Carnegie Mellon University

14 Query Planning – Part II

Intro to Database Systems
15-445/15-645
Fall 2021

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Carnegie Mellon University

ADMINISTRIVIA

Project #2 is due tomorrow, Thu Oct 21st @ 11:59pm

→ Check your score again on Gradescope with formatting!

Project #3 will be released today.
It is due Sun Nov 14th @ 11:59pm.

Homework #4 will be released next week.
It is due Sun Nov 7th @ 11:59pm.

UPCOMING DATABASE TALK

An Overview of the Starburst Trino Query Optimizer

→ Monday Oct 25th @ 4:30pm ET

QUERY OPTIMIZATION

Heuristics / Rules

→ Rewrite the query to remove stupid / inefficient things.
→ These techniques may need to examine catalog, but they do <u>not</u> need to examine data.

Cost-based Search

→ Use a model to estimate the cost of executing a plan.
→ Evaluate multiple equivalent plans for a query and pick the one with the lowest cost.

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TODAY'S AGENDA

Moe Cost Estimation (Statistics)

Plan Enumeration

COST MODEL COMPONENTS

Choice #1: Physical Costs

→ Predict CPU cycles, I/O, cache misses, RAM consumption, pre-fetching, etc…
→ Depends heavily on hardware.

Choice #2: Logical Costs

→ Estimate result sizes per operator.
→ Independent of the operator algorithm.
→ Need estimations for operator result sizes.

Choice #3: Algorithmic Costs

→ Complexity of the operator algorithm implementation.

STATISTICS

The DBMS stores internal statistics about tables, attributes, and indexes in its internal catalog.

Different systems update them at different times.

Manual invocations:

→ Postgres/SQLite: **ANALYZE**

→ Oracle/MySQL: **ANALYZE TABLE**

→ SQL Server: **UPDATE STATISTICS**

→ DB2: **RUNSTATS**

STATISTICS

For each relation **R**, the DBMS maintains the following information:

- → N_R: Number of tuples in **R**.
- → `V(A,R)`: Number of distinct values for attribute **A**.

DERIVABLE STATISTICS

The **selection cardinality** `SC(A,R)` is the average number of records with a value for an attribute `A` given N_R / `V(A,R)`

DERIVABLE STATISTICS

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Note that this formula assumes ***data uniformity*** where every value has the same frequency as all other values.

→ Example: 10,000 students, 10 colleges – how many students in SCS?

LOGICAL COSTS

Equality predicates on unique keys are easy to estimate.

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```
SELECT * FROM people
 WHERE id = 123
```

```
CREATE TABLE people (
  id INT PRIMARY KEY,
  val INT NOT NULL,
  age INT NOT NULL,
  status VARCHAR(16)
);
```

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  val INT NOT NULL,
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```

Computing the logical cost of complex predicates is more difficult…

```
SELECT * FROM people
 WHERE val > 1000
```

```
SELECT * FROM people
 WHERE age = 30
   AND status = 'Lit'
   AND age+id IN (1,2,3)
```

COMPLEX PREDICATES

The **selectivity** (`sel`) of a predicate `P` is the fraction of tuples that qualify.

Formula depends on type of predicate:
- → Equality
- → Range
- → Negation
- → Conjunction
- → Disjunction

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SELECTIONS – COMPLEX PREDICATES

Assume that **V(age,people)** has five distinct values (0–4) and $N_R = 5$

Equality Predicate: **A=constant**

→ sel(A=constant) = SC(P) / N_R

```
SELECT * FROM people
 WHERE age = 2
```

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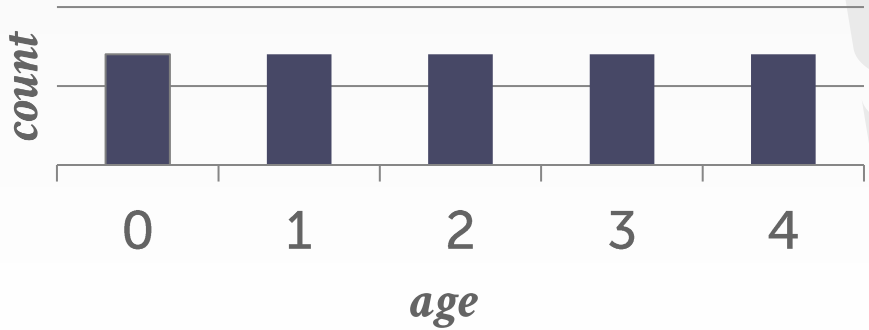

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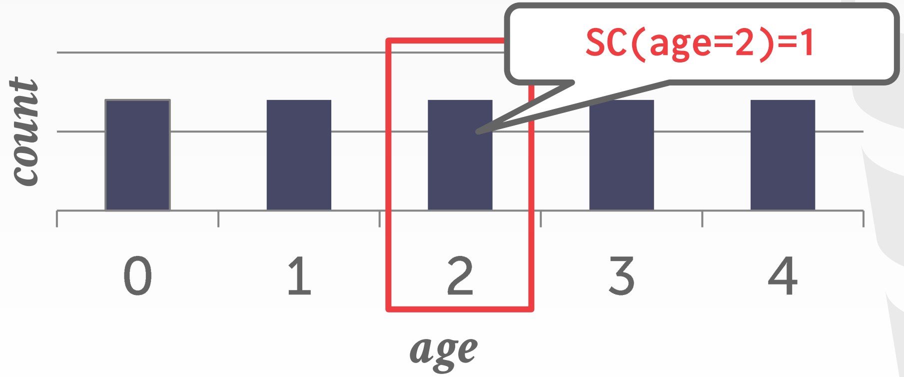

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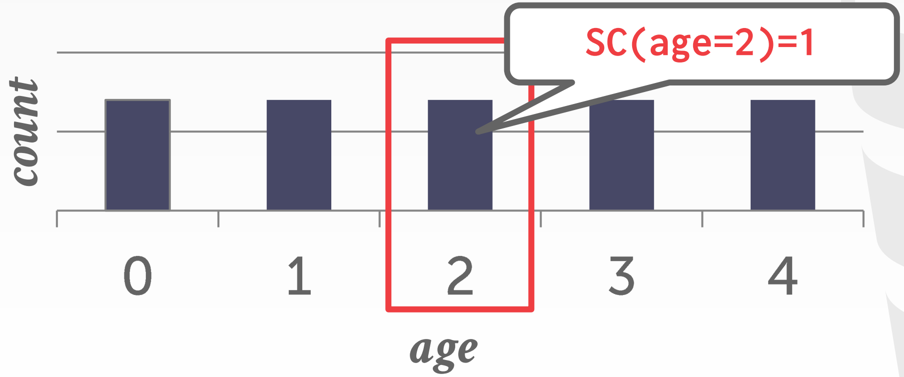

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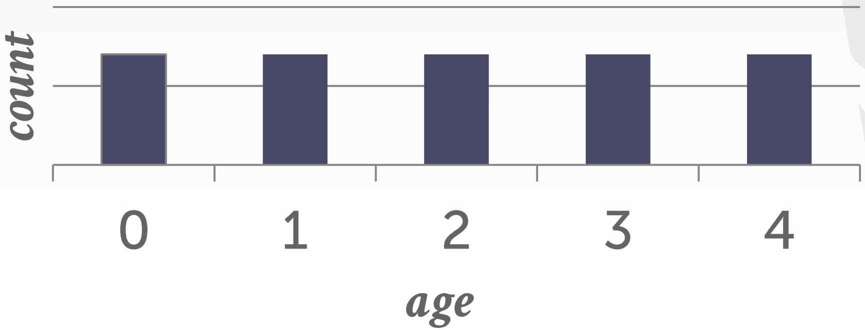
Range Predicate:

→ sel(A>=a) = $(A_{max} - a+1) / (A_{max} - A_{min}+1)$
→ Example: sel(age>=2)

```
SELECT * FROM people
 WHERE age >= 2
```



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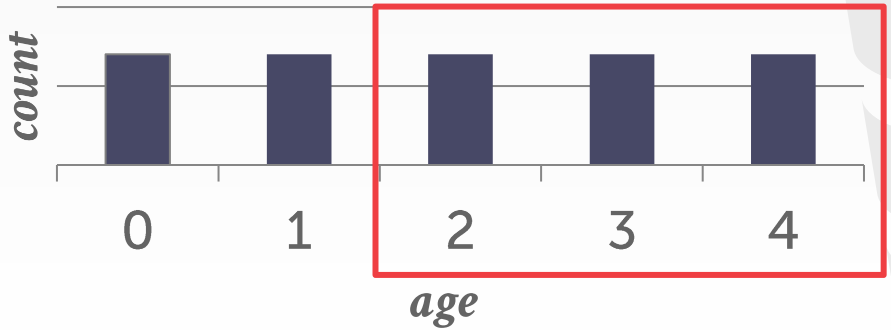

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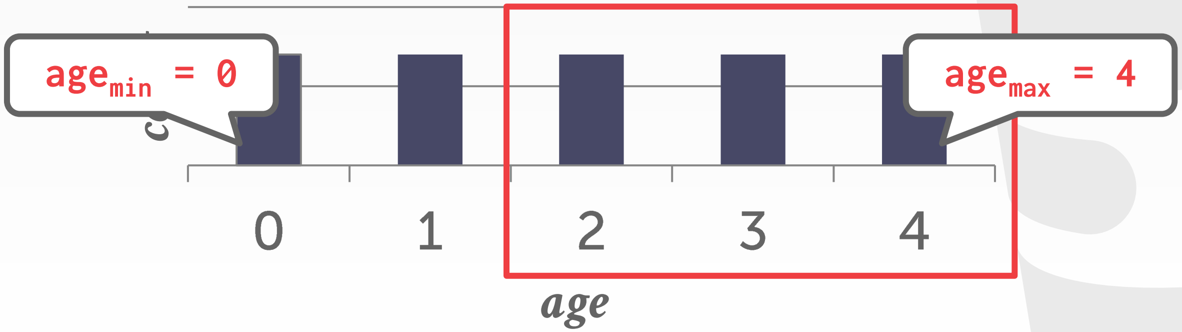

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Range Predicate:

→ `sel(A>=a) = (A`$_{max}$`- a+1) / (A`$_{max}$`- A`$_{min}$`+1)`

→ Example: `sel(age>=2) ≈ (4-2+1) / (4-0+1)`

`≈ 3/5`

```
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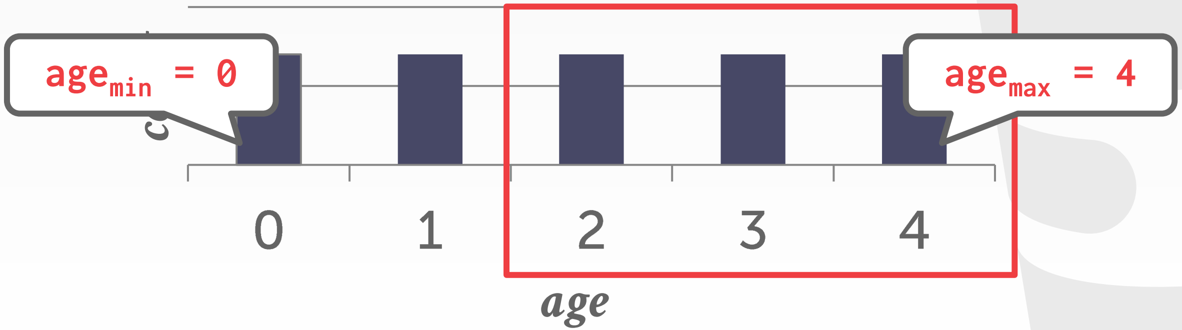

SELECTIONS – COMPLEX PREDICATES

Negation Query:

→ `sel(not P) = 1 - sel(P)`

→ Example: `sel(age != 2)`

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SELECT * FROM people
 WHERE age != 2
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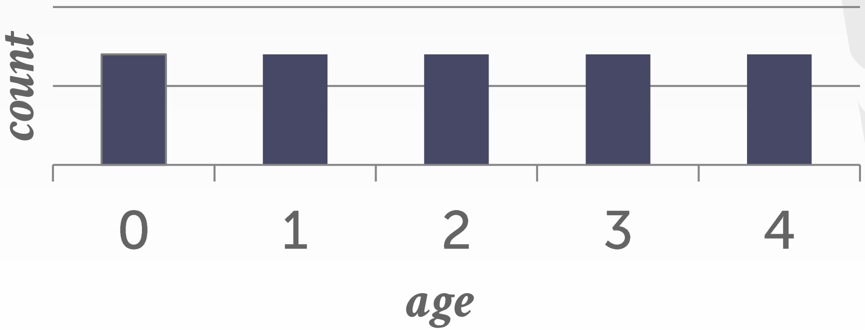

