CMSC 724: Database Management Systems
Query Processing and Optimization

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Outline

- Part 1 Slides
  - Query evaluation techniques for large databases, Skew Avoidance, Query compilation/vectorization
  - Query Optimization: Overview, How good are the query optimizers, really?, Reordering for Outerjoins, Query Rewriting
- Adaptive Query Processing
  - Eddies
  - Progressive Query Optimization
  - Compilation and adaptivity
- Worst case optimal joins
- Froid: Databases and UDFs

Traditional Optimization not Robust Enough

- In traditional settings:
  - Queries over many tables
  - Unreliability of traditional cost estimation
  - Success, maturity make problems more apparent, critical
- In new environments:
  - e.g. data integration, web services, streams, P2P...
  - Unknown dynamic characteristics for data and runtime
  - Increasingly aggressive sharing of resources and computation
  - Interactivity in query processing
- Note two distinct themes lead to the same conclusion:
  - Unknowns: even static properties often unknown in new environments and often unknowable a priori
  - Dynamics: environment changes can be very high
- Motivates intra-query adaptivity

Some Related Topics

- Autonomic/self-tuning optimization
  - Chen and Roussoupolous: Adaptive selectivity estimation [SIGMOD 1994]
  - LEO (@IBM), SITS (@MSR): Learning from previous executions
- Robust/least-expected cost optimization
- Parametric optimization
  - Choose a collection of plans, each optimal for a different setting of parameters
  - Select one at the beginning of execution
- Competitive optimization
  - Start off multiple plans... kill all but one after a while
- Adaptive operators

More details in our survey: “Adaptive Query Processing”; FnT 2007

AQP: Overview/Summary

- Low-overhead, evolutionary approaches
  - Typically apply to non-pipelined execution
  - **Late binding:** Don't instatntiate the entire plan at start
  - **Mid-query reoptimization:** At "materialization" points, review the remaining plan and possibly re-optimize
- Pipelined execution
  - No materialization points, so the above doesn't apply
  - The operators may contain complex states, raising correctness issues
  - **Eddies**
    - Always guarantee correct execution, but allows reordering during execution
- Lot of work in 1998-2008 timeframe -- not much since

AQP: Overview/Summary

- We will start with a general overview of AQP as presented in a later survey and tutorial

- Then go through the three papers (first two quickly, and the last one in more detail)
  - First two will be covered in the tutorial

Slides Adapted From:

Adaptive Query Processing Tutorial VLDB 2008

Amol Deshpande, University of Maryland

Zachary G. Ives, University of Pennsylvania

Vijayshankar Raman, IBM Almaden Research Center

Thanks to Joseph M. Hellerstein, University of California, Berkeley

Query Processing: Adapting to the World

Data independence facilitates modern DBMS technology

- Separates specification (“what”) from implementation (“how”)
- Optimizer maps declarative query → algebraic operations

Platforms, conditions are constantly changing:

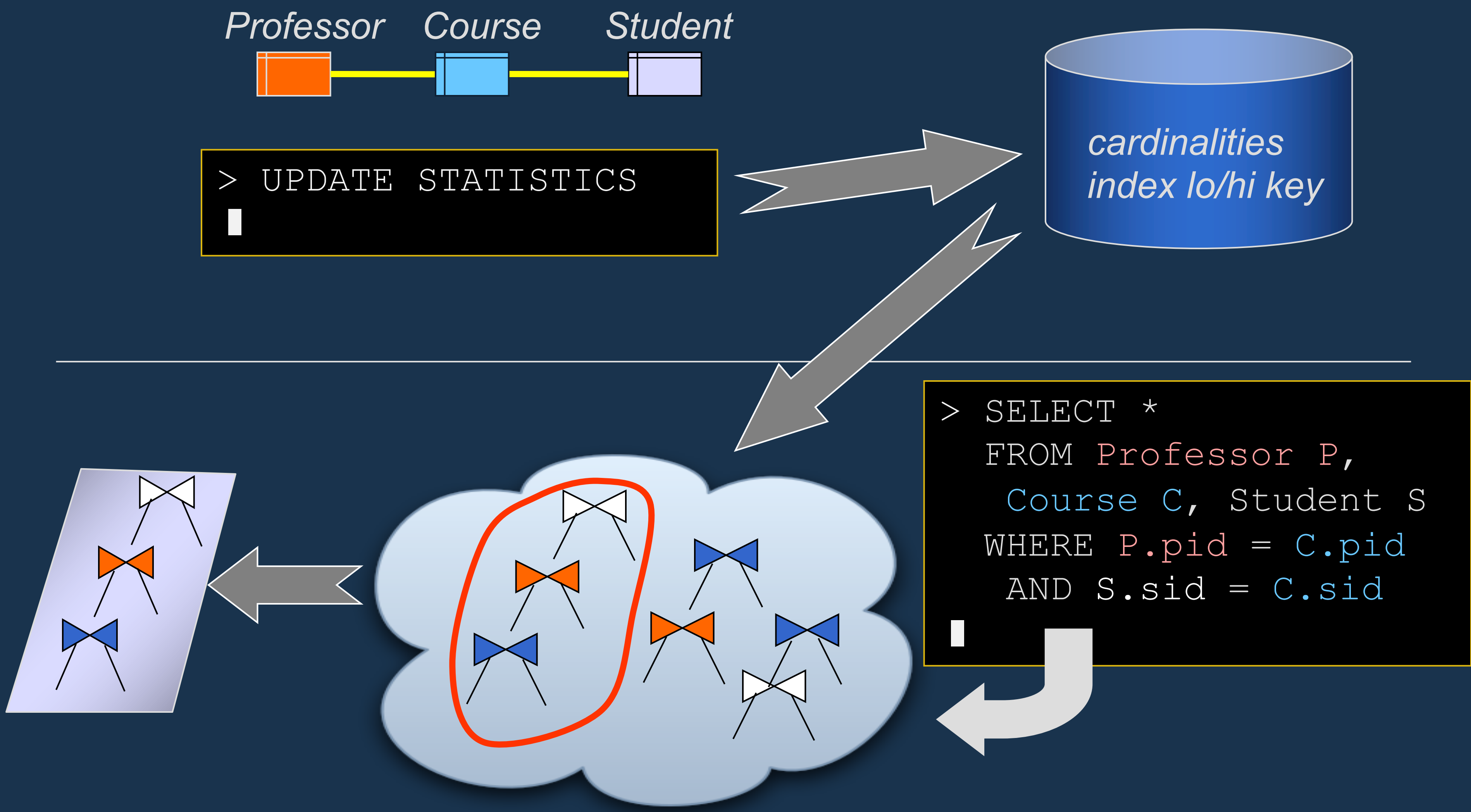
$$\frac{dapp}{dt} << \frac{denv}{dt}$$

Query processing **adapts** implementation to runtime conditions

- Static applications → dynamic environments

Query Optimization and Processing

(As Established in System R [SAC+'79])



```
> UPDATE STATISTICS
▌
```

```
> SELECT *
  FROM Professor P,
   Course C, Student S
  WHERE P.pid = C.pid
   AND S.sid = C.sid
▌
```

Dynamic Programming + Pruning Heuristics

Traditional Optimization Is Breaking

In traditional settings:

- Queries over many tables
- Unreliability of traditional cost estimation
- Success & maturity make problems more apparent, critical

In new environments:

- e.g. data integration, web services, streams, P2P, sensor nets, hosting
- Unknown and dynamic characteristics for *data* and *runtime*
- Increasingly aggressive sharing of resources and computation
- Interactivity in query processing

Note two distinct themes lead to the same conclusion:

- *Unknowns*: even static properties often unknown in new environments and often unknowable *a priori*
- *Dynamics*: ${}^{denv}\!/_{dt}$ can be very high

Motivates *intra-query adaptivity*

A Call for Greater Adaptivity

System R adapted query processing as stats were updated

- Measurement/analysis: periodic
- Planning/actuation: once per query
- Improved thru the late 90s (see [Graefe ’93] [Chaudhuri ’98])

  Better measurement, models, search strategies

INGRES adapted execution many times per query

- Each tuple could join with relations in a different order
- Different plan space, overheads, frequency of adaptivity

  Didn’t match applications & performance at that time

Recent work considers adaptivity in new contexts

Tutorial Focus

By necessity, we will cover only a piece of the picture here

- Intra-query adaptivity:
  - autonomic / self-tuning optimization [CR'94, CN'97, BC'02, …]
  - robust / least expected cost optimization [CHG'02, MRS+'04, BC'05, ...]
  - parametric or competitive optimization [A'93, INSS'92, CG'94, …]
  - adaptive operators, e.g., memory adaptive sort & hash join [NKT'88, KNT'89, PCL'93a, PCL'93b,…]
- Conventional relations, rather than streams
- Single-site, single query computation

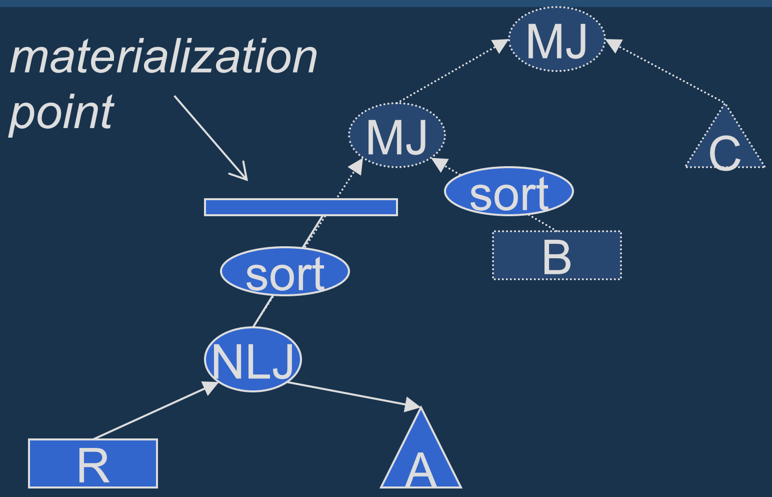
- For more depth, see our survey in now Publishers' *Foundations and Trends in Databases*, Vol. 1 No. 1

Tutorial Outline

- Motivation
- Non-pipelined execution
- Pipelined execution
  - Selection ordering
  - Multi-way join queries
- Putting it all in context
- Recap/open problems

Low-Overhead Adaptivity: Non-pipelined Execution

Late Binding; Staged Execution



Normal execution: pipelines separated by materialization points

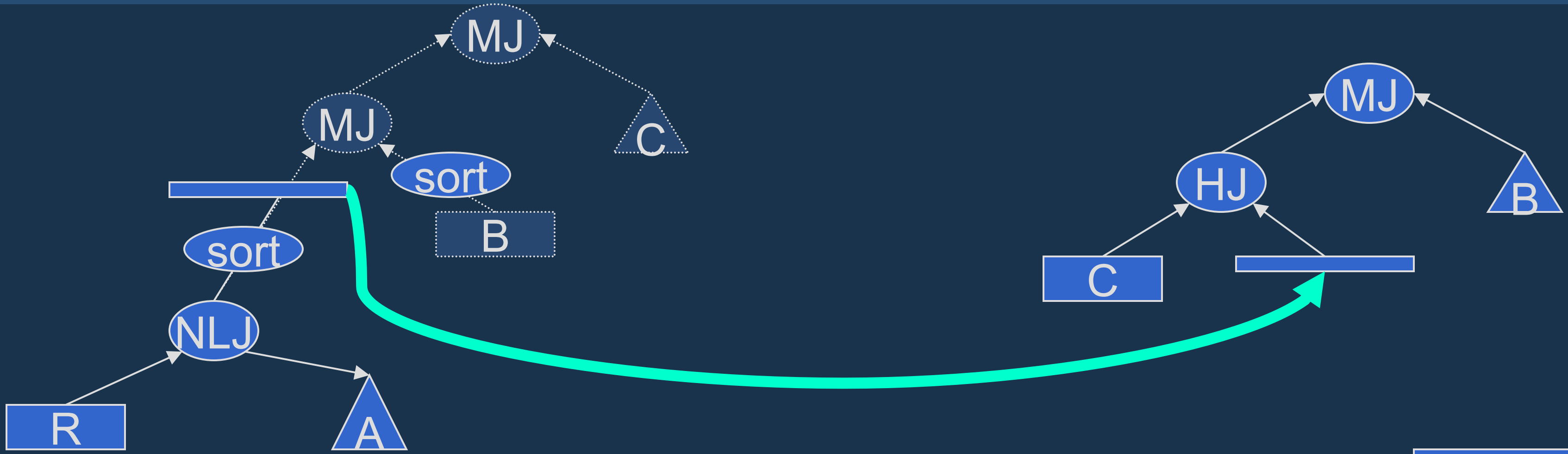
e.g., at a sort, GROUP BY, etc.

Materialization points make natural decision points where the *next* stage can be changed with little cost:

- Re-run optimizer at each point to get the next stage
- Choose among precomputed set of plans – *parametric* query optimization [INSS’92, CG’94, …]

Mid-query Reoptimization

[KD’98,MRS+04]



Choose *checkpoints* at which to monitor cardinalities

Where?

Balance overhead and opportunities for switching plans

If actual cardinality is too different from estimated,

When?

Avoid unnecessary plan re-optimization (where the plan doesn’t change)

Re-optimize **to switch to a new plan**

How?

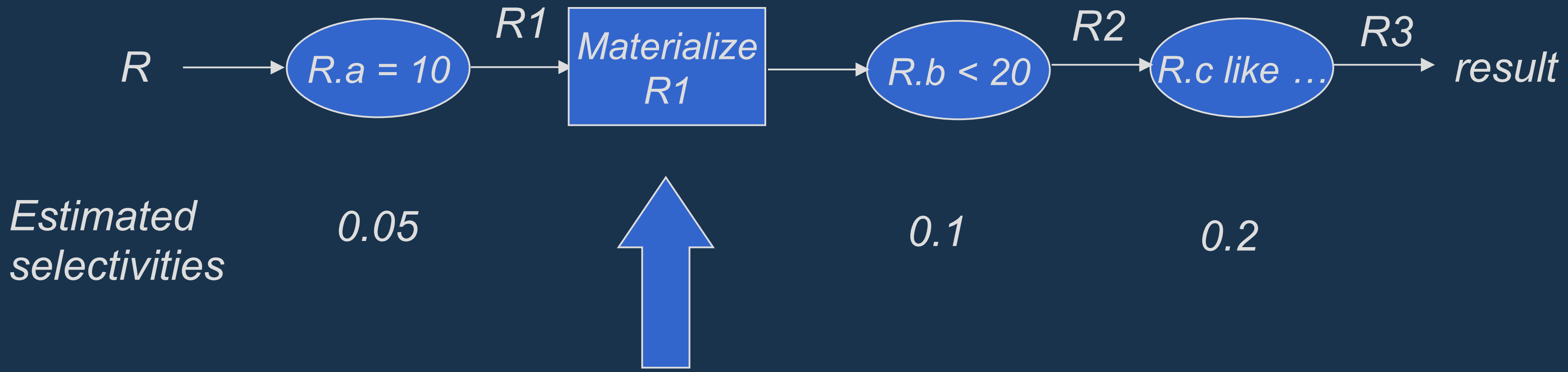
Try to maintain previous computation during plan switching

- Most widely studied technique:
  -- Federated systems (InterViso 90, MOOD 96), Red Brick, Query scrambling (96), Mid-query re-optimization (98), Progressive Optimization (04), Proactive Reoptimization (05), …

Mid-query Reoptimization

- At *materialization points,* re-evaluate the rest of the query plan
- Example:

Initial query plan chosen



R

R.a = 10

R1

Materialize R1

R.b < 20

R2

R.c like …

R3

result

Estimated selectivities

0.05

0.1

0.2

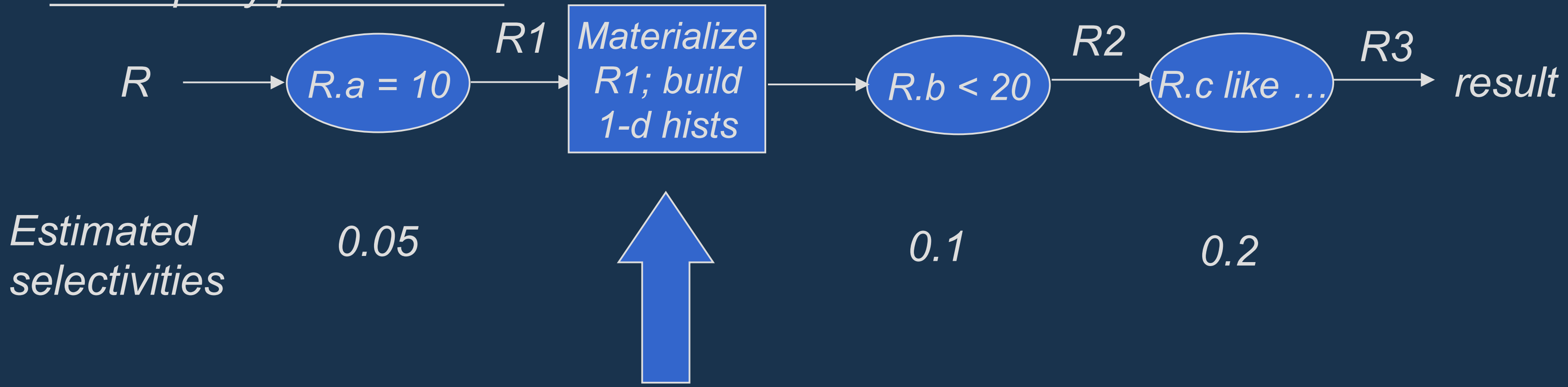
A *free* opportunity to re-evaluate *the rest of the query plan*

- Exploit by gathering information about the materialized result

Mid-query Reoptimization

- At *materialization points*, re-evaluate the rest of the query plan
- Example:

Initial query plan chosen

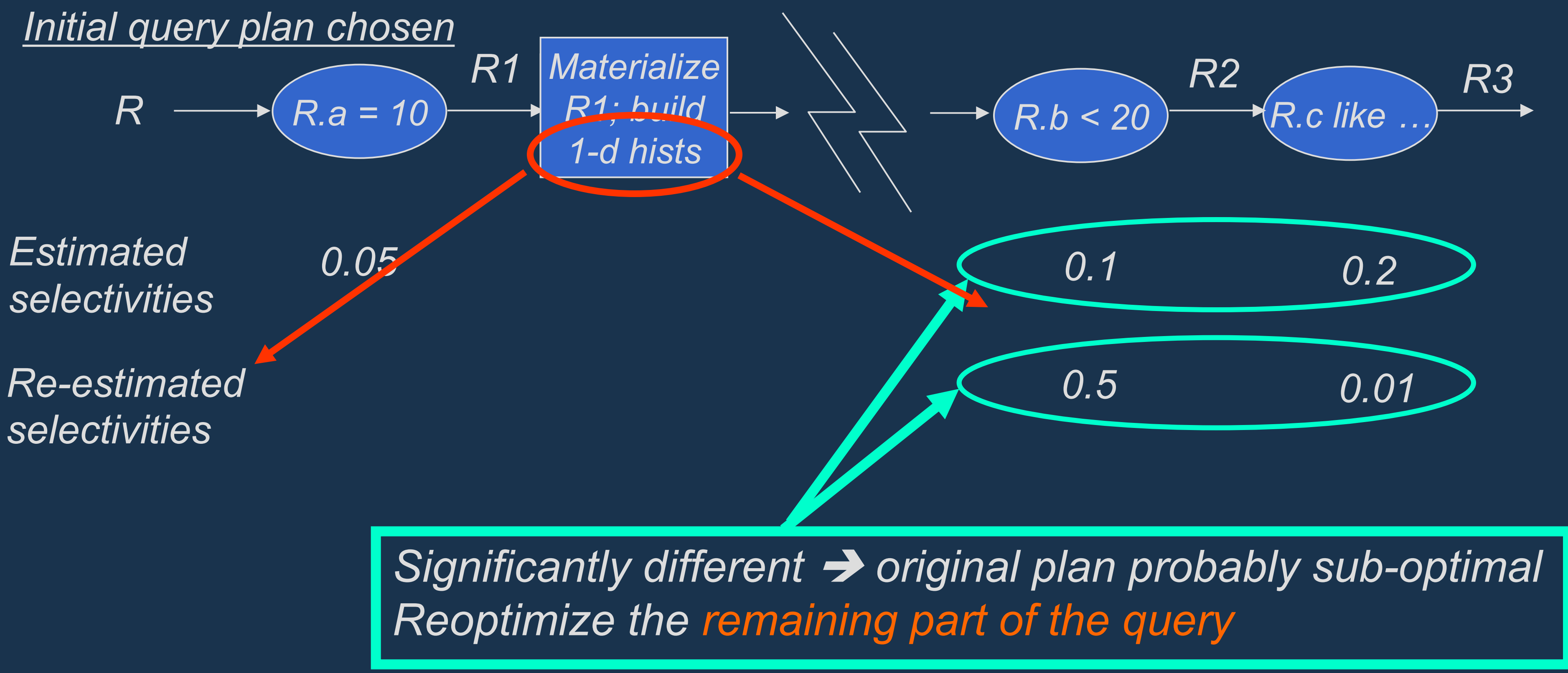


A *free* opportunity to re-evaluate *the rest of the query plan*

- Exploit by gathering information about the materialized result

Mid-query Reoptimization

- At *materialization points,* re-evaluate the rest of the query plan
- Example:



Initial query plan chosen

R

R.a = 10

R1

Materialize R1; build 1-d hists

R.b < 20

R2

R.c like …

R3

Estimated selectivities

0.05

0.1

0.2

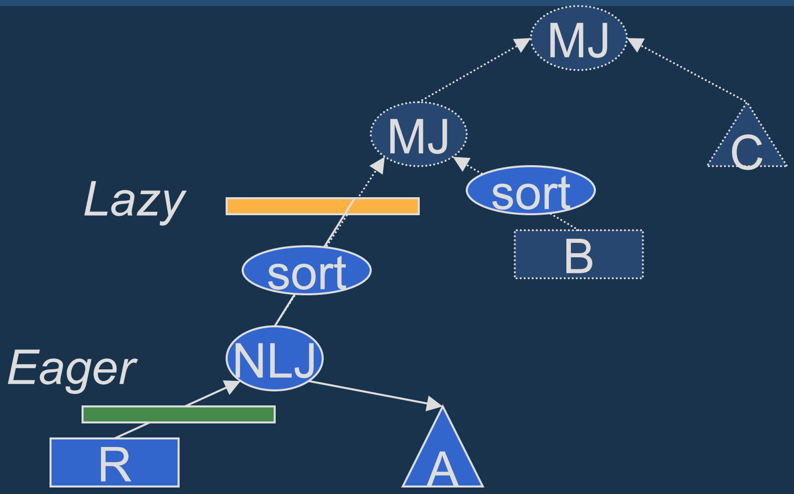
Re-estimated selectivities

0.5

0.01

Significantly different ➔ original plan probably sub-optimal
Reoptimize the remaining part of the query

Where to Place Checkpoints?



More checkpoints → more opportunities for switching plans

Overhead of (simple) monitoring is small [SLMK'01]

Consideration: it is easier to switch plans at some checkpoints than others

Lazy checkpoints: placed above materialization points

- No work need be wasted if we switch plans here

Eager checkpoints: can be placed anywhere

- May have to discard some partially computed results
- Useful where optimizer estimates have high uncertainty

When to Re-optimize?

- Suppose actual cardinality is different from estimates: how high a difference should trigger a re-optimization?

- Idea: do not re-optimize if current plan is still the best

1. Heuristics-based [KD'98]:

   e.g., re-optimize < time to finish execution

2. Validity range [MRS+04]: precomputed range of a parameter (e.g., a cardinality) within which plan is optimal
   - Place eager checkpoints where the validity range is narrow
   - Re-optimize if value falls outside this range
   - Variation: bounding boxes [BBD'05]

How to Reoptimize

Getting a better plan:

- Plug in actual cardinality information acquired during this query (as possibly histograms), and re-run the optimizer

Reusing work when switching to the better plan:

- Treat fully computed intermediate results as materialized views
    - Everything that is under a materialization point
- Note: It is optional for the optimizer to use these in the new plan

➢ Other approaches are possible (e.g., query scrambling [UFA'98])

Pipelined Execution

Adapting Pipelined Queries

Adapting pipelined execution is often necessary:

- Too few materializations in today's systems
- Long-running queries
- Wide-area data sources
- Potentially endless data streams

The tricky issues:

- Some results may have been delivered to the user
  - Ensuring correctness non-trivial
- Database operators build up *state*
  - Must reason about it during adaptation
  - May need to manipulate state

Adapting Pipelined Queries

We discuss three subclasses of the problem:

- *Selection ordering (stateless)*
  - Very good analytical and theoretical results
  - Increasingly important in web querying, streams, sensornets
  - Certain classes of join queries reduce to them
- *Select-project-join queries (stateful*)
  - *History-independent* execution
    - Operator state largely independent of execution history
      → Execution decisions for a tuple independent of prior tuples
  - *History-dependent* execution
    - Operator state depends on execution history
    - Must reason about the state during adaptation

Pipelined Execution Part I:
Adaptive Selection Ordering

Adaptive Selection Ordering

Complex predicates on single relations common

- e.g., on an employee relation:

  ((*salary* > *120000*) AND (*status* = 2)) OR

  ((*salary* between *90000* and *120000*) AND (*age* < *30*) AND (*status* = *1*)) OR …

Selection ordering problem:

Decide the order in which to evaluate the individual predicates against the tuples

We focus on *conjunctive predicates* (containing only AND’s)

Example Query

```
select * from R
where R.a = 10 and R.b < 20
and R.c like '%name%';
```

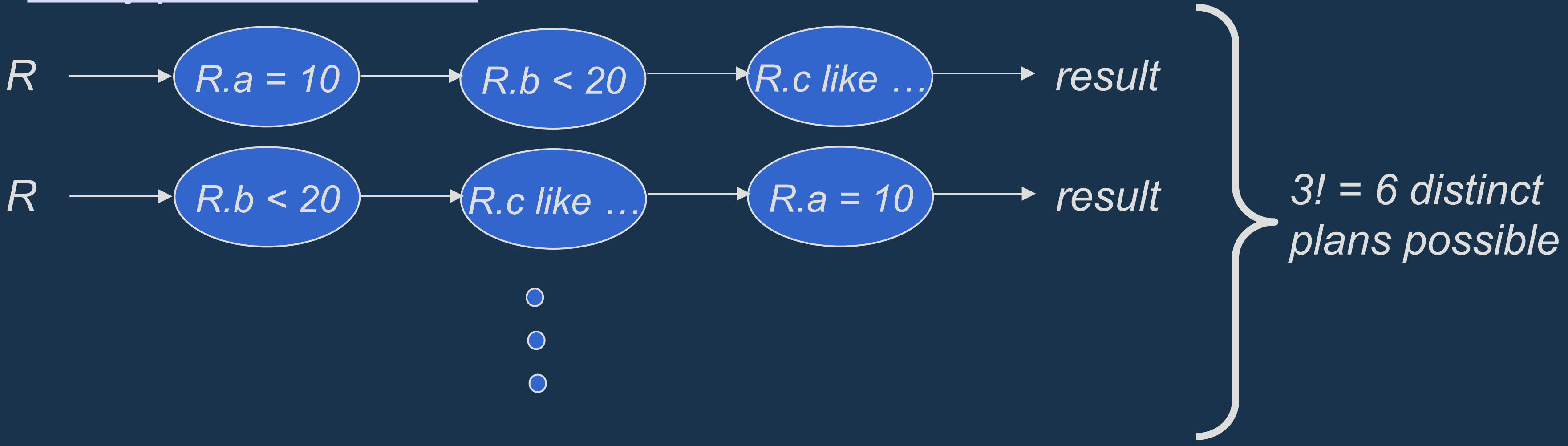
Basics: Static Optimization

Find a *single order of the selections* to be used for *all tuples*

Query

```
select * from R
where R.a = 10 and R.b < 20
and R.c like '%name%';
```

Query plans considered

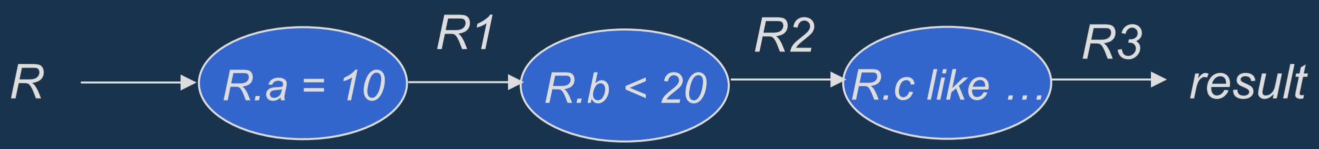


Static Optimization

Cost metric: CPU instructions

Computing the cost of a plan

- Need to know the *costs* and the *selectivities* of the predicates



costs	*c1*		*c2*		*c3*
selectivities	*s1*		*s2*		*s3*
cost per tuple	*c1*	+	*s1 c2*	+	*s1 s2 c3*

Independence assumption

*cost(plan) = |R| * (c1 + s1 * c2 + s1 * s2 * c3)*

Static Optimization

Rank ordering algorithm for *independent* selections [IK'84]

- Apply the predicates in the decreasing order of *rank:*

  (1 – s) / c

  where s = selectivity, c = cost

For *correlated* selections:

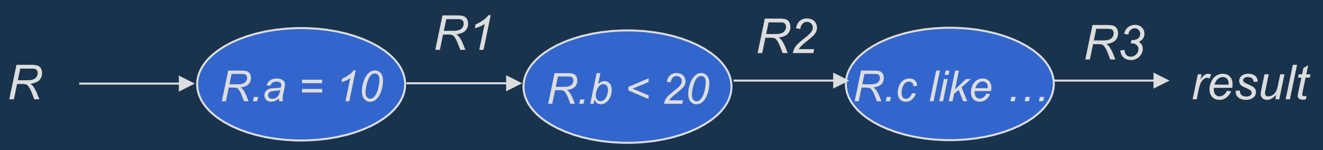
- NP-hard under several different formulations
  - e.g. when given a random sample of the relation

- Greedy algorithm, shown to be 4-approximate [BMMNW'04]:
  - Apply the selection with the highest *(1 - s)/c*
  - Compute the selectivities of remaining selections over the *result*
    - *Conditional selectivities*
  - Repeat

Eddies [AH'00]

Query processing as routing of tuples through operators

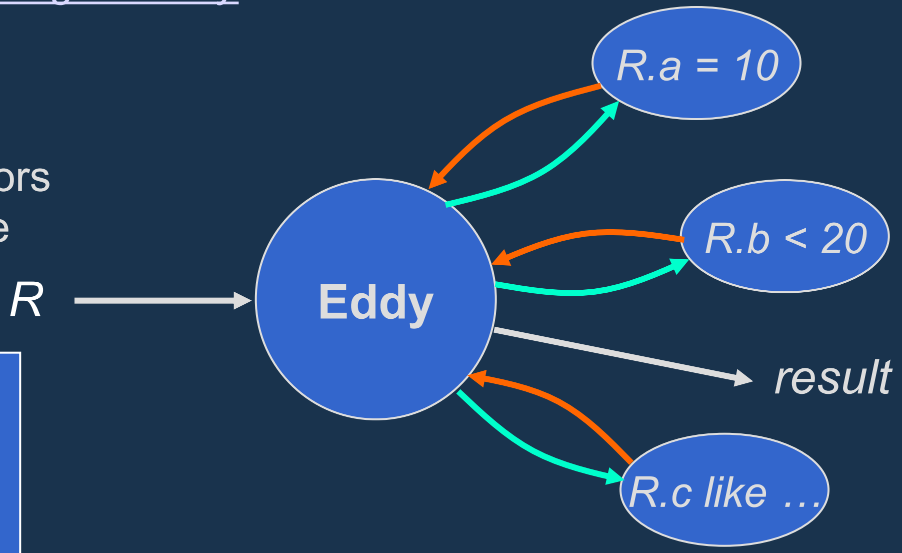
A traditional pipelined query plan



Pipelined query execution using an eddy

An *eddy* operator

- Intercepts tuples from sources and output tuples from operators
- Executes query by routing source tuples through operators

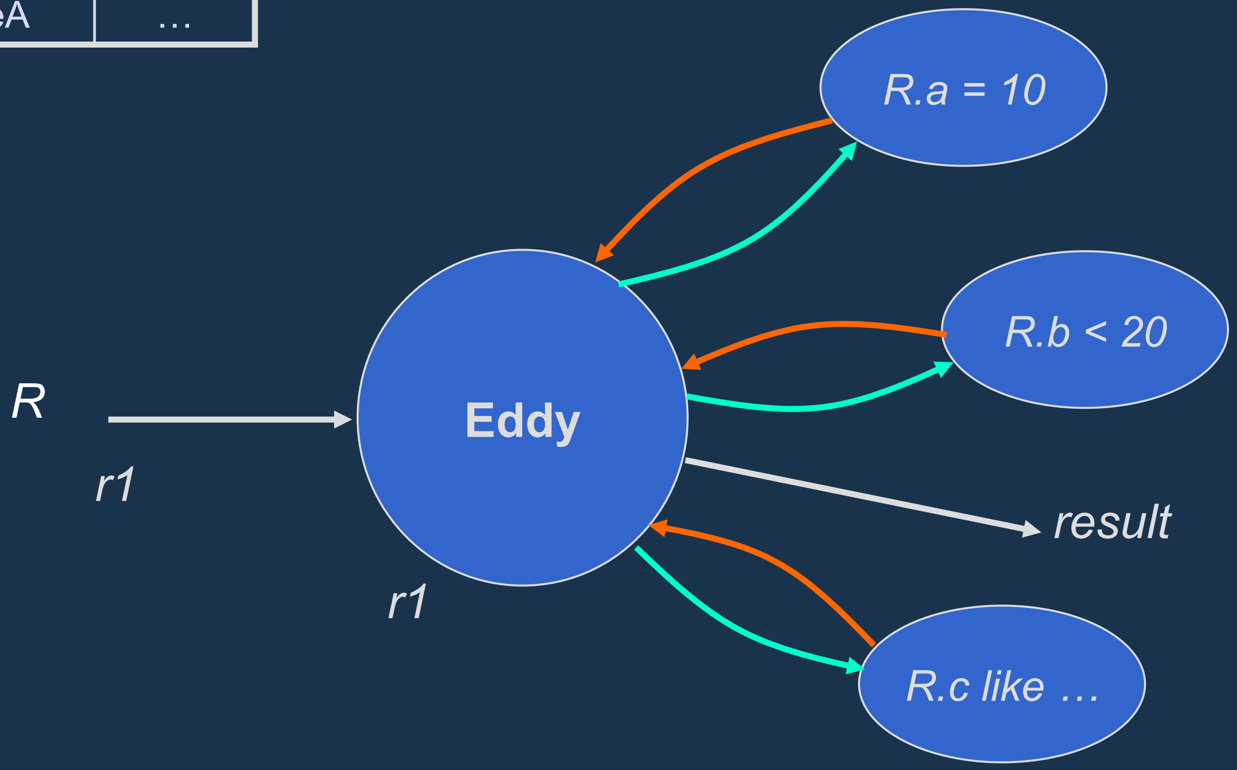


Encapsulates all aspects of adaptivity in a “standard” dataflow operator: measure, model, plan and actuate.

