

#### Database System Internals

# Query Optimization (part 2)

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# Today's Agenda

 Recap Partitioned Hash-join (from two lectures ago)

Finish discussing cardinality estimation

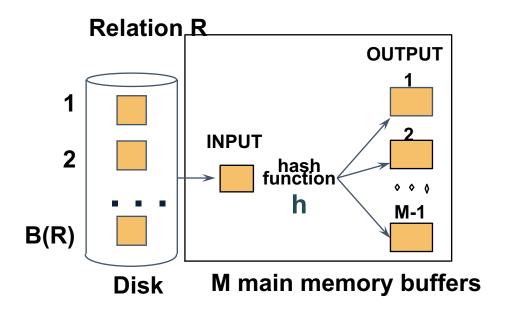
■ Partition R it into k buckets on disk: R<sub>1</sub>, R<sub>2</sub>, R<sub>3</sub>, ..., R<sub>k</sub>

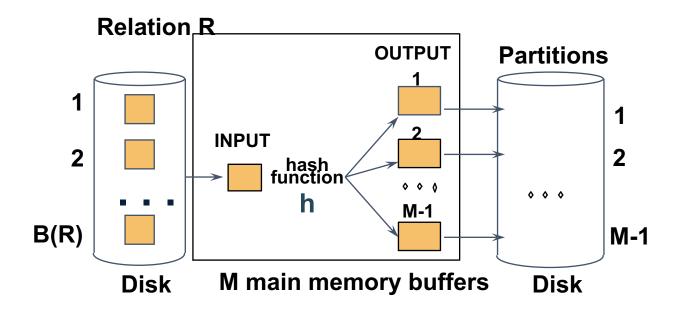
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  R<sub>1</sub>, R<sub>2</sub>, R<sub>3</sub>, ..., R<sub>k</sub>
- Assuming  $B(R_1)=B(R_2)=...=B(R_k)$ , we have  $B(R_i)=B(R)/k$ , for all i

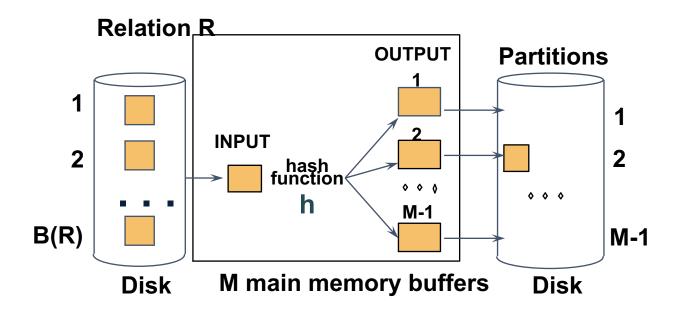
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- Assuming  $B(R_1)=B(R_2)=...=B(R_k)$ , we have  $B(R_i)=B(R)/k$ , for all i
- Goal: each  $R_i$  should fit in main memory:  $B(R_i) \le M$

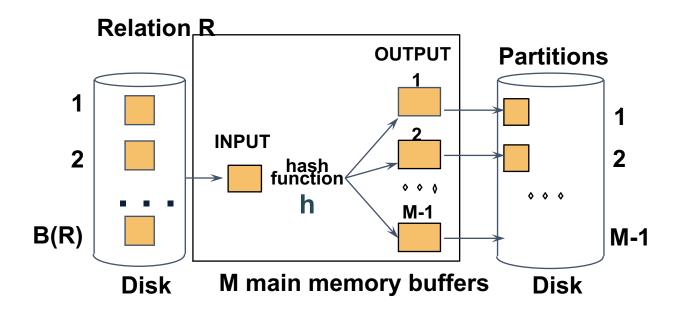
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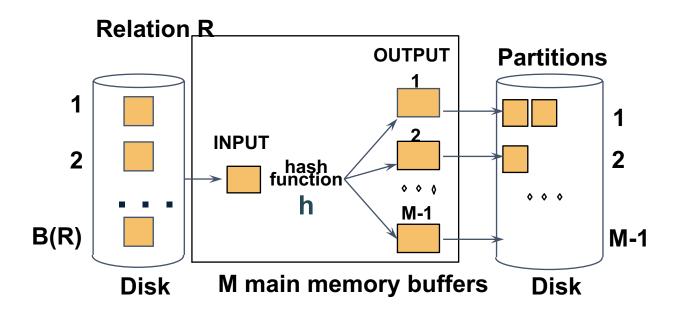
How do we choose k?

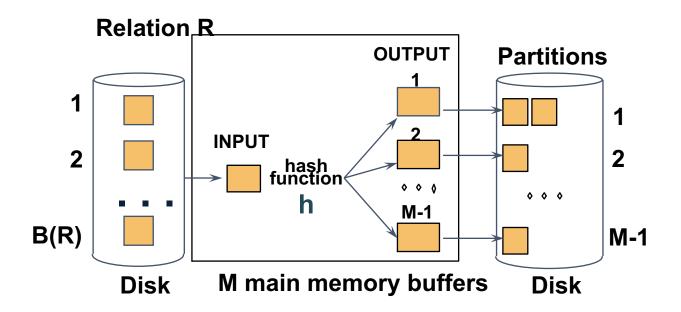


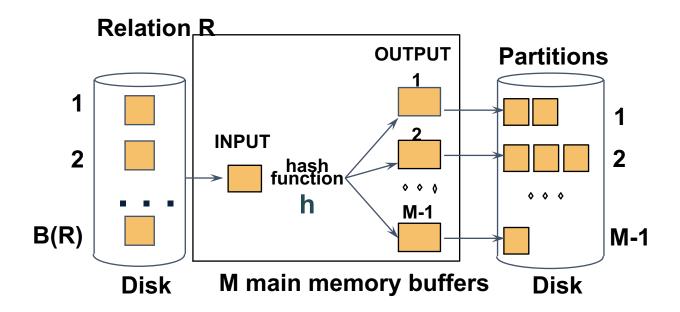




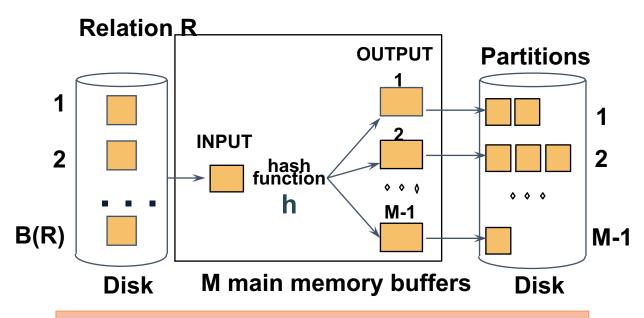








We choose k = M-1 Each bucket has size approx. B(R)/(M-1) ≈ B(R)/M



Assumption:  $B(R)/M \le M$ , i.e.  $B(R) \le M^2$ 

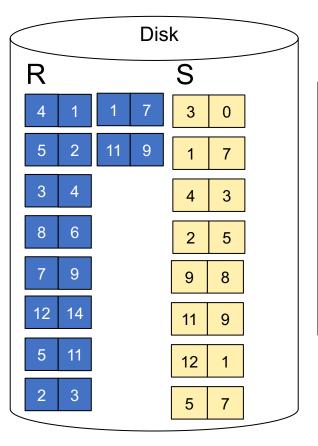
# Partitioned Hash Join (Grace-Join)