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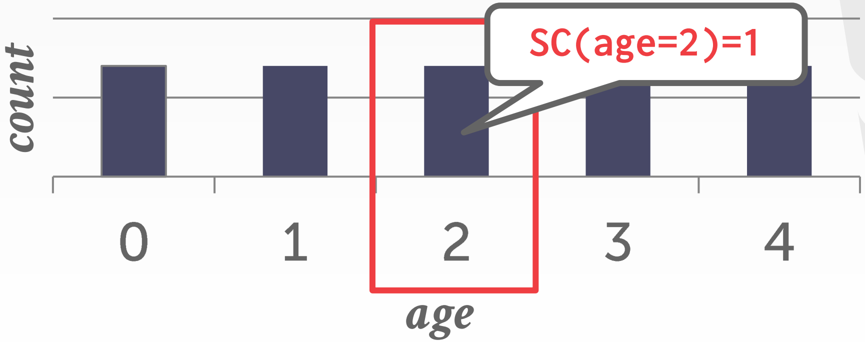

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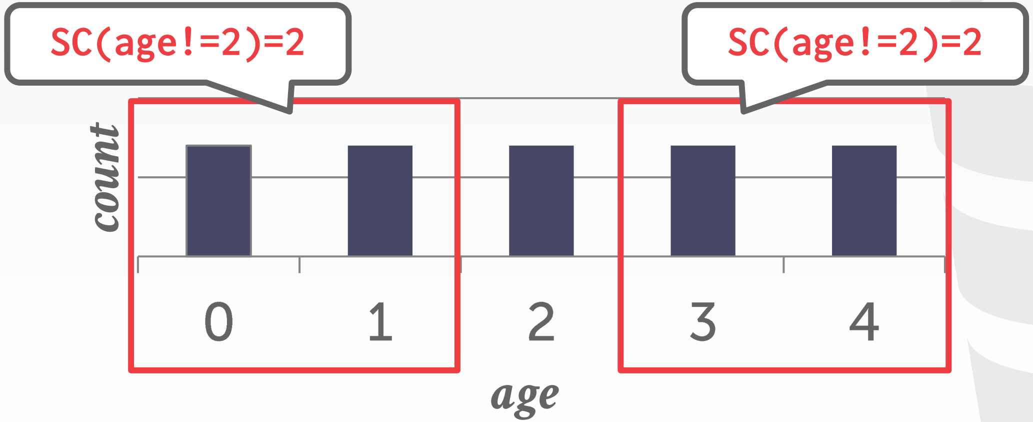

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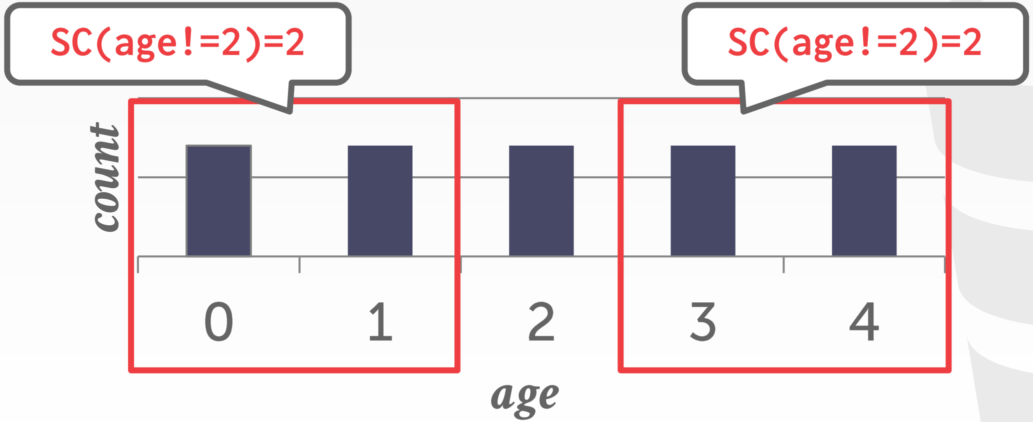

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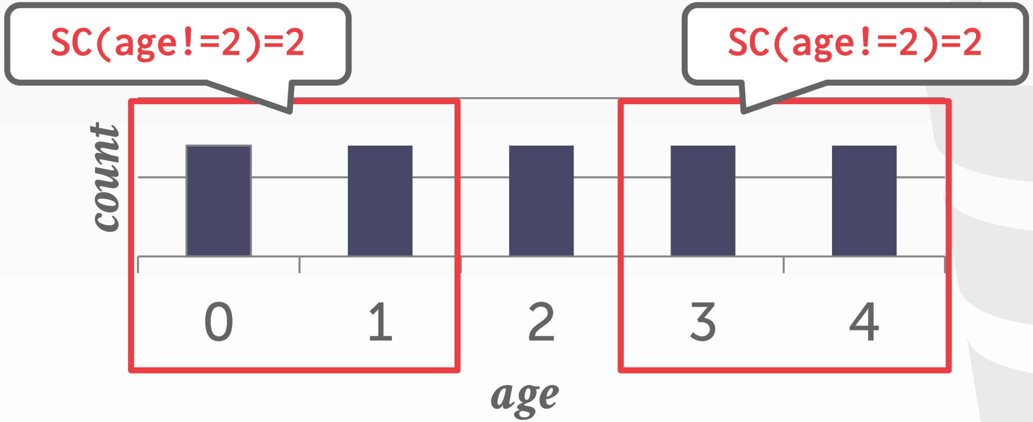
Observation: Selectivity ≈ Probability



SELECTIONS – COMPLEX PREDICATES

Conjunction:

→ sel(P1 ∧ P2) = sel(P1) • sel(P2)
→ sel(age=2 ∧ name LIKE 'A%')

This assumes that the predicates are **independent**.

```
SELECT * FROM people
 WHERE age = 2
   AND name LIKE 'A%'
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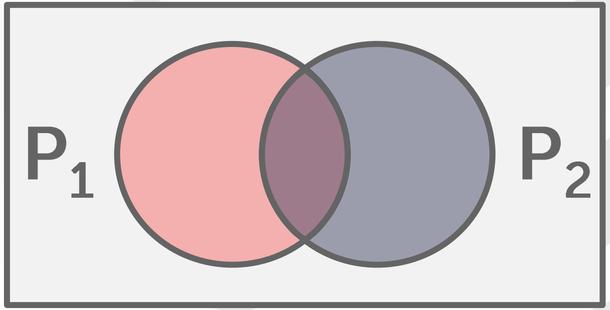

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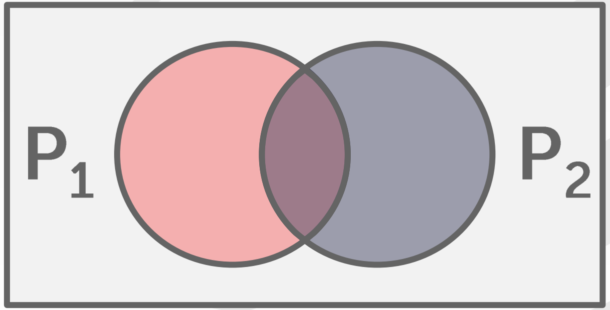

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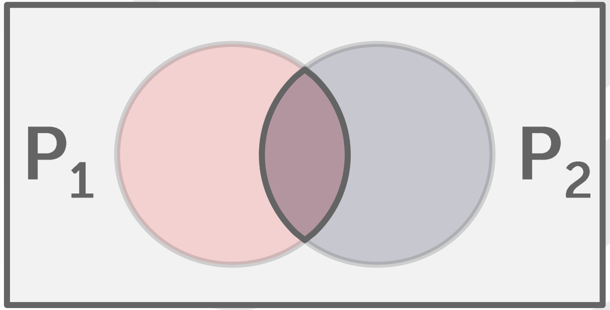

SELECTIONS – COMPLEX PREDICATES

Disjunction:

→ sel(P1 ⋁ P2)
 = sel(P1) + sel(P2) - sel(P1⋀P2)
 = sel(P1) + sel(P2) - sel(P1) • sel(P2)

→ sel(age=2 OR name LIKE 'A%')

```
SELECT * FROM people
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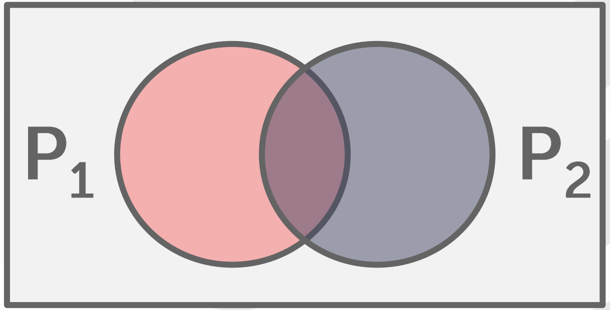

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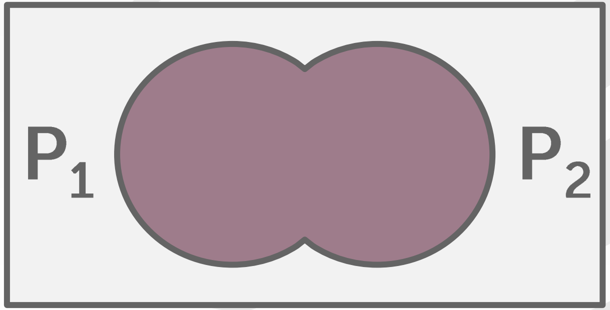

RESULT SIZE ESTIMATION FOR JOINS

Given a join of R and S, what is the range of possible result sizes in # of tuples?

In other words, for a given tuple of R, how many tuples of S will it match?

Assume each key in the inner relation will exist in the outer table

RESULT SIZE ESTIMATION FOR JOINS

General case: $R_{cols} \cap S_{cols} = \{A\}$ where **A** is not a primary key for either table.

→ Match each **R**-tuple with **S**-tuples:
$$estSize \approx N_R \cdot N_S \ / \ V(A,S)$$
→ Symmetrically, for **S**:
$$estSize \approx N_R \cdot N_S \ / \ V(A,R)$$

Overall:

→ $estSize \approx N_R \cdot N_S \ / \ max(\{V(A,S),\ V(A,R)\})$

SELECTION CARDINALITY

Assumption #1: Uniform Data

→ The distribution of values (except for the heavy hitters) is the same.

Assumption #2: Independent Predicates

→ The predicates on attributes are independent

Assumption #3: Inclusion Principle

→ The domain of join keys overlap such that each key in the inner relation will also exist in the outer table.

CORRELATED ATTRIBUTES

Consider a database of automobiles:

→ # of Makes = 10, # of Models = 100

And the following query:

→ `(make="Honda" AND model="Accord")`

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And the following query:

→ `(make="Honda" AND model="Accord")`

With the independence and uniformity assumptions, the selectivity is:

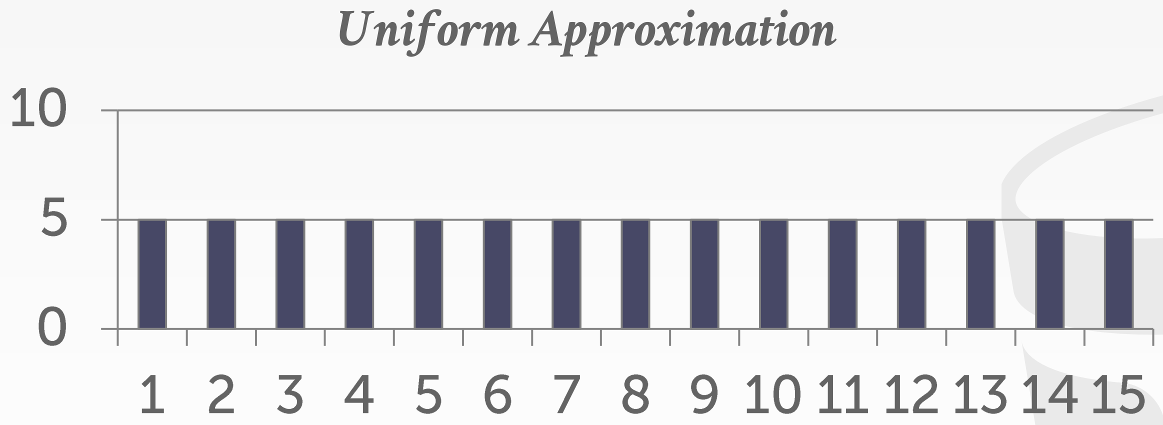
→ $1/10 \times 1/100 = 0.001$

But since only Honda makes Accords the real selectivity is $1/100 = 0.01$

Source: Guy Lohman

COST ESTIMATIONS

Our formulas are nice, but we assume that data values are uniformly distributed.



