Tuning Data and Control Structures for Incremental Computation

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Incremental computation permeates modern software. A computation is incremental if repeating it with a changed input is faster than from-scratch recomputation. Programmers implement most contemporary incremental functionality in an ad-hoc manner, built into the efficient implementation of the system being designed. I have been working on language- and library-based incremental computation methods in order to increase the efficiency of code in a more systematic way.

Background The state of the art in general purpose, or language based, incremental computation involves building dynamic dependency graphs of program control flow and maintaining memoization tables of prior results. Dependency graphs allow a program to mark all functions affected by an input change, and memoization tables provide results of prior computations that may be used to update an affected function's output without recomputing it. Dependency graphs may maintain a total order for efficiency, or a partial order for flexibility. Memoization tables often use keys with some computed value based on a function's arguments, to allow irrelevant minor changes to be ignored. Two of the standards currently competing on general purpose incremental computation performance are SAC and Adapton. "Self adjusting computation" or SAC [1] is a set of techniques based around a totally ordered dependency graph and annotated function calls. (Nominal) Adapton [4] is an incremental computation engine based on a partially ordered dependency graph and user-defined "names" to key its memoization tables.

Limitations General purpose incremental computation requires a lot of overhead in memory and time. Storing dependency graphs and memoization tables consumes memory. Creating these features and running the algorithms that search them consume time.

To address these limitations, programmers often organize functions and data so that dependency tracking and memoization act on groups rather than individual items. This technique requires direct interaction with the incremental system, and adds "tuning" parameters to control the size and extent of each group. Since this burden is on the programmer, and orthogonal to the program specification, human error becomes a source of bugs.

Approach I design data structures and higher-order functions in the Rust language with support for tuning. These items contain grouping markers and grouping code respectively. A user then runs these functions over these data structures, which implicitly perform the groupings based on the markers. The data structure defines data markers by keeping data in multiple separate arrays (Rust uses the term "vector"), and function markers by flags in its nodes. User code for processing data runs on the vectors through Rust aggregate features. Memoization of a function call occurs only if a target data structure node contains a flag. The memoized group including this call will contain any proceeding non-memoized calls.

Gauged Incremental Random Access Zipper I am designing and implementing an incremental form of the Random Access Zipper (Raz) [5]. The Raz represents a sequence with a tree structure internally, one that rebalances only on the path from an edited node to the root. Algorithms written this way ensure compatibility with incremental computation. My enhancement replaces individual elements with vectors of elements, with the expected size of the vector called the "gauge". The enhancement also adds markers for function memoization and names for use with Adapton. Lets call this new version of the Raz a "Giraz".

The Giraz does not exclusively perform incremental computations. When not involved in an incremental computation, or while preparing for one, the Gi-

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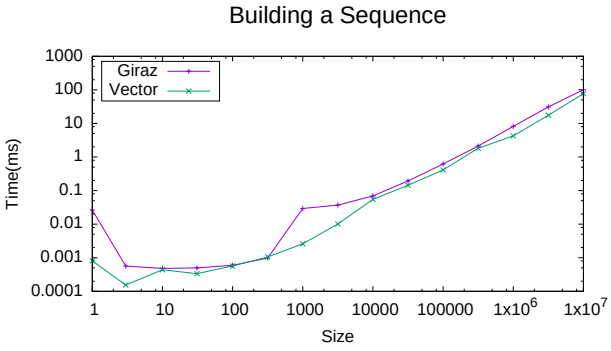

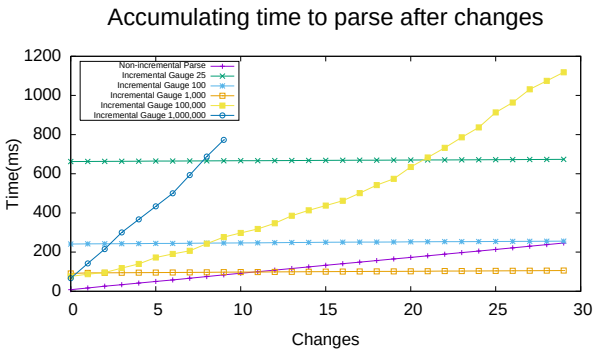

raz has similar performance to equivalent data structures. For example, the first figure shows the time to create a sequence from scratch using Rust's vector or the Giraz. The test that generated this data pushes elements into an empty data structure until it reaches the target size. During this process the vector needs to occasionally relocate when it reaches its carrying capacity. The test also switches the mode of the Giraz from "edit" to "compute" when it reaches the target size, which takes O(log n) time, where n is the number of vectors(elements/gauge). This test uses gauge 1000 and elements with a primitive copy operation.

Tuning Making a dependency graph node for every aspect of a program requires so much memory that traversing it to adjust after a change may take longer than recomputation. While grouping data and functions can reduce this effect, it does not guarantee better performance. Incrementally updating a computation with everything grouped into one dependency node is equivalent to from-scratch computation but with the overhead of the incremental techniques. The user of the Giraz needs to chose parameters that optimize the performance gains of incremental computation. The design of the Giraz allows for this tuning in newly added data.

The second figure shows the affects of different gauges on a non-trivial toy computation. This computation parses a string of numbers and addition symbols, interpreting the sequence like a reverse-polish calculation. It takes a sequence of 1M characters and returns a shorter sequence of integers. The native rust implementation of this requires under 10ms to parse a sequence. The incremental test folds over the Giraz, memoizing at the internal markers, in this case located at vector boundaries. The best initial incremental computation shown (gauge 1,000) takes at least 65ms. However, the plot accumulates the time to recompute after an insertion to the character sequence. There is a crossover point where it is faster to use incremental computation than to recompute after each edit. This occurs after ten changes to the input in our best case. The test clearly demonstrates the trade off described above: low gauges update fast with slow initial computation, while high gauges update slow with fast initial computation.

Related Work Prior work on SAC introduced abstract data types [2] to group data and functions to be memoized. That work concentrates on a generic interface for hand-crafted data types that can not be further tuned. Later work on SAC introduces "blocked lists" [3] similar to using vectors in the Giraz. The block boundaries are based on the data, allowing the possibility of degenerate blocks. Late in the paper is a "reduce" benchmark that is similar to one written for the Giraz. At low gauges (block sizes), our results are similar, with the Giraz taking slightly more memory, and slightly more recomputation time. At high gauges, however, this situation is reversed, and additionally, the Giraz initial computation time is over three times faster.

References

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