Autobahn Minimizer

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Abstract

While lazy evaluation has many advantages, it can result in serious performance costs. Fortunately, Haskell allows users to enforce eager evaluation at certain program points by inserting bangs, which are strictness annotations. However, manual placement of bangs is both labor intensive and difficult to reason about. The Autobahn optimizer uses genetic algorithms to automatically infer bang patterns that improve runtime performance. However, Autobahn often generates very large numbers of bangs for each program. This is an issue for the user because each bang that cannot be deemed safe by the GHC compiler requires manual inspection to prevent the bang from introducing program non-termination.

This paper presents an improved version of Autobahn, which uses GHC profiling feedback to reduce the number of unnecessary bangs generated. Autobahn 2.0 adds a pre-search phase before the genetic algorithm to adjust the search space size, and a post-search phase at the end to individually test and remove useless bangs. On average, the pre-search phase alone was able to eliminate 63 locations for potential bang placement per 100 LOC, and reduced the number of bangs eventually generated by 5 bangs per 100 LOC. Overall, Autobahn 2.0 reduced the number of bangs generated from 11 bangs to 1 bangs per 100 LOC, while only slowing program runtime by 3%. Autobahn used in conjunction with these two phases allows users to obtain faster versions of their programs without the burden of manually checking through large numbers of bangs.

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1 Introduction

1.1 Lazy Evaluation

Lazy evaluation is a property of Haskell that improves program efficiency and provides programmers the ability to use infinite data structures. Under lazy evaluation, expressions are only evaluated when their values are needed. Every unevaluated expression is stored in a *thunk*, and its evaluation is delayed until another expression demands the value of the current one. Most of the time, this greatly improves program performance as it avoids wasting time on evaluating unnecessary expressions. It also means that users can operate on infinite data structures by only evaluating finite portions of it.

While lazy evaluation reaps many benefits, it can also create serious performance slow downs when too much memory is allocated to a large number of thunks. We can reduce the quantity of thunks by avoiding creating them for expressions that we know will eventually be evaluated. To avoid the creation of a thunk, programmers can insert strictness annotations such as bang patterns at certain program points to enforce eager evaluation. However, programmers need to distinguish program points that will benefit from eager evaluation from program points that do not need to be evaluated or will not terminate when evaluated. This task is difficult and often reserved for expert Haskell programmers.

1.2 Autobahn

Autobahn is a Haskell optimizer that allows programmers to reduce thunks in their program by automatically inferring strictness annotations. Users provide Autobahn with an unoptimized program, representative input, and an optional configuration file to obtain an optimized version of the program over the course of a couple of hours.

Autobahn uses a genetic algorithm to randomly search for beneficial locations to place bangs in the program. The genetic algorithm iteratively measures the performances of a series of candidate bang placements. Candidates that improve upon the original program's performance are preserved, and candidates that trigger non-termination or worsen program performance are eliminated. Autobahn eventually returns the user with a list of well-performing candidates, ranked by how much each candidate improves program performance. Users can then inspect the candidate bang placements, and decide if they want to apply one of them to the program.

1.3 Too Many Bangs

Candidates should be inspected before being applied because they can potentially introduce program non-termination when new input is given. Because AUTOBAHN measures performance using representative input, the resulting candidate is optimized for that specific input. If a new type of input is supplied to the program after it is optimized, it could result in different behavior at program points that may cause the program to run forever. We can run GHC's static analysis after AUTOBAHN to check for safe bangs, but it on average only marks 10% of bangs as safe. This is because the analysis is necessarily conservative to guarantee termination on all inputs.

In reality, bangs only need to be safe on inputs that the user will run it with. Because only the user will know the range of potential input types, only the user can inspect candidate bang placements and decide if they are safe to be applied. However, users face a time-consuming task of inspecting a large number of bangs when AUTOBAHN generates too many bangs in a candidate. This occurs when the random genetic algorithm places many bangs throughout the program, including bangs that do not contribute much to program performance improvement. On average, AUTOBAHN generates 11 bangs per 100 lines of code in its best performing candidates, and the user must manually inspect every one of those.

1.4 Autobahn 2.0

This paper presents an improved version of AUTOBAHN that aims to reduce the number of generated bangs. We refer to the original Autobahn optimizer as AUTOBAHN 1.0, and the improved version for bang minimization as AUTOBAHN 2.0. A *pre-search* phase and *post-search* phase are each added before and after AUTOBAHN 1.0 to locate and eliminate unnecessary bangs using GHC profiling. GHC profiles show the amount of runtime and memory each location in the program used. The pre-search phase adjusts the number of files that AUTOBAHN 1.0 optimizes within a single program. AUTOBAHN 1.0 is instructed to optimize files that contain locations that cost a large amount of resources, and to avoid optimizing files that do not contain costly locations. After AUTOBAHN 1.0 runs, the post-search phase individually tests each produced bang that falls within a costly location. Bangs that produce an insignificant impact on improving program performance are eliminated. On average, the addition of these two phases allows AUTOBAHN 2.0 to produce 90.9% fewer bangs than AUTOBAHN 1.0, while maintain similar runtime improvements. In this paper, I

- demonstrate the effectiveness of the pre-search phase on programs from the NoFib benchmark suite that have had at least one file removed from consideration for optimization. There are 20 such programs in total. On average the pre-search phase reduced 63 potential bang locations per 100 LOC, and resulted in mean bang reductions of 63.38%.
- show that the pre-search phase's suggestions for additional files to optimize can improve AUTOBAHN 1.0's optimization results by 86.6% using the *sumList* microbenchmark.
- POSTSEARCHDATA
- show that AUTOBAHN 2.0 applied to the NoFib benchmark suite reduced the number of generated bangs from 11 bangs per 100 LOC to 1 bang per 100 LOC on average, while only increasing the optimized runtime by 3%.
- use AUTOBAHN 2.0 in a case study to optimize the performance of the `gcSimulator` garbage collector simulator. While the program runtime slowed down by 15%, the number of bangs generated decreased by 81.9%.
- apply AUTOBAHN 2.0 in a second case study to show that it can preserve the application-specific annotations inferred by AUTOBAHN 1.0 for the Aeson library.

2 Background

2.1 GHC Profiling and Cost Centres

GHC provides a time and memory profiling system to allow users to better understand where their program spends the most time on. The system adds annotations to the user's program and generates a report detailing the amount of time, memory allocations or heap usage each location used.

To generate these profiles, users simply run their program after re-compiling it with the profiling option and choose either a time and allocation or heap profile to generate, as well as the method in which the profiling system adds annotations. While users have the option to manually specify annotations, AUTOBAHN 2.0 uses the `-prof -fprof-auto` option, which automatically adds an annotation around every binding that is not marked INLINE in the program.

In the profile, these annotations are represented as cost centres with a certain cost associated with each of them. These costs indicate how much time or memory resources each cost centre used as a percentage of the whole program's resources.

In order to minimize the number of bangs in a program while maintaining similar program performance, we need to preserve the bangs in the most costly cost centres and eliminate those located in the less costly cost centres. AUTOBAHN 2.0 identifies a cost centre that consumes costs more than the *hotSpotCost* threshold as a *hot spot*. A cost centre that does not consume more than the *hotSpotCost* threshold is a *cold spot*. Currently, we set the *hotSpotCost* threshold to 6% of the the overall program runtime, although that threshold can be adjusted. As the threshold increases, fewer bangs are preserved at the risk of a higher possibility of compromised program performance.

