# An Adaptive Query Execution Engine for Data Integration

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## Outline

- Motivation for Tukwila
- Tukwila Architecture
- How is Tukwila Adaptive?
- Interleaved Optimization and Execution
- Adaptive Query Operators: dynamic collectors & double pipelined hash join

## The Motivation for Tukwila:

Key characteristics of the data integration problem:

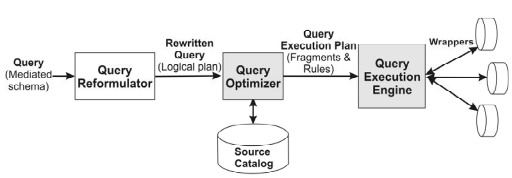
- No statistics
- Unpredictable data transfer rates
- Overlap & redundancy of data
- Quick initial results more important than total plan cost

Conclusion: Adaptivity is critical to performance! Traditional static query processing inadequate.

## Discussion #1

- Why does optimizing initial answers matter more in data integration?
- Can you imagine needing it elsewhere?

## Tukwila Architecture




## How is Tukwila adaptive?

- Between the optimizer & the execution engine via "***interleaved planning & execution***"
  - Compensates for lack of information and unpredictable data transfer rates
- Within the execution engine via "***adaptive query operators***"
  - Manage overlapping data sources (*dynamic collectors*)
  - Produce initial results quickly (*double pipelined hash join*)

## Interleaved Optimization & Execution

Query plans can be reoptimized or rescheduled by the query optimizer after the execution of each fragment by the query execution engine based on the event-condition-action rules.

## The Optimizer

Novel characteristics of Tukwila’s optimizer:

- The optimizer generates a ***query plan and a set of rules*** to define adaptive behaviour
- The query plan need not be complete - if essential statistics are missing or uncertain a ***partial query plan*** can be produced
- The optimizer ***conserves the state of its search space*** when it calls the execution engine; can resume optimization incrementally

## The Query Plan

- **Query plan** = a partially-ordered set of fragments + a set of rules
- **Fragment** = a fully pipelined tree of physical operators
- **Rules** = describe *w*hen and how to modify the implementation of certain operators at runtime if needed; detect opportunities for re-optimization.

The fragment is the source of ***adaptivity***

- At the end of each fragment, the rest of the plan can be re-optimized or rescheduled according to the rules

## The Rules

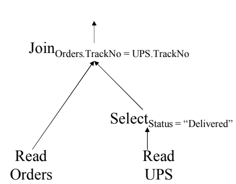
Implement one of four “adaptive” behaviours:

1. **Re-optimization**: if the optimizer’s cardinality estimate for the fragment’s result is significantly different from the actual size → re-invoke optimizer
2. **Contingent planning**: the execution engine checks properties of the result to select the next fragment
3. **Rescheduling**: if a source times out
4. **Adaptive operators**: overflow resolution for the double pipelined join; collector implementation

## Query Execution

The query plan (represented as an operator tree) is executed using the top-down “iterator” model:

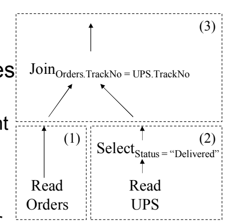
“Show which orders have been delivered”




- Control flow
  - Iterator (top-down)
    - Most common database model
    - Control flows from the node down to the leaves within each fragment

## Query Execution

- Multiple fragments; end at materialization points
- Execution engine generates ***events*** when execution state changes (e.g., fragment completes)
- Events trigger rules
  - E.g., Re-optimize remainder (terminate current plan & reinvoke optimizer, sending back statistics)




When(closed(1)):
if size_of(Orders) > 1000
then reoptimize {2, 3}

## Dynamic Collector

- Dynamic collectors provide a policy for guiding access to overlapping data sources
  - Provided by the optimizer based on estimates of the “overlap relationships” between sources
    - Data source access order
    - Potential fallback sources
  - Implemented by query execution engine by contacting data sources in parallel
    - Is flexible – can contact only some of the sources

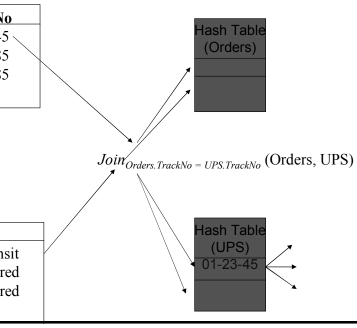
## Double Pipelined Hash Join

- Main features:
  - Each source relation has its own hash table in memory
  - As a tuple comes in, add to its own hash table and probe opposite hash table
- Benefits:
  - Produces results as soon as a tuple is received; time to first output tuple minimized!
  - Symmetric – no “inner” relation to wait for (as in nested loop joins & hash joins)
- Drawbacks:
  - Requires memory for two has tables
  - Data-driven, bottom-up execution model (but execution is top-down)

## Example

**Orders**

| OrderNo | TrackNo |
|---|---|
| 1234 | 01-23-45 |
| 1235 | 02-90-85 |
| 1399 | 02-90-85 |
| …… | …… |

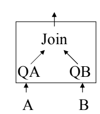



**UPS**

| TrackNo | Status |
|---|---|
| 01-23-45 | In Transit |
| 02-90-85 | Delivered |
| 03-99-10 | Delivered |
| …… | …… |

## Double-Pipelined Hash Join: Adapted to the Iterator Model

- Use multiple threads with queues
  - Each child (A or B) reads tuples until full, then sleeps & awakens parent
  - Join sleeps until awakened, then:
    - Joins tuples from QA or QB, returning all matches as output
    - Wakes owner of queue




## Double-Pipelined Hash Join: Handling Memory Overflow

- May not be able to fit hash tables in memory
  - Only feasible recovery strategy is flush portion of hash table to disk when system runs out of memory
- Two algorithms implemented in Tukwila:
  - Incremental Left Flush - read only from right, flush from left
  - Incremental Symmetric Flush - choose a bucket and flush from both sources

## Conclusions

Tukwila’s main contributions:

- Tukwila achieves adaptivity by segmenting a query plan into fragments and, interleaving the execution of these with reoptimization
- Tukwila minimizes the time to the first output tuple through its use of the double pipelined hash join

## Discussion #2

- How do you evaluate the double pipelined hash join?
- Is it efficient?
- Would you use it if you were not doing data integration, why or why not?