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Is Software Debloating Useful? - A Comparative Study

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In this course project we intend to understand, learn, run & compare some `state-of-the-art` sofware debloating tools available for debloating large `C` or `C++` software project. In our quest to implement the project, we first started with a set of 3 motivating examples which showed where software deblaoting tools shine and why compiler optimization passes alone cannot do the task.

In short we modify, build and run software deblaoting tools on some benchmarks and see their performance in reducing or removing such code parts or instrcutions which may not be useful in the current context of using a particular tool. Knowing what all to remove from the code via automated debloating is a hard task since it will require through modelling of the environemnt and then making a call as to whether a certain piece of code will get executed or not. We can clearly see that it is not a trival problem to solve and thus, automated debloating is quite challenging.

We explore such tools that don't need a through execution environment modelling. These tools under exploration allow us to write a complete and sound specification of the desired properties or features that we want a given tool to be executable on thus eliminating the task of complex execution environment modelling. Now the problem is simplified and it boils down to removing all the undesired parts of the code that will never get executed in the current execution context. We refer to debloating as a iterative process by which these tools can now remove the undesired code sections from the source code or eliminate those instructions and function calls that will never be invoked making the final binary a sleek and trimmer down version instead of a bloated one.

We explore different techniques of software debloating and iterative reductions and see what works best under different functional requirements. Below is a comprehensive report of the work we did and our understanding of techniques adopted by each of the tools under exploration.

***Index Terms*—Software Debloating, Software Engineering, Delta Debugging, Reinforcement Learning, Markov Decision Process.**

I. Project Objective

We introduce and explain the issue involving **software bloating** that comes in given the nature and varied options available to develop modern software. We restrict ourselves to `C` or `C++` projects especially the once used frequently as a part of `unix` or `darwin` oses. These projects are usually build and installed as standalone tools or as libraries for linking with other major tools.

We propose to debloat a piece of `C or C++ Code` via **Policy Based Reinforcement Learning** using techniques and approaches as laid out in the two research papers we have selected for accomplishing the task. Both the papers have demonstrated novel techniques for debloating the codebase for a given `C or C++ Software` using **Policy Based Reinforcement Learning**, the first paper mentioned does this by **Learning-Guided Delta Debugging** while the second paper does this by **Guided Function Specialization** technique.

In our project (based out of Paper 2), we model the debloating problem as **reinforcement learning** where action would be to specialize a program or not. The state of the model will be a **vector** containing all the required details about the **specialized code**. The **reward** will be a **reduction** of the number of **instructions or code size** in the program after the program is debloated. As the model keeps learning, we expect the rewards to be improved with more inputs.

Software deblaoting leads to reduction of attack surface and lesser code to build and install, given it is done meticulosuly. We use debloating techniques to perform debloating on these tools or library source code and report back the reductions we saw after debloating. As a part of the process we get a deeper understanding of each of the tools and how they function, modify them to get comparision metrics or implement them Eg. `DeepOCCAM` from research papers based on available source code.

At the end we have a comprehensive report and working implementation of the modifiactions or runs we do to either in the benchamrks or in the tool's `source code` to suite the needs of the project. Given the limited time we got, not all things were completely implemented, especially the runs on other common benchmarks would be needed for a clearer comparison of the tools. Nevertheless, we provide a comparison report based on the current runs and share our insghts on the suitability of use of each tool in different contexts `(What technique works better than the other?)`

II. What is Software debloating?

Software bloating is quite a common problem in any real world software project where the code base is plagued with LOCs that are not useful while the program runs in a given execution context, a common example being exposing too many **redundant APIs**, **default configurations** for each context or many **command line options** that are not used or never invoked in general but are still in the codebase. One primary reason for this is that it isn't possible to structure the code base before hand or to choose a strict design pattern for all components that we write. Many times code needs to be written on demand or ad-hoc basis because not all requirements are captured in the early stages of the project and that becomes the potential root cause for **software bloating**. **Software bloating** can lead to bugs, slower code execution and even expose vulnerabilities in the code base. The current techniques used are **manually thought** clever **metrics & heuristics** for identifying such **bloat sites** and refactoring the code to remove them.