2.2 Genes and Chromosomes

Cost centre profiling provides guidance for the otherwise random search that Autobahn performs using genetic algorithms. In the algorithm, any program source location where a bang may be added is represented as a *gene* that can be turned on or off. A *chromosome* is composed of all of the genes within a program and represented as a fixed-length bit vector, in which the bit value indicates the presence or absence of a bang. Since a program is a collection of source files, it is represented as a collection of bit vectors, or chromosomes.

2.3 Autobahn 1.0's Genetic Algorithm

Autobahn 1.0's genetic algorithm evaluates and manipulates randomly generated chromosomes. It repeatedly generates new chromosomes before measuring their performance using a fitness function. We call a chromosome that either significantly slows down program performance or causes non termination an *unfit* chromosome. If the fitness function determines that a chromosome is unfit, the chromosome is immediately discarded. If the fitness function determines that a chromosome behaved well, the chromosome is deemed *fit* and kept for future rounds of generation.

For each round of chromosome generation, Autobahn 1.0 introduces randomness by performing either a mutation or a crossover. A mutation flips a gene in the chromosome whenever a randomly chosen floating point number exceeds the *mutateProb* threshold. A crossover combines two chromosomes by randomly picking half of the genes from each parent chromosome. For either of these random operations, Autobahn 1.0 uses a unique number generator each time to guarantee randomness.

2.4 Representative Input

To run Autobahn 1.0, users need to provide representative input to their program. The input should be short enough for Autobahn 1.0 to finish execution in a reasonable amount of time while still be long enough for it to measure noticeable time improvements if there are any. Ideally, representative input should also be as similar to the typical use case of the program as possible to reduce chances of unexpected behavior after optimization when using different types of program input.

Similarly, the quality of representative input impacts the quality of Autobahn 2.0's performance as well, because different types of input may generate wildly different results in GHC profiles. Therefore, the user must carefully choose their program's representative input.

3 Autobahn 2.0

3.1 Why Too Many Bangs Are Generated

The first step to eliminating bangs is to identify categories of bangs and hypothesize the reason why each category exists. A *dangerous* bang is a bang that can significantly slow down program runtime or cause program non-termination. A *useful* bang improves program performance, and a *useless* bang neither improves nor worsens program performance.

While an unfit chromosome may perform poorly as a whole, it can contain a mixture of dangerous, useful and useless bangs. Autobahn 1.0 handles unfit chromosomes by discarding them entirely, but fails to provide a method of isolating the specific dangerous bangs in an unfit chromosome. It is necessary to isolate and remove dangerous bangs because they might otherwise reappear in later generations as a result of random mutation.

Fit chromosomes also face a similar issue. Autobahn 1.0 handles fit chromosomes by preserving the entire chromosome, without separately identifying the useful bangs from the useless ones. This is problematic for two reasons. Firstly, we might lose useful bangs in future rounds of generations because we cannot track them and guarantee that random methods of mutation and crossover will preserve them. Secondly, useless bangs could survive by being grouped with useful bangs even though they should be eliminated. The accumulation of such bangs can dramatically increase the number of bangs in a program, leaving it up to the user to identify potentially unsafe bangs from the safe ones.

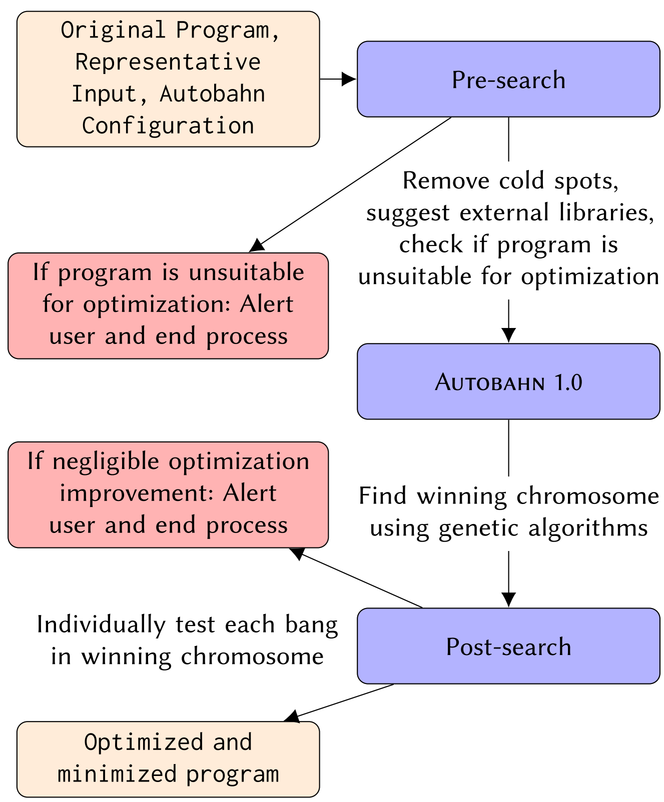
We hypothesize that Autobahn 1.0 generates copious amounts of bangs because it is incapable of identifying categories of bangs within the same chromosome. The further addition of randomness means that the entire chromosome is repeatedly searched as the search space is never definitively reduced. Because there is a fixed number of genes in a program, the search space for the genetic algorithm is also equivalently fixed. Therefore, as the program source code increases in size, the algorithm also generates significantly more bangs as chromosomes increase in size.

3.2 The Solution

Autobahn 2.0 uses GHC profiling to do what Autobahn cannot: isolate portions of a chromosome by their individual contributions to program performance. Cost centres not only break down a chromosome into smaller portions by source code bindings, but their associated costs also imply how likely a bang placement will affect program performance. If executing code at a hot spot occupied a significant portion of the overall program runtime, then a bang-induced change in performance at the hot spot will likely significantly affect overall runtime as well.

There are two ways to apply GHC profiling information to reduce the number of generated bangs. The first way is by reducing the previously fixed size of the initial chromosome. Because Autobahn 1.0's search space is directly correlated to the size of the program source code, we can reduce the search space by eliminating all files that only contain cold spots prior to Autobahn's optimization. Since useless bangs are most likely later generated and located within cold spots, early elimination of genes in cold spots is beneficial.

However, hot spots can contain a mixture of useful and useless bangs as well. To definitively eliminate useless bangs and preserve useful bangs, we can individually isolate and measure the performance of each bang in each hot spot. The effects of combining bangs is hard to predict, but the permutation size of all possible combinations of the remaining bangs can grow very large. To simplify the process, we adopt the method of individually turning off one bang at a time to test. We can then exhaustively test each bang because the number of hot spots in a program is limited. This testing process relies on Autobahn 1.0's randomly generated winning combination of bangs as a starting point. Both of these methods are later explained in full detail, and a diagram of the workflow is shown below.



3.3 Autobahn Coverage

By default, Autobahn optimizes all files in the program directory. Users can specify optimization coverage by manually adding or removing file paths while configuring Autobahn. Although Autobahn does not consider external libraries imported in the source code, users can manually add local copies of external libraries in the program directory for optimization.

However, just as manually reasoning about the placement of bangs is difficult, users generally find it difficult to reason about which files should or should not be optimized. By examining GHC profiles, we can have a much better idea of which files to eliminate based on whether or not they contain hot spots. Combining this knowledge with the option to configure Autobahn coverage, we can now manipulate the initial chromosome size by units of file sizes.