Eddies [AH'00]

An R Tuple: *r1*

a	b	c	…
15	10	AnameA	…



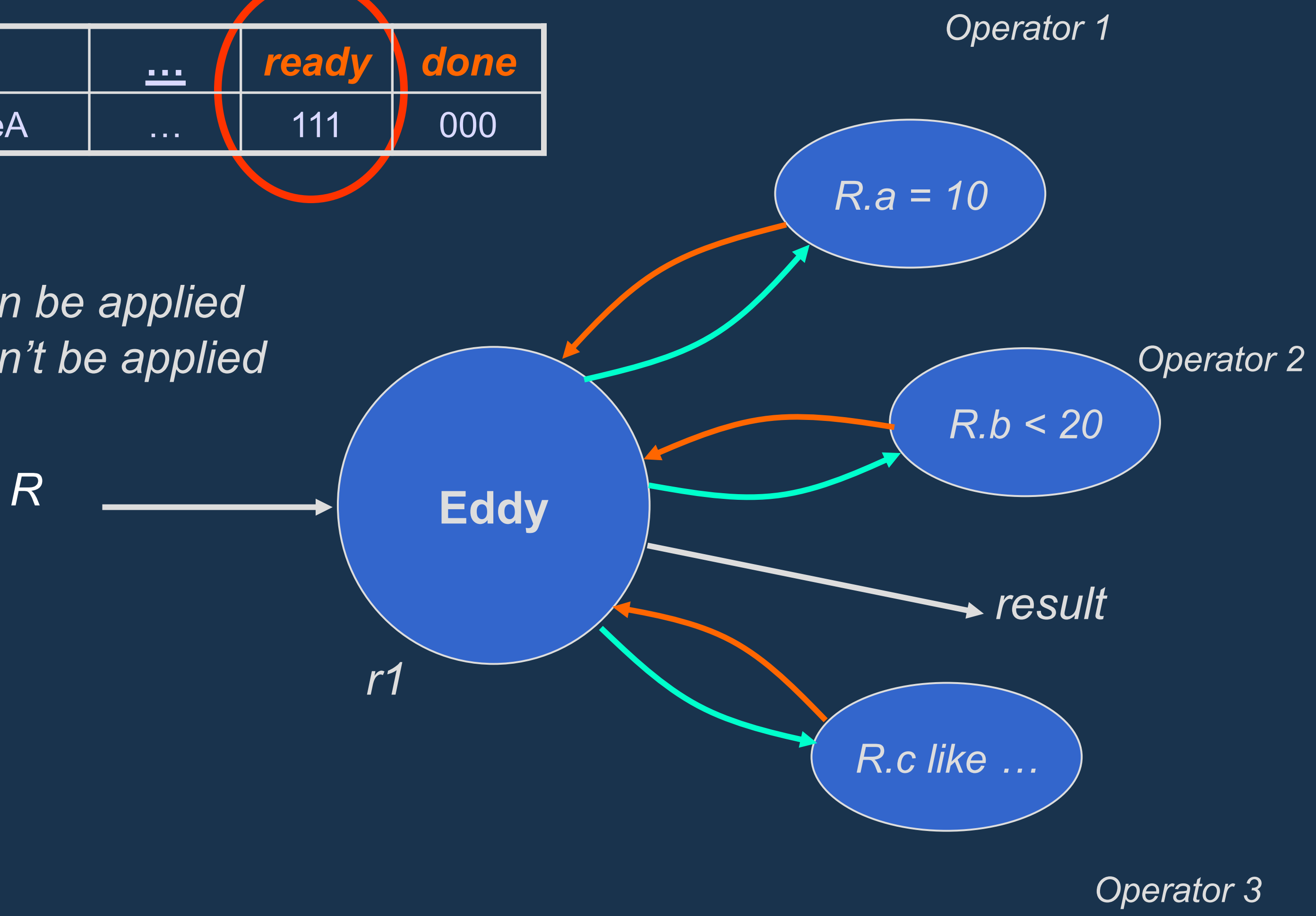
Eddies [AH’00]

An R Tuple: r1

a	b	c	…	ready	done
15	10	AnameA	…	111	000

ready bit i :

1 → operator i *can be applied*
0 → operator i *can’t be applied*



Eddies [AH'00]

An R Tuple: r1

a	b	c	…	*ready*	*done*
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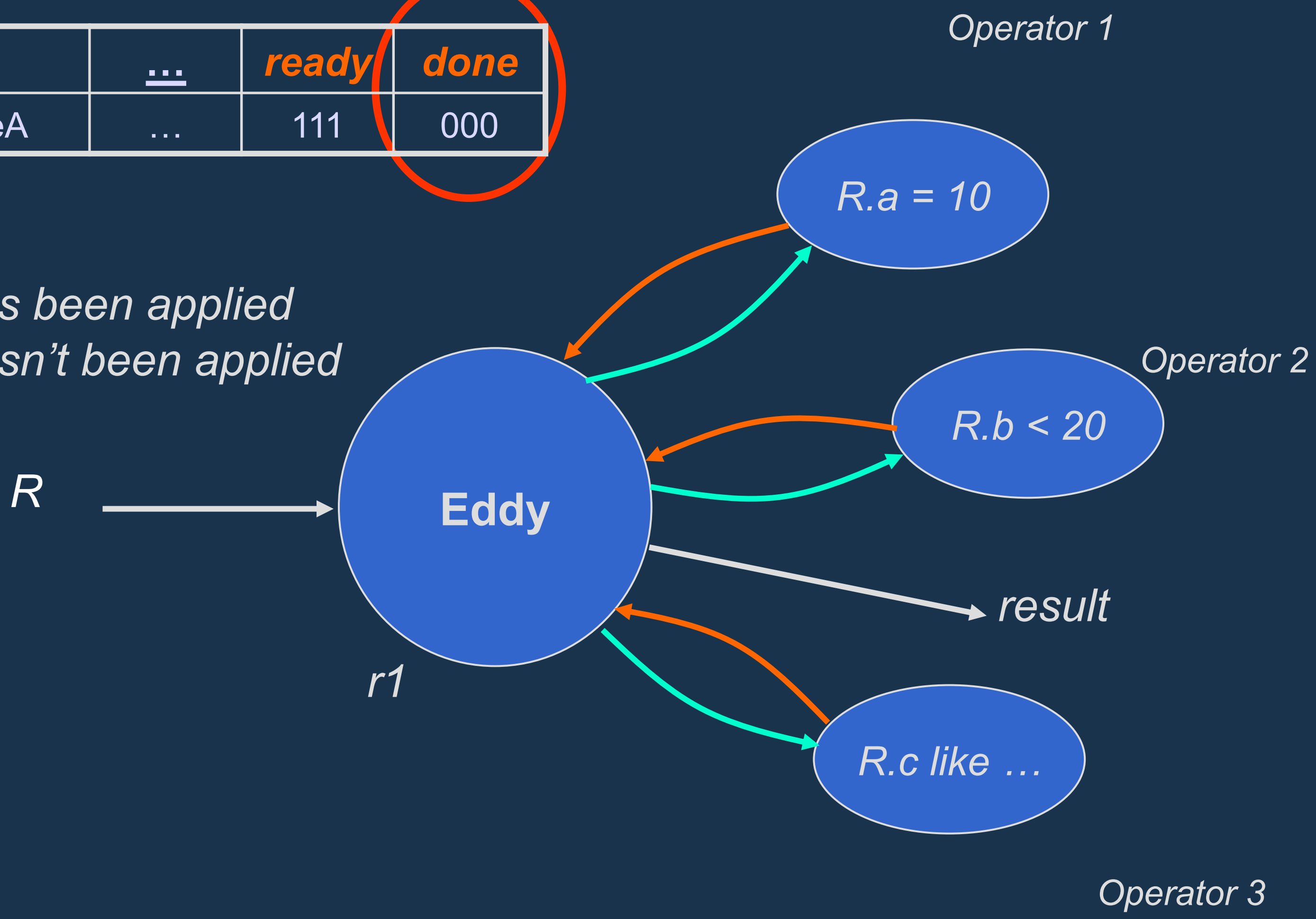
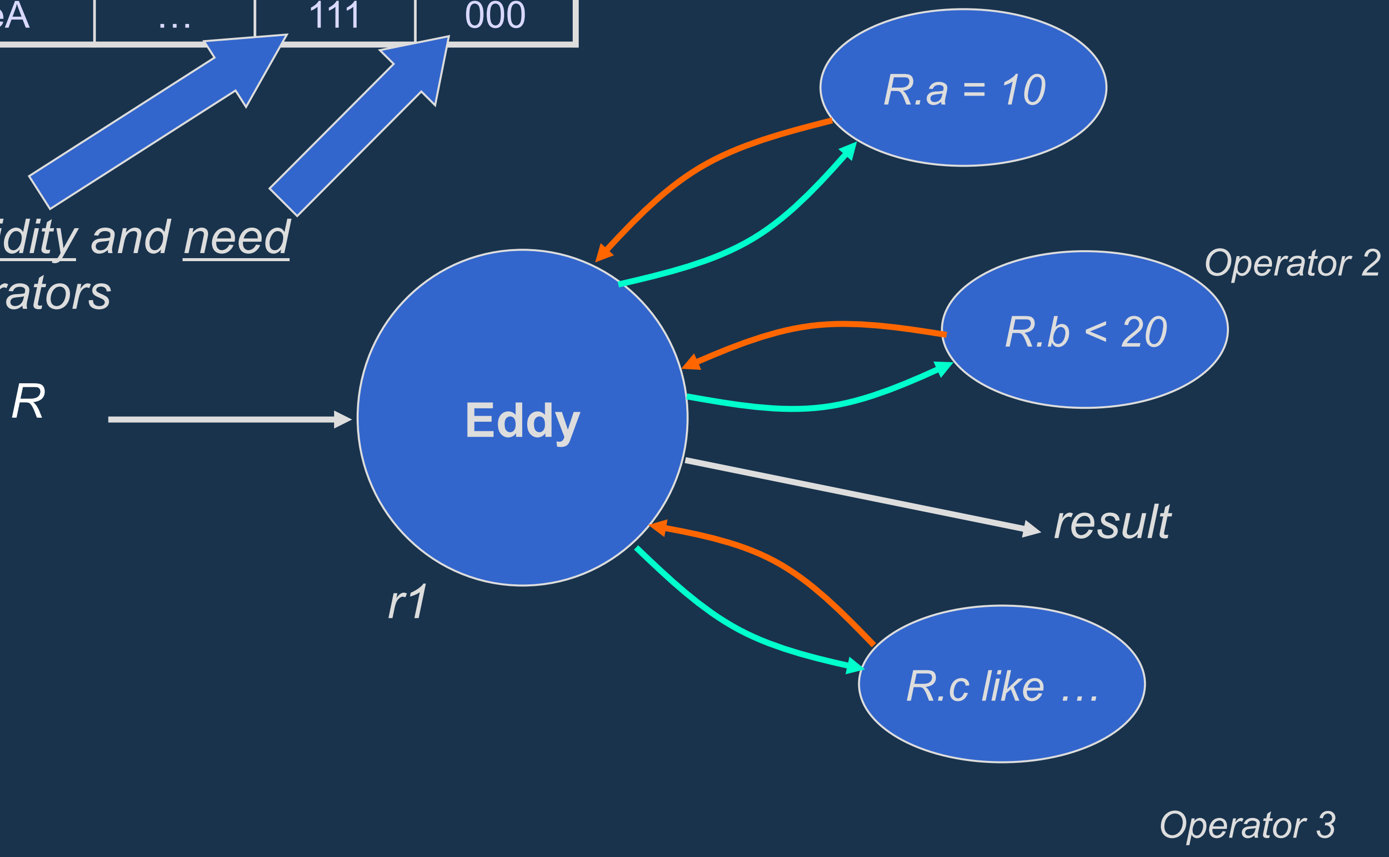


Eddies [AH’00]

An R Tuple: r1

a	b	c	…	***ready***	***done***
15	10	AnameA	…	111	000

Used to decide validity and need of applying operators

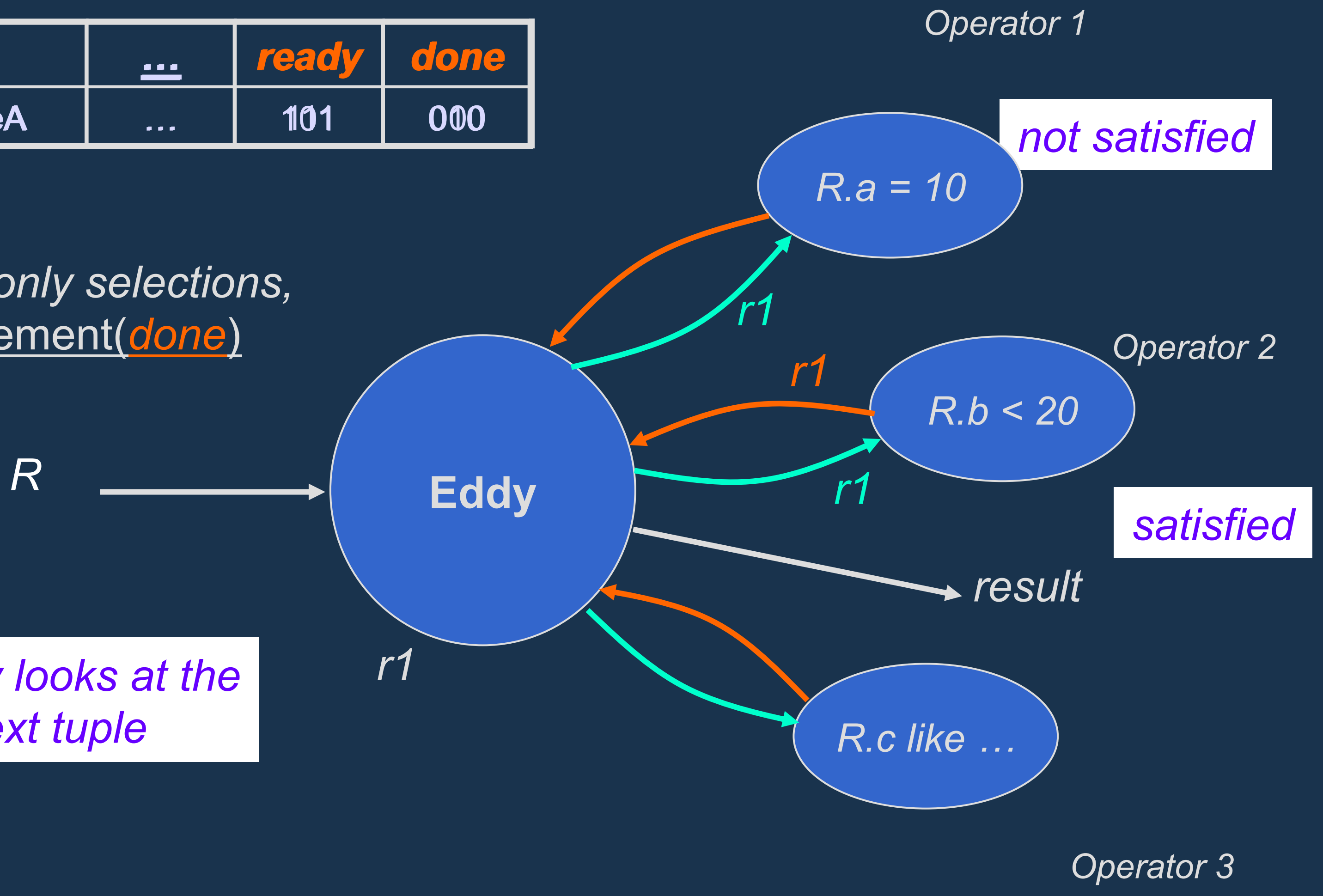


Eddies [AH'00]

An R Tuple: r1

a	b	c	...	***ready***	***done***
15	10	AnameA	…	101	000

For a query with only selections,
ready = complement(*done*)



not satisfied

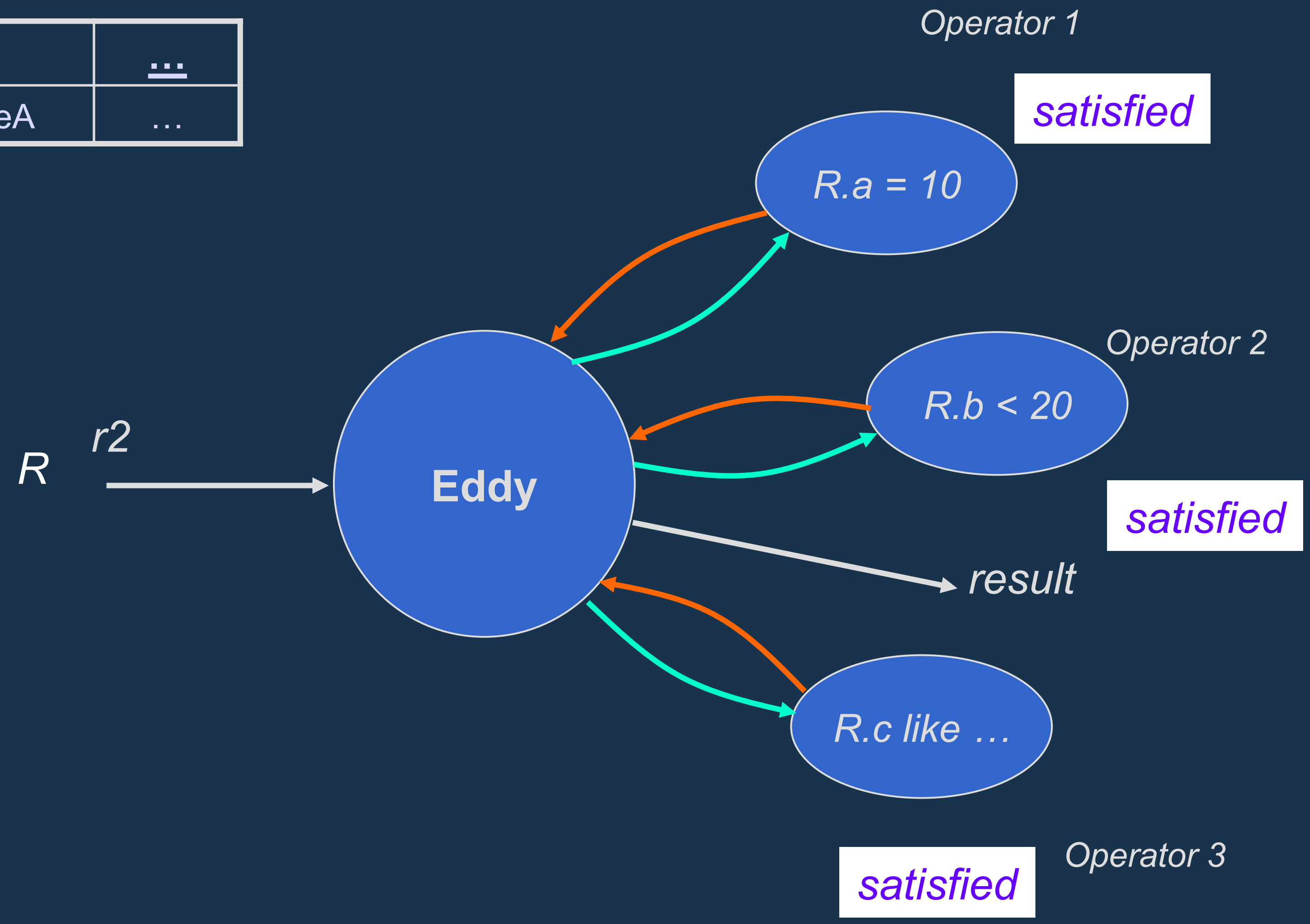
satisfied

eddy looks at the next tuple

Eddies [AH'00]

An R Tuple: r2

a	b	c	…
10	15	AnameA	…

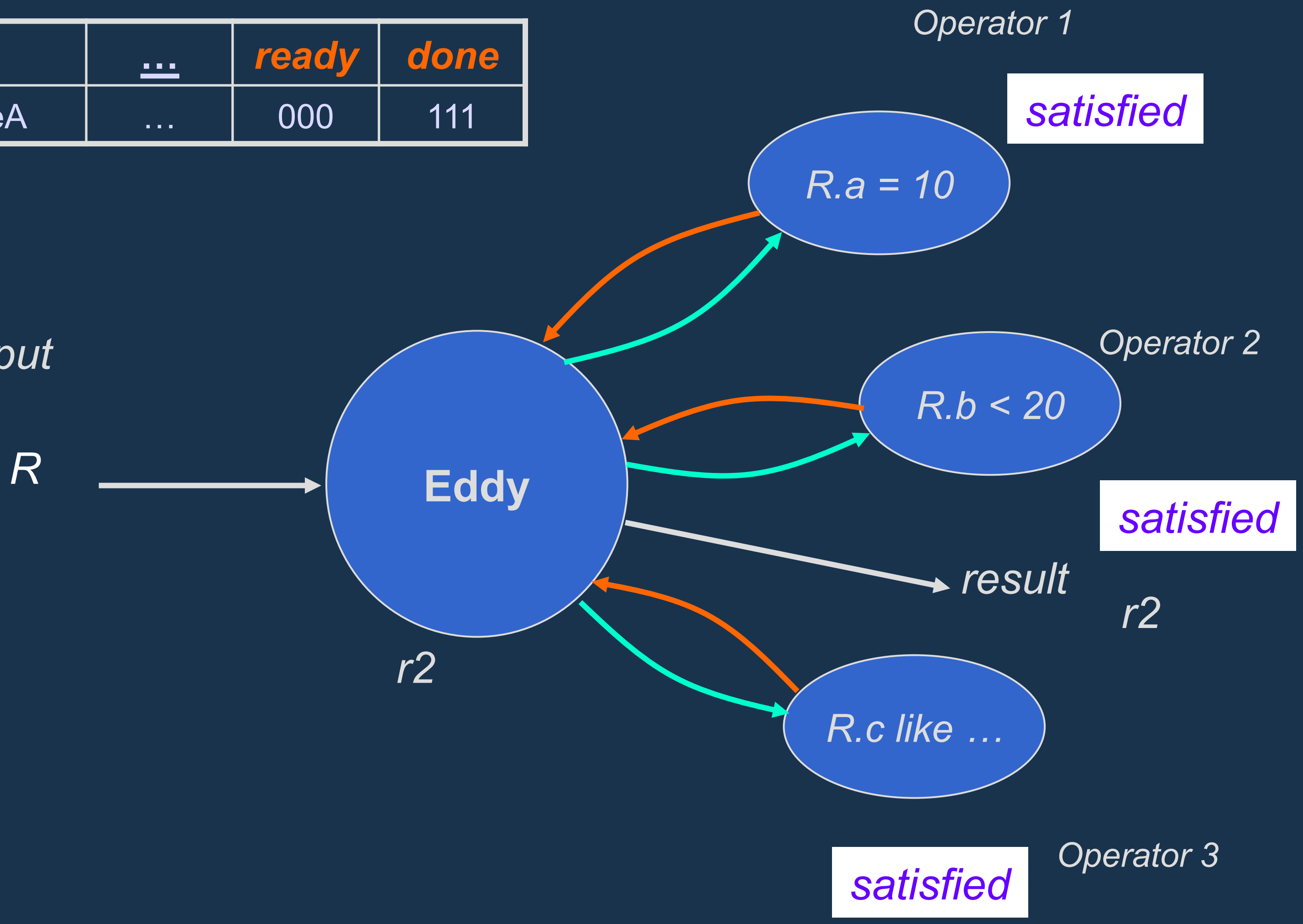


Eddies [AH'00]

An R Tuple: r2

a	b	c	…	*ready*	*done*
10	15	AnameA	…	000	111

if done = 111,
send to output



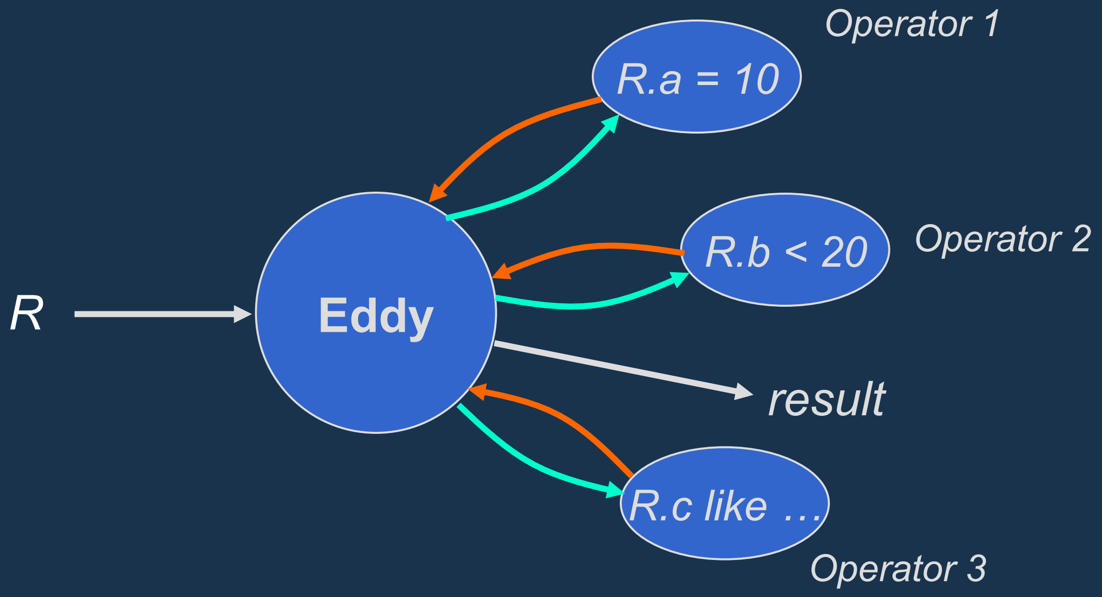
Eddies [AH'00]

Adapting order is easy

- Just change the operators to which tuples are sent
- Can be done on a per-tuple basis
- Can be done in the middle of tuple's "pipeline"

How are the *routing decisions* made?

Using a *routing policy*



Routing Policies that Have Been Studied

Deterministic [D03]

- Monitor costs & selectivities continuously
- Re-optimize periodically using rank ordering (or A-Greedy for correlated predicates)

Lottery scheduling [AH00]

- Each operator runs in thread with an input queue
- “Tickets” assigned according to tuples input / output
- Route tuple to next eligible operator with room in queue, based on number of “tickets” and “backpressure”

Content-based routing [BBDW05]

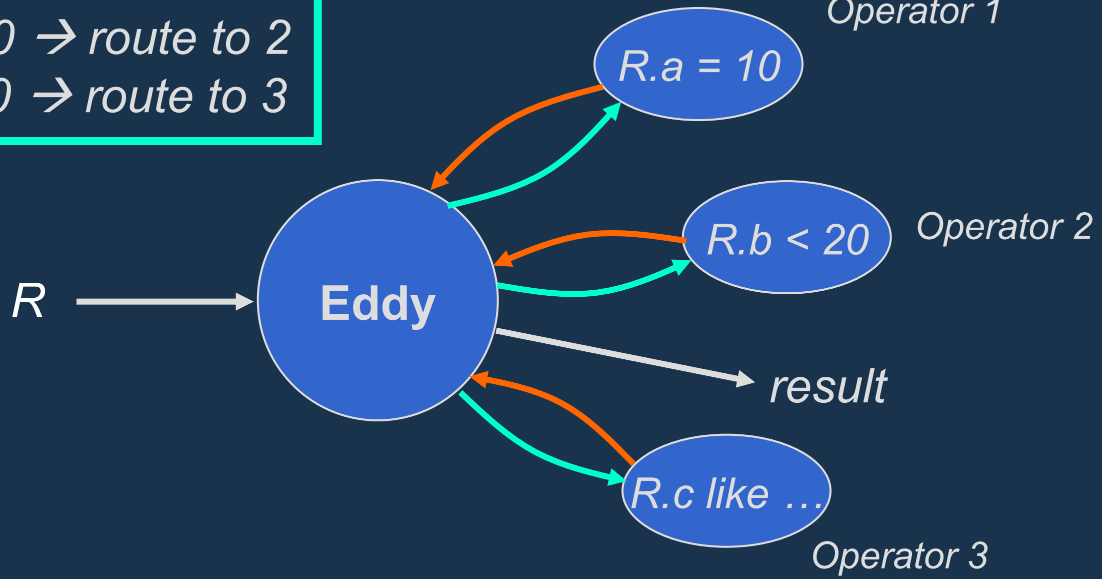
- Different routes for different plans based on attribute values

Routing Policy 1: Non-adaptive

- Simulating a single static order
  - E.g. operator 1, then operator 2, then operator 3

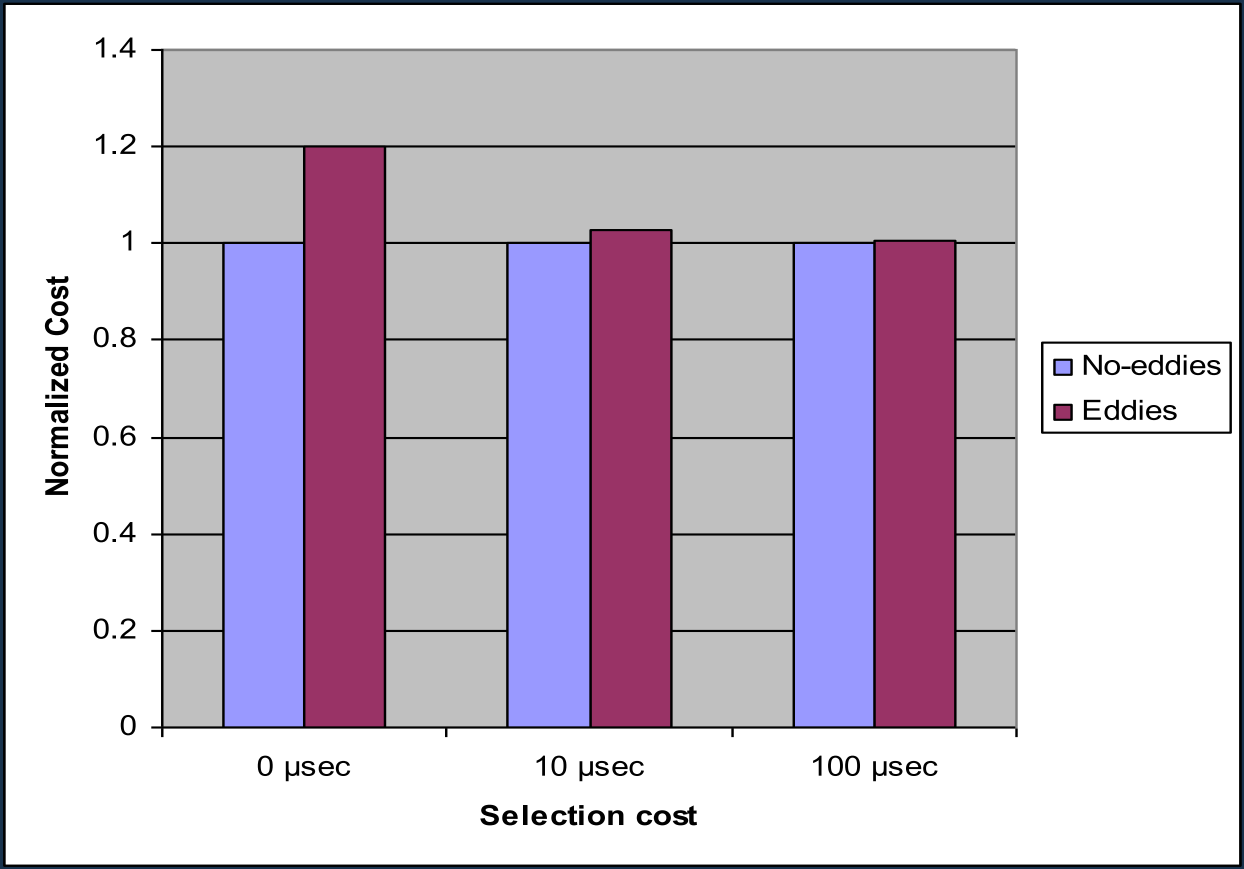
table lookups → very efficient

Routing policy:
*if **done** =*
000 → route to 1
100 → route to 2
110 → route to 3



Overhead of Routing

- PostgreSQL implementation of eddies using *bitset lookups* [Telegraph Project]
- Queries with 3 selections, of varying cost
  - Routing policy uses a *single static order,* i.e., no adaptation



Routing Policy 2: Deterministic

- Monitor costs and selectivities *continuously*
- Reoptimize *periodically* using KBZ

Can use specialized policies for correlated predicates

Statistics Maintained:

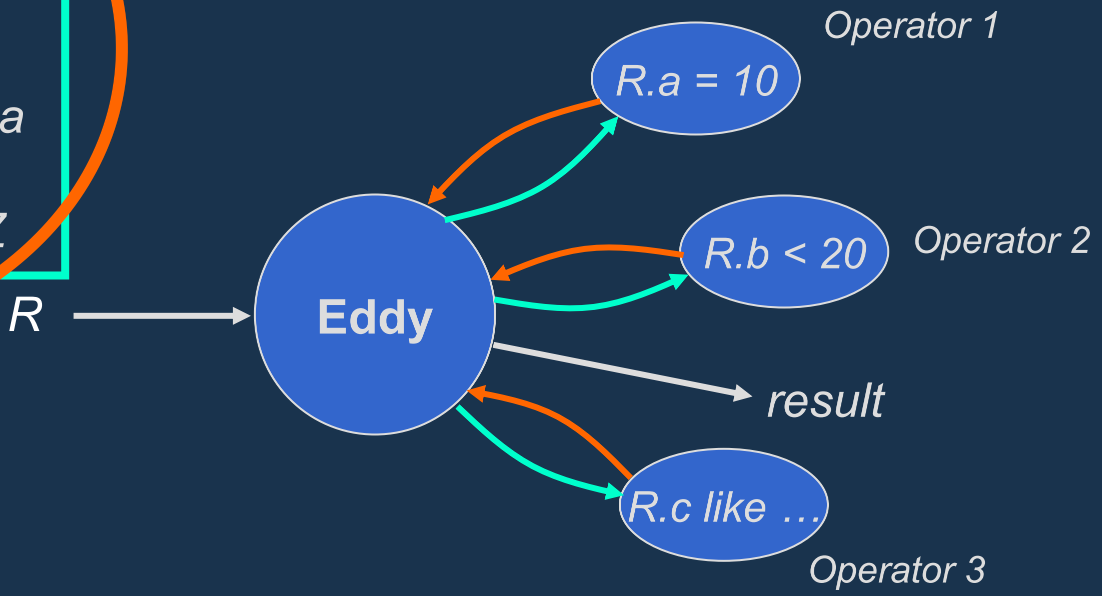
Costs of operators

Selectivities of operators

Routing policy:

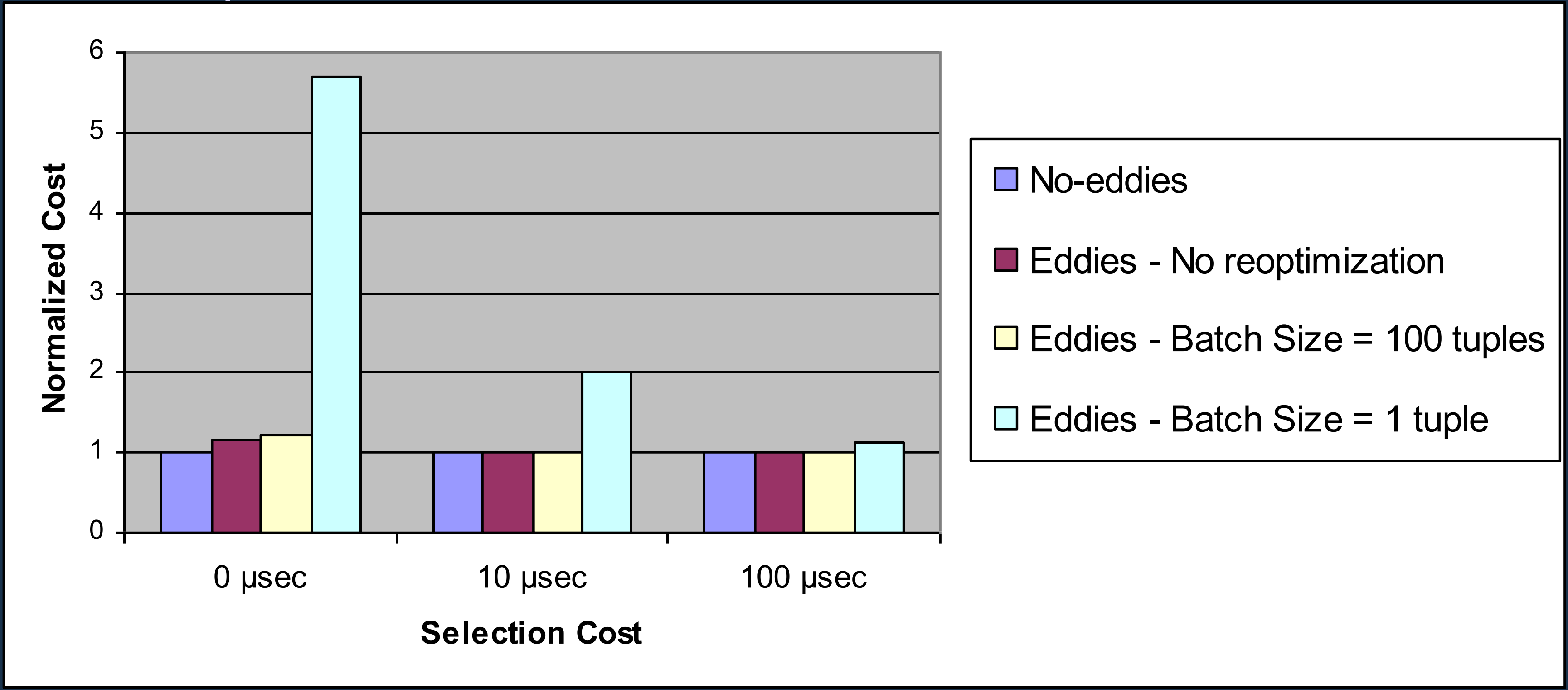
Use a single order for a batch of tuples

