Cost-Based Optimization

Database Systems: The Complete Book

Ch 2.3, 6.1-6.4,15, 16.4-16.5

Optimizing

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- Some equivalence rules are *always* good…
  - Which?

Optimizing

- Some equivalence rules are *always* good…
  - Which?

- Some equivalence rules are *sometimes* good
  - Which?
  - What do we do about it?

Cost Estimation

- Compare many different plans by…
  - … actually running the query
  - … estimating the plan's "cost"

Cost Estimation

THE AUTHOR OF THE WINDOWS FILE COPY DIALOG VISITS SOME FRIENDS.

Costs

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- Memory Cost (Working Set Size)

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- Compute Cost (“Big-O”)

Costs

- Memory Cost (Working Set Size)
- Compute Cost (“Big-O”)
- IO Cost (Pages read, Pages written)

The variable in all of these costs is the arity (size) of a relation.

How do you compute Arities?

- Heuristic Assumptions (Pick a “good enough” RF)
- Summary Statistics About The Data…
  - Upper/Lower Bounds or Value Domains
  - Distribution Summaries (Histograms)
  - Data Sampling

How do you compute Arities?

There is **no** perfect solution (yet)!

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We don’t need a perfect solution…
… we just need one that’s good enough

Summary Statistics

- Per-Attribute Bounds / Domain Statistics
  - Assume a Uniform Distribution.
- Per-Attribute Histograms
  - Use the histogram to model the data distribution
- Data Samples
  - Use the samples to measure the RF

Uniform Distribution

$$A = 1$$

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Chance of Hit = $^{1} / _{\text{\# of distinct values of A}}$

Uniform Distribution

$$A \in (1, 2, \ldots)$$

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Chance of Hit = $|(1,2,3,\ldots)|$ / # of distinct values of A

Uniform Distribution

$$A < 3$$

Uniform Distribution

$$A < 3$$

Chance of Hit = $^{3\text{-Low}(A)} / _{\text{High}(A)\ -\ \text{Low}(A)}$

Uniform Distribution

$$\bowtie_{R.A=S.B}$$

Uniform Distribution

$$\bowtie_{R.A=S.B}$$

Chance of Hit Per B = $^{1} / _{\#\text{ Distinct Values of A}}$

Chance of Hit Per B = 1 (If B is a FK Reference)

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Let's apply it

```
SELECT   O.Rank, COUNT(*),
FROM     Officers O
WHERE    O.Rank >= 2
  AND    O.Age > 20 AND O.Age < 30
GROUP BY O.Rank
HAVING   COUNT(DISTINCT O.Ship) > 2
```

What is the relational algebra plan for this expression?

Stats

O.Rank: 0-5 (Increments of 0.5; 11 total values)

O.Age: 16-100 (Increments of 1; 85 total values)

Officers: 40,000 tuples (over 500 pages)

Tree Indexes available over O.Age, O.Rank

What is the total cost in IOs?

What is the total cost in CPU/Tuples?

Histograms

Uniform Distributions are a strong assumption!

(data is often skewed)

Histograms

People

Name	Age	Rank
<"Alice",	21,	1 >
<"Bob",	20,	2 >
<"Carol",	21,	1 >
<"Dave",	19,	3 >
<"Eve",	20,	2 >
<"Fred",	20,	3 >
<"Gwen",	22,	1 >
<"Harry",	20,	3 >

```
SELECT Name
FROM People
WHERE Rank = 3
  AND Age = 20
```

VS

```
...
  AND Age = 19
```

$RF_{Age} = {}^{1}/_{nkeys} = {}^{1}/_{4}$

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Age is best!

Histograms

People

```
 Name          Age Rank
<“Alice”,  21, 1  >
<“Bob”,    20, 2  >
<“Carol”,  21, 1  >
<“Dave”,   19, 3  >
<“Eve”,    20, 2  >
<“Fred”,   20, 3  >
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```

```
SELECT Name
FROM People
WHERE Rank = 3
  AND Age = 20
```

vs

```
…
  AND Age = 19
```

$RF_{Age\text{-}20} = {}^{1}/_{2}$

$RF_{Rank} = {}^{1}/_{3}$

Age is worst!

Histograms

People

```
 Name         Age Rank
<“Alice”,   21, 1  >
<“Bob”,     20, 2  >
<“Carol”,   21, 1  >
<“Dave”,    19, 3  >
<“Eve”,     20, 2  >
<“Fred”,    20, 3  >
<“Gwen”,    22, 1  >
<“Harry”,   20, 3  >
```