3.4 Pre-search Profiling

Pre-search profiling does more than just reducing existing search space. Instead, it guides, redirects and expands the current search space to maximize efficiency and performance prior to Autobahn 1.0's optimization. Because chromosome sizes directly influence the number of generated bangs, search space manipulation can minimize the possibility of generating useless or dangerous bangs and maximize the chances of generating useful ones.

To reduce the initial search space, the pre-search phase begins by generating a GHC time and allocation profile for the unoptimized program with user provided representative input. Then, the files that contain at least one hot spot are identified. Files that do not contain hot spots are eliminated from the Autobahn coverage of files. Autobahn 1.0 then optimizes the program as usual, except using a much smaller set of files and thus chromosomes to begin its genetic algorithmic search.

There are three important impacts that pre-search profiling creates. First of all, it greatly reduces the number of bangs Autobahn generates by reducing the initial search space. Secondly, it identifies programs that are potentially unsuitable for Autobahn optimization. If a program contains a large set of cost centres that all contribute minimally to program runtime, there may not exist a single location in which placing a bang will make a significant difference in program runtime. If the pre-search identifies a program that only contains cold spots, it will alert the user and save them the time and effort of running Autobahn when they will most likely see minimal performance improvements. Lastly, if a hot spot is located in an external library file, the pre-search phase can suggest users which external libraries to add to the Autobahn coverage for better optimization results.

It is worth noting that although pre-search can reduce search space, it cannot reduce Autobahn 1.0's runtime as a result. Unless the search space is small enough to be exhaustively searched, Autobahn 1.0 will continue to search through it until the allotted runtime is up. So if a user allowed Autobahn 1.0 to run for four hours, it will continue to run for four hours regardless of search space size. However, reduced space allows Autobahn 1.0 to search more thoroughly and potentially find better results that it did not have time to find before.

3.5 Post-search Bang Elimination

After Autobahn 1.0 optimizes the search space and determines a winning chromosome, Autobahn 2.0 once again uses GHC profiling information to reduce the number of bangs in the winning chromosome. It begins by mapping each gene in the winning bit vector to their corresponding set of cost centres.

For each gene in the bit vector, the post-search phase filters out all of those that are already turned off and keep them turned off. It then examines genes that are turned on and fall within a cold spot, and turns them off before filtering them out as well. We can turn them off because those genes are most likely useless bangs.

The remaining genes are the interesting ones that both contain a bang and fall within a hot spot. These genes require further testing because even though hot spots are likely to significantly reduce overall runtime when their own runtimes are reduced, we are unsure if the cost centre runtime was reduced in the first place. That is, placing a bang in a cost centre may not always improve performance at the cost centre. Therefore, genes within hot spots that cannot be improved through the placement of bangs are also useless and should be discarded.

3.6 Testing hot spots

There are usually so few remaining genes that are both turned on and within a hot spot that it is possible to exhaustively test them. The post-search phase tests them by isolating and turning off each bang while keeping all other remaining bangs on. It then measures program runtime and compares it to the program performance of the winning chromosome determined by Autobahn.

If the absence of this bang slows down the program by the *absenceImpact* threshold, this bang is useful and kept in the pool of remaining bangs. If the bang's absence does not slow down the program by at least the *absenceImpact* threshold, the bang is deemed useless and discarded. The *absenceImpact* threshold is adjustable and currently set to 5%. The post-search phase repeats this process for every bang to be tested, and the minimization result is the combination of surviving bangs by the end of testing.

4 Implementation

4.1 Program Architecture

The addition of pre-search search space reduction and post-search bang reduction alters the original program architecture of Autobahn 1.0. Prior to optimization, the original program is first profiled and evaluated for search space manipulation in the pre-search phase. Pre-search builds the user's program with profiling enabled, and runs the unoptimized version with the user provided representative input to obtain a time and allocation profile. The profile is only generated once, and the rest of of Autobahn 2.0 refers to the same profile throughout the entire program. Depending on the location of hot spots indicated by the profile, the program's optimization coverage will either be automatically reduced or manually expanded by the user.

Then Autobahn 1.0 is uses the same genetic algorithm to find a winning chromosome. It uses the *haskell-src-exts* parser to parse source files and identify genes, then applies a genetic algorithm with a fitness function to search for the best performing chromosome.

The resulting chromosome is further tested and reduced using GHC profiling information in the post-search bang reduction phase. After an initial pass of elimination to get rid of all turned-off bangs and bangs located in cold spots, we individually test the impact of the absence of a turned-on bang in each hot spot. If a bang meets the *absenceImpact* threshold, it is kept in future rounds of testing and will remain in the final combination of bangs for the optimized program. If a bang does not meet the *absenceImpact* threshold, it is removed for future rounds of testing and will not appear in the final combination.

Bangs in hot spots are tested in order of decreasing costs. While we recognize that the order in which we test them may affect their performance, it is simply too time consuming to test every possible combination of bangs in every possible order. For simplicity, we chose to only consistently test each individual bang once in order of decreasing costs.

Finally, the post-search phase returns the final combination of bangs that have survived each round of testing. If Autobahn 1.0 failed to find a chromosome that improved program runtime by 6% to begin with, then the post-search phase will refuse to minimize because the insignificant performance improvement indicates that users are better off keeping the original unoptimized program instead.

4.2 Running Autobahn 2.0

A user runs Autobahn 2.0 the same way as they would run the Autobahn 1.0. The user provides a copy of their program source code, representative input, and an optional Autobahn configuration file. Because both search space reduction and minimization after Autobahn typically do not require a significant amount of time, the user should barely notice an increase in the amount of time needed for optimization.

If Autobahn 2.0 successfully ran, the user can find the minimized source code in the same project directory along with the usual Autobahn survivor and results directories. If pre-search profiling detected that the program is unsuitable for optimization, or if Autobahn 1.0 failed to significantly optimize the program, then Autobahn 2.0 would warn the user and halt the optimization process. If external libraries could be added to Autobahn's coverage to potentially boost optimization performance, the pre-search phase would alert the user and continue to optimize as normal.

4.3 Source Locations

Because each bit in a bit vector represents a gene in a chromosome, we modified the bit vector to indicate which cost centre each bit was located in as well. Cost centres are uniquely identified by source location in source files. We mapped each bit to its corresponding source line. To turn the bangs in a hot spot on or off, we can traverse the bit-location vector and manipulate the bits that are tagged with source lines that fall within the range of that hot spot's source location.

4.4 Removing Illegal Genes

Unfortunately, the *haskell-src-exts* parser that Autobahn 1.0 uses incorrectly identifies the left hand side of bindings within instance declarations as potential locations to place bangs. For that reason, files that contain instance declarations have been previously avoided and left unoptimized when testing Autobahn 1.0. We wanted to support the optimization of these files in Autobahn 2.0, so we removed any randomly generated illegal bangs prior to each round of fitness evaluation in the genetic algorithm. The rest of the genetic search and Autobahn 2.0 runs identically as before.

To keep track of whether a bang is legal, we used a validity-indicating boolean vector to represent whether each gene in the source code is legal. Prior to inserting bangs into a program, Autobahn 2.0 would check the validity of a gene against the boolean vector to make sure that the bang is located in a legal location.

Generically traversing the parser-generated AST using boilerplate code fails to identify illegal genes, so we needed to manually traverse it to construct the validity vector. As we traversed the tree, we kept track of whether a left hand side binding is within an instance declaration. If so, then that binding is an illegal bang location and is marked as a false boolean value in the validity vector. All other legal bang locations are marked as a true value.

