Adaptive Query Processing

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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:

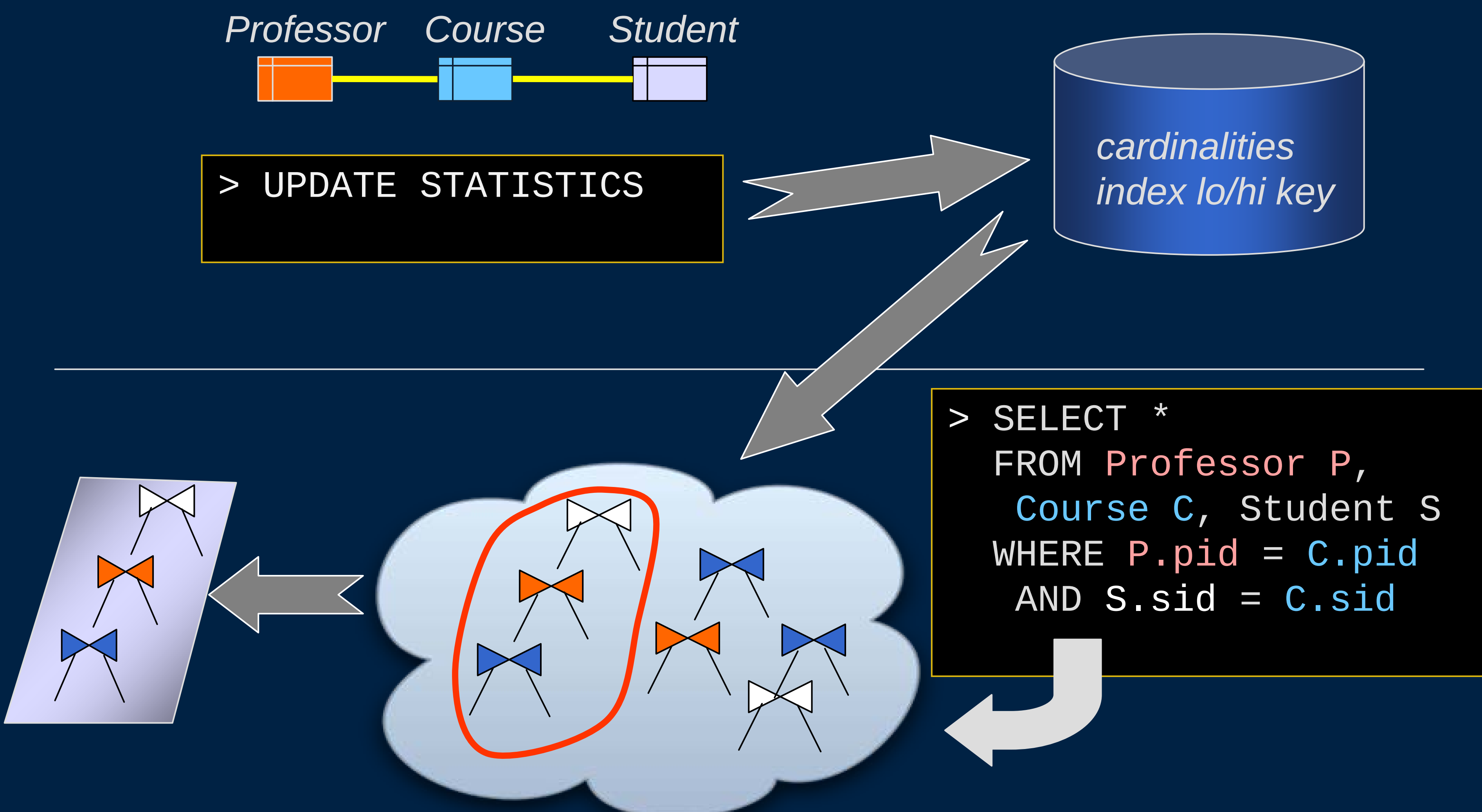
$$\frac{dapp}{dt} << \frac{denv}{dt}$$

Query processing **adapts** implementation to runtime conditions

- Static applications → dynamic environments

Query Optimization and Processing

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



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

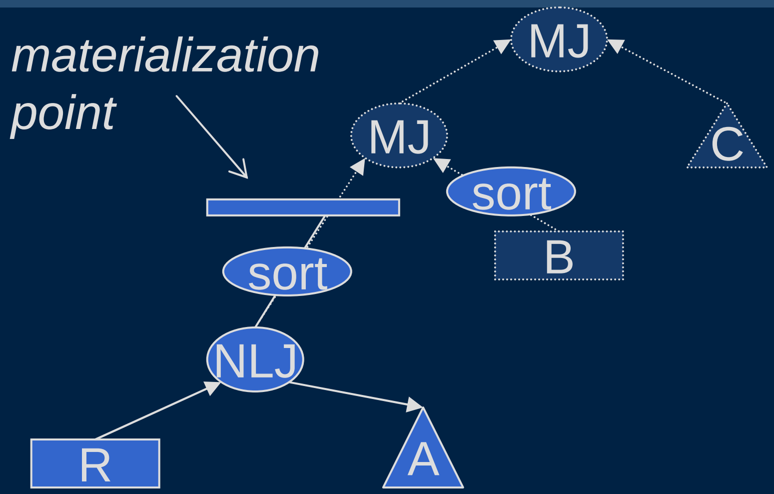
- For more depth, see our survey in now Publishers' *Foundations and Trends in Databases*, Vol. 1 No. 1

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?*

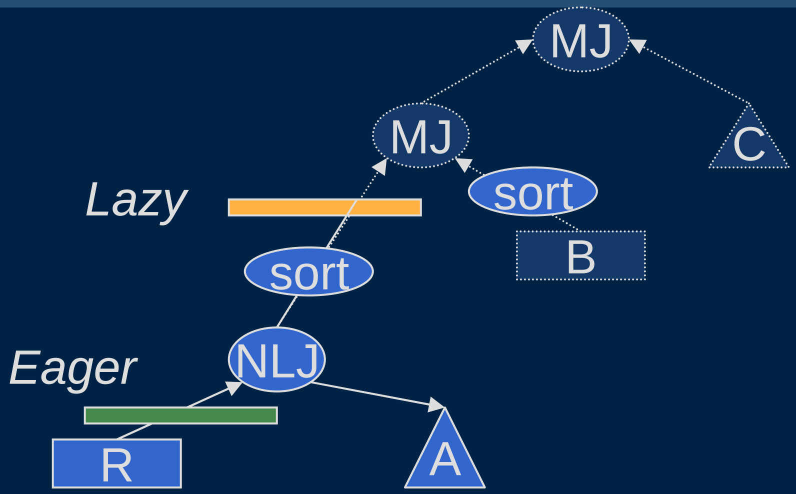
Avoid unnecessary plan re-optimization (where the plan doesn't change)