A. *Software Debloating Tools*

We focus on four popular tools we found for the purpose of software debloating of large scale `C or C++` projects, namely `Chisel`, `Trimmer`, `OCCAM` & `DeepOCCAM` tools. These tools vary in the way they do debloating and the specifications needed in order to do effective and sound debloating. By effective and sound deblaoting, we are referring to thier capacity to reduce `function calls`, `instructions`, `direct loops` etc from the original source code and produce a binary that is best suited to a given runtime environment context with out hampering the normal `desired` execution of the program. On different `environemnts`, based on the specifications we give and the way the binary is executed, the exact debloating effect of `reductions` may be differ significantly since the `desired` property specification may vary based on the `OSes` we run them on or the `settings/parameters` needed for normal run.

In each of these tools, we need to provide some information in the form of `desired` properties that we want our final program to meet under all safe condition and remove the other parts of the `code` or `instructions` that we dont need in the current execution context of the final binary produced.

B. Software Debloating Techniques

The techniques used by these tools for effective debloating varies from tool to tool but the the overall nature of the transformation can be catagorized into two types `source-to-source` & `source-to-binary` transformation.

In `source-to-source` transformation the tool's input is the bloated `source code` and the `specification` in the form of tests that need to pass under a given execution environment. The tool produces a `debloated` source code and binary from the input **`source`**. This is usually guided by a machine learning model and the reduction happens via techniques similar to `dead code elimination`. Some examples of tools running like this are `Chisel` & `Razor`

In `source-to-binary` transformation the tool's input is the bloated `source code` and the `specification` listing statically known arguments to the `main()` function and other `dynamic arguments` needed under a given execution environment. The tool produces a `debloated` binary from the input **`source`** but doesnot produce `debloated source code` unlike the technique mentioned above.

This is usually guided by hand crafted heuristics for `function specialization` at each `call-site` and the reduction happens via techniques similar to `dead code elimination` or other `compiler optimization` passes. Some examples of tools running like this are `Trimmer` & `OCCAM` but the exact algorithms for `constant propagation`, `function specialization` & `function inlining` differs in both the tools.

Another approach for `function specialization` at each `call-site` is by using machine learning to decide as to **`when to`** `specialize` and then do regular reduction in a similar fashion as above. `DeepOCCAM` is an example of this technique.

III. Motivating Examples

As a motivating example we show what current `compiler optimization` techniques fail to do and **why** special software deblaoting tools are needed for the purpose of `debloating`, we here show the working of the `Chisel` tool since `source-to-source` transforamtion is of `particular interest` to most software developers. We show the `original` source code

```
#include <stdio.h>
void run(int a) {
  if (a > 90) {
    printf("%d\n", a);
  }
}
long long int add(int a, int b)
{ return a + b; }
long long int sub(int a, int b)
{ return a - b; }
int main(int argc, char *argv[]) {
  int c = 0;
  c = -500;
  if (c > 0) {
    run(c);
    add(c, c + 1);
  } else {
    sub(c + 90, c);
  }
  return 0;
}
```

and the chiseled source code below it on a blank test case where nothing is desirable in the code.

```
  #include <stdio.h>
  int main(int argc, char *argv[]) {
    int c = 0;
    return 0;
  }
```

We were amazed at the amount by which Chisel was able to reduce the source code via reinforcement guided delta-debugging on this blank test case. We now show what gcc with -O3 optimization was able to do with the code. This is acceptable since the **gcc compiler** has no way to remove the code directly based on current techniques of code optimization and thus debloaters to the rescue.

