On how to avoid a false positive speedup

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***Abstract*—**
The usual way to do research in compilers, moreover in Feedback Directed Optimization is to construct a framework and devise an experiment based on single-run input training and single data testing. Recently some researchers have argued about the reliability of such experiments, and developed other approaches to this problem. Usually using repetition of experiments and collecting data to perform a reliable statistical analysis. This paper also discusses these issues and we aimed to construct an experiment to show a false speedup from actual data. We did this by just ignoring our multiple runs strategy and literally picking parts of our collected data to show that it could happen in a single-run scheme. In conclusion we state that the only way to avoid these problems is to define and use a reliable methodology based on solid statistical measurements. In this paper we also present our methodology called *combined profiling* (CP), and show that using it we can have reliable results. We showed that FDI decisions can be more accurate using CP instead of single-run evaluation.

I. Introduction

This paper describes an empirical research focused on the confidence of speedups (or slowdowns) results. This problem arises in every empirical research, and specially in compiler research this is a crucial matter, because it is usual to report smaller speedups than other areas. But, because compilers have to optimize code for various different kinds of applications, another major concern is the input set that should be used to test the improvements achieved for some transformation. Not only the size of the inputs employed, but mainly the type of input and the type of behavior the program will be expected to perform. The main issue though is on the methodology commonly applied for empirical research on compiler systems, the single-run for training and testing the programs.

Research in compiler transformations often demonstrates heroic efforts in both the identification and abstract analysis of opportunities to improve program efficiency, and in the concrete implementation of these ideas. However, standard practices at the evaluation stage of the scientific process are modest at best, perhaps because code transformations have a long history of providing significant benefits in practical, every-day situations. In most cases, compilers are evaluated using a collection of programs, with each program evaluated using a timing run on a single evaluation input. The deficiencies of this evaluation process are particularly prevalent, and especially disconcerting, when *feedback-directed optimization* (FDO) is used to guide a transformation. In this scenario, instrumentation is inserted into the program during an initial compilation in order to collect a profile of the run-time behavior of the program during one or more training runs. The profile is used in a second compilation of the program to help the compiler assess the benefit of code transformation opportunities. The current standard practice for evaluating an FDO compiler uses the profile of a single-training input to guide transformations, and evaluates the transformed program with a single evaluation input. These standard practices set program inputs as controlled variables. However, performance evaluation should be generalizable to real-world program workloads. Consequently, the program-input dimensions of a rigorous evaluation of compiler performance must be manipulated variables.

Previous work has not addressed the problem of representing and utilizing multi-run profiles. An FDO compiler should not simply add or average profiles from multiple runs, because such a profile does not provide any information about the variations in program behaviors observed between different inputs. [1] uses *Combined Profiling* (CP) to merge the profiles from multiple runs into a distribution model that

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allows code transformations to consider cross-run behavior variations. Experimental results demonstrate that meaningful behavior variation is present in the program workloads, and that this variation is successfully captured and represented by the CP methodology.

This research uses a different approach and its goal is to assess the results of *combined profiling* (CP). There have been some recent efforts trying to apply multiple profiles to FDO and also to evaluate the performance of a program from multiple inputs. CP can be applied to many different optimization techniques, such as inlining, loop unrolling, etc. We decided to apply CP to inlining as a case study, because it allows many other optimization techniques to be performed afterwards.

Although the usual way to do research in Feedback Directed Optimization is to perform a single-run input training and single data testing, recently are being developed other approaches to this problem. The main goal of these new approaches is to perform multiple-runs under multiple data, because some questions concerning the single-run approach arose, such as, is this method accurate, or proper, or reliable?

Recent work [2] states that execution time is a key measurement, for example 90 out of 122 papers presented in 2011 at PLDI, ASPLOS, and ISMM, or published in TOPLAS and TACO. As reported by [2], the overwhelming majority of these papers has shown results either impossible to repeat, or didn't demonstrate their performance claims, there were no measure of variation for their results. Our work also focus on execution time, and we expect to reinforce the use of a methodology that allows the researcher to control the measurement errors, or at least to provide sufficient evidence of performance improvement.

This paper discusses these issues by constructing a "false" speedup from actual data, just ignoring our multiple runs strategy and literally picking parts of our collected data to show that many results are possible in a single-run scheme. We also point out that a "false" slowdown can also be picked from our data. This way we reinforce the use of multiple-run methodologies.

Several open questions about the use of profiles collected from multiple runs of a program were addressed and assessed in [3]. Now there are still some questions, as multiple profiles are combined. What is the impact of CP in a controlled case study? FDO decisions can be more accurate using CP instead of single-run evaluation?

This paper addresses these questions by employing a case study of the CP process. As already mentioned the case proposed was for inlining, and we compared the CP process with the single-run process. The application of CP to other situations with multiple profiling instances, such as profiling program phases individually, is not within the scope of this paper.

The main contribution of this paper are:

- *Methodological considerations* The behavior of single-runs and CP-runs are compared and analyzed. We show that single-run methodologies are error-prone.
- *Case study* The case study illustrates that the single-run methodology can induce the researcher to serious errors, and that a methodology like CP is better suited to evaluate performance.

This paper has eight sections, the introduction, where the research problem is posed and the main ideas are shown. The inlining transformation is described in the next section, and then the next section describes the problem and the whole setting of this research. Following starts the section where the "speedup" is presented and also has a notice on a "slowdown" for the same problem. After this section, the environment is analyzed and provides sufficient statistical information to explain what happened in the previous section, and also what may happen in experiments using the same methodology. Following the data analysis employed in the latter section, the next section shows how this problem can be avoided by means of the CP methodology. This paper ends with a discussion on related work, and the conclusion.

II. Function Inlining

Function inlining, or simply inlining, is a classic code transformation that can significantly increase the performance of many programs. A compiler pass that decides which calls to inline, and in which order, is referred to as an inliner. The basic idea of inlining is straightforward: rather than making a function call, replace the call in the originating function with a copy of the body of the to-be-called function. Nonetheless, many inliner designs are possible; [1] describes the existing inliner in `LLVM`, and also the alternative approach used by a new feedback-directed inliner (FDI) that uses CP. All inlining discussed in this paper is implemented in the open-source `LLVM` compiler [4].

Some terminology is required to identify the various functions and calls involved in the inlining process. The function making a call is referred to as the *caller*, while the called function is the *callee*. The representation of a call in a compiler's *internal representation* (IR) is a *call site*; in `LLVM`, a call site is an instruction that indicates both the caller and the callee. Thus, inlining replaces a call site by a copy of that call site's callee. When a call is inlined, the callee may contain call sites, which are copied into the caller to produce new call sites. The call site where inlining occurs is called the *source* call site. A call site in the callee that is copied during inlining is called an *original* call site, and the new copy of the original call site inside the caller is called the *target* call site.

A. Barriers to Inlining

Not every call site can be inlined. Indirect calls use a pointer variable to identify the location of the called code, and arise from function pointers and dynamically-polymorphic call dispatching. These calls cannot be inlined, because the callee is unknown at compiler time. External calls into code not currently available in the compiler, such as calls into different modules or to statically-linked library functions cannot be inlined before link-time because the source representation of the callee is not available in the compiler. Calls to dynamically-linked libraries can never be inlined by definition. Moreover, if a callee uses a `setjump` instruction, it cannot be inlined. A `setjump` can redirect program control flow *anywhere*, including the middle of different function, without using the call/return mechanisms. Inlining the `setjump` could cause any manual stack management at the target of the jump to be incorrect; the inlined version would not be functionally equivalent to the original.