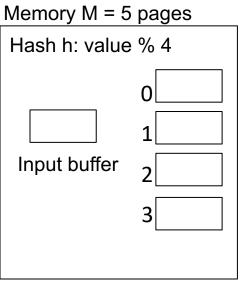
#### $R \bowtie S$

- Step 1:
  - Hash S into M-1 buckets
  - Send all buckets to disk
- Step 2
  - Hash R into M-1 buckets
  - Send all buckets to disk
- Step 3
  - Join every pair of buckets

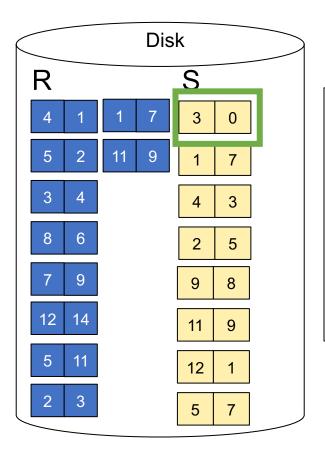
Note: partitioned hash-join is sometimes called *grace-join* 

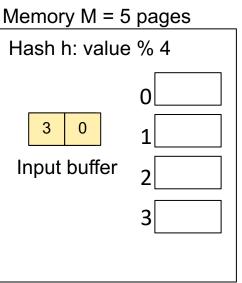
**Step 1:** Read relation S one page at a time and hash into M-1 (=4 buckets)



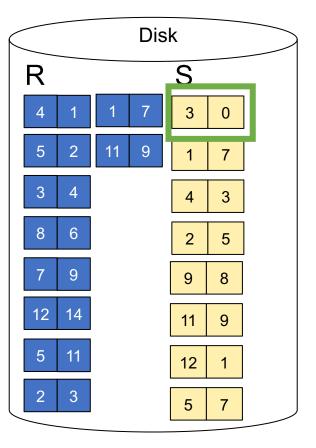


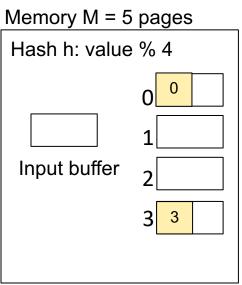
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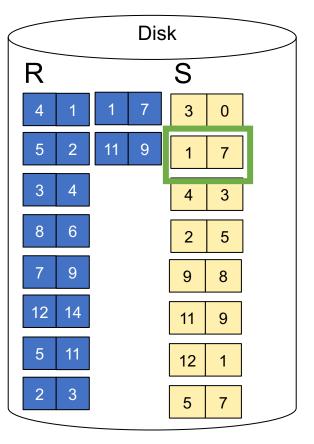


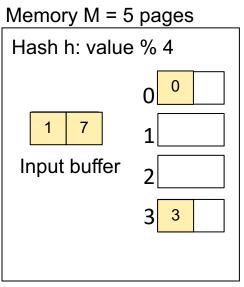
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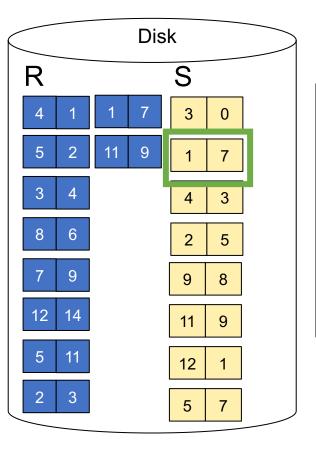


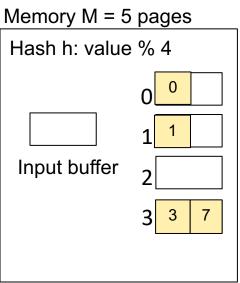
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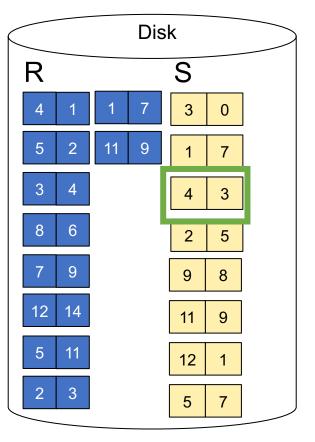


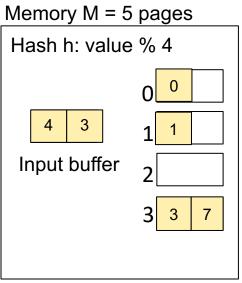
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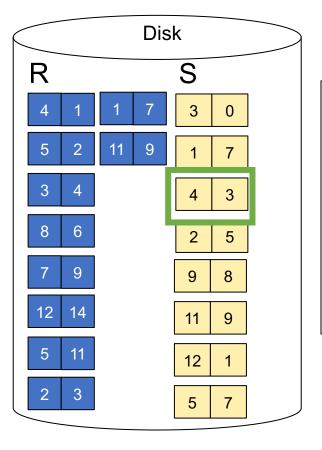


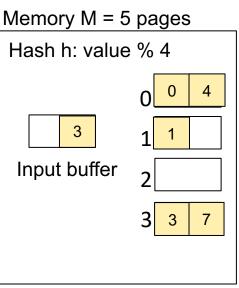
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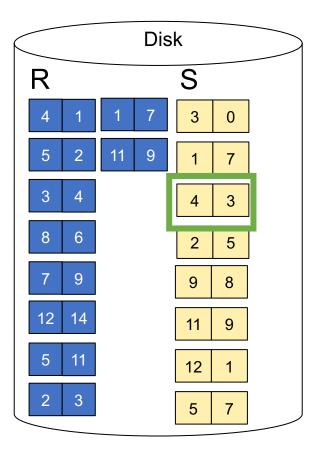


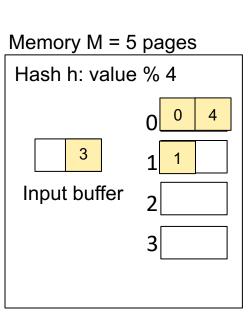
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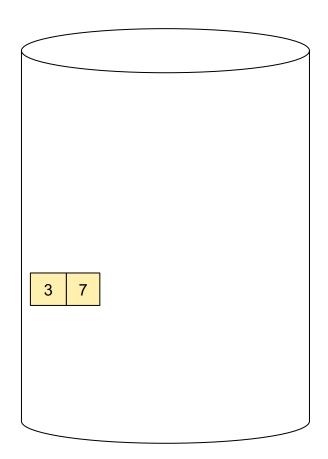




