An interactive visualization framework for performance analysis

Emilio Coppa
Dept. of Computer Science
Sapienza University of Rome
coppa@di.uniroma1.it

ABSTRACT

Input-sensitive profiling is a recent methodology for analyzing how the performance of a routine scales as a function of the workload size. As increasingly more detailed profiles are collected by an input-sensitive profiler, the information conveyed to a user can quickly become overwhelming. In this paper, we present an interactive graphical tool called `aprof-plot` for visualizing performance profiles. Exploiting curve fitting techniques, `aprof-plot` can estimate the asymptotic complexity of each routine, pointing the attention of the programmer to the most critical routines of an application. A variety of routine-based charts can be automatically generated by our tool, allowing the developer to analyze the performance scalability of a routine. Several examples based on real-world applications are discussed, showing how to conduct an effective performance investigation using `aprof-plot`.

Categories and Subject Descriptors

C.4 [**Performance of Systems**]: Measurement Techniques; H.5.2 [**User Interfaces**]: Graphical user interfaces (GUI)

General Terms

Performance, Measurement, Visualization.

1. INTRODUCTION

Performance optimization is a critical step during software development. Programmers make use of profilers to understand the application runtime behavior and to spot performance bugs. Traditional profilers help developers find out how specific portions of code are responsible for resource consumption, such as memory space and CPU time. Some recent works have made a step further by addressing the problem of designing and implementing performance profilers that return, instead of a single number representing the cost of a portion of code, a function that relates the cost to the input size (see, e.g., [4, 9, 21]). These approaches have been inspired by traditional asymptotic analysis of algorithms, and make it possible to analyze – and sometimes predict – the behavior of actual software implementations run on deployed systems and realistic workloads.

This paper is based on the input-sensitive profiling methodology described in [4]: this approach is able to automatically measure how the performance of individual routines scales as a function of the input size, yielding clues to their growth rate. From one or more runs of a program, an input-sensitive profiler collects several performance measurements related to the runtime behavior of an application and of its routines. These profile data are stored as text-based files and can quickly become very large as increasingly more detailed profiles are collected, making it really hard for a developer to take benefit of this valuable information. To overcome this problem, in this paper we present an interactive graphical viewer for input-sensitive profiles, written in Java and called `aprof-plot`. Several routine-based charts can be automatically generated by our tool, allowing the developer to analyze the performance scalability of a routine and to obtain useful insights on its workload. Exploiting curve fitting algorithms, `aprof-plot` automatically estimates the asymptotic complexity of each routine, pointing the attention of the programmer to the most critical routines of an application. Noise reduction techniques and other useful features support the user towards a more effective performance investigation. The tool is available at `http://code.google.com/p/aprof/`.

Related work. Performance profiling has been the subject of extensive research since the early 70's. For many years, analysis of profile data has been performed using command line tools [10], which provides limited user interaction. Today, the importance of visualization tools for evaluating program performance has been widely recognized and the majority of integrated development environments (IDEs) offer several interactive visualizers for inspecting the runtime behavior of an application. VisualVM [19] is a widespread graphical tool, built on top of the NetBeans IDE platform, for profiling the running time and memory usage of Java applications. Several recent works specifically help the user to understand, find, and eventually fix memory-related problems in their programs. AllocRay [17] is an animated interactive viewer for memory allocation events which shows the changes of the memory over time using 2D memory map plots. `dymem` [16] builds a directed acyclic graph depicting group-based object ownership: a compact tree-based representation of this graph can help a developer to identify common memory problems.

`KCachegrind` [20] is a well-known data visualization tool for profiles generated by `callgrind` [20] as well as other open

VALUETOOLS 2014, December 09-11, Bratislava, Slovakia

DOI 10.4108/icst.valuetools.2014.258172

source profilers. Using `KCachegrind`, besides analyzing how the running time has been spent during the execution of a program, a developer can inspect the call graph and identify performance bugs due to poor cache utilization. To the best of our knowledge, the lack of information about the workload of a routine does not allow these tools to evaluate how the performance of routines scale as a function of the workload size.