```
SELECT Name
FROM People
WHERE Rank = 3
  AND Age = 20
```

vs

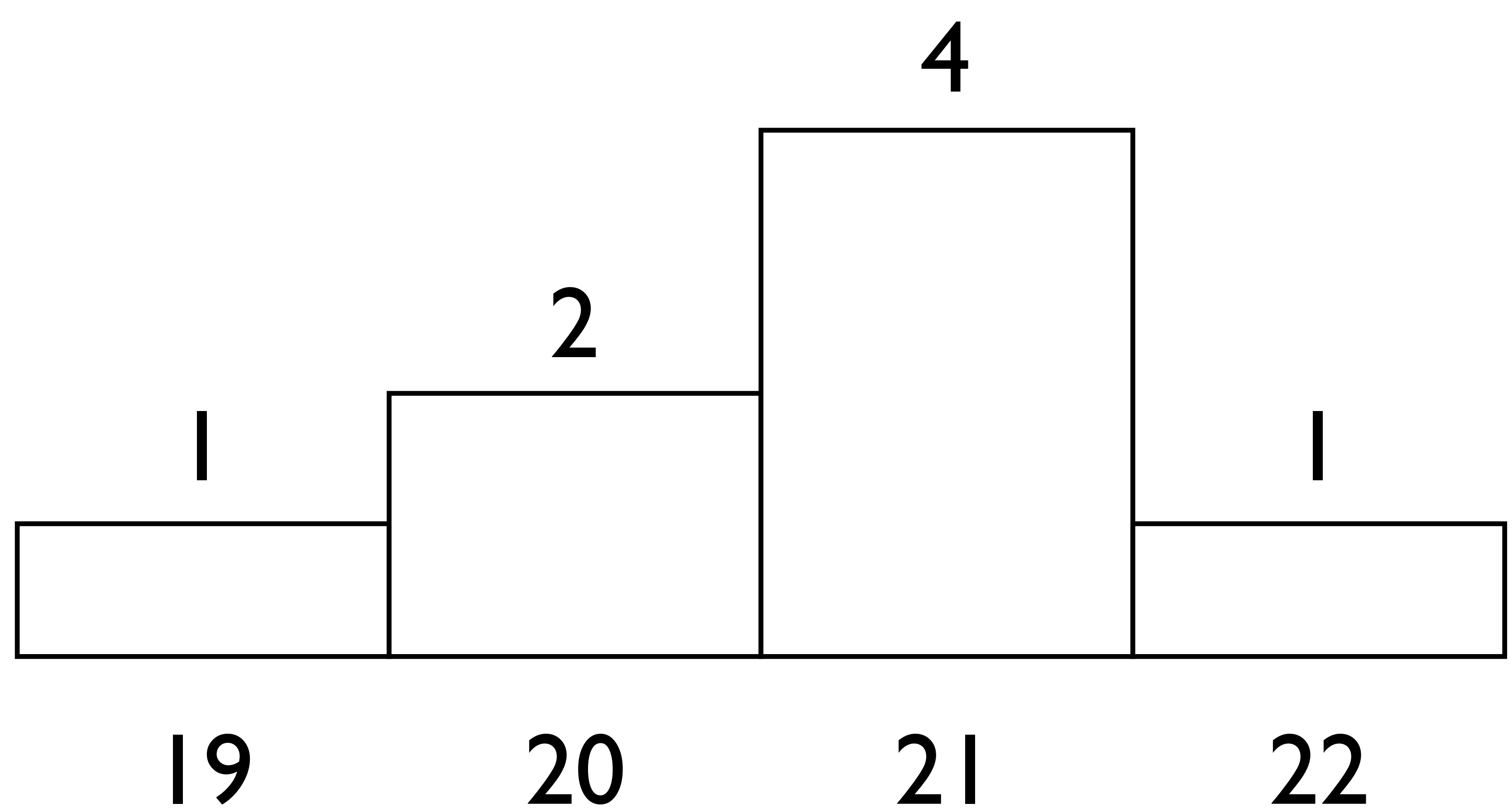
```
…
  AND Age = 19
```

$RF_{Age\text{-}19} = {}^{1}/_{8}$

