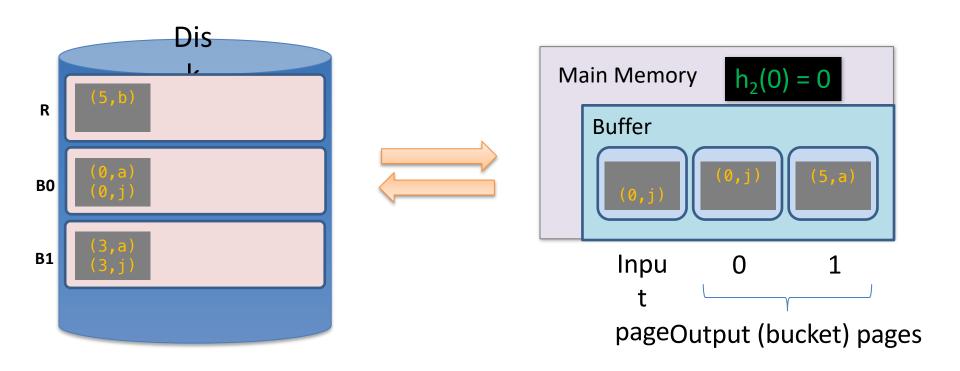
3. We repeat until the buffer bucket pages are full... then flush to disk





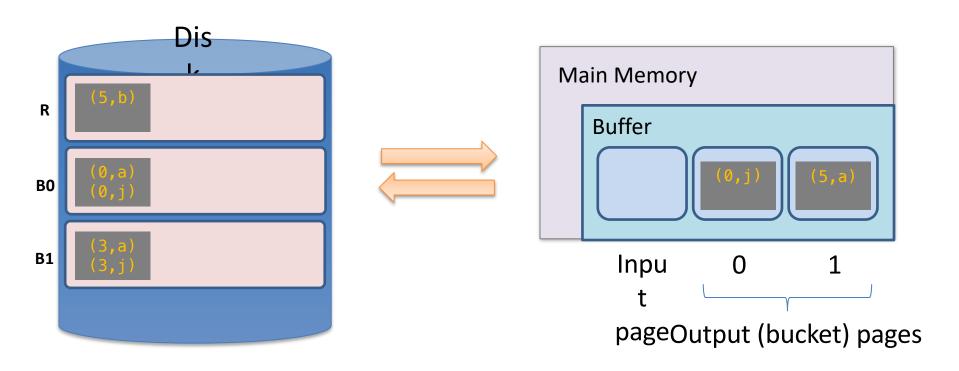
Given *B***+1 = 3** buffer pages

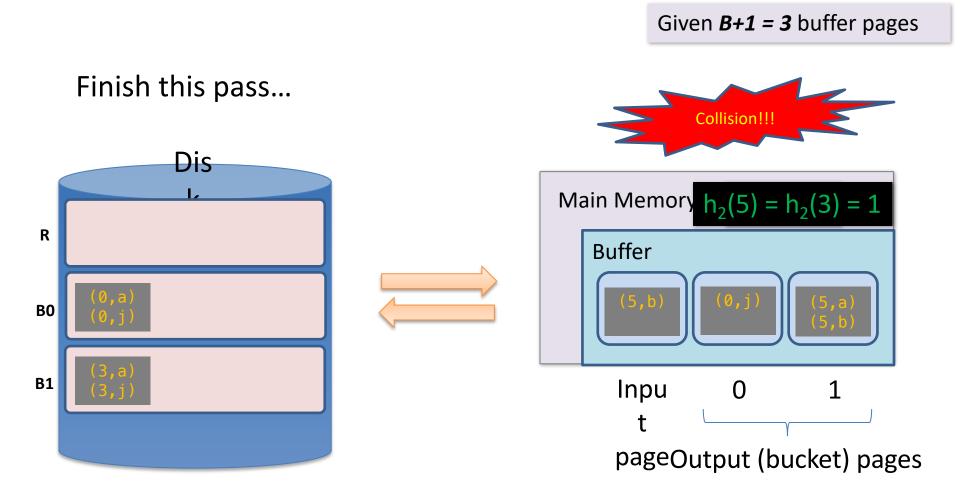
Finish this pass...