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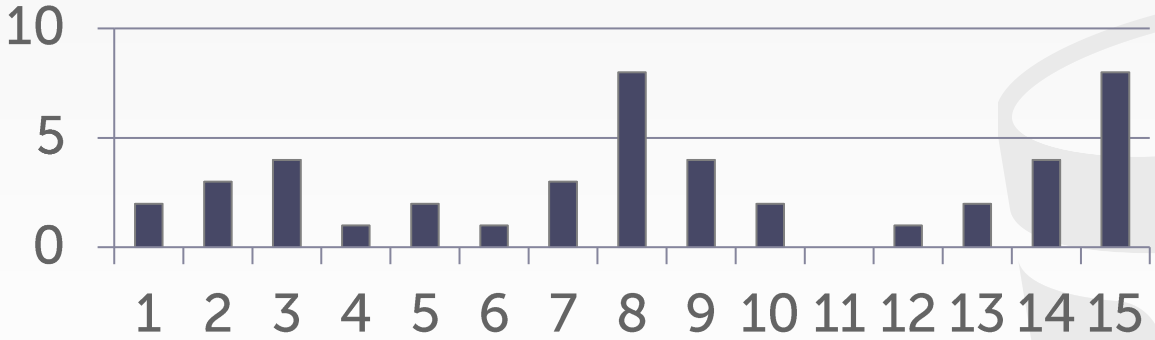

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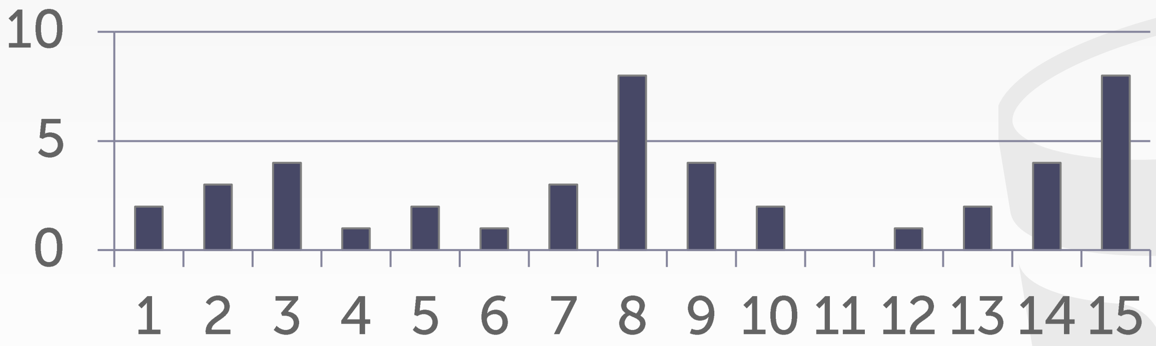
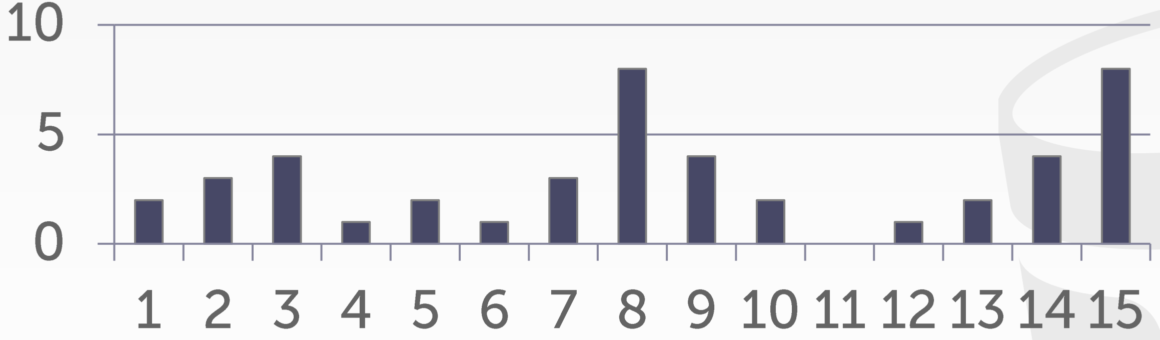


15 Keys × 32-bits = 60 bytes

EQUI-WIDTH HISTOGRAM

All buckets have the same width (i.e., the same number of values).

Non-Uniform Approximation



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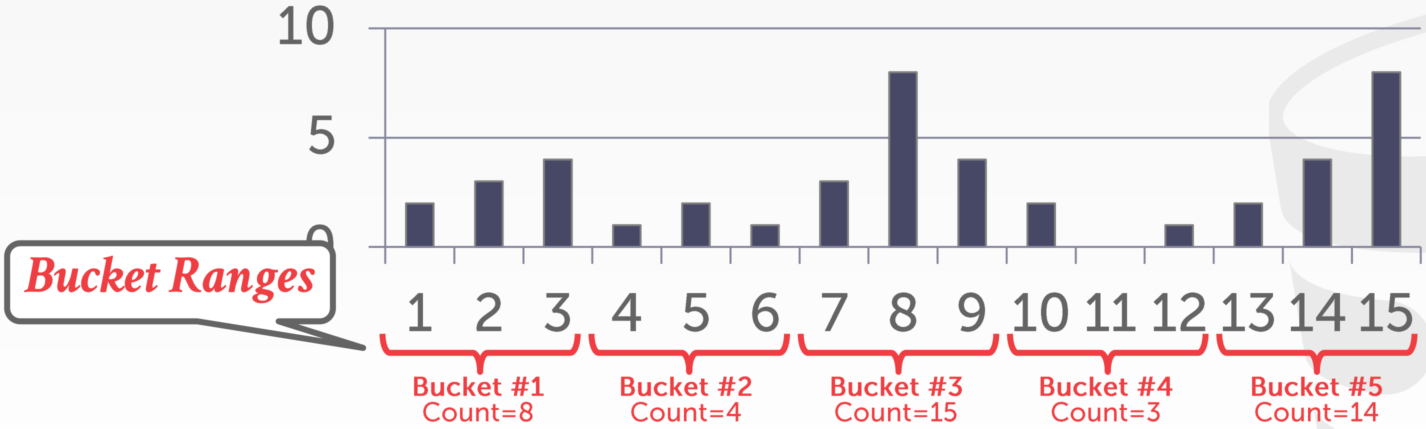

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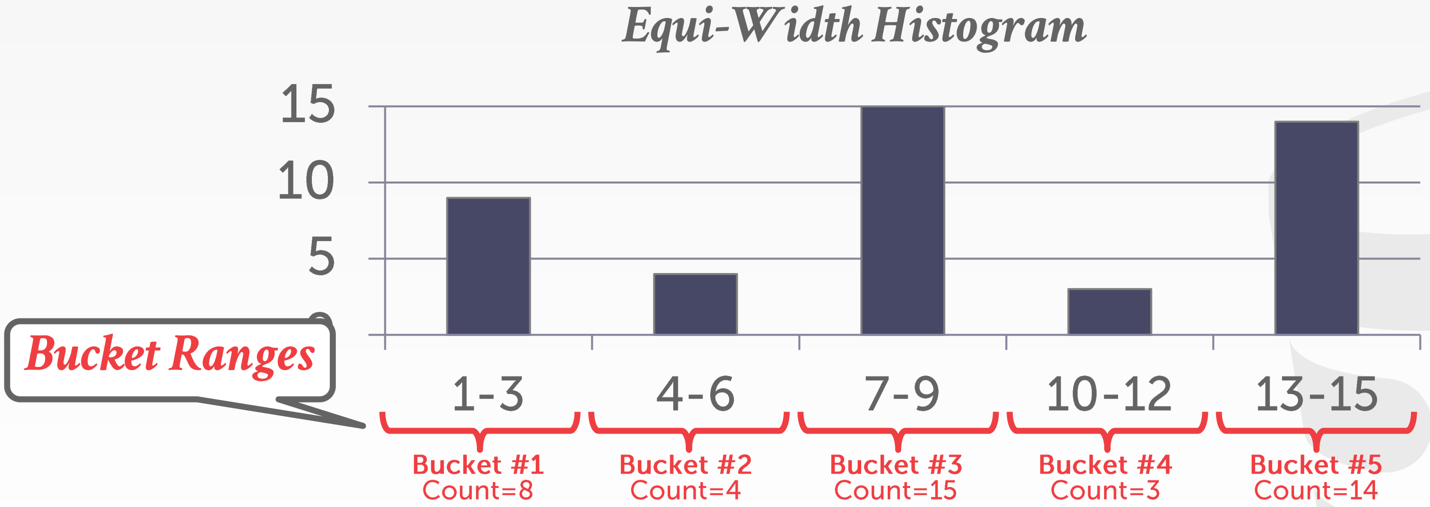
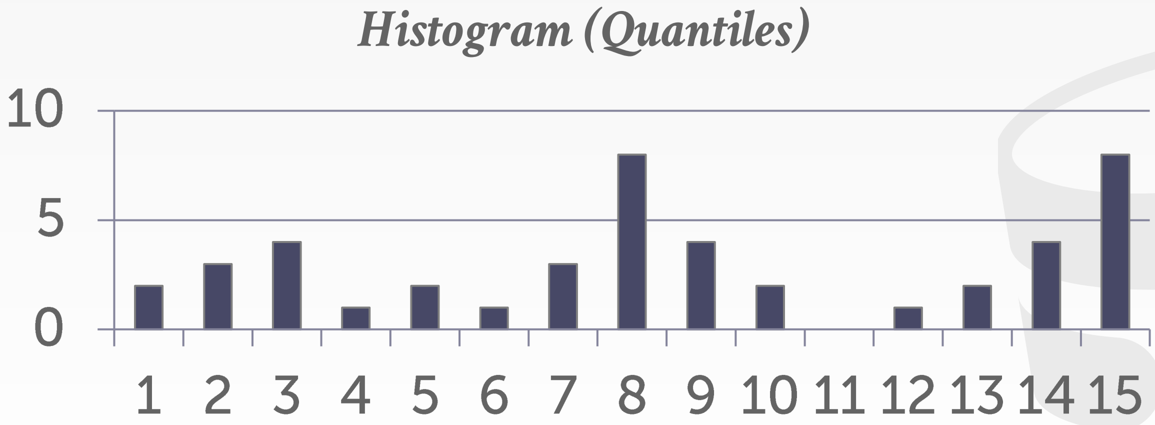


EQUI-DEPTH HISTOGRAMS

Vary the width of buckets so that the total number of occurrences for each bucket is roughly the same.



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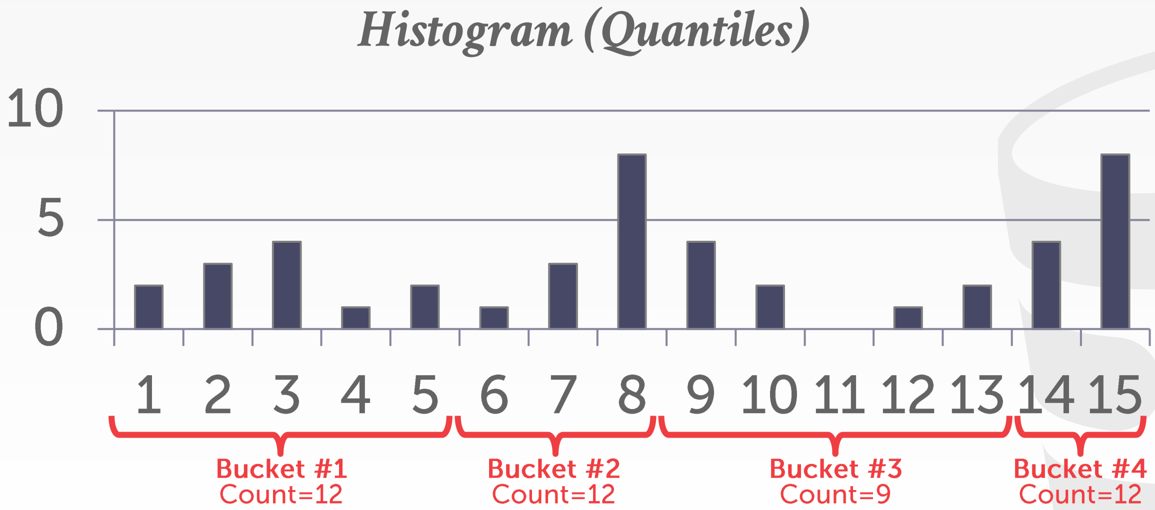

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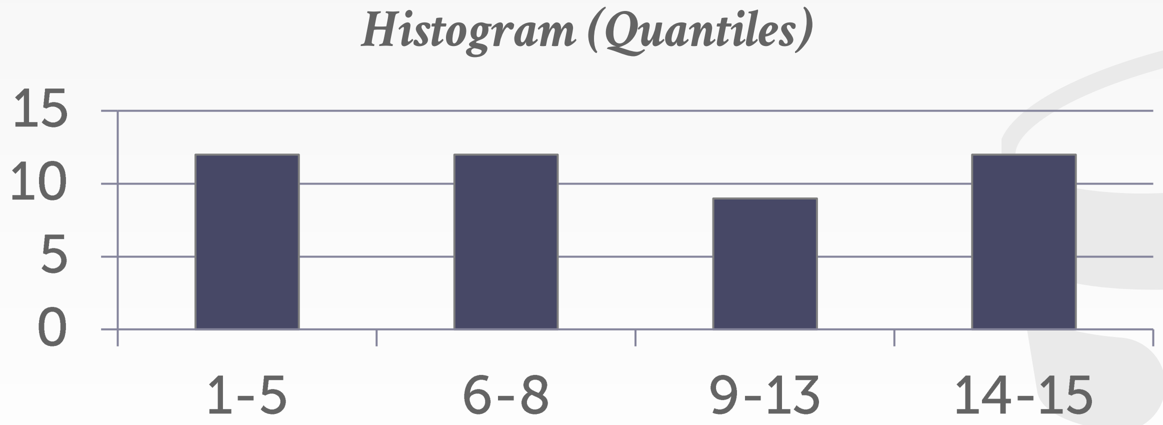