Paper organization. The remainder of this paper is organized as follows. In Section 2 we summarize the main ideas behind the input-sensitive profiling methodology. The design and the main features of our graphical tool are covered in Section 3: after discussing the motivation and goals of `aprof-plot`, several examples show how our tool can be effectively leveraged by programmers for performance analysis purposes. Section 4 concludes the paper, outlining directions for future work.

2. PROFILING METHODOLOGY

The main idea behind input-sensitive profiling is to aggregate performance measurements for individual routine calls by the size of the input on which each call operates. Differently from the classical analysis of algorithms based on theoretical cost models, where the input size of a procedure is a parameter known a priori, a key challenge of an automated approach is the ability to automatically infer the size of the data given as input to a function. This can be done using the *read memory size* metric introduced in [4]:

DEFINITION 1. *The* read memory size *(*RMS*) of the execution of a routine f is the number of distinct memory cells first accessed by f, or by a descendant of f in the call tree, with a read operation.*

The intuition behind this metric is the following. Consider the first time a memory location ℓ is accessed by a routine activation f: if this first access is a read operation, then ℓ contains an input value for f. Conversely, if ℓ is first written by f, then later read operations will not contribute to increase the RMS since the value stored in ℓ was produced by f itself.

Notice that the RMS definition, which is based on tracing low-level memory accesses made by the program, supports memory dereferencing and pointers in a natural way. However, the RMS metric ignores any communication between threads and data received via system calls from the OS kernel, failing to accurately characterize the behavior of routines executed in the context of modern concurrent and interactive applications. A more recent work [6] has extended the RMS metric in order to include dynamic input sources such as communication between threads and I/O. For the sake of presentation, in this paper we refer to the original metric, but any consideration can be naturally applied to the latter extension.

Input-sensitive profile. Given a metric for estimating the input size of a routine activation, an input-sensitive profiler collects several performance measures in order to evaluate the routine performance scalability. For each routine f, let $N_f = \{n_1, n_2, \ldots\}$ be the set of distinct input sizes on which f is called during the execution of a program. For each $n_i \in N_f$, the profiler collects a tuple $\langle n_i, c_i, max_i, min_i, sum_i, sq_i \rangle$, where:

benchmark	no. routines	profile size (MB)
`403.gcc`	2551	19.2
`445.gobmk`	1780	36.5
`454.calculix`	777	9.7
`471.omnetpp`	1125	2.1
`bodytrack`	617	3.1
`canneal`	631	0.8
`facesim`	776	0.5
`ferret`	906	16.4
`vips`	982	47
`352.nab`	361	3.4
`367.imagick`	685	0.3
`376.kdtree`	223	28

Table 1: Number of routines and profile sizes of several benchmarks taken from SPEC CPU2006, PARSEC 2.1, and SPEC OMP2012.

- c_i is the number of times the routine is called on input size n_i;
- max_i and min_i are the maximum and minimum costs required by any execution of f on input size n_i, respectively;
- sum_i and sq_i are the sum of the costs required by the executions of f on input size n_i and the sum of the costs' squares, respectively.

In principle, the term *cost* may refer to any performance metric, e.g., time, number of executed basic blocks, or cache misses. Since the focus of the input-sensitive profiling methodology is on modeling scalability rather than on exact running times, the results presented in this article are based on basic block counts, which have several advantages for studying the asymptotic behavior of a program, as explained in [9]. After running an application under an input-sensitive profiler, the programmer gets a text-based profile which contains a dump of all performance tuples collected for any executed routine.

3. VISUAL MINING OF INPUT-SENSITIVE PROFILES

As discussed in Section 2, several performance measurements are automatically collected by an input-sensitive profiler: although these data can be aggregated at runtime according to several criteria, the resulting profiles may easily become very large due to the high number of routines typically executed by real-world applications. Table 1 shows some profile statistics related to several applications taken from the SPEC CPU2006 suite [11], the Princeton Application Repository for Shared-Memory Computers (PARSEC 2.1) [2], and the SPEC OMP2012 suite [15]. The profiles have been obtained using the profiler `aprof-0.2.1` [1] while running these applications on their reference workloads. As an example, the GNU Compiler Collection release included in the SPEC suite (`403.gcc`) has executed more than 2500 distinct routines during our tests, resulting in 19.2 MB of profile data. But even benchmarks with fewer routines lead to huge profiles: for instance, `376.kdtree`, with only 223 routines, has generated a 28 MB report.