***Re-optimize* to switch to a new plan** — *How?*

Try to maintain previous computation during plan switching

Challenges

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%';
```

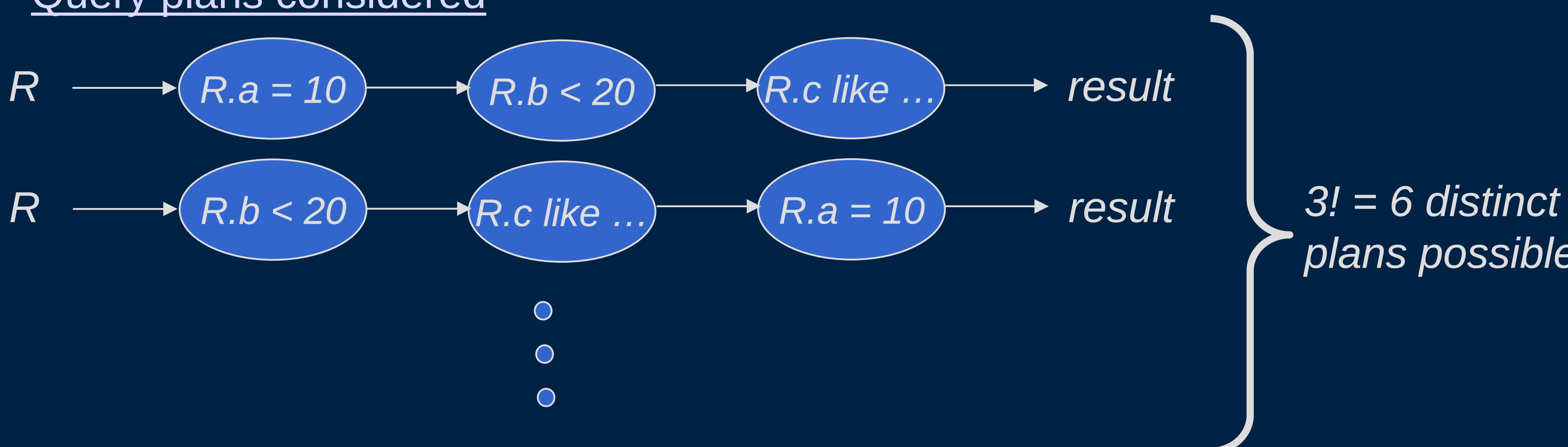
Basics: Static Optimization

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

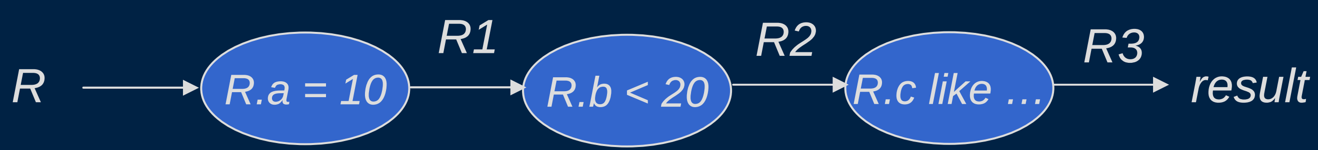


Static Optimization

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

Conditional Plans ? [DGHM'05]

Adaptive Greedy [BMMNW'04]

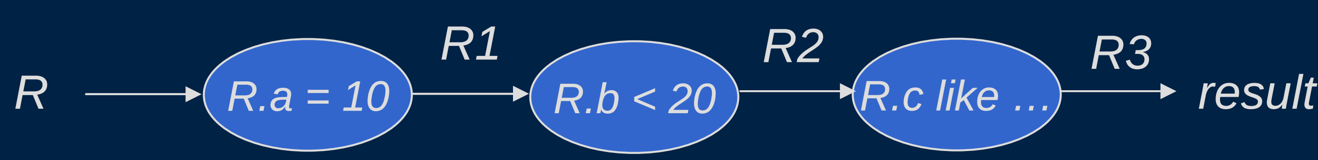
Context: Pipelined query plans over streaming data

Example:

Three <u>independent</u> predicates

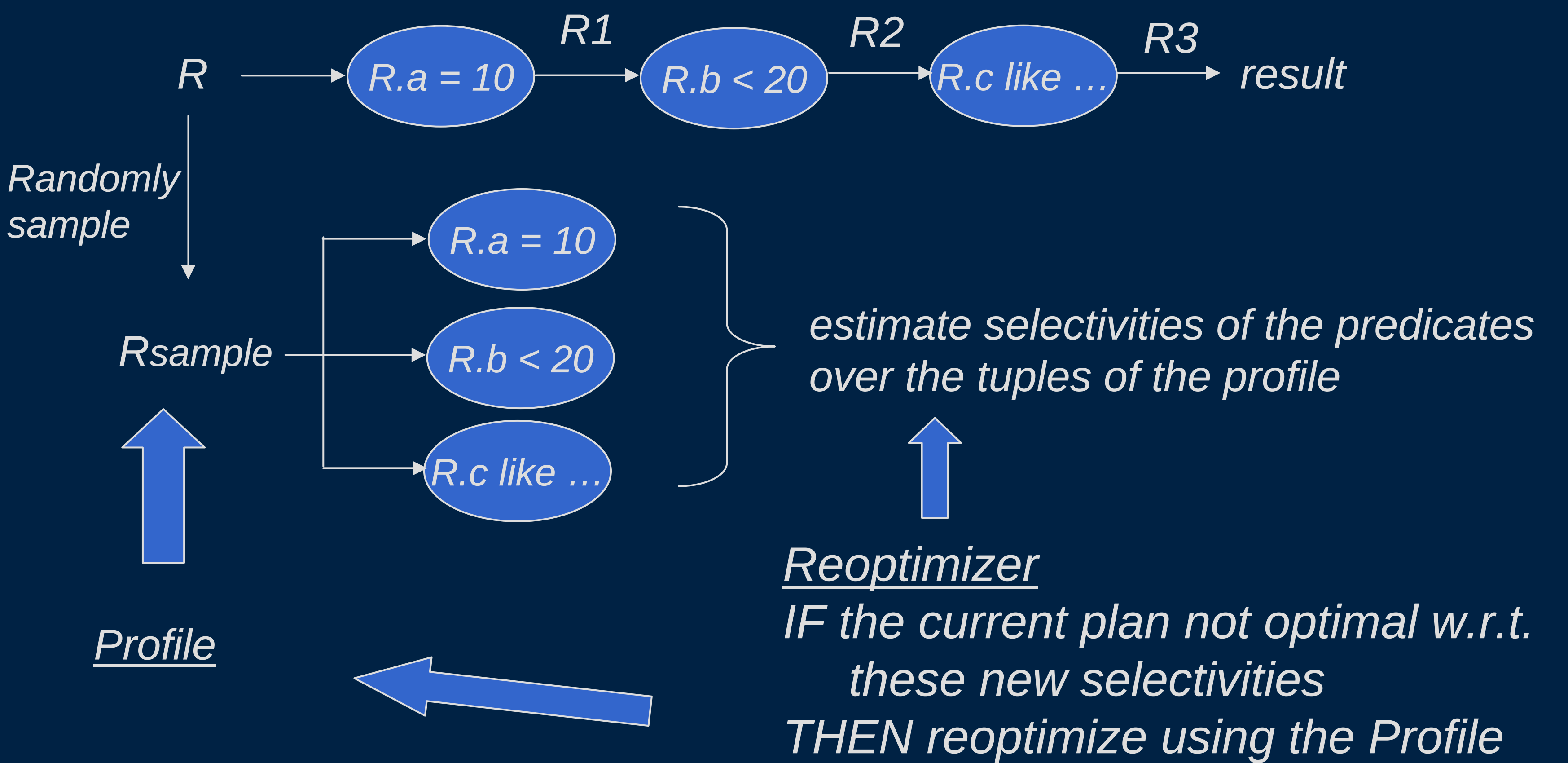
	R.a = 10	*R.b < 20*	*R.c like …*
Costs	*1 unit*	*1 unit*	*1 unit*
Initial estimated selectivities	*0.05*	*0.1*	*0.2*

Optimal execution plan orders by selectivities (because costs are identical)



Adaptive Greedy [BMMNW'04]

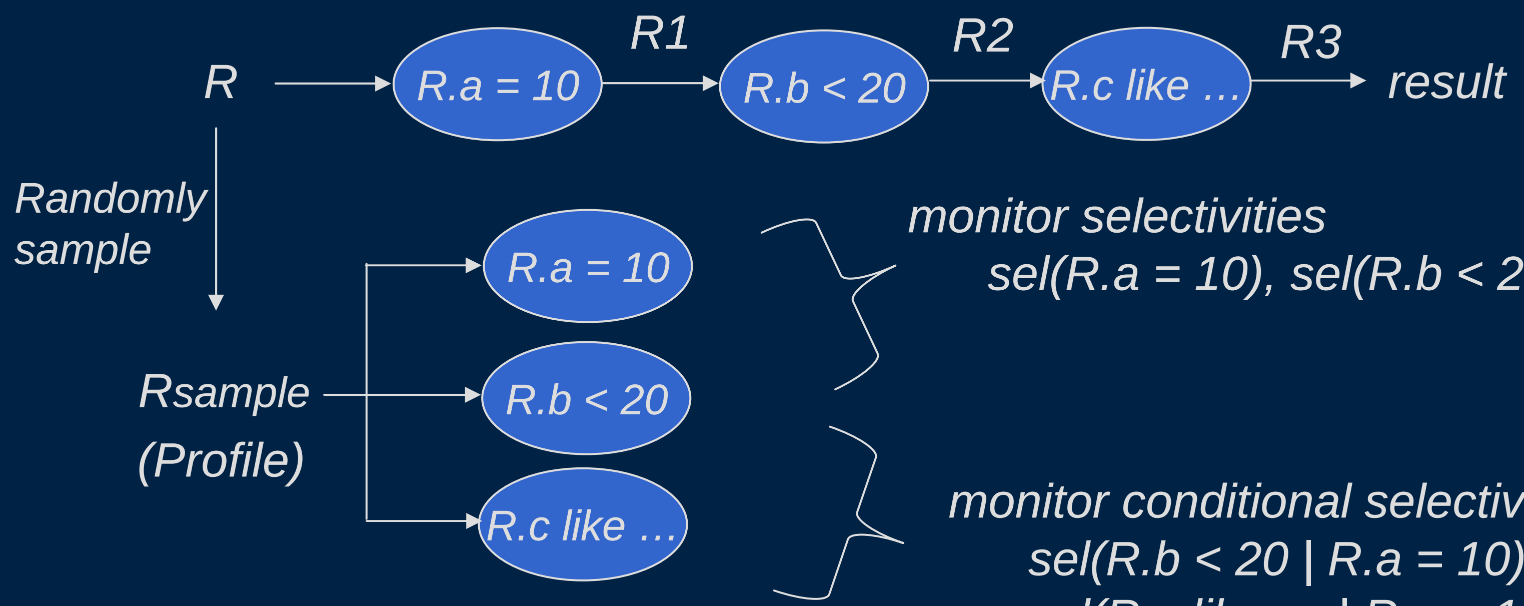
1. Monitor the selectivities over recent past (sliding window)
2. Re-optimize if the predicates not ordered by selectivities



Adaptive Greedy [BMMNW'04]

Correlated Selections

– Must monitor *conditional selectivities*



monitor selectivities

sel(R.a = 10), sel(R.b < 20), sel(R.c …)

monitor conditional selectivities

sel(R.b < 20 | R.a = 10)

sel(R.c like … | R.a = 10)

sel(R.c like … | R.a = 10 and R.b < 20)

<u>Reoptimizer</u>

Uses conditional selectivities to detect violations

Uses the profile to reoptimize

$O(n^2)$ selectivities need to be monitored

Adaptive Greedy [BMMNW'04]

Advantages:

- Can adapt very rapidly
- Handles correlations
- Theoretical guarantees on performance [MBMW'05]
  Not known for any other AQP algorithms

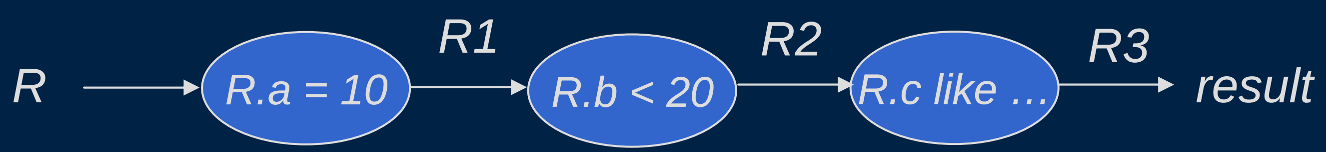
Disadvantages:

- May have high runtime overheads