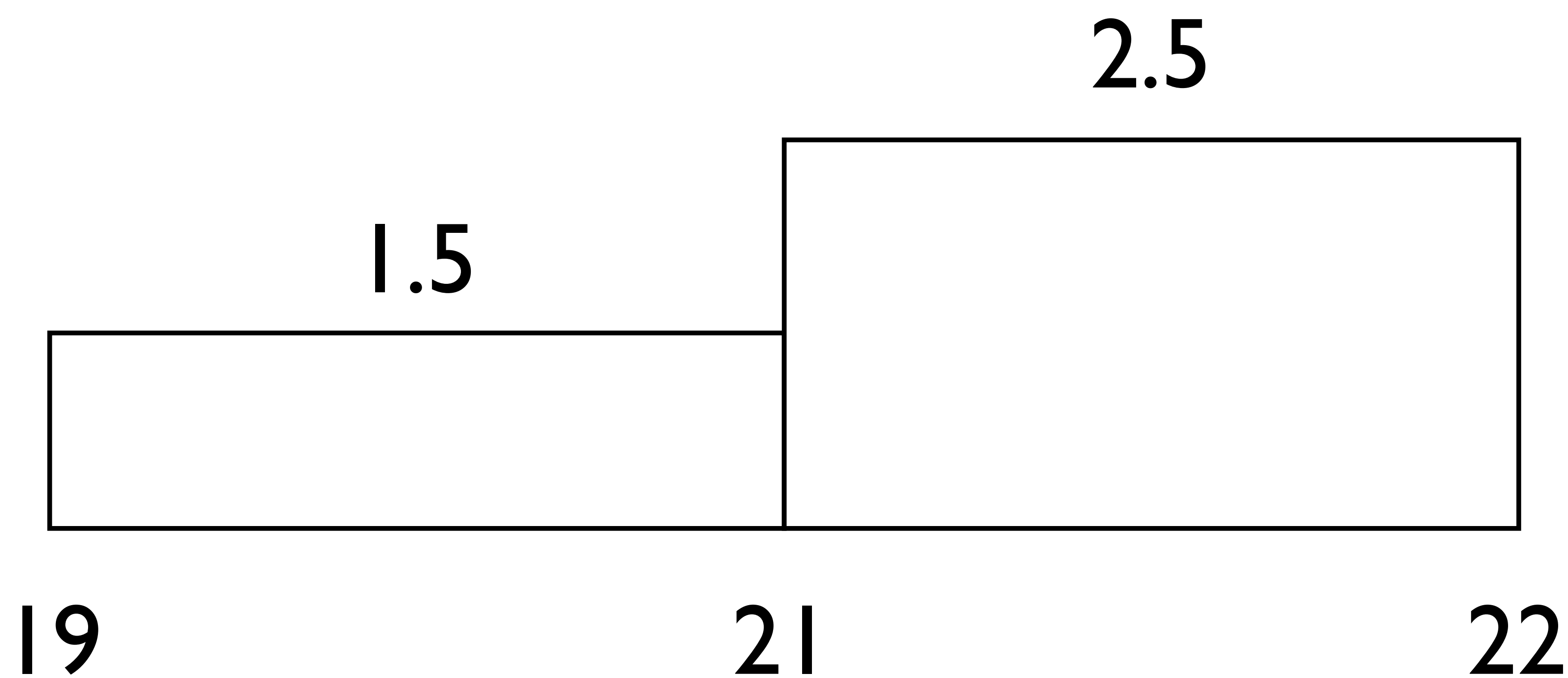
$RF_{Rank} = {}^{1}/_{3}$

Age is best!

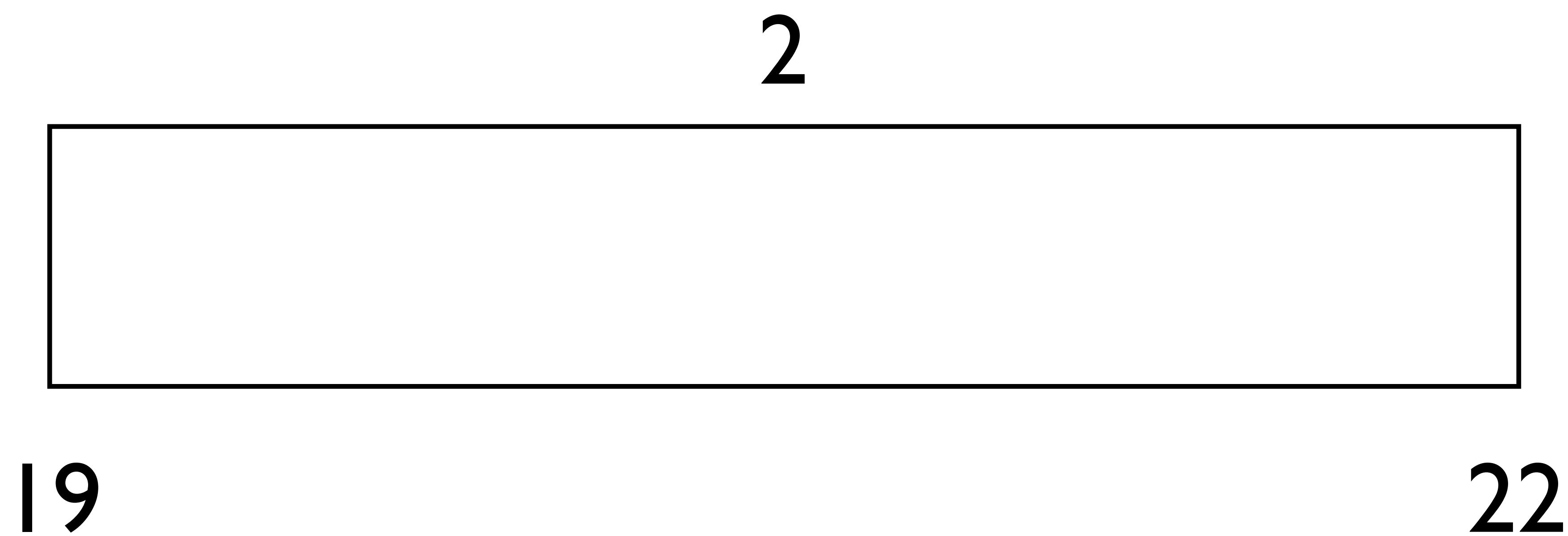
Histograms