Input-sensitive profiles are stored as text-based files. From our experience, manual inspection of these files turns out to be largely impractical for a common programmer even with profiles of just few kilobytes. For this reason, we have developed an interactive visualizer written in Java, called `aprof-`

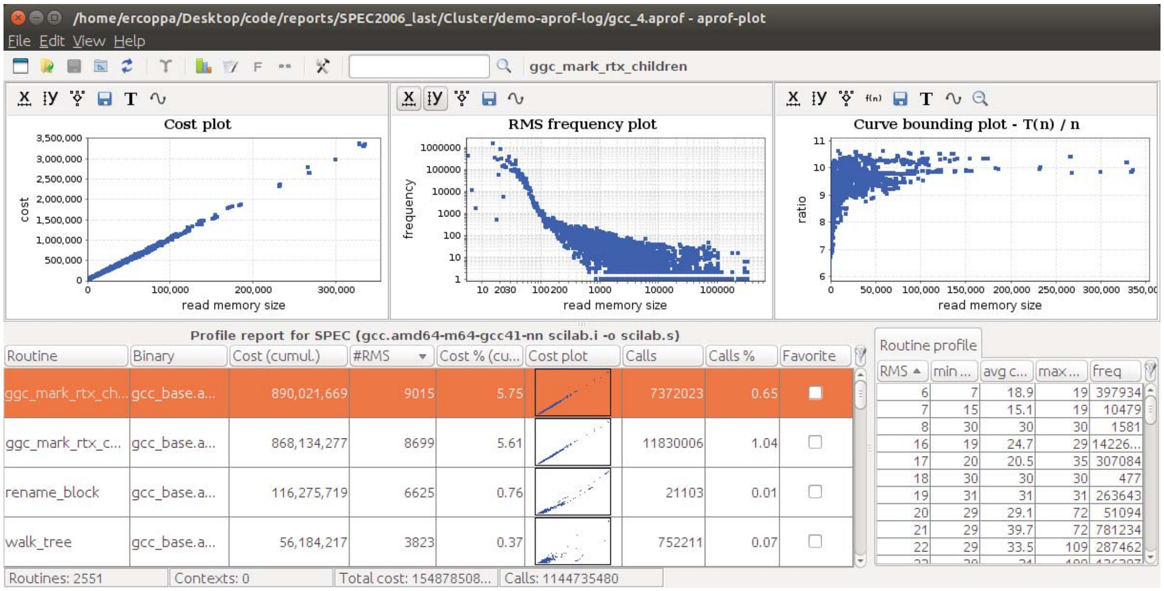


Figure 1: Main window of `aprof-plot`: list of profiled routines (bottom left), automatically generated charts (top) and list of performance tuples (bottom right) of a selected routine.

