Carnegie Mellon University

# Vatabase Systems Join Algorithms



15-445/645 FALL 2024 >> PROF. ANDY PAVLO

### **ADMINISTRIVIA**

Mid-term Exam on Wednesday Oct 9th @ 2:00pm

- $\rightarrow$  In-class in this room.
- $\rightarrow$  Study guide is available <u>online</u> (see <u>@295</u>)

Project #2 is due Sunday Oct 27th @ 11:59pm

 $\rightarrow$  Recitation on Thursday Oct 10<sup>th</sup> @ 8:00pm (Zoom)



# UPCOMING DATABASE TALKS

#### ParadeDB (DB Seminar)

- → Monday Oct 7<sup>th</sup> @ 4:30pm ET
- $\rightarrow$  Zoom

# ParadeDB

### **Spice.ai** (DB Seminar)

- → Monday Oct 21st @ 4:30pm
- $\rightarrow$  Zoom

### **Exon** (DB Seminar)

- → Monday Oct 28<sup>th</sup> @ 4:30pm
- $\rightarrow$  Zoom







### LAST CLASS

We started discussing how to implement algorithms to compute queries and handle data sets that are larger than available memory.

→ Common Pattern: <u>Divide-and-Conquer</u>

There are two high-level strategies to quickly find tuples with the same attribute values.

- → Sorting
- → Hashing



# WHY DO WE NEED TO JOIN?

We normalize tables in a relational database to avoid unnecessary repetition of information.

We then use the **join operator** to reconstruct the original tuples without any information loss.



# JOIN ALGORITHMS

We will focus on performing binary joins (two tables) using **inner equijoin** algorithms.

- $\rightarrow$  These algorithms can be tweaked to support other joins.
- → Multi-way joins exist primarily in research literature (e.g., worst-case optimal joins).

In general, we want the smaller table to always be the left table ("outer table") in the query plan.

→ The optimizer will (try to) figure this out when generating the physical plan.



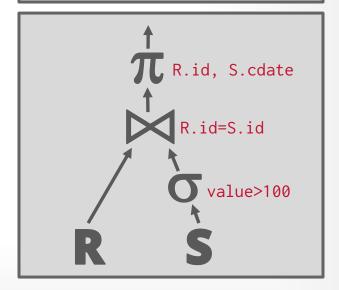
# **QUERY PLAN**

The operators are arranged in a tree.

Data flows from the leaves of the tree up towards the root.

→ We will discuss the granularity of the data movement next lecture.

The output of the root node is the result of the query.





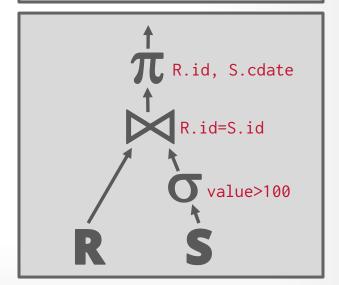
### JOIN OPERATORS

#### Decision #1: Output 早期物化 VS 延迟物化

→ What data does the join operator emit to its parent operator in the query plan tree?

### **Decision #2: Cost Analysis Criteria**

→ How do we determine whether one join algorithm is better than another?





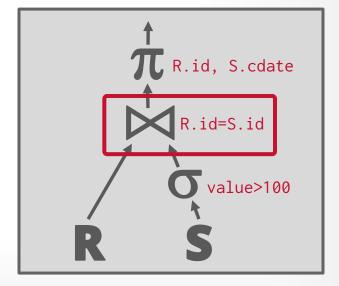
### OPERATOR OUTPUT

For tuple  $r \in R$  and tuple  $s \in S$  that match on join attributes, concatenate r and s together into a new tuple.

### Output contents can vary:

- → Depends on processing model
- → Depends on storage model
- → Depends on data requirements in query

```
FROM R JOIN S
ON R.id = S.id
WHERE S.value > 100
```





# OPERATOR OUTPUT: DATA

### **Early Materialization:**

→ Copy the values for the attributes in outer and inner tuples into a new output tuple.

从源端获取数据后,将元组内容全部构建出来.

SELECT R.id, S.cdate
FROM R JOIN S
ON R.id = S.id
WHERE S.value > 100

#### R(id, name) S(id, value, cdate)

id	name	<b>N A</b>	id	value	cdate
123	abc		123	1000	10/7/2024
			123	2000	10/7/2024

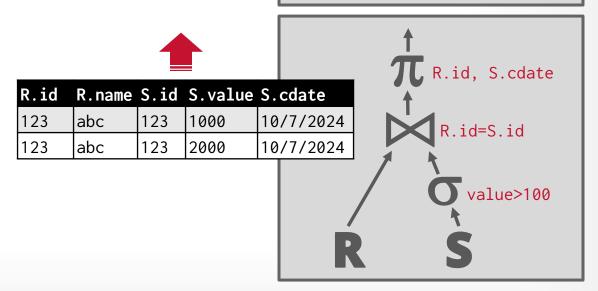
R.id	R.name	S.id	S.value	S.cdate
123	abc	123	1000	10/7/2024
123	abc	123	2000	10/7/2024



## OPERATOR OUTPUT: DATA

### **Early Materialization:**

→ Copy the values for the attributes in outer and inner tuples into a new output tuple.



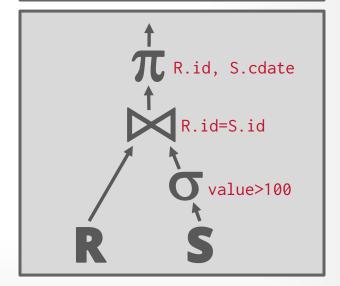


# OPERATOR OUTPUT: DATA

### **Early Materialization:**

→ Copy the values for the attributes in outer and inner tuples into a new output tuple.