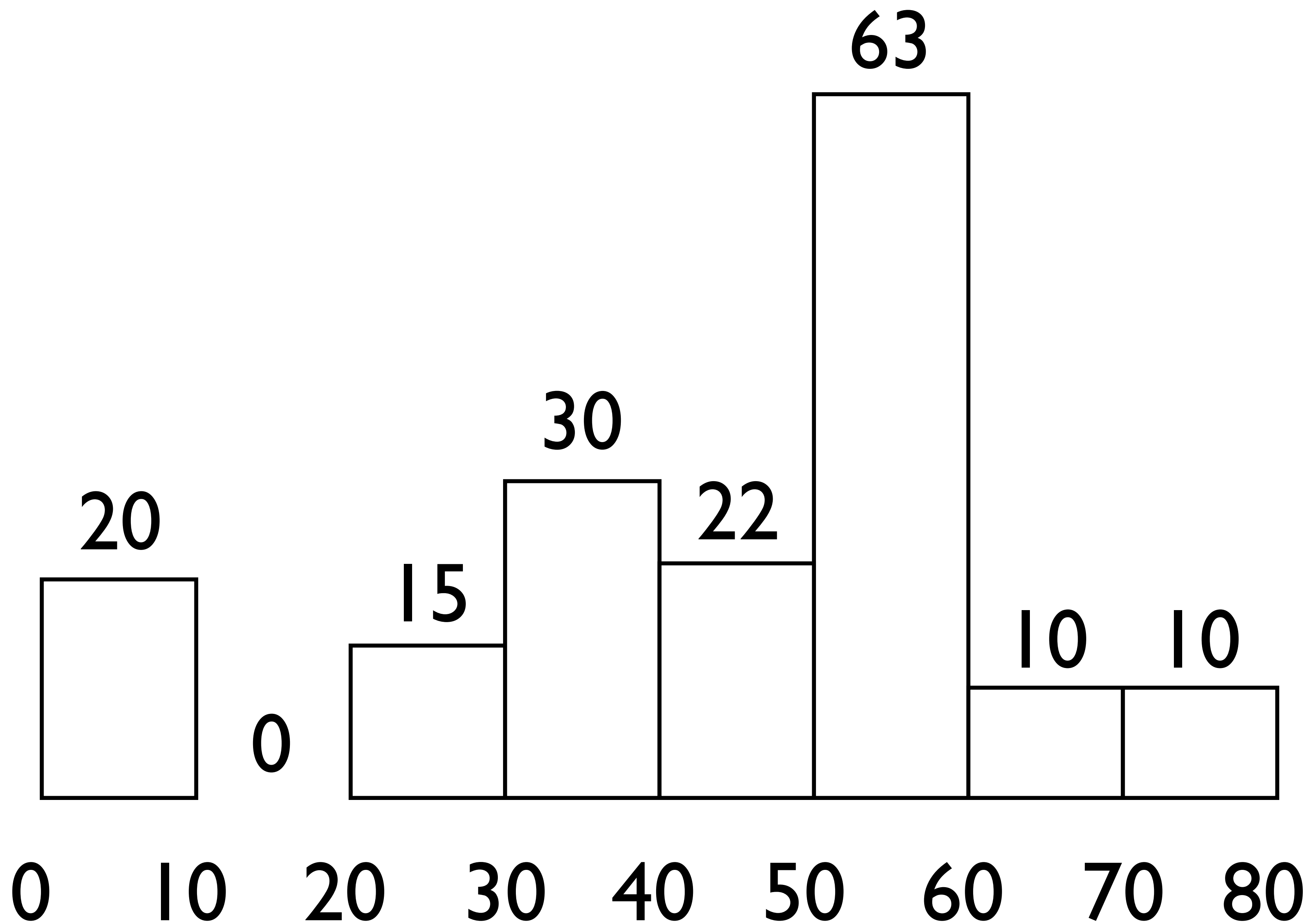
Histograms



Histograms

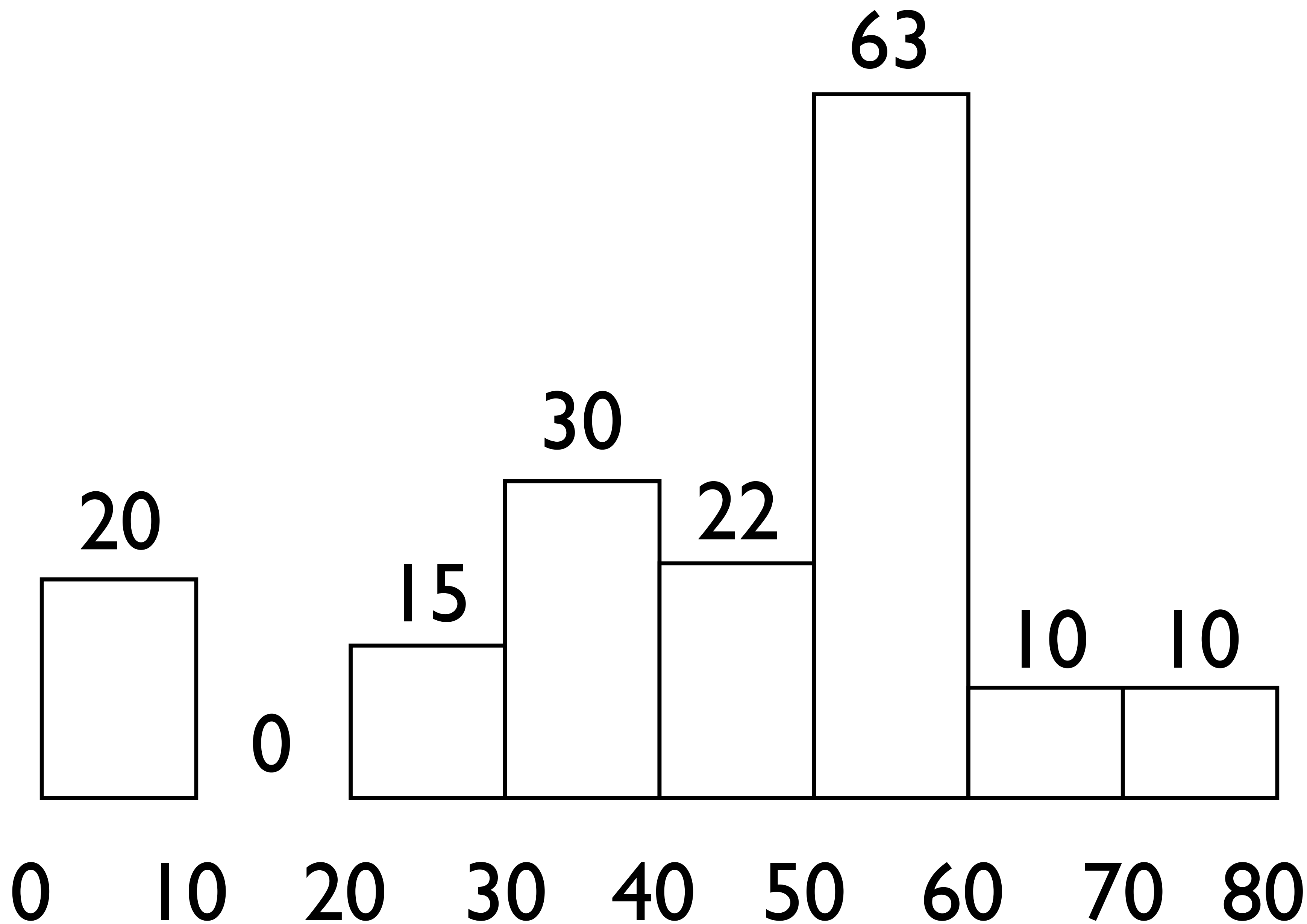


Histograms



`SELECT … WHERE A = 33`

Histograms