Periodically apply KBZ



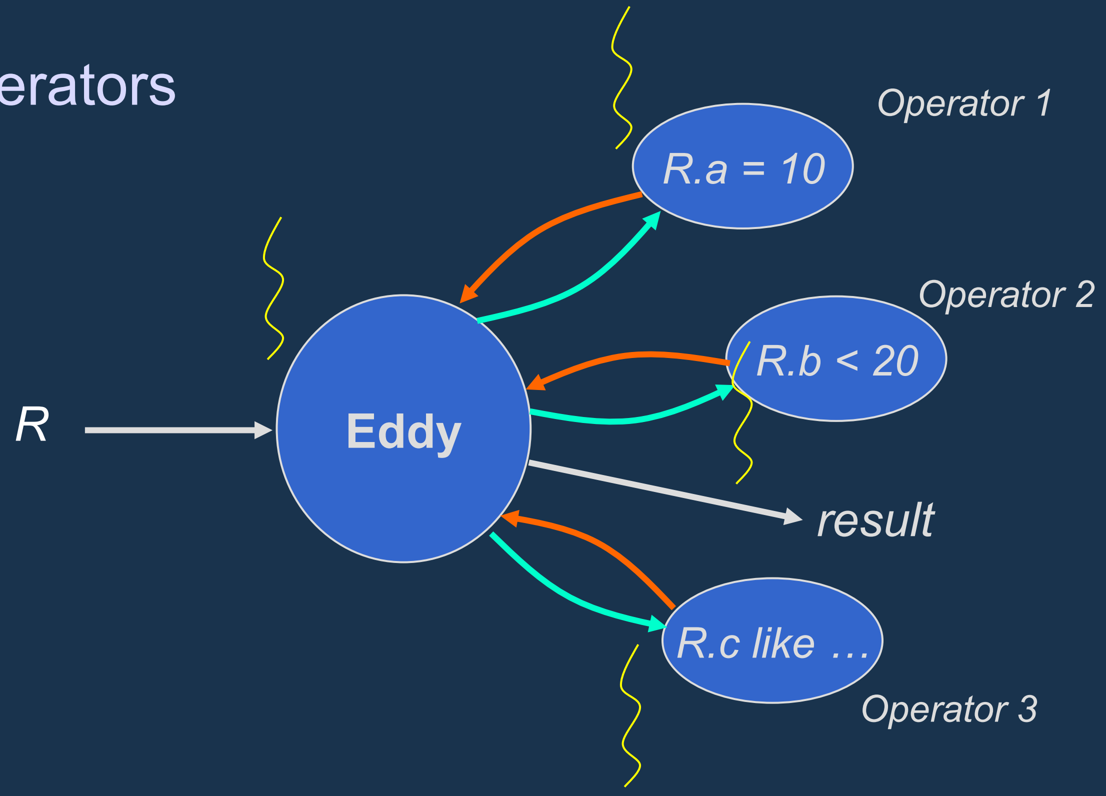
Overhead of Routing and Reoptimization

- Adaptation using *batching*
  - Reoptimized every *X* tuples using monitored selectivities
  - Identical selectivities throughout ➔ experiment measures only the overhead



Routing Policy 3: Lottery Scheduling

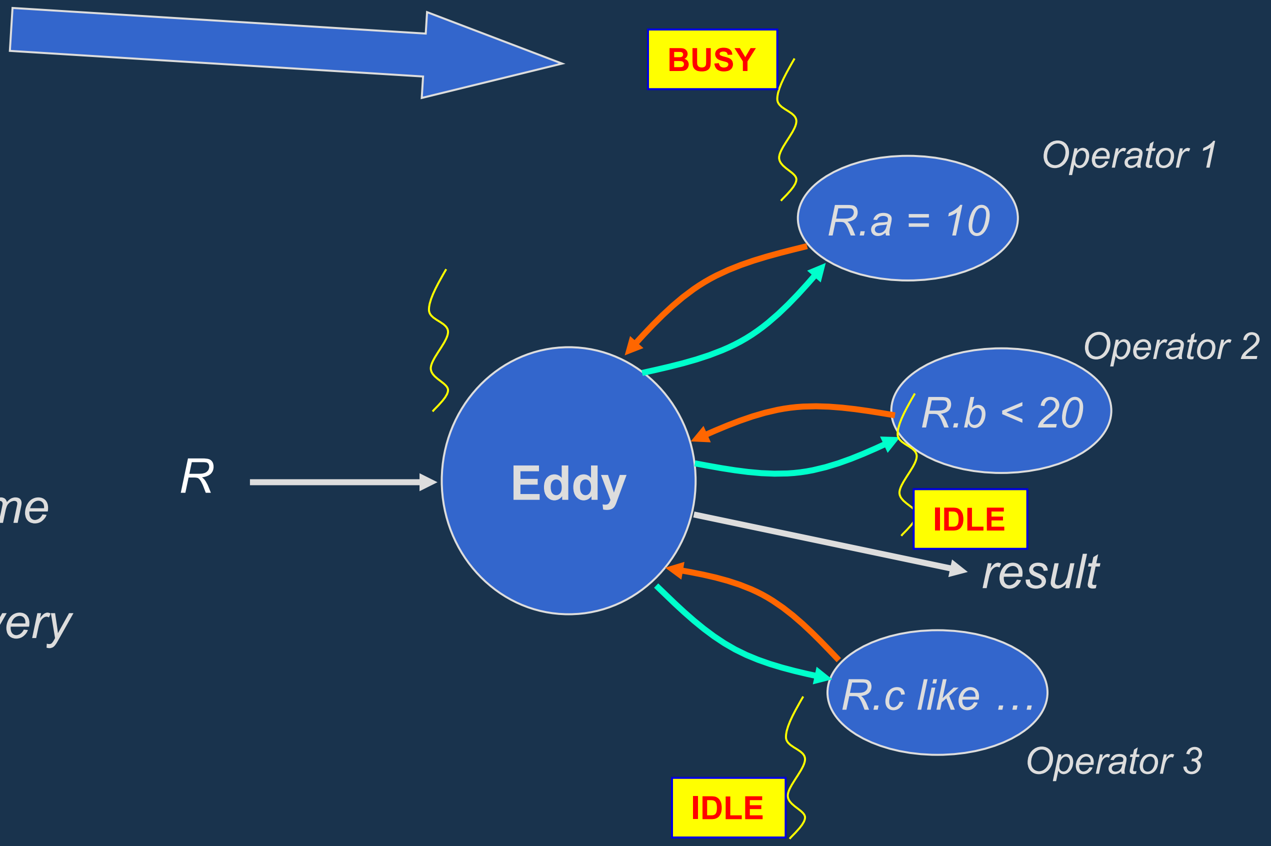
- Originally suggested routing policy [AH'00]
- Applicable only if each operator runs in a separate thread
- Uses two easily obtainable pieces of information for making routing decisions:
  - *Busy/idle status* of operators
  - *Tickets* per operator



Routing Policy 3: Lottery Scheduling

- Routing decisions based on busy/idle status of operators

Rule:
IF operator busy,
THEN do not route more tuples to it



Rationale:
Every thread gets equal time
SO IF an operator is busy,
THEN its cost is perhaps very high

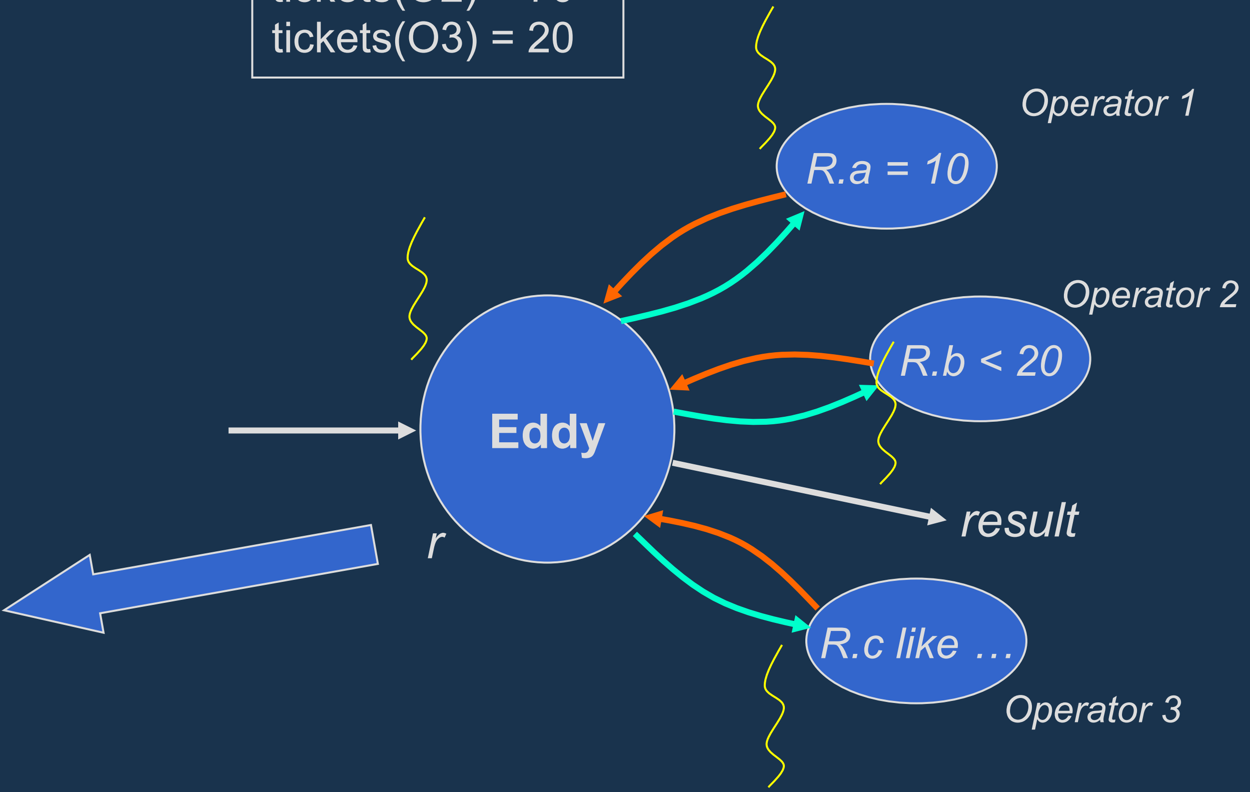
Routing Policy 3: Lottery Scheduling

- Routing decisions based on tickets

Rules:

1. Route a new tuple randomly weighted according to the number of tickets

tickets(O1) = 10
tickets(O2) = 70
tickets(O3) = 20



Will be routed to:

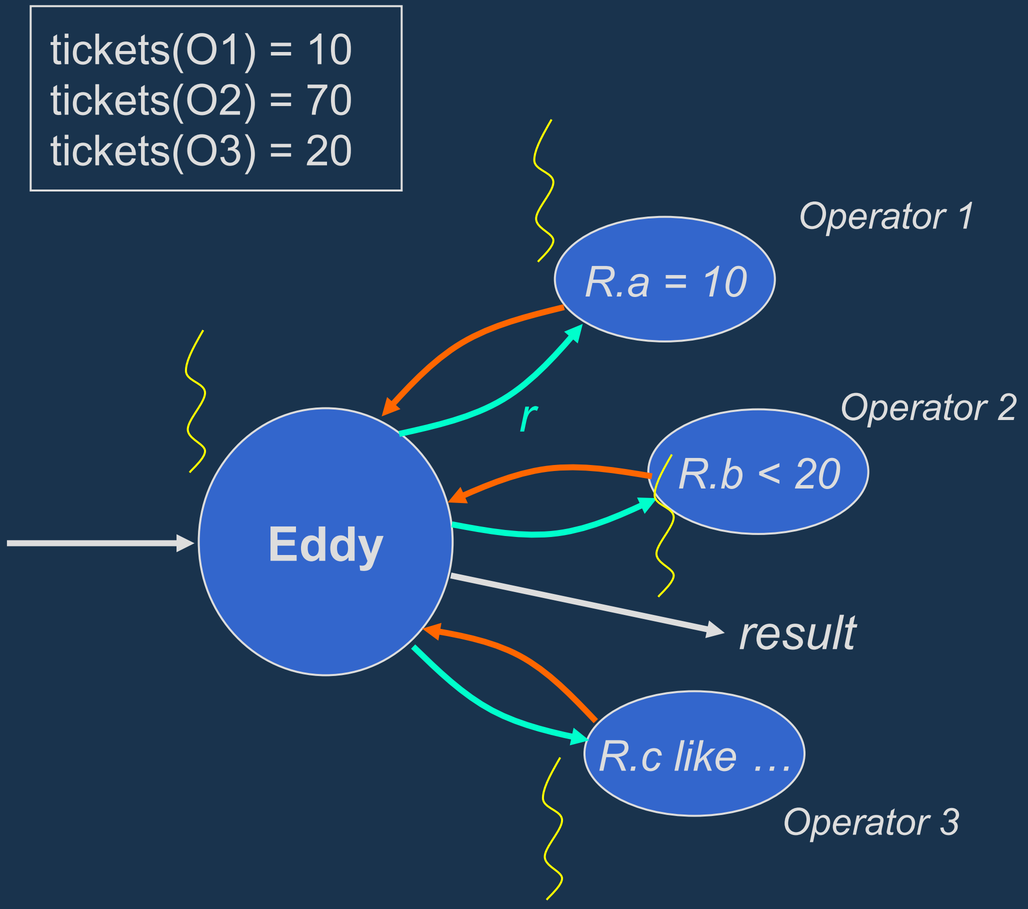
O1	*w.p.*	*0.1*
O2	*w.p.*	*0.7*
O3	*w.p.*	*0.2*

Routing Policy 3: Lottery Scheduling

- Routing decisions based on tickets

Rules:

1. *Route a new tuple randomly weighted according to the number of tickets*



tickets(O1) = 10
tickets(O2) = 70
tickets(O3) = 20

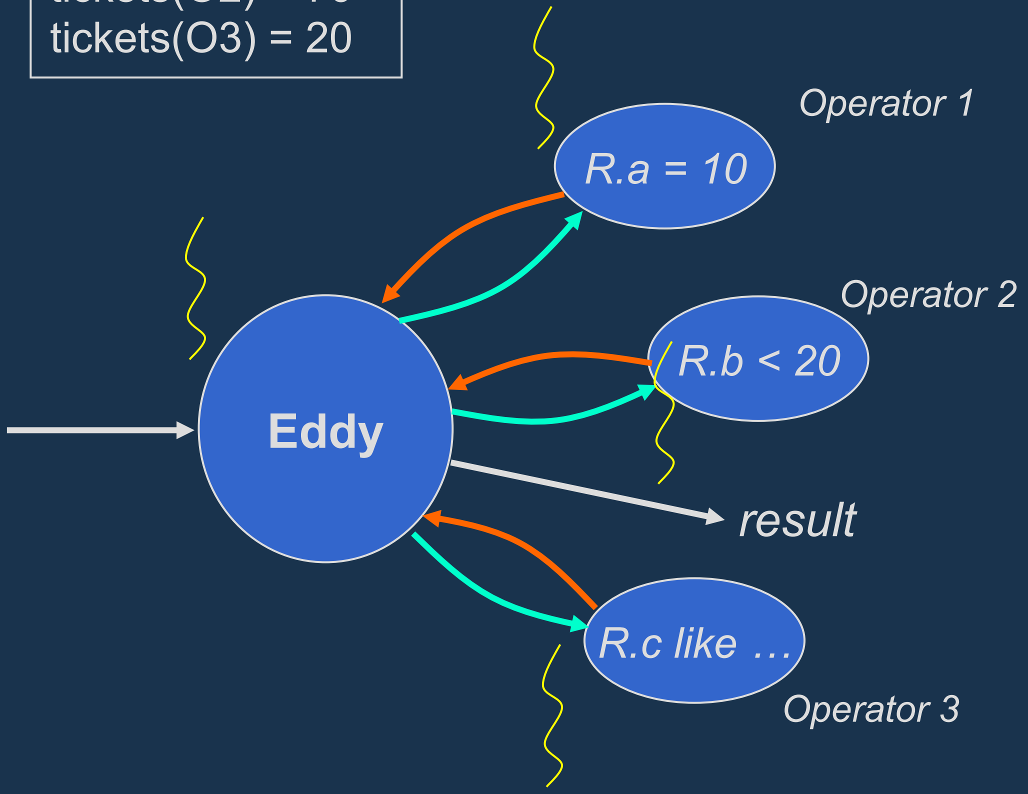
Routing Policy 3: Lottery Scheduling

- Routing decisions based on tickets

Rules:

1. *Route a new tuple randomly weighted according to the number of tickets*
2. *route a tuple to an operator O_i*
   $tickets(O_i)$ ++;

tickets(O1) = 11
tickets(O2) = 70
tickets(O3) = 20



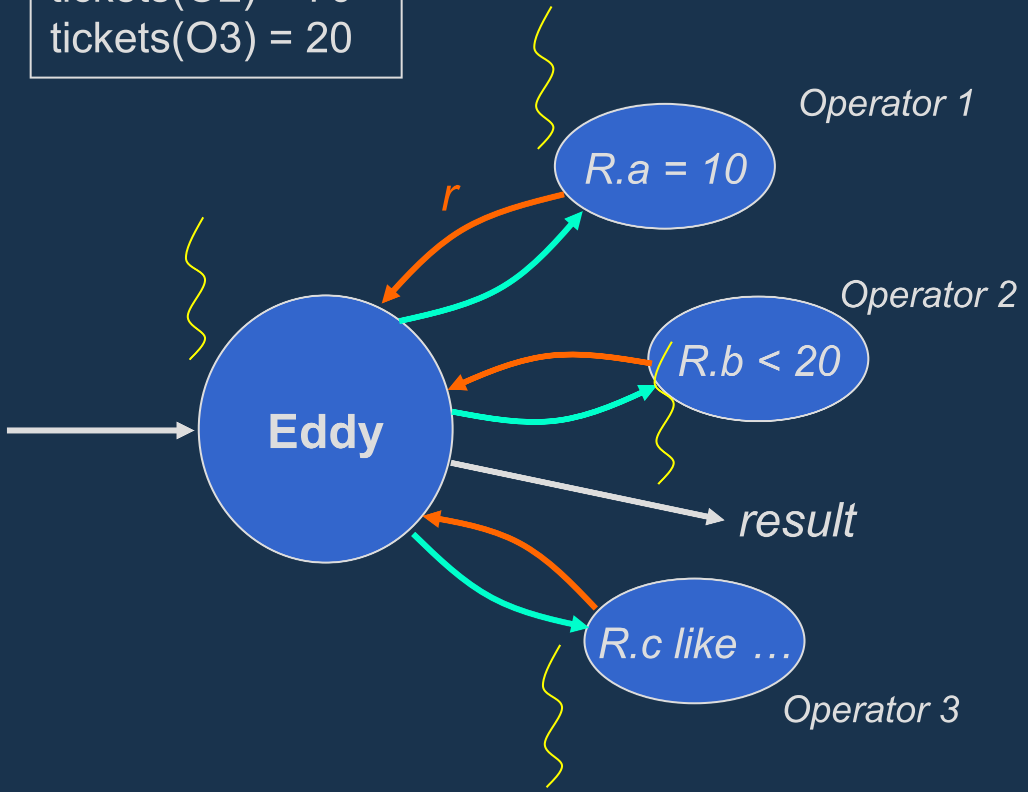
Routing Policy 3: Lottery Scheduling

- Routing decisions based on tickets

Rules:

1. *Route a new tuple randomly weighted according to the number of tickets*
2. *route a tuple to an operator O_i*
   tickets(O_i) ++;
3. *O_i returns a tuple to eddy*
   tickets(O_i) --;

tickets(O1) = 11
tickets(O2) = 70
tickets(O3) = 20



Routing Policy 3: Lottery Scheduling

- Routing decisions based on tickets

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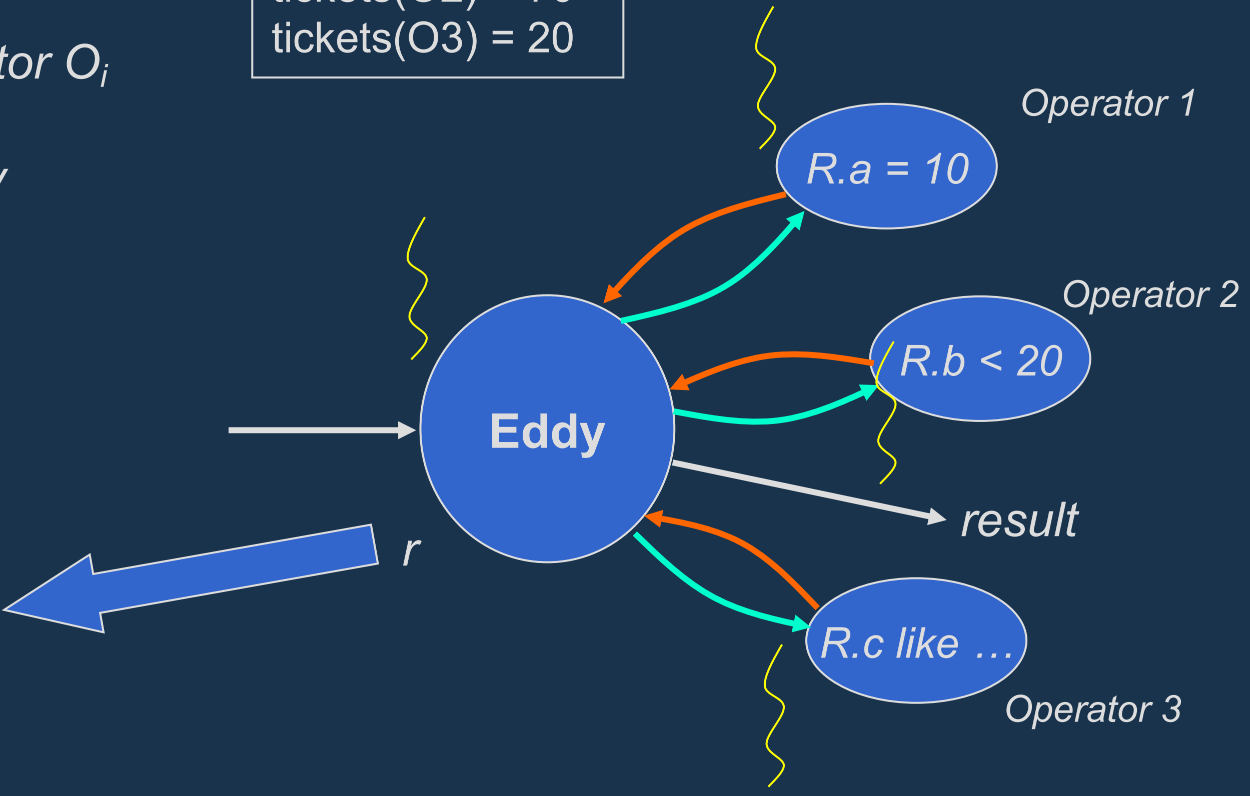
tickets(O2) = 70
tickets(O3) = 20



Will be routed to:

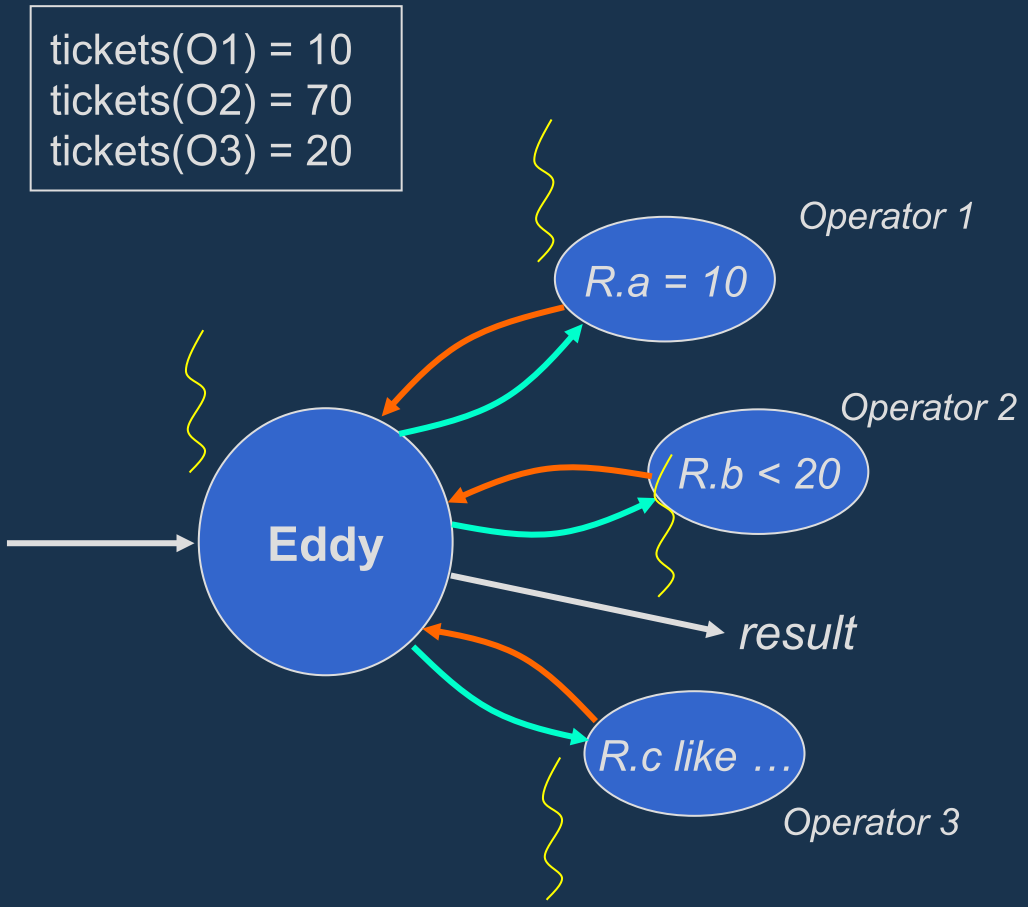
O2	*w.p.*	*0.777*
O3	*w.p.*	*0.222*

Routing Policy 3: Lottery Scheduling

- Routing decisions based on tickets

Rules:

1. *Route a new tuple randomly weighted according to the number of tickets*
2. *route a tuple to an operator O_i*
   tickets(O_i) ++;
3. *O_i returns a tuple to eddy*
   tickets(O_i) --;



tickets(O1) = 10
tickets(O2) = 70
tickets(O3) = 20

Rationale:

Tickets(O_i) roughly corresponds to (1 - selectivity(O_i))

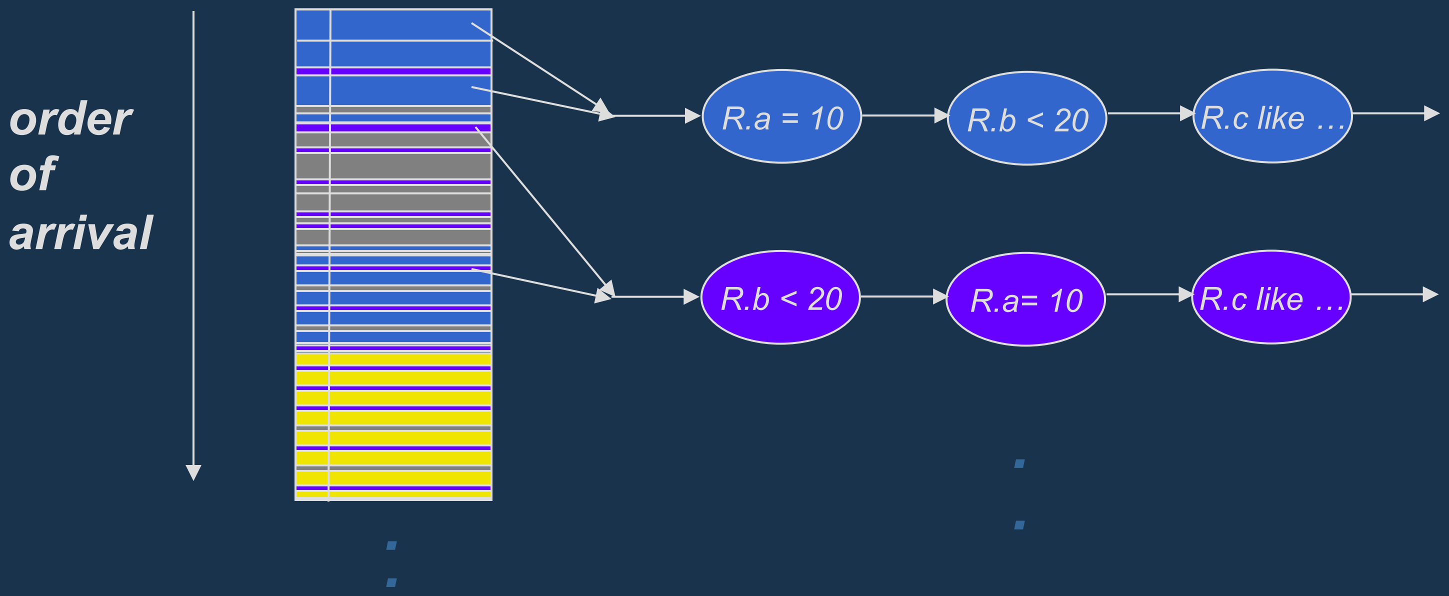
So more tuples are routed to highly selective operators

Routing Policy 3: Lottery Scheduling

- Effect of the combined lottery scheduling policy:
  - Low cost operators get more tuples
  - Highly selective operators get more tuples
  - Some tuples are knowingly routed according to sub-optimal orders
    - To *explore*
    - Necessary to detect selectivity changes over time

Eddies: Post-Mortem

- Plan Space explored
  - Allows arbitrary "*horizontal partitioning*"
  - Not necessarily correlated with order of arrival



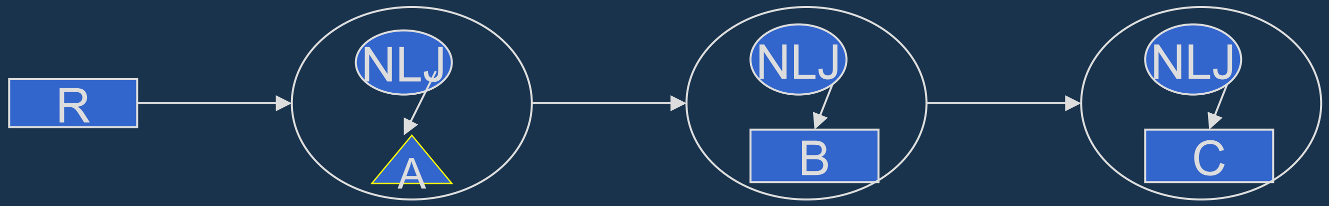
In a later paper, we looked at optimizing for horizontal partitioning directly

Pipelined Execution Part II: Adaptive Join Processing

Adaptive Join Processing: Outline

- Single streaming relation
  - Left-deep pipelined plans
- Multiple streaming relations
  - Execution strategies for multi-way joins
  - History-independent execution
  - History-dependent execution

Left-Deep Pipelined Plans

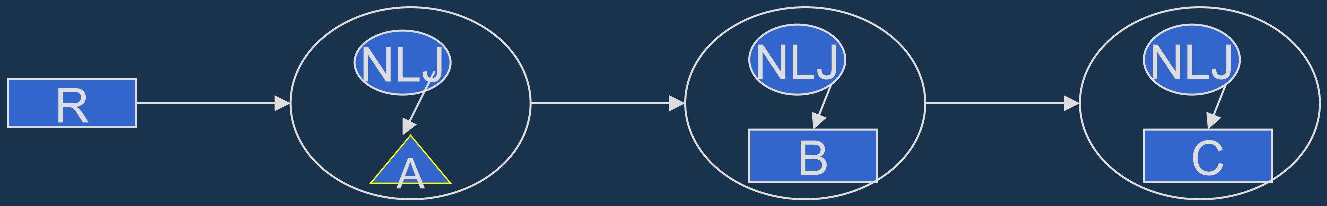


Simplest method of joining tables

- Pick a *driver* table (R). Call the rest *driven* tables
- Pick access methods (AMs) on the driven tables (*scan, hash, or index*)
- Order the driven tables
- Flow R tuples through the driven tables

```
For each r ∈ R do:
look for matches for r in A;
for each match a do:
        look for matches for <r,a> in B;
        …
```

Adapting a Left-deep Pipelined Plan



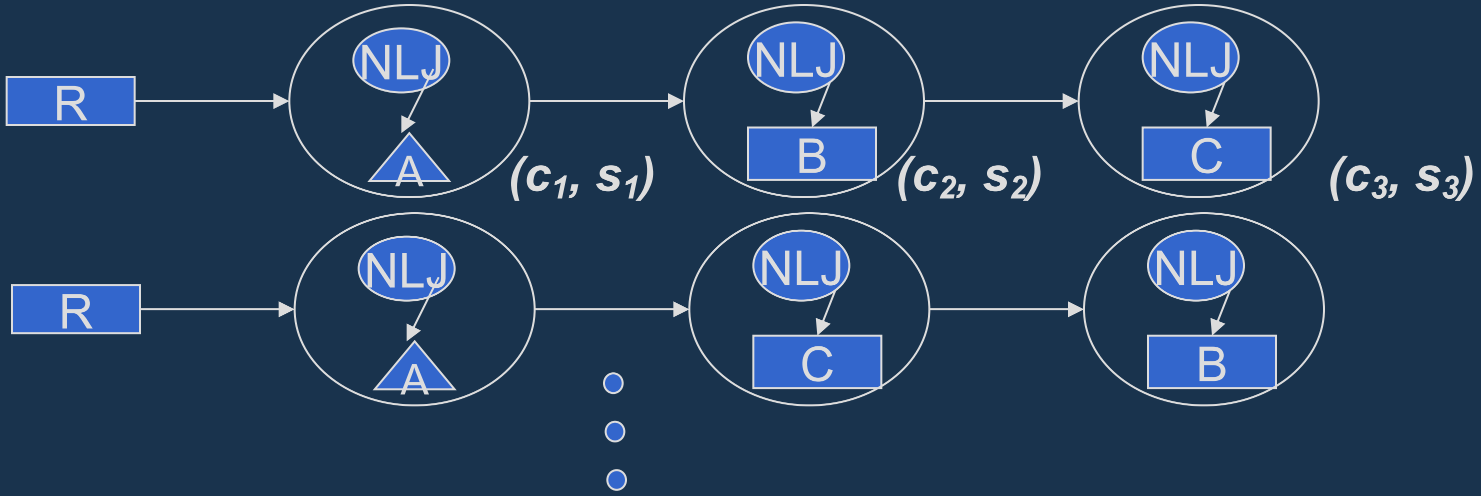
Simplest method of joining tables

- Pick a *driver* table (R). Call the rest *driven* tables
- Pick access methods (AMs) on the driven tables
- Order the driven tables
- Flow R tuples through the driven tables

Almost identical to selection ordering

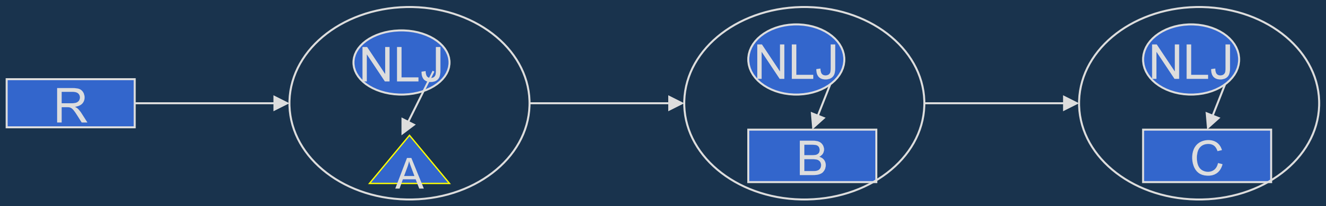
```
For each $r \in R$ do:
look for matches for r in A;
for each match a do:
        look for matches for <r,a> in B;
        …
```

Adapting the Join Order



- Let c_i = cost/lookup into i'th driven table,
  s_i = fanout of the lookup
- As with selection, cost = $|R| \times (c_1 + s_1 c_2 + s_1 s_2 c_3)$
- Caveats:
  - Fanouts $s_1, s_2, \ldots$ can be > 1
  - Precedence constraints
  - Caching issues
- Can use *rank ordering, A-greedy* for adaptation (subject to the caveats)

Adapting a Left-deep Pipelined Plan



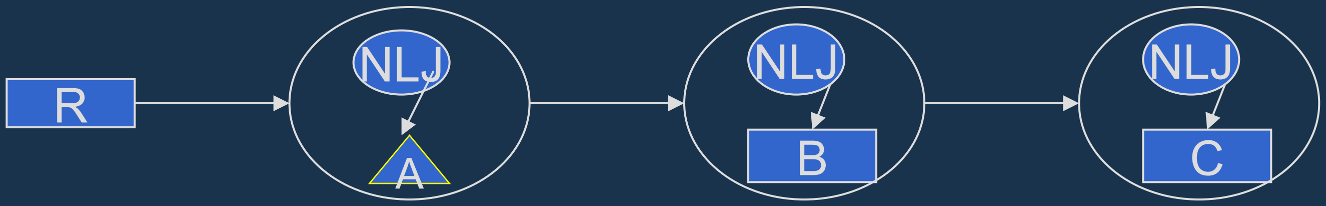
Simplest method of joining tables

- Pick a *driver* table (R). Call the rest *driven* tables
- Pick access methods (AMs) on the driven tables
- Order the driven tables
- Flow R tuples through the driven tables