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

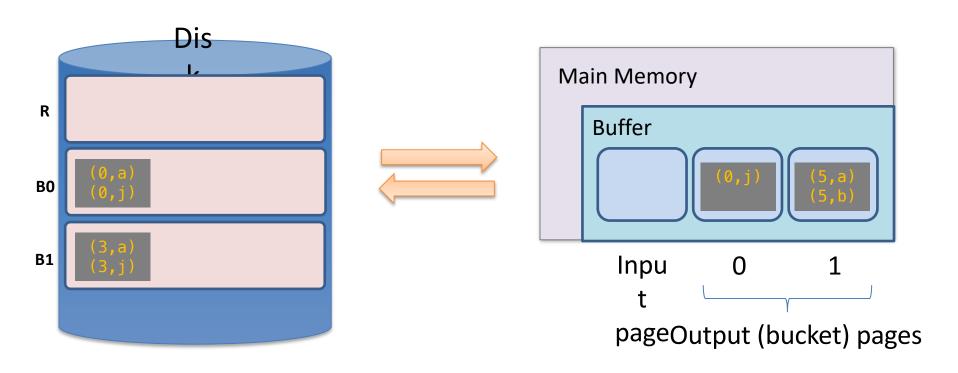
Finish this pass...



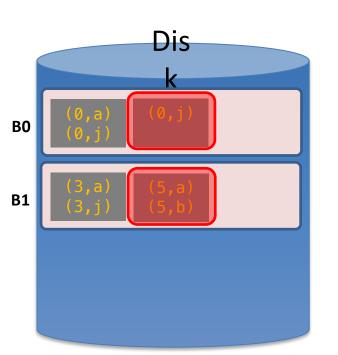


Given *B***+1** = *3* buffer pages

Finish this pass...



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



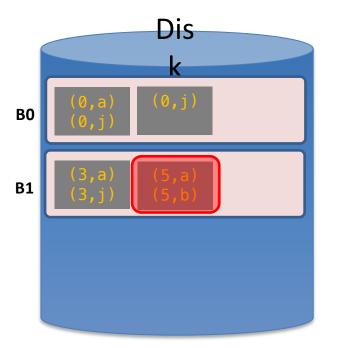
We wanted buckets of size *B-1* = 1... however we got larger ones due to:

(1) Duplicate join

keys

(2) Hash collisions

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

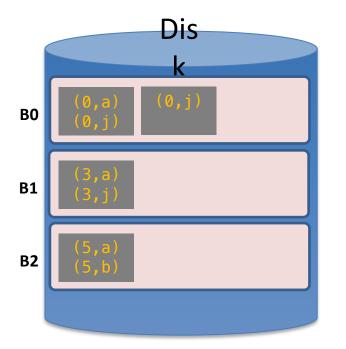


To take care of larger buckets caused by (2) hash collisions, we can just do another pass! What hash function should we use?

Do another pass with a different hash function, $h'_{2,}$ ideally such that:

 $h'_{2}(3) != h'_{2}(5)$

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

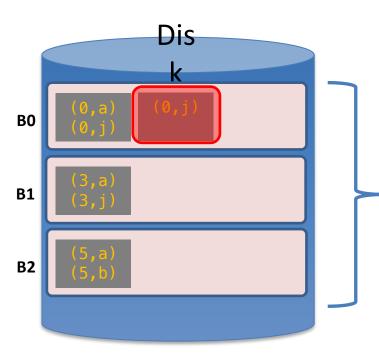


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Given *B***+1** = *3* buffer pages

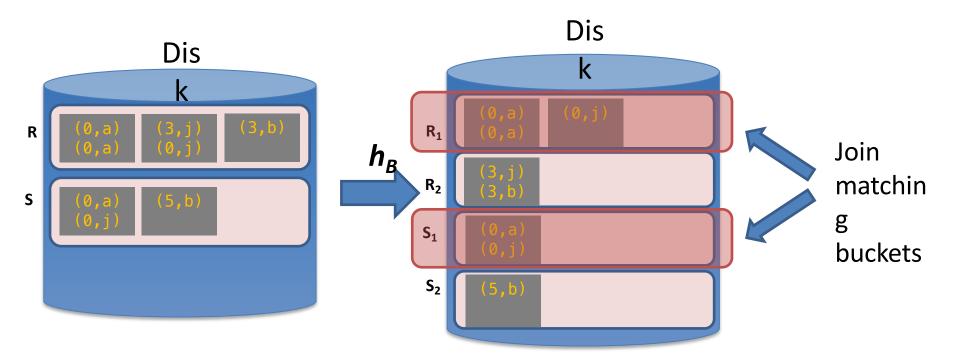


What about duplicate join keys? Unfortunately this is a problem... but usually not a huge one.

We call this unevenness in the bucket size **<u>skew</u>**

Now that we have partitioned R and S...