Subsequent operators in the query plan never need to go back to the base tables to get more data.





### OPERATOR OUTPUT: RECORD IDS

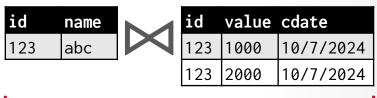
#### Late Materialization:

→ Only copy the joins keys along with the Record IDs of the matching tuples.

构建最小量数据.

SELECT R.id, S.cdate
FROM R JOIN S
ON R.id = S.id
WHERE S.value > 100

#### R(id, name) S(id, value, cdate)

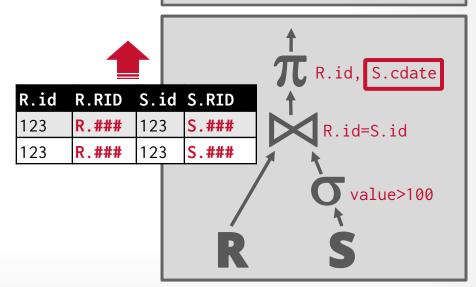


R.id	R.RID	S.id	S.RID
123	R.###	123	S.###
123	R.###	123	S.###

# OPERATOR OUTPUT: RECORD IDS

#### Late Materialization:

→ Only copy the joins keys along with the Record IDs of the matching tuples.



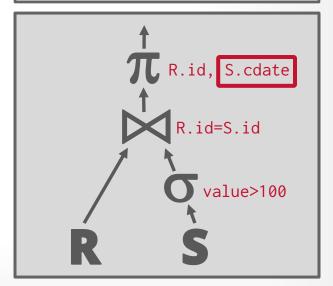


# OPERATOR OUTPUT: RECORD IDS

#### Late Materialization:

→ Only copy the joins keys along with the Record IDs of the matching tuples.

Ideal for column stores because the DBMS does not copy data that is not needed for the query.





### COST ANALYSIS CRITERIA

Given a query that joins table **R** with table **S**, assume the DBMS has the following information those tables:

- $\rightarrow$  *M* pages in table **R**, *m* tuples in **R**
- $\rightarrow$  **N** pages in table **S**, **n** tuples in **S**

SELECT R.id, S.cdate
FROM R JOIN S
ON R.id = S.id
WHERE S.value > 100

### Cost Metric: # of I/Os to compute join

- → Ignore result output costs because it depends on the data and is the same for all algorithms.
- $\rightarrow$  Ignore computation / network costs (for now).



# JOIN ALGORITHMS

### Nested Loop Join

- → Naïve
- $\rightarrow$  Block
- $\rightarrow$  Index

Sort-Merge Join

### Hash Join

- → Simple
- → GRACE (Externally Partitioned)
- → Hybrid



SELECT R.id, S.cdate
FROM R JOIN S
ON R.id = S.id
WHERE S.value > 100

#### R(id, name)

id	name
600	MethodMan
200	GZA
100	Andy
300	ODB
500	RZA
700	Ghostface
400	Raekwon

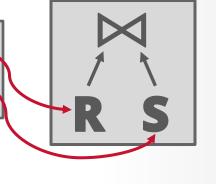
#### S(id, value, cdate)

id	value	cdate
100	2222	10/7/2024
500	7777	10/7/2024
400	6666	10/7/2024
100	9999	10/7/2024
200	8888	10/7/2024









#### R(id, name)

id	name
600	MethodMan
200	GZA
100	Andy
300	ODB
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400	Raekwon

#### S(id, value, cdate)

id	value	cdate
100	2222	10/7/2024
500	7777	10/7/2024
400	6666	10/7/2024
100	9999	10/7/2024
200	8888	10/7/2024



Why is this algorithm bad?

 $\rightarrow$  For every tuple in **R**, it scans **S** once

Cost:  $M + (m \cdot N)$ 

#### R(id, name)

*M* pages*m* tuples

id	name
600	MethodMan
200	GZA
100	Andy
300	ODB
500	RZA
700	Ghostface
400	Raekwon

#### S(id, value, cdate)

id	value	cdate
100	2222	10/7/2024
500	7777	10/7/2024
400	6666	10/7/2024
100	9999	10/7/2024
200	8888	10/7/2024



### Example database:

```
→ Table R: M = 1000, m = 100,000

→ Table S: N = 500, n = 40,000 \rightarrow 4 KB pages → 6 MB
```

### Cost Analysis:

- $\rightarrow M + (m \cdot N) = 1000 + (100000 \cdot 500) = 50,001,000 \text{ IOs}$
- $\rightarrow$  At 0.1 ms/IO, Total time  $\approx$  1.3 hours

What if smaller table (S) is used as the outer table?

- $\rightarrow N + (n \cdot M) = 500 + (40000 \cdot 1000) = 40,000,500 \text{ IOs}$
- $\rightarrow$  At 0.1 ms/IO, Total time  $\approx$  1.1 hours

```
foreach block B_R \in R: 数据按块存储: 以块为单位进行遍历. foreach block B_S \in S: foreach tuple r \in B_R: foreach tuple s \in B_S: if r and s match then emit
```

#### R(id, name)

id	name
600	MethodMan
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300	ODB
500	RZA
700	Ghostface
400	Raekwon

#### S(id, value, cdate)

id	value	cdate	
100	2222	10/7/2024	
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400	6666	10/7/2024	
100	9999	10/7/2024	
200	8888	10/7/2024	

**N** pages **n** tuples



*M* pages*m* tuples

This algorithm performs fewer disk accesses.

 $\rightarrow$  For every block in **R**, it scans **S** once.