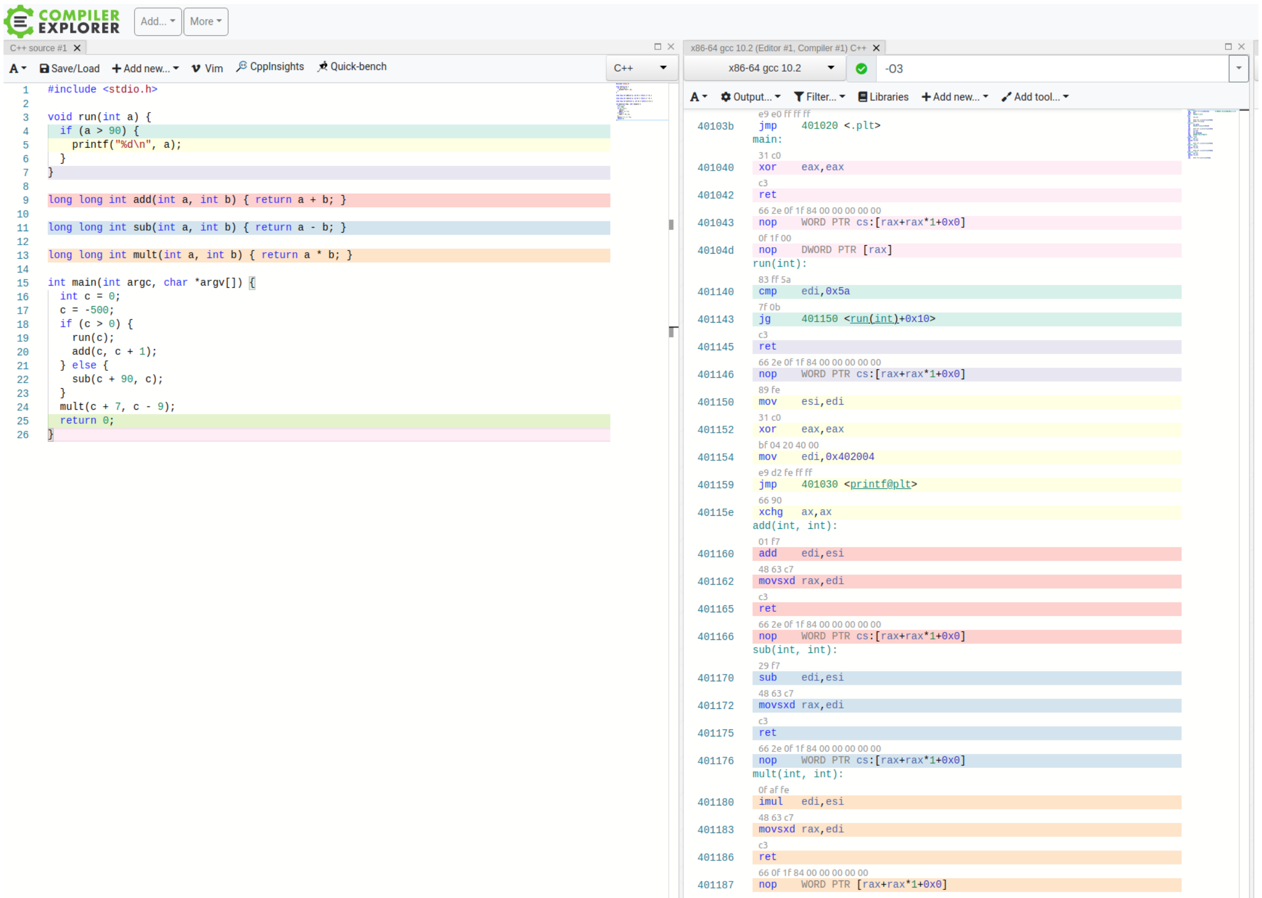
We now show Chisel tool in action.

```
Start global reduction
Running delta debugging - Size: 3
Start local reduction
Reduce process_aflag at test.c
Running delta debugging - Size: 1
Reduced - Size: 0
Reduce process_bflag at test.c
Running delta debugging - Size: 2
Reduced - Size: 1
Reduced - Size: 0
Reduce process_cflag at test.c
Running delta debugging - Size: 3
Reduced - Size: 1
Reduced - Size: 0
Reduce main at test.c
Running delta debugging - Size: 2
Reduced - Size: 1
Iteration 2 (Word: 58)
Start global reduction
Running delta debugging - Size: 3
Reduced - Size: 1
Reduced - Size: 0
Start local reduction
Reduce main at test.c
Running delta debugging - Size: 1
Iteration 3 (Word: 43)
Start global reduction
Running delta debugging - Size: 0
Start local reduction
Reduce main at test.c
Running delta debugging - Size: 1
Reduce File: test.c
Iteration 1 (Word: 43)
Start global reduction
Running delta debugging - Size: 0
Start local reduction
Reduce main at test.c
Running delta debugging - Size: 1
```