B. Benefits of Inlining

Inlining a call has a small direct benefit. Removing the call reduces the number of executed instructions. The `call` instruction in the caller is unnecessary, as is the `return` instruction in the callee. Furthermore, any parameters passed to the callee and any values returned no longer need to be pushed onto the stack[1].

However, the greatest potential benefit of inlining comes from additional code simplification it may enable by bringing the callee's code into the caller's scope [1]. Many code analysis algorithms work within the scope of a single function; inter-procedural analysis is usually fundamentally more difficult, and always more computationally expensive than intra-procedural analysis, because of the increased scope. A function call inhibits the precision of analyses and is a barrier to code motion because the caller sees the callee as a "black box" with unknown effect.

C. Costs of Inlining

Inlining non-profitable call sites can indirectly produce negative effects. The increased scope provided for analysis by inlining also increases the costs of these analyses. Most algorithms used by compilers have super-linear time complexity. Extremely large procedures may take excessively long to analyze; some compilers will abort an analysis that takes too long. Furthermore, a program must be loaded into memory from disk before it can be executed. A larger executable file size increases a program's start-up time. Finally, developers eschew unnecessarily large program binaries because of the costs associated with the storage and transmission of large files for both the developer and their clients. Therefore, inlining that does not improve performance should be avoided.

D. Inlining-Invariant Program Characteristics

While inlining a call causes a large change in the caller's code, it has a minimal direct impact of the use of memory system resources at run time [1]. Ignoring the subsequent simplifications the inlining enables, inlining proper has no appreciable impact on register use, or data or instruction cache efficiency. Regardless of inlining, the same dynamic sequence of instructions must process the same data in the same order to produce the same deterministic program result.

Inlining should have negligible impact register spills. The additional variables introduced into the caller by inlining place additional demands on the register allocator, and may increase the number of register spills introduced into the caller. However, without inlining, the calling convention requires the caller to save any live registers before making a call, or for the callee to save any registers before it uses them; in both cases, these registers must be restored before resuming execution in the caller. Thus, inlining merely shifts the responsibility for register management from the calling convention to the register allocator.

Similarly, inlining does not change the data memory accesses of a program. Whether in the caller or the callee, the same loads and stores, in the same order, are required for correct computation. Subsequent transformations may reorder independent memory accesses to better hide cache latency, or eliminate unnecessary accesses altogether, but this is not a direct consequence of inlining. Thus, data cache accesses do not change with inlining, and nor does the cache miss rate.

III. Description of the Experiments

The goal of benchmark-based evaluation is to predict the performance for the code transformation studied for actual applications that resemble the benchmark used in the evaluation. An issue with many of the performance evaluation of FDO-based code transformations published in the literature is the lack of exploration of the effect of different data input to the code on the reported results. An interesting question is how far off the mark a performance evaluation study that considers a single data input may be from the actual performance that the benchmark-based evaluation is predicting. The goal of this section is to investigate the potential error in the prediction for the case of FDIusing combined profiling. We designed an experiment to compare an FDI with the standard inliner from `LLVM`: (1) Select a reasonable set of data inputs for a given benchmark; (2) Execute all combinations of single-input profiling/single-input testing for the FDO inliners, repeating each test run a sufficient number of times needed to capture runtime variances;[2] ; (3) Run the `LLVM` inliner on all inputs — the same number of times as in (2) for each input; (4) To demonstrate a superior performance of FDI, select the best run amongst all profiling/testing combinations for a given test input and compare with the worst run for the `LLVM` inliner; (5) To demonstrate inferior performance of FDI, do the opposite, look for the worst FDI run and the best `LLVM` run for a given test input; (6) To find what the actual comparison is, use all but the test input to generate a combined profile and use this combined profile in FDI; execute this binary the necessary number of times and compare the average of these runs with the average of the same number of runs using the `LLVM` inliner.

This performance evaluation uses an infrastructure based on the `LLVM` development framework. This infrastructure includes a set of C++ programs and a set of scripts to control the machine-learning training, the compilation and the exaction of performance runs. This single infrastructure offers

[1]Some calling conventions allow values to pass between the caller and callee in registers.

[2]For the experiments described in this paper an empirical statistical study using 1000 runs revealed that three runs were sufficient.

the option of performing both single-run-training/single-run-testing FDOand CP-based FDOwith multiple-run performance evaluation. The number of runs used for CP and for the evaluation are parameters set by the experimenter [1].

The experiments were conducted on 20 Dell Optiplex 755 running Slackware Linux 2.6.32.39 each equipped with Intel Duo Core E6750 2.66 GHz processors, 4 GB RAM, DVD-RW drive, Intel Pro/1000 Gb ethernet, Gigabyte GeForce 8600 video cards, and 250 GB SATA II drive.

For the case study with the SPEC CPU 2006 `gcc`, each program is evaluated using a 15-input workload. The eleven inputs distributed with SPEC CPU 2006 are augmented with four SPEC 2000 benchmark programs used as input, after conversion to the single pre-processed file format required, to `gcc`: `bzip2`, `LBM`, `mcf`, and `parser`.

For the case studies with `bzip2` and `gzip`, the code used is not the one distributed by SPEC, but rather fully-functional versions of these programs. Using these versions eliminates the unrealistically-simplified profiling situation where mutually-exclusive use cases are combined into a single program run. Consequently, these programs cannot do decompression and compression, or multiple levels of compression, within the same run. These distinct use-cases must be covered by different inputs in the program workload.

The inputs for compression include images, ebooks in a variety of formats, movies in MP4 format, textual representation of proteins, audio books, and object files [1].

The experiments conducted had the purpose of demonstrating the inadequacy of single-run methodologies by exhibiting, with the same set of data, speedups and slowdowns, depending on which pairs of data are used to compare runtime outcomes. Alongside the input set used in the experiments was also stressed in a way to show that some great results can be a lot blurred with a more complete input set.

In the next section the single-run experiment is presented as if it was a great achievement, a result from a correct and proper experiment following a sound methodology. So, the data in next section was selected to produce the speedup. After that in Section V the speedups are statistically explained, and the full picture is shown.

IV. Reporting a speedup measured using FDI

To make a fair comparison on the inliners and have a reasonable and short input set, some experimental decisions were taken. Both inliners were also evaluated with respect to the baseline Never, which means never inline. The input set for each program was defined to be representative for the entire set of inputs, and are described as follows. The input set for the programs `bzip2`, `gzip`, and `gcc` is a small subset of the original 15-input set described in Section III. The results show a slight improvement over `LLVM`.

A. Presenting the results

As aforementioned the data points were selected as representing a single-run methodology for the experiments, and three benchmarks were used to test the hypotheses, `bzip2`, `gzip`, and `gcc`. The points selected were the best-run times for FDI and the worst-run times for `LLVM`. The results are presented in the following way, `bzip2` and `gzip`, are grouped, while `gcc` is separately described in other section, because the program behavior is completely different from the other two benchmarks.