?

```
For each r ∈ R do:
look for matches for r in A;
for each match a do:
        look for matches for <r,a> in B;
        …
```

Adapting a Left-deep Pipelined Plan



Key issue: Duplicates

Adapting the choice of driver table

[L+07] Carefully use indexes to achieve this

Adapting the choice of access methods

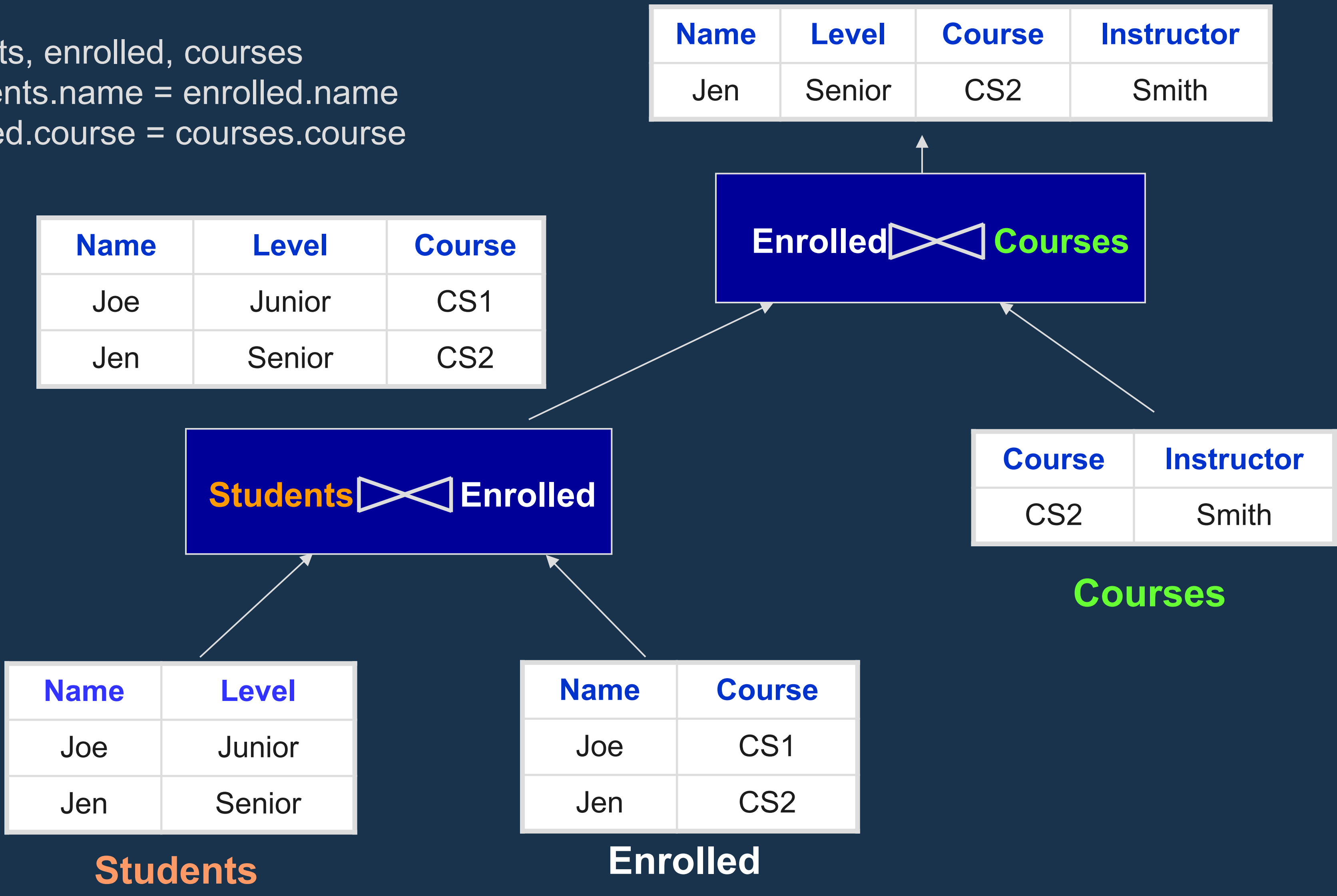
- Static optimization: explore all possibilities and pick best
- Adaptive: Run multiple plans in parallel for a while, and then pick one and discard the rest [Antoshenkov' 96]
  - Cannot easily explore combinatorial options

Adaptive Join Processing: Outline

- Single streaming relation
  - Left-deep pipelined plans
- Multiple streaming relations
  - Execution strategies for multi-way joins
  - History-independent execution
    - MJoins
  - History-dependent execution
    - Eddies with joins
    - Corrective query processing

Example Join Query & Database

```
select *
from students, enrolled, courses
where students.name = enrolled.name
  and enrolled.course = courses.course
```



Name	Level	Course	Instructor
Jen	Senior	CS2	Smith

Enrolled ⋈ Courses

Name	Level	Course
Joe	Junior	CS1
Jen	Senior	CS2

Students ⋈ Enrolled

Course	Instructor
CS2	Smith

Courses

Name	Level
Joe	Junior
Jen	Senior

Students

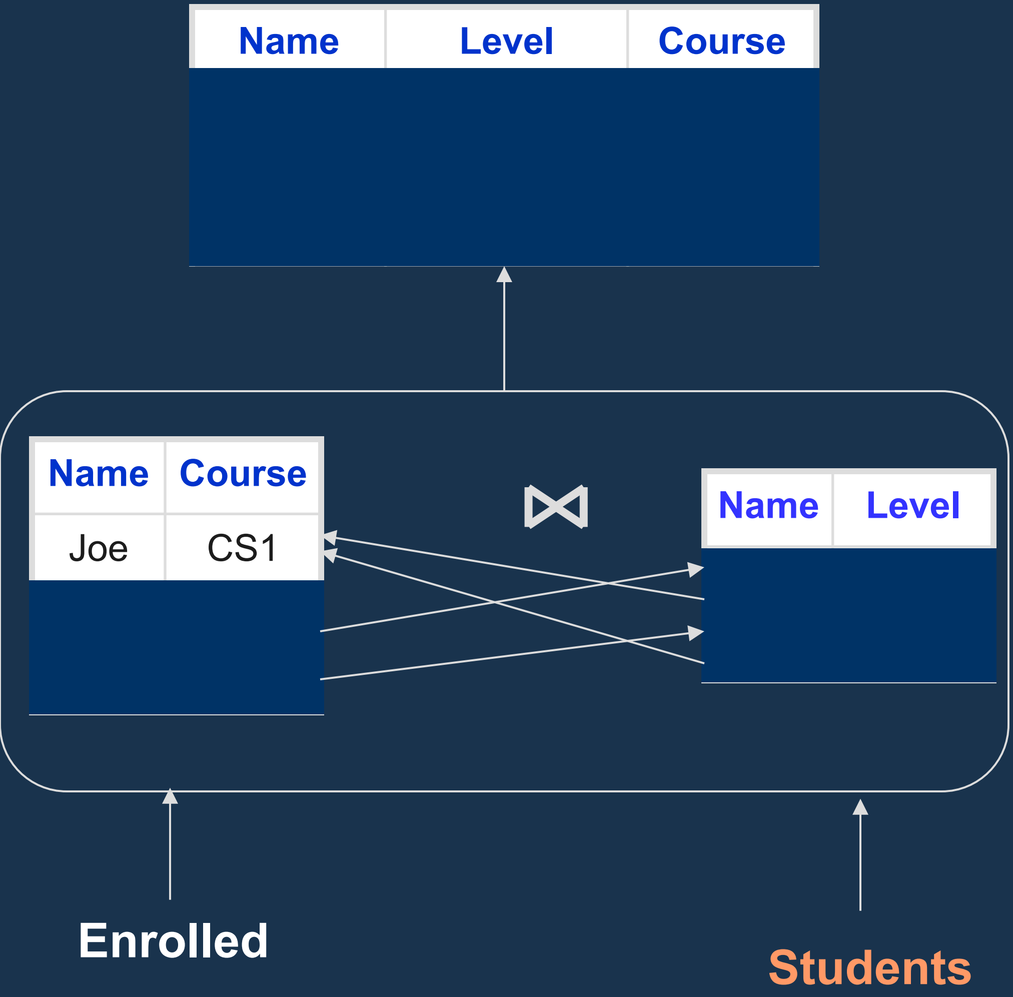
Name	Course
Joe	CS1
Jen	CS2

Enrolled

Symmetric/Pipelined Hash Join

[RS86, WA91]

select * from students, enrolled where students.name = enrolled.name



- Simultaneously builds and probes hash tables on both sides
- Widely used:
  - adaptive query processing
  - stream joins
  - online aggregation
  - …
- Naïve version degrades to NLJ once memory runs out
  - Quadratic time complexity
  - memory needed = sum of inputs
- Improved by XJoins [UF 00], Tukwila DPJ [IFFLW 99]

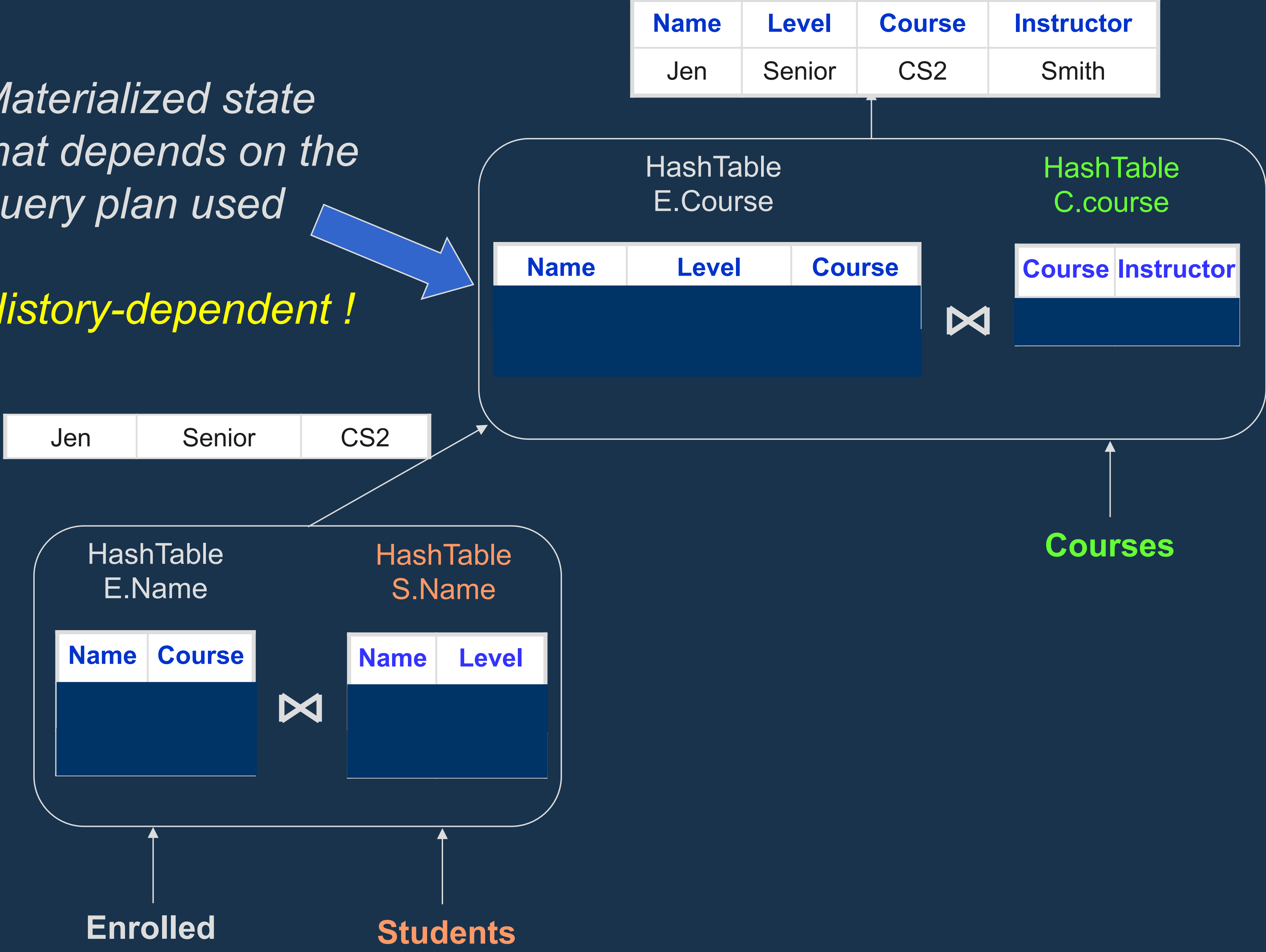
Multi-way Pipelined Joins over Streaming Relations

Alternatives

- Using binary join operators
- Using a single n-ary join operator (MJoin) [VNB'03]
- Some other options explored in the literature

Materialized state that depends on the query plan used

History-dependent !



Name	Level	Course	Instructor
Jen	Senior	CS2	Smith

HashTable E.Course

Name	Level	Course

⋈

HashTable C.course

Course	Instructor

Jen	Senior	CS2

HashTable E.Name

Name	Course

⋈

HashTable S.Name

Name	Level

Multi-way Pipelined Joins over Streaming Relations

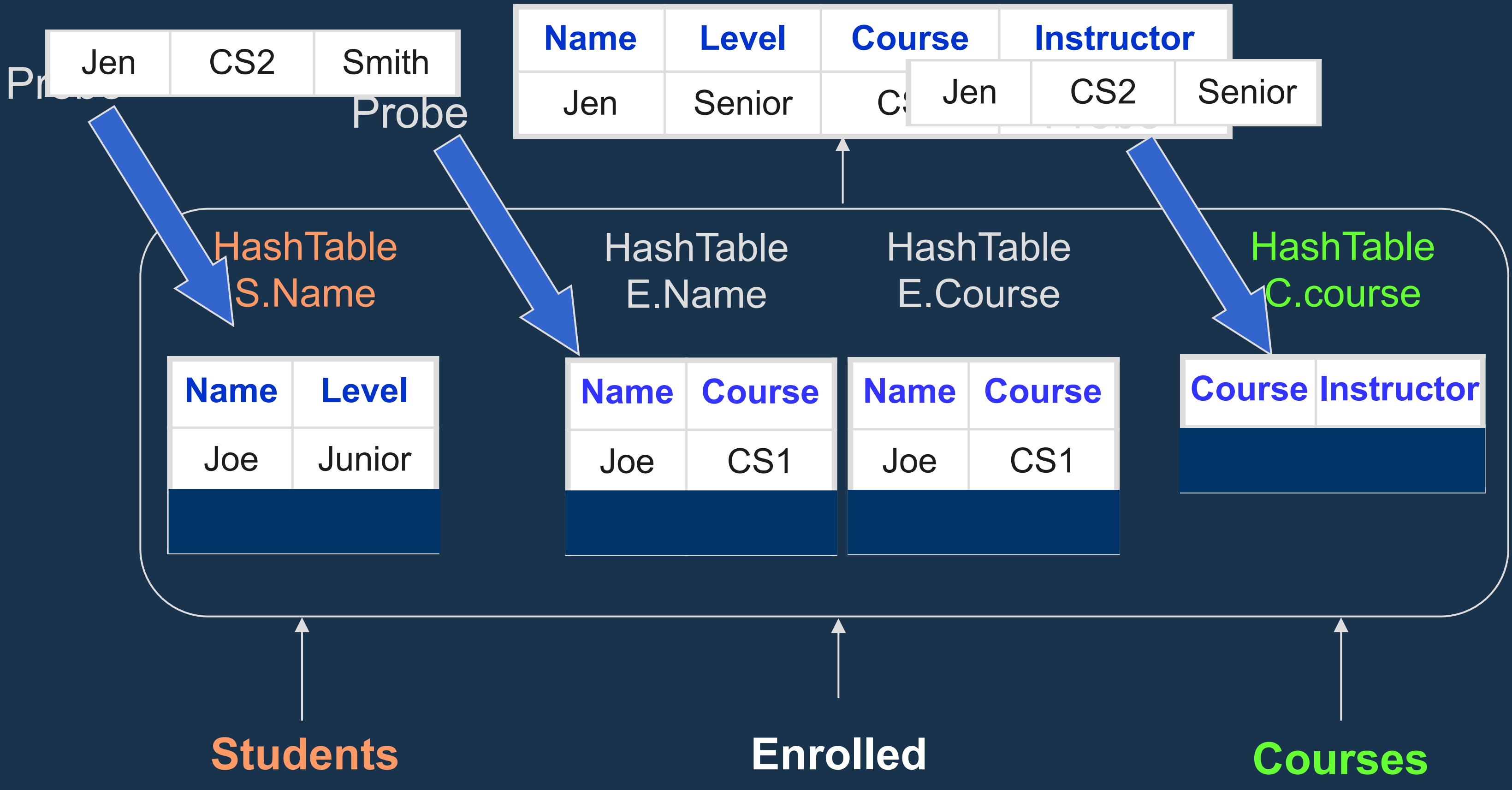
Three alternatives

- Using binary join operators
  - *History-dependent execution*
  - Hard to reason about the impact of adaptation
  - May need to migrate the state when changing plans
- Using a single n-ary join operator (MJoin) [VNB'03]

Probing Sequences

Students tuple: Enrolled, then Courses
Enrolled tuple: Students, then Courses
Courses tuple: Enrolled, then Students

Hash tables contain all tuples that arrived so far
Irrespective of the probing sequences used
History-independent execution !



Jen	CS2	Smith

Probe

Probe

Name	Level	Course	Instructor
Jen	Senior	C	

Jen	CS2	Senior

HashTable
S.Name

Name	Level
Joe	Junior

HashTable
E.Name

Name	Course
Joe	CS1

HashTable
E.Course

Name	Course
Joe	CS1

HashTable
C.course

Course	Instructor

Students

Enrolled

Courses

MJoins [VNB'03]

Choosing probing sequences

- For each relation, use a left-deep pipelined plan (based on hash indexes)
- Can use selection ordering algorithms

  Independently for each relation

Adapting MJoins

- Adapt each probing sequence independently

  e.g., StreaMon [BW'01] used A-Greedy for this purpose

A-Caching [BMWM'05]

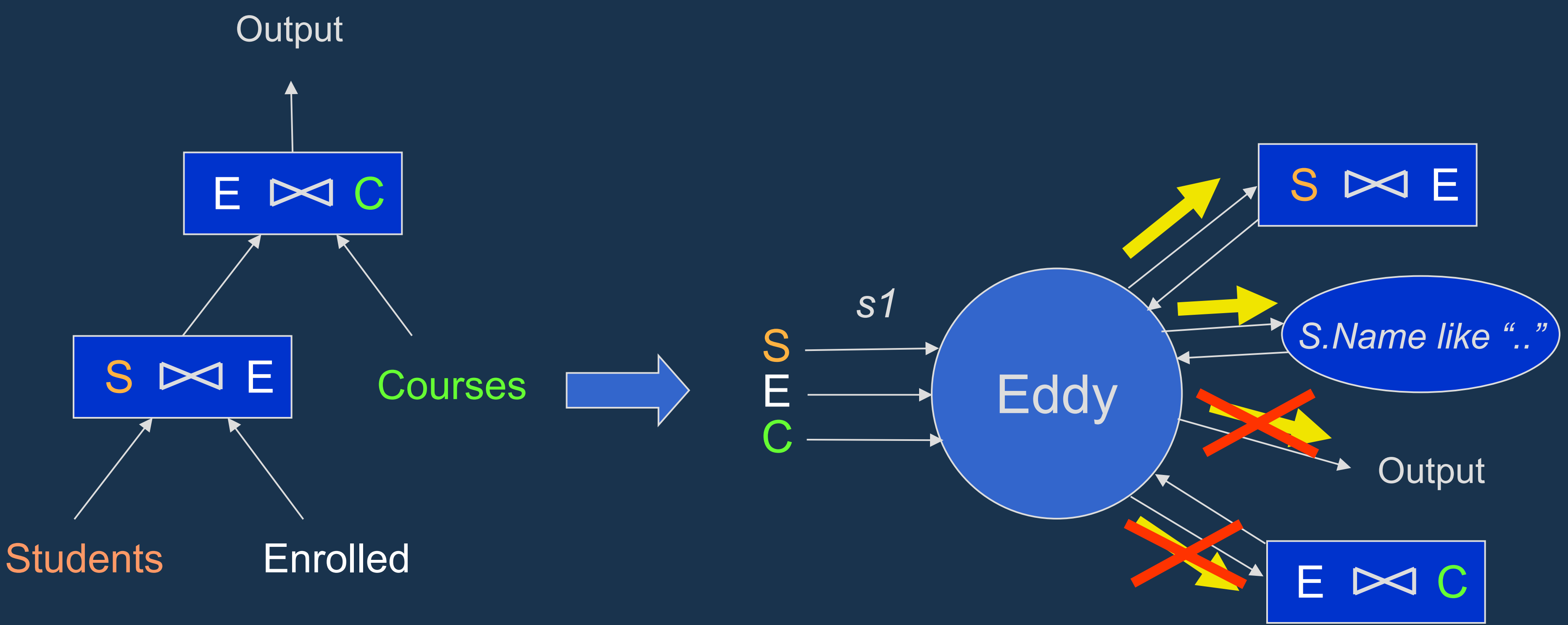
- Maintain intermediate caches to avoid recomputation
- Alleviates some of the performance concerns

Adaptive Join Processing: Outline

- Single streaming relation
  - Left-deep pipelined plans
- Multiple streaming relations
  - Execution strategies for multi-way joins
  - History-independent execution
    - MJoins
    - SteMs
  - History-dependent execution
    - Eddies with binary joins

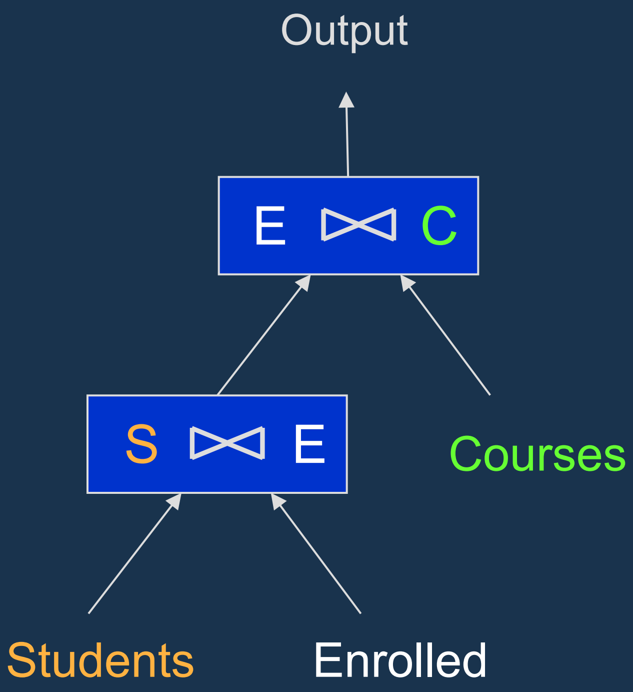
Eddies with Binary Joins [AH'00]

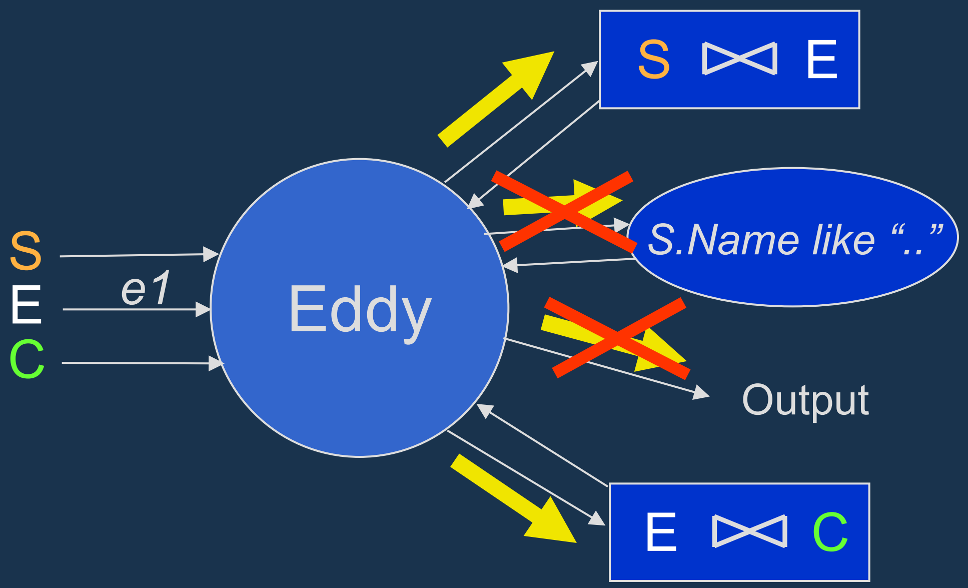
For correctness, must obey routing constraints !!



Eddies with Binary Joins [AH'00]

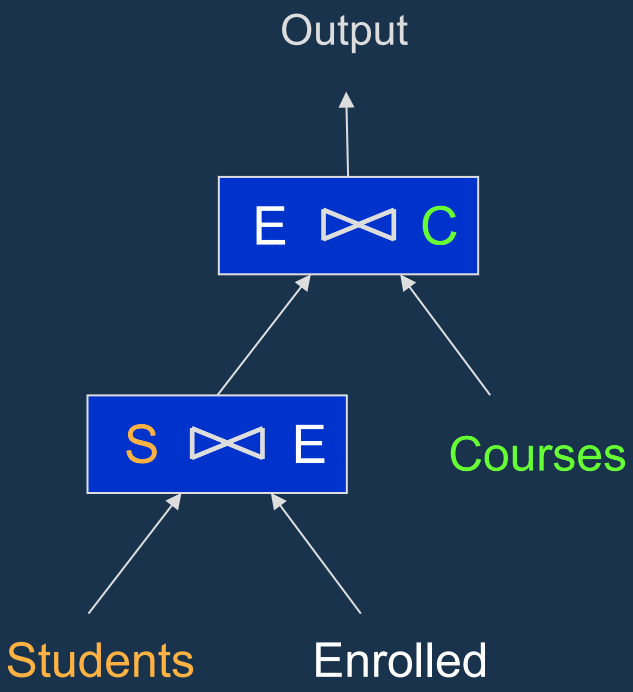
For correctness, must obey routing constraints !!

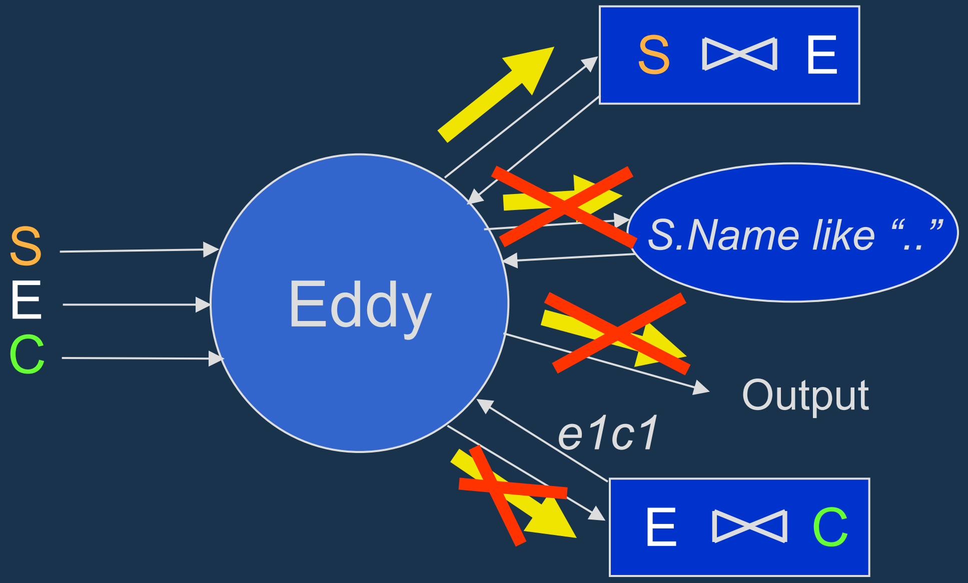




Eddies with Binary Joins [AH'00]

For correctness, must obey routing constraints !!
Use some form of *tuple-lineage*



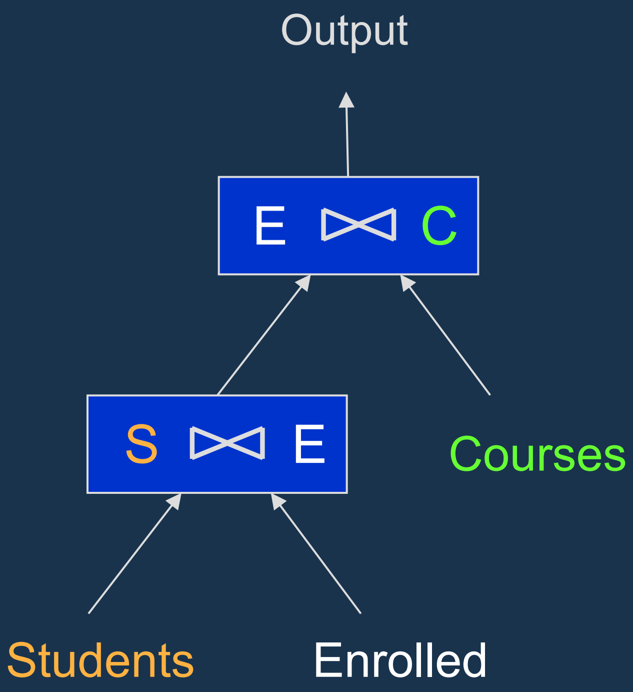


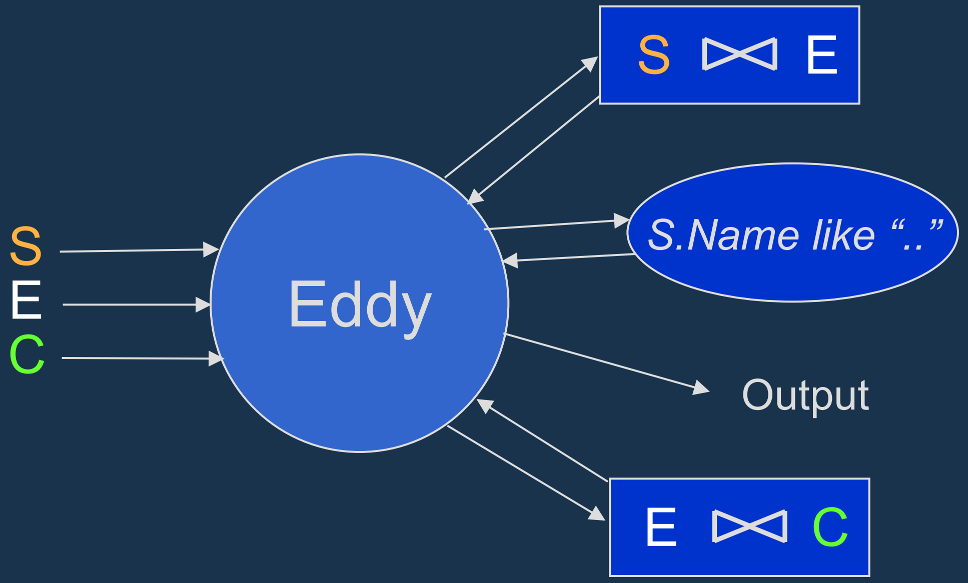
Eddies with Binary Joins [AH'00]

Can use any join algorithms

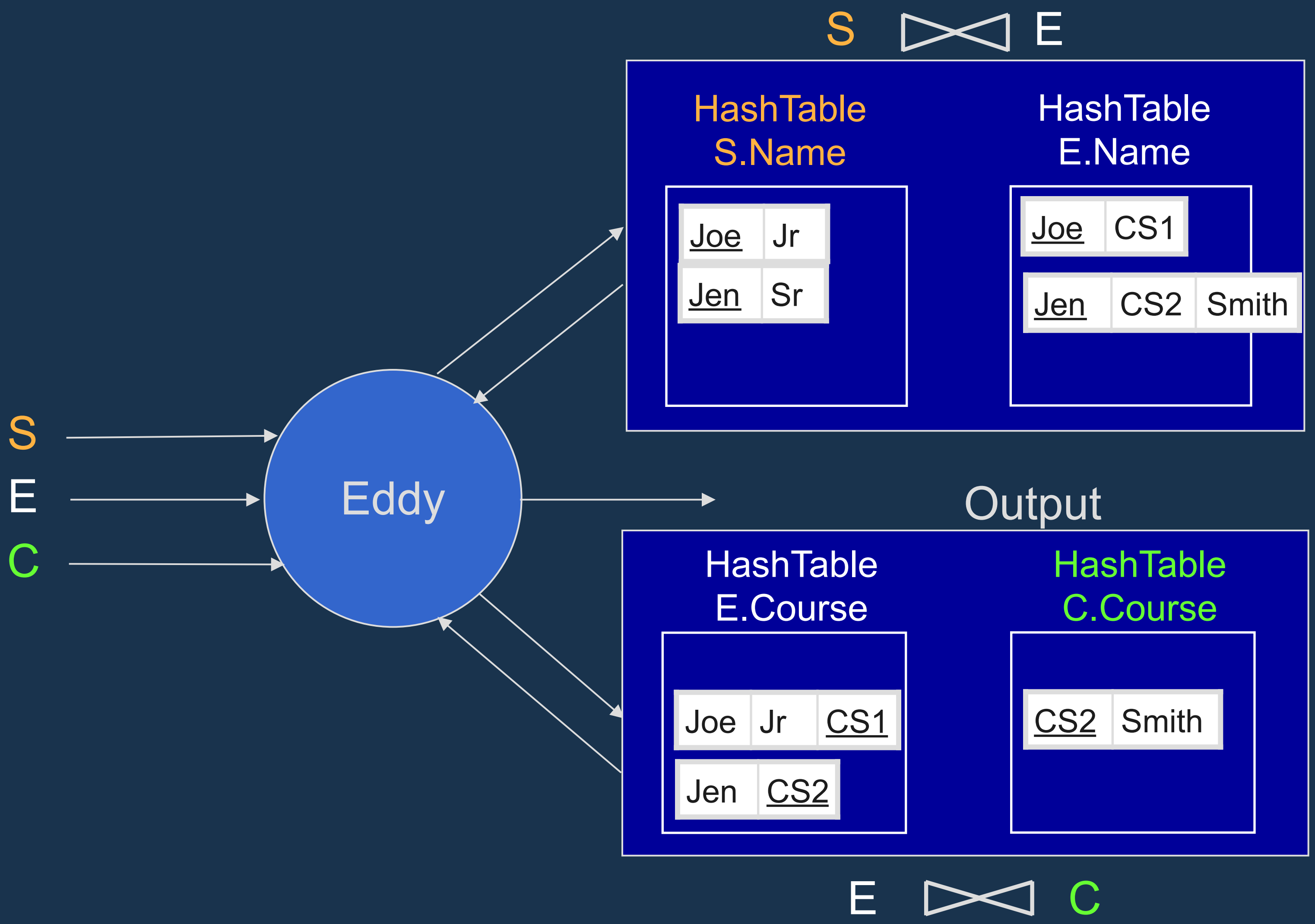
But, *pipelined* operators preferred

Provide quick feedback





Eddies with Symmetric Hash Joins



S ⋈ E

HashTable S.Name

Joe	Jr
Jen	Sr

HashTable E.Name

Joe	CS1	
Jen	CS2	Smith

S

E

C

Eddy

Output

HashTable E.Course

Joe	Jr	CS1
Jen	CS2	

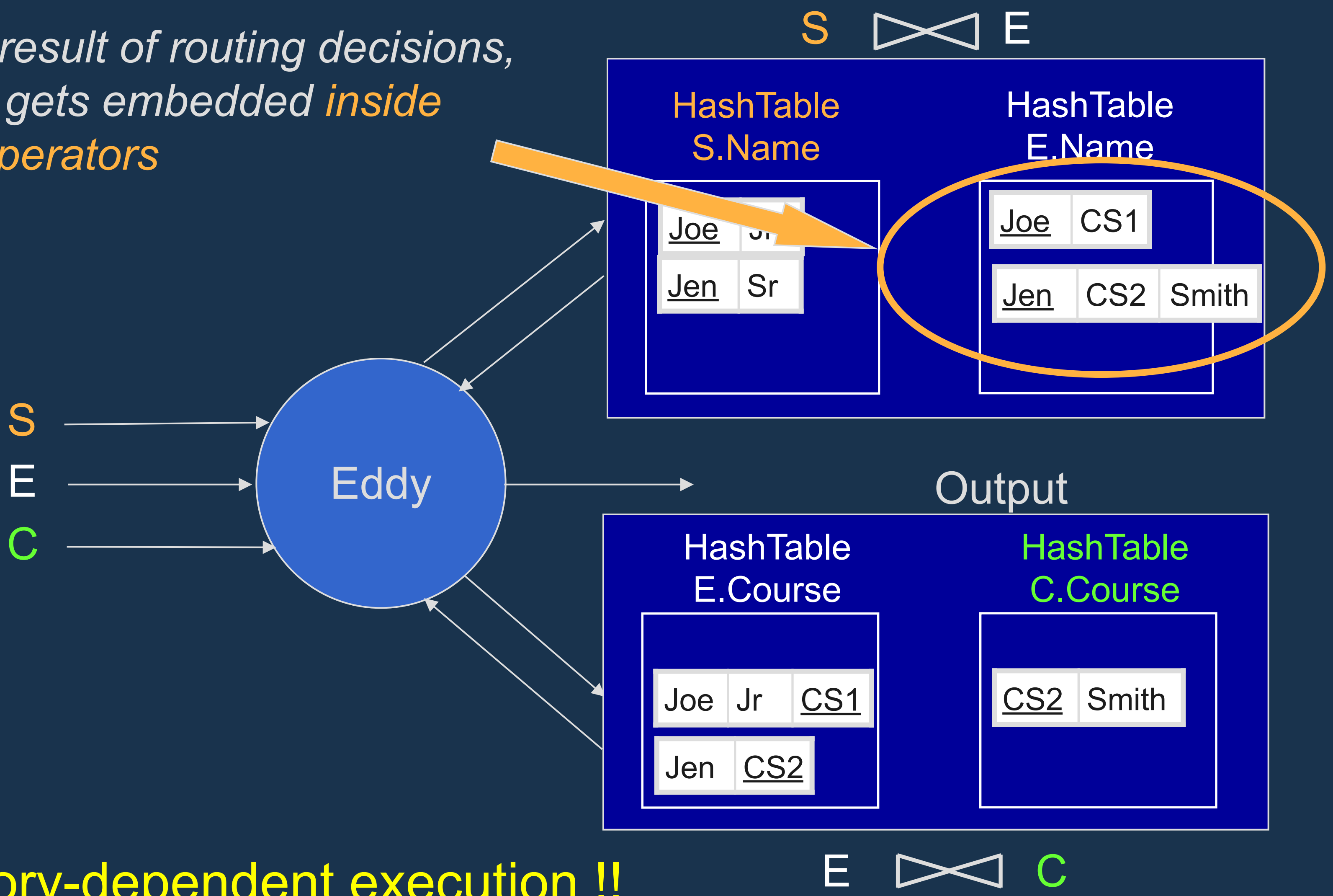
HashTable C.Course

CS2	Smith

E ⋈ C

Burden of Routing History [DH'04]

As a result of routing decisions, state gets embedded inside the operators



S ⋈ E

HashTable S.Name

Joe	Jr
Jen	Sr

HashTable E.Name

Joe	CS1	
Jen	CS2	Smith

S

E

C

Eddy

Output

HashTable E.Course

Joe	Jr	CS1
Jen	CS2	

HashTable C.Course

CS2	Smith

E ⋈ C

History-dependent execution !!