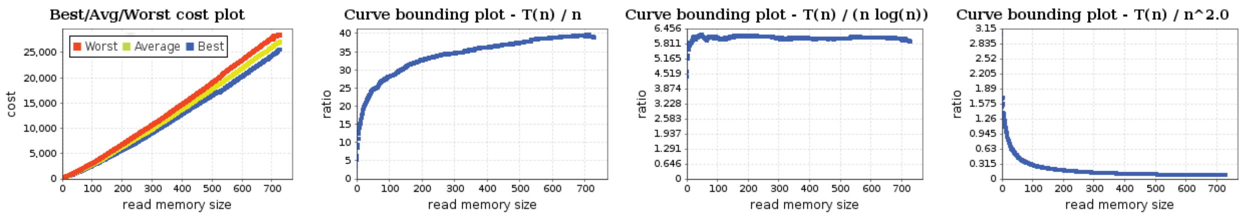
`plot`. The goal of this graphical tool is twofold. From one side, the user can inspect the scalability of a specific routine by analyzing several routine-based performance charts. On the other side, our tool attempts to focus the attention of the programmer to the most critical routines, possibly pinpointing unexpected performance trends. Before discussing how `aprof-plot` can support the user towards these two performance analysis' directions, we briefly provide an overview of its design. The main interface is shown in Figure 1. After selecting an input-sensitive profile, a list of routines is presented (bottom left) to the user with several pieces of information for each routine: alongside the routine signature and its executable binary, various cumulative performance metrics summarize the impact on the overall application execution (e.g., percentage of cost spent inside the routine, number of calls, number of collected performance tuples). Whenever the user selects from this list a specific routine, on the top part of the interface several routine charts are automatically generated. Each plot can be customized by the user through different tools available in the chart action bar. Finally, the performance tuples collected for the selected routine are listed in the bottom right part of the interface: this allows programmer to carefully inspect the routine profile and to find out details of performance behaviors graphically represented by the routine charts.

3.1 Routine performance analysis

Performance as a function of workload size. Input-sensitive profiling naturally allows the programmer to investigate how the running time of a routine scales as a function of its workload size. This kind of analysis is actually critical for any software: seemingly benign fragments of code may be fast on some testing workloads, passing unnoticed with traditional profilers, while all of a sudden they can become major performance bottlenecks when deployed on larger inputs (see, e.g., examples in [5]). To this aim, `aprof-plot` can automatically generate worst-case, average-case, and best-case cost plots. Indeed, given the tuples $\langle n_i, c_i, max_i, min_i, sum_i, sq_i\rangle$ collected for a routine f (see Section 2), the sets of points $\langle n_i, max_i\rangle$ and $\langle n_i, min_i\rangle$ can be used to estimate how the empirical worst-case and best-case costs of a routine grow as a function of the input size. The average behavior is instead given by the set $\langle n_i, avg_i\rangle$, where the average cost per invocation on input size n_i is obtained by computing $avg_i = sum_i/c_i$. An example of these charts is provided in Figure 2a and is based on routine `heapsort_pairs` of SPEC OMP2012 benchmark `352.nab`: the best-case, average-case, and worst-case trends appear to be relatively similar and rather smooth.

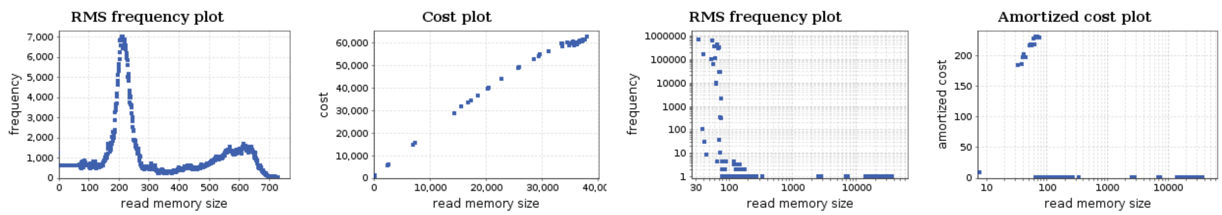
To get more precise insights on asymptotic performance of a routine, our tool allows the programmer to easily apply a technique known as curve bounding. In particular, the guess ratio rule (see [13] and [14]) estimates the trend of a function $f(n)$ by considering a guess function $h(n)$ and analyzing the trend of ratio $f(n)/h(n)$: the ratio stabilizes to a non negative constant if $f \in O(h(n))$, while it (eventually) increases if $f \notin O(h(n))$. In our example we divided the worst-case trend of Figure 2a by three different guess functions: n, $n \log n$, and n^2. The three resulting curves are shown in Figure 2b, Figure 2c, and Figure 2d, respectively. The cost of routine `heapsort_pairs` increases when divided by n, decreases when divided by n^2, and stabilizes to a positive constant when divided by $n \log n$. This confirms that the trend is $n \log n$, as expected from any bug-free implementation of the heapsort algorithm. An interactive popup menu, available when displaying the curve bounding plot in `aprof-plot`, allows the programmer to easily test several user-defined guess functions.