Input	FDO normalized	`LLVM` normalized	Speedup
166	0.9532	0.9755	0.9771
c-typeck	0.9400	0.9845	0.9548
Cp-decl	0.9589	0.9784	0.9800
expr	0.9208	0.9567	0.9624
expr2	0.9208	0.9686	0.9506
g23	0.9860	1.0441	0.9443
integrate	0.9810	1.0000	0.9810
s04	0.9987	1.0153	0.9836
lbm-all	0.9696	1.0303	0.9411
mcf-all	1.0000	1.0270	0.9736
Geomean			0.9630

TABLE I
SUMMARY OF THE DATA COLLECTED DURING THE EXPERIMENT WITH `gcc`

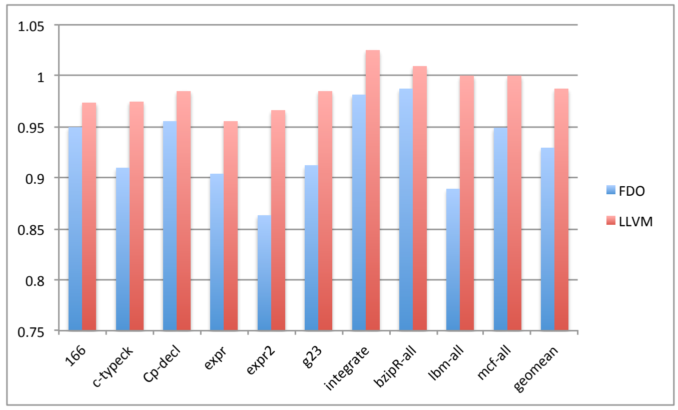


Fig. 1. Running times of the `gcc` inlined versions, normalized by Never

1) `Gcc` *Benchmark:* For the `gcc` benchmark the results show a speedup of 3.70% over `LLVM` and a 3.92% speedup over Never, whereas `LLVM` achieved a 0.23% speedup over Never, for the short input set used. This result is summarized in Table I below. The results are normalized by the baseline Never (no inlining).

The Figure 1 shows that the FDI inliner outperforms Never and `LLVM` through all the inputs, which explains the speedup.Rocha: The speedup figures for `gcc` are outdated, but the tables are correct

Nevertheless, this result can be improved by just selecting less inputs from the short input set applied without changing the set substantially. In this case the speedup reported is 4.56% over `LLVM`, as shown in Table II and Figure 2.

Input	FDO normalized	`LLVM` normalized	Speedup
c-typeck	0.9097	0.9745	0.9335
expr	0.9035	0.9552	0.9458
expr2	0.8630	0.9660	0.8934
g23	0.9119	0.9849	0.9259
lbm-all	0.8888	1.0000	0.8888
mcf-all	0.9487	1.0000	0.9487
Geomean			0.9224

TABLE II
EXTRACT OF THE DATA COLLECTED DURING THE EXPERIMENT WITH `gcc`

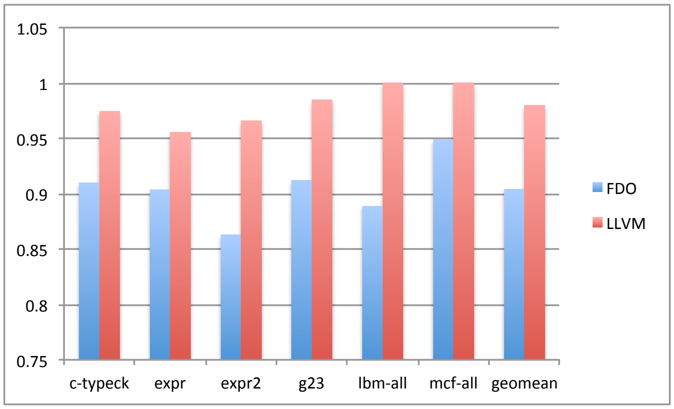


Fig. 2. Extract of the running times of the `gcc` inlined versions, normalized by Never

Input	FDO time (sec)	Never time (sec)	LLVM time (sec)	Speedup
auriel	7.66	7.88	7.94	0.9647
cards	29.52	29.79	29.76	0.9919
ocal	44.94	44.99	45.33	0.9913
proteins-2	79.6	81.11	80.71	0.9862
revelation	5.24	5.31	5.25	0.9980
Geomean				0.9864

TABLE III
SUMMARY OF THE DATA COLLECTED DURING THE EXPERIMENT WITH `bzip2`

2) Compressors / Decompressors: For the `bzip2` and `gzip` cases, the experiments showed a slight speedup over LLVM. The data collected from the `bzip2` runs are summarized in Table III. In this table the speedup achieved was a slight one, 1.36% over LLVM results, and 1.40% over Never (no inlining), whereas LLVM achieved a speedup of 0.04% over Never.

Figure 3 shows the running time normalized by the time of Never. And again the FDI inliner outperforms Never and LLVM through all the inputs, the same way the former experiments did.

The final speedup, despite being a slight improvement, represents that the FDI inliner can actually be employed instead of the LLVM inliner. And this result is significant because the program `bzip2` is small, simple, and not particularly fitted to inlining, leading to a conjecture that FDI inliner are better than static ones. Which opens a wide range of experiments with other programs to confirm this conjecture.

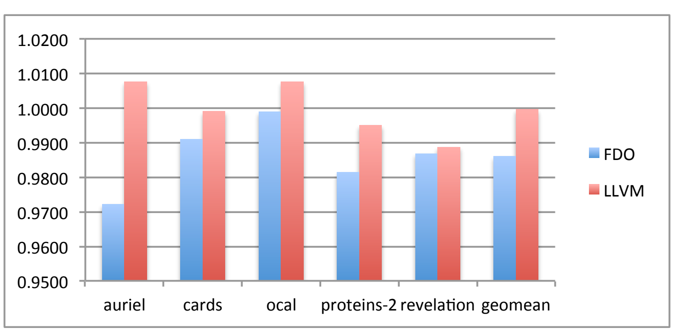


Fig. 3. Running times of the `bzip2` inlined versions, normalized by Never

Input	FDO normalized	LLVM normalized	Speedup
auriel	0.9924	0.9924	1.0000
cards	0.9801	1.0092	0.9712
ocal	0.9914	1.0122	0.9794
proteins-2	0.9905	1.0094	0.9811
revelation	0.9708	1.0072	0.9637
Geomean			0.9790

TABLE IV
SUMMARY OF THE DATA COLLECTED DURING THE EXPERIMENT WITH `gzip`

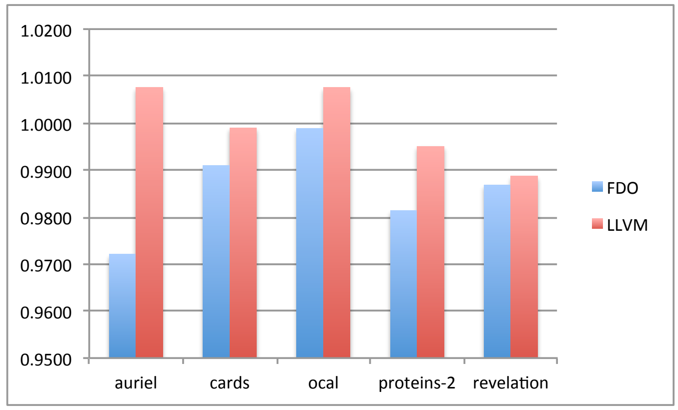


Fig. 4. Running times of the `gzip` inlined versions, normalized by Never

The experiment with `gzip` was a starting point to test the conjecture, and the results are quite similar to those from `bzip2`, and confirmed a speedup of 2.09% over LLVM results, and a speedup of 1.50% over Never (no inlining) and LLVM got a slowdown of 0.61% over Never. These results can be seen in Table IV, where the times are already normalized by the baseline Never (no inlining). Figure 4 shows the normalized running time for `gzip`, and it also outperforms Never and LLVMthrough all inputs.