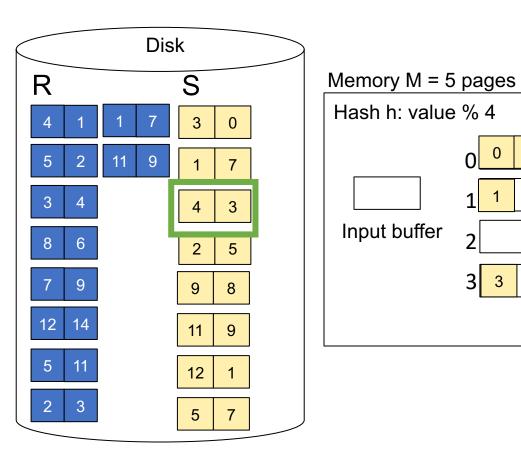
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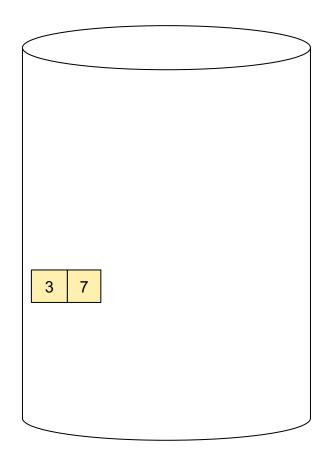




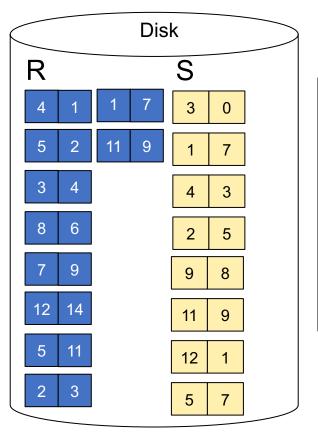


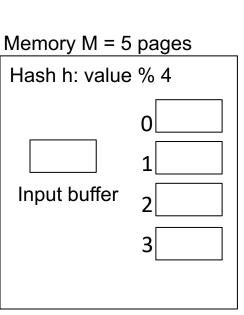
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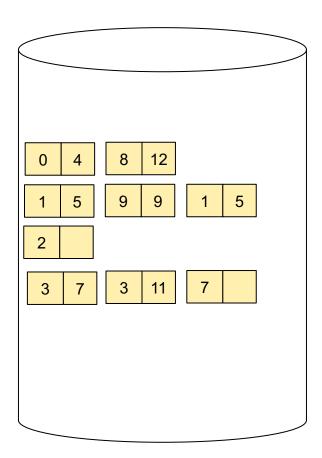




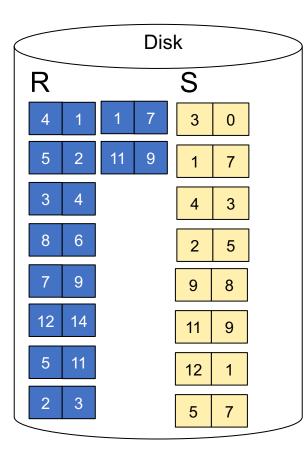
**Step 1:** Read relation S one page at a time and hash into the 4 buckets At the end, we get relation S back on disk split into 4 buckets

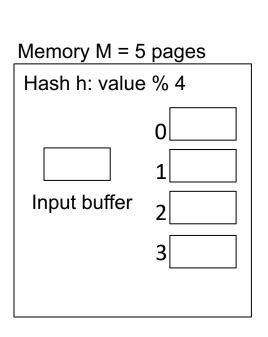


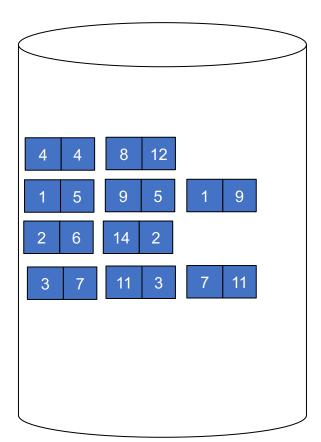




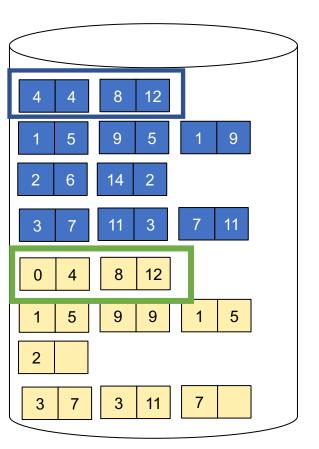
**Step 2:** Read relation R one page at a time and hash into same 4 buckets

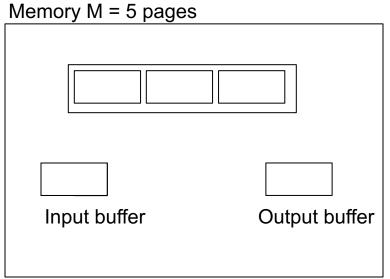






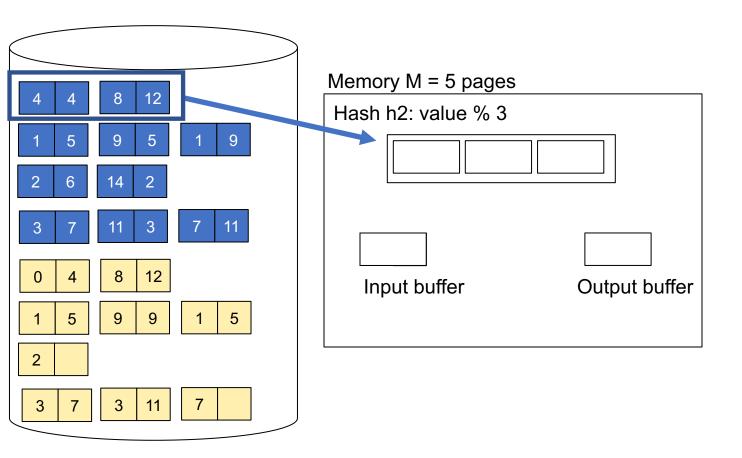
Step 3: Read one partition of R and create hash table in memory using a different hash function



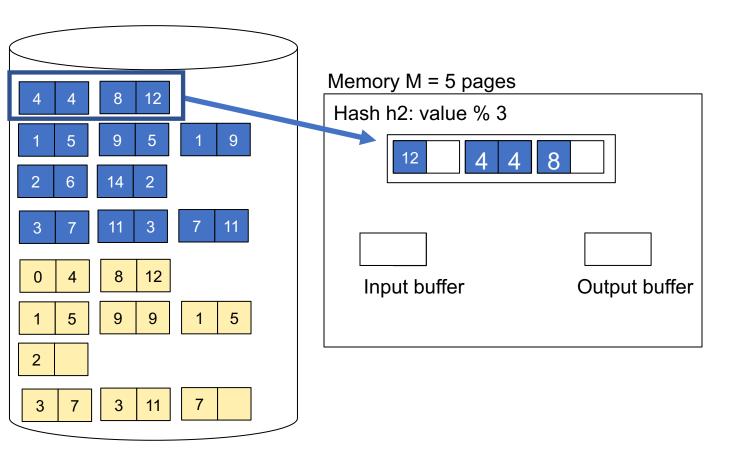


Join R1 with S1

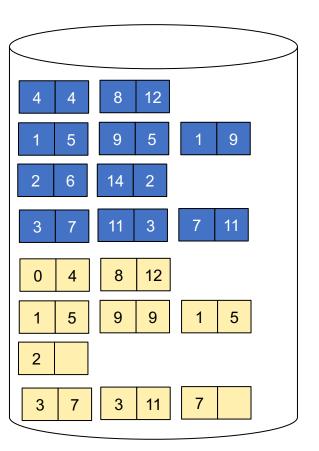
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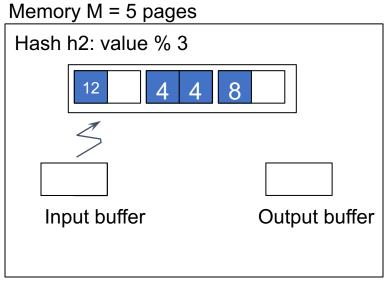