Workload analysis. A natural question is which are the typical workloads of a routine. Even more interesting is in-



(a) (b) (c) (d)

Figure 2: Cost plot and curve bounding plots related to routine `heapsort_pairs` of benchmark `352.nab` [15].

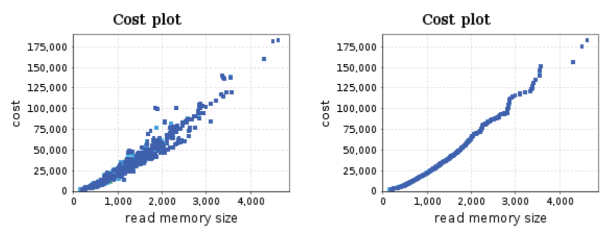


(a) (b) (c) (d)

Figure 3: (a) Frequency plot of routine `heapsort_pairs`. Routine std::vector::push_back: cost plot (b), frequency plot (c), and amortized cost plot (d).

vestigating how the actual workload is impacting the routine performance. Two orthogonal considerations can be made. From one side, `aprof-plot` can give insights on the typical workloads on which a routine is called during the execution of a program: as an example, Figure 3a depicts the frequency distribution of the workload sizes observed for routine `heapsort_pairs`: a peak around the RMS value 200 provides a rough estimation about the typical size of arrays sorted by this routine in this specific application. In general, this information might be very useful not only for code optimization, but also for algorithmic improvements, even theoretical, in specific scenarios. For instance, if an application always needs to sort arrays with less than 16 items, it may be convenient to use a non-optimal sorting algorithm with runtime n^2 instead of an asymptotically optimal one with runtime $n \log n$. A case study of this flavour is discussed in [5].

On the other side, in many scenarios a routine may be generally cheap, but sporadically require a high cost. Consider for instance an operation that appends an item at the end of a resizable array such as `std::vector`'s `push_back` function of the C++ STL. If the array capacity is not exceeded, then the operation takes constant time. Otherwise, the array must be reallocated, typically requiring an expensive copy of all items from the current array to a new larger one. Expanding the array by a constant multiplicative factor at each reallocation (e.g., doubling the array), the expensive append calls can be guaranteed to be exponentially less frequent than constant append calls [7]. This kind of analysis, which measures the average time of a function over a sequence of invocations, is called *amortized analysis* [18]. The *amortized cost* metric given in [5] can be be computed in terms of the profiling tuples introduced in Section 2. Due to lack of space, we omit the definition of this metric whose main idea is that the cost of expensive but infrequent calls can be amortized over frequent but cheap calls. Exploiting this intuition, more informative plots can be generated by shaving off expensive peaks, leaving just the points where most of the routine work is performed. For instance, Figure 3 reports an example based on C++ STL routine `std::vector::push_back`. Even if the cost plot of this routine presents a linear trend (Figure 3b), expensive calls are rather infrequent (Figure 3c). A careful analysis of the routine performance tuples reveals that less than 0.000025% of the routine calls has executed more than 250 basic blocks. The goal of the amortized cost plot is to automatically expose this kind of consideration: as shown by Figure 3d, calls over RMS values larger than 80 can be amortized (zeroed points), leaving only inexpensive calls which actually characterize most of the routine work.