The results of the experiment are also consistent with other similar findings in the literature, whereas employing single-run experiments does not generate any kind of disturbance in the analysis, and the speedup result are statistically sound. So we can confirm a speedup over the static inliner for the `bzip2` and `gzip` cases.

3) A slowdown: Proceeding as described in Section III, the data points for these experiments were selected as the worst-run times for FDI and the best-run times for LLVM. This time the single-run experiments report a slowdown. The slowdown over LLVM measured is of 2.14% for `bzip2`, 5.87% for `gzip`, and a slowdown of 2.06% for `gcc`, as shown in Table V, Table VI, and Table VII.

Input	Normalized FDO	Normalized LLVM	Slowdown
auriel	0.9961	1.0025	0.9936
cards	1.0457	0.9882	1.0581
ocal	1.0035	0.9984	1.0051
proteins-2	1.0012	0.9931	1.0080
revelation	1.0359	0.9905	1.0458
Geomean			1.0218

TABLE V
DATA REFLECTING A SLOWDOWN ON `bzip2`

Input	Normalized FDO	Normalized LLVM	Slowdown
auriel	1.1278	1.0000	1.1278
cards	1.0052	1.0079	0.9973
ocal	1.1234	0.9987	1.1248
proteins-2	1.0706	1.0081	1.0620
revelation	1.0072	1.0000	1.0072
Geomean			1.0624

TABLE VI
DATA REFLECTING A SLOWDOWN ON `gzip`

Input	FDO normalized	LLVM normalized	Speedup
166	0.9755	0.9755	1.0000
c-typeck	0.9845	0.9845	1.0000
Cp-decl	0.9784	0.9784	1.0000
expr	0.9686	0.9567	1.0124
expr2	0.9686	0.9686	1.0000
g23	1.0574	1.0441	1.0127
integrate	1.0253	1.0000	1.0253
bzipR-all	1.0315	1.0055	1.0258
lbm-all	1.0909	1.0303	1.0588
mcf-all	1.1081	1.0270	1.0789
Geomean			1.0210

TABLE VII
DATA REFLECTING A SLOWDOWN ON `gcc`

V. STATISTICAL CONSIDERATIONS ON SPEEDUPS AND SLOWDOWNS

How could the misleading results shown in Section IV be reported for an experimental evaluation of the same code transformation? There are two issues that lead to that erroneous reporting: (1) the representation of a space of program behaviours by a single point in that space; and (2) the modelling of the effect of uncontrolled variables on the result of the experiments. The use of CP with a leave-one-out evaluation methodology leads to a more appropriate evaluation of the space of behaviour variations due to data input. The repetition of each experiment a reasonable number of times and the reporting of the average of these runs with a corresponding confidence interval to inform about this variation improves on the accounting for the uncontrolled variables that affect the results of the experiments. With this additional care, the prediction of performance obtained from the benchmark-based evaluation is expected to be more accurate.

Uncontrolled variables include processes running in background, operating system calls, interruptions, memory allocation, and other sources, including the measurement process itself. Hence, it is important to have a good understanding of the sources of performance disturbances in the system [2]. Kalibera and Jones state that the majority of the experimental studies lack a rigorous statistical methodology [2]. A methodology to deal with the effect of uncontrolled variables is to examine the distribution of the data and identify measurements that can safely be eliminated because they are tainted with the effect of these variables. For instance Figure 5 depicts a scatter plot of 1000 sequential runs of the program `bzip2` compiled using the Static inliner (LLVM) and run with the `ebooks` input. The figure reveals a gaussian noise around the median plus some outliers that are the result of regular operating system activity. These outliers can safely be filtered out from the data set. They are easily discarded because they have much more variance (more than one deviation from the median).

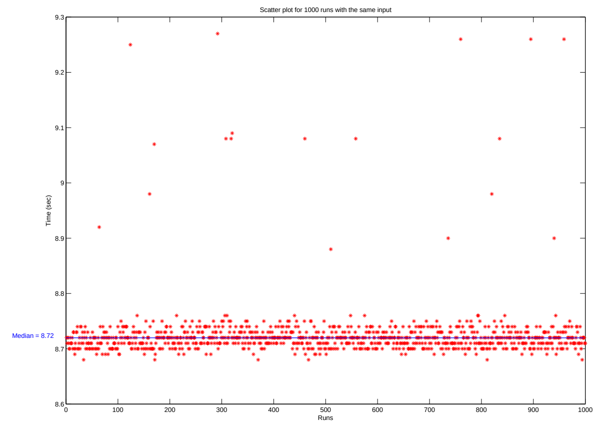


Fig. 5. Running 1000 times the same program with the same input data

Length	Mean	Median	StD Mean	StD Median
10	8.7160	8.7150	0.0100	0.0050
100	8.7328	8.7200	0.0187	0.0100
1000	8.7248	8.7200	0.0197	0.0100

TABLE VIII
SIMPLE STATISTICS ON THE EXPERIMENT

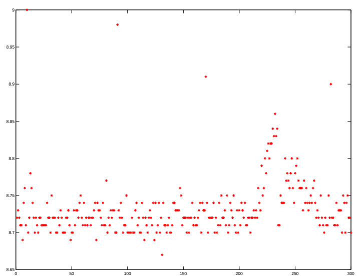
After running three independent experiments, the first is the 10-times experiment, then 100-times and, after that, 1000-times, there can be found evidence to discard the outliers. They can be discarded because this experiment confirmed that there is no difference on their means, and also that the behavior of the program remained unchanged in these three experiments. To make sure that they are robust measures, some simple statistics were run, to know the mean, the median, the standard-deviation from the mean (std-mean), and the standard-deviation from the median (std-median). The simple statistical results are shown in Table VIII. Also the results of the t-tests that were run on each sample pairs to verify if their means were the same, are shown in Table IX.

The t-tests in Table IX show that the null hypothesis cannot be discarded, as the value 0 in each line of the *t-test* column confirms. The *p-values* illustrate the confidence in the hypothesis, in this case, that the means are different are not high.