Recap: Eddies with Binary Joins

Routing constraints enforced using tuple-level lineage

Must choose access methods, join spanning tree beforehand

- SteMs relax this restriction [RDH’03]

The operator state makes the behavior unpredictable

- Unless only one streaming relation

Routing policies explored are same as for selections

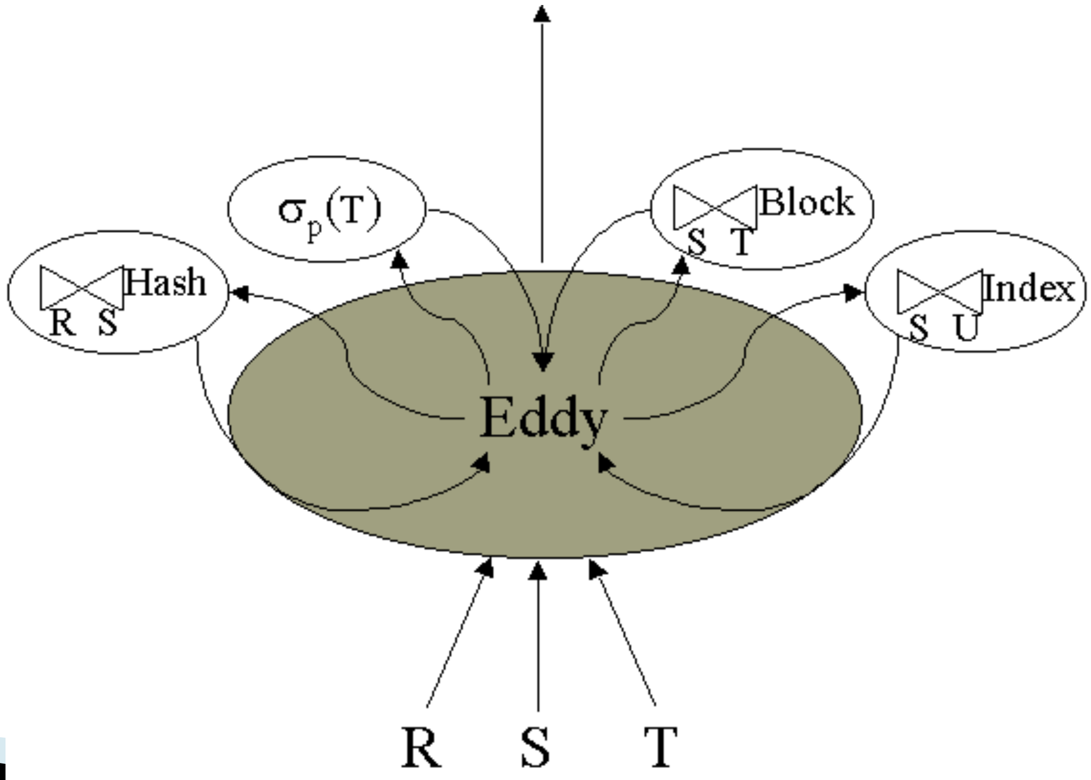
- Can tune policy for interactivity metric [RH’02]

Outline

- Query evaluation techniques for large databases, Skew Avoidance, Query compilation/vectorization
- Query Optimization: Overview, How good are the query optimizers, really?, Reordering for Outerjoins, Query Rewriting
- Adaptive Query Processing
  - Eddies
  - Progressive Query Optimization
  - Compilation and adaptivity

Overview

- Continuously ”reorder” operators as the query is executing
  - By changing the “order” in which tuples visit operators
  - Obviate the need for selectivity estimation and optimization entirely
  - Naturally handles situations where the selectivities change over time (for long-running queries)

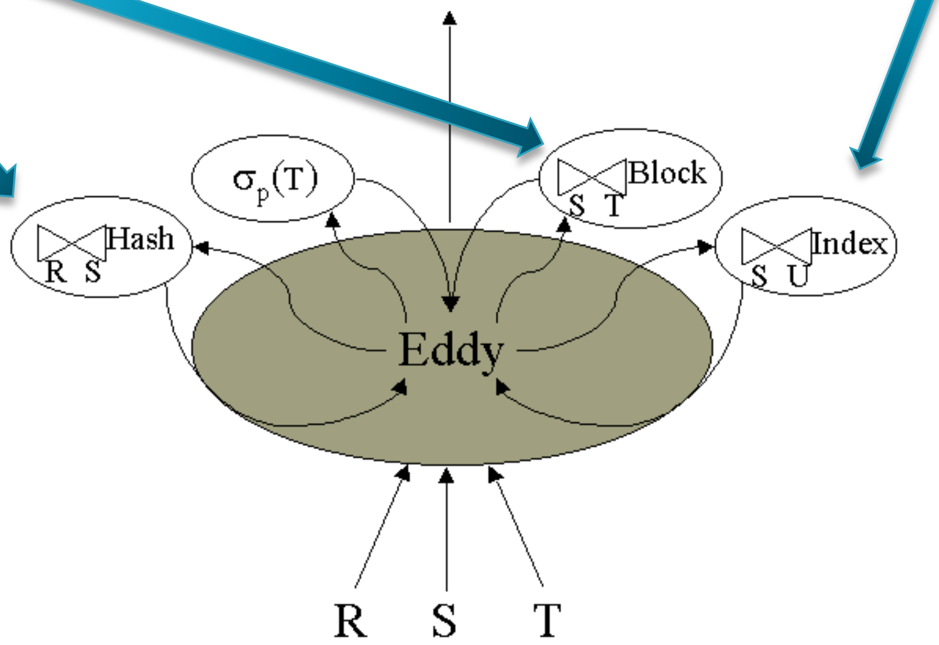


Eddies and Joins

- Selections are arbitrarily reorderable
- What about joins?

- An index lookup can be treated as a “selection”
- Send an S tuple, get back augmented tuples
- Note: decision to use the index cannot be “adapted”

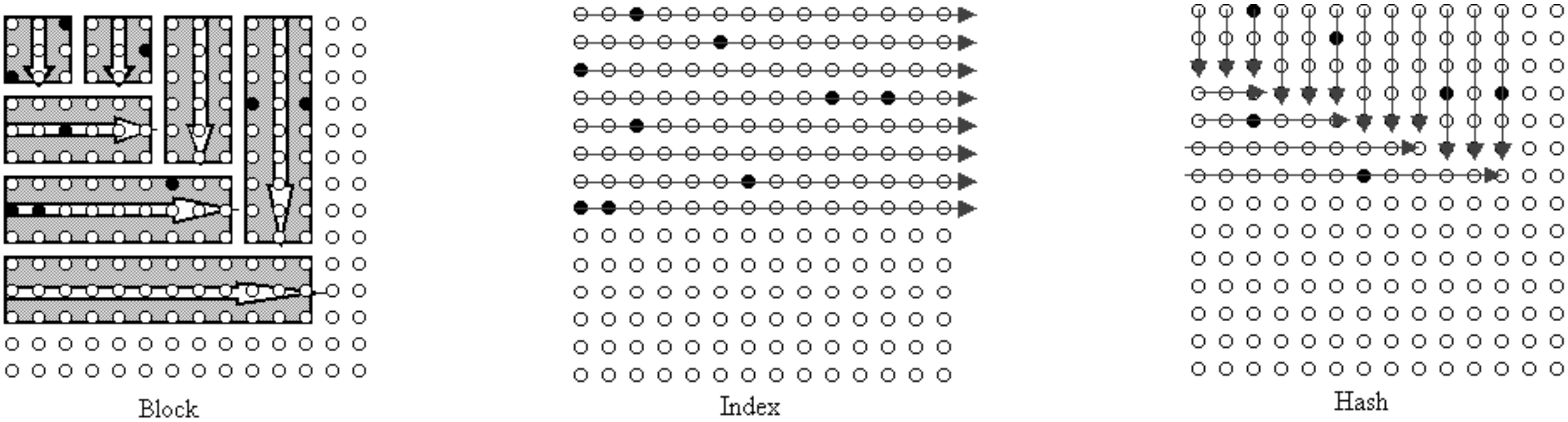
- These two are tricky
- Nested loops requires iterating over all of inner
- Hash join requires building a hash table on inner



Reorderability of Plans

- Synchronization Barriers
  - Many operators explicitly enforce an order in which tuples must be read from the inputs
  - e.g., Sort-merge joins: at most points, the next tuple to read must be read from a specific input
  - Hash joins: need to read all of ”inner” before outer tuples can be read
- Moments of Symmetry
  - Sort-merge join is symmetric
  - But Nested-loops is not
    - However, can change the outer/inner at specific points
- Join operators with more moments of symmetric preferred
  - e.g., Symmetric Hash Join Operator

Reorderability of Plans



Block

Index

Hash

Figure 3: Tuples generated by block, index, and hash ripple join. In block ripple, all tuples are generated by the join, but some may be eliminated by the join predicate. The arrows for index and hash ripple join represent the *logical* portion of the cross-product space checked so far; these joins only expend work on tuples satisfying the join predicate (black dots). In the hash ripple diagram, one relation arrives 3× faster than the other.

Eddies

- Implemented in the context of River project
- Eddy is a separate module that talks to all other operators
  - Uses “ready” and “done” bitsets to direct traffic
- Lottery scheduling-based routing policy
  - Promising initial results, but bunch of caveats

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Overview

- Trigger re-optimization during query execution if errors too high
- Through use of CHECK operators inserted into the query plan
  - Succeeds if the observed values within a range around the estimates
- If optimizer estimates accurate, the only overhead is the “couting” done by CHECK

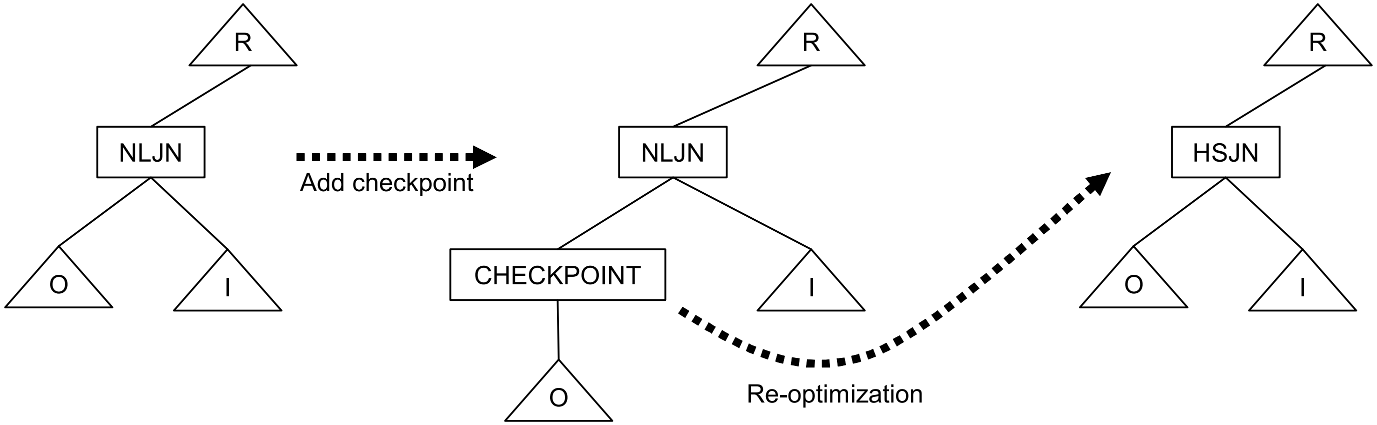


Figure 2: Adding CHECK to the outer of a NLJN

Overview

- Trigger re-optimization during query execution if errors too high
- Through use of CHECK operators inserted into the query plan
  - Succeeds if the observed values within a range around the estimates
- If optimizer estimates accurate, the only overhead is the "couting" done by CHECK
- If CHECK detects significant error, then "reoptimize"
  - Partial results made available to the optimizer to use if it wants (in the form of a materialized view)

Architecture

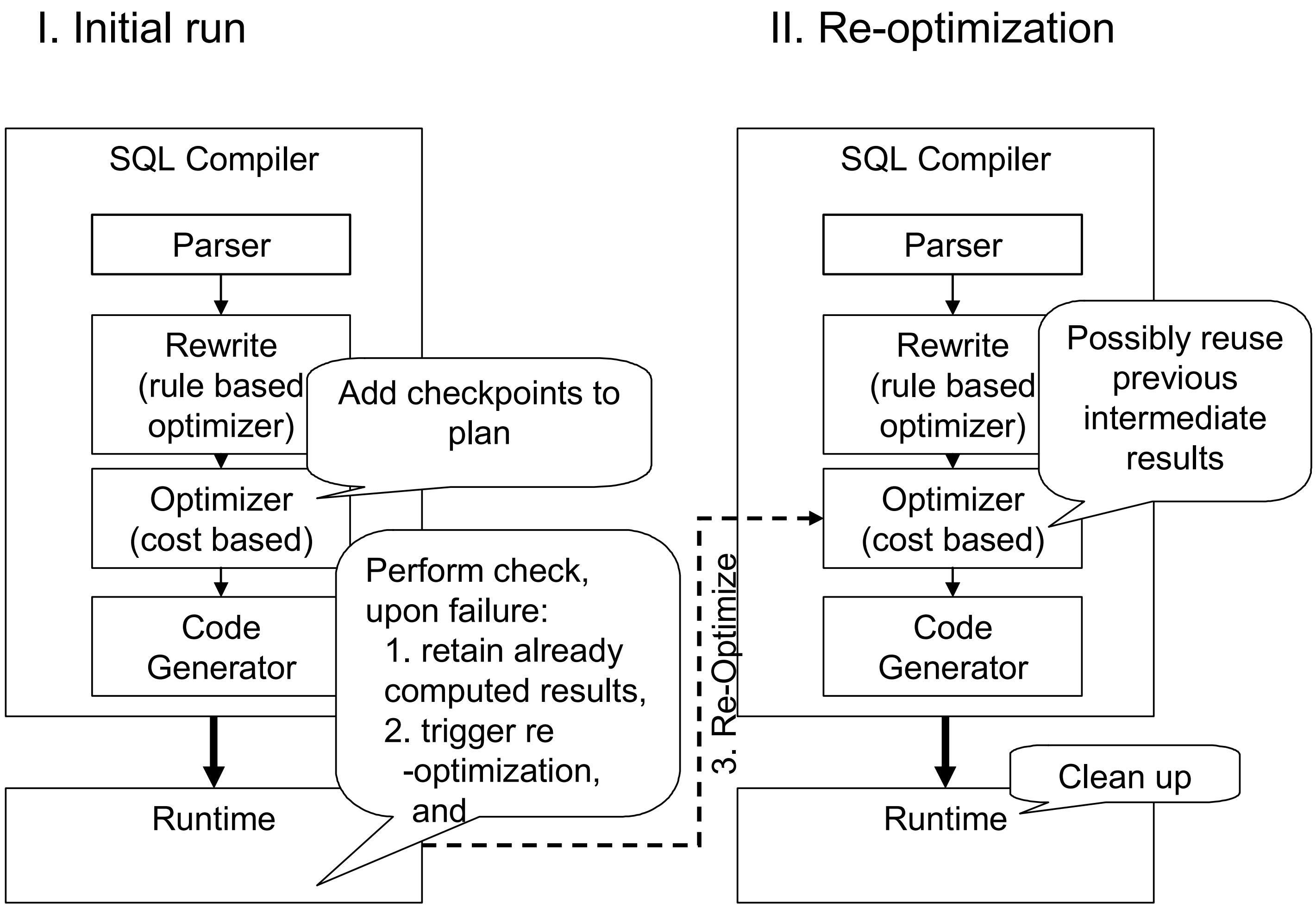
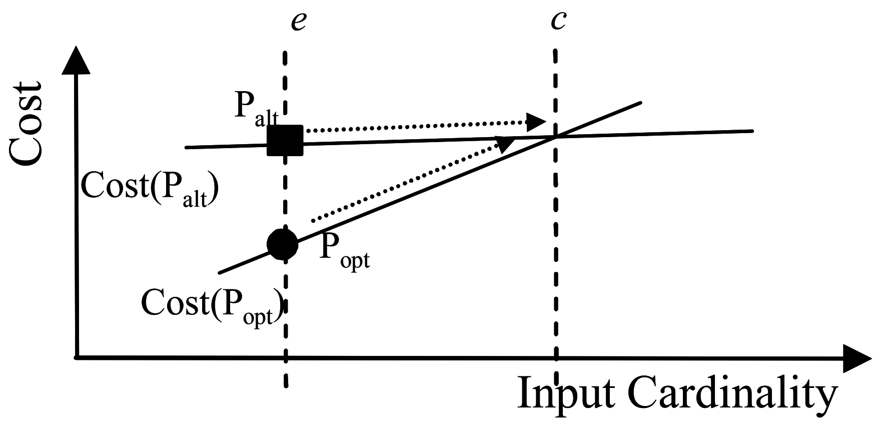


Figure 1: Progressive Optimization architecture

Computing Validity Ranges

- Helps only re-optimize when necessary
- The general problem is that of "parametric" optimization
  - i.e., find the best plan for each combination of parameters
  - Too expensive
- Instead:
  - Consider P1 and P2 -- two identical plans except for the top operator
  - Let cost(P1) < cost(P2) per the estimates → we would choose P1 over P2
  - Let "x" denote an edge into the top operator, and let "result(x) = e" denote the result flowing along "x"
  - Figure out: at what value of |result(x)|, we would have chosen P2 instead



Computing Validity Ranges

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  - Let “x” denote an edge into the top operator, and let “result(x) = e” denote the result flowing along “x”
  - Figure out: at what value of |result(x)|, we would have chosen P2 instead
- Use numerical techniques to find these validity ranges

Reusing Partial Results

- Treat it as a materialized view, and let the optimizer decide
- If the plan under CHECK has a side-effect (e.g., update), then must reuse that plan (i.e., not redo that portion)
- In many cases, better not to use the partial result

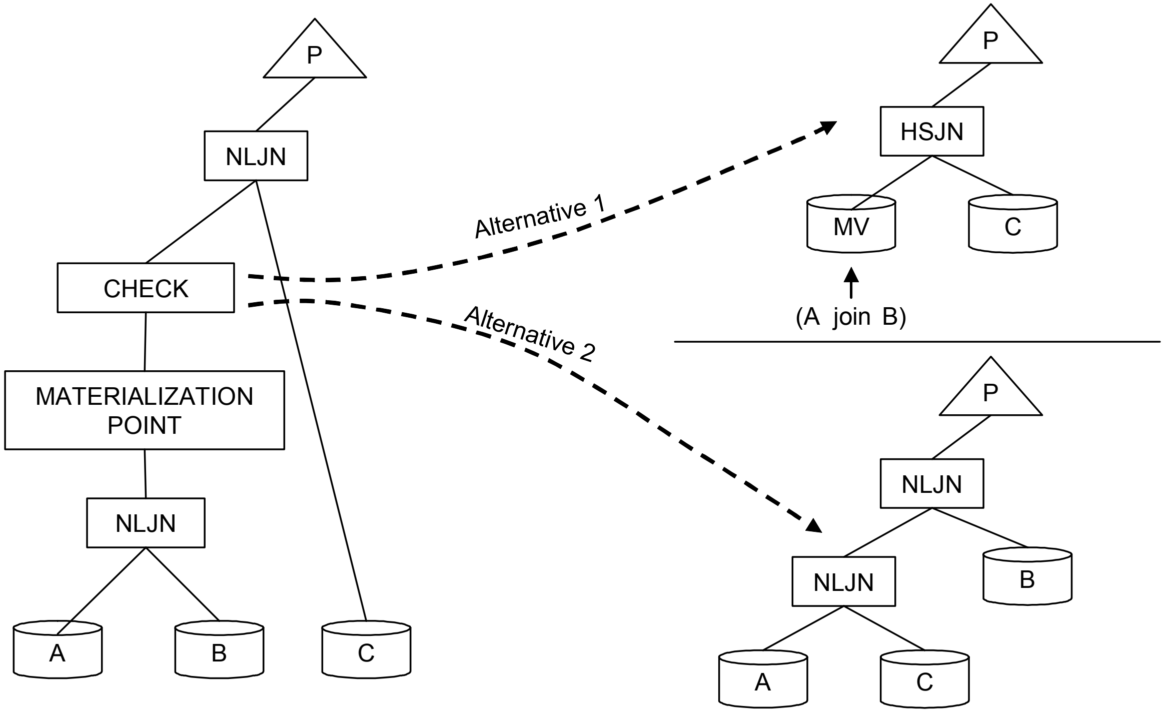


Figure 6: Two alternatives considered in re-optimization

Lazy vs Eager Checking

- If there is already a materialization point, can add CHECK there for free (lazy)
- Can add explicit materialization along with a CHECK
  - Extra overhead in doing that
- Eager CHECKs don't wait for materialization
- ECWC (Eager without compensation)
  - There is a materialization afterwards → no results will be output to the user
  - So can easily reoptimize without worrying about compensation

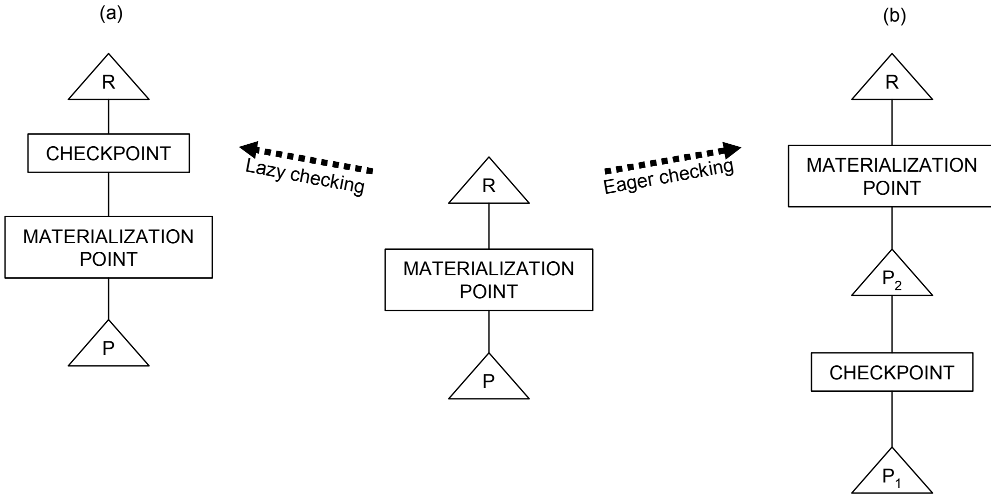


Figure 7: Lazy checking (LC) and eager checking without compensation (ECWC)

Eager Checking

- With Buffering: Buffer results until you are sure things are okay
  - Delays the pipeline for some time

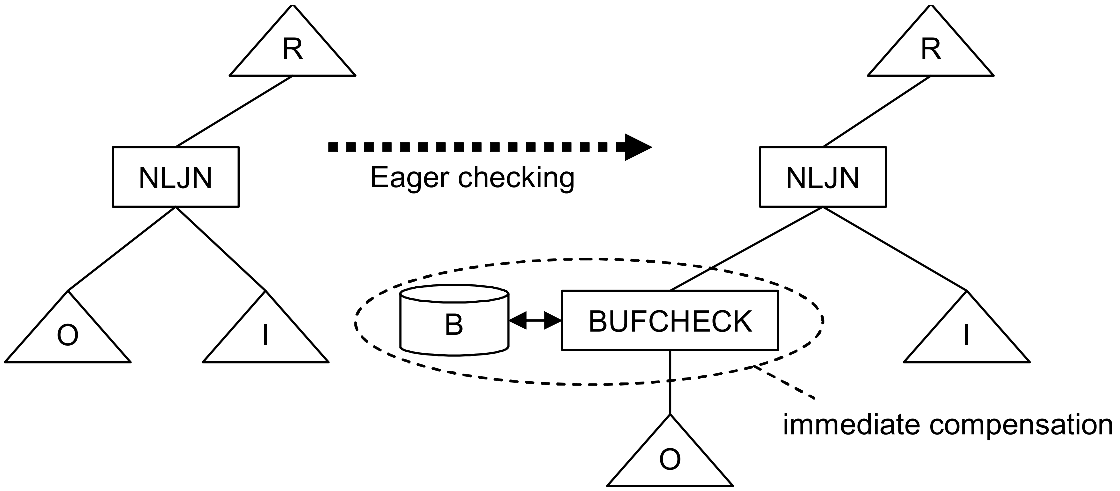
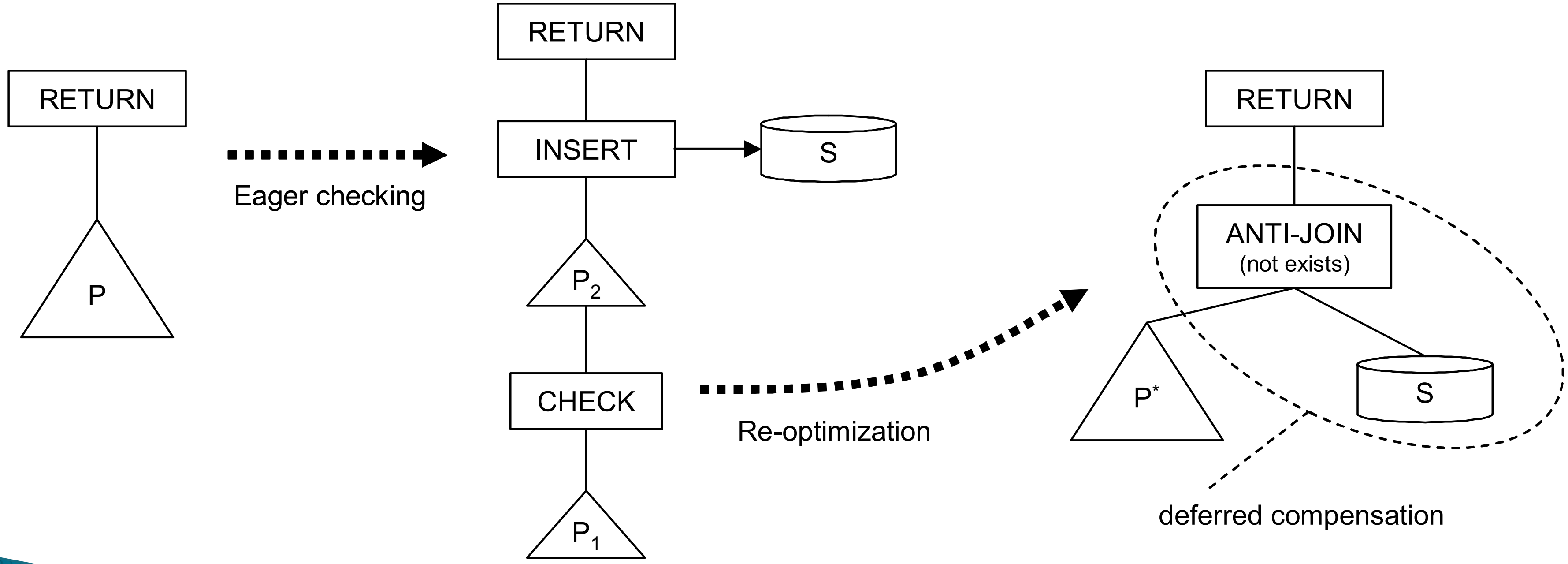


Figure 8: Eager checking with Buffering

Eager Checking

- With Deferred Compensation
  - Keep track of what tuples have already been output
  - Check that side table before outputting new tuples after reoptimization
  - Potentially a lot of repeated work



Experiments

- Degradation in some cases -- sometimes two errors cancelled each other out in the original plan

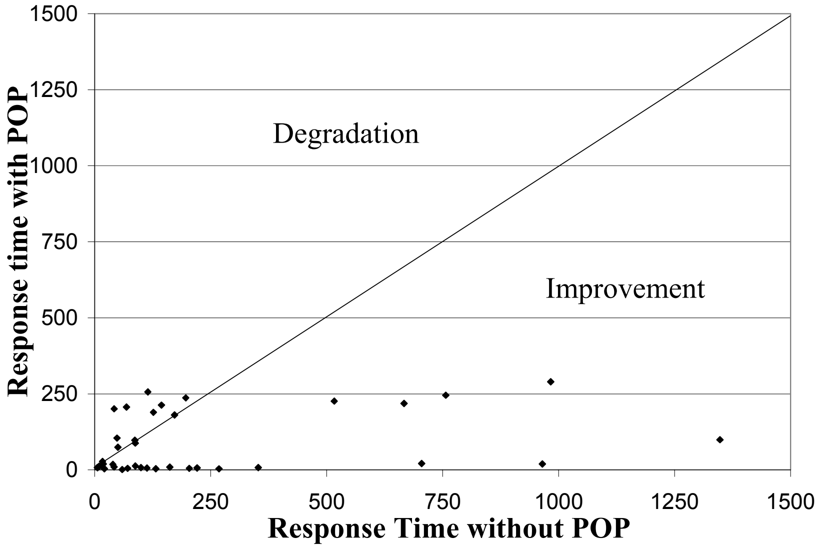


Figure 15: Scatter Plot of Response Times with and without POP on the DMV database

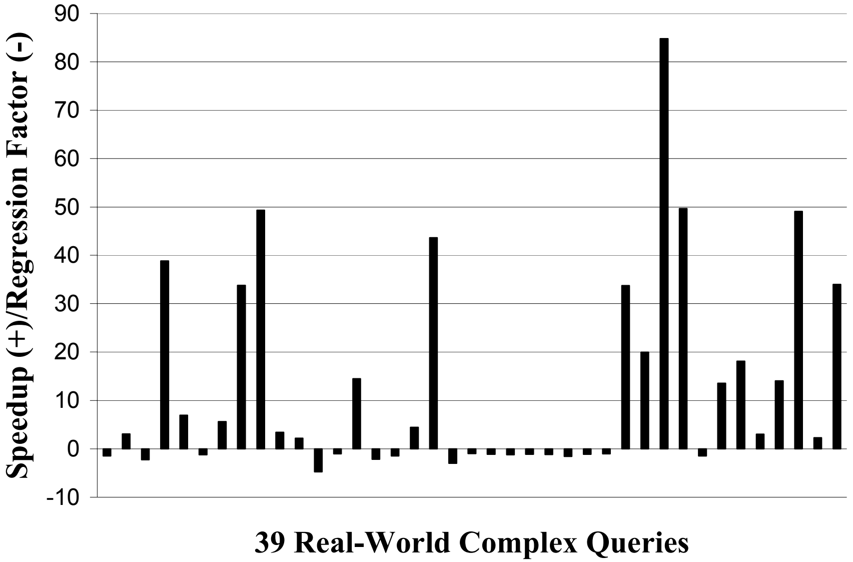


Figure 16: Speedup and Regression of each Query

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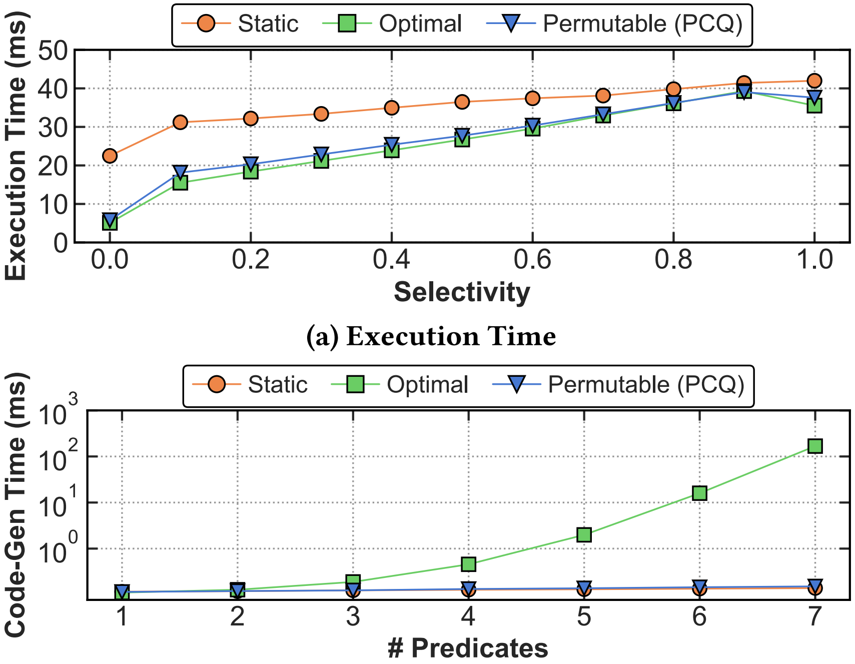
  - Compilation and adaptivity

Motivation

- Adaptive query processing (POP-style) works well with interpretable query plans, but not as well with compilation
  - Compiling a new query plan too expensive



(a) Execution Time

(b) Code-Generation Time

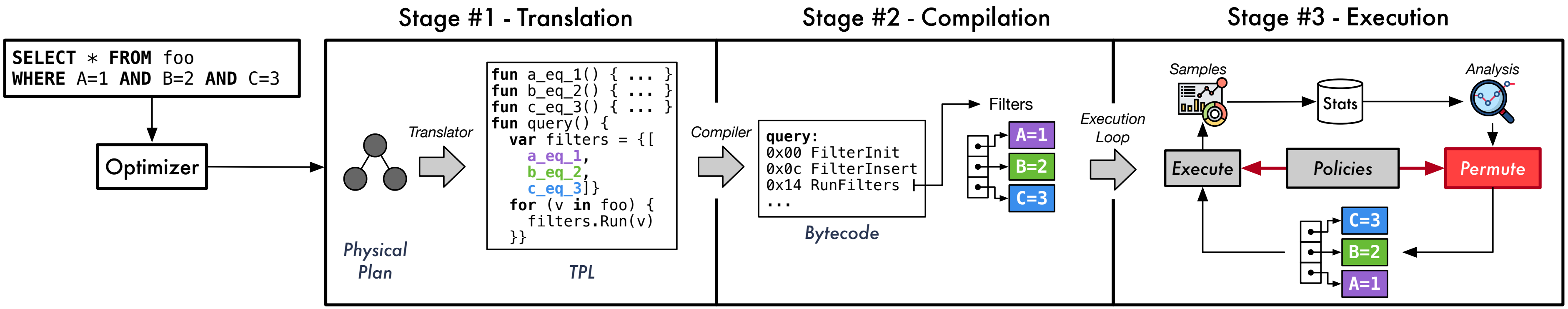
Figure 1: Reoptimizing Compiled Queries – PCQ enables near-optimal execution through adaptivity with minimal compilation overhead.