  - Profile maintenance
    - Must evaluate a (random) fraction of tuples against *all* operators
  - Detecting optimality violations
  - Reoptimization cost
    - Can require multiple passes over the profile

Eddies [AH'00]

Query processing as routing of tuples through operators

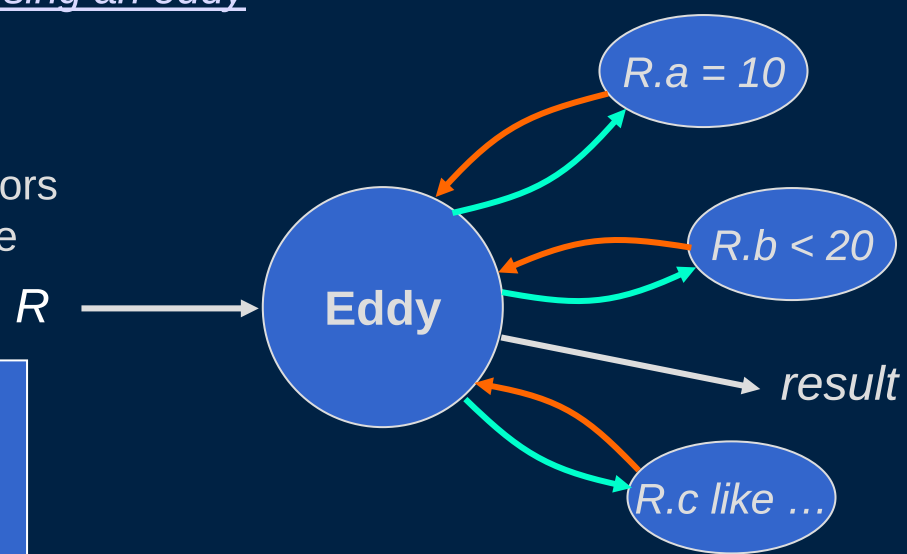
A traditional pipelined query plan



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

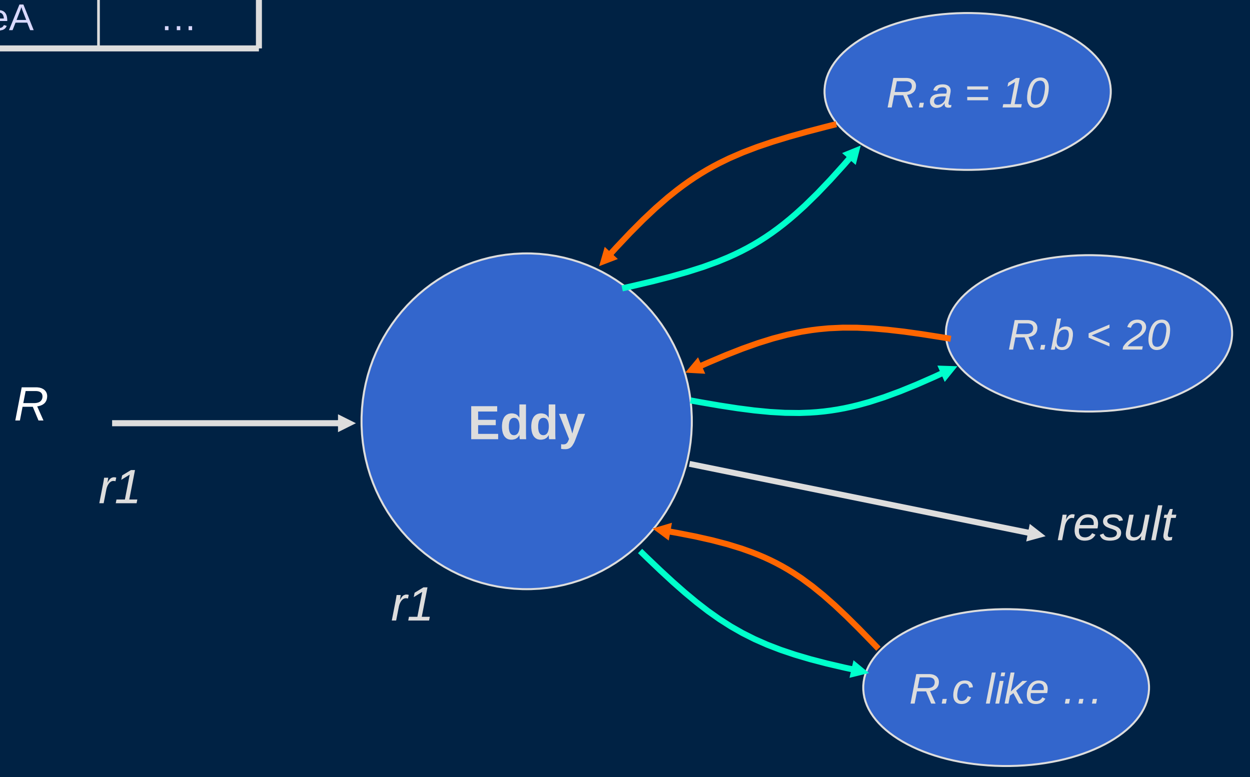


Encapsulates all aspects of adaptivity in a "standard" dataflow operator: measure, model, plan and actuate.

Eddies [AH'00]

An R Tuple: r1

a	b	c	…
15	10	AnameA	…



Eddies [AH'00]

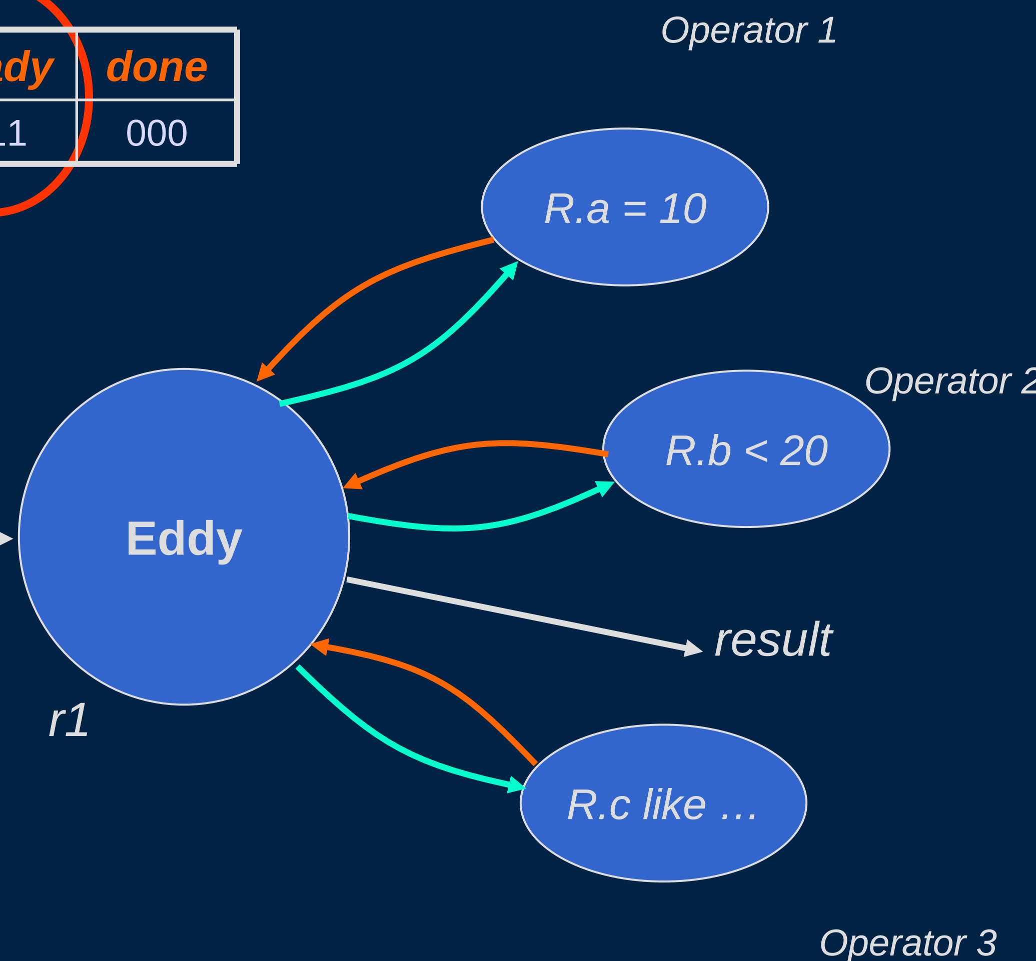
An R Tuple: *<u>r1</u>*

<u>a</u>	<u>b</u>	<u>c</u>	<u>...</u>	***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]

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

done *bit i :*

1 → operator i *has been applied*

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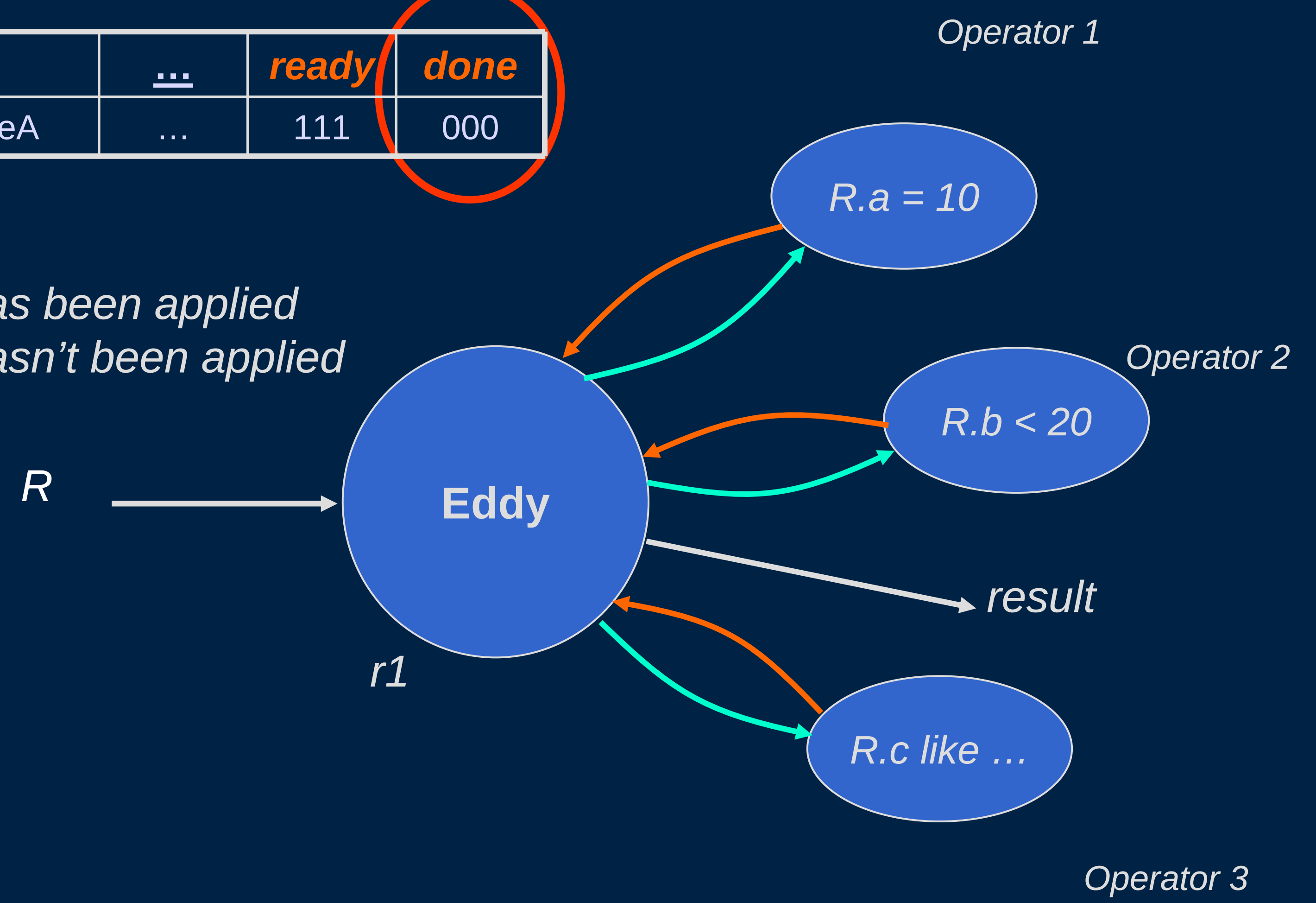
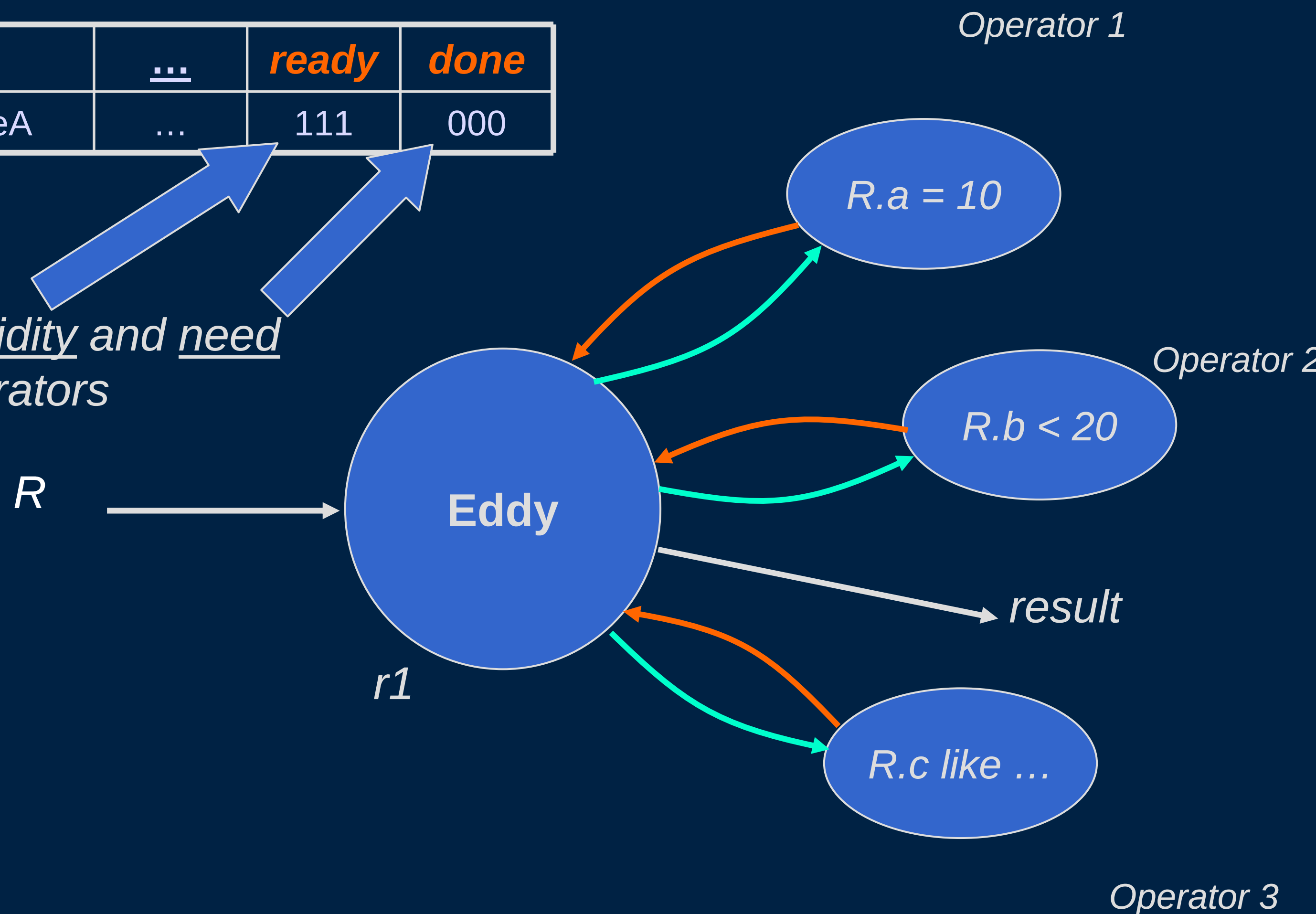


Eddies [AH'00]

An R Tuple: <u>r1</u>

<u>**a**</u>	<u>**b**</u>	<u>**c**</u>	<u>**...**</u>	***ready***	***done***
15	10	AnameA	…	111	000

Used to decide <u>validity</u> and <u>need</u> of applying operators

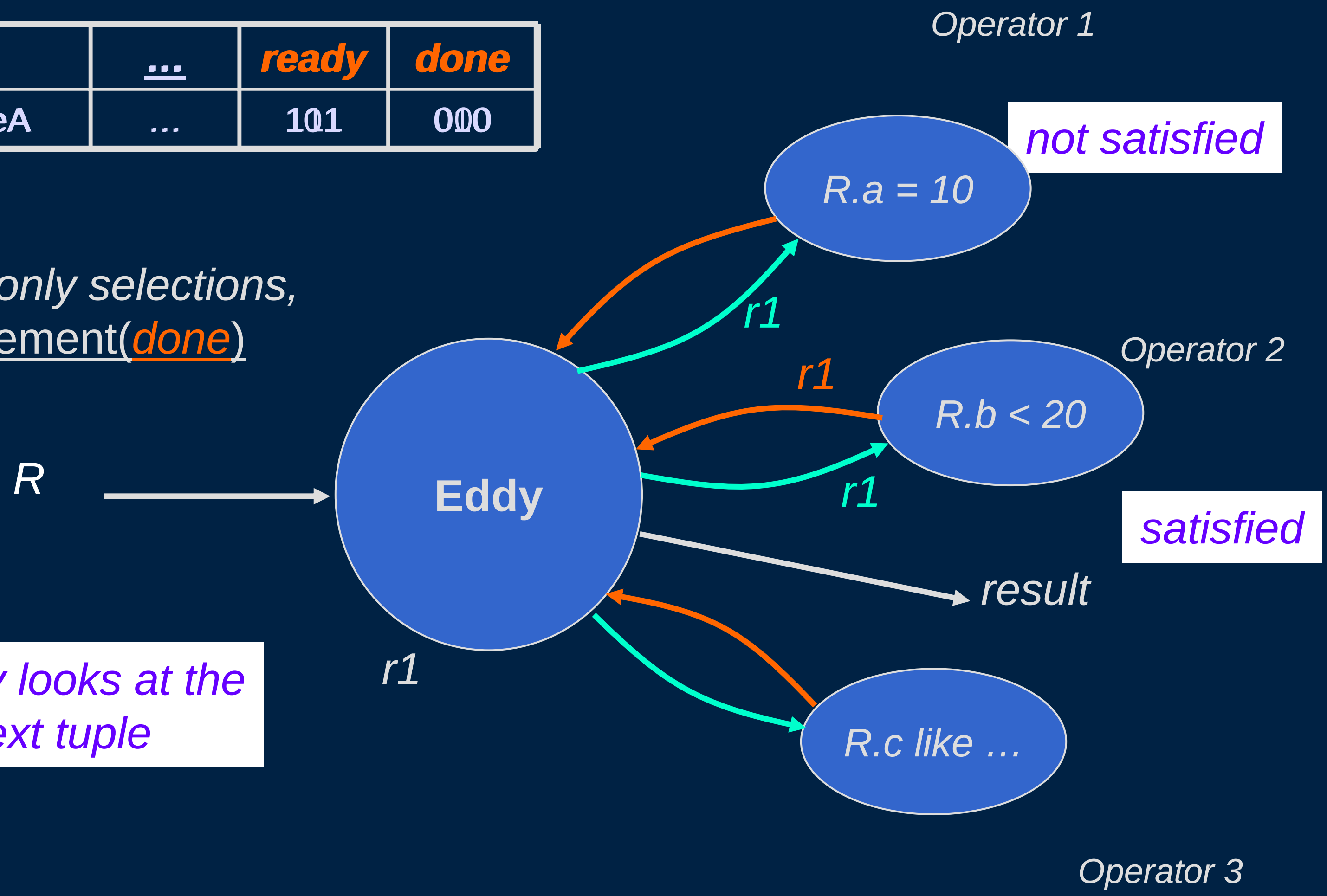


Eddies [AH'00]

An R Tuple: *r1*

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

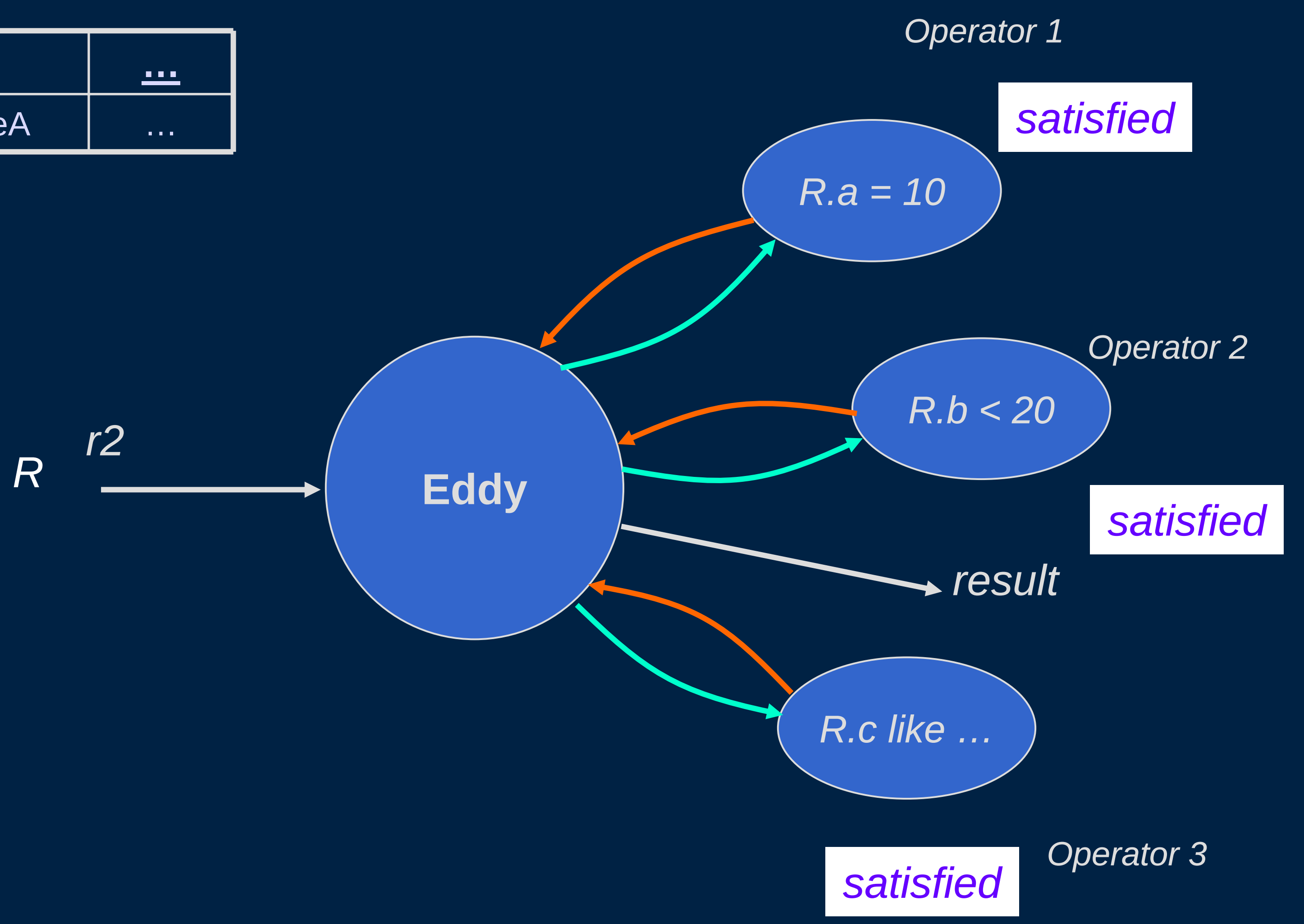
For a query with only selections,
ready = complement(*done*)



Eddies [AH'00]

An R Tuple: r2

a	b	c	...
10	15	AnameA	…

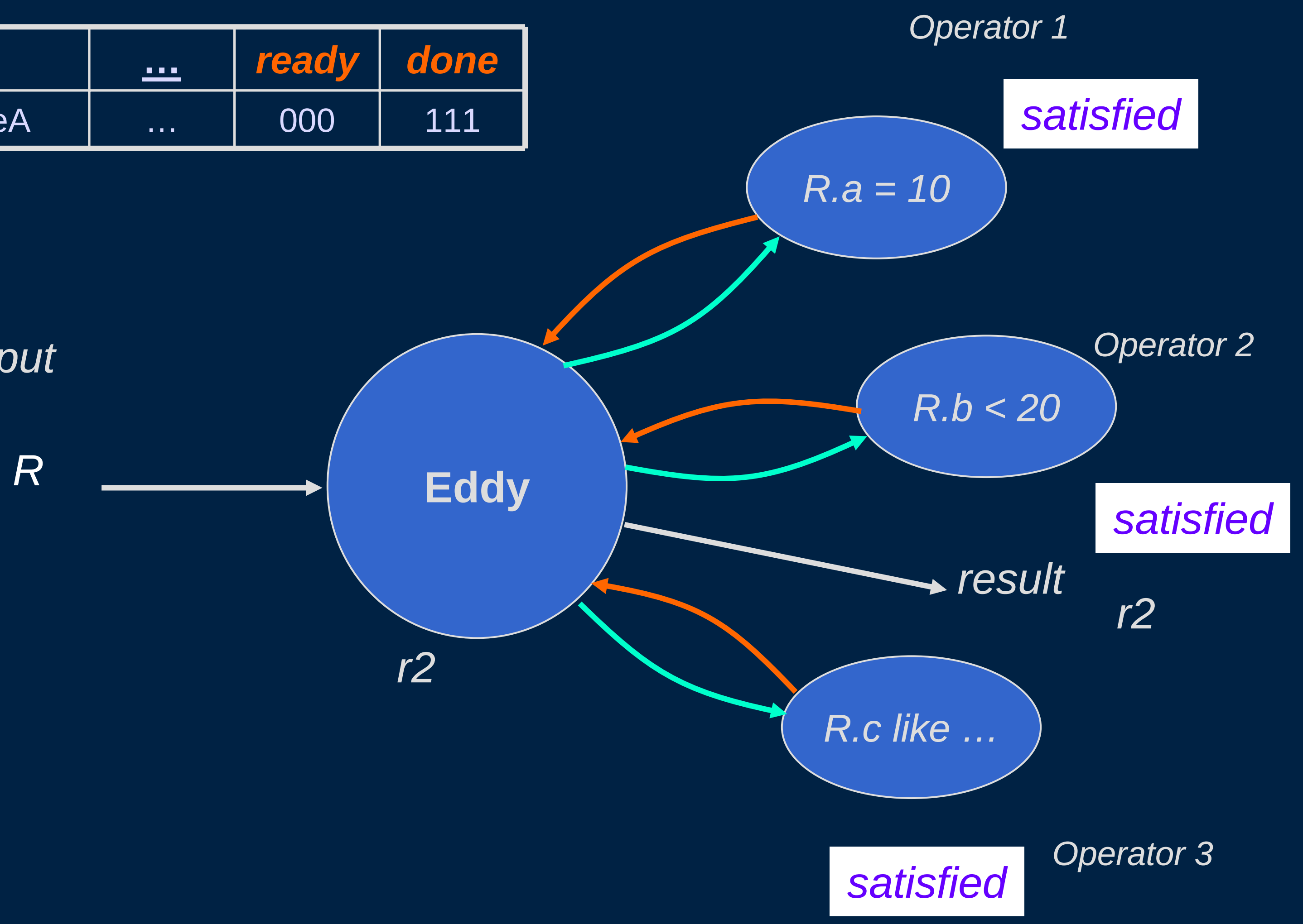


Eddies [AH'00]

An R Tuple: r2

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

if done = 111,
send to output



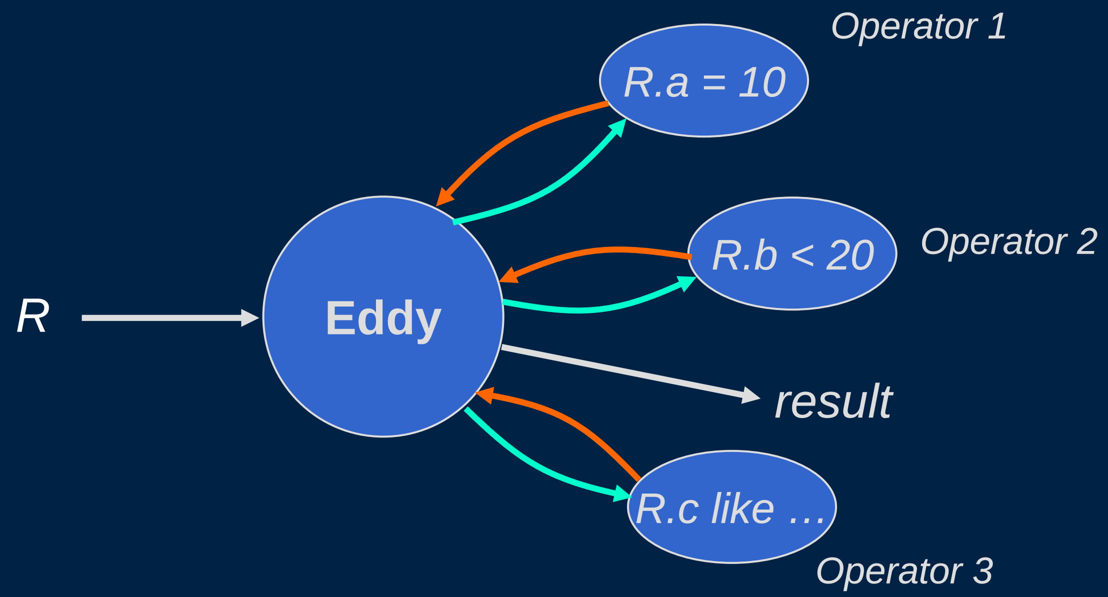