Autobahn 2.0 successfully uses this method to avoid inserting bangs into illegal locations after being misguided by the parser. As a result, it allows us to optimize files that include instance declarations, which we previously avoided altogether when using Autobahn 1.0.

5 Evaluation

5.1 Experiment Setup

All versions of Autobahn were compiled using GHC version `8.0.2`. The NoFib benchmarks were also compiled with GHC version `8.0.2`, `-XBangPatterns` and enabled profiling along with NoFib's default flags. Our research did not test the certain benchmarks in the NoFib suite that failed to compile and run on their own and benchmarks that Autobahn 1.0 refuses to minimize because they already had very fast runtimes. There were 61 total remaining benchmarks that we ran experiments on.

In the runtime graphs for all sections below, a runtime value of 2.0 indicates that the optimized version of the program is *non-terminating*. A runtime value of 1.0 indicates that the optimized version of the program had an identical runtime compared to the original version and is *unimproved*.

5.2 Pre-search Search Space Reduction

To test how much search space can be reduced by the pre-search phase of Autobahn 2.0, we ran Autobahn 1.0 with pre-search profiling on the NoFib benchmark suite. To account for fluctuation, we took the mean of running the program ten times on the benchmark suite. All runs were optimized on runtime only, and the *hotSpotCost* and *absenceImpact* thresholds were both set to 6%.

Out of the 60 benchmarks, only 20 benchmarks had at least one file that was eliminated during the pre-search phase. The other 40 benchmarks either only had one file in the program to begin with or had zero files eliminated in the pre-search phase. These benchmarks would be optimized identically as running only Autobahn 1.0 would, so their results are not represented in a graph below. The 40 benchmarks also includes benchmarks that had zero files remaining after the pre-search phase and were marked as unsuitable for optimization. Those benchmarks are discussed in detail in Section 5.3.

Figure 1 includes results from the 20 benchmarks that had at least one file that was eliminated during the pre-search phase. The number of eliminated genes shows the number of potential bang locations that were eliminated before Autobahn 1.0 ran. Because most benchmarks do not have bangs in the original versions of their programs, the number of original bangs in Figure 1 is usually 0. Not every benchmark succeeded every time it was being optimized, and the failure run column indicates how often the benchmark was left unoptimized using pre-search and Autobahn 1.0.

The `anna`, `expert`, and `symalg` benchmarks are particularly interesting because Autobahn 1.0 consistently failed to find winning chromosomes for them, so no bangs were generated. However, after reducing the search space using pre-search, Autobahn 1.0 was able to more thoroughly search a smaller and more focused space to find meaningful bangs. Therefore, Autobahn 1.0 was able to discover a set of performance-impacting bangs with the help of the pre-search phase.

Figure 2 shows the corresponding runtime performance of results generated by Autobahn 1.0 and Autobahn 1.0 with the pre-search phase. The graph shows that even when a large number of genes are eliminated prior to optimization, the optimizer is still able to find useful bangs that result in similar runtime improvement. This confirms that the eliminated genes were truly insignificant bang locations that are not worth spending time searching through.

5.3 Pre-search File Elimination

We have found six benchmarks in the NoFib suite that the pre-search phase identifies as unsuitable for optimization when the *hotSpotCost* threshold is set to 6%. These are `awards`, `callback001`, `callback002`, `mutstore2`, `sorting`, and `threads007`. As expected, when attempting to optimize `awards`, `sorting` and `threads007`, Autobahn 1.0 consistently fails

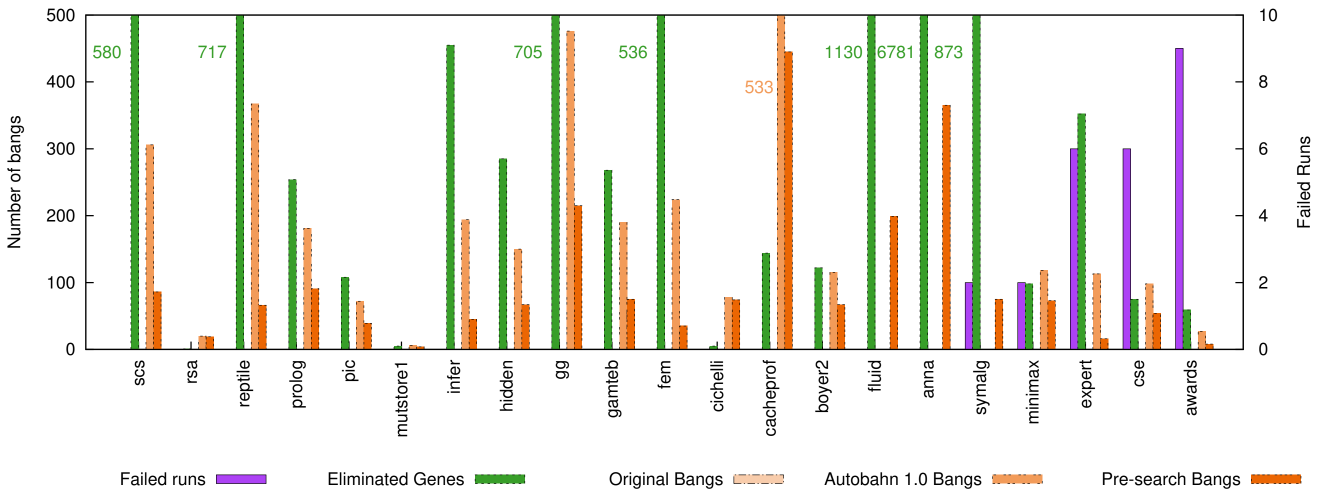


Figure 1. Number of bangs generated by Autobahn 1.0 vs. pre-search phase combined with Autobahn 1.0 compared across 20 benchmarks. Columns that exceed the maximum axis value are labelled with their actual values.

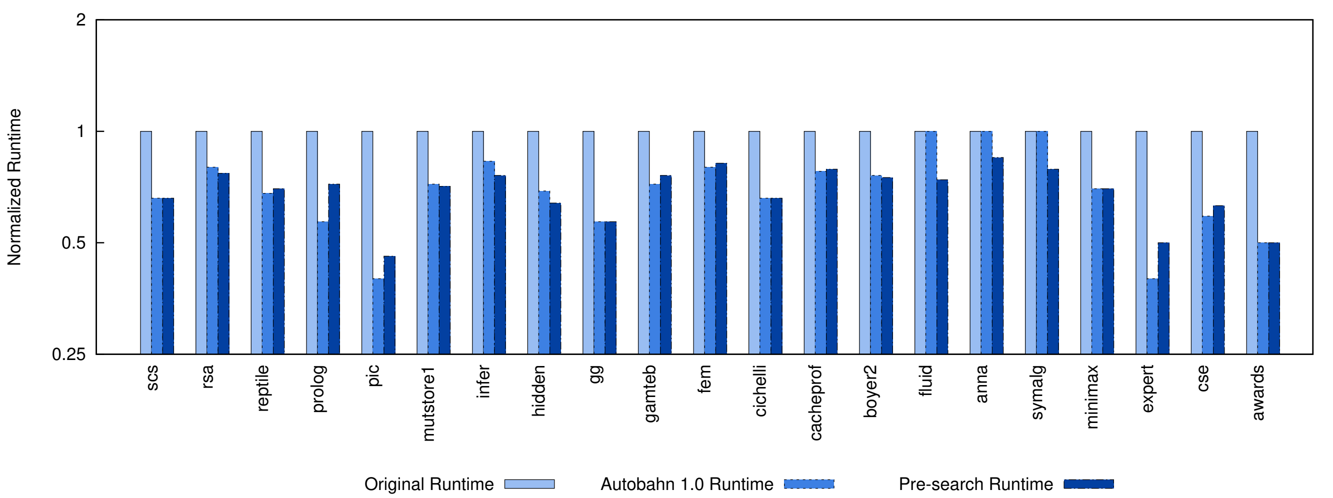


Figure 2. Normalized runtime of Autobahn 1.0 results vs. pre-search phase combined with Autobahn 1.0 results across 20 benchmarks. The x-axis normalized runtime is on a log scale of base 2. Columns that exceed the maximum axis value are labelled with their actual values.