Cost:  $M + (M \cdot N)$ 

#### R(id, name)

*M* pages*m* tuples

id	name
600	MethodMan
200	GZA
100	Andy
300	ODB
500	RZA
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400	Raekwon

#### S(id, value, cdate)

id	value	cdate
100	2222	10/7/2024
500	7777	10/7/2024
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100	9999	10/7/2024
200	8888	10/7/2024



The smaller table should be the outer table.

We determine size based on the number of pages, not the number of tuples.

#### R(id, name)

*M* pages*m* tuples

id	name
600	MethodMan
200	GZA
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700	Ghostface
400	Raekwon

#### S(id, value, cdate)

id	value	cdate	
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100	9999	10/7/2024	
200	8888	10/7/2024	



#### If we have **B** buffers available:

- $\rightarrow$  Use **B-2** buffers for each block of the outer table.
- $\rightarrow$  Use one buffer for the inner table, one buffer for output.

#### R(id, name)

*M* pages*m* tuples

id	name
600	MethodMan
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400	Raekwon

#### S(id, value, cdate)

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400	6666	10/7/2024	
100	9999	10/7/2024	
200	8888	10/7/2024	



```
\begin{array}{l} \textbf{foreach} \ \textit{B} - \textbf{2} \ \textit{pages} \ \textit{p}_{R} \in R ; \\ \textbf{foreach} \ \textit{page} \ \textit{p}_{S} \in \textbf{S} ; \\ \textbf{foreach} \ \textit{tuple} \ \textit{r} \in \textit{B} - \textbf{2} \ \textit{pages} ; \\ \textbf{foreach} \ \textit{tuple} \ \textit{s} \in \textit{p}_{s} ; \\ \textbf{if} \ \textit{r} \ \textit{and} \ \textit{s} \ \textit{match} \ \textit{then} \ \textit{emit} \end{array}
```

#### R(id, name)

id	name
600	MethodMan
200	GZA
100	Andy
300	ODB
500	RZA
700	Ghostface
400	Raekwon

#### S(id, value, cdate)

id	value	cdate	
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400	6666	10/7/2024	
100	9999	10/7/2024	
200	8888	10/7/2024	

**N** pages **n** tuples



*M* pages*m* tuples

This algorithm uses **B-2** buffers for scanning **R**.

Cost: 
$$M + (\lceil M / (B-2) \rceil \cdot N)$$

If the outer relation fits in memory (M < B-2):

- $\rightarrow$  Cost: M + N = 1000 + 500 = 1500 I/Os
- $\rightarrow$  At 0.1ms per I/O, Total time  $\approx$  0.15 seconds

If we have B=102 buffer pages:

- $\rightarrow$  Cost:  $M + (\lceil M / (B-2) \rceil \cdot N) = 1000 + 10.500 = 6000 I/Os$
- $\rightarrow$  Or can switch inner/outer relations, giving us cost: 500 + 5.1000 = 5500 I/Os



# NESTED LOOP JOIN

Why is the basic nested loop join so bad?

→ For each tuple in the outer table, we must do a sequential scan to check for a match in the inner table.

We can avoid sequential scans by using an index to find inner table matches.

 $\rightarrow$  Use an existing index for the join.



### INDEX NESTED LOOP JOIN

```
foreach tuple r \in R: foreach tuple s \in Index(r_i = s_j):内部表的 join key 上有索引. if r and s match then emit
```

#### R(id, name)

id	name
600	MethodMan
200	GZA
100	Andy
300	ODB
500	RZA
700	Ghostface
400	Raekwon

#### S(id, value, cdate)

id	value	cdate
100	2222	10/7/2024
500	7777	10/7/2024
400	6666	10/7/2024
100	9999	10/7/2024
200	8888	10/7/2024

Index(S.id)

**N** pages **n** tuples



*M* pages*m* tuples

### INDEX NESTED LOOP JOIN

Assume the cost of each index probe is some constant *C* per tuple.

Cost:  $M + (m \cdot C)$ 

#### R(id, name)

*M* pages*m* tuples

id	name
600	MethodMan
200	GZA
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#### S(id, value, cdate)

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100	9999	10/7/2024
200	8888	10/7/2024





# NESTED LOOP JOIN SUMMARY

### Key Takeaways

- $\rightarrow$  Pick the smaller table as the outer table.
- $\rightarrow$  Buffer as much of the outer table in memory as possible.
- $\rightarrow$  Loop over the inner table (or use an index).

### **Algorithms**

- → Naïve
- $\rightarrow$  Block
- $\rightarrow$  Index



#### Phase #1: Sort

- $\rightarrow$  Sort both tables on the join key(s).
- → You can use any appropriate sort algorithm
- → These phases are distinct from the sort/merge phases of an external merge sort, from the previous class

### Phase #2: Merge

- → Step through the two sorted tables with cursors and emit matching tuples.
- → May need to backtrack depending on the join type.



```
sort R,S on join keys
cursor_R \leftarrow R_{sorted}, cursor_S \leftarrow S_{sorted}
while cursor, and cursors:
   if cursor<sub>R</sub> > cursor<sub>S</sub>:
     increment cursors
   if cursor<sub>R</sub> < cursor<sub>s</sub>:
      increment cursor<sub>R</sub>
     backtrack cursor<sub>s</sub> (if necessary)
  elif cursor, and cursor, match:
      emit
     increment cursors
```



#### R(id, name)

id	name
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400	Raekwon



#### S(id, value, cdate)

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200	8888	10/7/2024
400	6666	10/7/2024
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#### R(id, name)