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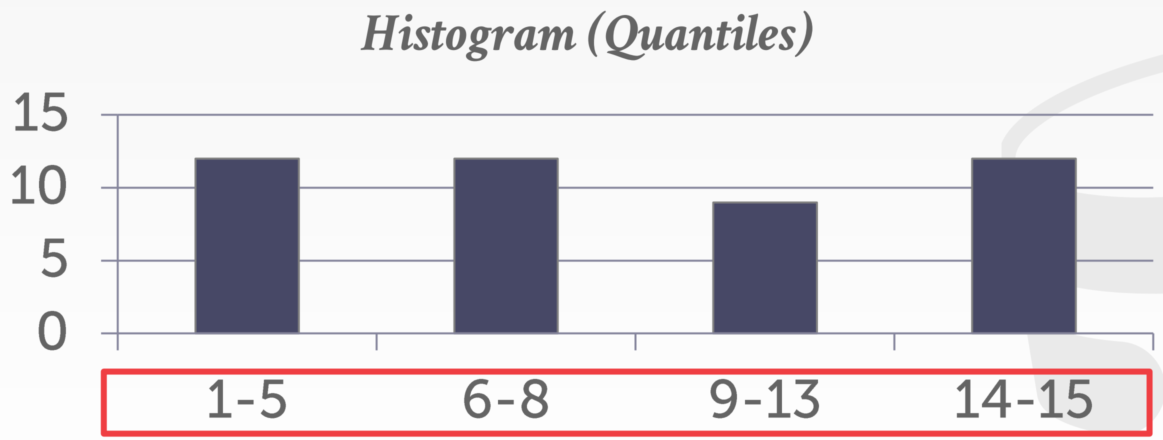

SKETCHES

Probabilistic data structures that generate approximate statistics about a data set.

Cost-model can replace histograms with sketches to improve its selectivity estimate accuracy.

Most common examples:

→ Count-Min Sketch (1988): Approximate frequency count of elements in a set.

→ HyperLogLog (2007): Approximate the number of distinct elements in a set.

SAMPLING

Modern DBMSs also collect samples from tables to estimate selectivities.

Update samples when the underlying tables changes significantly.

```
SELECT AVG(age)
  FROM people
 WHERE age > 50
```

id	name	age	status
1001	Obama	59	Rested
1002	Kanye	41	Weird
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⋮

1 billion tuples

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sel(age>50) = 1/3

OBSERVATION

Now that we can (roughly) estimate the selectivity of predicates, and subsequently the cost of query plans, what can we do with them?

QUERY OPTIMIZATION

After performing rule-based rewriting, the DBMS will enumerate different plans for the query and estimate their costs.

→ Single relation.
→ Multiple relations.
→ Nested sub-queries.

It chooses the best plan it has seen for the query after exhausting all plans or some timeout.

SINGLE-RELATION QUERY PLANNING

Pick the best access method.

→ Sequential Scan

→ Binary Search (clustered indexes)

→ Index Scan

Predicate evaluation ordering.

Simple heuristics are often good enough for this.

OLTP queries are especially easy…

OLTP QUERY PLANNING

Query planning for OLTP queries is easy because they are **sargable** (**S**earch **Arg**ument **Able**).

→ It is usually just picking the best index.

→ Joins are almost always on foreign key relationships with a small cardinality.

→ Can be implemented with simple heuristics.

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  ⋮
);
```

```
SELECT * FROM people
 WHERE id = 123;
```

OLTP QUERY PLANNING

Query planning for OLTP queries is easy because they are **sargable** (**S**earch **Arg**ument **Able**).

→ It is usually just picking the best index.
→ Joins are almost always on foreign key relationships with a small cardinality.
→ Can be implemented with simple heuristics.

```
CREATE TABLE people (
  id INT PRIMARY KEY,
  val INT NOT NULL,
  ⋮
);
```

```
SELECT * FROM people
 WHERE id = 123;
```

MULTI-RELATION QUERY PLANNING

As number of joins increases, number of alternative plans grows rapidly

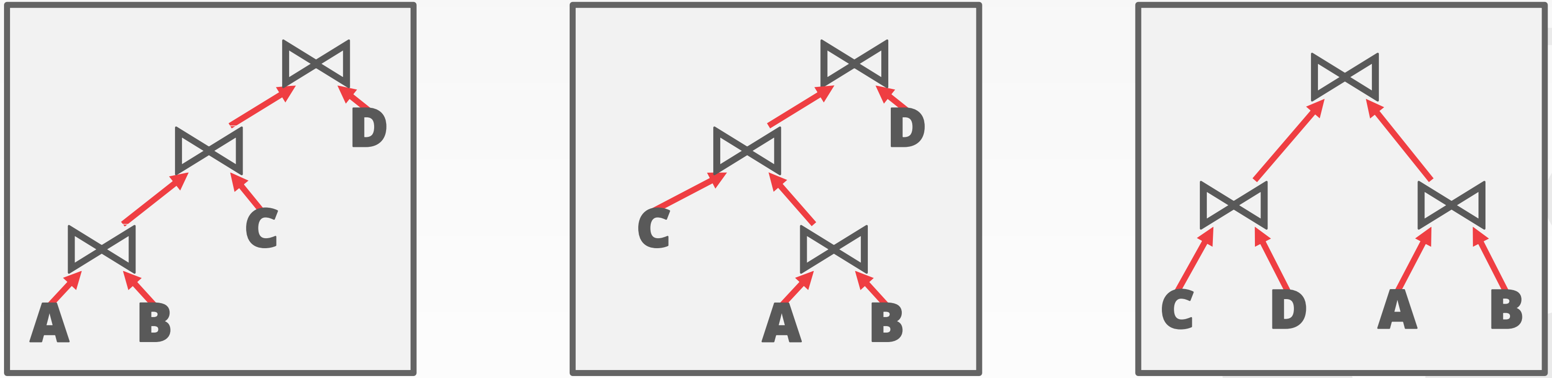
→ We need to restrict search space.

Fundamental decision in **System R**: only left-deep join trees are considered.

→ Modern DBMSs do not always make this assumption anymore.

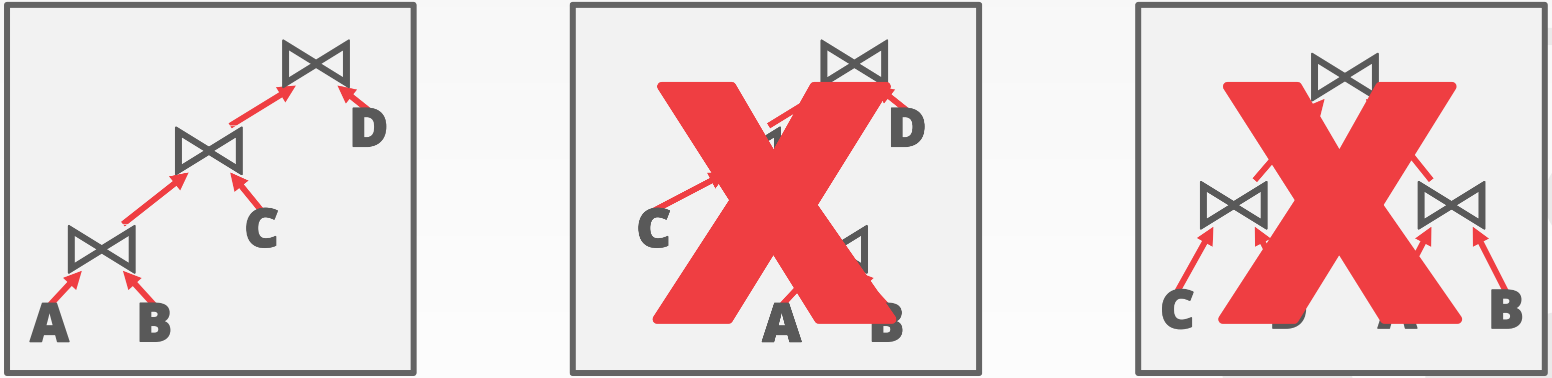
MULTI-RELATION QUERY PLANNING

Fundamental decision in **System R**: Only consider left-deep join trees.



MULTI-RELATION QUERY PLANNING

Fundamental decision in **System R**: Only consider left-deep join trees.



MULTI-RELATION QUERY PLANNING

Fundamental decision in **System R** is to only consider left-deep join trees.

Allows for fully pipelined plans where intermediate results are not written to temp files.

→ Not all left-deep trees are fully pipelined.

MULTI-RELATION QUERY PLANNING

Enumerate the orderings

→ Example: Left-deep tree #1, Left-deep tree #2…

Enumerate the plans for each operator

→ Example: Hash, Sort-Merge, Nested Loop…

Enumerate the access paths for each table

→ Example: Index #1, Index #2, Seq Scan…

MULTI-RELATION QUERY PLANNING

Enumerate the orderings
→ Example: Left-deep tree #1, Left-deep tree #2…

Enumerate the plans for each operator
→ Example: Hash, Sort-Merge, Nested Loop…

Enumerate the access paths for each table
→ Example: Index #1, Index #2, Seq Scan…

Use **dynamic programming** to reduce the number of cost estimations.

DYNAMIC PROGRAMMING

```
SELECT * FROM R, S, T
 WHERE R.a = S.a
   AND S.b = T.b
```

R
S
T

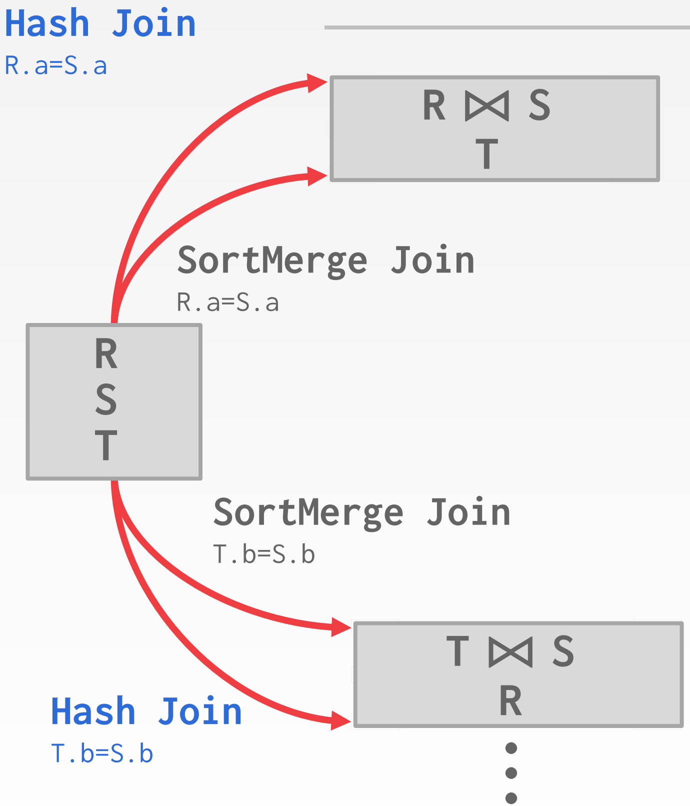
R ⋈ S
T

T ⋈ S
R

•
•
•

R ⋈ S ⋈ T

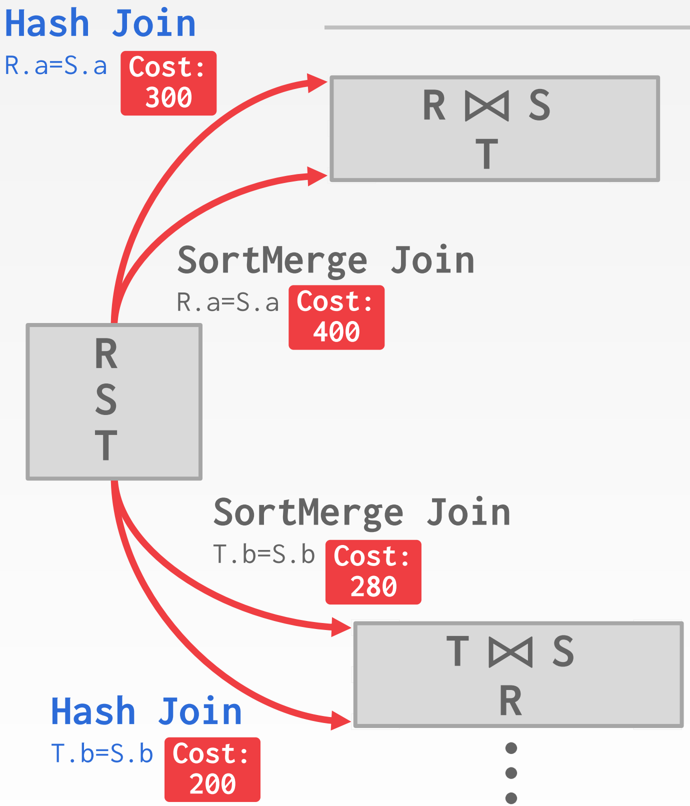
DYNAMIC PROGRAMMING