to optimize and returns the unimproved runtime code. However, Autobahn was able to successfully optimize the other programs. Through inspection, we concluded that `callback002` would've benefited from a lower *hotSpotCost* threshold as its most costly hot spot takes up 3.9% of the program runtime. Both `callback001` and `threads007` would've benefited from inspecting heap profiles instead of time and allocation profiles as the costs associated with their hot spots were noticeably larger in heap allocations while remaining insignificant in runtime costs. The `mutstore2` program's performance fluctuated wildly even without bangs in it. For example, its measured runtime was as low as 60% - 80% of its original runtime in one third of the experiments we ran with no bangs in the program. Therefore, the optimization results were likely skewed by the fluctuating runtime.

5.4 Pre-search File Addition

To demonstrate the effectiveness of using the pre-search phase to expand Autobahn's coverage for improved optimization results, we tested our approach on the `sumList` microbenchmark. We created `sumList` to simulate the scenario in which a programmer references code from an external library or external file that contains hot spots but is not within their current coverage range.

The `sumList` program's `Main.hs` file contains only one function: a main function that constructs a list of integers from 1 to 1,000,000, and calculates the sum of all integers in the list using an external *sum* function located in `Sum.hs`. The user may decide to set the optimization coverage to [`Main.hs`], because they are interested in making the main program run faster. However, as demonstrated in table 1, Autobahn 1.0 was only able to improve program performance by 3%, even when it was able to exhaustively search the only six lines of code in the main function. Upon inspecting the results, the user may be mistaken in believing that their program runtime cannot be possibly improved further.

But there are indeed other opportunities to speed up *sumList* located in places that the user did not think about. The user decides to rerun the Autobahn 1.0 using the pre-search phase as well. GHC's time and allocation profile indicates that the largest *hotSpotCost* was 9.5% and located in lines 7 to 8 in the *sum* function in `Sum.hs`. The *sum* function is entirely lazy and did not immediately compute the sum of each integer as it recursed through the list. In the resulting log file, the user is alerted about this fact through a message that advises them to consider adding `Sum.hs` to the list of files that Autobahn 1.0 optimizes. After expanding the coverage and running optimization again, `sumList` was able to run at only 13% of the original runtime, a dramatic improvement compared to optimizing using Autobahn 1.0 alone.

Although the `sumList` example is short and simple, it shows the larger potential for users to obtain much better optimization results when running the pre-search phase in conjunction with Autobahn 1.0. Programmers often build upon each other's code and use external functions that they may not be entirely familiar with or did not consider optimizing. The pre-search phase identifies valuable missed opportunities and improves Autobahn 1.0's optimization results. Of course, the addition of more files to optimize means that more bangs might be generated. It is up to the user to decide if they want to add the suggested files for better optimization results at the risk of them needing to inspect more bangs.

Version	Coverage	Normalized Runtime	No.Bangs
Original	N/A	1	0
Autobahn 1.0	[`Main.hs`]	0.97	2
Pre-optimization	[`Main.hs`, `Sum.hs`]	0.13	4

5.5 Post-search Bang Reduction

To test the efficiency of reducing bangs using the post-search phase, we compared the results of running only Autobahn 1.0 with Autobahn 1.0 and the post-search phase. Similarly, we took the mean of running the program ten times on the NoFib benchmark suite while optimizing on runtime only, and set both *hotSpotCost* and *absenceImpact* thresholds to 6%.

A benchmark is successfully optimized if Autobahn 1.0 improved its performance by at least 6% after optimization. Figure 3 and Figure 4 include results from the 22 benchmarks that were consistently successfully optimized by Autobahn 1.0 in each run. [*TODO insert inconsistently successful benchmarks results here*]

Figure 3 shows that the number of bangs eliminated by the post-search phase is quite significant. Figure 4 shows the corresponding runtime performance of each optimized program. In most benchmarks, the post-search phase does a little worse than running only Autobahn 1.0, because the *absenceImpact* threshold limits the remaining bangs to those that affect program runtime by at least 6%. If a user wants to maintain more similar runtime results, they can lower the *absenceImpact* threshold so the minimizer becomes less aggressive in bang elimination. That way, more bangs will be preserved, but runtime performance will improve.

The interesting results for programs `anna` and `fluid` show that while Autobahn 1.0 found bangs that triggered a non-terminating runtime code, post-search bang elimination was able to get rid of the dangerous bangs that caused non termination.

5.6 Combining pre-search and post-search

To test for the overall effectiveness of running Autobahn 2.0, we took the average results of running both the pre-search and post-search phase together on the 61 Autobahn benchmarks again. Out of those 61 benchmarks, 5 benchmarks were eliminated during the pre-search phase for having no hot spots and 4 benchmarks were consistently unable to be optimized by either Autobahn 2.0 or Autobahn 1.0. The remaining 52 benchmarks succeeded to optimize at least once during the ten runs, and their results are presented in figure 7, 8, 9 and 10. The benchmarks are sorted in increasing order of failure rate and split into two sets of graphs of 26 benchmarks each. Figure 7 and 9 show the results of bang reduction, and figure 8 and 10 show the corresponding runtime performances of each benchmark.

While most benchmarks consistently showed significant bang reduction with minimally compromised performance, a few benchmarks stand out. The `expert` and `calendar` benchmark not only had bangs reduced by 79.41% and 97.63% respectively, but also experienced a performance speed up by 27.59% and 14.82% respectively. Although it is worth noting that both benchmarks failed more times than they succeeded, so such results are not guaranteed to be replicable in every run. The `atom` benchmark also has interesting results because the post-search phase eliminated all bangs generated by Autobahn 1.0, yet it still ran at 78% of it's original runtime. This potentially suggests that `atom`'s original runtime fluctuates by a significant amount on its own. It also potentially suggests that `atom`'s overall performance improvement is achieved through the accumulation of speedups at many low-cost cost centres, so lowering Autobahn 2.0's *hotSpotCost*