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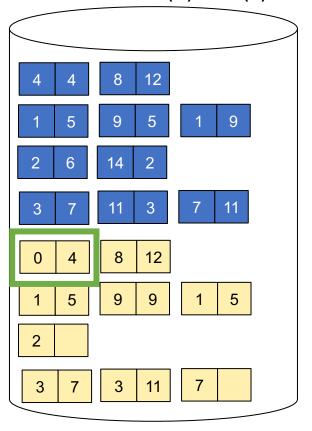
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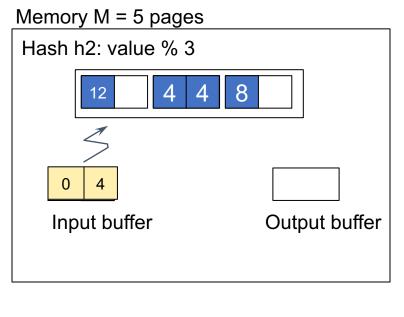




**Step 4:** Scan matching partition of S and probe the hash table

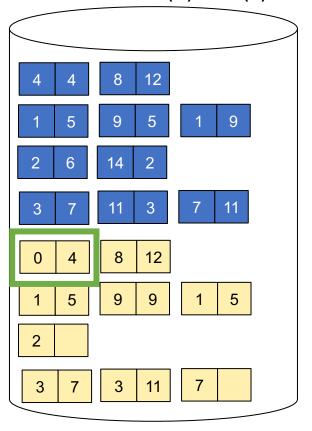
**Step 5**: Repeat for all the buckets

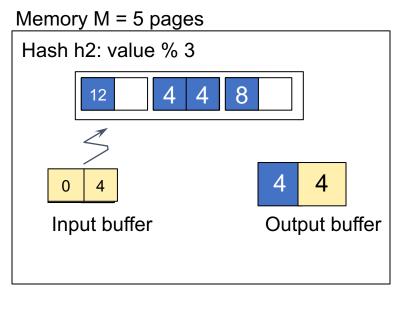




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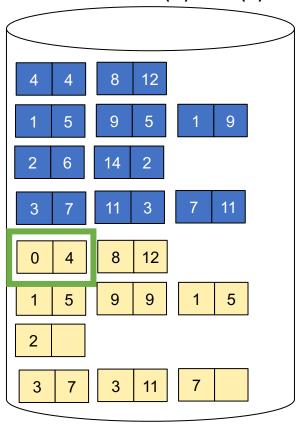
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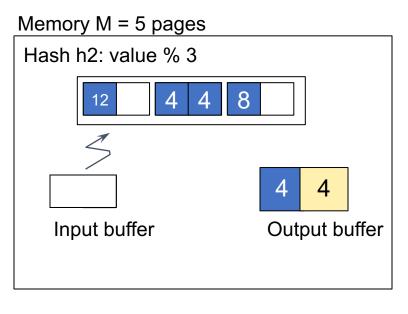




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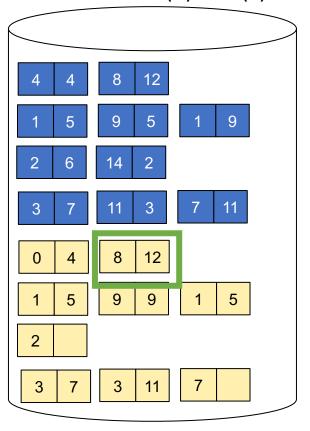
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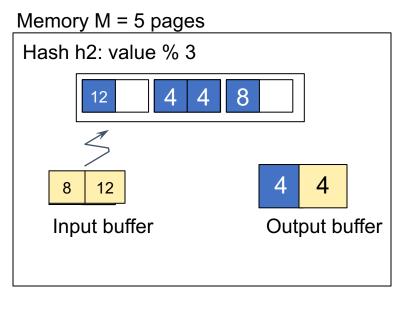




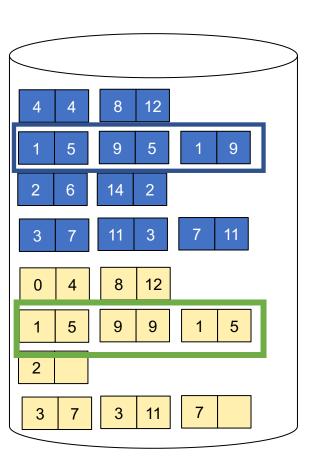
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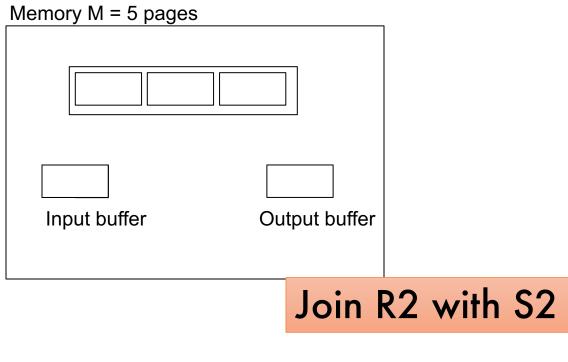
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Step 3: Read one partition of R and create hash table in memory using a different hash function



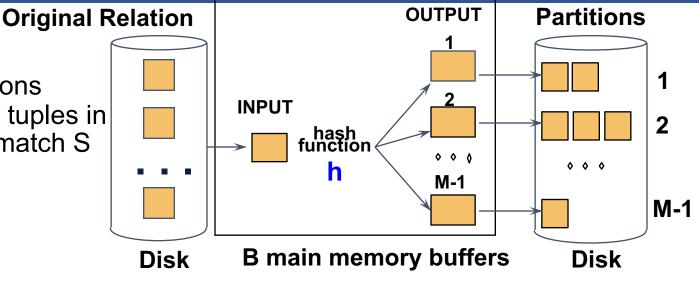


Join Rk with Sk

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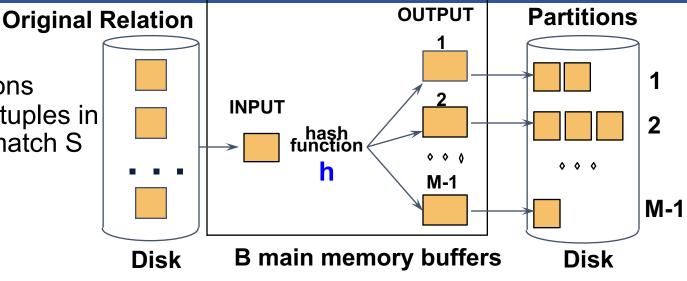
#### Partitioned Hash-Join

 Partition both relations using hash fn h: R tuples in partition i will only match S tuples in partition i.