```
SELECT * FROM R, S, T
 WHERE R.a = S.a
   AND S.b = T.b
```

R ⋈ S ⋈ T

DYNAMIC PROGRAMMING




```
SELECT * FROM R, S, T
 WHERE R.a = S.a
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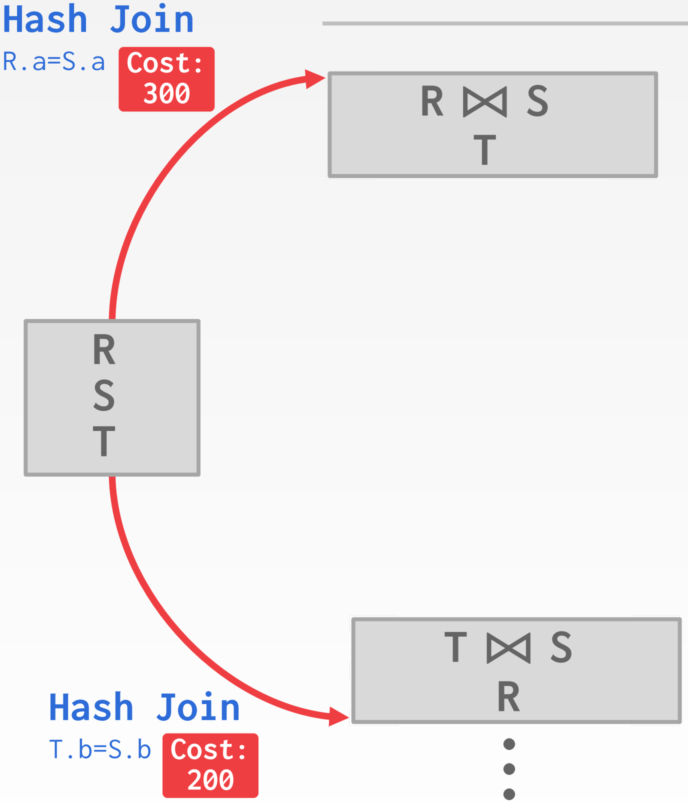
```

DYNAMIC PROGRAMMING




```
SELECT * FROM R, S, T
 WHERE R.a = S.a
   AND S.b = T.b
```

DYNAMIC PROGRAMMING

```
SELECT * FROM R, S, T
 WHERE R.a = S.a
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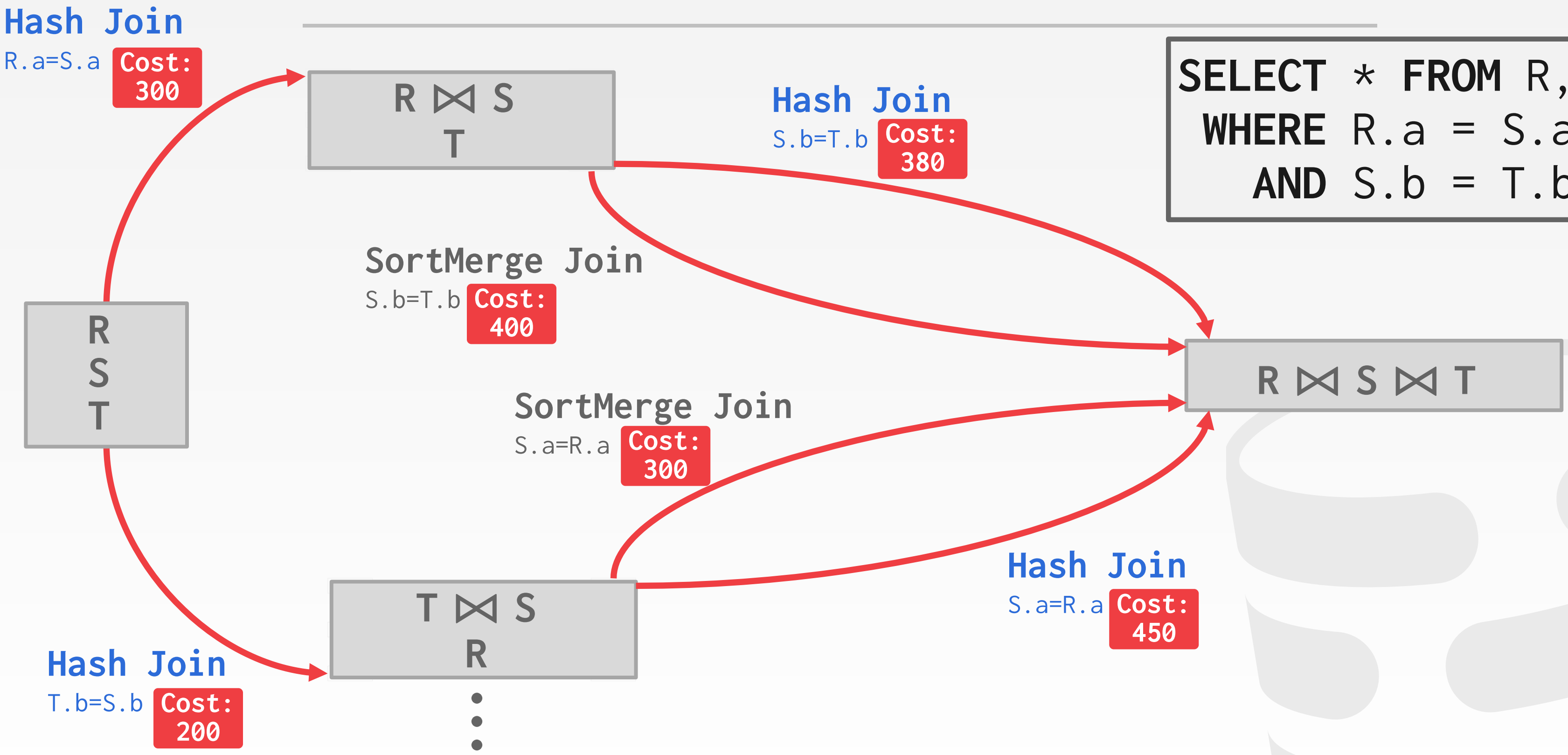
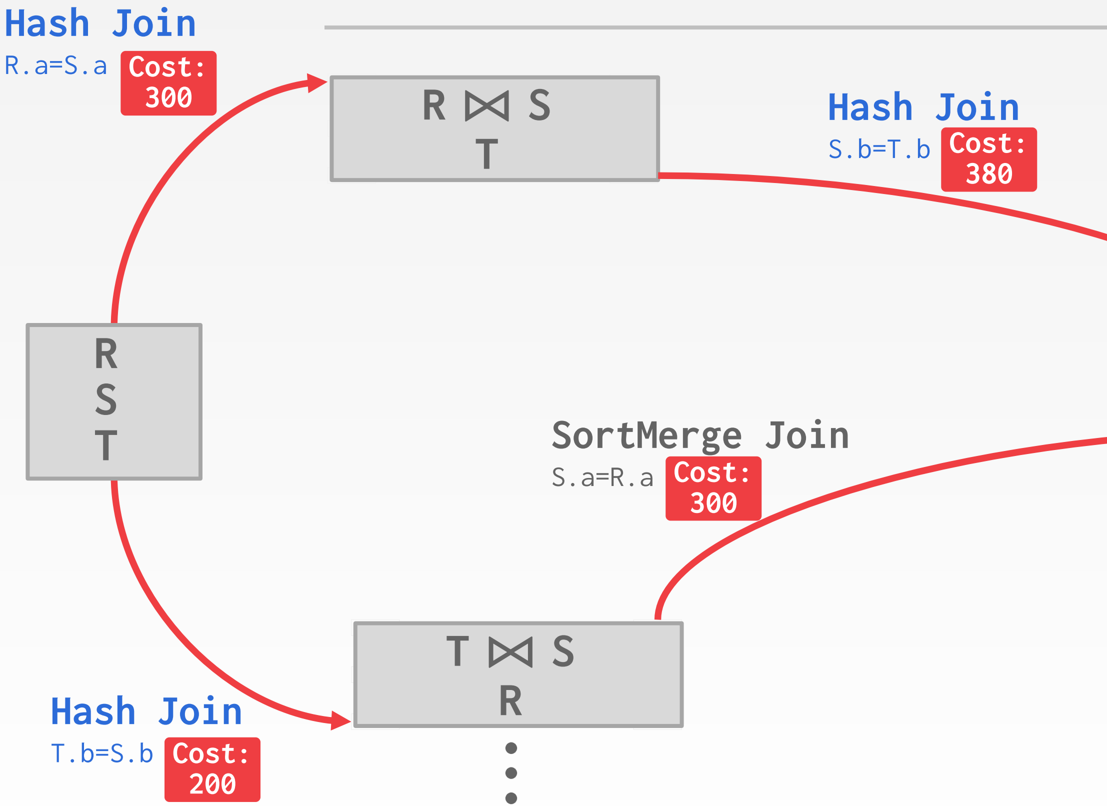
```



DYNAMIC PROGRAMMING

```
SELECT * FROM R, S, T
 WHERE R.a = S.a
   AND S.b = T.b
```



DYNAMIC PROGRAMMING

```
SELECT * FROM R, S, T
 WHERE R.a = S.a
   AND S.b = T.b
```

R ⋈ S
T

R
S
T

SortMerge Join
S.a=R.a
Cost: 300

R ⋈ S ⋈ T

Hash Join
T.b=S.b
Cost: 200

T ⋈ S
R

⋮

CANDIDATE PLAN EXAMPLE