Permutable Compiled Queries (PCQ)

- Adaptive query processing (POP-style) works well with interpretable query plans, but not as well with compilation
  - Compiling a new query plan too expensive

- Instead:
  - Precompile a bunch of different plans at optimization time itself
  - Add indirections to the compiled code to make it easy to switch/permute operators
  - Add hooks for collecting runtime performance metrics
    - To be used to decide whether to switch

Permutable Compiled Queries (PCQ)



```
SELECT * FROM foo
WHERE A=1 AND B=2 AND C=3
```

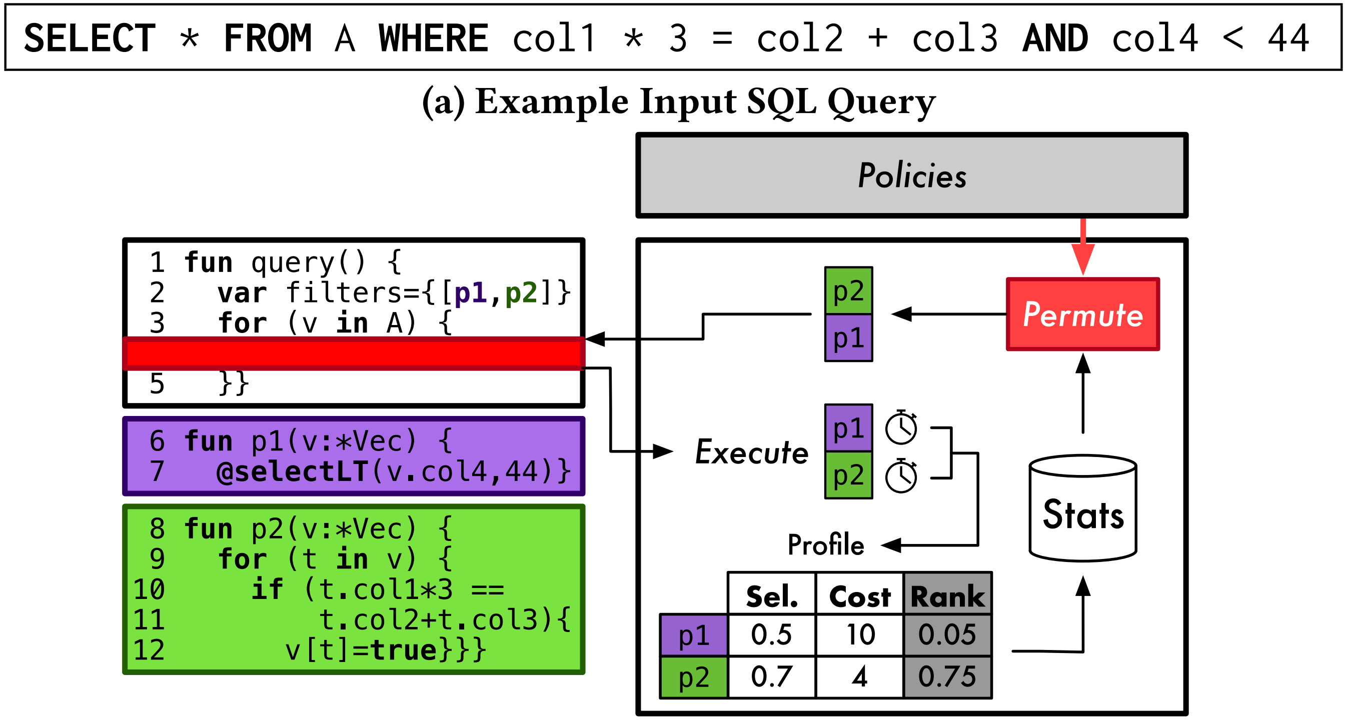
```
fun a_eq_1() { ... }
fun b_eq_2() { ... }
fun c_eq_3() { ... }
fun query() {
  var filters = {[
    a_eq_1,
    b_eq_2,
    c_eq_3]}
  for (v in foo) {
    filters.Run(v)
  }}
```

```
query:
0x00 FilterInit
0x0c FilterInsert
0x14 RunFilters
...
```

Figure 2: System Overview – The DBMS translates the SQL query into a DSL that contains indirection layers to enable permutability. Next, the system compiles the DSL into a compact bytecode representation. Lastly, an interpreter executes the bytecode. During execution, the DBMS collects statistics for each predicate, analyzes this information, and permutes the ordering to improve performance.

Adaptive Filter Ordering

Vectorization effect???
The code suggests filters applied to all tuples, so no point in reordering



```
SELECT * FROM A WHERE col1 * 3 = col2 + col3 AND col4 < 44
```

(a) Example Input SQL Query

```
fun query() {
  var filters={[p1,p2]}
  for (v in A) {

  }}
```

```
fun p1(v:*Vec) {
  @selectLT(v.col4,44)}
```

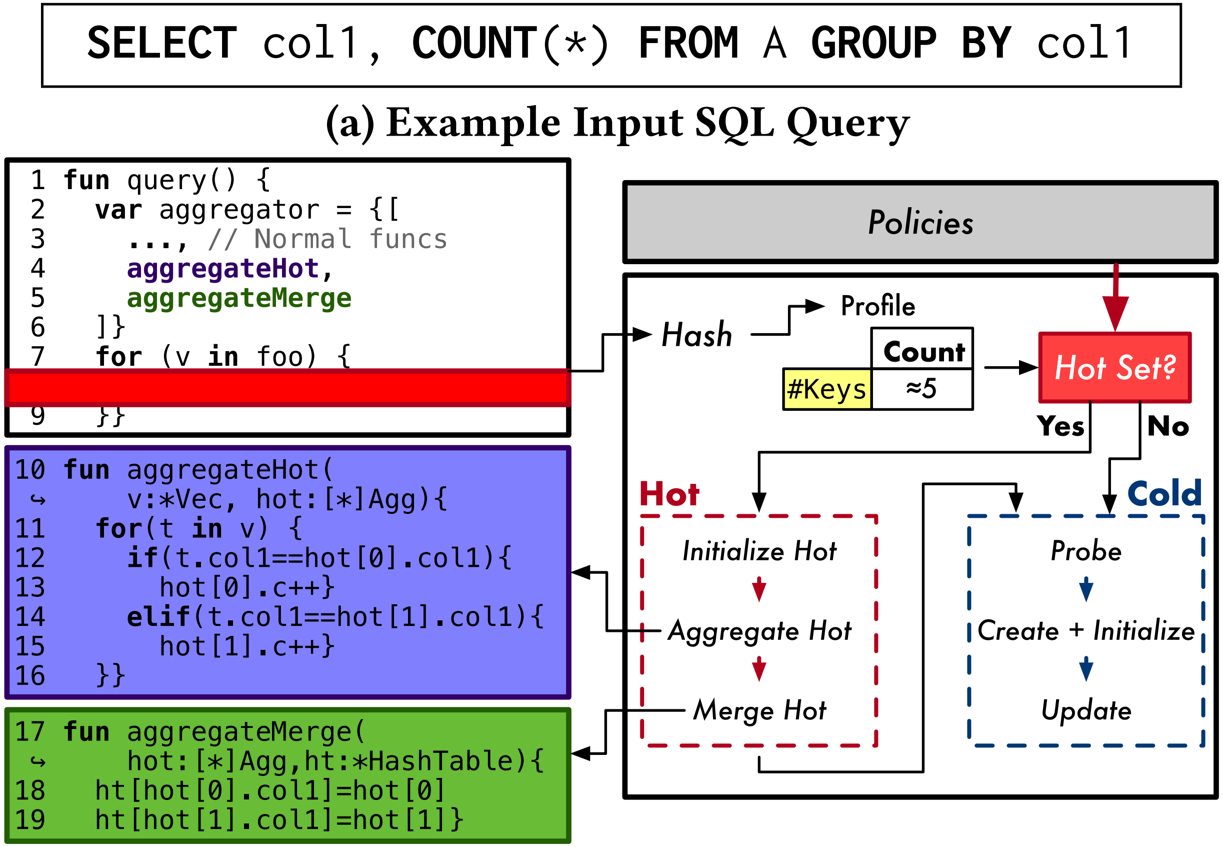
```
fun p2(v:*Vec) {
  for (t in v) {
    if (t.col1*3 ==
        t.col2+t.col3){
      v[t]=true}}}
```

	Sel.	Cost	Rank
p1	0.5	10	0.05
p2	0.7	4	0.75

(b) Generated Code and Execution of Permutable Filter

Figure 3: Filter Reordering – The Translator converts the query in (a) into the TPL on the left side of (b). This program uses a data structure template with query-specific filter logic for each filter clause. The right side of (b) shows how the policy collects metrics and then permutes the ordering.

Adaptive Aggregations



```
SELECT col1, COUNT(*) FROM A GROUP BY col1
```

(a) Example Input SQL Query

```
fun query() {
  var aggregator = {[
    ..., // Normal funcs
    aggregateHot,
    aggregateMerge
  ]}
  for (v in foo) {
[redacted]
  }}
```

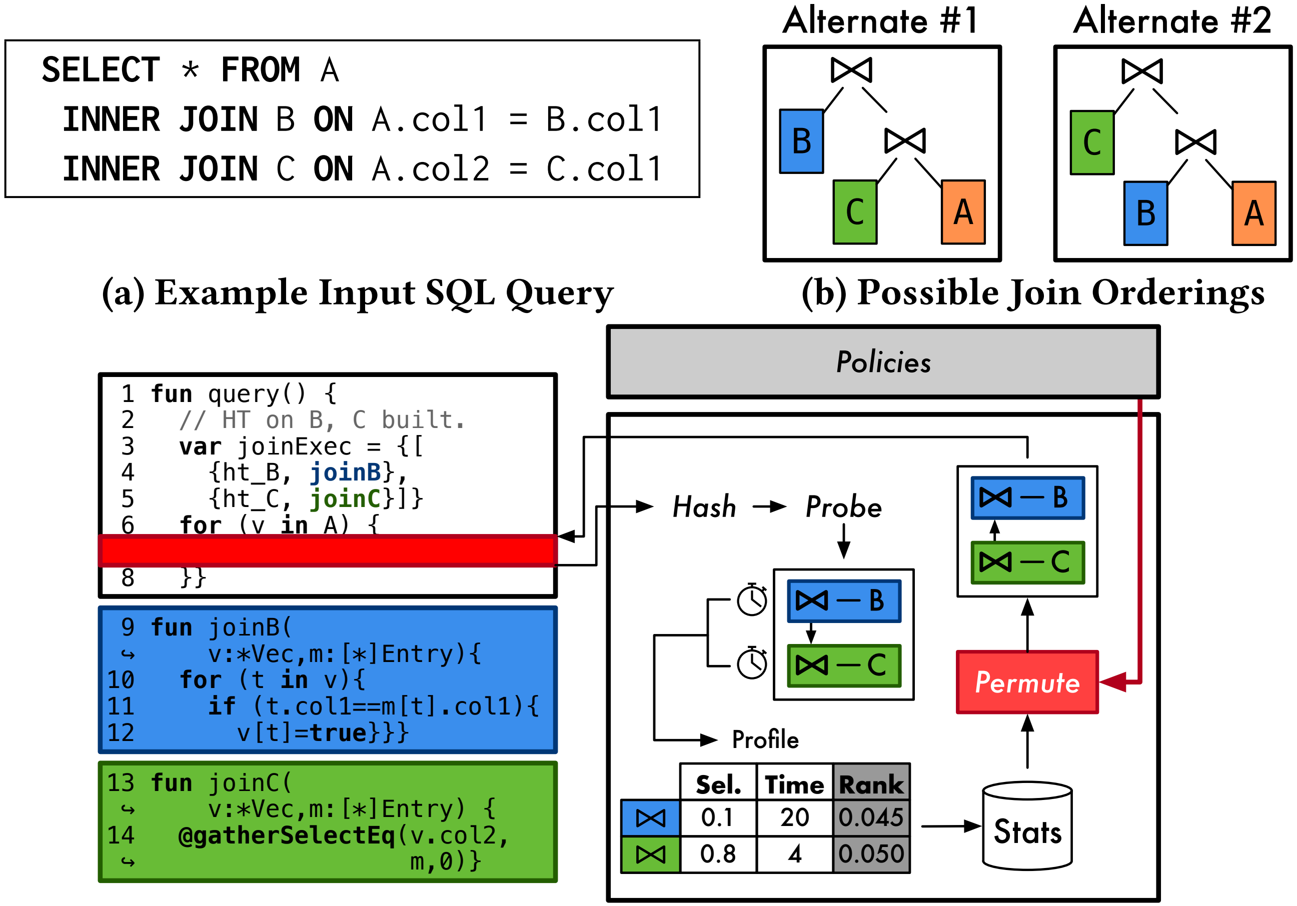
```
fun aggregateHot(
    v:*Vec, hot:[*]Agg){
  for(t in v) {
    if(t.col1==hot[0].col1){
      hot[0].c++}
    elif(t.col1==hot[1].col1){
      hot[1].c++}
  }}
```

```
fun aggregateMerge(
    hot:[*]Agg,ht:*HashTable){
  ht[hot[0].col1]=hot[0]
  ht[hot[1].col1]=hot[1]}
```

(b) Generated Code and Execution of Adaptive Aggregation

Figure 4: Adaptive Aggregations – The input query in (a) is translated into TPL on the left side of (b). The right side of (b) steps through one execution of PCQ aggregation.

Adaptive Joins



```
SELECT * FROM A
  INNER JOIN B ON A.col1 = B.col1
  INNER JOIN C ON A.col2 = C.col1
```

(a) Example Input SQL Query

(b) Possible Join Orderings

```
fun query() {
  // HT on B, C built.
  var joinExec = {[
    {ht_B, joinB},
    {ht_C, joinC}]}
  for (v in A) {

  }}
```

```
fun joinB(
↪   v:*Vec,m:[*]Entry){
  for (t in v){
    if (t.col1==m[t].col1){
      v[t]=true}}}
```

```
fun joinC(
↪   v:*Vec,m:[*]Entry) {
  @gatherSelectEq(v.col2,
↪               m,0)}
```

	Sel.	Time	Rank
⋈	0.1	20	0.045
⋈	0.8	4	0.050

(c) Generated Code and Execution of Permutable Joins

Figure 5: Adaptive Joins – The DBMS translates the query in (a) to the program in (c). The right side of (c) illustrates one execution of a permutable join that includes a metric collection step.

Experimental Evaluation

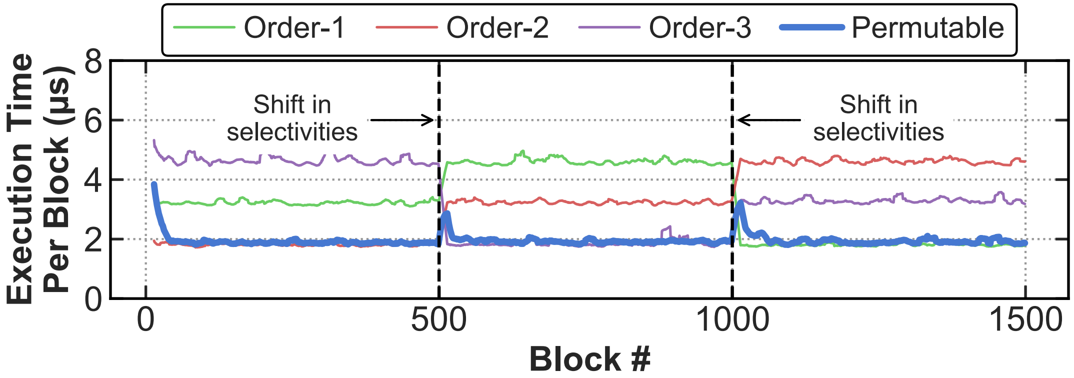


Figure 6: Performance Over Time – Execution time of three static filter orderings and our PCQ filter during a sequential table scan.

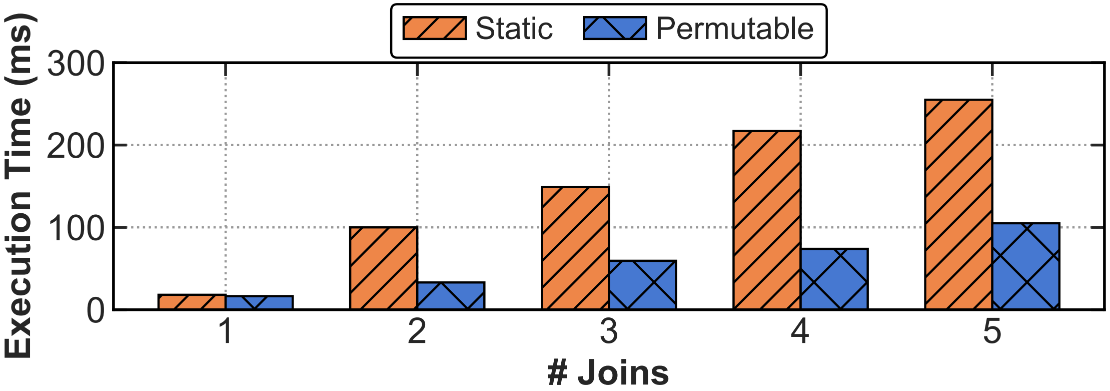
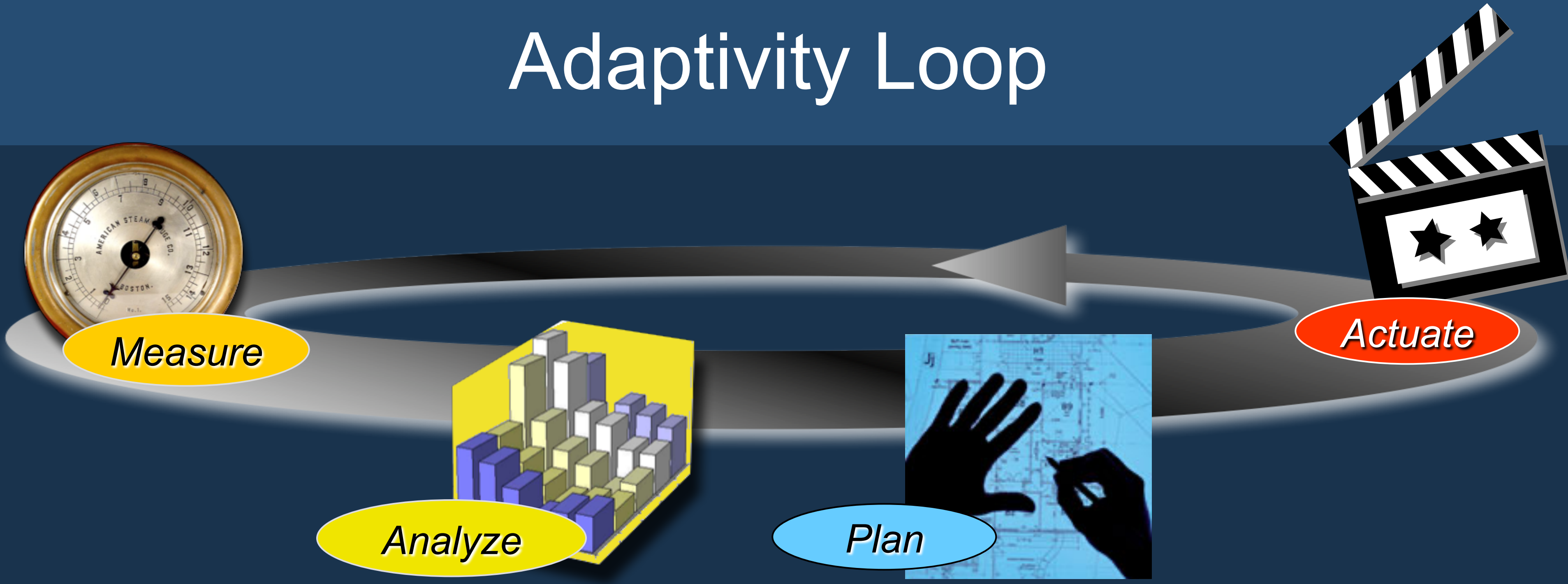


Figure 12: Varying Number of Joins – Execution time to perform a multi-step join while keeping the overall join selectivity at 10%.

Adaptivity Loop



Measure what ?

Cardinalities/selectivities, operator costs, resource utilization

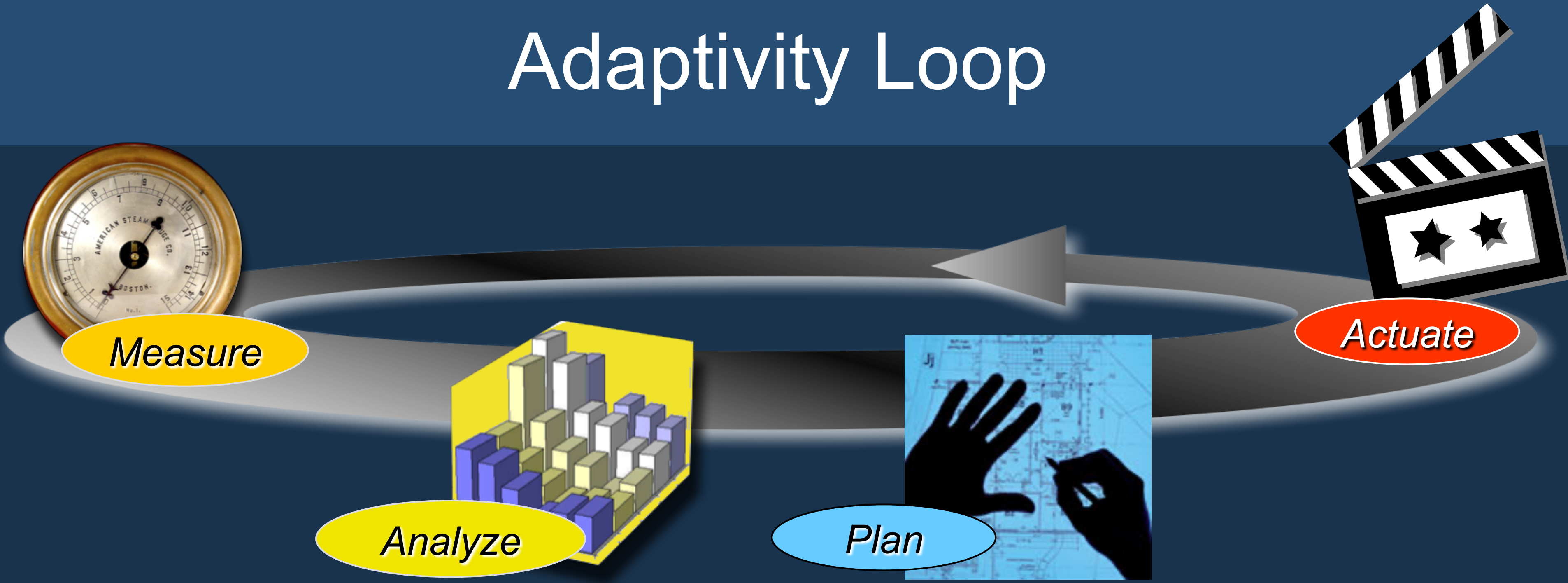
Measure when ?

Continuously (eddies); using a random sample (A-greedy); at materialization points (mid-query reoptimization)

Measurement overhead ?

Simple counter increments (mid-query) to very high

Adaptivity Loop



Analyze/replan what decisions ?

(Analyze actual vs. estimated selectivities)

Evaluate costs of alternatives and switching (keep state in mind)

Analyze / replan when ?

Periodically; at materializations (mid-query); at conditions (A-greedy)

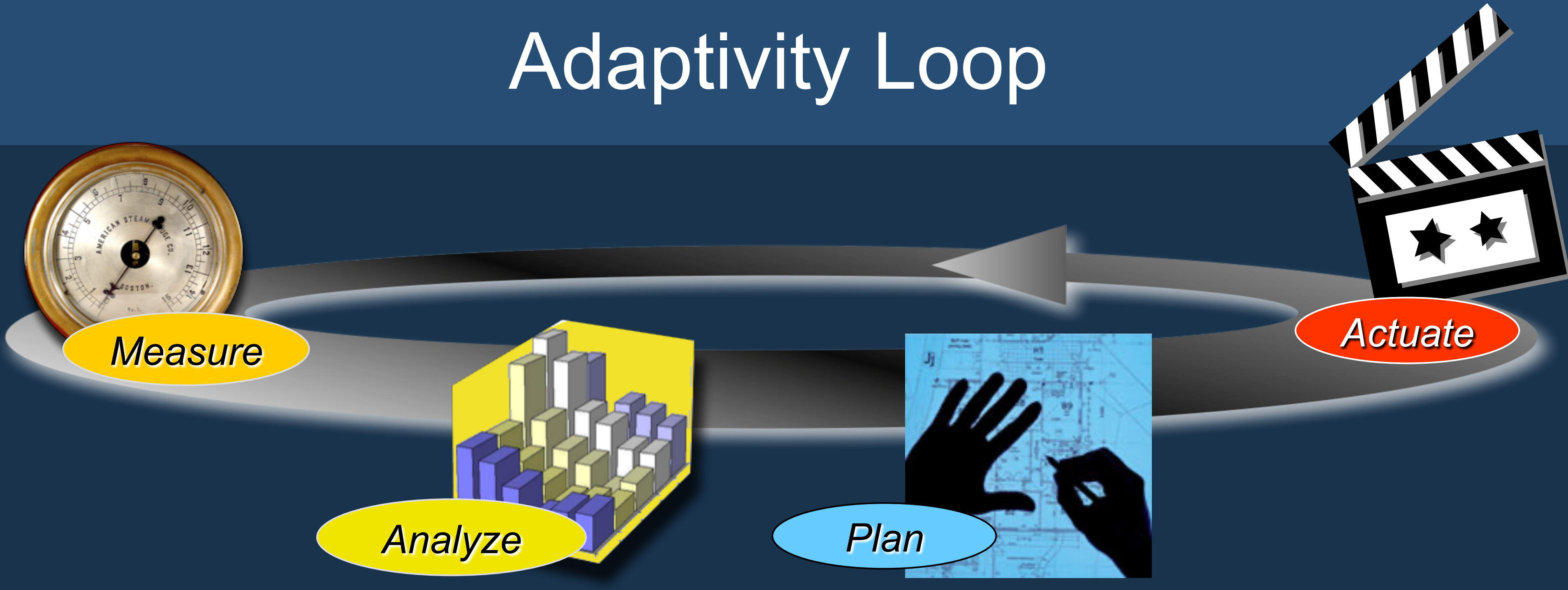
Plan how far ahead ?

Next tuple; batch; next stage (staged); possible remainder of plan (CQP)

Planning overhead ?

Switch stmt (parametric) to dynamic programming (CQP, mid-query)

Adaptivity Loop



Actuation: How do they switch to the new plan/new routing strategy ?

Actuation overhead ?

At the end of pipelines → free (mid-query)

During pipelines:

History-independent → Essentially free (selections, MJoins)

History-dependent → May need to migrate state (STAIRs, CAPE)

Recap/Thoughts

- Not much work on adaptive query processing in the last 10 years
  - SkinnerDB [2019] another relevant work
- More work on adapting the execution of a single operator
  - e.g., changing things based on available resources
- Likely to re-emerge as an important topic in the next few years
  - As QP in many systems becomes more mature…
  - As SQL starts becoming more and more common as the query language (e.g., in Spark, Pandas, etc).

Outline

- Query evaluation techniques for large databases, Skew Avoidance, Query compilation/vectorization
- Query Optimization: Overview, How good are the query optimizers, really?, Reordering for Outerjoins, Query Rewriting
- Adaptive Query Processing
- Worst-case Optimal Join Processing
- Froid: UDFs and Databases

Motivation

- Consider an ”edges” relation with N edges, capturing an “undirected” graph,
- And a query to find the number of ”triangles”

source	target
v1	v2
v2	v1
v1	v3
v3	v1
v2	v3
v3	v2

```
select count(*)/6
from edges e1, edges e2, edges e3
where e1.target = e2.source and
         e2.target = e3.source and
         e3.target = e1.source
```

Any “binary joins” plan will be “sub-optimal”
Worst case = O(N^2)
However, output size bounded by O(N^1.5)

Yannakakis Algorithm [1981]

q() :- R(A, B), S(B, C), T(C, D)

Boolean Conjunctive Query
Answer is a True/False

A	B
a1	b1
a2	b1
a3	b1
a4	b1
a5	b1
a6	b1
…	…

1M tuples with B = b1

B	C
b1	c1
b1	c2
b1	c3
…	…
b2	c0
b3	c0
…	…

1M tuples with C = c0
1M tuples with B = b1

C	D
c0	d1
c0	d2
c0	d3
c0	d4
c0	d5
c0	d6
…	…

1M tuples with C = c0

However: No results in the output

Yannakakis Algorithm [1981]

q() :- R(A, B), S(B, C), T(C, D)

A	B
a1	b1
a2	b1
a3	b1
a4	b1
a5	b1
a6	b1
…	…

1M tuples with B = b1

B	C
b1	c1
b1	c2
b1	c3
…	…
b2	c0
b3	c0
…	…

1M tuples with C = c0
1M tuples with B = b1

C	D
c0	d1
c0	d2
c0	d3
c0	d4
c0	d5
c0	d6
…	…

1M tuples with C = c0

No Binary Join Tree Works

R JOIN S == generates 1 trillion tuples
(none of which match T)

S JOIN T == generates 1T tuples

R JOIN T == cross product == 1T tuples

Yannakakis Algorithm [1981]

q() :- R(A, B), S(B, C), T(C, D)

A	B
a1	b1
a2	b1
a3	b1
a4	b1
a5	b1
a6	b1
…	…

1M tuples with B = b1

B	C
b1	c1
b1	c2
b1	c3
…	…
b2	c0
b3	c0
…	…

1M tuples with C = c0
1M tuples with B = b1

C	D
c0	d1
c0	d2
c0	d3
c0	d4
c0	d5
c0	d6
…	…

1M tuples with C = c0

First, do S SEMIJOIN R

B	C
b1	c1
b1	c2
b1	c3
…	…

Removes tuples from S that don’t contribute to the final output
(e.g., (b2, c0) will never join with anything from R)

Yannakakis Algorithm [1981]

q() :- R(A, B), S(B, C), T(C, D)

A	B
a1	b1
a2	b1
a3	b1
a4	b1
a5	b1
a6	b1
…	…

1M tuples with B = b1

B	C
b1	c1
b1	c2
b1	c3
…	…
b2	c0
b3	c0
…	…

1M tuples with C = c0
1M tuples with B = b1

C	D
c0	d1
c0	d2
c0	d3
c0	d4
c0	d5
c0	d6
…	…

1M tuples with C = c0

First, do S SEMIJOIN R

B	C
b1	c1
b1	c2
b1	c3
…	…

Then: X1 = T SEMIJOIN
(S SEMIJOIN R)

C	D

Then, do X2 = S SEMIJOIN X1

To further "reduce" S by removing tuples that don't join with anything from T

Yannakakis Algorithm [1981]

q() :- R(A, B), S(B, C), T(C, D)

A	B
a1	b1
a2	b1
a3	b1
a4	b1
a5	b1
a6	b1
…	…

1M tuples with B = b1

B	C
b1	c1
b1	c2
b1	c3
…	…
b2	c0
b3	c0
…	…

1M tuples with C = c0
1M tuples with B = b1

C	D
c0	d1
c0	d2
c0	d3
c0	d4
c0	d5
c0	d6
…	…

1M tuples with C = c0

First, do S SEMIJOIN R

B	C
b1	c1
b1	c2
b1	c3
…	…

Then: X1 = T SEMIJOIN (S SEMIJOIN R)

C	D

Then, do X2 = S SEMIJOIN X1

Finally, do X3 = R SEMIJOIN X2

Yannakakis Algorithm [1981]

- Called “semi-join reducer sequences”
  - Basically get rid of tuples from each relation that don’t contribute to the output
  - Result EMPTY in our example, but in general, only relevant tuples will be left

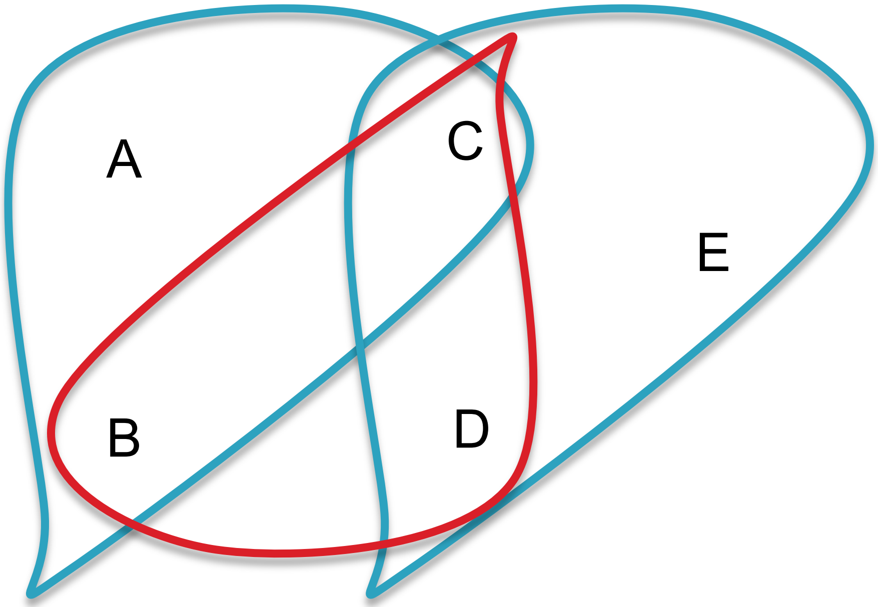
- Once this is done, you can do join in any order
  - Guaranteed that the total time is “linear” in the total size of the inputs and output
  - Can’t avoid dependence on the output -- the join query may do a Cartesian product

- Can be generalized to any “acyclic” query

Acyclic Queries?

- Conjunctive queries as “hypergraphs”

q() :- R1(A, B, C), R2(B, C, D), R3(C, D, E)

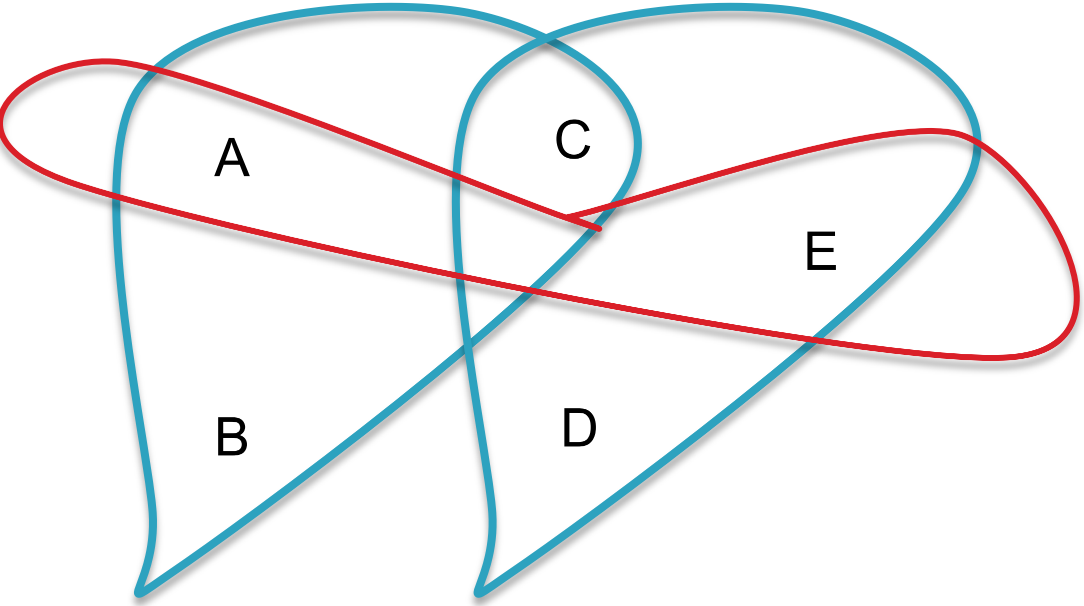


Each attribute == a vertex
Each relation == a “hyperedge”

Acyclic Queries?

- Conjunctive queries as “hypergraphs”

q() :- R1(A, B, C), R2(C, D, E), R3(A, E)

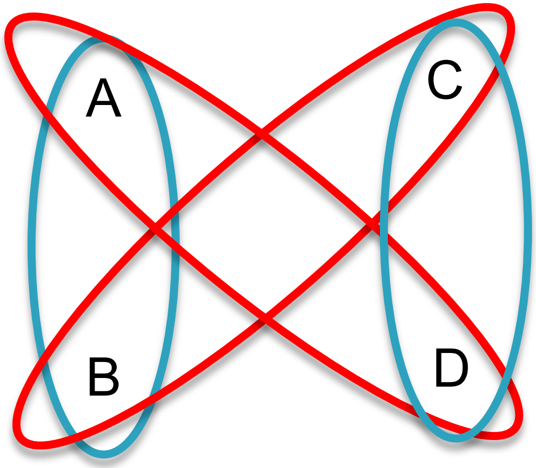


Each attribute == a vertex
Each relation == a “hyperedge”

Acyclic Queries?