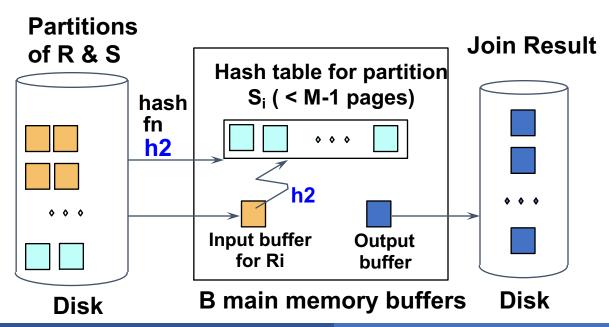


#### Partitioned Hash-Join

 Partition both relations using hash fn h: R tuples in partition i will only match S tuples in partition i.



 Read in a partition of R, hash it using h2 (<> h!).
 Scan matching partition of S, search for matches.



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#### Partitioned Hash-Join

- Cost: 3B(R) + 3B(S)
- Assumption: min(B(R), B(S)) <= M<sup>2</sup>

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### Hybrid Hash Join Algorithm (see book)

■ Partition S into k << M buckets t buckets S<sub>1</sub>, ..., S<sub>t</sub> stay in memory k-t buckets S<sub>t+1</sub>, ..., S<sub>k</sub> to disk

- Partition R into k buckets
  - First t buckets join immediately with S
  - Rest k-t buckets go to disk
- Finally, join k-t pairs of buckets: (R<sub>++1</sub>, S<sub>++1</sub>), (R<sub>++2</sub>, S<sub>++2</sub>), ..., (R<sub>k</sub>, S<sub>k</sub>)

Works well when B(S) > M but is not very large

### **Query Optimization**

- Returning to query optimization...
- Three components:
  - Cost/cardinality estimation
  - Search space
  - Search algorithm
- We are discussing cardinality estimation:
  - Main idea: selectivity factor
  - Many assumptions: uniformity, independence, preservation of values, inclusion of values

T(Supply) = 10000T(Supplier) = 1000

### Key Foreign-key Join

```
SELECT sname
FROM Supplier x, Supply y
WHERE x.sid = y.sid
```

How large is T(Q)?

```
SELECT sname
FROM Supplier x, Supply y
WHERE x.sid = y.sid
```

Answer 1: T(Q) = T(Supply) (why?)

```
SELECT sname
FROM Supplier x, Supply y
WHERE x.sid = y.sid
```

- Answer 1: T(Q) = T(Supply) (why?)
- Answer 2:

```
T(Q) = T(Supply ⋈ Supplier)
= T(Supply)*T(Supplier) / max(V(Supply,sid),V(Supplier,sid))
```

```
SELECT sname
FROM Supplier x, Supply y
WHERE x.sid = y.sid
```

- Answer 1: T(Q) = T(Supply) (why?)
- Answer 2:

```
We know
this V(Supplier,sid) = T(Supplier)
V(Supply,sid) ≤ V(Supplier,sid)
```

```
T(Q) = T(Supply \bowtie Supplier)
= T(Supply)*T(Supplier) / max(V(Supply,sid),V(Supplier,sid))
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SELECT sname
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How large is T(Q)?

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- Answer 2:

```
We know this V(Supplier,sid) = T(Supplier) V(Supply,sid) ≤ V(Supplier,sid)
```

Containment of values assumption

```
T(Q) = T(Supply ⋈ Supplier)
= T(Supply)*T(Supplier) / max(V(Supply,sid),V(Supplier,sid))
= T(Supply)*T(Supplier) / V(Supplier,sid) = T(Supply)
```

T(Supply) = 10000 T(Supplier) = 1000 V(Supplier, sstate) = 10

#### Preservation of Values

```
SELECT sname
FROM Supplier x, Supply y
WHERE x.sid = y.sid
and x.sstate = 'WA'
```

T(Supply) = 10000 T(Supplier) = 1000 V(Supplier, sstate) = 10

#### Preservation of Values

```
SELECT sname
FROM Supplier x, Supply y
WHERE x.sid = y.sid
and x.sstate = 'WA'
```

```
T(Q) = T(\sigma_{sstate='WA'}(Supply \bowtie Supplier))
= T(Supply \bowtie Supplier) / V(Supply \bowtie Supplier, sstate)
```

T(Supply) = 10000 T(Supplier) = 1000 V(Supplier, sstate) = 10

#### Preservation of Values

How large is T(Q)?

Preservation of values assumption

```
SELECT sname
FROM Supplier x, Supply y
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V(Supply ⋈ Supplier, sstate) = V(Supplier, sstate) = 10

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T(Q) = T(\sigma_{sstate='WA'}(Supply \bowtie Supplier))
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T(Q) = T(\sigma_{sstate='WA'}(Supply \bowtie Supplier))
= T(Supply \bowtie Supplier) / V(Supply \bowtie Supplier, sstate)
= T(Supply \bowtie Supplier) / V(Supplier, sstate)
= T(Supply) / 10
```

### Example

 Enumerate logical plans, estimate T(temp relations)

```
FROM Supplier x, Supply y
WHERE x.sid = y.sid
    and y.pno = 2
    and x.scity = 'Seattle'
    and x.sstate = 'WA'
```

 For each logical plan, enumerate physical plans, estimate Cost

# Logical Query Plan 1

```
Π<sub>sname</sub>
O<sub>pno=2</sub> ∧ scity='Seattle' ∧ sstate='WA'
                 sid = sid
```

```
SELECT sname
FROM Supplier x, Supply y
WHERE x.sid = y.sid
    and y.pno = 2
    and x.scity = 'Seattle'
    and x.sstate = 'WA'
```

#### Supply

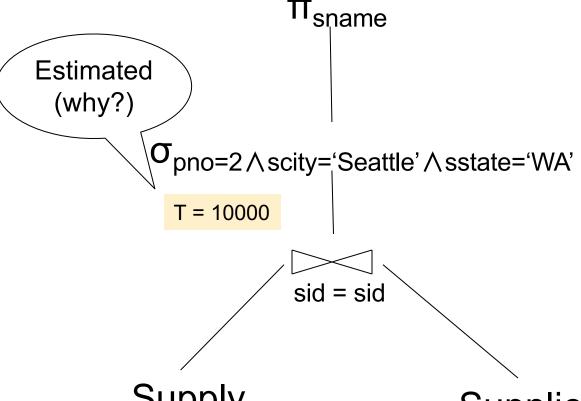
T(Supply) = 10000B(Supply) = 100V(Supply, pno) = 2500

#### Supplier

T(Supplier) = 1000B(Supplier) = 100 V(Supplier, scity) = 20 V(Supplier, state) = 10

M = 11

# Logical Query Plan 1