Eddies [AH'00]

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]

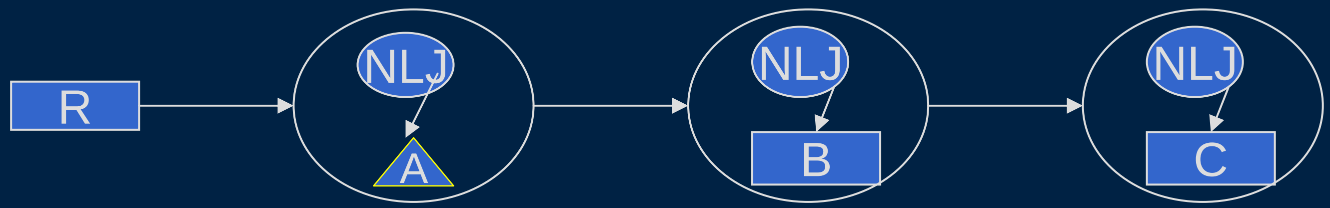
- Different routes for different plans based on attribute values

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

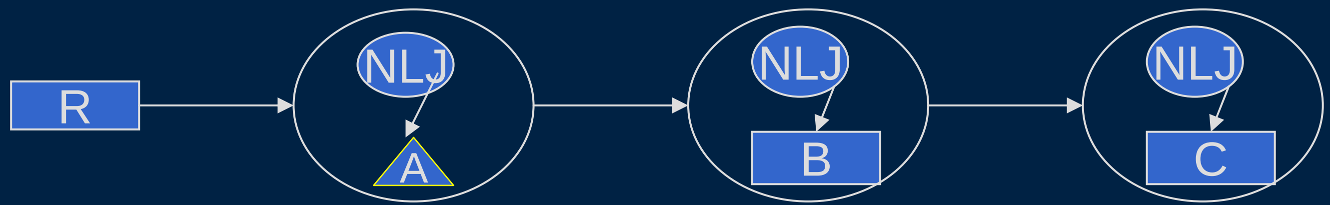


Simplest method of joining tables

- 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



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- Pick a *driver* table (R). Call the rest *driven* tables
- Pick access methods (AMs) on the driven tables
- Order the driven tables
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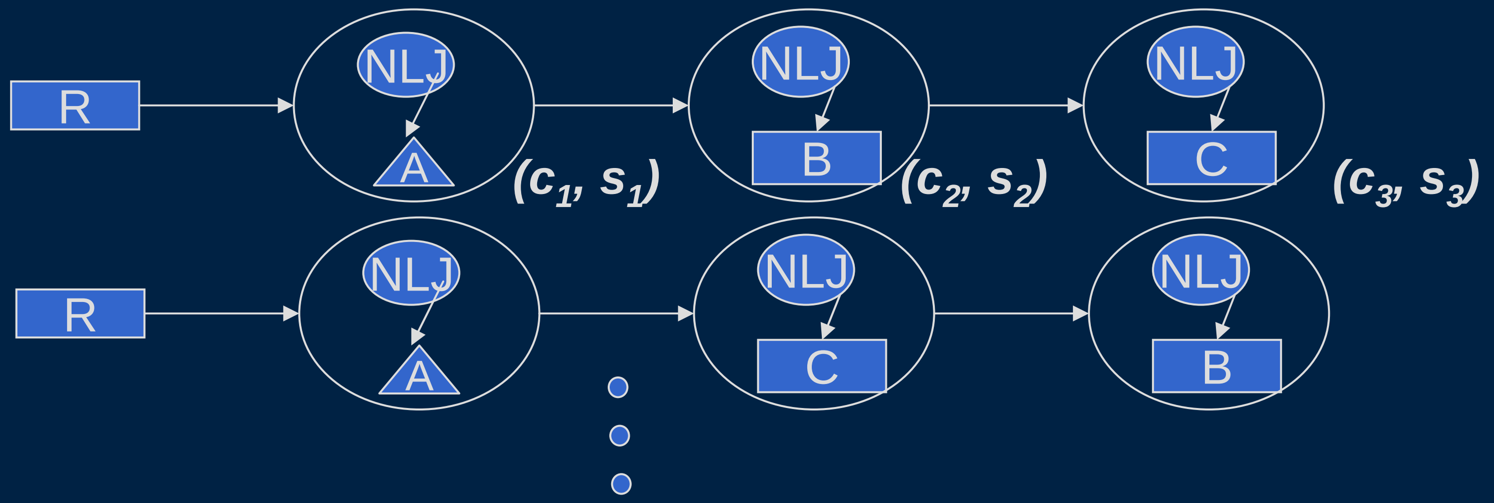
Almost identical to selection ordering

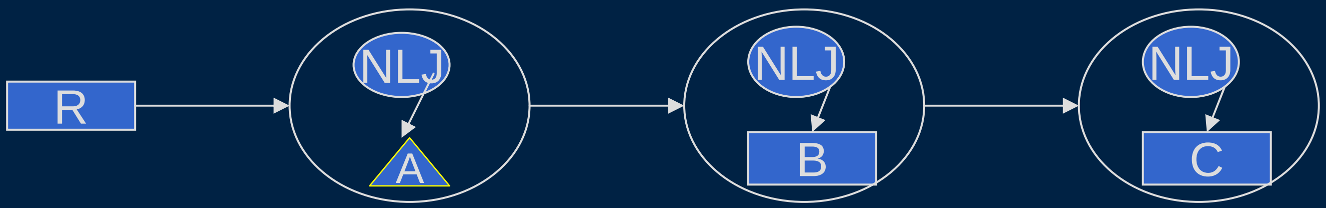
For each r $\in$ R do:
look for matches for r in A;
for each match a do:
    look for matches for <r,a> in B;
    …

Adapting the Join Order



- Let c_i = cost/lookup into i'th driven table,
  s_i = fanout of the lookup
- As with selection, cost = $|R| \times (c_1 + s_1c_2 + s_1s_2c_3)$
- 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



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?

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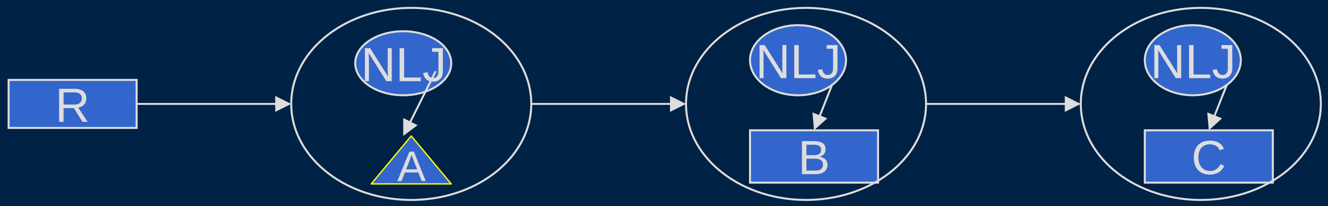
Adapting a Left-deep Pipelined Plan



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

SteMs [RDH'03] handle both as well

Adaptive Join Processing: Outline

- Single streaming relation
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- Multiple streaming relations
  - Execution strategies for multi-way joins
  - History-independent execution
    - MJoins
    - SteMs
  - 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

Name	Level	Course
Jen	Senior	CS2
Joe	Junior	CS1

Name	Course
Joe	CS1
Jen	CS2

$\bowtie$