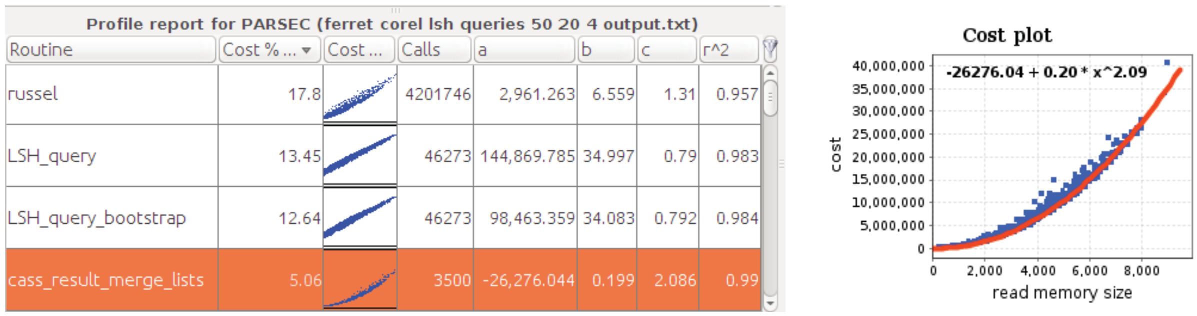


(a) (b)

Figure 4: Worst-case cost plots of `403.gcc`'s routine `cse_basic_block`: before (a) and after (b) applying smoothing.

3.2 Plot customization and noise reduction

`aprof-plot` supports different kinds of interaction, allowing the programmer to perform a more effective performance investigation. Several useful features can be triggered by the user in order to customize a routine chart. For instance, the x and y axes of a plot can be set to logarithmic scales (see, e.g., Figure 3c). Furthermore, since the interesting behavior



Profile report for PARSEC (ferret corel lsh queries 50 20 4 output.txt)

Routine	Cost % ...	Cost ...	Calls	a	b	c	r^2
russel	17.8		4201746	2,961.263	6.559	1.31	0.957
LSH_query	13.45		46273	144,869.785	34.997	0.79	0.983
LSH_query_bootstrap	12.64		46273	98,463.359	34.083	0.792	0.984
cass_result_merge_lists	5.06		3500	-26,276.044	0.199	2.086	0.99

(a) (b)

Figure 5: (a) Routine list of PARSEC 2.1 benchmark `ferret` sorted by percentage of cost, showing preview of cost plot, number of calls, and best-fit parameters. (b) Cost plot of routine `cass_result_merge_lists` with regression trend obtained by least-squares fitting

of a routine may be confined to a specific area of a chart, the user can zoom in and out from a specific set of points.
A common (and more important) issue when analyzing a routine is due to noisy profile data. To this aim, we have implemented two noise reduction techniques: *point aggregation* and *smoothing*. The first approach decreases the number of points, while the second one preserves the cardinality of the original set. Given the set of N points (x, y) of a chart sorted by the x values, point aggregation partitions this set in groups of d points and then computes the arithmetic mean within each group. Notice that d is a positive constant value which can be customized by the user. Smoothing, instead, calculates the centered moving average [12]:

$$\forall k,\ \frac{w}{2} \leq k \leq N - \frac{w}{2}: \qquad {y_k}' = \frac{1}{w} \sum_{i=k-w/2}^{k+w/2} y_i$$

where w is the user-customizable size of the moving window. Figure 4b provides an example based on the routine `cse_basic_block` of the SPEC benchmark `403.gcc`: the original noisy trend (Figure 4a) has been smoothed applying a moving window $w = 256$.
Finally, we implemented in `aprof-plot` a source code browsing feature that allows the programmer to analyze the code while she is still looking at the routine charts. After choosing the source directory of a C/C++ application, `aprof-plot` can automatically open the appropriate source code file and show the relevant piece of code inside a text-editor widget. This makes it easier for programmers to find out why a certain piece of code exhibits some performance behaviors.