- If all relations are 2 attributes, then the hypergraph is same as a graph

q() :- R1(A, B), R2(B, C), R3(C, D), R4(D, A)



Acyclic queries in this case == the graph has no cycles, i.e., the graph is a tree

More complex for hypergraphs

Structural Approaches

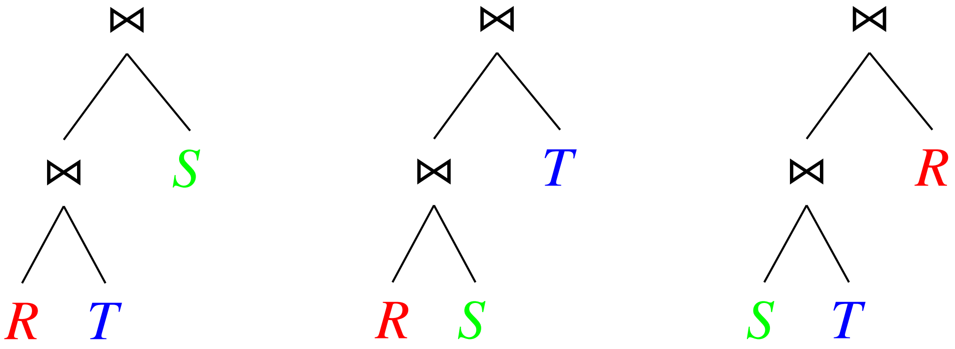
- For “acyclic” queries, can always find a semijoin reducer sequence
  - Can be done in optimal time: linear in size of inputs + output

- What about non-acyclic queries?
  - Try to define how “far” from acyclic-ness
  - Captured as ”width” of the hypergraph
    - Width of acyclic hypergraphs = 1

- AGM [FOCS, 2008] defined “fractional hypertree width”, and an algorithm that runs in O(N^(fhw+1) log N)
- Several more practical algorithms since then, including one that was implemented before it was proved optimal

Triangle Query

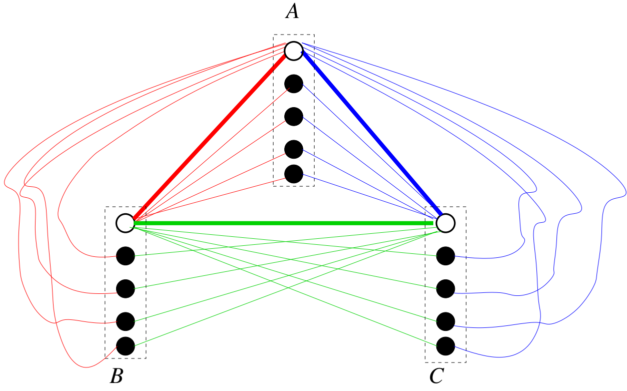
$$Q_{\triangle} = R(A,B) \bowtie S(B,C) \bowtie T(A,C).$$



$$R = \{a_0\} \times \{b_0, \ldots, b_m\} \cup \{a_0, \ldots, a_m\} \times \{b_0\}$$

$$S = \{b_0\} \times \{c_0, \ldots, c_m\} \cup \{b_0, \ldots, b_m\} \times \{c_0\}$$

$$T = \{a_0\} \times \{c_0, \ldots, c_m\} \cup \{a_0, \ldots, a_m\} \times \{c_0\}$$



Each relation has: 2m + 1 tuples
Output = 3m + 1
Any pairwise join has size: m^2 + m
Projections/Semi-joins don’t help

Algorithm 1: Power of Two Choices

Skew in the relations: a_0 generates a lot of intermediate tuples, but not as many output tuples

$$Q_{\triangle}[a_i] := \pi_{B,C}(\sigma_{A=a_i}(Q_{\triangle})).$$

Call a_i heavy if:

$$|\sigma_{A=a_i}(R \bowtie T)| \geqslant |Q_{\triangle}[a_i]|.$$

Two Choices for each a_i:

If a_i is light

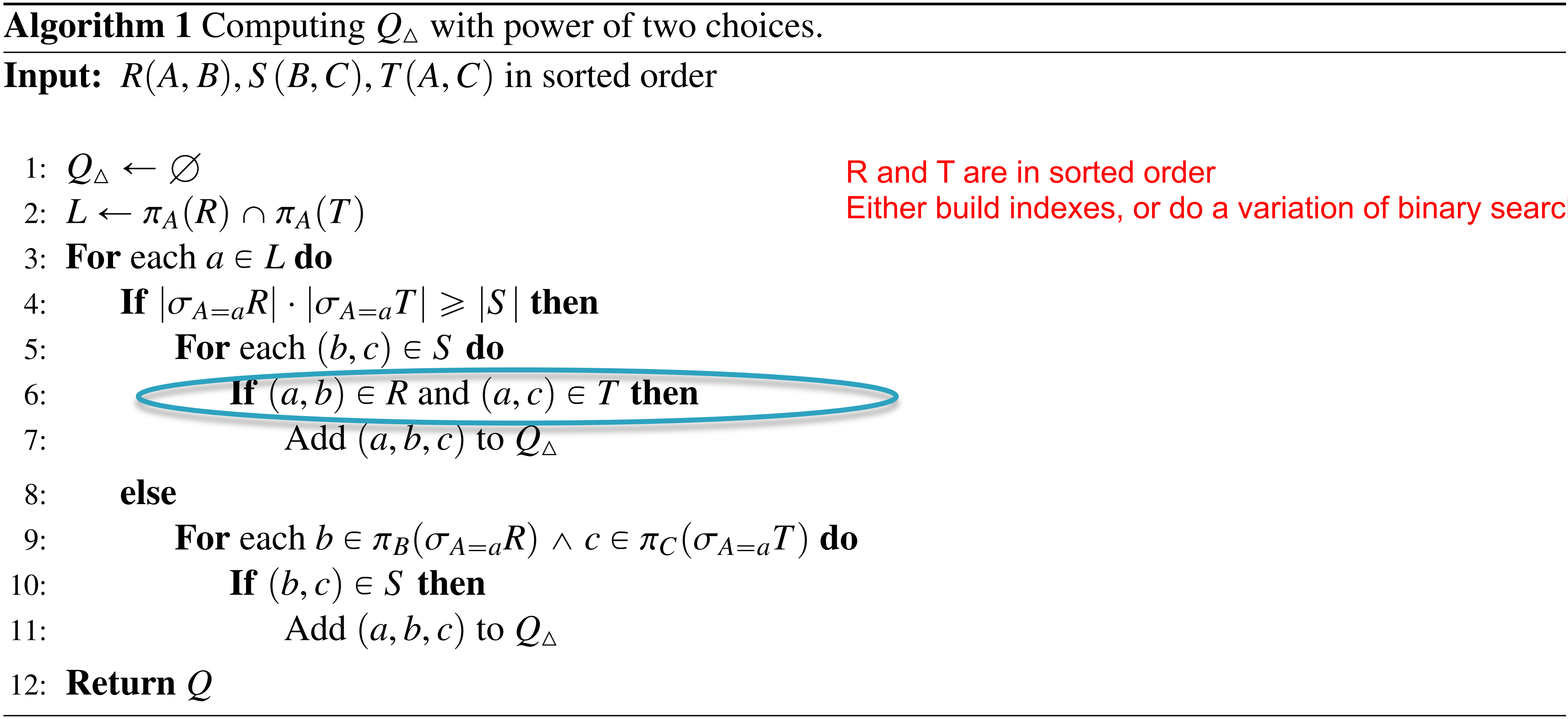
(i) Compute $\sigma_{A=a_i}(R) \bowtie \sigma_{A=a_i}(T)$ and filter the results by probing against S or

(ii) Consider each tuple in $(b,c) \in S$ and check if $(a_i, b) \in R$ and $(a_i, c) \in T$.

If a_i is heavy

Can prove to run in : O(N^1.5)

Algorithm 1: Power of Two Choices



Algorithm 1 Computing $Q_\triangle$ with power of two choices.

Input: $R(A,B), S(B,C), T(A,C)$ in sorted order

```
$Q_\triangle \leftarrow \emptyset$
$L \leftarrow \pi_A(R) \cap \pi_A(T)$
**For** each $a \in L$ **do**
    **If** $|\sigma_{A=a}R| \cdot |\sigma_{A=a}T| \geqslant |S|$ **then**
        **For** each $(b,c) \in S$ **do**
            **If** $(a,b) \in R$ and $(a,c) \in T$ **then**
                Add $(a,b,c)$ to $Q_\triangle$
    **else**
        **For** each $b \in \pi_B(\sigma_{A=a}R) \wedge c \in \pi_C(\sigma_{A=a}T)$ **do**
            **If** $(b,c) \in S$ **then**
                Add $(a,b,c)$ to $Q_\triangle$
**Return** $Q$
```

R and T are in sorted order

Either build indexes, or do a variation of binary search

Algorithm 2: Delay Computation

For each value a_i, compute valid values of B that join with it:

$$\pi_B(\sigma_{A=a_i}R) \cap \pi_B S$$

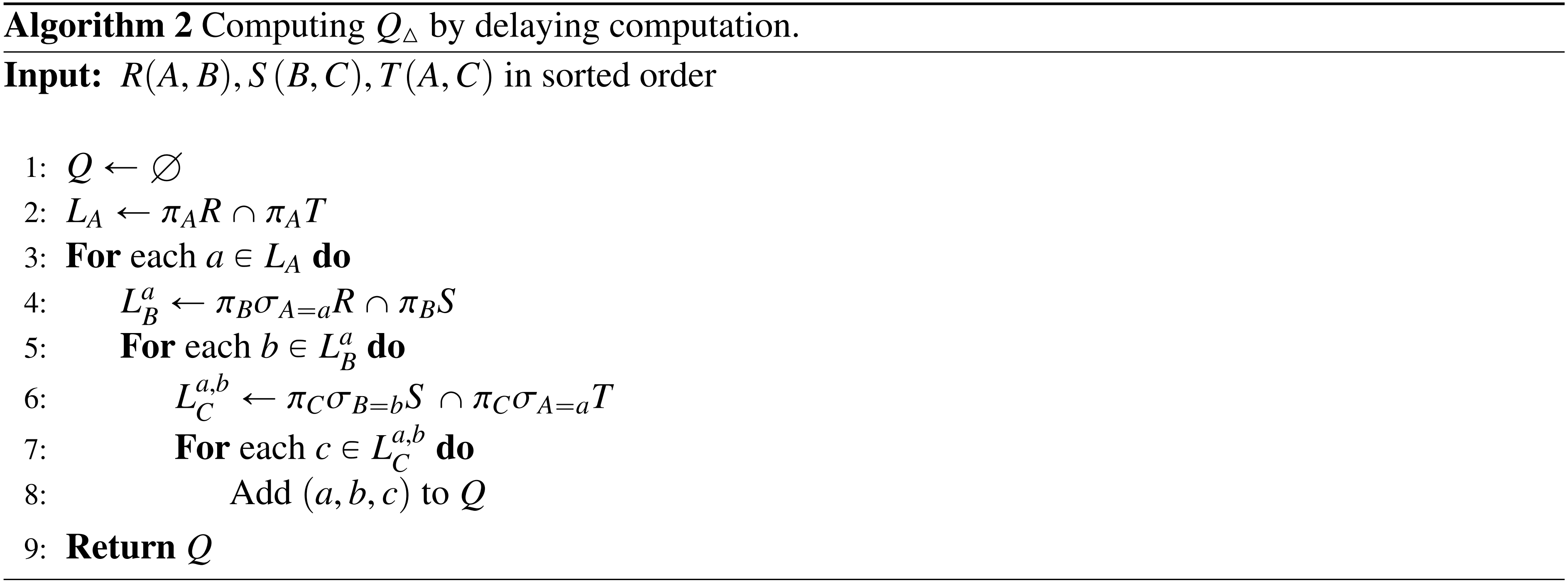
For each value of b in the above result, compute valid values of C:

$$\pi_C(\sigma_{B=b}S) \cap \pi_C(\sigma_{A=a_i}T).$$

Can prove to run in : O(N) on our bad example

General worst-case complexity the same as the previous algorithm

Algorithm 2: Delay Computation



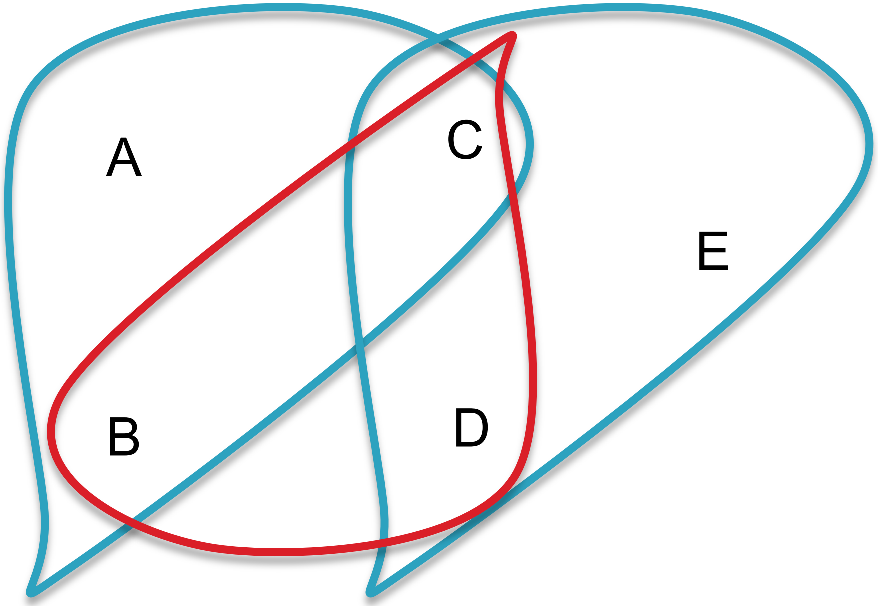
Algorithm 2 Computing $Q_\triangle$ by delaying computation.

Input: $R(A,B), S(B,C), T(A,C)$ in sorted order

```
$Q \leftarrow \emptyset$
$L_A \leftarrow \pi_A R \cap \pi_A T$
**For** each $a \in L_A$ **do**
    $L_B^a \leftarrow \pi_B \sigma_{A=a} R \cap \pi_B S$
    **For** each $b \in L_B^a$ **do**
        $L_C^{a,b} \leftarrow \pi_C \sigma_{B=b} S \cap \pi_C \sigma_{A=a} T$
        **For** each $c \in L_C^{a,b}$ **do**
            Add $(a,b,c)$ to $Q$
**Return** $Q$
```

AGM Bound on Join Sizes

q() :- R1(A, B, C), R2(B, C, D), R3(C, D, E)



Assign a weight to each of R1, R2, and R3

Say:
R1 → 0.5
R2 → 0.5
R3 → 0.5

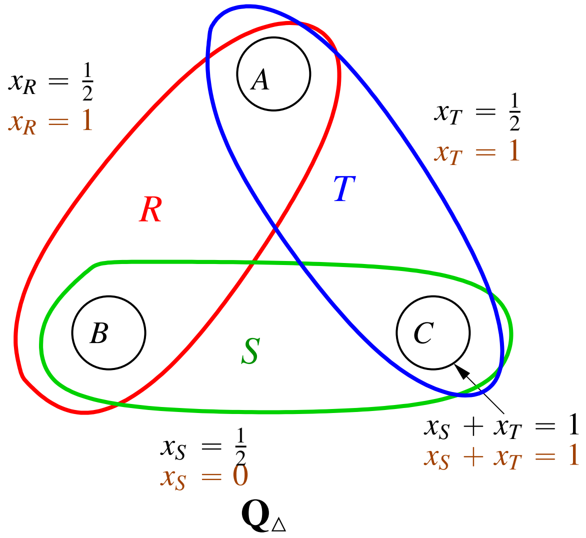
Total for B = 0.5 + 0.5 >= 1
B is "covered"
C (1.5), and D (1) are covered

A and E are not covered.

A set of weights is called "fractional edge cover" if all attributes are covered
Infinite number of fractional edge covers

AGM Bound on Join Sizes

Examples, with some fractional edge covers



AGM Bound on Join Sizes

Why do we care?

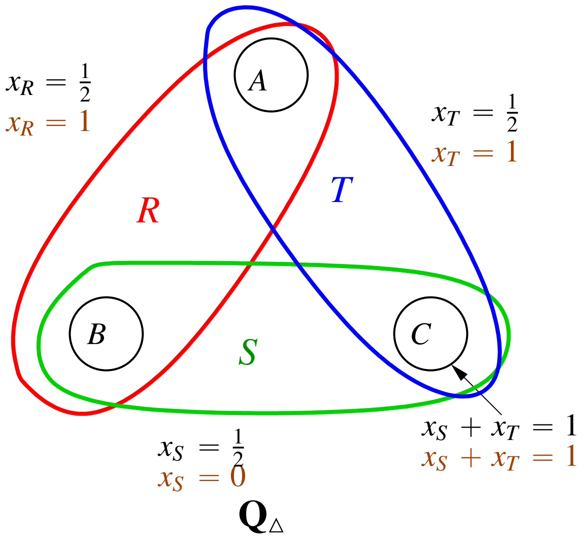
Say we have “l” relations in a query **q**, with sizes N_j, j = 1, …, l

Let **u** denote any fractional edge cover -- so u_j is the weight for relation with size N_j

Then, the size of the result is bounded by:

$$|q| \leq \prod_{j=1}^{\ell} N_j^{u_j}$$

AGM Bound on Join Sizes



Using the first cover, result size bounded by:

$$|Q_\triangle| \leqslant \sqrt{|R| \cdot |S| \cdot |T|}.$$

If |R| = |S| = |T|, then the bound is N^1.5 -- which is tight

But if |R| = |T| = 1, and |S| = N, then the bound is sqrt(N)
-- Far from tight -- there can only be 1 triangle

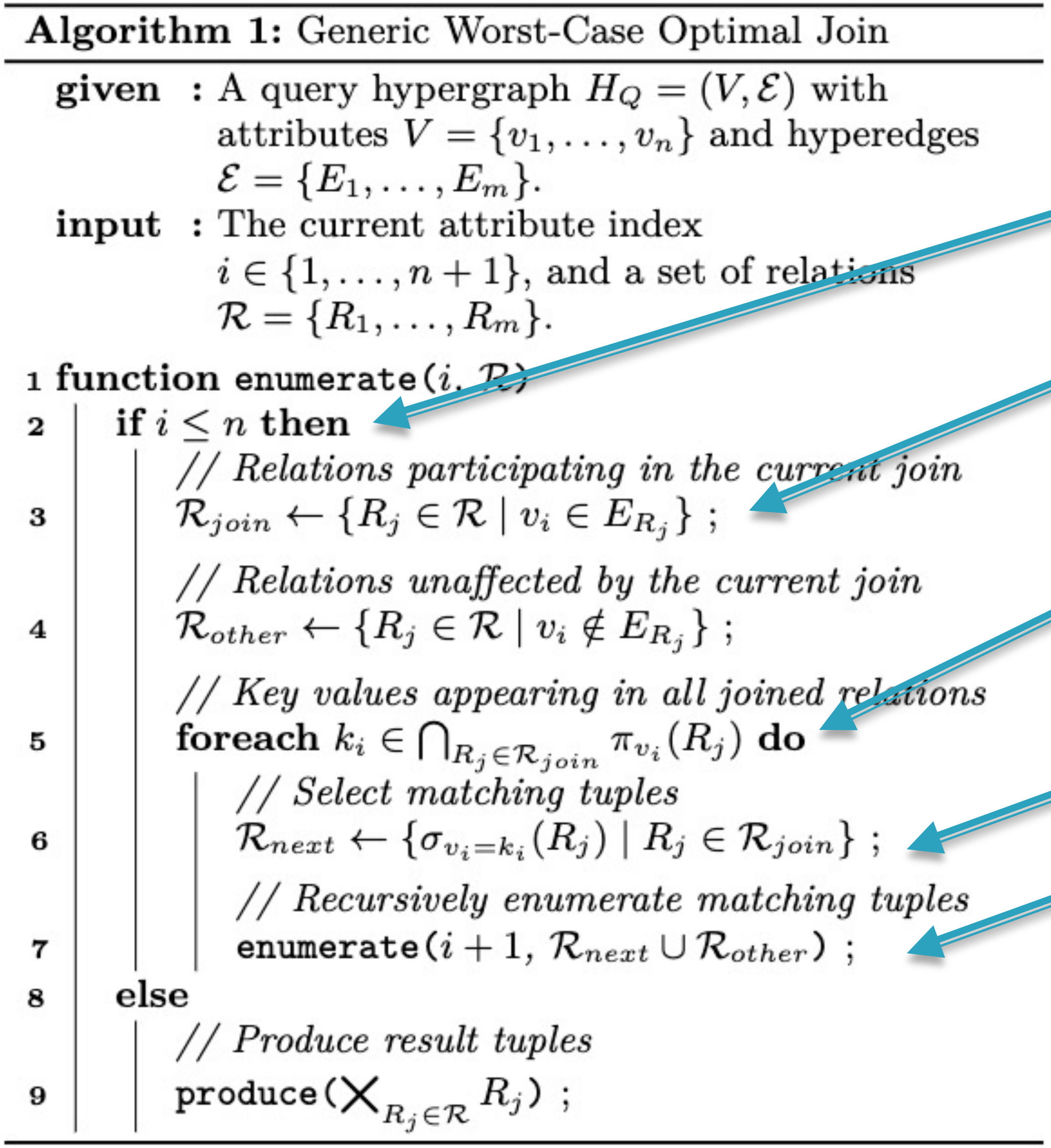
Using the second cover, result size bounded by:

$$|Q_\triangle| \leqslant |R| \cdot |T|.$$

If |R| = |S| = |T|, then the bound is N^2 -- not great

But if |R| = |T| = 1, and |S| = N, then the bound is 1

A Generic Algorithm



Algorithm 1: Generic Worst-Case Optimal Join

```
given : A query hypergraph $H_Q = (V, \mathcal{E})$ with
        attributes $V = \{v_1, \ldots, v_n\}$ and hyperedges
        $\mathcal{E} = \{E_1, \ldots, E_m\}$.
input : The current attribute index
        $i \in \{1, \ldots, n+1\}$, and a set of relations
        $\mathcal{R} = \{R_1, \ldots, R_m\}$.

function enumerate($i$, $\mathcal{R}$)
    if $i \leq n$ then
        // Relations participating in the current join
        $\mathcal{R}_{join} \leftarrow \{R_j \in \mathcal{R} \mid v_i \in E_{R_j}\}$ ;
        // Relations unaffected by the current join
        $\mathcal{R}_{other} \leftarrow \{R_j \in \mathcal{R} \mid v_i \notin E_{R_j}\}$ ;
        // Key values appearing in all joined relations
        foreach $k_i \in \bigcap_{R_j \in \mathcal{R}_{join}} \pi_{v_i}(R_j)$ do
            // Select matching tuples
            $\mathcal{R}_{next} \leftarrow \{\sigma_{v_i = k_i}(R_j) \mid R_j \in \mathcal{R}_{join}\}$ ;
            // Recursively enumerate matching tuples
            enumerate($i + 1$, $\mathcal{R}_{next} \cup \mathcal{R}_{other}$) ;
    else
        // Produce result tuples
        produce($\bigtimes_{R_j \in \mathcal{R}} R_j$) ;
```

Process each attribute (variable) at a time

Find all relations that contain that attribute

Do an intersection across all the relations for that attribute

For each value that is present for v_i in all of R_join:

- Select from each relation only those where v_i = k_i
- Recurse with those relations plus the rest of the relations

Recap/Thoughts

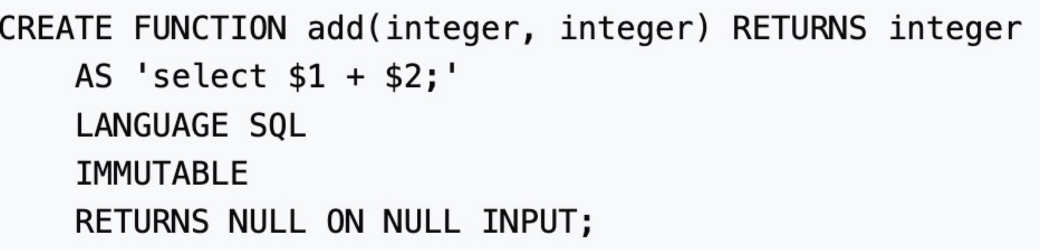
- Quite a bit of work on this topic in the last 10 years
- Several implementations
  - Often in the context of graph querying
  - Usually require significant pre-computations and specialized indexes
    - The “intersection” step in the previous slide is a key one
  - Some recent work (VLDB 2020) on a more practical implementation using hash indexes instead of sort-based tries
- Still not clear when to use them and when to use binary joins
- Open theoretical issues
- What about outerjoins, etc?

Outline

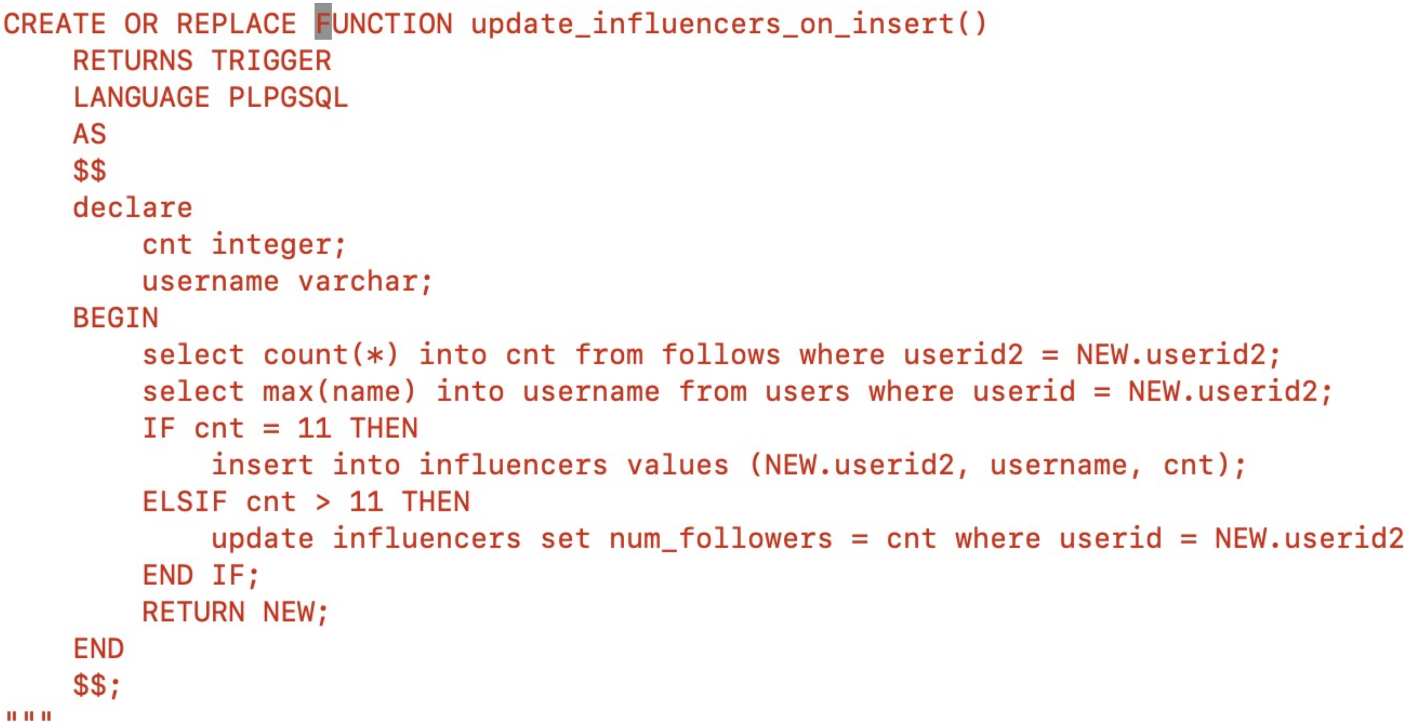
- Part 1 Slides
  - Query evaluation techniques for large databases, Skew Avoidance, Query compilation/vectorization
  - Query Optimization: Overview, How good are the query optimizers, really?, Reordering for Outerjoins, Query Rewriting
- Adaptive Query Processing
- Worst-case Optimal Join Processing
- Froid: UDFs and Databases
  - Background
  - Froid

User-defined Functions/Procedures

- Supported by database systems since late 80s



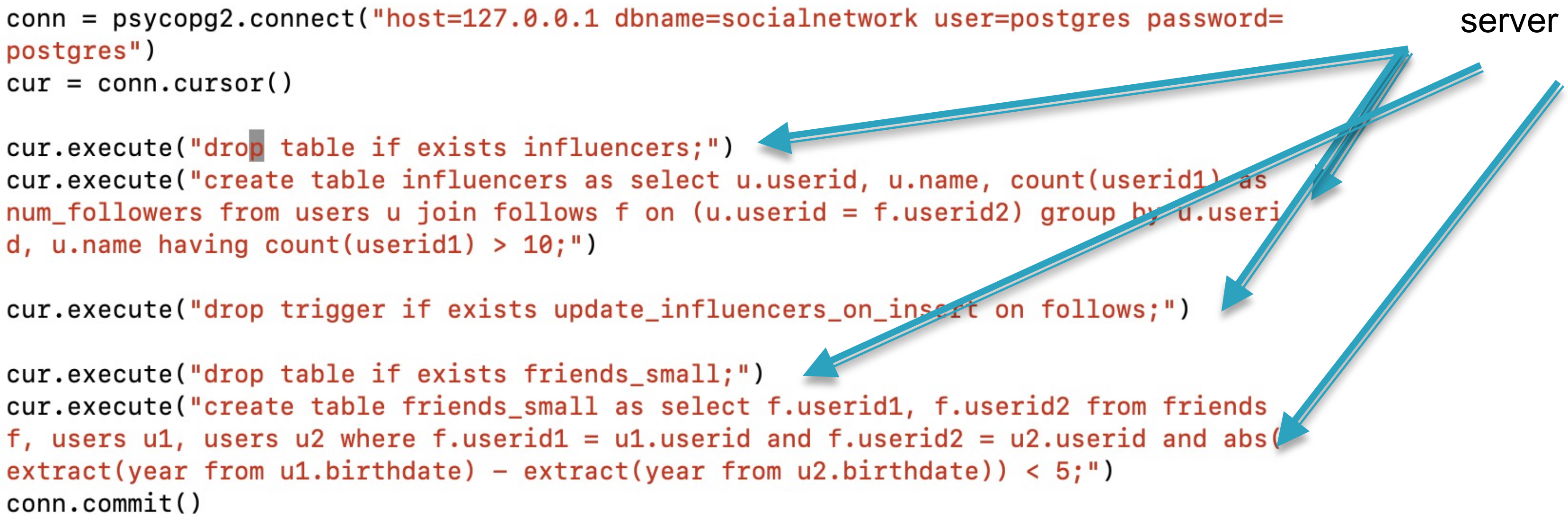
```
CREATE FUNCTION add(integer, integer) RETURNS integer
    AS 'select $1 + $2;'
    LANGUAGE SQL
    IMMUTABLE
    RETURNS NULL ON NULL INPUT;
```



```
CREATE OR REPLACE FUNCTION update_influencers_on_insert()
    RETURNS TRIGGER
    LANGUAGE PLPGSQL
    AS
    $$
    declare
        cnt integer;
        username varchar;
    BEGIN
        select count(*) into cnt from follows where userid2 = NEW.userid2;
        select max(name) into username from users where userid = NEW.userid2;
        IF cnt = 11 THEN
            insert into influencers values (NEW.userid2, username, cnt);
        ELSIF cnt > 11 THEN
            update influencers set num_followers = cnt where userid = NEW.userid2
        END IF;
        RETURN NEW;
    END
    $$;
"""
```

User-defined Functions/Procedures

- Supported by database systems since late 80s
- Three main benefits:
  - Modular code
  - Easier to write some code in an imperative language (e.g., ML)
  - Fewer round-trips between application and database
    - Significant performance issues if done repeatedly (e.g., for every order)



```
conn = psycopg2.connect("host=127.0.0.1 dbname=socialnetwork user=postgres password=
postgres")
cur = conn.cursor()

cur.execute("drop table if exists influencers;")
cur.execute("create table influencers as select u.userid, u.name, count(userid1) as
num_followers from users u join follows f on (u.userid = f.userid2) group by u.useri
d, u.name having count(userid1) > 10;")

cur.execute("drop trigger if exists update_influencers_on_insert on follows;")

cur.execute("drop table if exists friends_small;")
cur.execute("create table friends_small as select f.userid1, f.userid2 from friends
f, users u1, users u2 where f.userid1 = u1.userid and f.userid2 = u2.userid and abs(
extract(year from u1.birthdate) - extract(year from u2.birthdate)) < 5;")
conn.commit()
```

Each of these is a separate call from the application to the server

User-defined Functions/Procedures

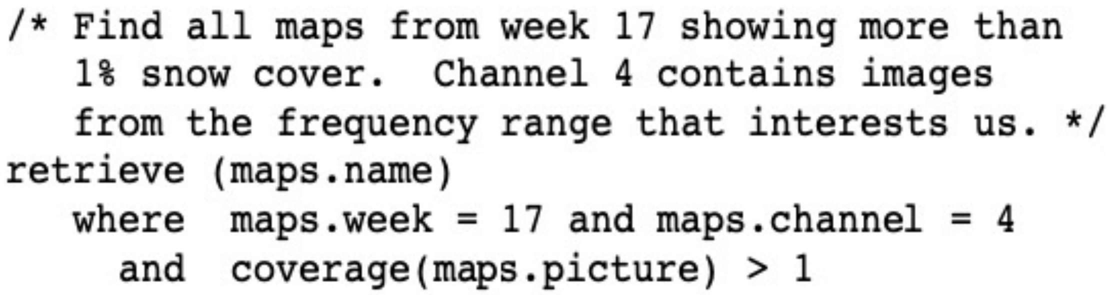
- Supported by database systems since late 80s
- Three main benefits:
  - Modular code
  - Easier to write some code in an imperative language (e.g., ML)
  - Fewer round-trips between application and database
    - Significant performance issues if done repeatedly (e.g., for every order)
- Stonebraker notes the latter as the primary reason for adoption of OR features (”what comes around goes around” paper)
  - “Put differently, the major contribution of the OR efforts turned out to be a better mechanism for stored procedures and user-defined access methods.”
- Also called “stored procedures”, with some minor differences across systems

Terminology

- User-defined functions
  - Scalar (return a single value) or Table Functions (return a relation)
  - Can be used in queries (WHERE/SELECT/FROM, etc), depending on scalar or table function
  - UDFs typically not allowed to make changes to the database
- Stored procedures
  - Similar, but can only be executed using a CALL or EXECUTE command
  - Usually mutate the state of the database
- Triggers
  - Something that happens because of an event (e.g., an insert in orders results in an insert in another table)
  - Similar to stored procedures for the actual action

UDF Challenges

- Optimization
  - UDFs can be very expensive -- coverage() does image analysis of some form
  - Cost of UDFs is hard to estimate -- may depend on the inputs
  - Selectivity of UDFs is hard to estimate -- statistics don’t really help



```
/* Find all maps from week 17 showing more than
   1% snow cover.  Channel 4 contains images
   from the frequency range that interests us. */
retrieve (maps.name)
   where  maps.week = 17 and maps.channel = 4
     and  coverage(maps.picture) > 1
```

Example from: “Predicate Migration; Hellerstein and Stonebraker; SIGMOD 1993

UDF Challenges

- Optimization
  - UDFs can be very expensive -- coverage() does image analysis of some form
  - Cost of UDFs is hard to estimate -- may depend on the inputs
  - Selectivity of UDFs is hard to estimate -- statistics don’t really help
- UDFs cannot be parallelized easily
  - May result in single-threaded execution
- Forces tuple-at-a-time execution
  - Hard to use any of subquery decorrelation techniques
- Often interpreted execution
- Well-known issues resulting in bad performance in many practical scenarios