Name	Level
Jen	Senior
Joe	Junior

Enrolled

Students

- 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

Three alternatives

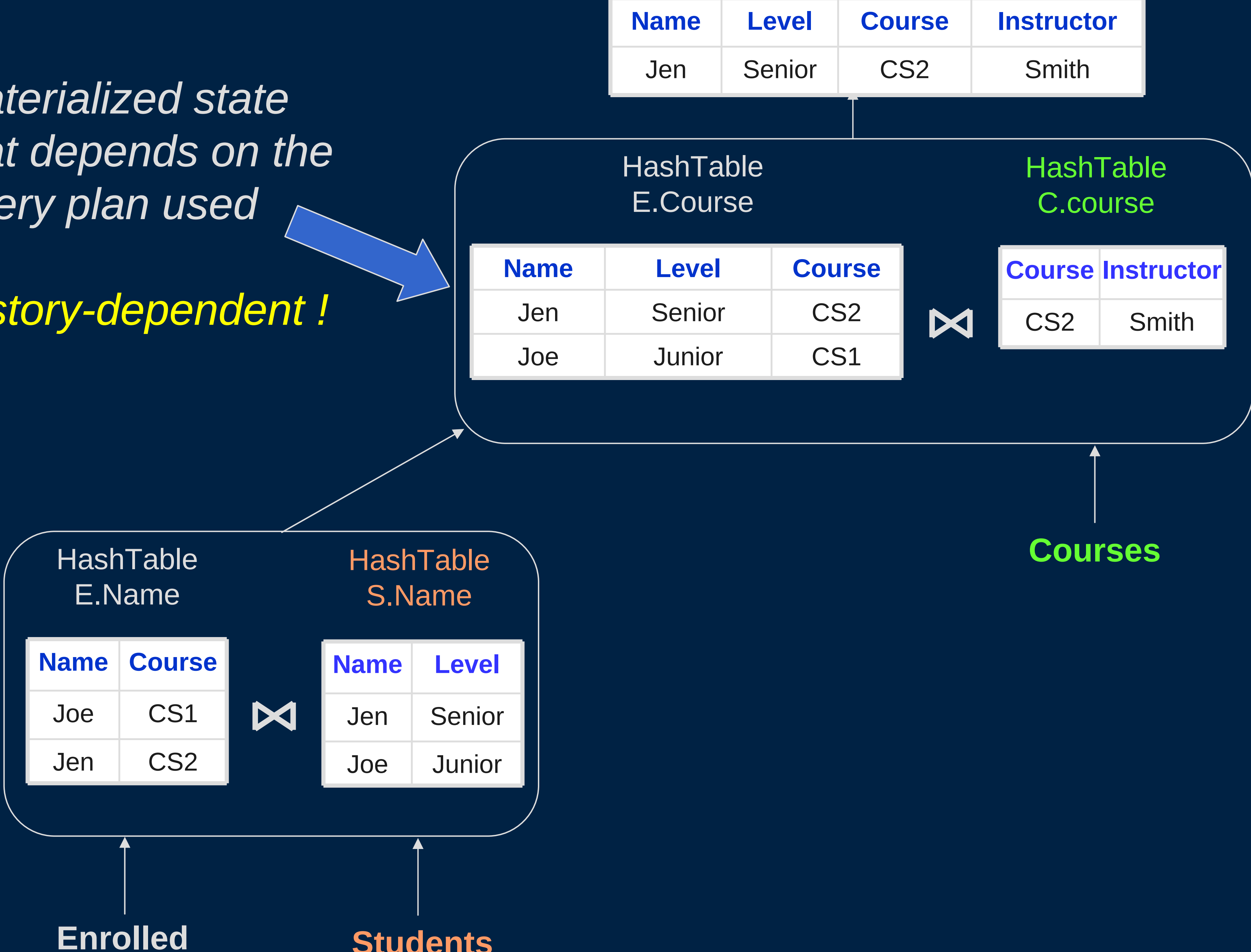
- Using binary join operators

- Using a single n-ary join operator (MJoin) [VNB’03]

- Using unary operators [RDH’03]

Materialized state that depends on the query plan used

History-dependent !



Name	Level	Course	Instructor
Jen	Senior	CS2	Smith

Name	Level	Course
Jen	Senior	CS2
Joe	Junior	CS1

Course	Instructor
CS2	Smith

Name	Course
Joe	CS1
Jen	CS2

Name	Level
Jen	Senior
Joe	Junior

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]
- Using unary operators [RDH'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 !

HashTable
S.Name

Name	Level
Joe	Junior
Jen	Senior

HashTable
E.Name

Name	Course
Joe	CS1
Jen	CS2

HashTable
E.Course

Name	Course
Joe	CS1
Jen	CS2

HashTable
C.course

Course	Instructor
CS2	Smith

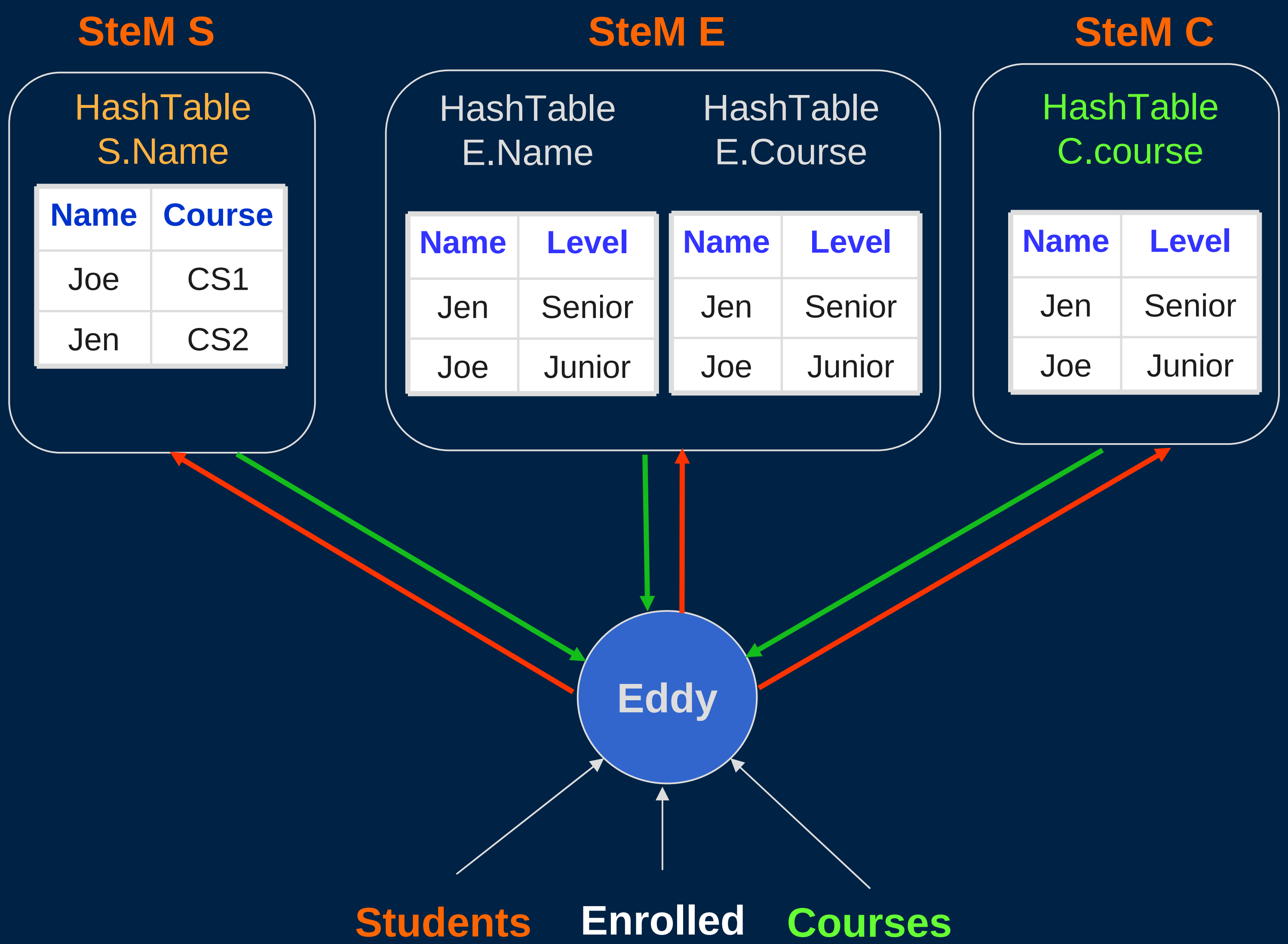
Students **Enrolled** **Courses**

Multi-way Pipelined Joins over Streaming Relations

Three alternatives

- Using binary join operators
  - *History-dependent execution*
- Using a single n-ary join operator (MJoin) [VNB'03]
  - *History-independent execution*
  - Well-defined state easy to reason about
    - Especially in data stream processing
  - Performance may be suboptimal [DH'04]
    - No intermediate tuples stored → need to recompute
- Using unary operators [RDH'03]

Breaking the Atomicity of Probes and Builds in an N-ary Join [RDH'03]



Multi-way Pipelined Joins over Streaming Relations

Three alternatives

- Using binary join operators
  - *History-dependent execution*
- Using a single n-ary join operator (MJoin) [VNB'03]
  - *History-independent execution*
  - Well-defined state easy to reason about