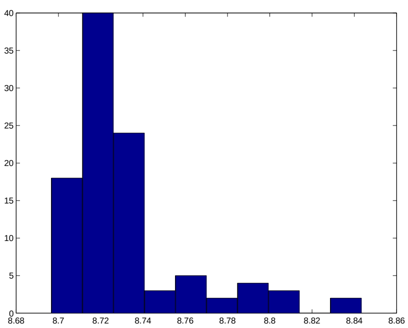
Our experiments have also shown that the variance when running the same data just three times in a row is not quite different from the one running 100 times. When it is considered that each 'input-run' is a 3-consecutive run – which means that the experiment ran 300 times the same experiment –. For this experiment a 'full-run' is considered to be a 3-consecutive run for each input. This experiment ran

Runs	t-test	p-value
(10-100)	0	0.3424
(10-1000)	0	0.6025
(100-1000)	0	0.1528

TABLE IX
T-TESTS APPLIED PAIRWISE TO THE 10, 100, AND 1000 RUNS



(a) 100-time runs of the 3-consecutive execution of input `ebooks` for program `bzip2`



(b) Histogram for the `auriel` input

Fig. 6. 100-times running 3-consecutive experiment

Run	Mean	Median	StD Mean	StD Median
1	8.7233	8.72	0.0044	
2	8.71	8.71	0.0067	0.01
3	8.72	8.73	0.02	0.01
4	8.7067	8.7	0.0089	0.00
5	8.71	8.71	0.0067	0.01
6	8.7933	8.74	0.0778	0.01
7	8.73	8.73	0.0067	0.01
8	8.7233	8.71	0.0178	0.00
9	8.73	8.73	0.0067	0.01
10	8.7033	8.71	0.0089	0.00
33	8.71	8.71	0.0067	0.01
34	8.7267	8.73	0.0044	0.00
35	8.71	8.7	0.0133	0.00
36	8.81	8.73	0.1133	0.01
37	8.72	8.72	0.0133	0.02
70	8.72	8.71	0.0133	0.00
71	8.7133	8.72	0.0089	0.00
72	8.7233	8.72	0.0044	0.00
73	8.7233	8.72	0.0044	0.00
74	8.743333	8.74	0.0111	0.01
75	8.7667	8.76	0.0156	0.01
76	8.7967	8.8	0.0111	0.01
77	8.8133	8.82	0.0089	0.00
78	8.83	8.83	0.0067	0.01
79	8.8433	8.84	0.0111	0.01
80	8.74	8.74	0	0.00
81	8.7833	8.78	0.0111	0.01
82	8.77	8.77	0.0067	0.01
83	8.7667	8.76	0.0222	0.02
84	8.79	8.79	0.0067	0.01
85	8.7633	8.76	0.0044	0
86	8.7533	8.76	0.0156	0.01
87	8.7467	8.74	0.0089	0.00
88	8.74	8.74	0.0067	0.01
89	8.7567	8.76	0.0111	0.01
90	8.7267	8.72	0.0156	0.01
91	8.71	8.71	0.0067	0.01
92	8.7133	8.71	0.0044	0
93	8.79	8.75	0.0733	0.03
94	8.7167	8.72	0.0044	0
95	8.72	8.71	0.0133	0
96	8.73	8.73	0.00	0.00
97	8.73	8.74	0.02	0.01
98	8.73	8.74	0.02	0.01
99	8.7133	8.72	0.0089	0
100	8.7367	8.74	0.0178	0.02

TABLE X
DEVIATION FROM THE MEAN AND FROM THE MEDIAN IN THE EXPERIMENT

100 'full-runs' in this experiment, and also some extra noise was injected by its end.

What this means is that even though the effect of the noise can mask the correct values, we can treat them in order to assure robustness. This is the way we employed to empirically verify the soundness of the CP methodology. As Figure 6 below shows, the deviation from the mean is not large, but here is a subtle knob increasing the running time of the all programs in the experiment by its end. It was caused by the execution of another system at the same time competing for the same resources. In (Figure 6(a)) the running time for each program at each 3-consecutive run can be found in the y-axis, the number of the full-run is depicted on the x-axis. It can be also visualized in the histogram (Figure 6(b)). These figures show the 3-consecutive run for the input data `ebooks`, where in the x-axis we depicted the running time for the program and on the y-axis we depicted the number of runs at each bin.

The figures Figure 6 and Figure 5 show that collecting data from single execution can produce erroneous results, even using machines with no other running program, there can still be some noise due to operating system activities, interruptions, etc. And also that a simple inclusion of a simple job during the running cycle can perturb the execution time, as can be observed by the knob in Figure 6.

The robustness is achieved only if we can statistically assure that the variance on the data is not large. The data used in the experiment are shown in Table X, and the deviations from the mean (and median) to each 3-consecutive run are summarized as the average, minimum, and maximum values, all found on the 300-times experiment.

To confirm that the means are statistically representing the same distribution the t-tests were also run. This is summarized in Table XI below. It is easy to see very that there are little amount of outliers, except for the knob region, because the runtime was being raised during certain amount of time pushing a gradient to increase the time values, and after it, what happened was the other way around, decreasing the time values. Both tables Table X and Table XI are shown for the runs.

This kind of experiment can bring confidence in the data collected. In our case it brought confidence in the machine learning method devised to tune-in the inlining parameters of the compiler. One possibility considered was to increase the number of times each individual run needed to be performed in order to achieve low variance in the data; hence we could trust the results. As this experiment has shown, the 3-consecutive run is a good choice, because it does not penalize much the total running time. Also, was shown that single-run testbeds are error-prone because they doesn't take the variance in the data into account.

Runs	t-test	p-value
1	0	0.706108
2	0	0.328462
3	0	0.598565
4	0	0.259765
5	0	0.328462
6	1	0.006947
7	0	0.938929
8	0	0.706426
9	0	0.938929
10	0	0.201735
33	0	0.328462
34	0	0.820524
35	0	0.328682
36	1	0.00085
37	0	0.598316
70	0	0.598233
71	0	0.408107
72	0	0.706108
73	0	0.706108
74	0	0.600263
75	0	0.116071
76	1	0.003654
77	1	0.000274
78	1	0.000013
79	1	0.000001
80	0	0.70832
81	1	0.02056
82	0	0.085091
83	0	0.116484
84	1	0.008985
85	0	0.154594
86	0	0.330314
87	0	0.500169
88	0	0.708384
89	0	0.261142
90	0	0.820684
91	0	0.328462
92	0	0.408
93	1	0.010463
94	0	0.498166
95	0	0.598233
96	0	0.938915
97	0	0.939012
98	0	0.939012
99	0	0.408107
100	0	0.823099

TABLE XI
TEST ON THE MEANS

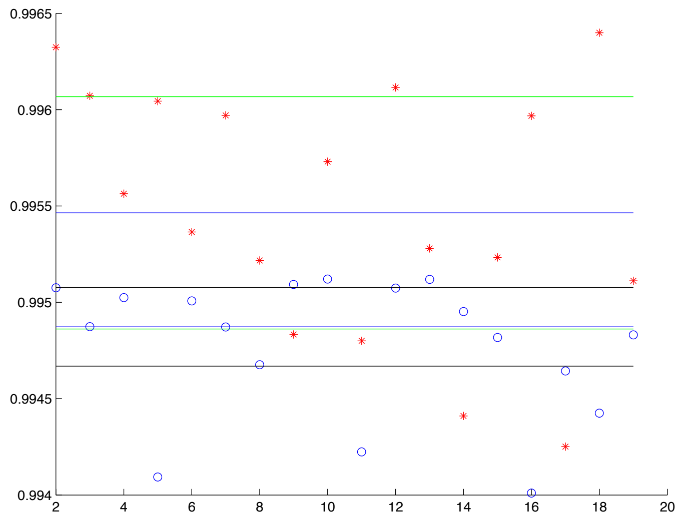


Fig. 7. The 18 different settings for `bzip2` of the same setup

A. Analyzing the speedup results

As aforementioned, each program is evaluated using a 15-input workload, and the inputs are described in Section IV. One way to generate the speedups is to select the best runtime values for the programs when inlined by FDI and the worst runtime values for `LLVM`, generating a speedup. In the opposite way, selecting the worst runtime values for FDI and best runtime values for `LLVM` generates a slowdown. Our experiment collected 3 running times for each program at each input, hence it was just a matter of choosing least and greatest values.