3.3 Spotting critical routines

In Section 3.1, we have discussed how `aprof-plot` can enable a deep analysis of relevant aspects of a routine's behavior. However, since real-world applications may be composed by thousands of routines, this kind of analysis could easily become overwhelming for a developer. For this reason, `aprof-plot` attempts at pointing the attention of the programmer to the most critical routines of an application. In particular, it helps developers prioritize their analysis by highlighting routines which are likely to contain performance issues. By sorting routines based on the percentage of cost, a developer can immediately understand how the running time has been spent during the execution of the program. Several filtering strategies can help to refine this list: uninteresting routines, such as library functions, can be filtered out based on the executable binary, while insignificant routines can be hidden using different metric thresholds (e.g., by filtering routines with small cost percentage or with a small number of performance tuples). Exploiting these tools, the number of routines which needs to be analyzed by a developer can be significantly reduced. However, since the ultimate goal of input-sensitive profiling is to detect the routines with high asymptotic cost, we have implemented in `aprof-plot` an automatic approach for estimating the asymptotic complexity of a routine. Using regression analysis techniques [3], our tool constructs for each routine a mathematical function that has the best fit to its data points. In particular, we choose as a cost model the function $b \cdot n^c + a$, which generalizes both the power law and the linear models (when $a = 0$ and $c = 1$, respectively).
After estimating the fitting coefficients for any program routine, `aprof-plot` can sort routines based on their asymptotic complexity (i.e., the c coefficient), allowing the developer to possibly detect unexpected performance trends. Since this kind of analysis crucially depends on the quality of the fitting results, `aprof-plot` allows the user to filter routines which have low fitting quality (e.g., $R^2 \leq 0.92$) or unrealistic coefficient values (e.g., $b < 0.001$). The validity of this approach has been empirically assessed in [5].
Figure 5a provides an excerpt taken from the routine list of the PARSEC benchmark `ferret`. The original 906 routines have been filtered according to the following criteria: more than 10 performance tuples ($|N| > 10$), high fitting quality ($R^2 > 0.92$), and reasonable b coefficient value ($b > 0.01$). After filtering, 75 routines remain and are sorted based on the percentage of executed basic blocks (i.e., their cost): among the top four routines (shown by Figure 5a), an interesting example is provided by `cass_result_merge_lists`. This routine has been called 3500 times, requiring 5.06% of the total program cost, and `aprof-plot` has been able to automatically estimate a quadratic asymptotic complexity ($c = 2.086$). As discussed in [5], apart from specific algorithmically-critical routines usually well known to the programmer, most benign routines appear to have a subquadratic trend and many common programming mistakes tend to introduce quadratic inefficiencies, e.g., by invoking a

subroutine in a loop under the incorrect assumption that it takes constant time. Since the fitting quality is rather high ($R^2 = 0.99$), routine `cass_result_merge_lists` is a good candidate for further performance investigation. The worst-case cost plot is given in Figure 5b: the regression curve accurately predicts the actual cost trend. By inspecting the source of this routine, we were able to conclude that its algorithm is indeed $\Theta(n^2)$ due to a doubly-nested loop used for merging two input lists. Although this quadratic trend is not given by any trivial programming mistake, we believe that some algorithmic optimizations could be implemented to improve the running time of this routine.

As shown by this example, the filtering and ranking strategies implemented by `aprof-plot` can significantly support the developer towards performance investigation of the most critical routines, possibly revealing unexpected performance issues.

4. CONCLUSIONS

In this paper we have presented an interactive visualization framework for performance analysis of input-sensitive profiles. The key benefit of `aprof-plot` is to allow the programmer to investigate how the running time of a routine scales as a function of the workload size. Exploiting techniques such as curve fitting and bounding, our tool can focus the attention of the programmer to the most critical routines of an application, possibly pinpointing unexpected scalability problems. Useful insights on the typical workload sizes can help developers optimize their programs.

As a future direction, it would be interesting to improve the support in `aprof-plot` for input-sensitive profiles with calling-contexts annotations [8]. This further level of performance characterization can help developers analyze routines with context-dependent performance trends.

Another interesting improvement would be to implement ad-hoc fitting algorithms, specifically tailored to curves related to execution costs. In particular, we notice that a routine may exhibit rather different performance trends based on several runtime conditions and workload features. Since a classical curve fitting algorithm is unable to detect multiple trends, `aplot-plot` fails to automatically estimate the asymptotic complexity of the routine, forcing the user towards manual performance analysis.

Acknowledgements

We would like to thank Camil Demetrescu and Irene Finocchi for their valuable feedback during the development of `aprof-plot` and for many useful discussions. We are also indebted to Bruno Aleandri for developing an earlier version of `aprof-plot`.