    - Especially in data stream processing
  - Performance may be suboptimal [DH'04]
    - No intermediate tuples stored → need to recompute
- Using unary operators [RDH'03]
  - Similar to MJoins, but enables additional adaptation

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 joins
    - Corrective query processing

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

State Modules (SteMs) [RDH'03]

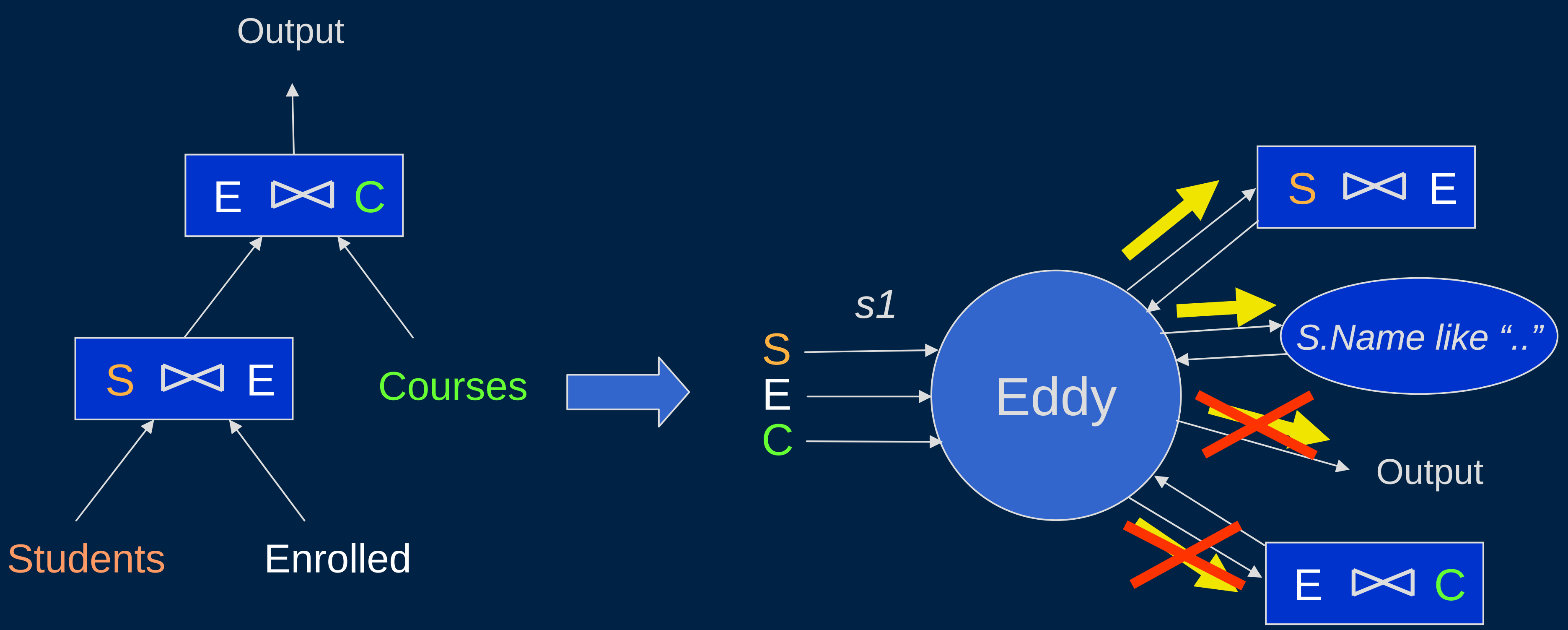
- SteM is an abstraction of a unary operator
  - Encapsulates the state, access methods and the operations on a single relation
- By adapting the routing between SteMs, we can
  - Adapt the join ordering (as before)
  - Adapt access method choices
  - Adapt join algorithms
    - Hybridized join algorithms
      - e.g. on memory overflow, switch from hash join → index join
    - Much larger space of join algorithms
  - Adapt join spanning trees
- Also useful for sharing state across joins
  - Advantageous for continuous queries [MSHR'02, CF'03]

Adaptive Join Processing: Outline

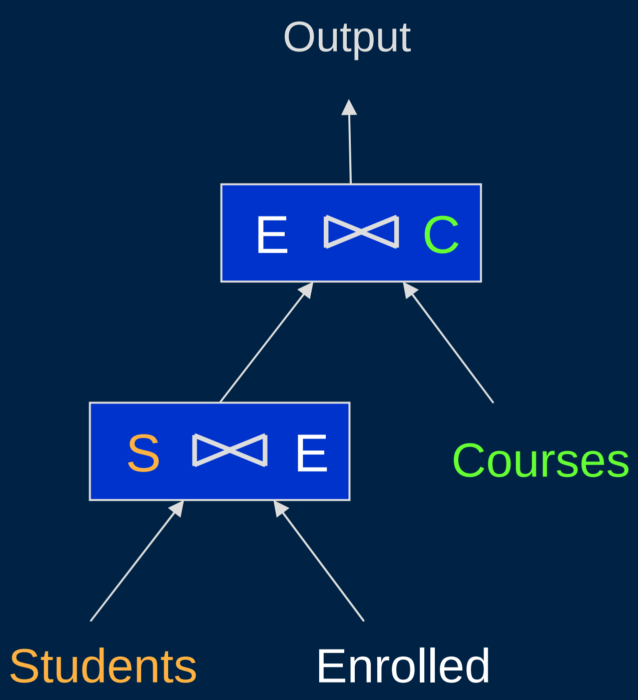
- Single streaming relation
  - Left-deep pipelined plans
- Multiple streaming relations
  - Execution strategies for multi-way joins
  - History-independent execution
    - MJoins
    - SteMs
  - History-dependent execution
    - Eddies with binary joins
      - State management using STAIRs
    - Corrective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

Eddies with Binary Joins [AH'00]

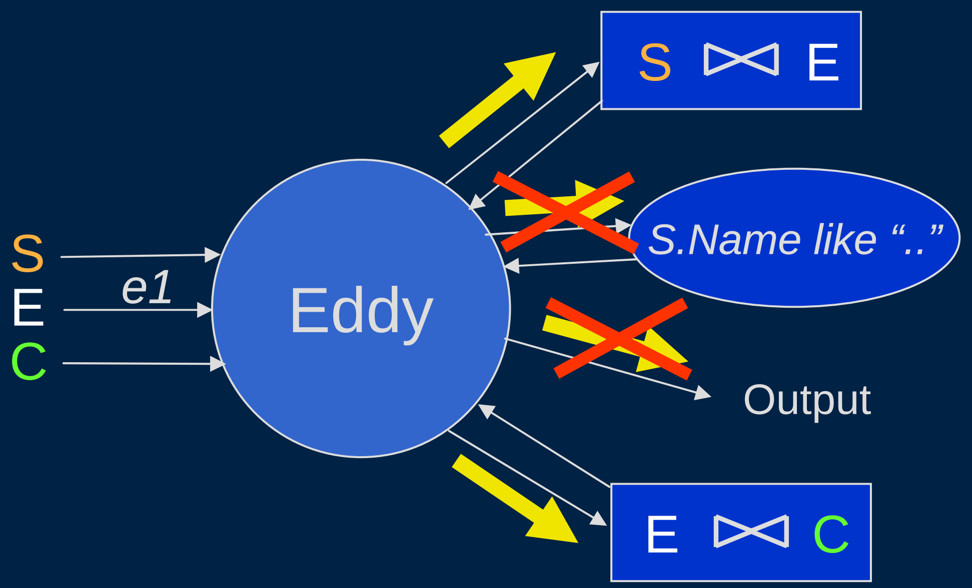
For correctness, must obey routing constraints !!



Eddies with Binary Joins [AH'00]

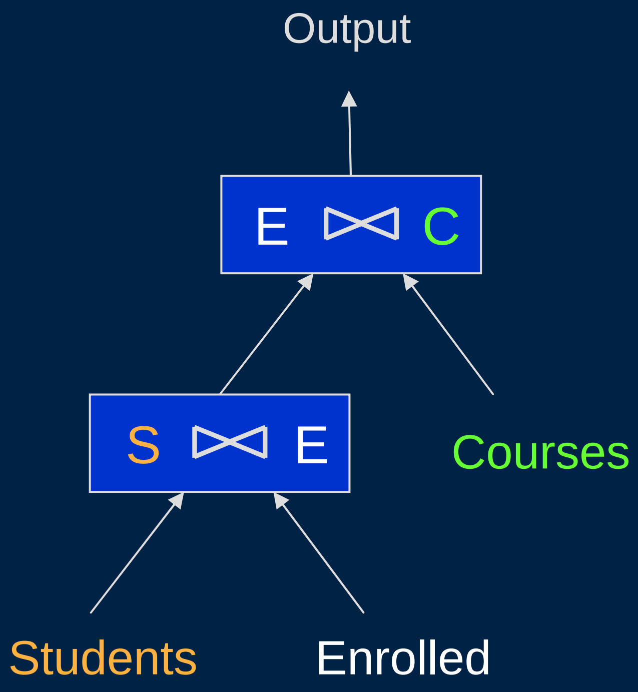


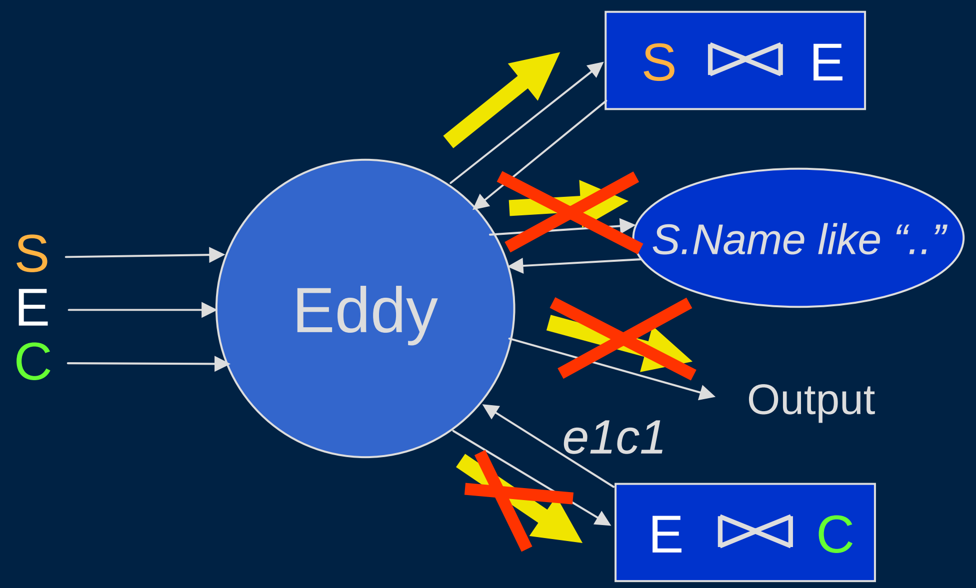
For correctness, must obey routing constraints !!



Eddies with Binary Joins [AH'00]