```
SELECT … WHERE A > 33
```

Using Constraints

- A Key attribute has one distinct value per row (equality selects exactly one row)
- Foreign Key joins generate one row for each row in the **referencing** relation.
- Cascade relationship guarantees EXACTLY one row per reference.

Sampling

- Take a bunch of tuples from each relation.
- Run 2-3 different query plans on these tuples.
  - Estimate the sampling factors for each operator in the plan based on how many survive.

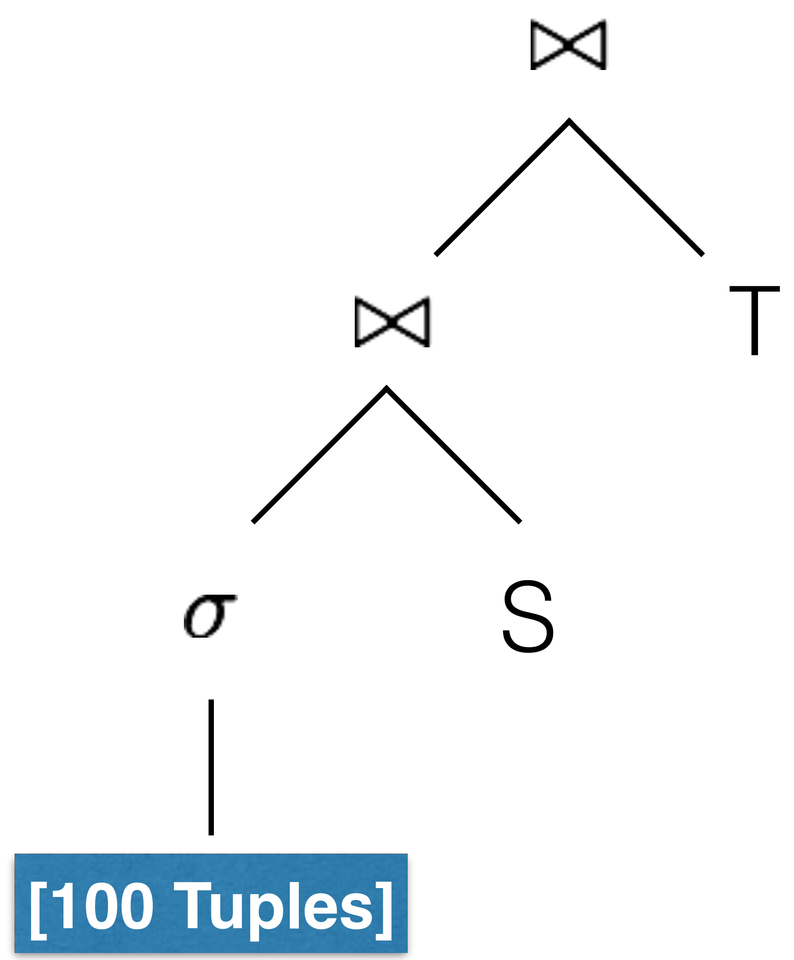
Sampling

How big is a “bunch?”

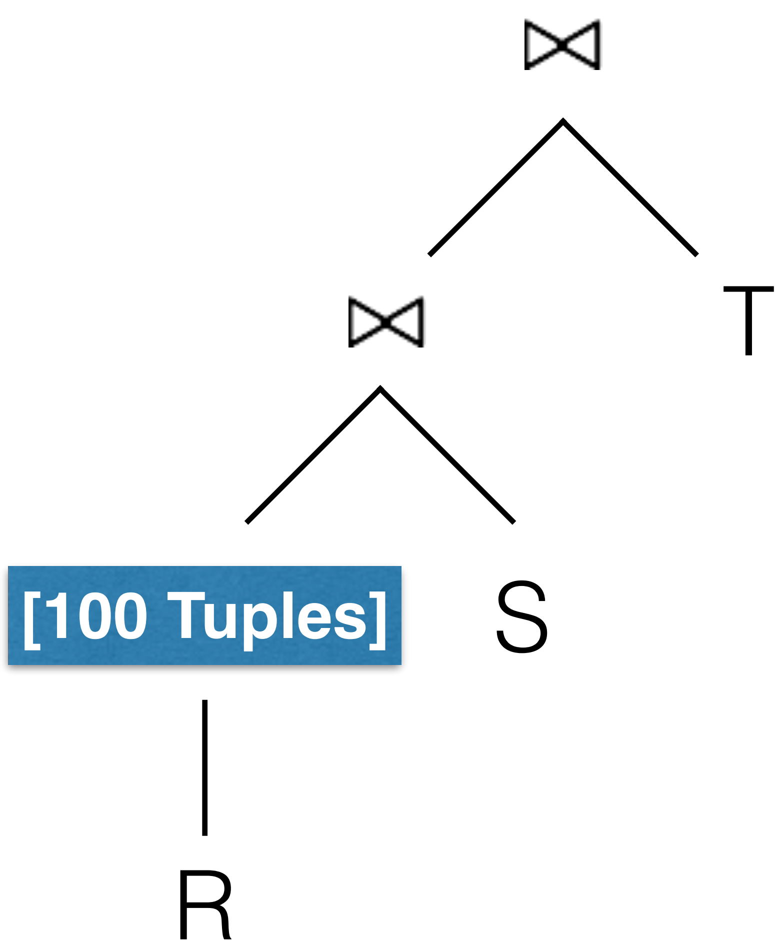