The complete and correct values are described below, and the compress/decompress programs were put together, but `gcc` was analyzed separately. This section end with a figure that was generated by our framework, where the error bars are clearly depicted in it, showing that the speedup geometric means have a variance attached.

1) Compressor / Decompressor: After analyzing the inlining environment and having the confidence that the results are trustful, the first program to run the experiments was `bzip2`. Collecting data from the same setup (hardware and software) in 18 different settings was the first step. Figure 7 shows the data collected. The vertical axis shows the normalized execution geometric mean time for each setting, the baseline is Never (no inlining), and the horizontal axis shows the settings organized by number. The red "*" represent the normalized geomean time of the FDI inlined program, and the blue "o" represent the normalized geomean for `LLVM` inlined program.

The blue lines in the figure show each median value for the geometric means, the green lines represent one standard deviation from the median for the FDI case, while the black lines represent the standard deviation from the median for the `LLVM` case. As it can be seen, not only the values are too similar, varying only from the fourth decimal digit, but also the medians and their standard deviations overlap, collapse. This is a strong indicator that there is no significant difference between those measures.

So, to accomplish the task, just consider that a single-run experiment could have measured any one of the 3-consecutive run values individually, moreover, a single run may have also collected the best, or the worst values for the actual times of the experiment. Hence, to outcome a speedup for FDI collected the worst running time for `LLVM` inlined program, and the best running time for the FDI inlined program.

Even though this biased data showed a speedup, it was really worthless, only 0.46%. Therefore, to reinforce that the input set is also a big issue, the data were "adjusted", leaving the slowdowns and some of the tiny speedups gathered from the list of inputs off the final list to be shown. This way a tiny, but possibly measurable speedup, was presented in Section IV. Nevertheless, define a list of inputs is an issue and has to be treated as part of the experiment design, as this "speedup" have shown. That is why a complete list of inputs containing all the explanations is a requirement when presenting data as well. The full data for the "speedup" experiment are shown in table Table XII.

On the other hand, in Section IV-A3 the opposite was performed, choosing the worst individual running time for the FDI inlined program and the best running time for the `LLVM` inlined program. Proceeding this way it was easy to present, from "a different" individual measuring, a slowdown. And as both results followed the same methodology, they are both

Input	Normalized FDO	Normalized LLVM	Speedup
auriel	0.9720	1.0076	0.9647
avernum	0.9922	0.9905	1.0017
cards	0.9909	0.9989	0.9919
ebooks	0.9909	0.9920	0.9988
gcc	0.9966	1.0059	0.9907
lib-a	0.9940	0.9970	0.9970
mohicans	1.0000	1.0048	0.9951
ocal	0.9988	1.0075	0.9913
paintings	1.0000	1.0051	0.9949
potemkin	0.9916	0.9887	1.0029
proteins-1	0.9977	0.9910	1.0068
proteins-2	0.9813	0.9950	0.9862
revelation	0.9868	0.9887	0.9980
sherlock	1.0000	1.0020	1.0125
usrlib	1.0000	0.9875	1.0458
Speedup			0.9953 (0.46 %)

TABLE XII
SUMMARY OF THE NORMALIZED DATA USED TO PRODUCE A SPEEDUP FOR `bzip2`

Input	FDO normalized	LLVM normalized	Speedup
166	0.9532	0.9755	0.9771
200	0.9594	0.9594	1.0000
c-typeck	0.9400	0.9845	0.9548
cccp	0.9646	0.9646	1.0000
Cp-decl	0.9589	0.9784	0.9800
expr	0.9208	0.9567	0.9624
expr2	0.9208	0.9686	0.9506
g23	0.9860	1.0441	0.9443
integrate	0.9810	1.0000	0.9810
s04	0.9987	1.0153	0.9836
scilab	0.9886	0.9886	1.0000
bzipR-all	0.9907	1.0055	0.9852
lbm-all	0.9696	1.0303	0.9411
mcf-all	1.0000	1.0270	0.9736
parser-all	0.9970	1.0059	0.9911
Geomean			0.9748 (2.52 %)

TABLE XIII
SUMMARY OF THE NORMALIZED DATA USED TO PRODUCE A SPEEDUP FOR `gcc`

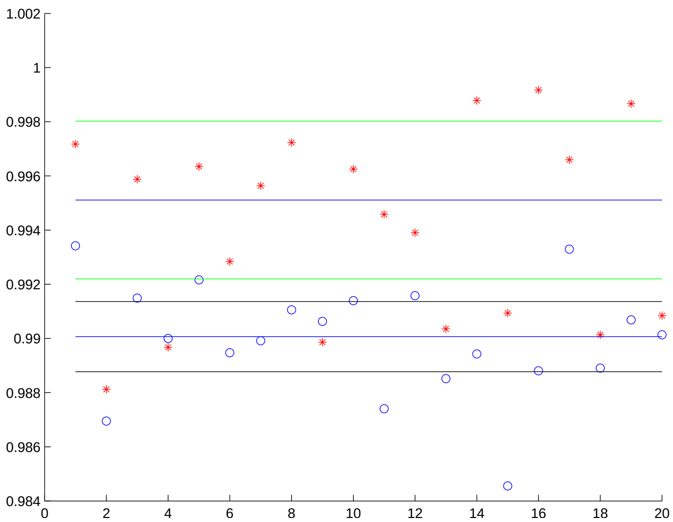


Fig. 8. The 20 different settings for `gzip` of the same setup

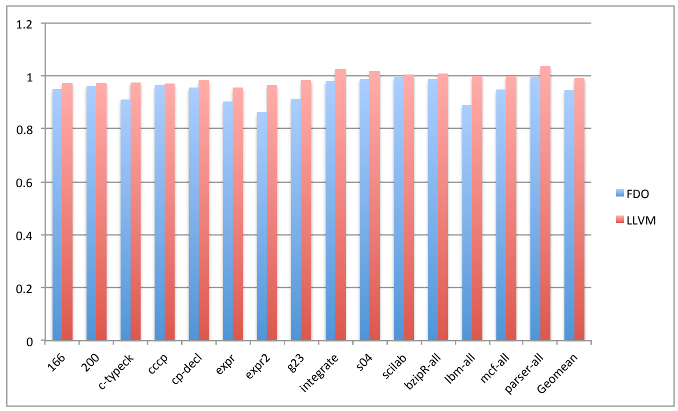


Fig. 9. The 20 different settings for `gcc` of the same setup

correct, and this is unexplainable unless considering that there is variance on the data collected.