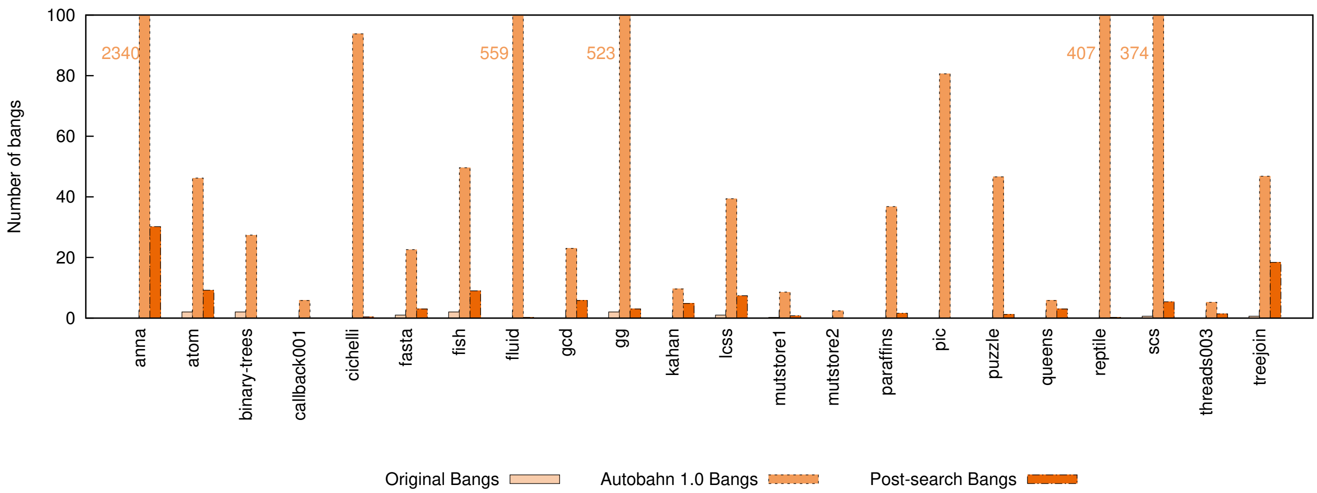


Figure 3. Number of bangs generated by Autobahn 1.0 vs. post-search phase combined with Autobahn 1.0 across 22 benchmarks. Columns that exceed the maximum axis value are labelled with their actual values.

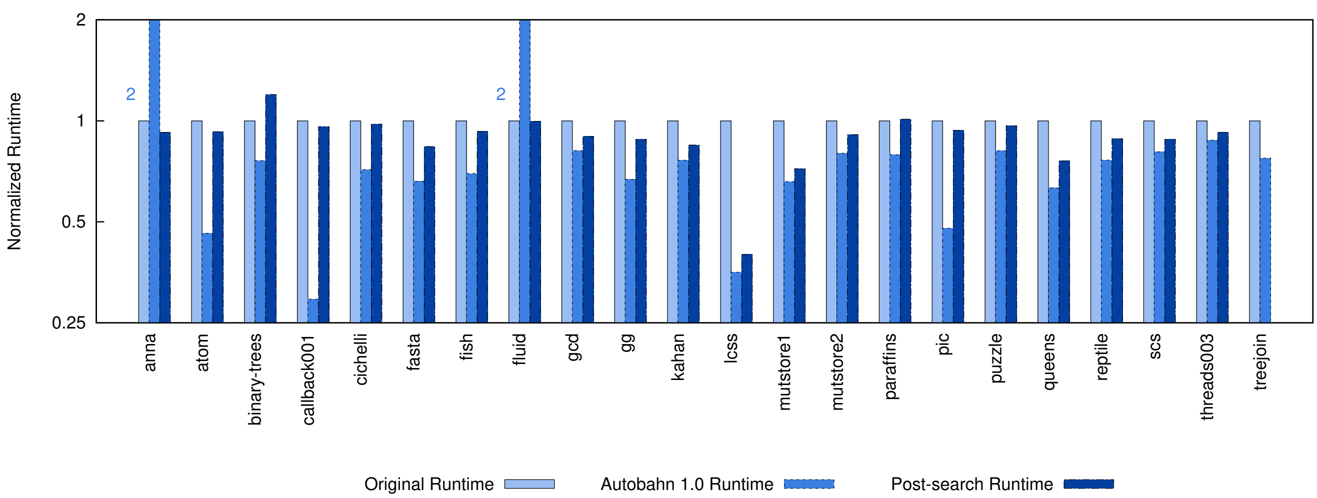


Figure 4. Normalized runtime of Autobahn 1.0 results vs. post-search phase combined with Autobahn 1.0 results across 22 benchmarks. The x-axis normalized runtime is on a log scale of base 2. Columns that exceed the maximum axis value are labelled with their actual values. Benchmarks that did not terminate are indicated with a 2.0 non-terminating code runtime.

would help capture those cost centres with lower associated costs and result in better performance improvement.

TODO WHY PRE-aut-post HAS MORE BENCHMARKS THAN PRE-AUT

5.7 Autobahn 2.0 On Larger Programs

We ran Autobahn 2.0 on the gcSimulator garbage collector to see how well it performs on larger programs. To keep optimization runtime within reasonable ranges, we used the first 1M of the batik trace file as the representative input. For gcSimulator, we lowered the *absenceImpact* threshold to 1% because it does not have many hot spots to begin with. Once Autobahn 2.0 was done optimizing, we tested the resulting program on larger trace file sizes of 100M and 500M. Because running the garbage collector on the full 6184M trace size took too long with or without optimization, we did not record results for the full trace.

The original Autobahn 1.0 was able to produce results that not only ran faster on representative input, but also on larger trace files as well. Autobahn 2.0 was also able to generate similar results with much fewer bangs, as demonstrated in the table below.

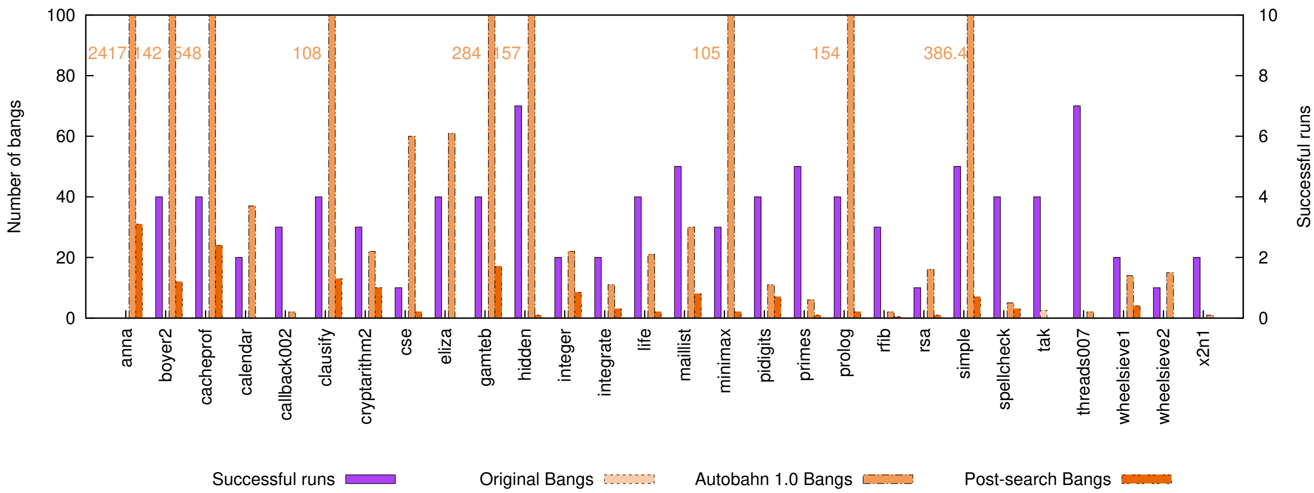


Figure 5. Number of bangs generated by Autobahn 1.0 vs. post-search phase combined with Autobahn 1.0 across 28 benchmarks. Success rate out of 10 runs is shown. Columns that exceed the maximum axis value are labelled with their actual values.