Sampling

- **Problem**: Very Selective Predicates
- **Problem**: Joins and the Birthday Paradox
- **Problem**: Counting Aggregate Groups

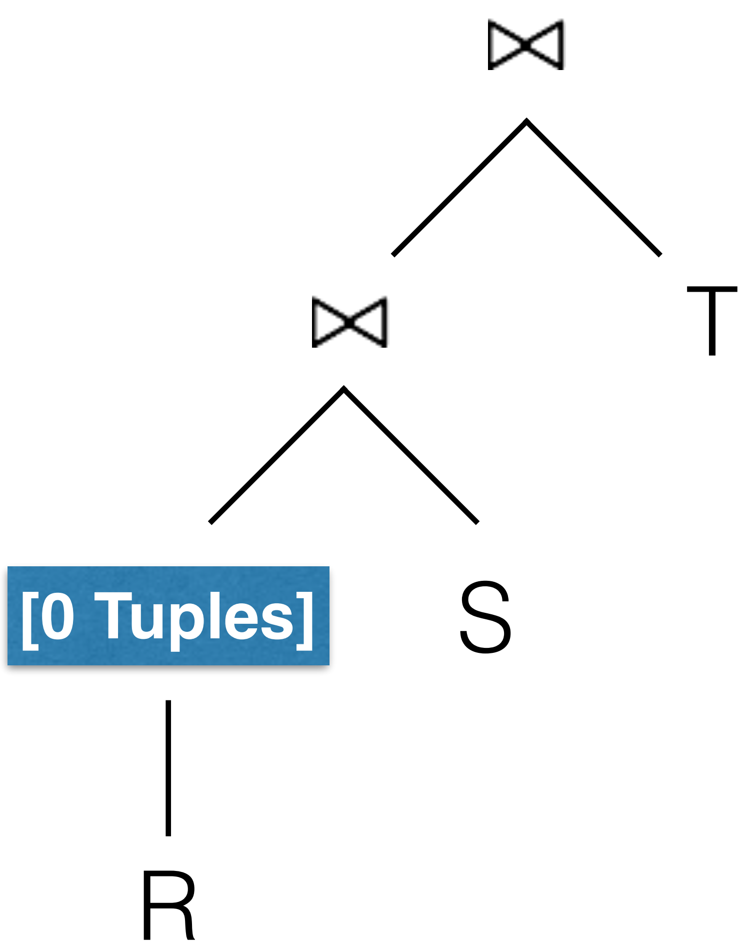
Very Selective Predicates



Very Selective Predicates



Very Selective Predicates



Join Conditions

Image: Wikipedia

Join Conditions

<u>Birthday Paradox</u>

Need $O(\sqrt{|R|+|S|})$ tuples to reliably guess RF for equijoin

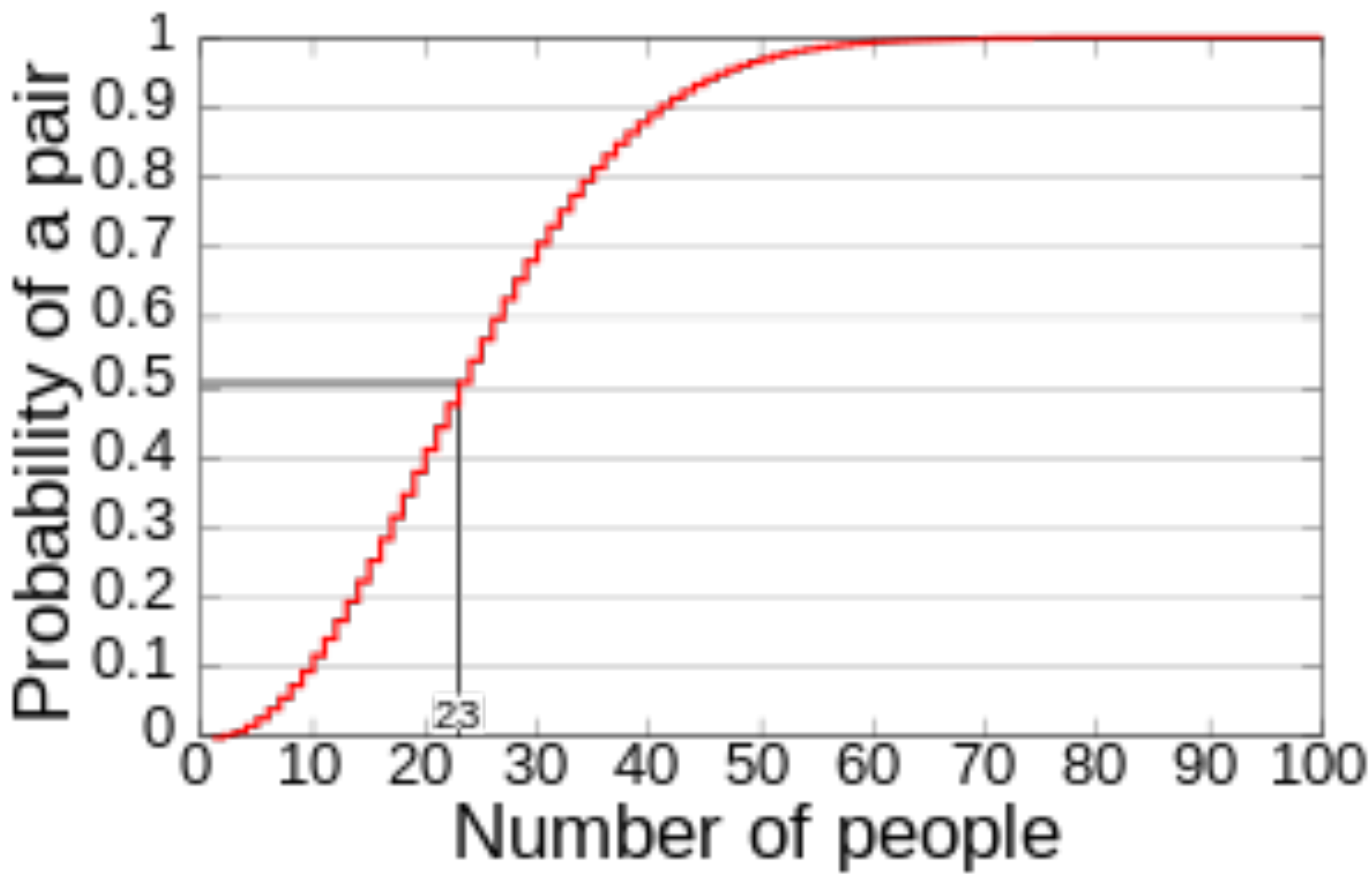


Image: Wikipedia

Estimating Join Costs

How many query plans are there?

$$R \bowtie S \bowtie T \bowtie U$$

