Declarative query processing in imperative managed runtimes

Stratis D. Viglas

Google, US & School of Informatics, University of Edinburgh, UK sviglas@google.com

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Multi-tier applications



What's changing?



What's changing?



In this talk

- Code generation for just-in-time query compilation
 - Starting from compiling SQL to C
 - Moving on to managed runtimes and language-integrated queries
- Write-limited algorithms for persistent memory
 - Staging algorithms for query processing
 - API to enable dynamic optimization
 - A runtime to support the API

Part I

Just-in-time code generation for query processing

Database systems architecture

- Roughly decomposed into four main building blocks
 - Query engine
 - Storage manager
 - Transaction manager
 - Recovery manager



- Relatively orthogonal aspects
 - Improvements in one block improve the system overall
 - Or, at least, we try to abide by that rule

Zooming in to query processing

- Queries go through a sequence of transformations
 - Parsing
 - SQL to abstract syntax tree (AST)
 - Rewriting
 - AST to logical plan
 - Potentially more than one rewriting passes
 - Optimization
 - Logical plan to physical plan
- Interpretation-based approach
 - Query engine interprets the query plan to produce results



Holistic techniques

- Template-inspired approach
 - Languages like C++ generate type-specific code in their standard library
 - Reduces bloat of generic implementations
 - Operators are templated and instantiated per query
- At the same time, look at the query holistically
 - Collapse operations when possible
 - Generate type-specific code
 - Eliminate function calls apart from the necessary
 - Source to source transformation: from SQL to C
- Leave orthogonal aspects of the system unaffected
- Treat SQL truly as a managed runtime with just-in-time compilation capability

HIQUE – the Holistic Integrated Query Engine



Example generated code

```
/* Inlined code to stage inputs */
hash: /* examine corresponding partitions together */
for (k = 0; k < M; k++) {
  /* algorithm bookkeeping */
  /* loop over pages */
                                                                      nested loops
 for (p_1 = start_page_1; p_1 <= end_page_1; p_1++) {</pre>
    page_struct *page_1 = read_page(p_1, partition_1[k]);
    for (p_2 = start_page_2; p_2 <= end_page_2; p_2++) {</pre>
      page_struct *page_2 = read_page(p_2, partition_2[k]);
      . . .
      for (p m = start page m; p m <= end page m; p m++) {</pre>
        page_struct *page_m = read_page(p_m, partition_m[k]);
        /* for each page loop over tuples in the page */
                                                                  fixed strides
        for (t 1 = 1; t 1 <= page 1->num tuples; t 1++) {
          void *tuple_1 = page_1->data + t_1 * tuple_size_1;
          for (t 2 = 1; t 2 <= page 2->num tuples; t 2++) {
            void *tuple 2 = page 2->data + t 2 * tuple size 2;
            int *t1 = tuple 1 + offset 1;
            int *t2 = tuple 2 + offset 2;
                                                 type-specific computation
            if (*t1 != *t2) {
              merge: /* update bounds for all loops */
              continue; }
              . . .
              for (t_m = 1; t_m <= page_m->num_tuples; t_m++){
\{ \ldots, \}\}
```

Language-integrated query (C[#])



LINQ-to-objects in more detail



Standard execution



- Virtual function calls to propagate objects through pipeline
- Lambda expression calls to allow generic implementations
- Compiler cannot inline because target not known at compile time

Query compilation

• Dynamically compile queries at run-time

- Single, specialized operator that evaluates the entire query

```
IEnumerable<Decimal> Query (List<Order> src) {
  foreach (Order s in src) {
    if (s.orderdate > new DateTime (1/1/1999))
        yield return (s.price * (1 - s.discount));
    }
}
```



Compilation architecture

• Query compiler is implemented as a LINQ query provider



The bad news

- Basic approach is limited by performance of C[#]
- Relies on (cache) inefficient memory layout dictated by garbage collection



Planning ahead

- Preferably we would like to perform query processing in native C code and have control over data layout
 - Not possible to access managed objects in C
 - Not possible to control data layout of objects
- But: structs are value types (in C[#]) and, hence
 - Are not managed by garbage collector
 - Allow some control over data layout

Adding more C into C[#]

- Represent dataset as arrays of structs
- Dual operator approach:
 - C[#] operator interacts with application code by returning query result
 - C operator processes query on arrays of structs



Staged query processing (from C[#] to C and back)

- Store data as collections of objects
- Stage data in C[#] (as arrays of structs) and perform heavy-lifting of query in C on staged data
- Fall back to basic approach for simple operations