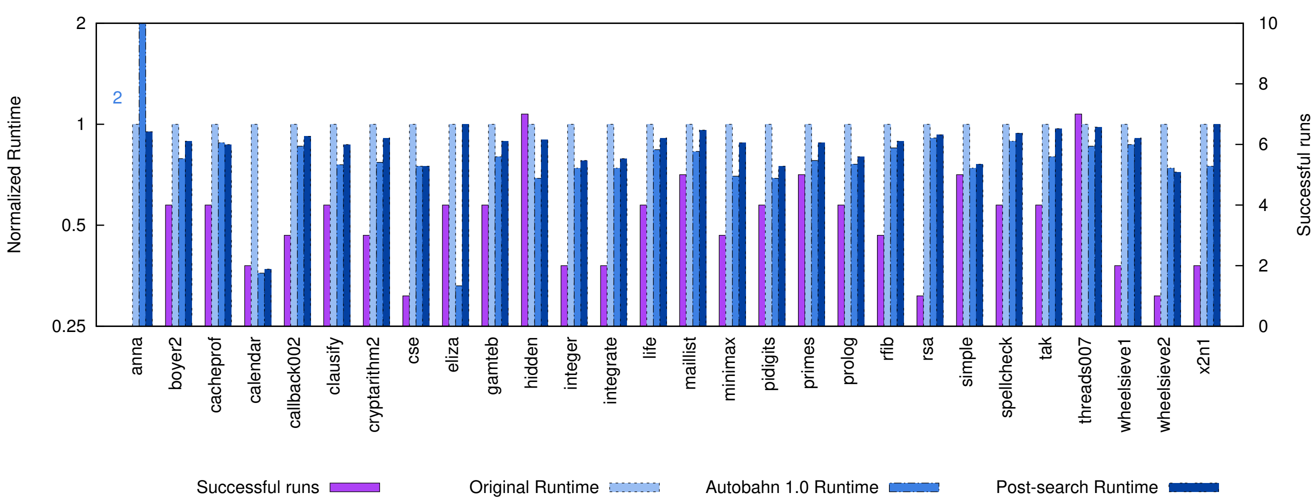


Figure 6. Normalized runtime of Autobahn 1.0 results vs. post-search phase combined with Autobahn 1.0 results across 28 benchmarks. The x-axis normalized runtime is on a log scale of base 2. Success rate out of 10 runs is shown. Columns that exceed the maximum axis value are labelled with their actual values. Benchmarks that did not terminate are indicated with a 2.0 non-terminating code runtime.

Version	File Size (M)	Runtime	No.Bangs
Original	1	0.40	0
	100	43.13	0
	500	216.71	0
Autobahn 1.0	1	0.18	690
	100	14.19	690
	500	68.98	690
Autobahn 2.0	1	0.23	125
	100	15.75	125
	500	81.66	125

5.8 Autobahn 2.0 On Aeson

The original Autobahn 1.0 experiments also showed that its genetic algorithm was able to infer application-specific bang patterns for the `Aeson` program. The `Aeson` program is a `JSON` file parser that can be used with one of two drivers that operate differently on the `JSON` file it parses. The `validate` driver checks if the file is a valid `JSON` file without the need to completely evaluate each `JSON` value. The `convert` driver converts the `JSON` file into a Haskell data structure, and thus it needs to completely evaluate each `JSON` value. If the `Aeson` parser is paired with the `validate` driver, it performs the

Figure 7. Number of bangs generated by Autobahn 1.0 vs. Autobahn 2.0 across 25 benchmarks. Success rate out of 10 runs is shown. Columns that exceed the maximum axis value are labelled with their actual values.

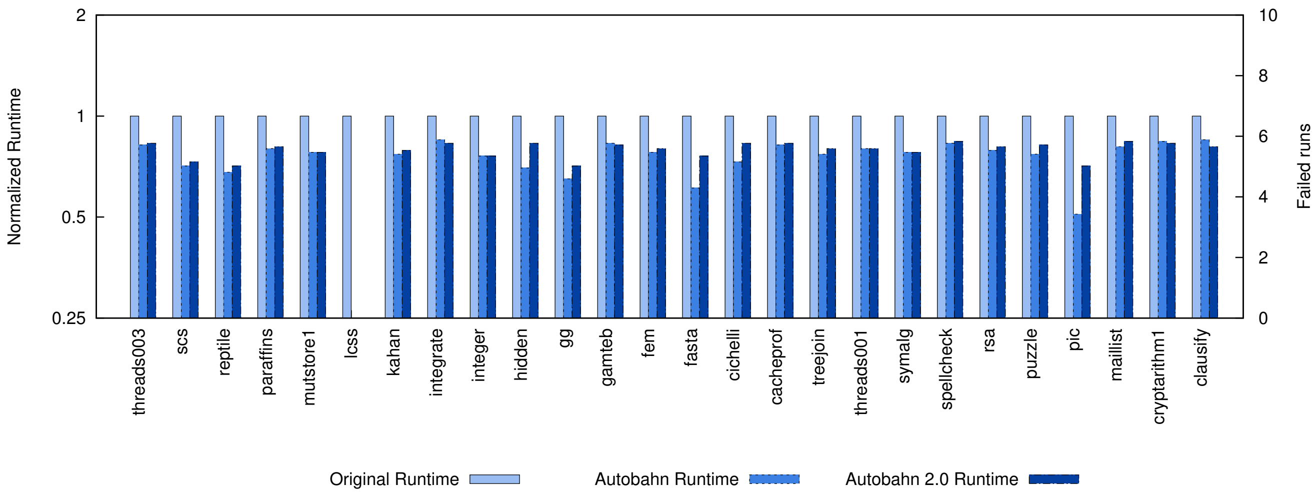


Figure 8. Normalized runtime of Autobahn 1.0 results vs. Autobahn 2.0 results across 25 benchmarks. The x-axis normalized runtime is on a log scale of base 2. Success rate out of 10 runs is shown. Columns that exceed the maximum axis value are labelled with their actual values.

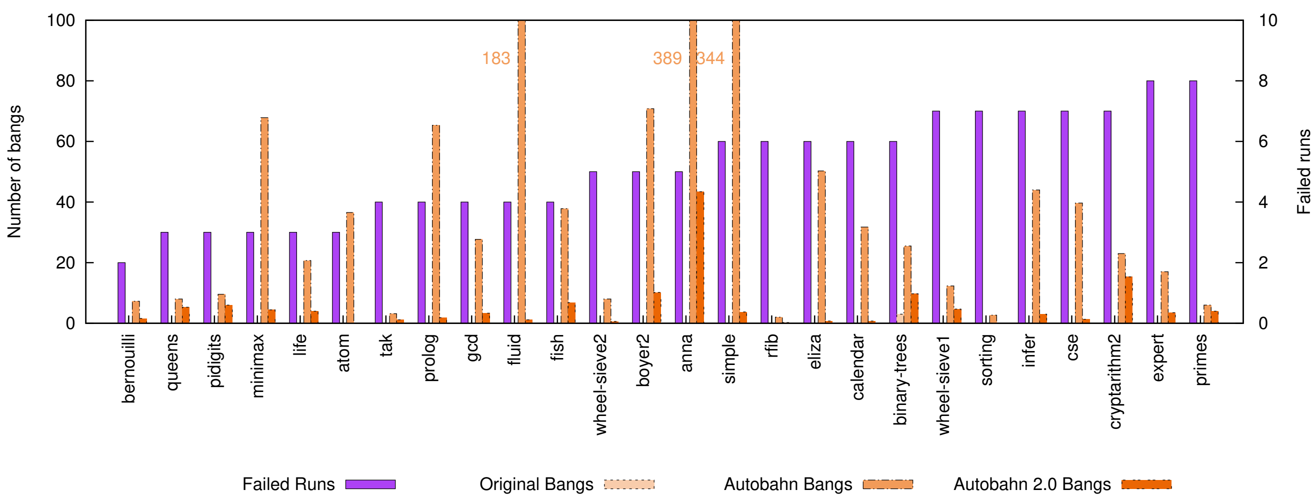


Figure 9. Number of bangs generated by Autobahn 1.0 vs. Autobahn 2.0 across 24 benchmarks. Success rate out of 10 runs is shown. Columns that exceed the maximum axis value are labelled with their actual values.

best when it evaluates its parsing functions lazily. If Aeson is paired with the convert driver, it performs the best when it evaluates all parsing functions eagerly.