```
SELECT sname
FROM Supplier x, Supply y
WHERE x.sid = y.sid
    and y.pno = 2
    and x.scity = 'Seattle'
    and x.sstate = 'WA'
```

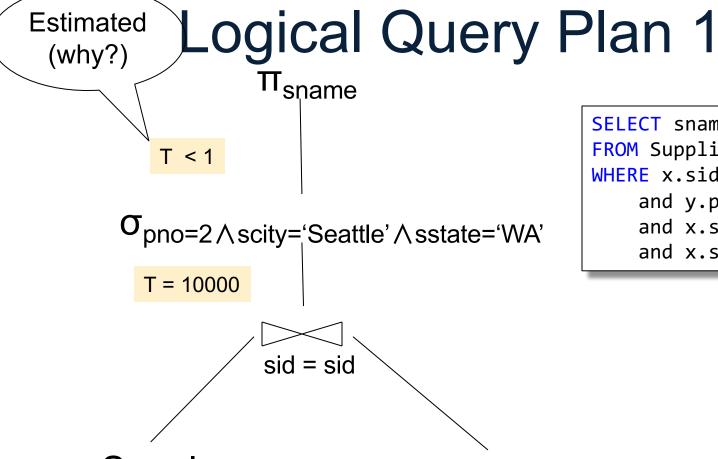
```
Supply
```

```
T(Supply) = 10000
B(Supply) = 100
V(Supply, pno) = 2500
```

#### Supplier

```
T(Supplier) = 1000
B(Supplier) = 100
V(Supplier, scity) = 20
V(Supplier, state) = 10
```

M = 11