Estimating Join Costs

There are (N-1)! (factorial) different ways (plans) to evaluate this join.

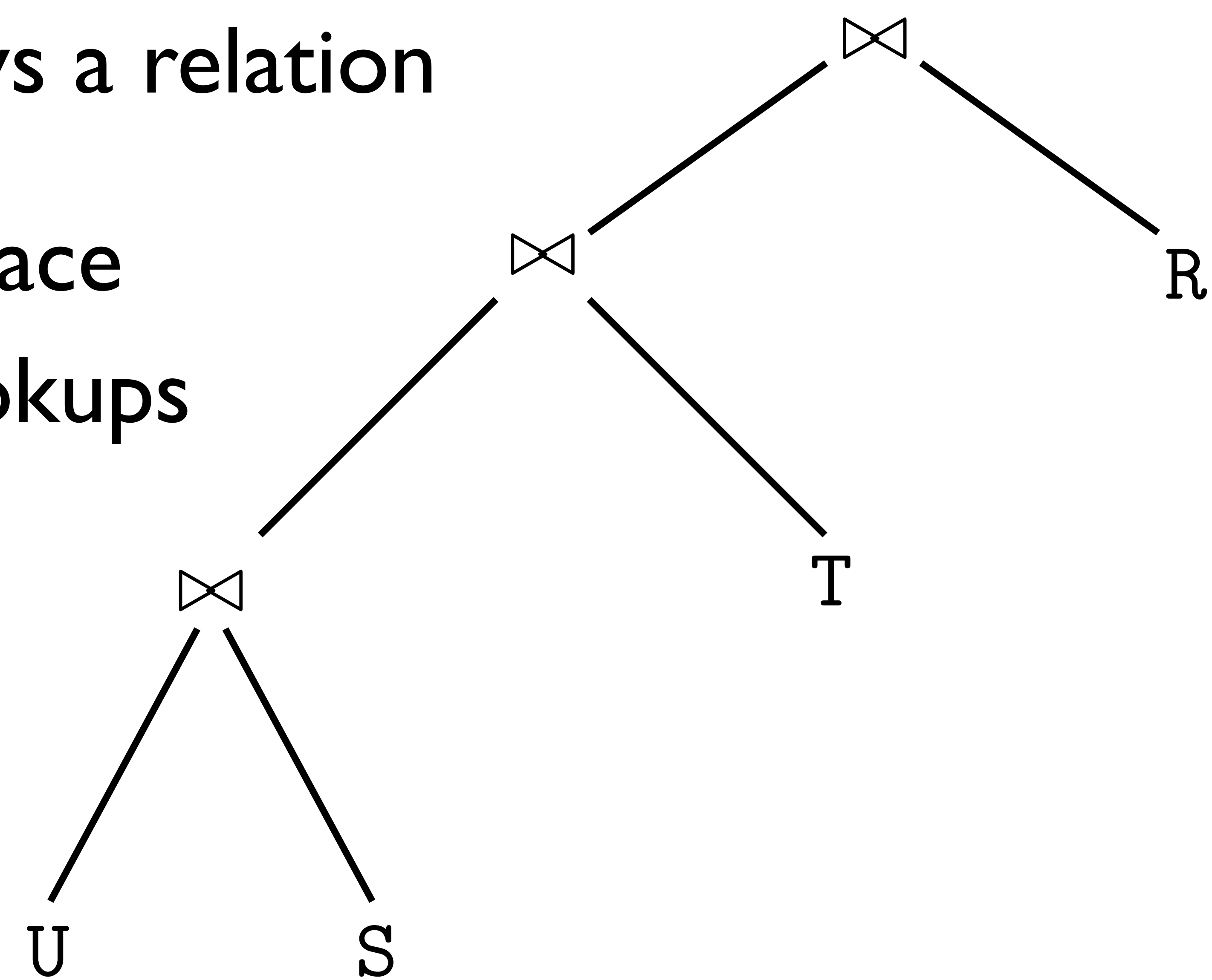
Computing costs for all of these plans is expensive!

Left-Deep Plans

RHS Join Input is always a relation

1) Shrinks join search space
2) Allows index scans/lookups

Technique Pioneered by
the System R Optimizer



In Practice

Heuristics, Histograms and Sampling are "good enough" to optimize the common cases.

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Some relational databases have manual overrides.

Oracle