The same process was employed for the `gzip` case, using 20 different settings, the Figure 8 shows the data collected in a similar way of what was presented in Figure 7. In Figure 8 we can notice that there is possibly a slowdown compared to LLVM for this setup, and even though it was not hard to report a speedup.

These cases were artificially constructed using our empirical actual data, considering that if we used a single-run methodology these results could appear. But using CP methodology, the researcher is able to correctly identify that there is no statistical difference between both inliners, for the setup proposed. This result, in a certain way, reinforces the result of [5], where they reported no speedup of $-O2$ over $-O3$ for all benchmarks they analyzed, when code randomization is applied.

2) Analysis of `gcc`: The same process was used for the `gcc` case, the best running times for FDI inlined program in the setting were selected, and the worst running times for LLVM inlined programs were also selected. These data were select for each input, and from this our speedup experiment was constructed. In a single-run framework it is perfectly reasonable that this result can actually appear. But in this case we came up with a result considering a somewhat reduced input set, which produced an even better speedup. Again, this was done to raise the question about the proper set of inputs to be employed. In fact, the set presented in Section IV was already an extract from the SPEC CPU 2006 benchmark suite.

In reality the full SPEC CPU 2006 benchmark suite was applied, and 4 more inputs, which were converted from the SPEC 2000 benchmark, were added fulfilling the 15-input set to each program, as described in Section III. If the full input-set is taken, the experiment would have produced a different result, the speedup in the case of the best run-times, would be of 2.52%, as shown in Table XIII and in Figure 9.

Therefore, the input-set matters, as much as a sound methodology. To summarize this section and illustrate the outcomes of our framework, employing CP methodology Figure 10 presents one of the figures automatically generated by the framework. In this figure it can be observed that there was no speedups, nor slowdowns for the `gcc` case, the error bars present in Figure 10 demonstrates the level of confidence in the geometric mean results.

As already mentioned, this figure was automatically generated by our system, and reflects the geometric mean of all inputs for twelve different FDI inliners, the LLVM inliner (called static in the figure) and another static inliner called benefit.

Next section (Section VI) describes the CP methodology in more detail, explaining its use and how to measure the results,

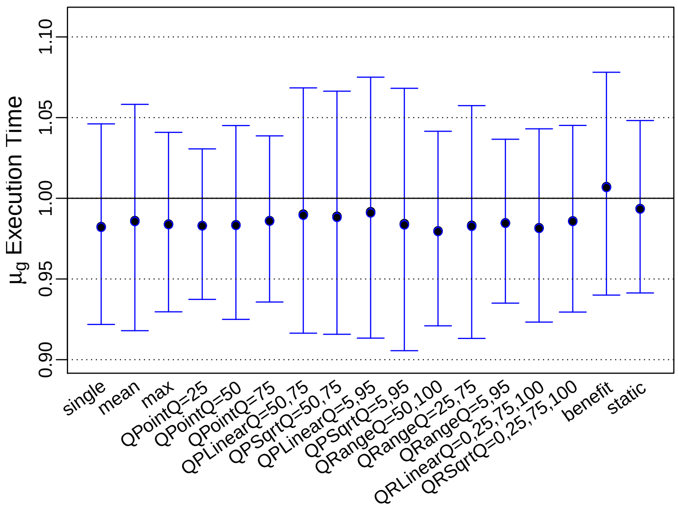


Fig. 10. The actual result for `gcc` returned by our CP framework

in order to avoid the problems highlighted by the example in Section IV.

VI. Combined Profiling Methodology

Capturing behavior variations across inputs is important in the design of an FDO compiler. A number of speculative code transformations are known to benefit from FDO, including speculative partial redundancy elimination [6], [7], trace-based scheduling and others [8], [9].

This section argues that the behavior variations in an application due to multiple inputs should be evaluated by FDO decisions. It also argues that a full parametric estimation of a statistical distribution is not only unnecessary, but it may also mislead FDO decisions if the wrong distribution is assumed or there is insufficient data to accurately estimate the parameters.

A major challenge in the use of traditional single-training-run FDO is the selection of a profiling data input that is representative of the execution of the program throughout its lifetime. For large and complex programs dealing with many use cases and used by a multitude of users, assembling an appropriately representative workload may be a difficult task. Picking a solitary training run to represent such a space is far more challenging, or potentially impossible, if use-cases are mutually-exclusive. While benchmark programs can be modified to combine such use-cases into a single run, this approach is obviously inapplicable to real programs. Moreover, user workloads are prone to change over time. Ensuring stable performance across all inputs in today's workload prevents performance degradation due to changes in the relative importance of workload components.

The *Combined Profiling* (CP) statistical modeling technique presented in [1] produces a *Combined Profile* (CProf) from a collection of traditional single-run profiles, thus facilitating the collection and representation of profile information over multiple runs. The use of many profiling runs, in turn, eases the burden of training-workload selection and mitigates the potential for performance degradation. There is no need to select a single input for training because data from any number of training runs can be merged into a combined profile. More importantly, CP preserves variations in execution behavior across inputs. The distribution of behaviors can be queried and analyzed by the compiler when making code-transformation decisions. Modestly profitable transformations can be performed with confidence when they are beneficial to the entire workload. On the other hand, transformations expected to be highly beneficial on average can be suppressed when performance degradation would be incurred on some members of the workload.

Combining profiles is a three-step process [3]:

1) Collect raw profiles via traditional profiling.
2) Apply *Hierarchical Normalization* (HN) to each raw profile.
3) Apply CP to the normalized profiles to create the combined profile.

CP and HN have been presented in previous work [10], [3]. However, a clearer and expanded version, based on previous versions, can be found in [1], particularly the description of CP's histograms and the discussion of queries.

CP [1] provides a data representation for profile information, but does not specify the semantics of the information stored in the combined profile. Raw profiles cannot be combined naively.

A. Hierarchical Normalization

There is a problem when pairs of measurements are taken under different conditions. Thus, when combining these measurements, all values recorded for a monitor must be normalized relative to a common fixed reference. *Hierarchical normalization* (HN) [1] is a profile semantic designed for use with CP that achieves this goal by decomposing a CFG into a hierarchy of dominating regions.

HN is presented for edge profiling. Vertex profiles are treated identically, but use the domination relationships between vertexes instead of edges. Domination is usually defined in terms of vertexes. In order to use an existing implementation of a vertex dominator-tree algorithm with edge profiles, use the line graph of the CFG instead of the CFG itself. The line graph contains one vertex for each edge in the CFG, and edges in the line graph correspond to adjacencies between the edges of the CFG.

B. Denormalization

The properties of a monitor R_a can only be directly compared to those of a monitor R_b when $dom(a) = dom(b)$. However, more generalized reasoning about R_a may be needed when considering code transformations. Similarly, when code is moved by a transformation, its profile information must be correctly updated. *Denormalization* reverses the effects of hierarchical normalization to lift monitors out of nested domination regions by marginalizing-out the distribution of the dominators above which they are lifted. Denormalization is a heuristic method rather than an exact statistical inference because it assumes statistical independence between monitors.