```
SELECT sname
FROM Supplier x, Supply y
WHERE x.sid = y.sid
    and y.pno = 2
    and x.scity = 'Seattle'
    and x.sstate = 'WA'
```

#### Supply

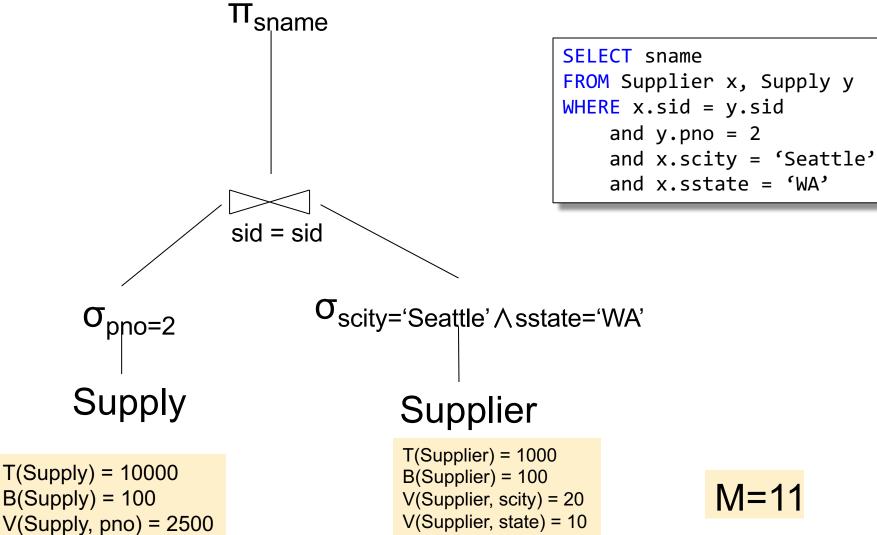
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T(Supply) = 10000
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T(Supplier) = 1000
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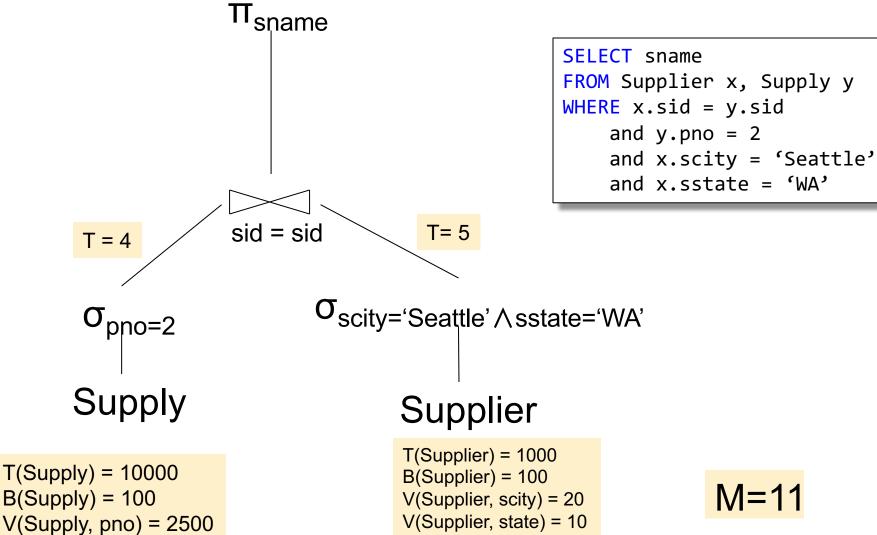
M=11

# Logical Query Plan 2



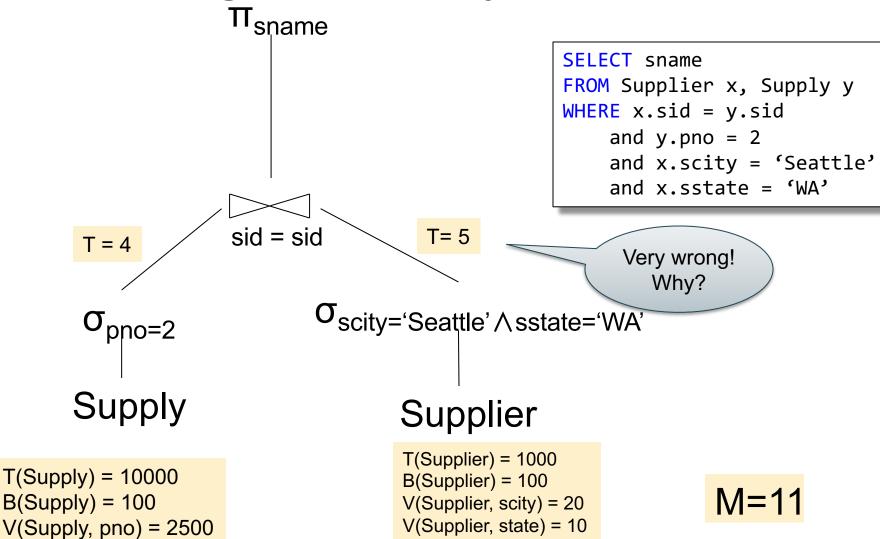
M = 11

# Logical Query Plan 2

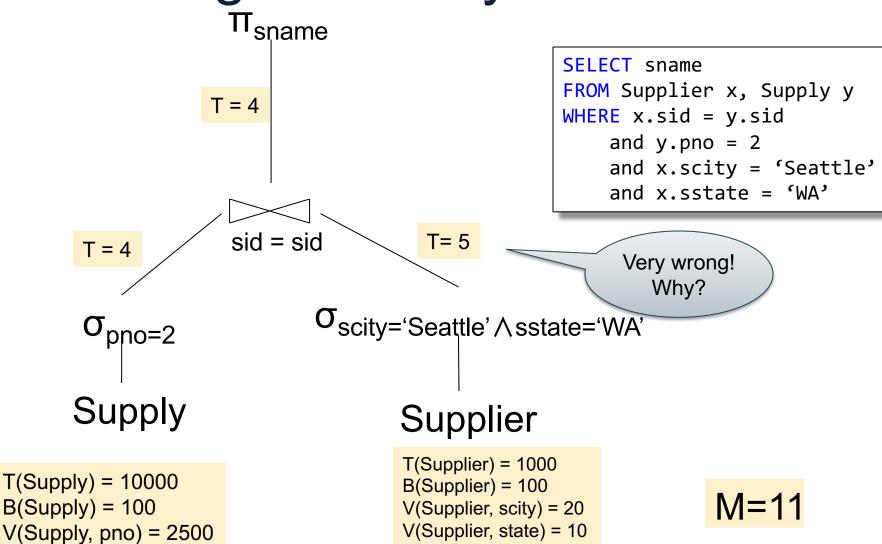


M = 11

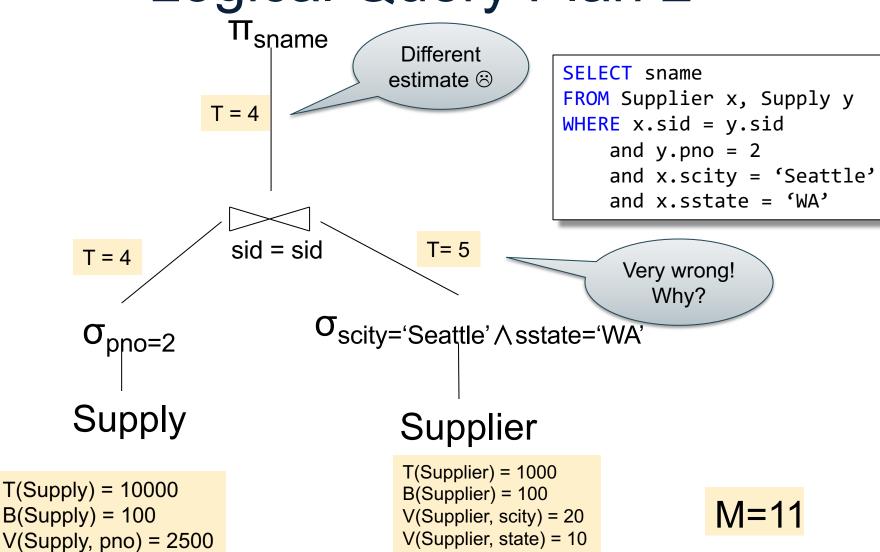
# Logical Query Plan 2



# Logical Query Plan 2



# Logical Query Plan 2



# Physical Plan 1

 $\Pi_{\text{sname}}$ T < 1

σ<sub>pno=2 ∧ scity='Seattle' ∧ sstate='WA'</sub>

T = 10000

Total cost:

sid = sidBlock nested loop join

Scan

Supply

Scan

Supplier

T(Supply) = 10000B(Supply) = 100V(Supply, pno) = 2500

T(Supplier) = 1000B(Supplier) = 100V(Supplier, scity) = 20 V(Supplier, state) = 10

M = 11

# Physical Plan 1

π<sub>sname</sub>

σ<sub>pno=2 ∧ scity='</sub>Seattle' ∧ sstate='WA'

T = 10000

T < 1

Total cost: 100+100\*100/10 = 1100

sid = sid

Block nested loop join

Scan

Supply

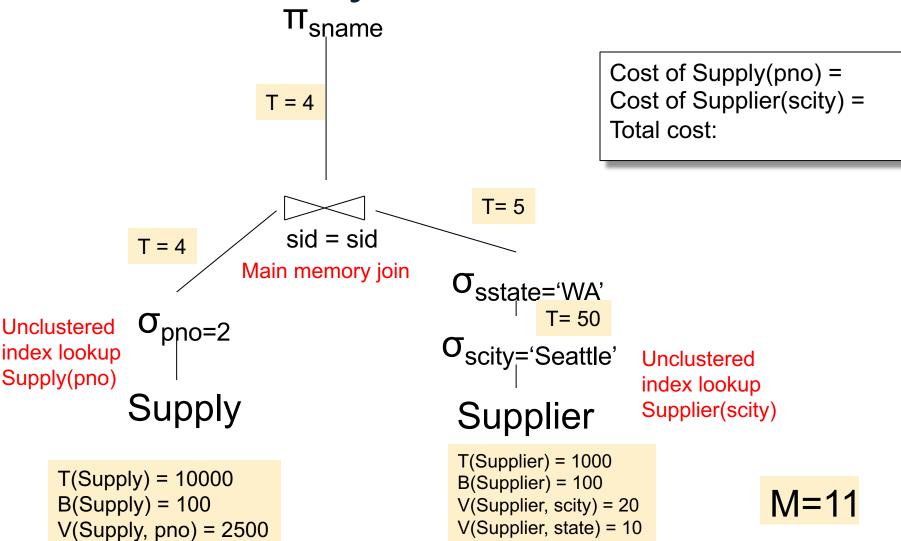
Scan

Supplier

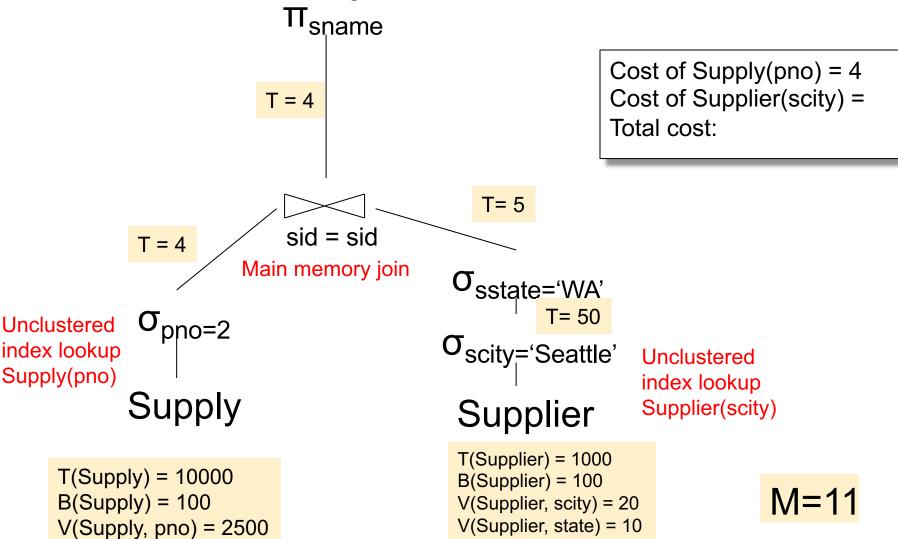
T(Supply) = 10000 B(Supply) = 100 V(Supply, pno) = 2500 T(Supplier) = 1000 B(Supplier) = 100 V(Supplier, scity) = 20 V(Supplier, state) = 10

M=11

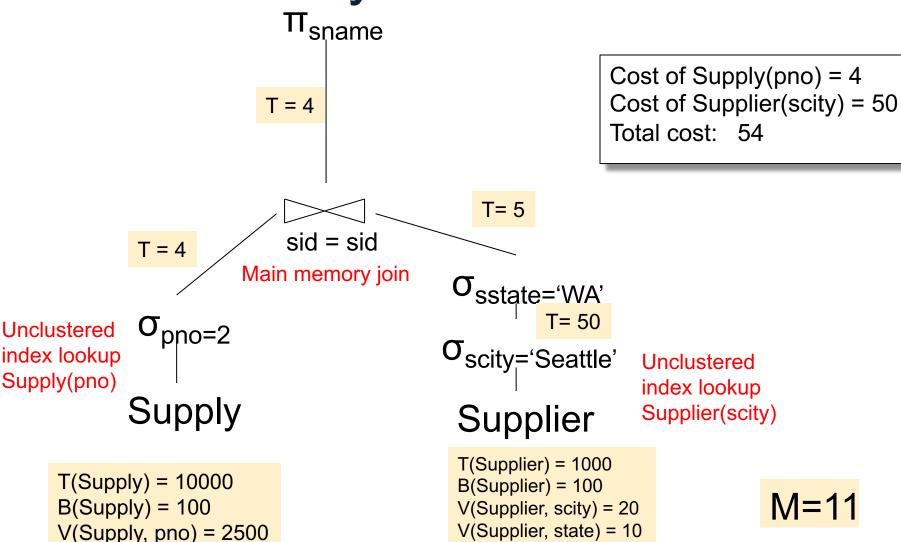
# Physical Plan 2



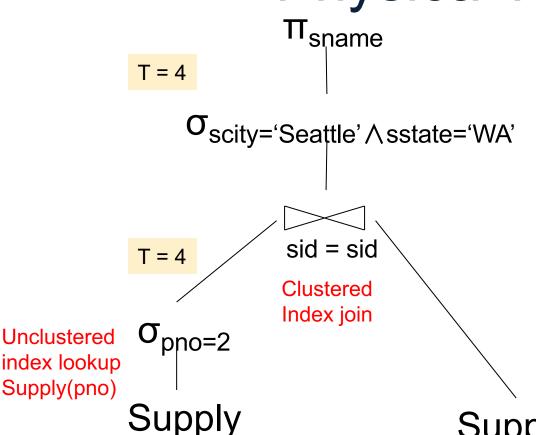
# Physical Plan 2



# Physical Plan 2



# Physical Plan 3



Cost of Supply(pno) = Cost of Index join = Total cost:

T(Supply) = 10000B(Supply) = 100V(Supply, pno) = 2500

Unclustered

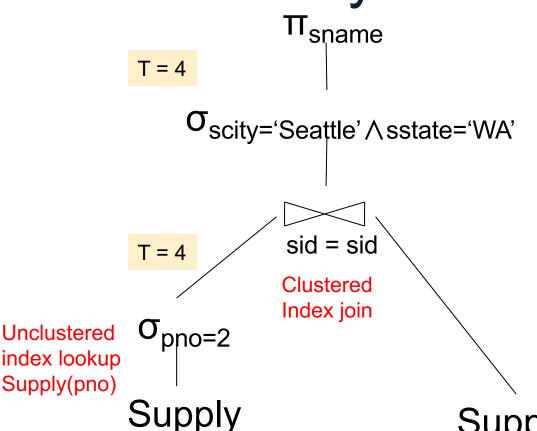
Supply(pno)

Supplier

T(Supplier) = 1000B(Supplier) = 100V(Supplier, scity) = 20 V(Supplier, state) = 10

M = 11

# Physical Plan 3



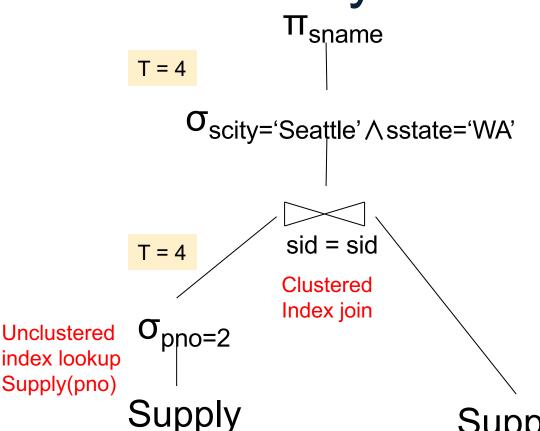
Cost of Supply(pno) = 4 Cost of Index join = Total cost:

T(Supply) = 10000 B(Supply) = 100 V(Supply, pno) = 2500 Supplier

T(Supplier) = 1000 B(Supplier) = 100 V(Supplier, scity) = 20 V(Supplier, state) = 10

M=11

# Physical Plan 3



Cost of Supply(pno) = 4Cost of Index join = 4 Total cost: 8

T(Supply) = 10000B(Supply) = 100V(Supply, pno) = 2500

Unclustered

Supply(pno)

Supplier

T(Supplier) = 1000B(Supplier) = 100V(Supplier, scity) = 20 V(Supplier, state) = 10

M = 11

• Relax uniformity assumption:  $T(\sigma_{A=v}(R)) = T(R) / V(R,A)$ 

- Histogram:
  - Partition R into buckets by the values of A
  - For each bucket, store T(bucket) and other stats
- RDBMS maintain histograms on some attributes of some tables; recomputed periodically using sampling

### Employee(ssn, name, age)