```
SELECT /*+ INDEX (employees emp_department_ix)*/
       employee_id, department_id
  FROM employees
  WHERE department_id > 50;
```

Postgres

```
SELECT attname, inherited, n_distinct,
       array_to_string(most_common_vals, E'\n') as most_common_vals
FROM pg_stats
WHERE tablename = 'road';
```

```
 attname | inherited | n_distinct |          most_common_vals
---------+-----------+------------+------------------------------------
 name    | f         |  -0.363388 | I- 580                        Ramp+
         |           |            | I- 880                        Ramp+
         |           |            | Sp Railroad                       +
         |           |            | I- 580                            +
         |           |            | I- 680                        Ramp
 name    | t         |  -0.284859 | I- 880                        Ramp+
         |           |            | I- 580                        Ramp+
         |           |            | I- 680                        Ramp+
         |           |            | I- 580                            +
         |           |            | State Hwy 13                  Ramp
```

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All relational databases have an "EXPLAIN" operator

Postgres

```
EXPLAIN SELECT sum(i) FROM foo WHERE i < 10;

                          QUERY PLAN
----------------------------------------------------------------------
 Aggregate  (cost=23.93..23.93 rows=1 width=4)
   ->  Index Scan using fi on foo  (cost=0.00..23.92 rows=6 width=4)
         Index Cond: (i < 10)
```

Backup Slides

Join Algorithm Comparison

	Can Support Pipelining?	But?
Hybrid Hash	**Yes**	RHS Hash Table needs to fit in memory
Index Nested Loop	**Yes**	RHS Table needs an index on the join key
Sort/Merge Join	**Yes**	LHS and RHS must both be sorted on the join key
(Block) Nested Loop	**Yes**	RHS Table needs to fit in memory
Hash Join	No	No buts. Hash Join always materializes

Join Algorithm IO Costs

$R \bowtie S$	IO Cost
Hybrid Hash	[#pages of S] (if fits in mem)
Index Nested Loop	|R| * [cost of one scan/lookup on S]
Sort/Merge Join	[#pages of S] (+sorting costs)
Nested Loop	[#pages of S] (if fits in mem)
Block Nested Loop	[#pages of R] + [#of block pairs] * ([#pages per block of R]+[#pages per block of S])
Hash Join	2*([#pages of R]+[#pages of S]) + [#pages of S]

Data Access IO Costs

	Full Scan	Range Scan	Lookup
Raw File	N	N	N
Sorted File	N	$\log_2(N)+\|R\|$	$\log_2(N)$
Static Hash Index	>N	>N	~1
Extendible Hash Index	>N+|D| (random)	>N+|D| (random)	2
Linear Hash Index	>N	>N	~1
ISAM Tree Index	~N	$\sim\log_{\|T\|}(N)+\|R\|$	$\sim\log_{\|T\|}(N)$
B+ Tree Index	N (random)	$\log_{\|T\|}(N)+\|R\|$ (random)	$\log_{\|T\|}(N)$