Staging in more detail

- Apply selections (fewer elements copied)
- Apply implicit projections (fewer fields copied)
- Flatten-out nested objects (removes references)



Indicative results over TPC-H

Normalized response time

LINQ-to-objects Compiled C# Compiled C Staged



Part II

Write-limited algorithms for persistent memory

Properties of persistent memory



- Latency comparable to DRAM
 - But not DRAM
- Asymmetry: writes more expensive than reads (up to 15x)
 - Similar to flash memory; much faster overall, but more pronounced asymmetry
- Not a block device
 - Byte-addressable, behaves as memory
 - Potentially accessed through CPU loads and stores
 - Game-changing property

Incorporating persistent memory

- Persistent memory bridges the gap between disk and memory
 - Universal device, universal optimization objectives
- But how should it be treated?
 - As byte-addressable, albeit somewhat slower memory?
 - Or as block-addressable but faster persistent storage?
 - Neither? Both?
- What is the impact on system aspects?
- This work
 - Optimization of fundamental query processing algorithms and a runtime to support them

In more detail

- Design and implementation of persistent-memory-friendly algorithms for query processing
 - And a runtime to support them
- Focus on two fundamental operations
 - Sorting and join processing
- Why these two?
 - Well, we are doing databases after all!
 - But the goal is farther-reaching
- Write-limited algorithms
 - Trade writes for reads with tunable write-intensity
 - Guarantee when they outperform existing algorithms

General setup

- Overarching goal: trade writes for reads
- Persistent memory I/O takes place in cacheline-sized units (termed buffers)
- Under the assumption there is a ratio λ=w/r where w is the write cost of the medium; r is the read cost; λ > 1
- Two general classes of algorithms
 - Split processing into a write-incurring and a write-limited part; or
 - Process lazily by performing extra reads and incur writes only when the accumulated read cost is too high

System overview



Limiting writes in sorting: segment sort

write-incurring mergesort on x%

read-only selection sort on (1-x)%



Limiting writes in join processing: lazy join

- Objective: process input one hash partition at a time
- Instead of scanning and materializing the partitioned input
 - Extract each partition by rescanning the entire input
 - Keep track of saved cost (by not writing) and penalty (by rescanning)
 - Materialize when cost exceeds savings



Runtime support: procrastination is bliss

- Each operator belongs to an operator context
- Express algorithms in terms of a common API
 - Record the workflow in a control flow graph
- Do not materialize any collection until it is accessed
 - Upon access, assess() it to see if it should be materialized
 - If collection is to be materialized, produce() it by walking the control flow graph
 - If not, go to the last materialized parent and apply recorded operations dynamically to produce

An API for recording algorithmic workflow

- split(T, n, T_l, T_h)
 - Split collection T at position n into T_l and T_h
- partition(T, h(), k, $[T_i], [s_i] = |T|/k$)
 - Partition collection T into k partitions T₁ to T_k using h() as the partitioning function
 - Size of each partition expected to be s_1 to s_k
 - Last argument optional and reverts to |T|/k
- filter($T, p(), f, T_p$)
 - Filter collection T into T_p using predicate p()
 - Output size expected to be f | T | (where $f \in [0, 1]$)
- merge($T_l, T_r, m(), T$)
 - Merge collections T_{l} and T_{r} into T using m() as the merging function

Example control flow graph



Optimizing the workflow



- Use the sum to decide whether cheaper to keep subsequent collection deferred or materialize
- Trigger materialization using rules based on heuristics for access pattern detection

Implementation alternatives

- Four alternatives for incorporating persistent memory into the hierarchy
 - RAM disk: a full-blown file system running on top of main memory (with true file system overheads)
 - PMFS: a persistent memory file system, optimized for byte-addressable storage
 - Dynamic array: the typical collection one would use for expandable arrays when programming for main-memory
 - Blocked memory: an optimized blocked memory implementation of expandable arrays

Indicative results: sorting 1M records



Sorting 1M records: implementation alternatives



Summary

- Large memories means that data processing will likely be memory-bound
 - No need for separate runtimes for application logic and data management
 - Data processed in the managed runtime, using language-integrated querying
 - Just-in-time code generation for query processing
- Memories not only large, but also non-volatile
 - With different performance characteristics
 - Write-limited algorithms and a dynamic runtime to optimize performance
- Management at all levels
 - Different applications require different representations for the same data
 - Workload-driven dynamic data placement

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