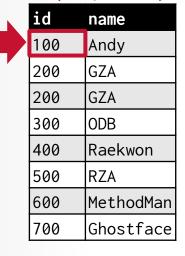


#### S(id, value, cdate)

id	value	cdate
100	2222	10/7/2024
100	9999	10/7/2024
200	8888	10/7/2024
400	6666	10/7/2024
500	7777	10/7/2024

Last Value: ---

#### R(id, name)



#### S(id, value, cdate)

id	value	cdate
100	2222	10/7/2024
100	9999	10/7/2024
200	8888	10/7/2024
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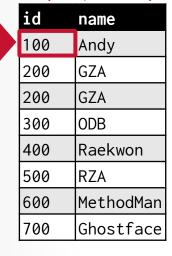
Last Value: ---

SELECT R.id, S.cdate
FROM R JOIN S
ON R.id = S.id
WHERE S.value > 100

R.id	R.name	S.id	S.value	S.cdate
100	Andy	100	2222	10/7/2024



#### R(id, name)



#### S(id, value, cdate)

	id	value	cdate
	100	2222	10/7/2024
	100	9999	10/7/2024
	200	8888	10/7/2024
	400	6666	10/7/2024
	500	7777	10/7/2024

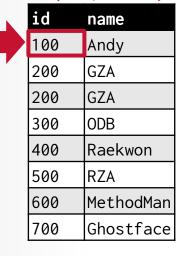
Last Value: ---

SELECT R.id, S.cdate
FROM R JOIN S
ON R.id = S.id
WHERE S.value > 100

R.id	R.name	S.id	S.value	S.cdate
100	Andy	100	2222	10/7/2024
100	Andy	100	9999	10/7/2024



#### R(id, name)



#### S(id, value, cdate)

id	value	cdate
100	2222	10/7/2024
100	9999	10/7/2024
200	8888	10/7/2024
400	6666	10/7/2024
500	7777	10/7/2024

Last Value: 100

SELECT R.id, S.cdate
FROM R JOIN S
ON R.id = S.id
WHERE S.value > 100

R.id	R.name	S.id	S.value	S.cdate
100	Andy	100	2222	10/7/2024
100	Andy	100	9999	10/7/2024



#### R(id, name)



#### S(id, value, cdate)

id	value	cdate
100	2222	10/7/2024
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Last Value: 100

SELECT R.id, S.cdate
FROM R JOIN S
ON R.id = S.id
WHERE S.value > 100

R.id	R.name	S.id	${\tt S.value}$	S.cdate
100	Andy	100	2222	10/7/2024
100	Andy	100	9999	10/7/2024
200	GZA	200	8888	10/7/2024



#### R(id, name)



#### S(id, value, cdate)

id	value	cdate
100	2222	10/7/2024
100	9999	10/7/2024
200	8888	10/7/2024
400	6666	10/7/2024
500	7777	10/7/2024

Last Value: 200

SELECT R.id, S.cdate
FROM R JOIN S
ON R.id = S.id
WHERE S.value > 100

R.id	R.name	S.id	${\tt S.value}$	S.cdate
100	Andy	100	2222	10/7/2024
100	Andy	100	9999	10/7/2024
200	GZA	200	8888	10/7/2024



#### R(id, name)

id	name
100	Andy
200	GZA
200	GZA
300	ODB
400	Raekwon
500	RZA
600	MethodMan
700	Ghostface

#### S(id, value, cdate)

id	value	cdate
100	2222	10/7/2024
100	9999	10/7/2024
200	8888	10/7/2024
400	6666	10/7/2024
500	7777	10/7/2024

Last Value: 200

SELECT R.id, S.cdate
FROM R JOIN S
ON R.id = S.id
WHERE S.value > 100

R.id	R.name	S.id	${\tt S.value}$	S.cdate
100	Andy	100	2222	10/7/2024
100	Andy	100	9999	10/7/2024
200	GZA	200	8888	10/7/2024



#### R(id, name)

id	name
100	Andy
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#### S(id, value, cdate)

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100	9999	10/7/2024
200	8888	10/7/2024
400	6666	10/7/2024
500	7777	10/7/2024

Last Value: 200

SELECT R.id, S.cdate
 FROM R JOIN S
 ON R.id = S.id
 WHERE S.value > 100

R.id	R.name	S.id	${\tt S.value}$	S.cdate
100	Andy	100	2222	10/7/2024
100	Andy	100	9999	10/7/2024
200	GZA	200	8888	10/7/2024
200	GZA	200	8888	10/7/2024



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id	name
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400	6666	10/7/2024
500	7777	10/7/2024

Last Value: 200

SELECT R.id, S.cdate
FROM R JOIN S
ON R.id = S.id
WHERE S.value > 100

R.id	R.name	S.id	${\tt S.value}$	S.cdate
100	Andy	100	2222	10/7/2024
100	Andy	100	9999	10/7/2024
200	GZA	200	8888	10/7/2024
200	GZA	200	8888	10/7/2024



#### R(id, name)

id	name
100	Andy
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id	value	cdate
100	2222	10/7/2024
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200	8888	10/7/2024
400	6666	10/7/2024
500	7777	10/7/2024

Last Value: 200

SELECT R.id, S.cdate
FROM R JOIN S
ON R.id = S.id
WHERE S.value > 100

R.id	R.name	S.id	S.value	S.cdate
100	Andy	100	2222	10/7/2024
100	Andy	100	9999	10/7/2024
200	GZA	200	8888	10/7/2024
200	GZA	200	8888	10/7/2024
400	Raekwon	200	6666	10/7/2024



#### R(id, name)

id	name
100	Andy
200	GZA
200	GZA
300	ODB
400	Raekwon
500	RZA
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	·