5. REFERENCES

[1] aprof: an input-sensitive profiler. `https://code.google.com/p/aprof/`.

[2] C. Bienia, S. Kumar, J. P. Singh, and K. Li. The PARSEC benchmark suite: characterization and architectural implications. In *PACT*, pages 72–81, 2008.

[3] J. M. Chambers, W. S. Cleveland, B. Kleiner, and P. A. Tukey. *Graphical Methods for Data Analysis*. Chapman and Hall, New York, 1983.

[4] E. Coppa, C. Demetrescu, and I. Finocchi. Input-sensitive profiling. In *Proc. of the 33rd ACM SIGPLAN Conf. on Programming Language Design and Implementation (PLDI)*, pages 89–98, 2012.

[5] E. Coppa, C. Demetrescu, and I. Finocchi. Input-sensitive profiling. *IEEE Transactions on Software Engineering*, 2014. To appear.

[6] E. Coppa, C. Demetrescu, I. Finocchi, and R. Marotta. Estimating the empirical cost function of routines with dynamic workloads. In *12th Annual IEEE/ACM Int. Symposium on Code Generation and Optimization (CGO)*, pages 230–239, 2014.

[7] T. H. Cormen, C. E. Leiserson, R. L. Rivest, and C. Stein. *Introduction to Algorithms*. MIT Press and McGraw-Hill, 2009.

[8] D. C. D'Elia, C. Demetrescu, and I. Finocchi. Mining hot calling contexts in small space. In *PLDI*, pages 516–527, 2011.

[9] S. Goldsmith, A. Aiken, and D. S. Wilkerson. Measuring empirical computational complexity. In *ESEC/SIGSOFT FSE*, pages 395–404, 2007.

[10] S. L. Graham, P. B. Kessler, and M. K. McKusick. gprof: a call graph execution profiler (with retrospective). In K. S. McKinley, editor, *Best of PLDI*, pages 49–57. ACM, 1982.

[11] J. L. Henning. SPEC CPU2006 benchmark descriptions. *SIGARCH Comput. Archit. News*, 34:1–17, 2006.

[12] MATLAB documentation: moving average filter. `http://www.mathworks.com/help/econ/filtering.html`.

[13] C. C. McGeoch, D. Precup, and P. R. Cohen. How to Find Big-Oh in Your Data Set (and How Not to). In *IDA*, pages 41–52, 1997.

[14] C. C. McGeoch, P. Sanders, R. Fleischer, P. R. Cohen, and D. Precup. Using finite experiments to study asymptotic performance. In *Experimental Algorithmics*, LNCS 2547, pages 93–126, 2002.

[15] M. S. Müller and *et al.* SPEC OMP2012 – an application benchmark suite for parallel systems using OpenMP. In *Proc. 8th Int. Conf. on OpenMP in a Heterogeneous World*, pages 223–236, 2012.

[16] S. P. Reiss. Visualizing the Java heap. In *Proc. of the 32Nd ACM/IEEE Int. Conf. on Software Engineering*, ICSE '10, pages 251–254, 2010.

[17] G. G. Robertson, T. Chilimbi, and B. Lee. Allocray: Memory allocation visualization for unmanaged languages. In *SOFTVIS*, pages 43–52, 2010.

[18] R. E. Tarjan. Amortized computational complexity. *SIAM Journal on Algebraic and Discrete Methods*, 6(2):306–318, 1985.

[19] Visual VM: All-in-One Java Troubleshooting tool. `http://visualvm.java.net/`.

[20] J. Weidendorfer, M. Kowarschik, and C. Trinitis. A tool suite for simulation based analysis of memory access behavior. In *Int. Conf. on Computational Science*, volume 3038 of *LNCS*, pages 440–447, 2004.

[21] D. Zaparanuks and M. Hauswirth. Algorithmic profiling. In *Proc. of the 33rd ACM SIGPLAN Conf. on Programming Language Design and Implementation (PLDI)*, pages 67–76, 2012.