```
SELECT * FROM R, S, T
 WHERE R.a = S.a
   AND S.b = T.b
```

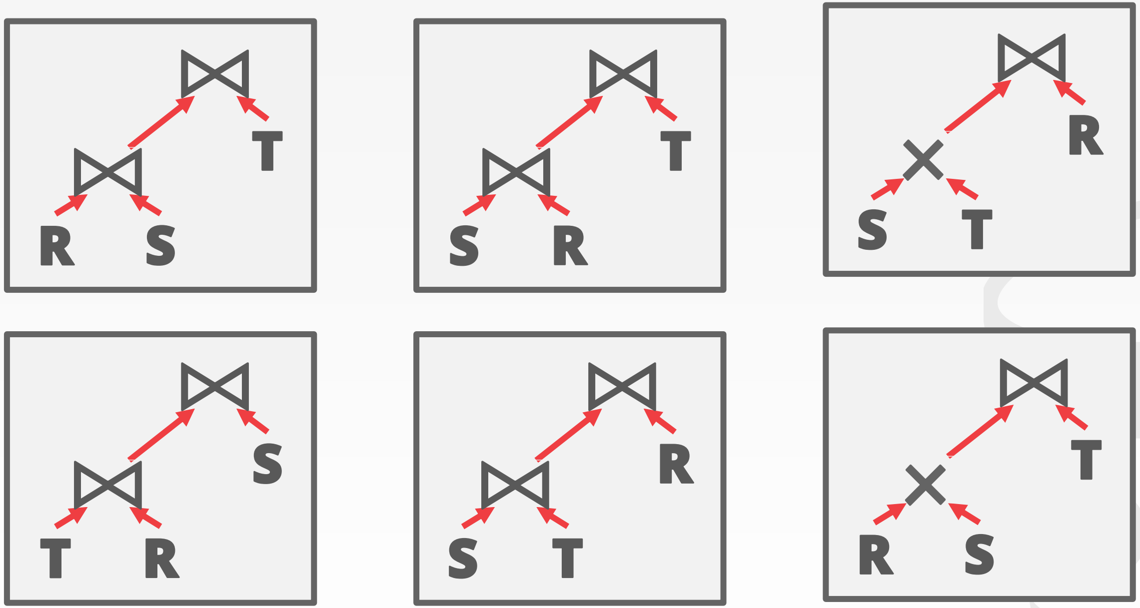
How to generate plans for search algorithm:

→ Enumerate relation orderings
→ Enumerate join algorithm choices
→ Enumerate access method choices

No real DBMSs does it this way.
It's actually more messy…

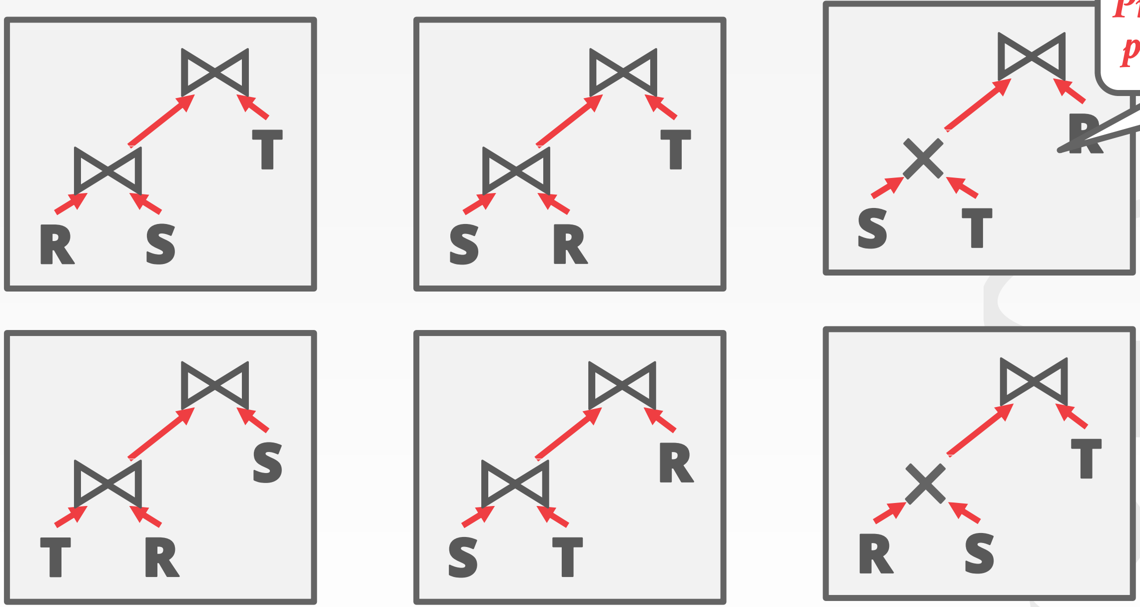
CANDIDATE PLANS

Step #1: Enumerate relation orderings



CANDIDATE PLANS

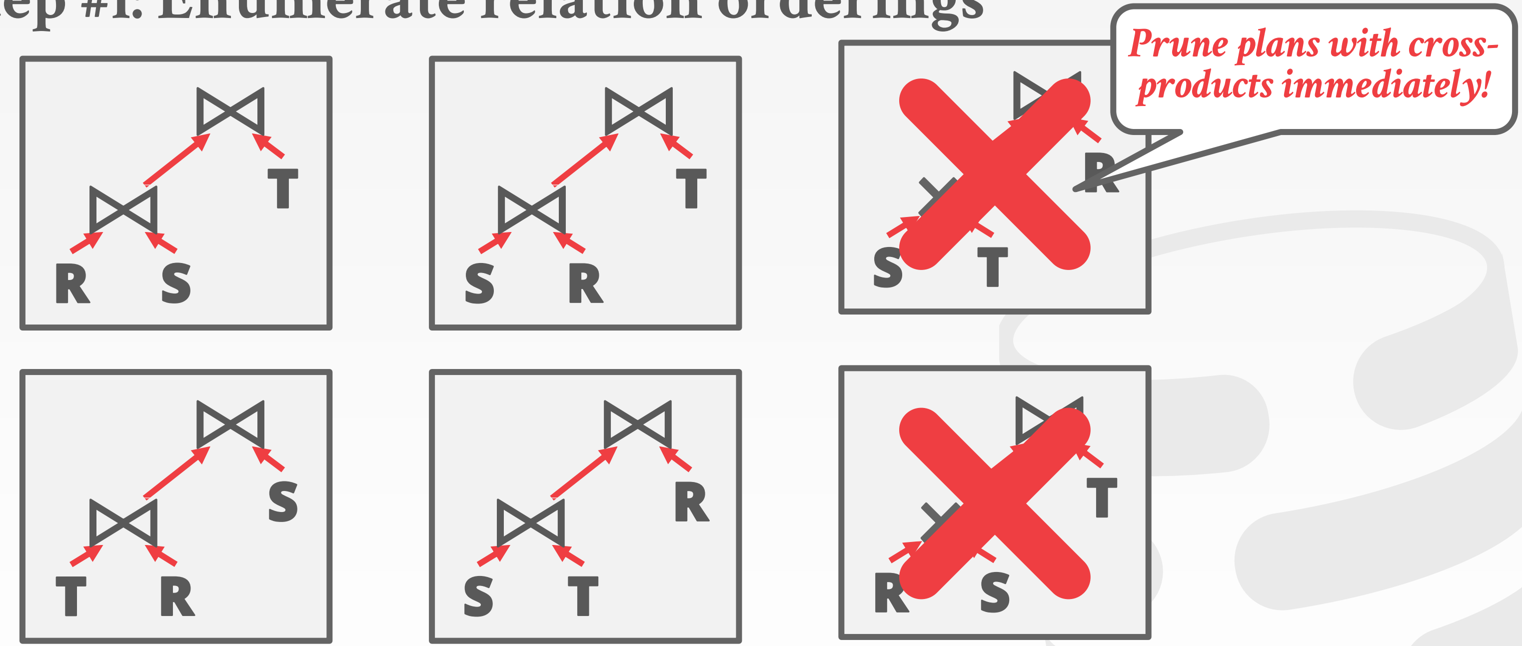
Step #1: Enumerate relation orderings



Prune plans with cross-products immediately!

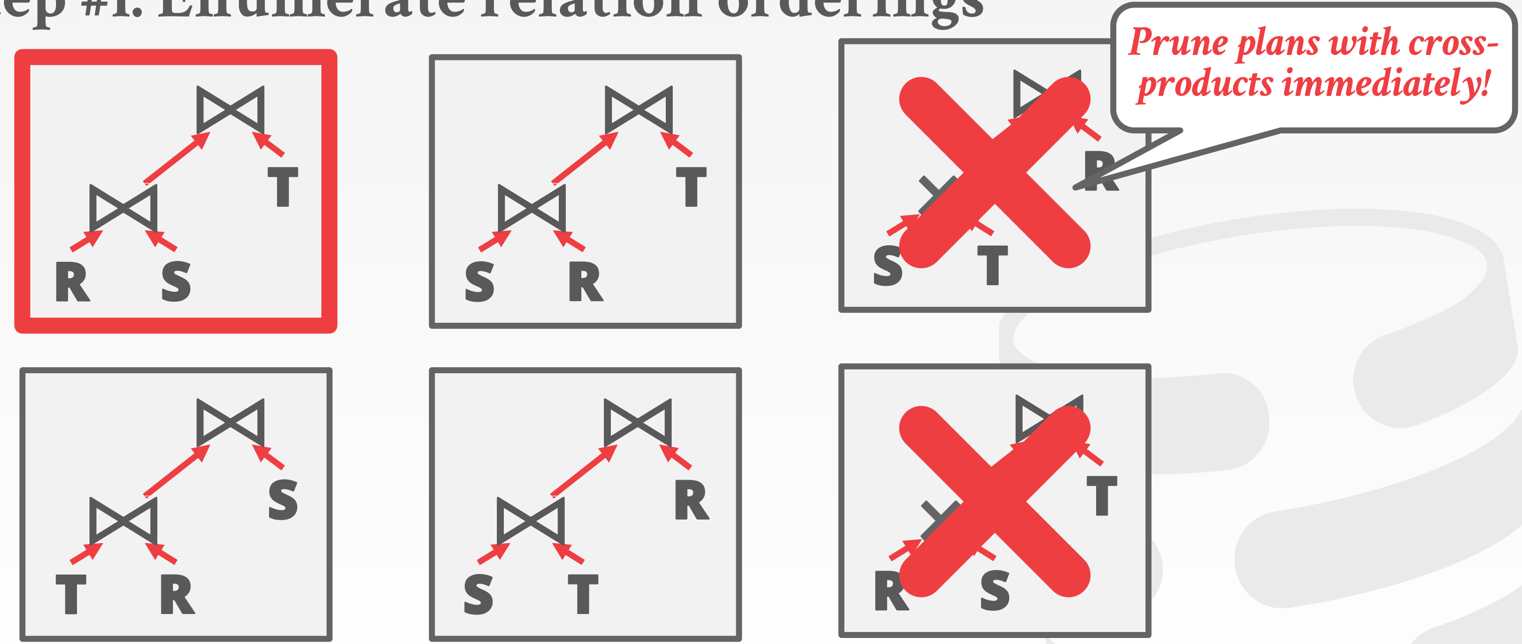
CANDIDATE PLANS

Step #1: Enumerate relation orderings



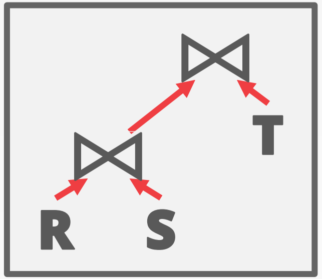
CANDIDATE PLANS

Step #1: Enumerate relation orderings



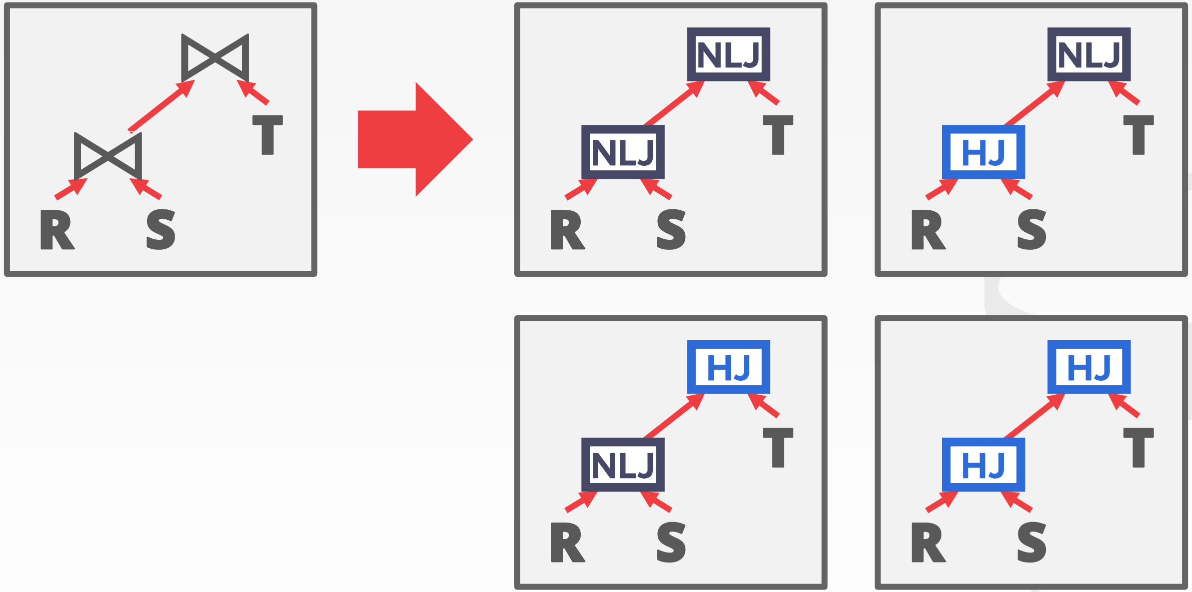
CANDIDATE PLANS

Step #2: Enumerate join algorithm choices



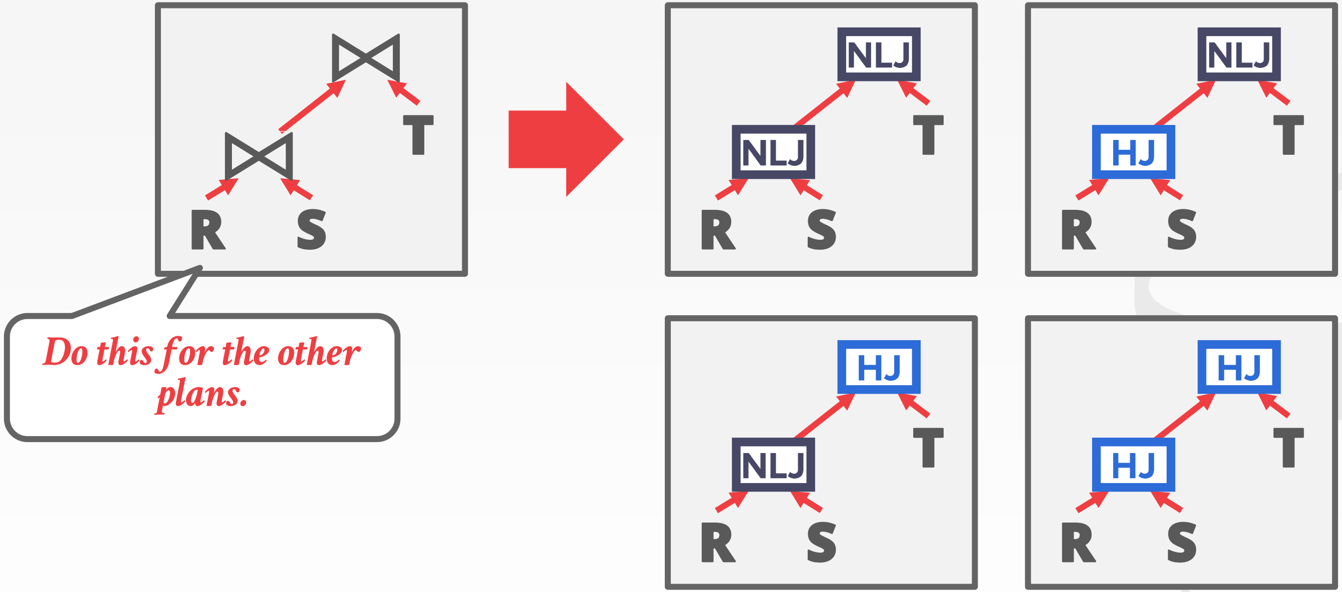
CANDIDATE PLANS

Step #2: Enumerate join algorithm choices



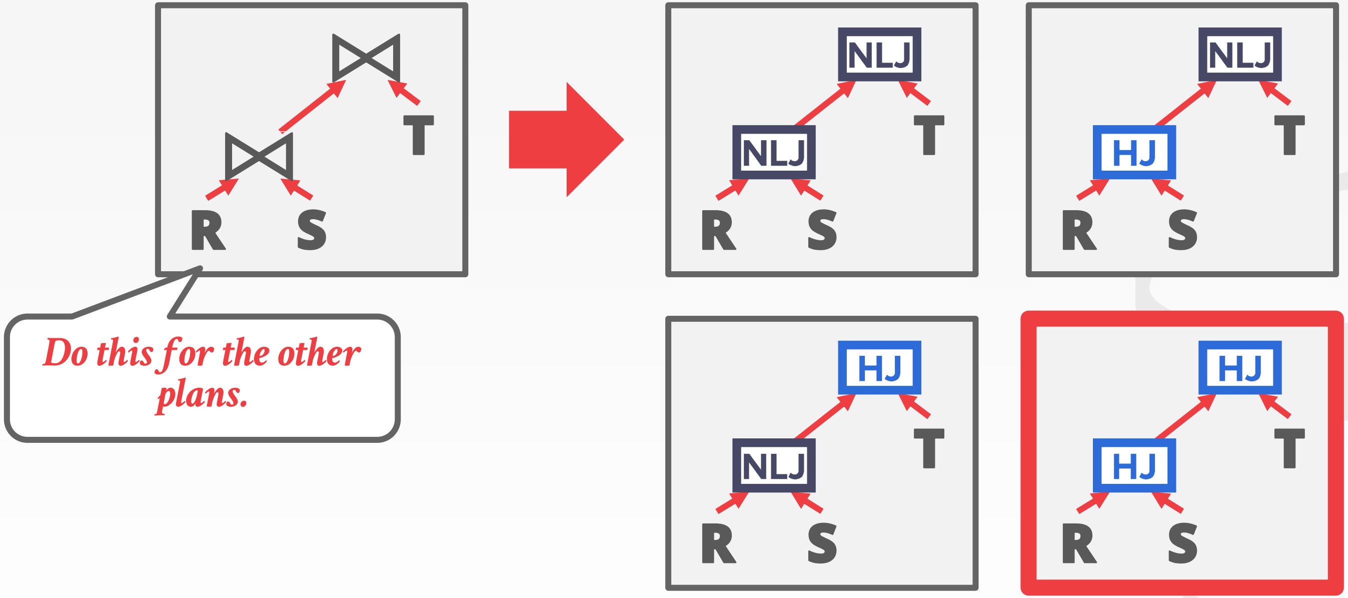
CANDIDATE PLANS

Step #2: Enumerate join algorithm choices



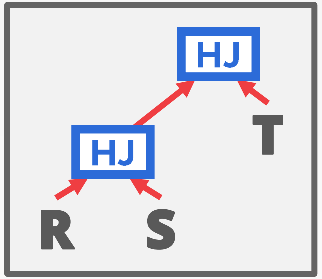
CANDIDATE PLANS

Step #2: Enumerate join algorithm choices



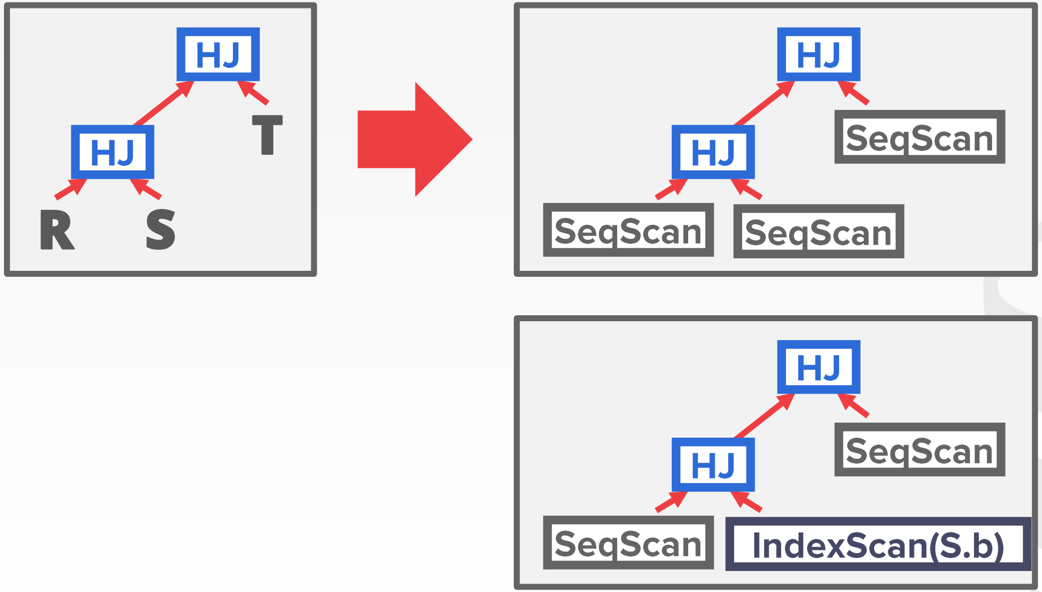
CANDIDATE PLANS

Step #3: Enumerate access method choices



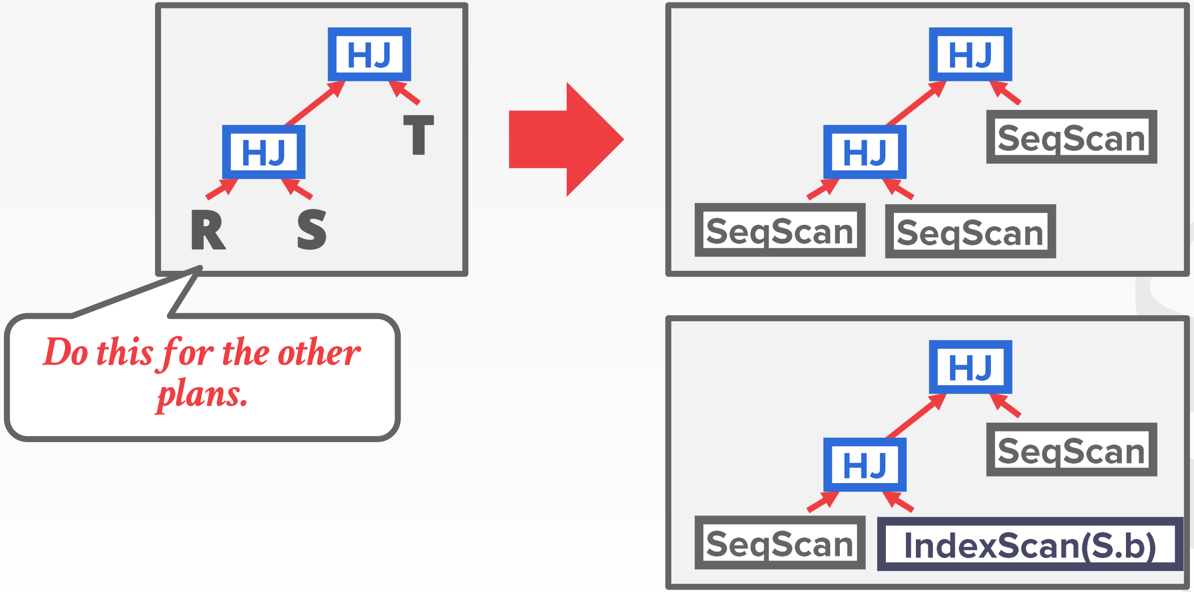
CANDIDATE PLANS

Step #3: Enumerate access method choices



CANDIDATE PLANS

Step #3: Enumerate access method choices



POSTGRES OPTIMIZER

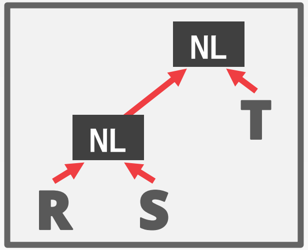
Examines all types of join trees
→ Left-deep, Right-deep, bushy

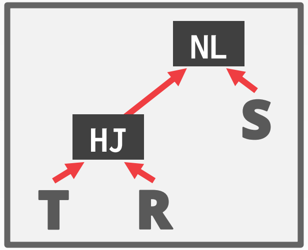
Two optimizer implementations:
→ Traditional Dynamic Programming Approach
→ Genetic Query Optimizer (GEQO)

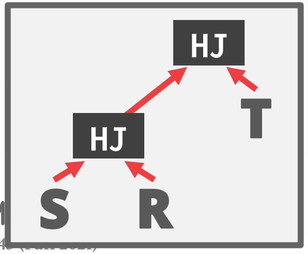
Postgres uses the traditional algorithm when # of tables in query is **less** than 12 and switches to GEQO when there are 12 or more.

POSTGRES GENETIC OPTIMIZER

1st Generation

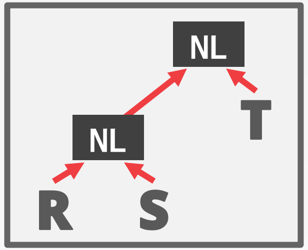




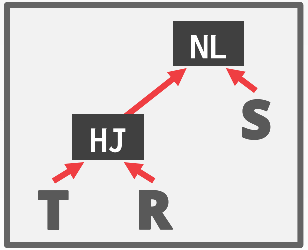


POSTGRES GENETIC OPTIMIZER

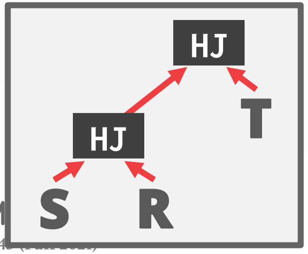
1st Generation



Cost: 300

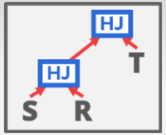


Cost: 200



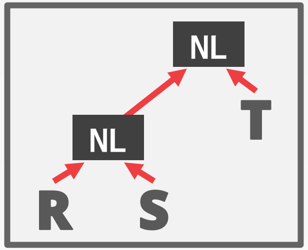
Cost: 100

POSTGRES GENETIC OPTIMIZER

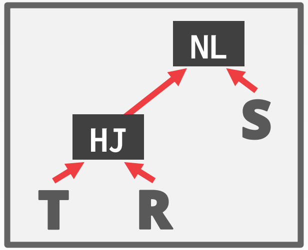


Best:100

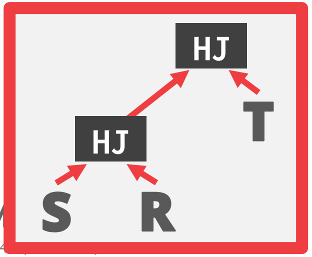
1st Generation



Cost: 300

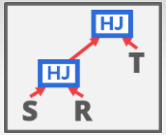


Cost: 200



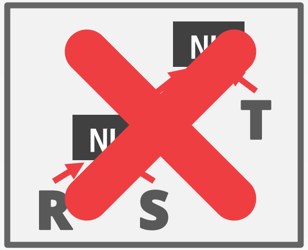
Cost: 100

POSTGRES GENETIC OPTIMIZER

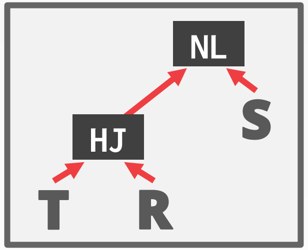


Best:100

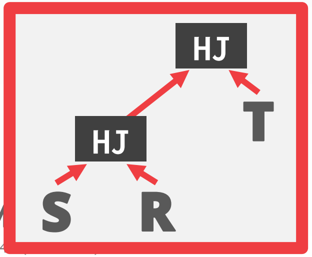
1st Generation



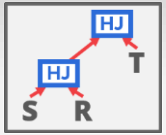
Cost:
300



Cost:
200



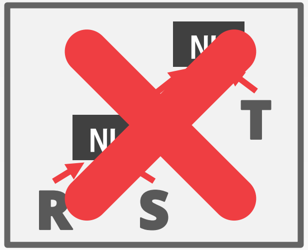
Cost:
100



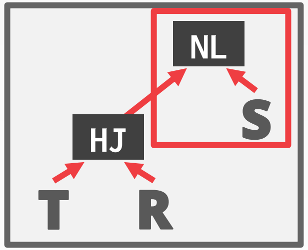
Best:100

POSTGRES GENETIC OPTIMIZER

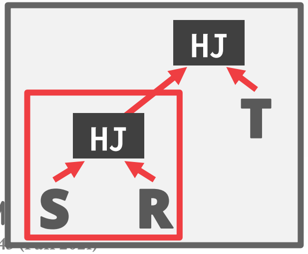
1st Generation



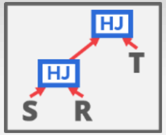
Cost: 300



Cost: 200



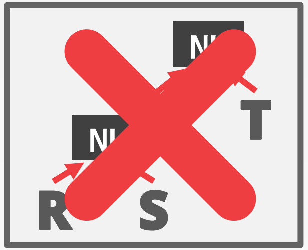
Cost: 100



POSTGRES GENETIC OPTIMIZER

Best:100

1st Generation



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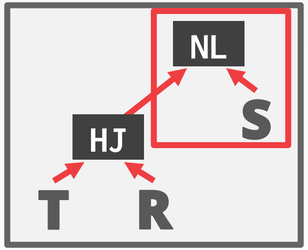

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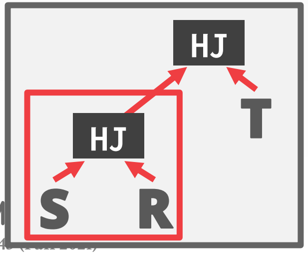