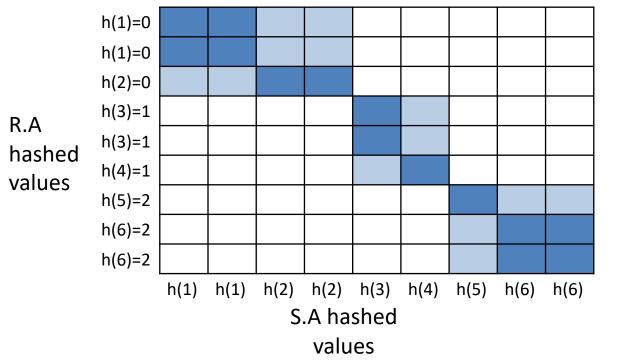
• Now, we just join pairs of buckets from R and S that have the same hash value to complete the join!



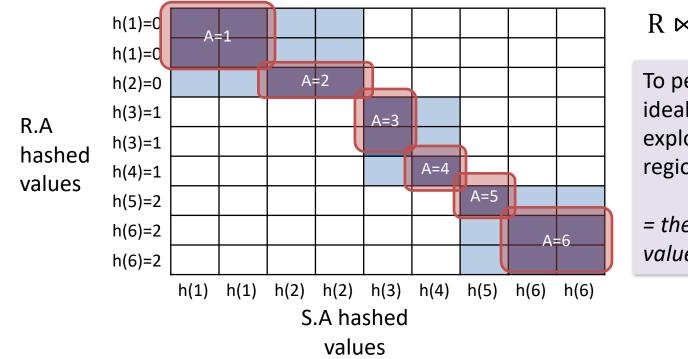
- Note that since x = y → h(x) = h(y), we only need to consider pairs of buckets (one from R, one from S) that have the same hash function value
- If our buckets are ~B 1 pages, can join each such pair using BNLJ in linear time; recall (with P(R) = B-1):

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 <= B-1 pages)



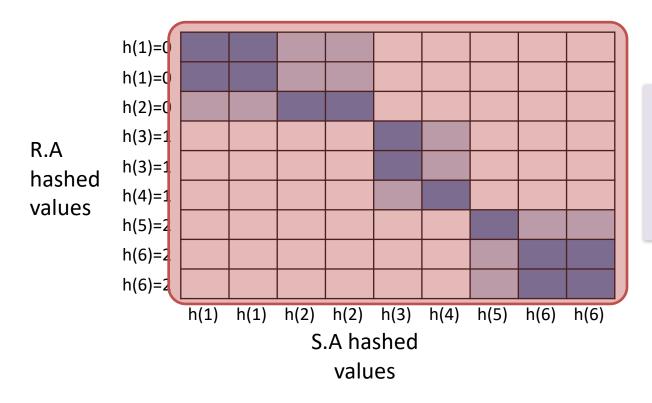




$$R \bowtie S \text{ on } A$$

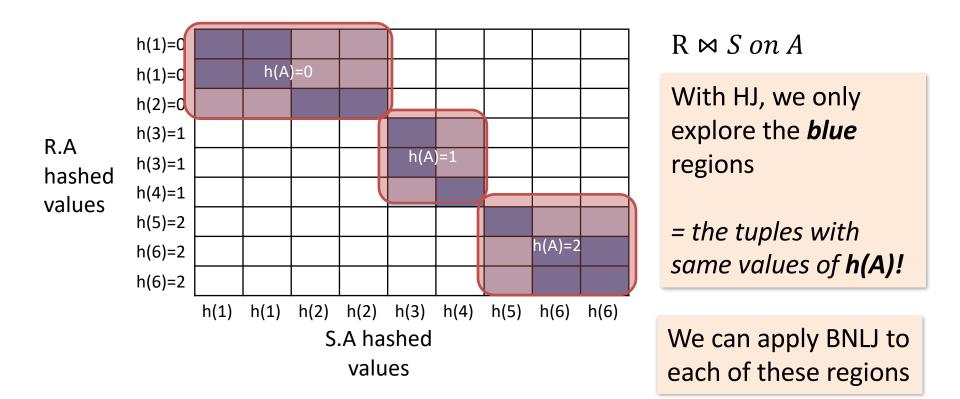
To perform the join, we ideally just need to explore the dark blue regions

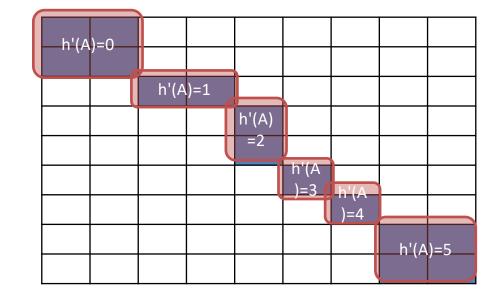
= the tuples with same values of the join key A



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

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





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

An alternative to applying BNLJ:

We could also hash again, and keep doing passes in memory to reduce further!



S.A hashed values

Hash Join Summary

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 ~3(P(R)+P(S)) + OUT IOs!
```