In the original Autobahn 1.0 experiment, two versions of Aeson were optimized. Each used one of the drivers and had the incorrect set of bangs pre-inserted to allow for room for improvement. After optimization, Autobahn 1.0 was able to correct the incorrect set of bangs by either inserting bangs in correct locations or removing bangs from incorrect locations. We were interested in seeing if Autobahn 2.0 preserves the same results, so we ran Autobahn 2.0 with identical experiment conditions to see if it preserves the correct bangs that Autobahn 1.0 produces.

In the pre-search phase, Autobahn 2.0 identified that Aeson's top hot spots were in fact located in external libraries. We followed the program's suggestions to include Data.Attoparsec.Internal.Types as a local file in Autobahn 1.0's optimization coverage. However, results showed that the inclusion of this file did not significantly improve Autobahn 1.0's ability to optimize Aeson. It is possible that external libraries and files that were suggested by the pre-search phase do not improve Autobahn 1.0's optimization runtime results, in which case it is the user's decision if they still wish to include the external files as a part of the optimization coverage. In our case, we decided to remove the

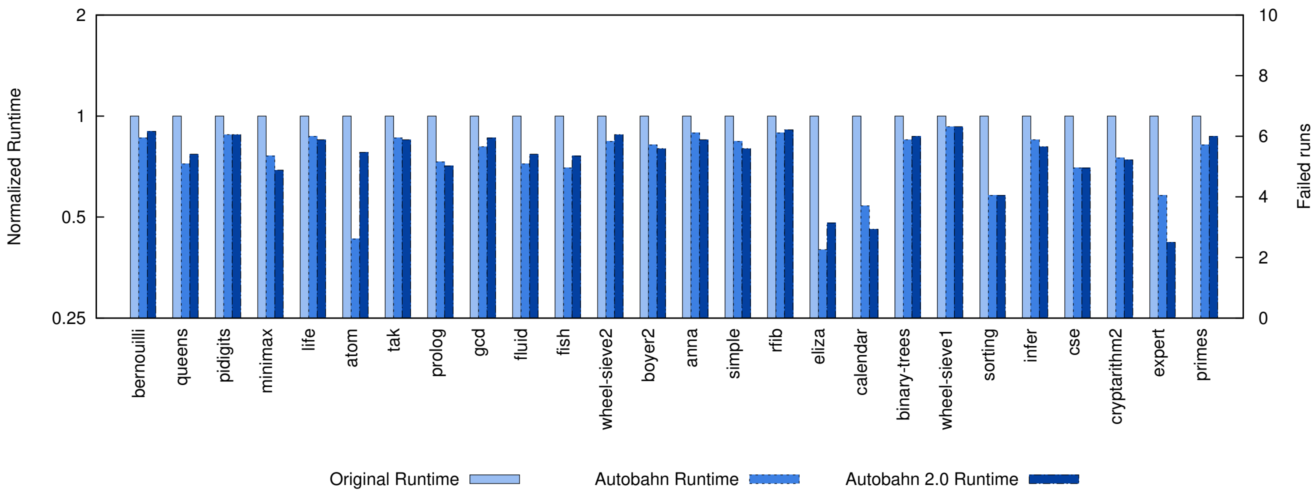


Figure 10. Normalized runtime of Autobahn 1.0 results vs. Autobahn 2.0 results across 24 benchmarks. The x-axis normalized runtime is on a log scale of base 2. Success rate out of 10 runs is shown. Columns that exceed the maximum axis value are labelled with their actual values.

newly added external file, and reran the experiment using the original setup.

In our second run of the experiment, Autobahn 1.0 was unable to generate the correct bang patterns prior to the pre-search phase. Because Autobahn 1.0's genetic algorithm is random, every experiment will turn out slightly differently every time it is run. We were unable to use Autobahn 1.0 to reproduce the exact application-specific bang patterns for `Aeson`'s two drivers that the original paper was able to produce. Therefore, we manually inserted the correct bangs into the optimization results and resumed the bang reduction process to see if the pre-search phase could eliminate the useless bangs and preserve the correct bangs. We also lowered the *hotSpotCost* threshold to 0.2% because most of the high-cost hot spots were located in external libraries.

Autobahn 2.0 was able to identify the key parsing function as a hot spot and preserved the bang pattern in the parsing function. Therefore, the correct bang patterns produced by Autobahn 1.0 were successfully preserved in the results of Autobahn 2.0. The following table illustrates the runtime and bang reduction results.

Version	Driver	Normalized Runtime	No. Bangs
Original	convert	1	2
	validate	1	4
Autobahn 2.0	convert	0.91	46
	validate	0.86	93
Autobahn 1.0	convert	0.93	7
	validate	0.85	2

6 Related Work and Future Work

6.1 Autobahn 1.0 and Other Methods of Removing Laziness

The current strictness analyzer in GHC uses backward abstract interpretation to identify locations that can be eagerly evaluated. The analysis is approximate because the analysis is static. The analysis also conservatively binds locations as strict only if it can guarantee program termination because it is a part of the compiler. Autobahn has the advantage of both being dynamic and not needing to guarantee termination on all inputs as it is not a a part of the compiler. Instead, it allows users to decide the safety of suggested strictness annotations based on the intended application of the program. Other approaches to reduce laziness include Strict Haskell, which allows users to make entire modules strict rather than lazy by default using the -XStrict and -XStrictData language pragmas. Chang and Felleisen starts with a program written in a strict language, and inserts laziness annotations into it using dynamic profiling. It would be interesting to see if Chang and Felleisen's method could be applied to introduce laziness to Strict Haskell programs.

6.2 Profiling Haskell Programs

Apart from the profiling system that GHC provides, there exists a variety of other cost-based profiling systems for Haskell.

6.3 Autobahn 2.0 Improvements

For future developments, it would be worth exploring the additional use of heap profiles to locate hot spots instead of solely using time and allocation profiles. Furthermore, our experiments show that the ideal values for *hotSpotCost* and *absenceImpact* thresholds vary by program to program. Adopting more flexible thresholds that automatically adjust themselves based on the results of cost centre profiling might yield better results than using set values or asking users to provide them.

7 Conclusion

Laziness is a double edged sword: While it provides many benefits, excessive laziness often causes poor performance. Strictness annotations allow programmers to force eager evaluation, but its use is limited to programmers with extensive experience and high levels of expertise. Autobahn uses a genetic algorithm to automatically infer annotations for better program performance, but it often suggests too many bangs for users to inspect. We have built Autobahn 2.0, which uses GHC profiling feedback to perform search space manipulation to improve the efficiency of genetic algorithms, and eliminates bangs based on their associated performance costs. On average, experiments show that Autobahn 2.0 was able to reduce 90.9% of generated bangs while only compromising 3% runtime.