C. Queries

In an AOT compiler, profiles are used to predict program behavior. Thus, raw profiles are statistical models that use a single sample to answer exactly one question: *"What is the expected frequency of X?"* where X is an edge or path in a CFG or a Call Graph (CG). A CP is a much richer statistical model that can answer a wide range of queries about the measured program behavior. The implementation of CP used in this work provides the following statistical queries as methods of a monitor's histogram:

H.min; H.max
H.mean($incl0s$)
H.stdev($incl0s$)
H.estProbLessThan(v)
H.quantile(q)
H.applyOnRange($F(w, v)$, $vmin$, $vmax$)
H.applyOnQuantile($F(w, v)$, $qmin$, $qmax$)
H.coverage
H.span

CP enables the accurate assessment of the potential performance impact of transformations informed by variable-behavior monitors in a variety of ways, and with adjustable confidence in the result. Concrete examples of this kind of analysis are provided by the implementation of an FDO inliner using CP described in [1].

D. Alternative Usage

The empirical-distribution methodology of CP is orthogonal to the techniques used to collect raw profiles. CP is applicable whenever multiple profile instances are collected, including intra-run phase-based profiles, profiles collected from hardware performance-counter, and sampled profiles. The main issue when combining profiles is how normalization should be done in order to preserve program-behavior characteristics.

VII. Related Work

There are several researchers concerned with the problem of reliability in performance measures. Kalibera *et al.* [2] propose a rigorous methodology for measuring time, and claim that the measurements are still done in reasonable time. Their methodology considers that the environment, consisting of hardware and software, versions of the operating system, versions of the compiler used to measure data, they all change scarcely. For this reason their methodology asserts that before starting to take any measurement the whole environment has to be deeply investigated to find how many repeated iterations are required to achieve an independent state (the execution times of benchmark iterations are statistically independent). They provide means to calculate the number of runs are needed to achieve independent states for a benchmark analysis, also for measuring speedups. They used different benchmarks in their experiments and showed that there are different number of repetition counts for them. Our methodology does not assume that the environment changes scarcely, and we don't need a huge number of repetitions.

Mytkowicz *et al.* [11] ran some experiments using SPEC CPU benchmarks and found significant systematic measurement errors in some sources, that could produce biased results. Their suggestion is to randomise the experimental setup to eliminate the bias. The idea of ramdomising is fully incorporated in Stabiliser [5]. Stabiliser is an LLVM-based compiler and runtime environment for randomisation of code, stack and heap layout. The purpose of randomisation is to reduce the need for repeated execution. Randomising the whole program in fact introduces more variation than in real systems, also some compiler transformations can become useless. Our approach is much less intrusive than theirs and we don't break compiler transformations.

Georges *et al.* [12] shows that different methodologies can lead to different conclusions. They work with Java benchmarks and recommends running multiple iterations of each Java benchmark within a single VM execution, and also multiple VM executions. Our work is not focused in Java, but their recommendation remains true, it is necessary to use a reliable experimental methodology.

A. *FDO-related*

Most compilers take a single-run approach to FDO: a single training run generates a profile, which is used to guide compiler transformations. Some profile file formats support the storage of multiple profiles (*e.g.*, `LLVM`), but when such a file is provided to a compiler, either all profiles except the first are ignored, or a simple sum or average is taken across the frequencies in the collected profiles.

Input characterization and workload reduction are not new problems. However, the similarity metrics used for clustering in [1] are unique in their applicability to workload reduction for an FDO compiler. Most input similarity and clustering work is done in the area of computer architecture, where research is largely simulation-based, thus necessitating small workloads of representative programs using minimally-sized inputs. The architectural metrics of benchmark programs are repeatedly scrutinized for redundancy, while smaller inputs are compared with large inputs. Alternatively, some work bypasses program behavior and examines the inputs directly.

Arnold *et al.*. present an inlining strategy similar to that used in modern compilers [13]. They use a call-site sensitive call graph profile, thus allocating procedure executions frequencies to individual call sites. Using code size expansion as the cost and call site frequency as the benefit, call sites are inlined in decreasing cost/benefit order up to a code expansion limit. They find that a 1% code size expansion limit accounts for 73% of dynamic calls and reduces execution time by 9% to 57%.

Arnold *et al.*. use histograms to combine the profile information collected by a Java JIT system over multiple program runs [14]. The online profiler detects hot methods by periodically sampling the currently-executing method. After each run of a program, histograms for the hot methods stored in a profile repository are updated.

Salverda *et al.* model the critical paths of a program by generating synthetic program traces from a histogram of profiled branch outcomes [15]. To better cover the program's footprint, they do an ad-hoc combination of profiles from SPEC training and reference inputs. In contrast, combined profiling and hierarchical normalization provide a systematic method to combine profile information for multiple runs.

Savari and Young build a branch and decision model for branch data [16]. Their model assumes that the next branch and its outcome are independent of previous branches, an assumption that is violated by computer programs (*e.g.*, correlated branches). One distribution is used to represent *all events* from a run; distributions from multiple runs are combined using relative entropy — a sophisticated way to find the weights for a weighted geometric average across runs. The model cannot provide specific information about a particular branch, which is exactly the information needed by FDO. However, this information is provided by combined profiles because each event is represented separately.

VIII. Conclusion

As mentioned in Section I a case study was proposed to study the inlining transformation. The experiment was designed to make a clear point about applying single-run methodologies and also about the definition of the input-set. Our experiment compared the CP process with the single-run process. Any other transformation could have been chosen, because the CP methodology can be applied in all general cases.

In Section IV it was shown an erroneous speedup, considering that it was measured by a single-run experiment. It was constructed considering that any of the measurements that ran independently could have happened in a single-run experiment. Hence searching the collected data it was not hard to find some outliers, or at least some data at extreme points. So, gathering these data points and defining two specific cases: `Best-runtime` and `Worst-runtime` for our FDO-based inliner, and for a static inliner, in this case the `LLVM` inliner.

With these data points just selecting the ideal pairs it is possible to create the illusion of a speedup and a slowdown:

- `Best-runtime` for FDO and `Worst-runtime` for `LLVM`, creating a speedup;
- `Worst-runtime` for FDO and `Best-runtime` for `LLVM`, creating a slowdown.

With these pairs and assuming a single-run methodology, it was not hard to produce a statistical analysis showing a speedup (or slowdown), and, it is worth to state again, for this experiment these pairs of data can be devised as being representative cases of single-run experiments. Therefore, each pair (speedup or slowdown) can be viewed as a result of a single-run experiment. Even if the researcher is extremely cautious the methodology is error-prone, a bias can be introduced without the knowledge, or intention, of the researcher. So the real message is to define and use a reliable methodology based on solid statistical measurements.

With our experiments some of the open questions posed in the Section I can be answered. We know for sure, and showed it in Section V, that FDI decisions can be more accurate using CP instead of single-run evaluation. For the case of the impact of CP in a controlled case study, we can definitely state that as each program was run more than once, that's the price to pay for more reliability, but the impact is acceptable if the number of repetitions is not too high. In our experiments running three times was enough.

A. Future work

For future work our plans can be divided in two different paths:

- *Fine-tuning* Using the CP methodology fine tune our FDI inliner for some different benchmarks. We have already finished some experiments and now we are defining some changes in our algorithms;
- *Apply CP* Applying CP to different compiler transformations is another research path.

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