#### S(id, value, cdate)

id	value	cdate
100	2222	10/7/2024
100	9999	10/7/2024
200	8888	10/7/2024
400	6666	10/7/2024
500	7777	10/7/2024

Last Value: 400

SELECT R.id, S.cdate
FROM R JOIN S
ON R.id = S.id
WHERE S.value > 100

R.id	R.name	S.id	S.value	S.cdate
100	Andy	100	2222	10/7/2024
100	Andy	100	9999	10/7/2024
200	GZA	200	8888	10/7/2024
200	GZA	200	8888	10/7/2024
400	Raekwon	200	6666	10/7/2024



#### R(id, name)

id	name
100	Andy
200	GZA
200	GZA
300	ODB
400	Raekwon
500	RZA
600	MethodMan
700	Ghostface

#### S(id, value, cdate)

id	value	cdate
100	2222	10/7/2024
100	9999	10/7/2024
200	8888	10/7/2024
400	6666	10/7/2024
500	7777	10/7/2024

Last Value: 400

SELECT R.id, S.cdate
FROM R JOIN S
ON R.id = S.id
WHERE S.value > 100

R.id	R.name	S.id	S.value	S.cdate
100	Andy	100	2222	10/7/2024
100	Andy	100	9999	10/7/2024
200	GZA	200	8888	10/7/2024
200	GZA	200	8888	10/7/2024
400	Raekwon	200	6666	10/7/2024
500	RZA	500	7777	10/7/2024



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id	value	cdate
100	2222	10/7/2024
100	9999	10/7/2024
200	8888	10/7/2024
400	6666	10/7/2024
500	7777	10/7/2024

Last Value: 500

SELECT R.id, S.cdate
FROM R JOIN S
ON R.id = S.id
WHERE S.value > 100

R.id	R.name	S.id	S.value	S.cdate
100	Andy	100	2222	10/7/2024
100	Andy	100	9999	10/7/2024
200	GZA	200	8888	10/7/2024
200	GZA	200	8888	10/7/2024
400	Raekwon	200	6666	10/7/2024
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Last Value: 500

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R.id	R.name	S.id	S.value	S.cdate
100	Andy	100	2222	10/7/2024
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200	GZA	200	8888	10/7/2024
400	Raekwon	200	6666	10/7/2024
500	RZA	500	7777	10/7/2024



```
Sort Cost (R): 2M \cdot (1 + \lceil \log_{B-1} \lceil M / B \rceil \rceil)
```

Sort Cost (S):  $2N \cdot (1 + \lceil \log_{B-1} \lceil N/B \rceil \rceil)$ 

Merge Cost: (M + N)

**Total Cost: Sort + Merge** 



### Example database:

- → **Table R**: M = 1000, m = 100,000
- → **Table S**: N = 500, n = 40,000

With B=100 buffer pages, both R and S can be sorted in two passes:

- $\rightarrow$  Sort Cost (**R**) = 2000 · (1 +  $\lceil \log_{99} 1000 / 100 \rceil$ ) = **4000 I/Os**
- $\rightarrow$  Sort Cost (S) = 1000 · (1 +  $\lceil \log_{99} 500 / 100 \rceil$ ) = 2000 I/Os
- $\rightarrow$  Merge Cost = (1000 + 500) = 1500 I/Os
- $\rightarrow$  Total Cost = 4000 + 2000 + 1500 = 7500 I/Os
- $\rightarrow$  At 0.1 ms/IO, Total time  $\approx$  0.75 seconds



The worst case for the merging phase is when the join attribute of all the tuples in both relations contains the same value.

Cost:  $(M \cdot N) + (sort cost)$ 



### WHEN IS SORT-MERGE JOIN USEFUL?

One or both tables are already sorted on join key. Output must be sorted on join key.

The input relations may be sorted either by an explicit sort operator, or by scanning the relation using an index on the join key.



### HASH JOIN

#### 在外部表上构建哈希表, 内部表作探测表.

If tuple  $r \in R$  and tuple  $s \in S$  satisfy the join condition, then they have the same value for the join attributes.

If that value is hashed to some partition  $\mathbf{i}$ , the  $\mathbf{R}$  tuple must be in  $\mathbf{r_i}$  and the  $\mathbf{S}$  tuple in  $\mathbf{s_i}$ .

Therefore, R tuples in  $r_i$  need only to be compared with S tuples in  $s_i$ .



#### Phase #1: Build

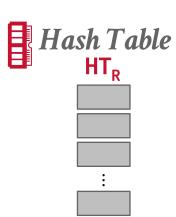
- $\rightarrow$  Scan the outer relation and populate a hash table using the hash function  $\mathbf{h}_1$  on the join attributes.
- → We can use any hash table that we discussed before but in practice linear probing works the best.

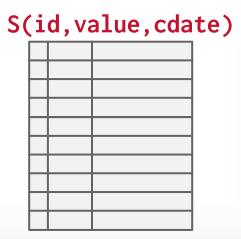
#### Phase #2: Probe

 $\rightarrow$  Scan the inner relation and use  $h_1$  on each tuple to jump to a location in the hash table and find a matching tuple.