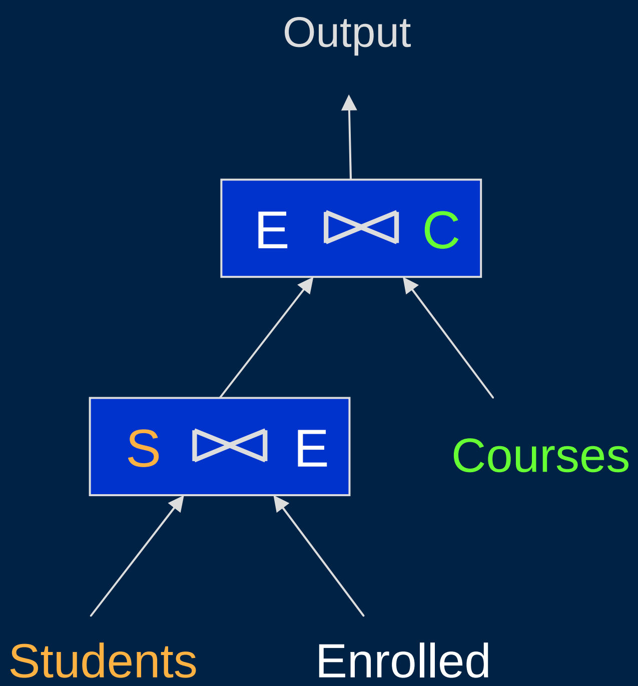
For correctness, must obey routing constraints !!
Use some form of *tuple-lineage*

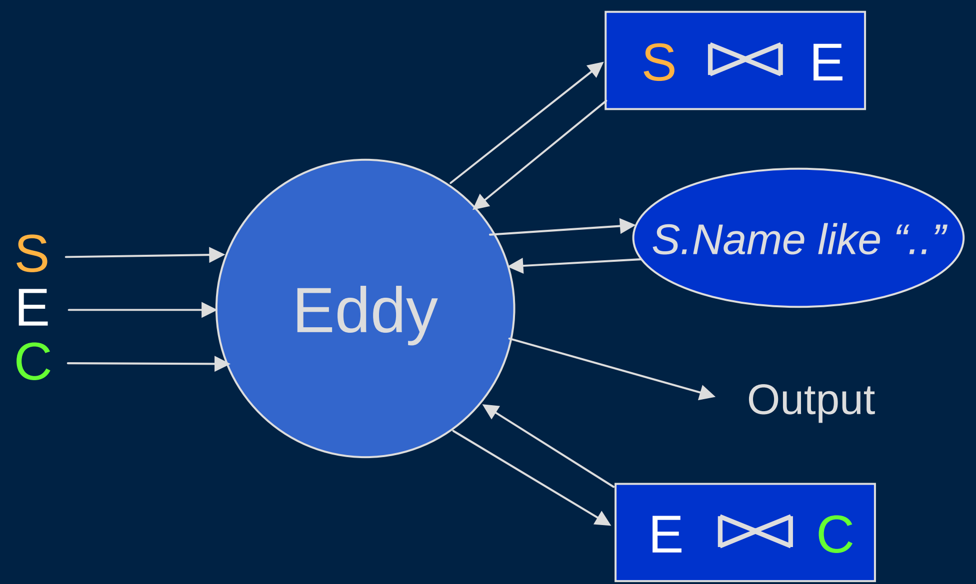




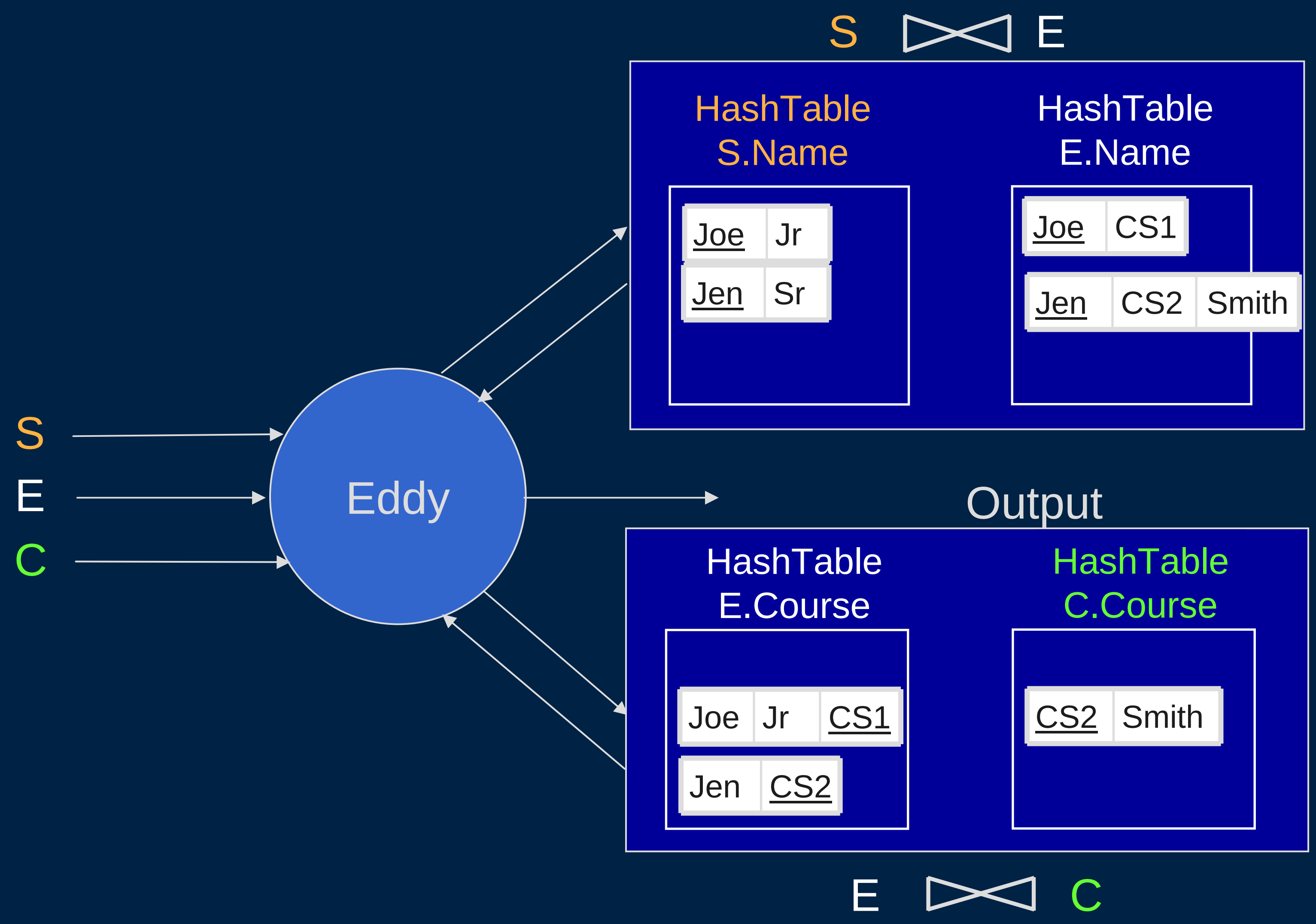
Eddies with Binary Joins [AH'00]

Can use any join algorithms
But, *pipelined* operators preferred
Provide quick feedback



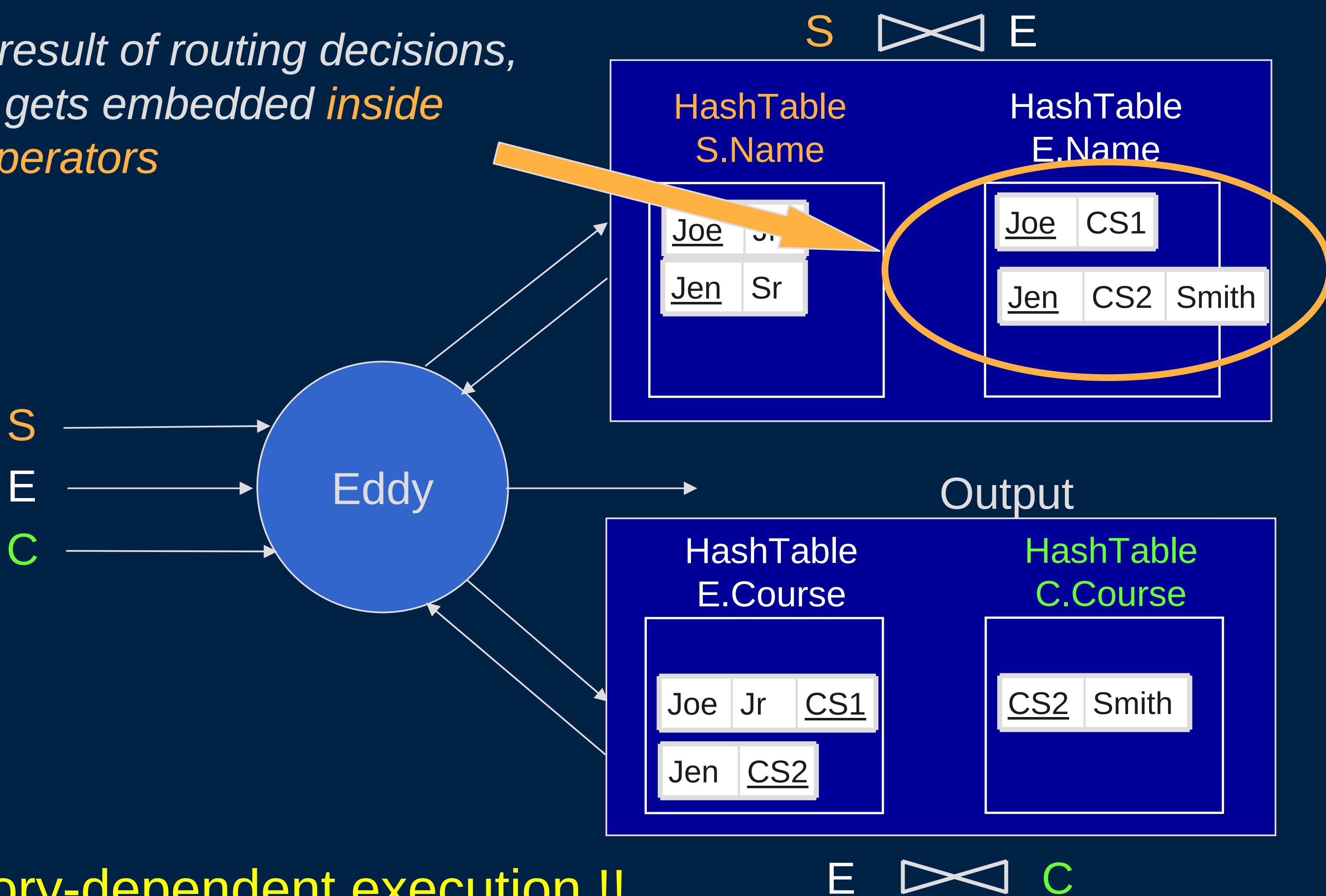


Eddies with Symmetric Hash Joins



Burden of Routing History [DH'04]

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



History-dependent execution !!

Modifying State: STAIRs [DH'04]

Observation:

- Changing the operator ordering not sufficient
- Must allow manipulation of state

New operator: STAIR

- Expose join state to the eddy
  - By splitting a join into *two halves*
- Provide state management primitives
  - That guarantee correctness of execution
  - Able to lift the burden of history
- Enable many other adaptation opportunities
  - e.g. adapting spanning trees, selective caching, pre-computation

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]

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      - State management using STAIRs
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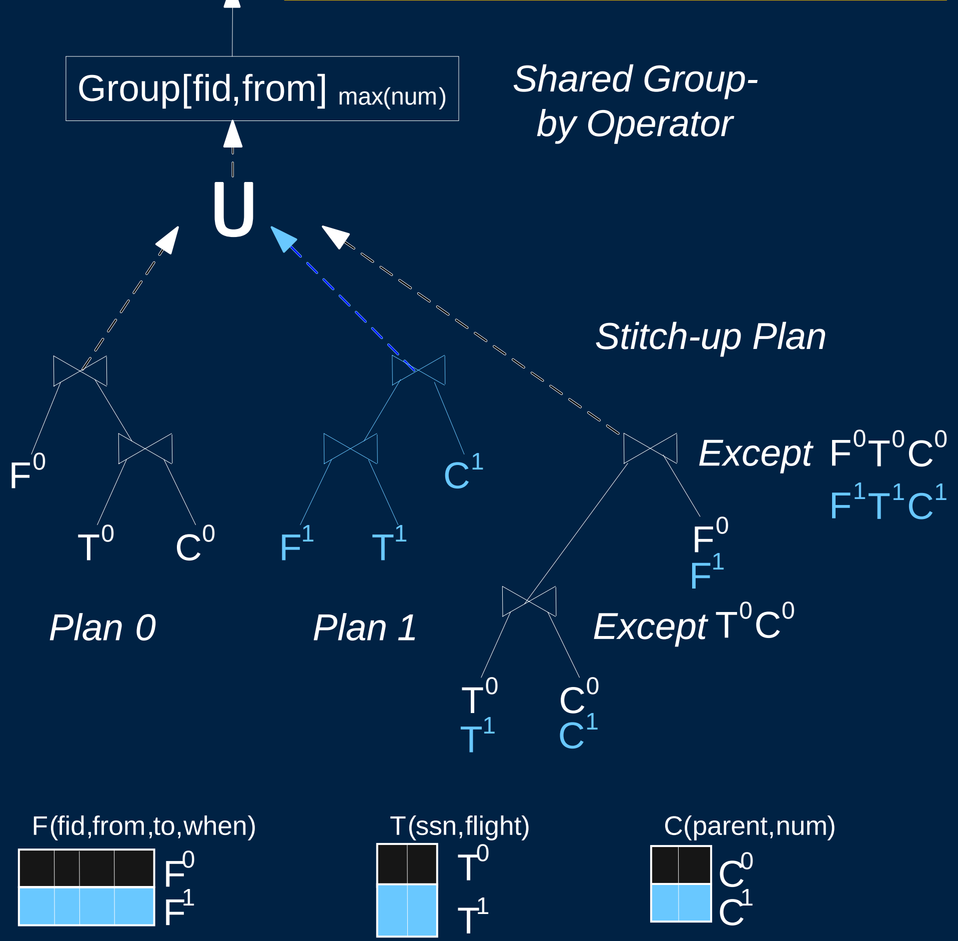
Carefully Managing State: Corrective Query Processing (CQP) [I'02,IHW'04]

- Focus on stateful queries:
  - Join cost grows over time
    - Early: few tuples join
    - Late: may get x-products
  - Group-by may not produce output until end
- Consider long-term cost, switch in mid-pipeline
  - Optimize with cost model
  - Use pipelining operators
  - *Measure* cardinalities, compare to estimates
  - *Replan* when different
  - *Execute* on new data inputs
- *Stitch-up* phase computes cross-phase results