We now show a working of the OCCAM tool on a different getopt() based C example. We pass in some default static arguments to the program and see the OCCAM tool in action on it.

We present the static analysis details for OCCAM run in before & after all inter & intra specialization passes have been completed. The example C code is as below. It accepts three flags namely -a, -b & -c and call a function based on the flag recieved.

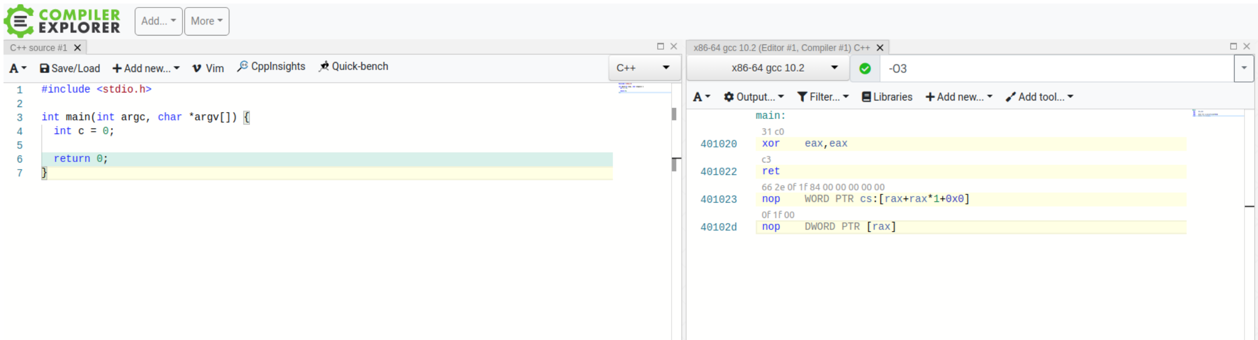
```
#include <stdio.h>
#include <stdlib.h>

void process_aflag(int a)
{ printf("%d\n", a + 90); }

void process_bflag(int a) {
  a = 80 * a;
  process_aflag(a);
}

void process_cflag(int a) {
  a = a << 20;
  process_aflag(a);
  process_bflag(a);
}
// Example based on : http://osr507doc.sco.com/
    en/tools/ccs_stdio_args.html
```



```c
#include <stdio.h>

void run(int a) {
  if (a > 90) {
    printf("%d\n", a);
  }
}

long long int add(int a, int b) { return a + b; }

long long int sub(int a, int b) { return a - b; }

long long int mult(int a, int b) { return a * b; }

int main(int argc, char *argv[]) {
  int c = 0;
  c = -500;
  if (c > 0) {
    run(c);
    add(c, c + 1);
  } else {
    sub(c + 90, c);
  }
  mult(c + 7, c - 9);
  return 0;
}
```

```
          e9 e0 ff ff ff
40103b    jmp    401020 <.plt>
        main:
          31 c0
401040    xor    eax,eax
          c3
401042    ret
          66 2e 0f 1f 84 00 00 00 00 00
401043    nop    WORD PTR cs:[rax+rax*1+0x0]
          0f 1f 00
40104d    nop    DWORD PTR [rax]
        run(int):
          83 ff 5a
401140    cmp    edi,0x5a
          7f 0b
401143    jg     401150 <run(int)+0x10>
          c3
401145    ret
          66 2e 0f 1f 84 00 00 00 00 00
401146    nop    WORD PTR cs:[rax+rax*1+0x0]
          89 fe
401150    mov    esi,edi
          31 c0
401152    xor    eax,eax
          bf 04 20 40 00
401154    mov    edi,0x402004
          e9 d2 fe ff ff
401159    jmp    401030 <printf@plt>
          66 90
40115e    xchg   ax,ax
        add(int, int):
          01 f7
401160    add    edi,esi
          48 63 c7
401162    movsxd rax,edi
          c3
401165    ret
          66 2e 0f 1f 84 00 00 00 00 00
401166    nop    WORD PTR cs:[rax+rax*1+0x0]
        sub(int, int):
          29 f7
401170    sub    edi,esi
          48 63 c7
401172    movsxd rax,edi
          c3
401175    ret
          66 2e 0f 1f 84 00 00 00 00 00
401176    nop    WORD PTR cs:[rax+rax*1+0x0]
        mult(int, int):
          0f af fe
401180    imul   edi,esi
          48 63 c7
401183    movsxd rax,edi
          c3
401186    ret
          66 0f 1f 84 00 00 00 00 00
401187    nop    WORD PTR [rax+rax*1+0x0]
```