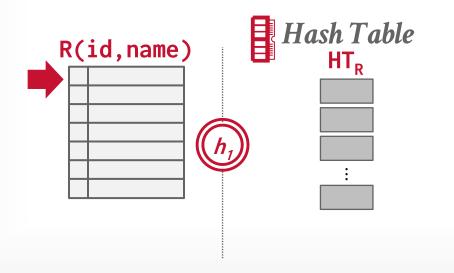


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	Ш						
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			J				



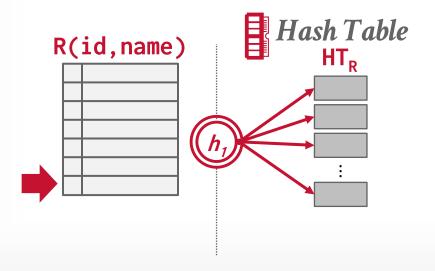


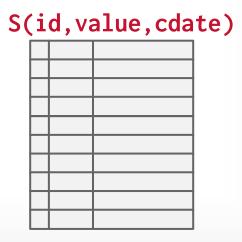




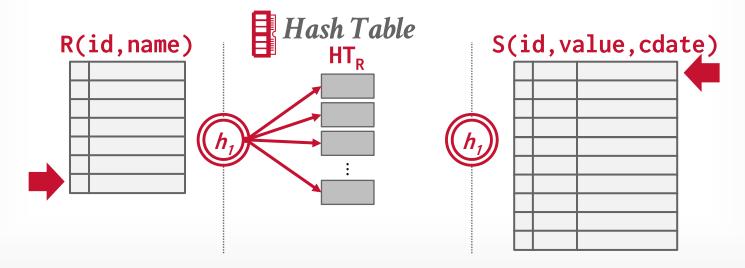
S(id,value,cdate)						
	L					
	H					
	H					
	Н					



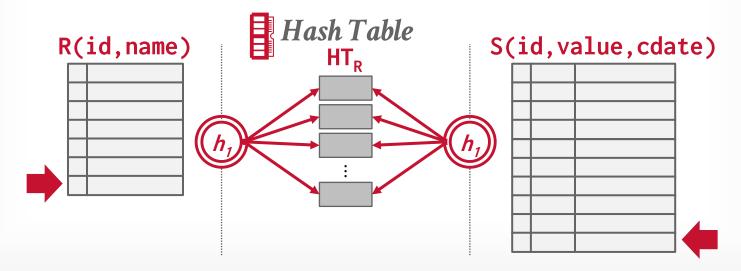














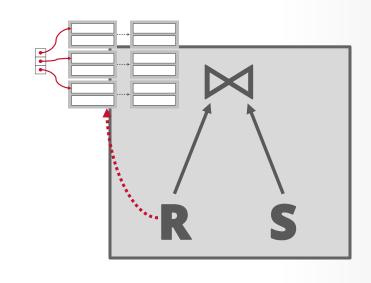
### OPTIMIZATION: PROBE FILTER

Create a probe filter (<u>Bloom Filter</u>) as the DBMS builds the hash table on the outer table in the first phase.

- → Always check the filter before probing the hash table.
- → Faster than probing hash table because the filter fits in CPU cache.

使用布隆过滤器探测的成本低于哈希表的探测成本.

This technique is sometimes called sideways information passing.

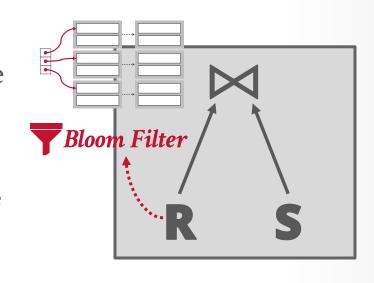


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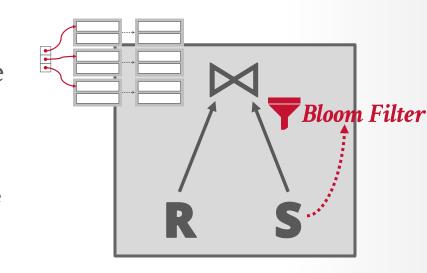


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- → Faster than probing hash table because the filter fits in CPU cache.

This technique is sometimes called sideways information passing.



### HASH JOINS OF LARGE RELATIONS

What happens if we do not have enough memory to fit the entire hash table?

We do not want to let the buffer pool manager swap out the hash table pages at random.



### PARTITIONED HASH JOIN

# Hash join when tables do not fit in memory.

- → **Partition Phase:** Hash both tables on the join attribute into partitions.
- → Probe Phase: Compares tuples in corresponding partitions for each table.

### Sometimes called GRACE Hash Join.

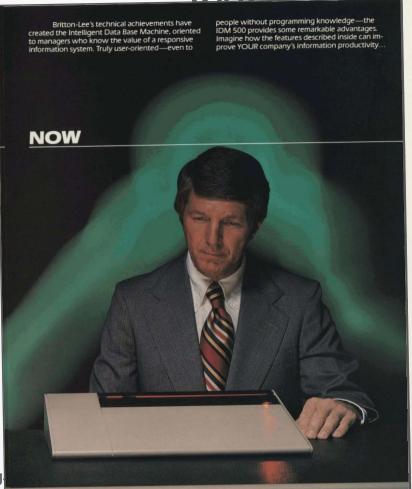
→ Named after the GRACE <u>database</u> machine from Japan in the 1980s.



**GRACE**University of Tokyo



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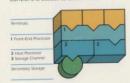


#### The IDM 500 A Logical Development

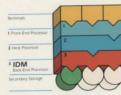
As data systems have evolved, the presence of special-purpose elements has become increasingly important, as these diagrams will illustrate:



In the 1960's, a single central processing unit (CPU) was required to monitor time-sharing among terminal users; to batch process computing tasks, and to control the access to stored data.



Through the development of frontend communication processors, the workload on the CPU was reduced. It was then able to perform its basic task of data processing much more efficiently. But the task of managing the data base was still imposed upon it.



Now Britton-Lee's IDM 500 specialpurpose, back-end data-base processor brings full efficiency to the host computer and intelligent terminals, so that they can properly perform their correct functions.