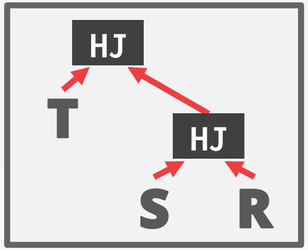
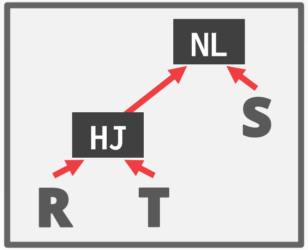
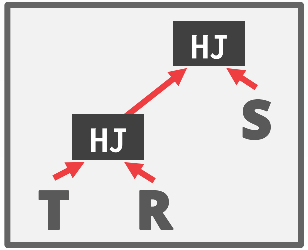


Cost: 100

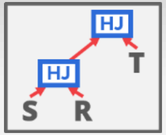
2nd Generation





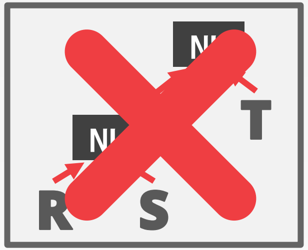


POSTGRES GENETIC OPTIMIZER

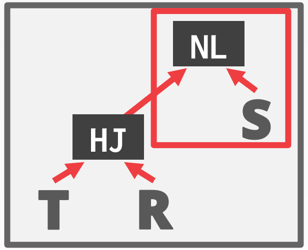


Best:100

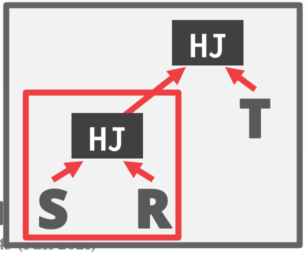
1st Generation



Cost: 300

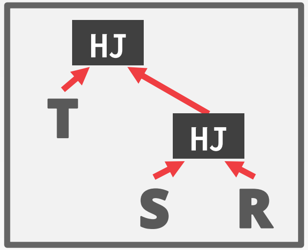


Cost: 200

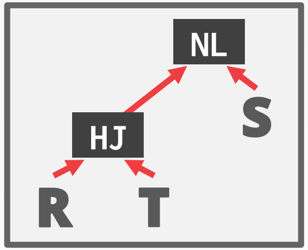


Cost: 100

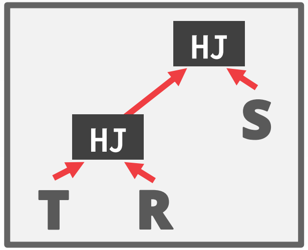
2nd Generation



Cost: 80

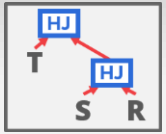


Cost: 200



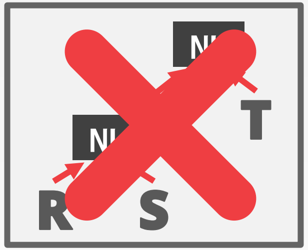
Cost: 110

POSTGRES GENETIC OPTIMIZER

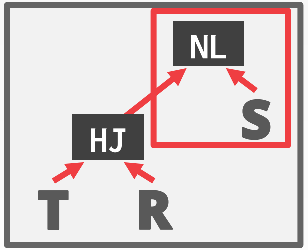


Best:80

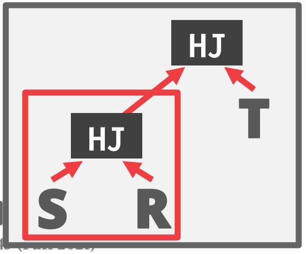
1st Generation



Cost: 300

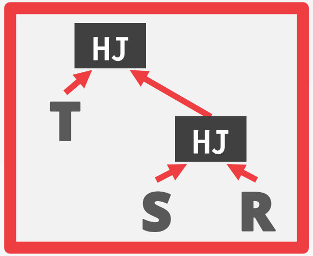


Cost: 200

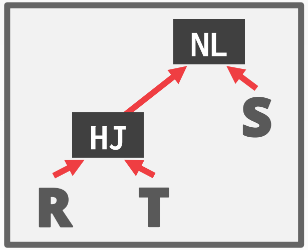


Cost: 100

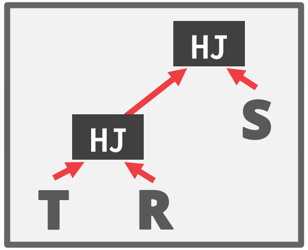
2nd Generation



Cost: 80

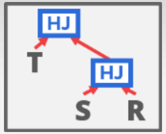


Cost: 200



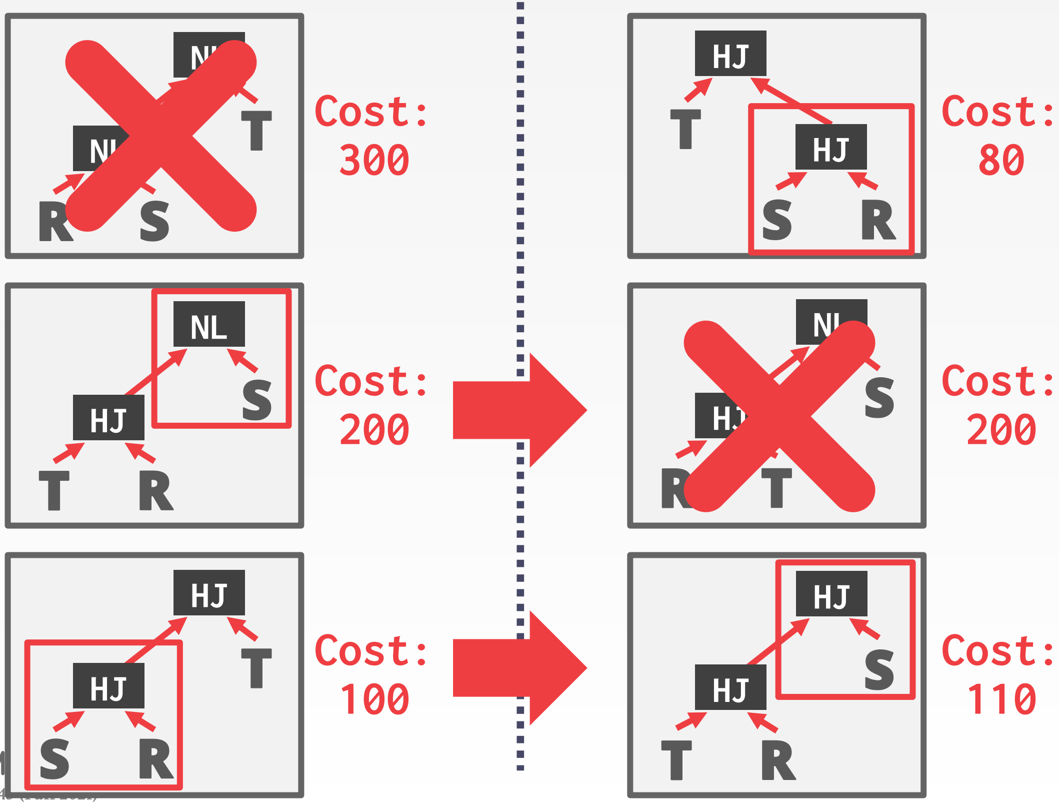
Cost: 110

POSTGRES GENETIC OPTIMIZER



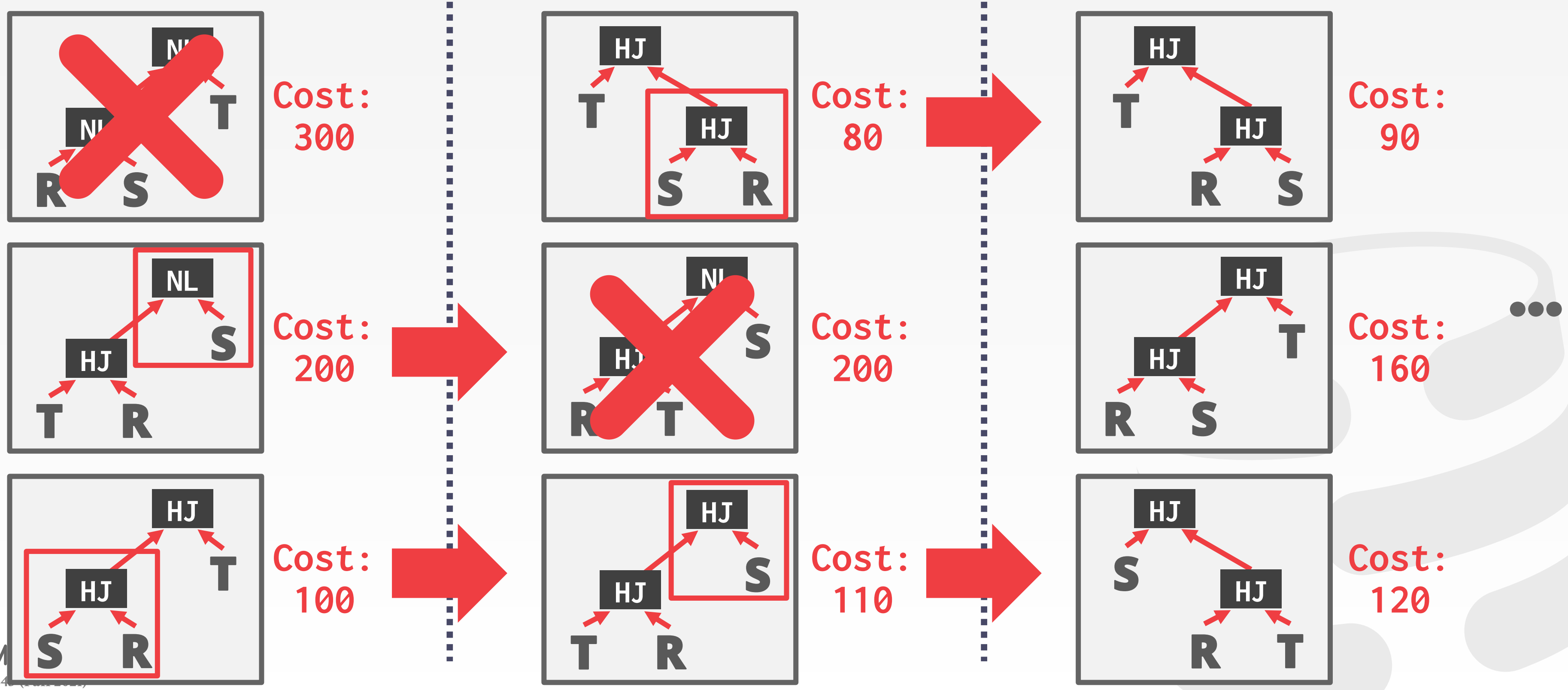
Best:80

1st Generation *2nd Generation*



POSTGRES GENETIC OPTIMIZER

1st Generation | *2nd Generation* | *3rd Generation*



CONCLUSION

Filter early as possible.

Selectivity estimations
→ Uniformity
→ Independence
→ Inclusion
→ Histograms
→ Join selectivity

Dynamic programming for join orderings

Again, query optimization is hard…

NEXT CLASS

Transactions!

→ aka the second hardest part about database systems