Figure 1: **C Code** Example before **Chisel** tool processing on **blank test** case



```c
#include <stdio.h>

int main(int argc, char *argv[]) {
  int c = 0;

  return 0;
}
```

```
        main:
          31 c0
401020    xor    eax,eax
          c3
401022    ret
          66 2e 0f 1f 84 00 00 00 00 00
401023    nop    WORD PTR cs:[rax+rax*1+0x0]
          0f 1f 00
40102d    nop    DWORD PTR [rax]
```

Figure 2: **C Code** Example after **Chisel** tool processing on **blank test** case

```c
int main(int argc, char *argv[]) {
  /* Function flags */
  int aflag = 0;
  int bflag = 0;
  int cflag = 0;
  int ch;

while ((ch = getopt(argc, argv, "abc")) != -1)
  {
/* For options present */
/* set flag to some value */
/* else write out an error statement */
switch (ch) {
  case 'a':
    aflag = 10;
    fprintf(stdout, "aflag set !\n");
```

```
      process_aflag(aflag);
      break;
    case 'b':
      bflag = 20;
      fprintf(stdout, "bflag set !\n");
      process_bflag(bflag);
      break;
    case 'c':
      cflag = 30;
      fprintf(stdout, "cflag set !\n");
      process_cflag(cflag);
      break;
    default:
      (void)fprintf(stderr, "Usage: %s [-abc]\n
          ", argv[0]);
      return (2);
    }
  }
  if (aflag < 0) {
    process_cflag(90);
  }
  /* Do other processing controlled by aflag,
      bflag, cflag. */
  process_bflag(60)
  return (0);
}
```

The `Manifest file` we used for running `OCCAM` in `aggressive mode`

```
{ "main" : "test.o.bc"
, "binary"  : "test"
, "modules"    : []
, "native_libs" : []
, "static_args"    : ["-a", "90"]
, "name"    : "test"
}
```

`OCCAM` log after run was complete. We see that there was reduction of the code size that was finally complied to binary.

```
Statistics for  before specialization
[CFG analysis]
4   Number of functions
0   Number of specialized functions
0   Number of bounced functions added by devirt
15  Number of basic blocks
81  Number of instructions
13  Number of direct calls
6   Number of external calls
0   Number of assembly calls
0   Number of indirect calls
0   Number of unknown calls
1   Number of loops
0   Number of bounded loops
[Memory analysis]
37  Number of memory instructions
32  Statically safe memory accesses
5   Statically unknown memory accesses

Statistics for  after specialization
[CFG analysis]
4   Number of functions
0   Number of specialized functions
0   Number of bounced functions added by devirt
15  Number of basic blocks
60  Number of instructions
13  Number of direct calls
7   Number of external calls
0   Number of assembly calls
0   Number of indirect calls
0   Number of unknown calls
1   Number of loops
0   Number of bounded loops
[Memory analysis]
19  Number of memory instructions
15  Statically safe memory accesses
4   Statically unknown memory accesses
```

IV. OCCAM Tool

OCCAM is a debloating tool that works on the principle of winnowing and object culling. Winnowing is a static analysis and code specialization technique based on the partial evaluation algorithm. It is a code optimization technique where all the static inputs computations are processed during compile time. Also, all the function arguments are replaced with constant value (if statically known) and optimization passes by LLVM is applied after that. PE helps to achieve the residual program which runs faster than the original program with reduction in gadgets and instruction count.