TBM GE

IBM DB2 Analytics Accelerator - GSE Management Summit

#### Choosing the best fit

#### Key indicators

#### **IBM Netezza**

- Performance and Price/performance leader
- Speed and ease of deployment and administration

#### IBM Netezza standalone appliance

- Strategic requirement for standalone decision support system
- If primary data feeds are from distributed applications
- Deep analytics applications or in-database mining

#### IBM DB2 Analytics Accelerator for z/OS

### Teradata IntelliFlex

100% Solid State Performance

Up to: 7.5x Performance for Com Intensive Analytics



4.5x Performance for Date Warehouse Analytic

3.5x Data Capacity

2.0x Performance per k

CLUSTRIX APPLIANCE



Clustrix Appliance 3 Node Cluster (CLX 4110)

- 24 Intel Xeon CPU cores
- 144GB RAM
- 6GB NVRAM
- 1.35TB Intel SSD protected

10 7TD rawl data canacity

# **Complete Family Of Database Machines**

For OLTP, Data Warehousing & Consolidated Workloads

Oracle Exadata X2-2



Quarter, Half, Full and Multi-Racks

Oracle Exadata X2-8



Full and Multi-Racks



Note: comparisons to the previous generation IntelliFlex platform are on a per cabinet basis. Workloads will see up to this amount of benefit

CLUSTRIV AD

#### IBM DB2 Analytics Accelerator - GSE Management Summit Choosing the best fit



#### Teradata IntelliFlex 100% Solid State Perform

#### Up to:



# Yellowbrick Data Warehouse Architecture

Real-time Feeds Ingest IoT or OLTP data Capture 100,000s of rows per second

Periodic Bulk Loads

Load and Transform Use existing ETL tools including intensive push-down ELT

Source: yellowbrickdata.com

Capture terabytes of data, petabytes over time





Interactive Applications Serve short queries in

under 100 milliseconds



**Powerful Analytics** Respond to complex BI queries in just a few seconds

**Business Critical Reporting** Workload management for prioritized responses

### Database Machines

de Cluster (CLX 4110)

res

ected

anacity

& Consolidated Workloads

Oracle Exadata X2-8



Full and Multi-Racks

### 4.5x Performance for Date Warehouse Analytic

3.5x Data Capacity

2.0x Performance per k



Quarter, Half, Full and Multi-Racks

Note: comparisons to the previous generation IntelliFlex platform are on a per cabinet basis. Workloads will see up to this amount of benefit



ORACLE

Clustrix

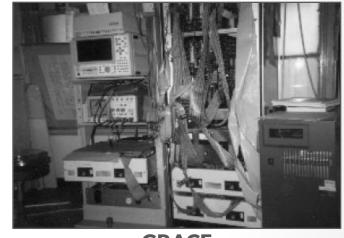
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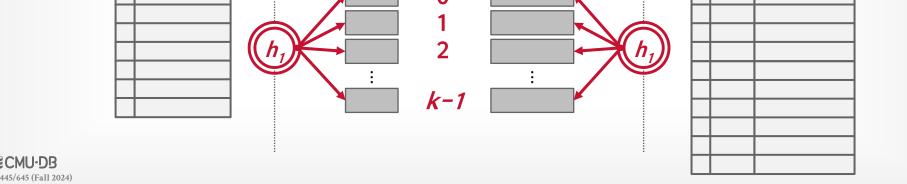
### PARTITIONED HASH JOIN PARTITION PHASE

Hash R into k buckets.

Hash **S** into *k* buckets with same hash function.

Write buckets to disk when they get full.

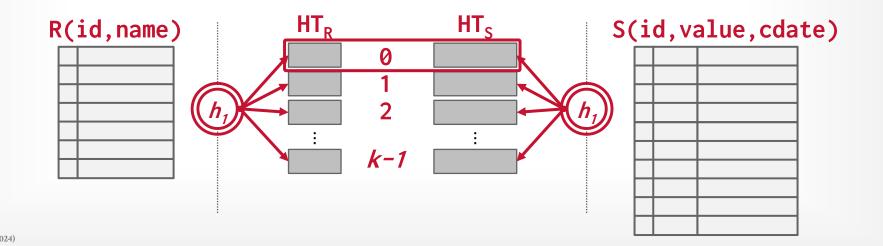
 $HT_S$  $HT_R$ R(id, name) S(id, value, cdate)



在同一级桶上进行 join 计算.

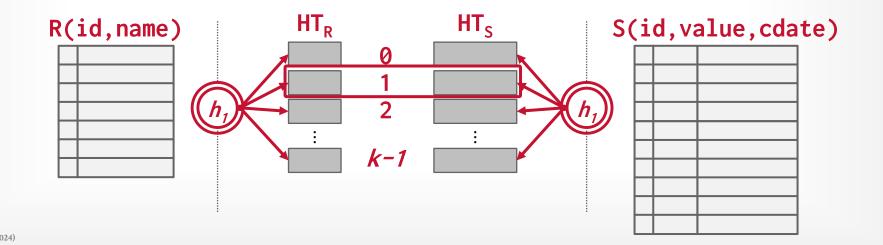
# PARTITIONED HASH JOIN PROBE PHASE

Read corresponding partitions into memory one pair at a time, hash join their contents.



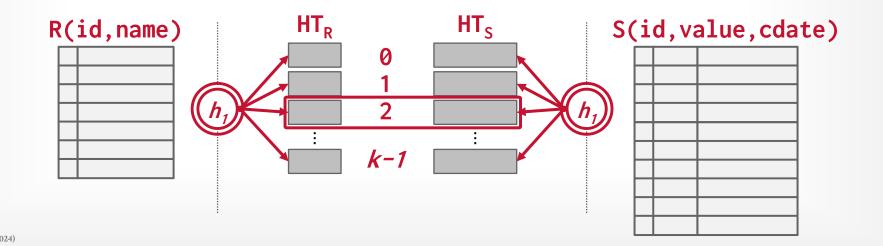
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Read corresponding partitions into memory one pair at a time, hash join their contents.