Outline

- Part 1 Slides
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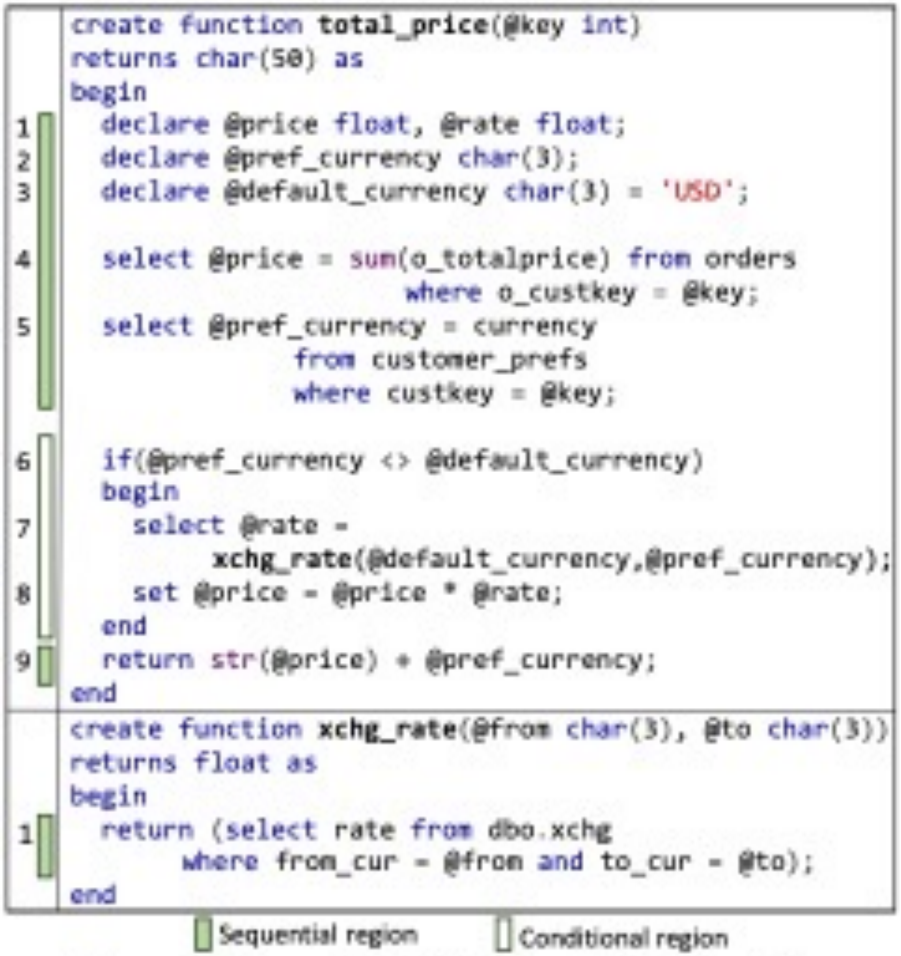
Background on T-SQL

- SQL Server supports: UDFs (cannot modify state), and Stored Procedures (can modify state)



```
create function total_price(@key int)
returns char(50) as
begin
  declare @price float, @rate float;
  declare @pref_currency char(3);
  declare @default_currency char(3) = 'USD';

  select @price = sum(o_totalprice) from orders
                        where o_custkey = @key;
  select @pref_currency = currency
            from customer_prefs
            where custkey = @key;

  if(@pref_currency <> @default_currency)
  begin
    select @rate =
         xchg_rate(@default_currency,@pref_currency);
    set @price = @price * @rate;
  end
  return str(@price) + @pref_currency;
end
```

```
create function xchg_rate(@from char(3), @to char(3))
returns float as
begin
  return (select rate from dbo.xchg
       where from_cur = @from and to_cur = @to);
end
```

🟩 Sequential region   □ Conditional region

Figure 1: Example T-SQL User defined functions

select *c_name*, ***dbo.total_price***(*c_custkey*)
from *customer*;

UDF Evaluation in SQL Server

- Steps
  - Parsing, binding, normalization: scalar UDFs bound as a UDF operator, but the definition not analyzed
  - Cost-based optimization: Query plans (including for each statement in a UDF) are cached
  - Execution: For each tuple, scalar evaluation sub-system is called
    - May make calls back to the relational execution engine
    - Compilation for an UDF happens on the first call
- Drawbacks
  - Iterative invocations (one at a time) -- leads to repeated context switches
  - No costing, Interpreted statement-by-statement (with caching of plans)
  - No intra-query parallelism (as of 2017)

Froid Framework

- Inline the UDFs by analyzing the code

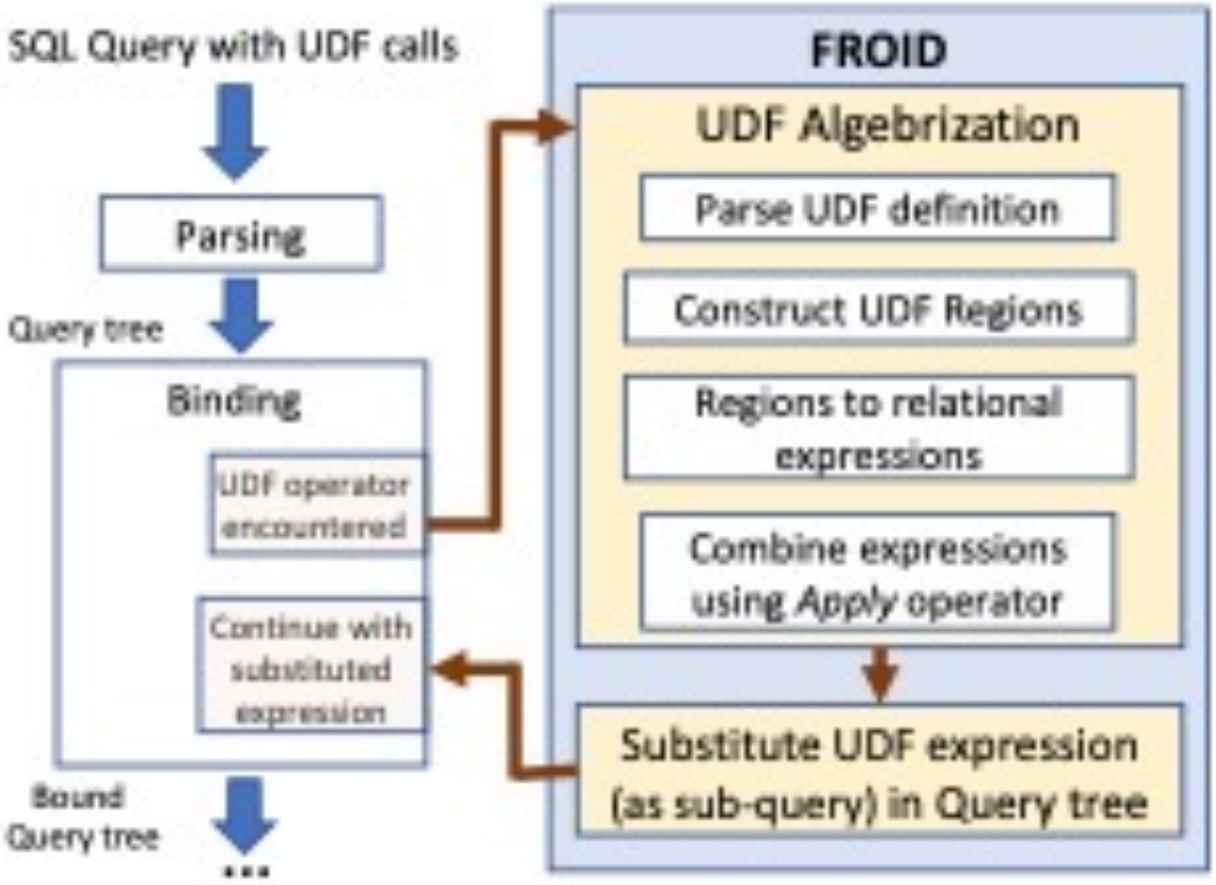

SQL Query with UDF calls
Parsing
Query tree
Binding
UDF operator encountered
Continue with substituted expression
Bound Query tree
...
FROID
UDF Algebrization
Parse UDF definition
Construct UDF Regions
Regions to relational expressions
Combine expressions using *Apply* operator
Substitute UDF expression (as sub-query) in Query tree

Figure 3: Overview of the Froid framework

Froid Framework

- Makes use of APPLY Operator
  - Basically a “flatmap”
  - For each tuple r of R, combine it with each output of E(r) to generate new tuples

$$R \ \mathcal{A}^{\otimes} \ E = \bigcup_{r \in R} (\{r\} \otimes E(r))$$

  - The “join” can be: cross product, left outer-join, left-semijion, or left-antijoin

- SQL Server already uses these extensively for subquery decorrelation (as we saw earlier)

Froid Framework

- Supports imperative constructs in scalar UDFs

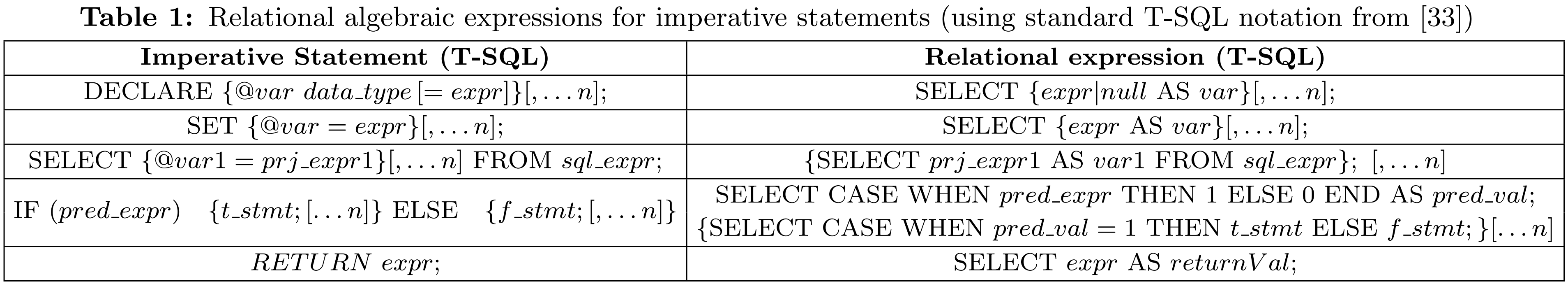


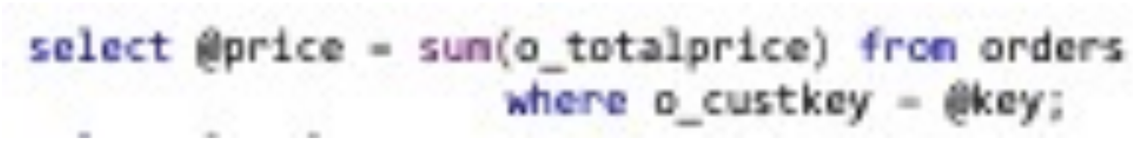
Table 1: Relational algebraic expressions for imperative statements (using standard T-SQL notation from [33])

Imperative Statement (T-SQL)	**Relational expression (T-SQL)**
DECLARE $\{@var\ data\_type\,[= expr]\}[, \ldots n];$	SELECT $\{expr \mid null$ AS $var\}[, \ldots n];$
SET $\{@var = expr\}[, \ldots n];$	SELECT $\{expr$ AS $var\}[, \ldots n];$
SELECT $\{@var1 = prj\_expr1\}[, \ldots n]$ FROM $sql\_expr;$	$\{$SELECT prj_expr1 AS $var1$ FROM $sql\_expr\};\ [, \ldots n]$
IF $(pred\_expr)$ $\{t\_stmt; [\ldots n]\}$ ELSE $\{f\_stmt; [, \ldots n]\}$	SELECT CASE WHEN $pred\_expr$ THEN 1 ELSE 0 END AS $pred\_val;$ $\{$SELECT CASE WHEN $pred\_val = 1$ THEN t_stmt ELSE $f\_stmt;\}[\ldots n]$
$RETURN\ expr;$	SELECT $expr$ AS $returnVal;$

UDF Algebrization

- Construction of regions
  - Basic sequential regions, condition regions (if-else), and loop regions (loops)
  - Hierarchical (regions can contain regions)
- Relational expressions for each region
  - Variable declarations/assignments

set *@default_currency* = *'USD'*; → **select** *'USD'* **as** *default_currency*.



```
select @price = sum(o_totalprice) from orders
                 where o_custkey = @key;
```

→ **select**(**select** *sum(o_totalprice)* **from** *orders*
where *o_custkey* = *@key*) **as** *price*

UDF Algebrization

- Relational expressions for each region
  - Variable declarations/assignments
  - Conditional statements

```
if (@total > 1000)
    set @val = 'high';
else
    set @val = 'low';
```

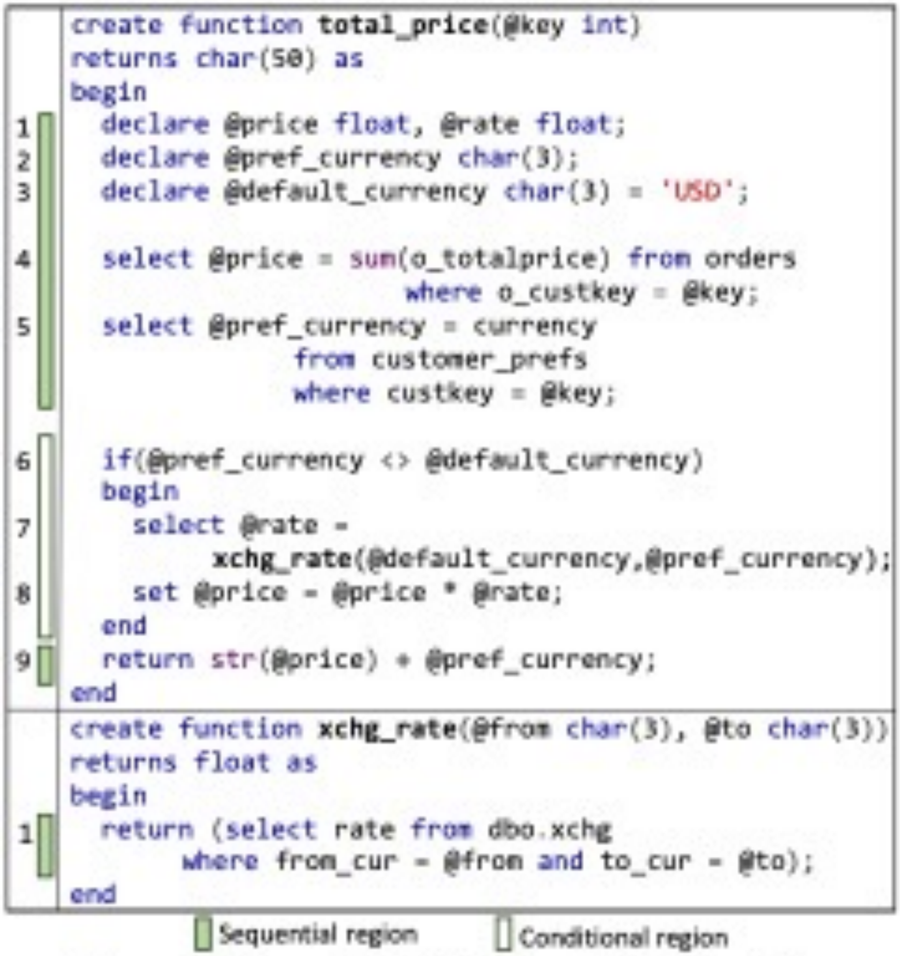
→

```
select ( case when total > 1000 then 'high'
            else 'low' end ) as val.
```

  - Return statements
    - Code may have multiple return points
    - Modeled as a "jump" to the end of the codeblock
    - Implemented through use of "probe" and "pass-through" of APPLY

UDF Algebrization

- Combining expressions for multiple statements
  - For each statement: compute a “read-set” and a “write-set”



```
  create function total_price(@key int)
  returns char(50) as
  begin
1   declare @price float, @rate float;
2   declare @pref_currency char(3);
3   declare @default_currency char(3) = 'USD';

4   select @price = sum(o_totalprice) from orders
                    where o_custkey = @key;
5   select @pref_currency = currency
              from customer_prefs
              where custkey = @key;

6   if(@pref_currency <> @default_currency)
    begin
7     select @rate =
          xchg_rate(@default_currency,@pref_currency);
8     set @price = @price * @rate;
    end
9   return str(@price) + @pref_currency;
  end
```

```
  create function xchg_rate(@from char(3), @to char(3))
  returns float as
  begin
1   return (select rate from dbo.xchg
        where from_cur = @from and to_cur = @to);
  end
```

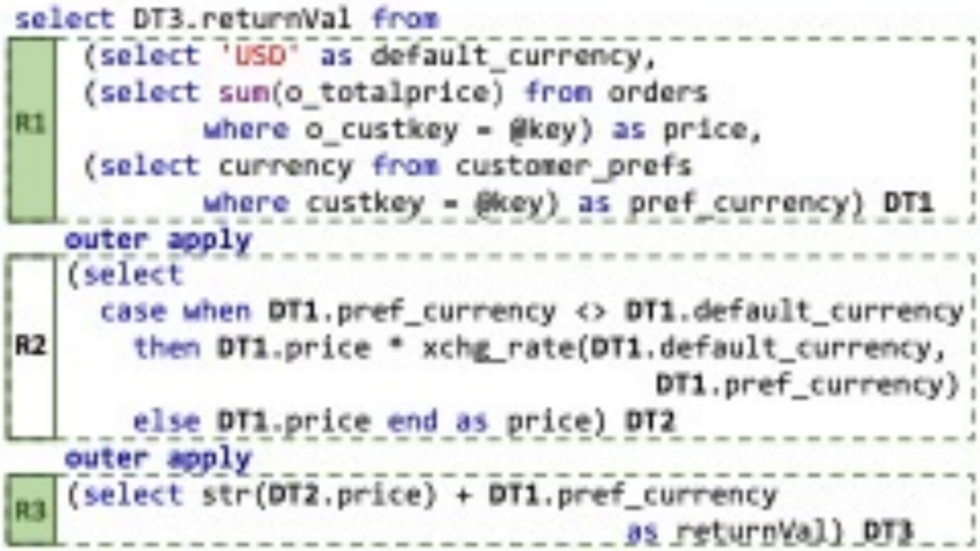
🟩 Sequential region □ Conditional region

Figure 1: Example T-SQL User defined functions

Table 2: Derived tables for regions in function *total_price*.

Region	Write-sets (Derived table schema)
R1	DT1 (price *float*, rate *float*, default_currency *char(3)*, pref_currency *char(3)*)
R2	DT2 (price *float*, rate *float*)
R3	DT3 (returnVal *char(50)*)

Use these as the “schemas” of derived tables to be computed



```
select DT3.returnVal from
R1  (select 'USD' as default_currency,
    (select sum(o_totalprice) from orders
          where o_custkey = @key) as price,
    (select currency from customer_prefs
          where custkey = @key) as pref_currency) DT1
outer apply
R2  (select
      case when DT1.pref_currency <> DT1.default_currency
        then DT1.price * xchg_rate(DT1.default_currency,
                                   DT1.pref_currency)
        else DT1.price end as price) DT2
outer apply
R3  (select str(DT2.price) + DT1.pref_currency
                            as returnVal) DT3
```

Figure 4: Relational expression for UDF total_price

UDF Algebrization

- Combining expressions for multiple statements
  - For each statement: compute a “read-set” and a “write-set”
  - Use these as schemas of derived tables
  - Connect the regions using APPLY (with pass-through in case of multiple return statements)

- Correctness?
  - Each individual transformation correct by itself
  - All derived tables contain a single tuple
  - Outer apply preserves the semantics of combined execution

- Note: Doesn’t handle loops -- may be trickier to model

Substitution and optimization

- Replace the scalar UDF with the relational expression (not as SQL, but rather operators)
- Let the optimizer de-correlate and optimize
- Resulting plan looks complex, but decorrelates as desired

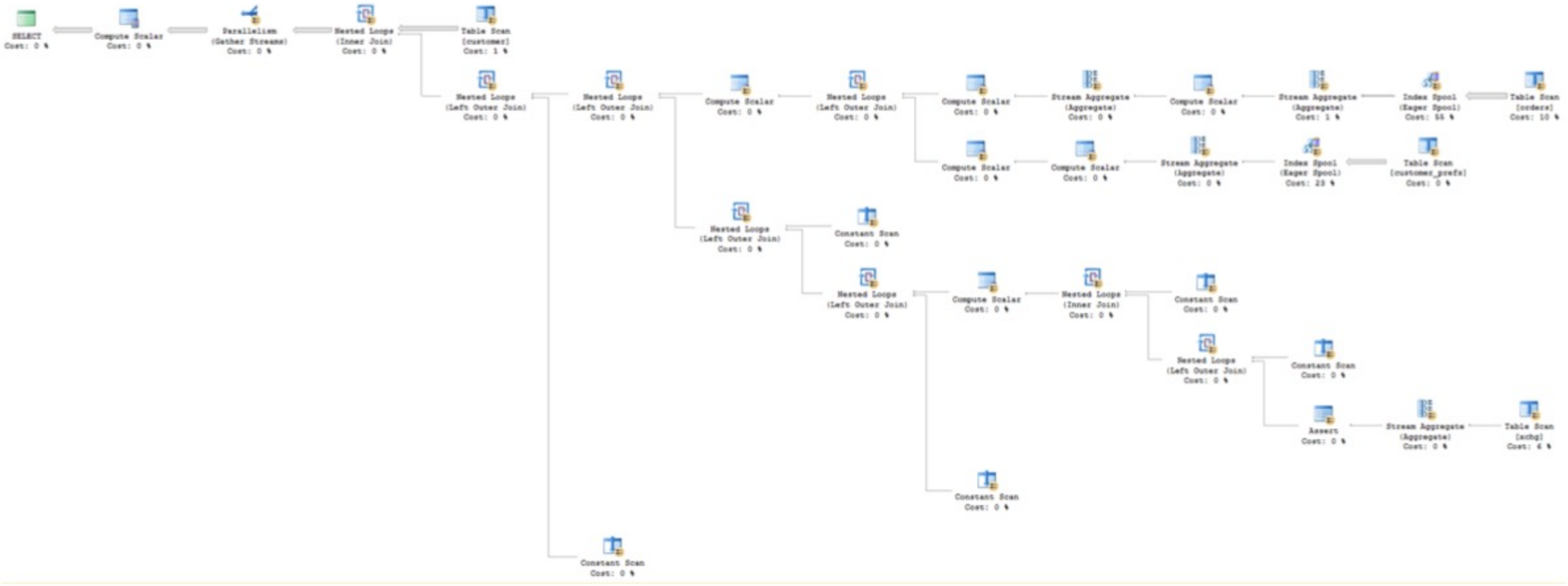
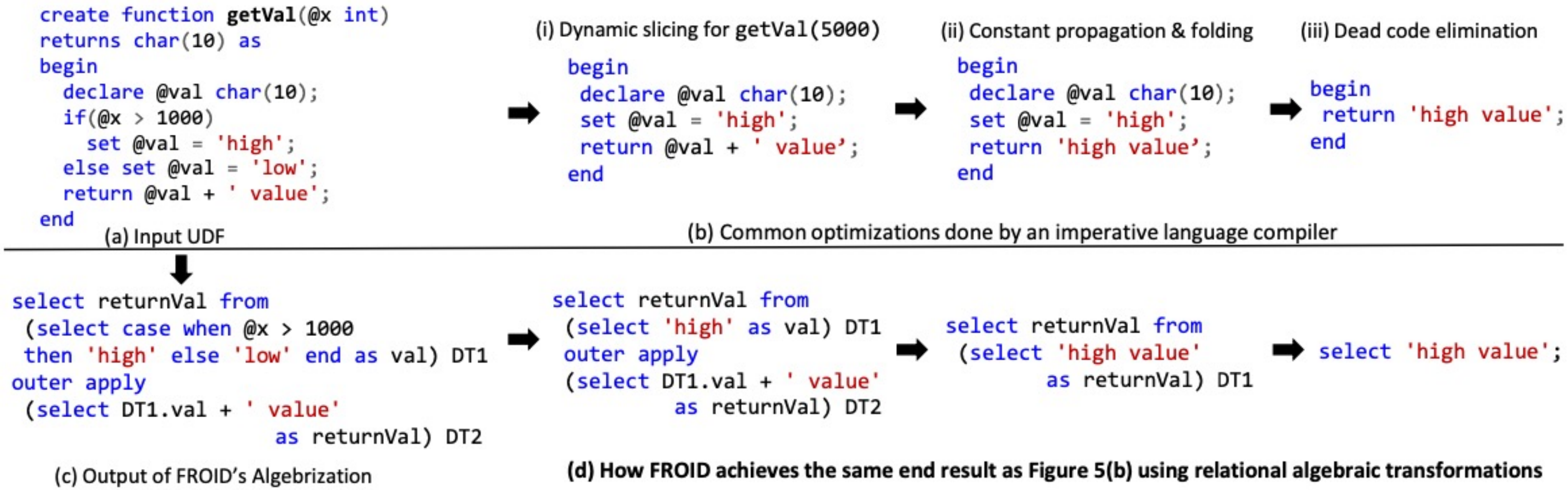

SELECT Cost: 0 %
Compute Scalar Cost: 0 %
Parallelism (Gather Streams) Cost: 0 %
Nested Loops (Inner Join) Cost: 0 %
Table Scan [customer] Cost: 1 %
Nested Loops (Left Outer Join) Cost: 0 %
Nested Loops (Left Outer Join) Cost: 0 %
Compute Scalar Cost: 0 %
Nested Loops (Left Outer Join) Cost: 0 %
Compute Scalar Cost: 0 %
Stream Aggregate (Aggregate) Cost: 0 %
Compute Scalar Cost: 0 %
Stream Aggregate (Aggregate) Cost: 1 %
Index Spool (Eager Spool) Cost: 55 %
Table Scan [orders] Cost: 10 %
Compute Scalar Cost: 0 %
Compute Scalar Cost: 0 %
Stream Aggregate (Aggregate) Cost: 0 %
Index Spool (Eager Spool) Cost: 23 %
Table Scan [customer_prefs] Cost: 0 %
Nested Loops (Left Outer Join) Cost: 0 %
Constant Scan Cost: 0 %
Nested Loops (Left Outer Join) Cost: 0 %
Compute Scalar Cost: 0 %
Nested Loops (Inner Join) Cost: 0 %
Constant Scan Cost: 0 %
Nested Loops (Left Outer Join) Cost: 0 %
Constant Scan Cost: 0 %
Assert Cost: 0 %
Stream Aggregate (Aggregate) Cost: 0 %
Table Scan [xchg] Cost: 6 %
Constant Scan Cost: 0 %
Constant Scan Cost: 0 %

Figure 5: Plan for inlined UDF total_price of Figure 1

Compiler Optimizations

- Dynamic slicing: use compile-time constants to simplify queries
- Constant folding and propagation: already done by SQL server
- Dead code elimination: optimizer handles these during project pushdown



```
create function getVal(@x int)
returns char(10) as
begin
  declare @val char(10);
  if(@x > 1000)
    set @val = 'high';
  else set @val = 'low';
  return @val + ' value';
end
```

(a) Input UDF

(i) Dynamic slicing for getVal(5000)

```
begin
 declare @val char(10);
 set @val = 'high';
 return @val + ' value';
end
```

(ii) Constant propagation & folding

```
begin
 declare @val char(10);
 set @val = 'high';
 return 'high value';
end
```

(iii) Dead code elimination

```
begin
 return 'high value';
end
```

(b) Common optimizations done by an imperative language compiler

```
select returnVal from
 (select case when @x > 1000
 then 'high' else 'low' end as val) DT1
outer apply
 (select DT1.val + ' value'
                   as returnVal) DT2
```

(c) Output of FROID's Algebrization

```
select returnVal from
 (select 'high' as val) DT1
outer apply
 (select DT1.val + ' value'
           as returnVal) DT2
```

```
select returnVal from
 (select 'high value'
          as returnVal) DT1
```

```
select 'high value';
```

(d) How FROID achieves the same end result as Figure 5(b) using relational algebraic transformations

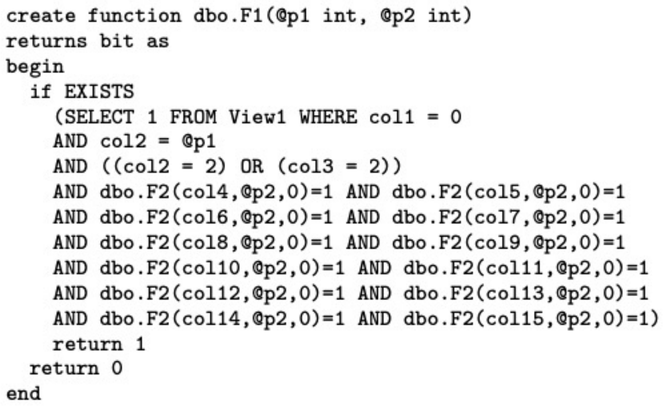
Figure 5: Compiler optimizations as relational transformations. For ease of presentation, (c) and (d) are shown in SQL; these are actually transformations on the relational query tree representation.

Design and Implementation

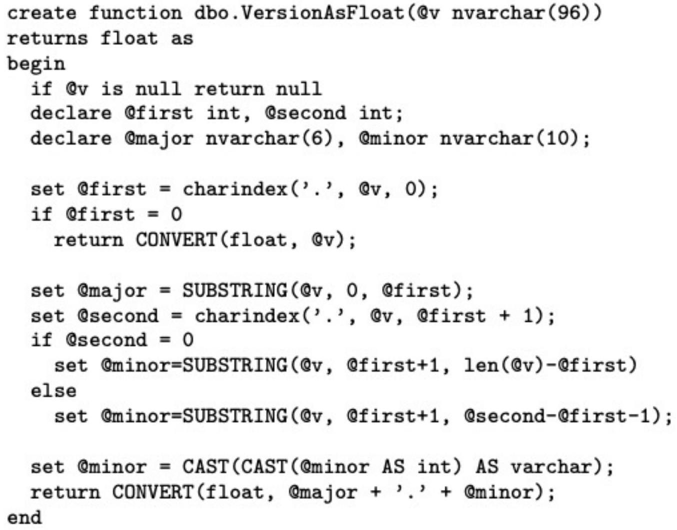
- Should this inlining be done in a cost-based manner?
  - Influences whether it takes place during binding or during query optimization
  - Experiments showed it is almost always beneficial + hard to modify optimizers ➔ do it in the binding phase
- Constraints
  - Put a constraint on the maximum size of UDFs that can be algebrized
- Froid is extensible -- could handle other languages as well
- Security and permissions
  - A user may not have permission on the UDF but on the tables, and vice versa
  - Need to be careful with caches as well

Evaluation

- Applicability
  - Used top 100 customer workloads from Azure SQL → 85329 scalar UDFs
  - Froid could handle 60% or so



```
create function dbo.F1(@p1 int, @p2 int)
returns bit as
begin
  if EXISTS
    (SELECT 1 FROM View1 WHERE col1 = 0
    AND col2 = @p1
    AND ((col2 = 2) OR (col3 = 2))
    AND dbo.F2(col4,@p2,0)=1 AND dbo.F2(col5,@p2,0)=1
    AND dbo.F2(col6,@p2,0)=1 AND dbo.F2(col7,@p2,0)=1
    AND dbo.F2(col8,@p2,0)=1 AND dbo.F2(col9,@p2,0)=1
    AND dbo.F2(col10,@p2,0)=1 AND dbo.F2(col11,@p2,0)=1
    AND dbo.F2(col12,@p2,0)=1 AND dbo.F2(col13,@p2,0)=1
    AND dbo.F2(col14,@p2,0)=1 AND dbo.F2(col15,@p2,0)=1)
    return 1
  return 0
end
```

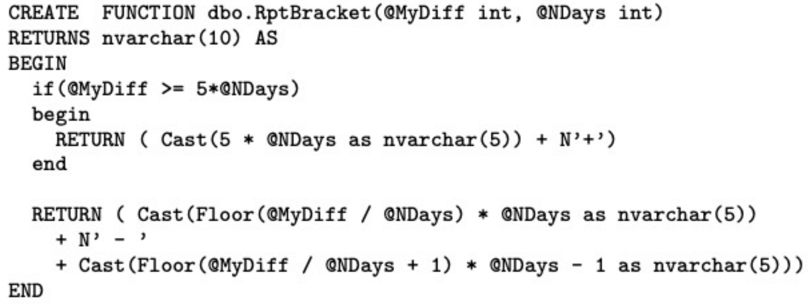


```
create function dbo.VersionAsFloat(@v nvarchar(96))
returns float as
begin
  if @v is null return null
  declare @first int, @second int;
  declare @major nvarchar(6), @minor nvarchar(10);

  set @first = charindex(’.’, @v, 0);
  if @first = 0
    return CONVERT(float, @v);

  set @major = SUBSTRING(@v, 0, @first);
  set @second = charindex(’.’, @v, @first + 1);
  if @second = 0
    set @minor=SUBSTRING(@v, @first+1, len(@v)-@first)
  else
    set @minor=SUBSTRING(@v, @first+1, @second-@first-1);

  set @minor = CAST(CAST(@minor AS int) AS varchar);
  return CONVERT(float, @major + ’.’ + @minor);
end
```



```
CREATE  FUNCTION dbo.RptBracket(@MyDiff int, @NDays int)
RETURNS nvarchar(10) AS
BEGIN
  if(@MyDiff >= 5*@NDays)
  begin
    RETURN ( Cast(5 * @NDays as nvarchar(5)) + N’+’)
  end

  RETURN ( Cast(Floor(@MyDiff / @NDays) * @NDays as nvarchar(5))
    + N’ - ’
    + Cast(Floor(@MyDiff / @NDays + 1) * @NDays - 1 as nvarchar(5)))
END
```

Evaluation

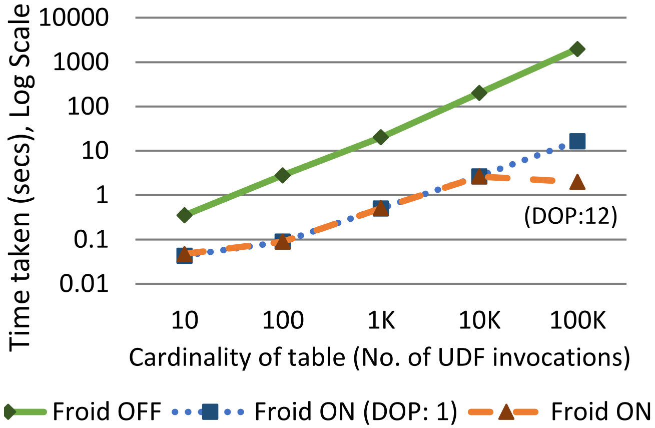


Figure 6: Varying the number of UDF invocations

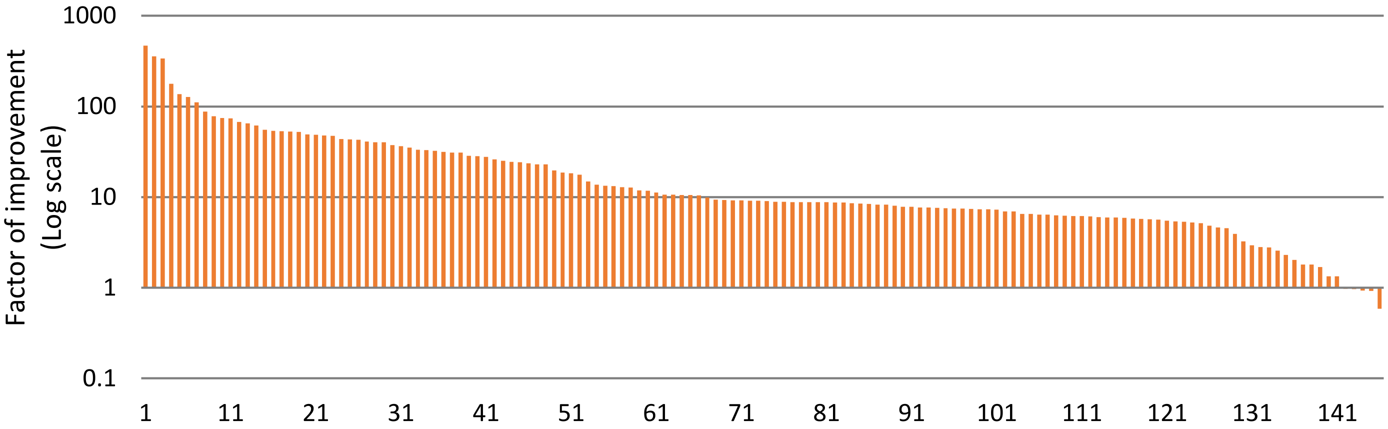


Figure 10: Improvement for UDFs in workload W1

Converting UDFs to CTEs

- CTE == Common Table Expressions (i.e., WITH clause)
- Another approach taken by a recent paper
    - Functional-style SQL UDFs with a Capital ‘F’; SIGMOD 2020

```
CREATE FUNCTION pow(x int, n int)
RETURNS int AS
$$
 DECLARE
  i int = 0;
  p int = 1;
 BEGIN
  WHILE i < n LOOP
   p = p * x;
   i = i + 1;
  END LOOP;
  RETURN p;
 END;
$$
```

```
WITH RECURSIVE
  run("call?",i1,p1,x,n,result) AS (

     SELECT true,0,1,x,n,NULL

   UNION ALL
    SELECT iter.* FROM run, LATERAL (

     SELECT false,0,0,0,0,p1
      WHERE i1 >= n
        UNION ALL
     SELECT true,i1+1,p1*x,x,n,0
      WHERE i1 < n

    ) AS iter("call?",i1,p1,x,n,result)
    WHERE run."call?"
)
SELECT * FROM run;
```