```
SELECT fid, from, max(num)
FROM F, T, C
WHERE fid=flight
      AND parent=ssn
GROUP BY fid, from
```



CQP Discussion

Each plan operates on a horizontal partition: Clean algebraic interpretation!

Easy to extend to more complex queries

- Aggregation, grouping, subqueries, etc.

Separates two factors, conservatively creates state:

- Scheduling is handled by pipelined operators
- CQP chooses plans using long-term cost estimation
- Postpones cross-phase results to final phase
  - Assumes settings where computation cost, state are the bottlenecks
- Contrast with STAIRS, which move state around once it's created!

Putting it all in Context

How Do We Understand the Relationship between Techniques?

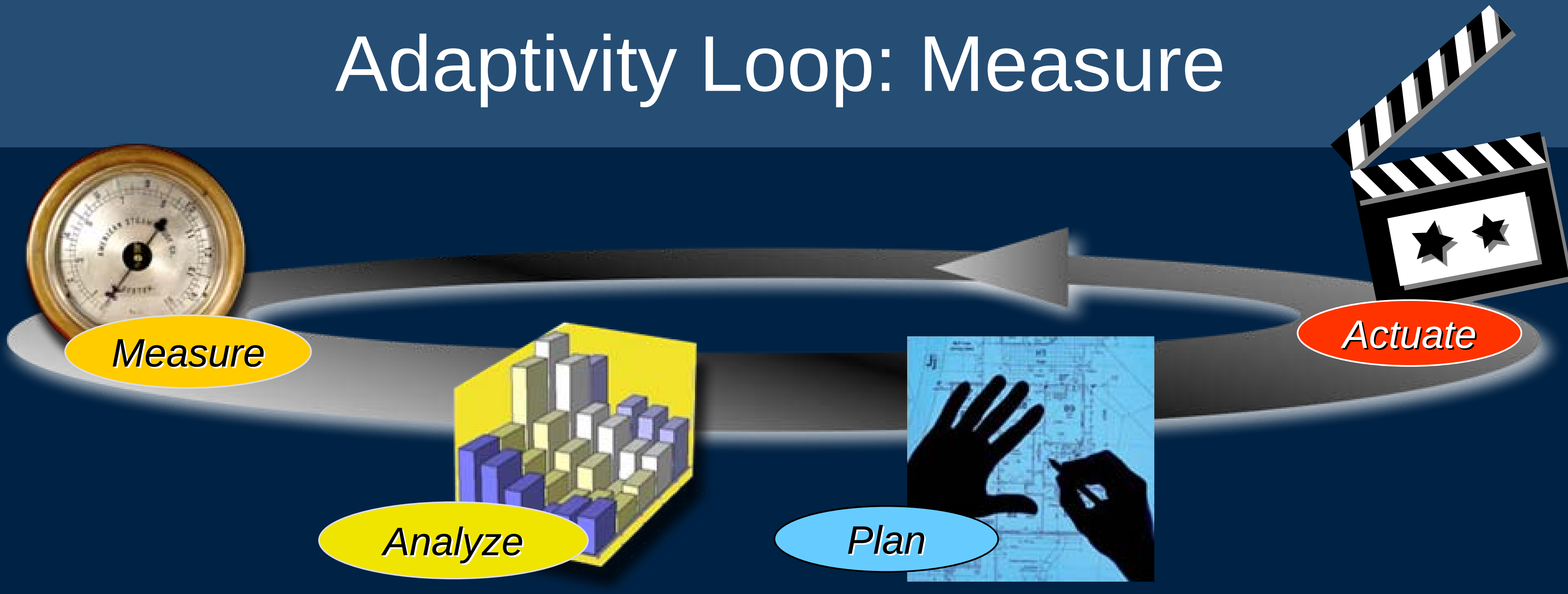
Several different axes are useful:

- When are the techniques applicable?
  - Adaptive selection ordering
  - History-independent joins
  - History-dependent joins

- How do they handle the different aspects of adaptivity?

- How to EXPLAIN adaptive query plans?

Adaptivity Loop: Measure



Measure what ?

Cardinalities/selectivities, operator costs, resource utilization

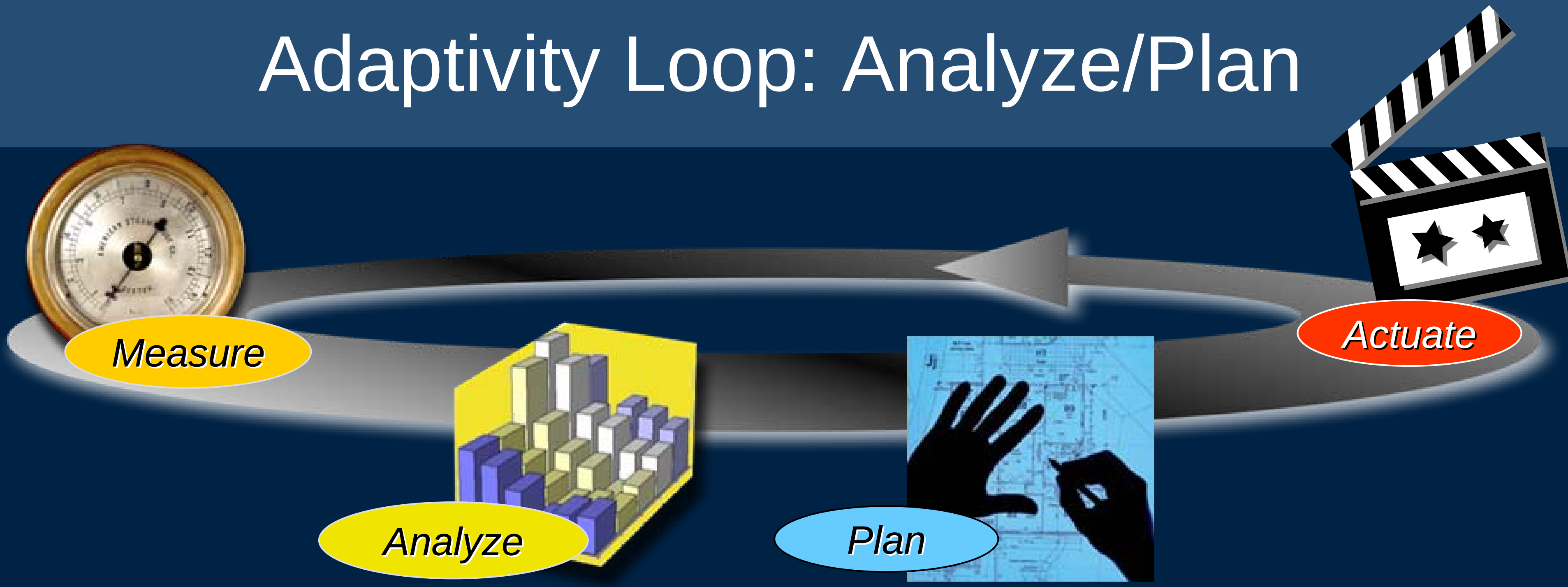
Measure when ?

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/Plan



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)

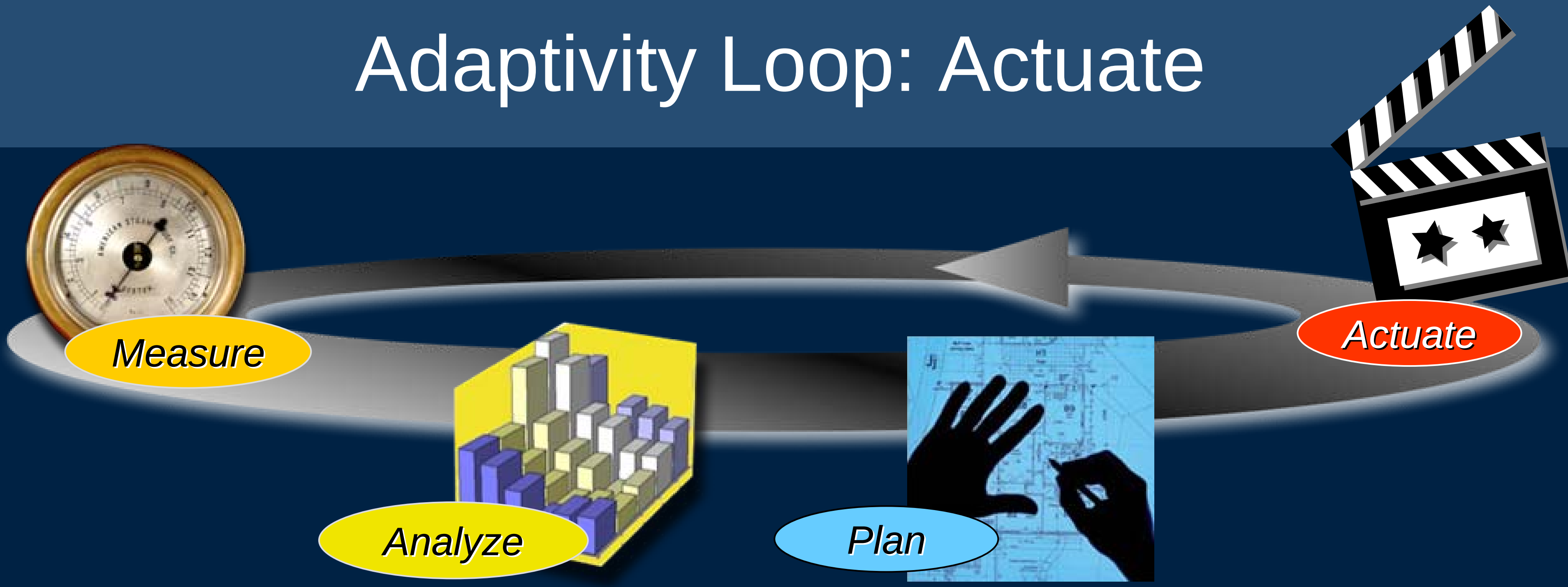
Plan how far ahead ?

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

Planning overhead ?

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

Adaptivity Loop: Actuate



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)

Adaptive Query Processing "Plans": *Post-Mortem Analyses*

After an adaptive technique has completed, we can explain what it did over time in terms of data partitions and relational algebra

e.g., a selection ordering technique may effectively have partitioned the input relation into multiple partitions…

… where each partition was run with a different order of application of selection predicates

- These analyses highlight understanding how the technique manipulated the query plan
  - See our survey in now Publishers' *Foundations and Trends in Databases*, Vol. 1 No. 1

Research Roundup

Measurement & Models

- Combining static and runtime measurement

- Finding the right model granularity / measurement timescale
  - How often, how heavyweight? Active probing?

- Dealing with correlation in a tractable way

- There are clear connections here to:
  - Online algorithms
  - Machine learning and control theory
    - Bandit problems
    - Reinforcement learning
  - Operations research scheduling

Understanding Execution Space

Identify the “complete” space of post-mortem executions:

- Partitioning
- Caching
- State migration
- Competition & redundant work
- Sideways information passing
- Distribution / parallelism!

What aspects of this space are important? When?

- A buried lesson of AQP work: “non-Selingerian” plans can win big!
- Can we identify robust plans or strategies?

Given this (much!) larger plan space, navigate it efficiently

- Especially on-the-fly

Wrap-up

Adaptivity is the future (and past!) of query processing

Lessons and structure emerging

- The adaptivity "loop" and its separable components

  Relationship between measurement, modeling / planning, actuation

- Horizontal partitioning "post-mortems" as a logical framework for understanding/explaining adaptive execution in a post-mortem sense

- Selection ordering as a clean "kernel", and its limitations

- The critical and tricky role of state in join processing

A lot of science and engineering remain!!!

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