```
T(Employee) = 25000, V(Empolyee, age) = 50
min(age) = 19, max(age) = 68
```

$$\sigma_{\text{age}=48}(\text{Empolyee}) = ? \quad \sigma_{\text{age}>28 \text{ and age}<35}(\text{Empolyee}) = ?$$

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$$\sigma_{\text{age}=48}(\text{Empolyee}) = ? \quad \sigma_{\text{age}>28 \text{ and age}<35}(\text{Empolyee}) = ?$$





Estimate = 
$$25000 / 50 = 500$$

Estimate = 25000 \* 6 / 50 = 3000

### Employee(ssn, name, age)

T(Employee) = 25000, V(Empolyee, age) = 50min(age) = 19, max(age) = 68

$$\sigma_{\text{age}=48}(\text{Empolyee}) = ? \quad \sigma_{\text{age}>28 \text{ and age}<35}(\text{Empolyee}) = ?$$

Age:	0-20	20-29	30-39	40-49	50-59	> 60
Tuples	200	800	5000	12000	6500	500

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Age:	020	2029	30-39	40-49	50-59	> 60
Tuples	200	800	5000	12000	6500	500

Estimate = 1200

Estimate = 1\*80 + 5\*500 = 2580

### Types of Histograms

• How should we determine the bucket boundaries in a histogram?

### Types of Histograms

• How should we determine the bucket boundaries in a histogram?

- Eq-Width
- Eq-Depth
- Compressed
- V-Optimal histograms

### Employee(ssn, name, age)

#### **Eq-width:**

Age:	020	2029	30-39	40-49	50-59	> 60
Tuples	200	800	5000	12000	6500	500

#### **Eq-depth:**

Age:	0-33	33-38	38-43	43-45	45-54	> 54
Tuples	1800	2000	2100	2200	1900	1800

Compressed: store separately highly frequent values: (48,1900)

### V-Optimal Histograms

- Defines bucket boundaries in an optimal way, to minimize the error over all point queries
- Computed rather expensively, using dynamic programming
- Modern databases systems use V-optimal histograms or some variations

- Small number of buckets
  - · Hundreds, or thousands, but not more
  - MHAs

- Not updated during database update, but recomputed periodically
  - MHAs

- Multidimensional histograms rarely used
  - MHAs

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  - WHY? All histograms are kept in main memory during query optimization; plus need fast access
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- Multidimensional histograms rarely used
  - WHY? Too many possible multidimensional histograms, unclear which ones to choose