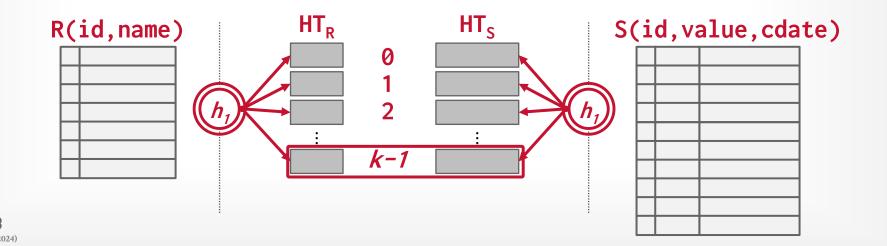
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Read corresponding partitions into memory one pair at a time, hash join their contents.



#### PARTITIONED HASH JOIN EDGE CASES

If a partition does not fit in memory, recursively partition it with a different hash function

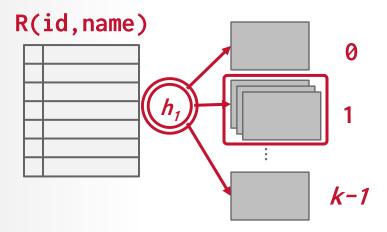
- → Repeat as needed
- → Eventually hash join the corresponding (sub-)partitions

If a single join key has too many matching records that do not fit in memory, use a **block nested loop** join just for that key.

→ Avoids random I/O in exchange for sequential I/O.

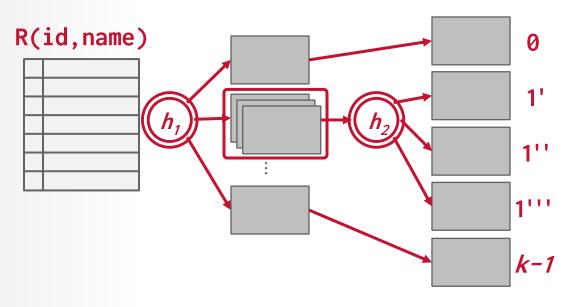


## RECURSIVE PARTITIONING



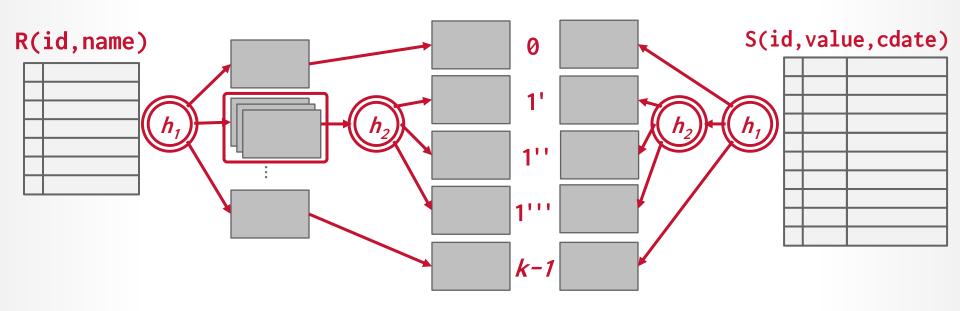


## RECURSIVE PARTITIONING





## RECURSIVE PARTITIONING





## COST OF PARTITIONED HASH JOIN

If we do not need recursive partitioning:

 $\rightarrow$  Cost: 3(M + N)

#### Partition phase:

- → Read+write both tables
- $\rightarrow$  2(M+N) I/Os

#### Probe phase:

- → Read both tables (in total, one partition at a time)
- $\rightarrow$  M+N I/Os



#### PARTITIONED HASH JOIN

#### Example database:

- $\rightarrow$  **M** = 1000, **m** = 100,000
- $\rightarrow$  **N** = 500, **n** = 40,000

#### Cost Analysis:

- $\rightarrow$  3(M + N) = 3 · (1000 + 500) = 4,500 IOs
- $\rightarrow$  At 0.1 ms/IO, Total time  $\approx$  0.45 seconds

#### OPTIMIZATION: HYBRID HASH JOIN

If the keys are skewed, then the DBMS keeps the hot partition in-memory and immediately perform the comparison instead of spilling it to disk.

→ Difficult to get to work correctly. Rarely done in practice.

R(id, name)

O

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#### HASH JOIN OBSERVATIONS

The inner table can be any size.

→ Only outer table (or its partitions) need to fit in memory

If we know the size of the outer table, then we can use a static hash table.

→ Less computational overhead

If we do not know the size, then we must use a dynamic hash table or allow for overflow pages.



## JOIN ALGORITHMS: SUMMARY

Algorithm IO Cost	Example
ive Nested Loop Join $M + (m \cdot N)$	1.3 hours
ock Nested Loop Join $M + (\lceil M / (B-2) \rceil \cdot N)$	0.55 seconds
lex Nested Loop Join $M + (m \cdot C)$	Variable
Sort-Merge Join $M + N + (sort cost)$	0.75 seconds
Hash Join $3 \cdot (M + N)$	0.45 seconds



#### CONCLUSION

Hashing is almost always better than sorting for operator execution.

#### Caveats:

- $\rightarrow$  Sorting is better on non-uniform data.
- $\rightarrow$  Sorting is better when result needs to be sorted.

Good DBMSs use either (or both).



#### **NEXT CLASS**

# Mid-Term Exam!