A. *Overview*

We detail out a bit more about the OCCAM tool here. Function inlining only replaces the function call by the function definition but PE takes an extra step and evaluates the function before the execution of program using statically known arguments via constant folding or constant propagation in the function body. Static (compile time) analysis is seperate from dynamic (run time) analysis with this algorithm and thus we present details of the tool runs in two sections Static Analysis and Dynamic Analysis.

OCCAM takes two inputs: a source code in C/C++ and a manifest file in JSON format. The debloated binary of the original source code produced by the OCCAM tool is used by the Gadget set Analyser to get the gadgets count. The original source code is also compiled by a compiler and feed to GSA tool. Both debloated and original binaries are then compared for reduction in metric counts. Dead code elimination in OCCAM works in five ways:

- Aggressive Non-Recursive DCE.
- Inter-Procedural DCE. (accross function calls/-bodies).
- Intra Procedural DCE. (for basic blocks in function body).
- Sparse Conditional Constant Propagation based DCE. (for OCCAM-T, we enable this pass).
- Abstract Interpretation based DCE. (Seahorn Crab based DCE pass).

B. *Working Procedure*

Partial evaluation works in two steps, first being optimization and second is specialization. In optimization phase compile time constants are identified, dead codes are eliminated and the control flow of the program is reduced. In specialization phase, program is effectively specialized across function boundaries.

V. Trimmer Tool

`Trimmer` is a software debloaing tool used to `specialize` the target function at a call-site with respect to the user defined configurations in-terms of statically known formal arguments.

A. *Overview*

The configuration contains the usage context of application. Compiler transformation are included in this tool for good debloating. Inter-procedural constant propagation is used in the tool which aggressively removes the unnecessary codes. With the reduction in the unused program codes, the gadget count of the program is also reduced and helps to improve the security performance of the system.

B. *Working Procedure*

The source code is converted to LLVM IR and given as an input to the trimmer tool along with the manifest file consisting of user defined configuration. The `Trimmer` first performs input `specialization` where is replaces the value of the formal arguments to the program (usually the `main()` function) with values from the mainfest file. The second part is a `specialized bounded loop unrolling` based on a `cost modelling` approach. The loop unrolling becomes an important step to make inter-procedural constant propagation easier. Inter-procedural constant propagation is the final stage in the tool accross the basic blocks of the call-site functions in the `CFG`. The specialized code processed by the `Trimmer` is then given as input to the linker. The linker also reads the linker flags from the manifest file and generates a final specialized binary executable file after sucessfull linking.

VI. Chisel Tool

We share a brief information about the tool. **Chisel** tool works by learning a **policy** for **delta debugging** by **reinforcement learning** which guarantees **1-minimal P*** & $O(|P|^2)$ runtime. The abstraction is that a **markov decision process** is being used to model the **reinforcement learning** problem for meaningful **guidance** to learn the **policy** in a better way. All global declarations, variables, functions etc. are first reduced by the delta-debugging principle as state above and thereafter local variables, loop declarations and arguments to functions are optimized. After both the local and global level reductions are done, **Chisel** invokes a run of the **global level reduction** again and repeats the process continually until the **1-minimal P*** version of the program is found.

A. Overview

Chisel tool's working is based on syntax guided hierarchical delta debugging algorithm. The tool ensures that the reduced program are compilable, core functionalities of source program are preserved and undefined behaviours for non core functionalities does not show up. CHISEL also keeps all the criteria required for the system to work properly in order. The criteria are minimality,naturalness,efficiency,robustness and generality. The probabilistic model is used in CHISEL to accelerate the delta debugging algorithm and Markov Decision Process is used to search a proper policy for learning the machine learning algorithm. Model based Reinforcement algorithm is used to converge to the solution quickly.

B. Working Procedure

The input to the **CHISEL** tool is a C/C++ source file (test.c) which is to be debloated. Along with the source file , we give a specialized script which contains the high level specification of the desired output. The CHISEL tool then generates binary of the source code(test.c.chisel.c). Both the source and debloated program are then compiled by g++ or any other compiler and the binaries generated by the compiler are given to the ROP gadgets or Gadget Set Analyser(GSA) . The ROP gadget outputs the count of the gadgets before and after debloating respectively.

C. State Encoding

Markov Decision Process is used for Delta debugging algorithm. For delta debugging algorithm two things are required and the tuple of these two things defines the state of the model at any time. The first thing is the pair of the program to be tested and second thing is the number of partitions into which a program is broken. The initial state consist the entire program represented as a list into two partitions. The program can be broken inti tokens,identifiers ,statements or even a finer granularity is reached to obtain the minimal state.

D. Delta Debugging

Delta debugging is an algorithm or technique to remove the unnecessary part of the input which is not responsible for test case failure. DD makes testing easier as it divides input into smaller subsets because smaller and simplified testcases are easy to handle. Delta debugging algorithm is used till we reach 1-minimal expression. DD is an iterative algorithm.Markov Decision Process for delta debugging is deployed to build a statistical model to get 1-minimal solution with lesser number of iterations than delta debugging alone.

E. 1-minimal Program

Suppose we have a testcase T which fails the program P. When T is given as input to P, the entire part of T may not be responsible for causing failure to the program P. Therefore, we are interested in the exact part of T which causes the program to fail. In short, we can say failing test case can have relevant and non-relevant information. To filter out the relevant information from the test case, we use Delta debugging algorithm.If a test case T fails the program P, then the expression T' derived from T is 1-minimal iff any deviation causes the test case failure to go away.

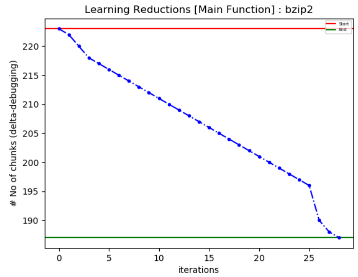


Figure 3: Learning plot for mkdir

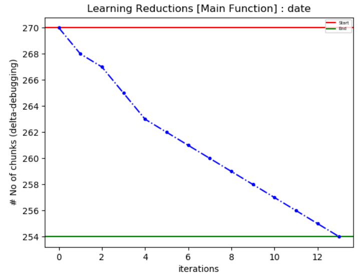


Figure 4: Learning plot for date

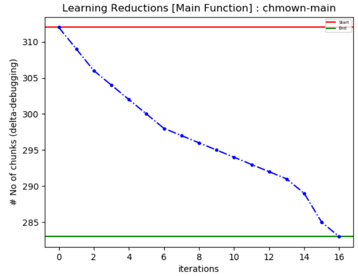


Figure 5: Learning plot for chown

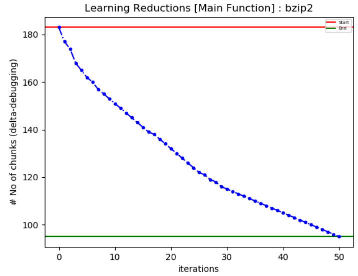


Figure 6: Learning plot for bzip2

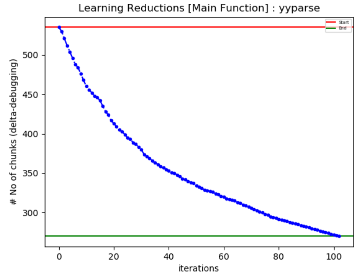


Figure 7: Gadgets plot for yyparse

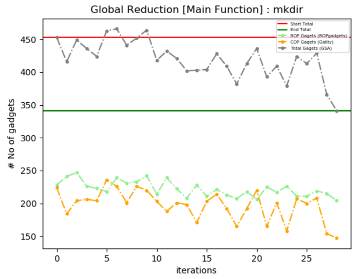


Figure 8: Gadgets plot for mkdir

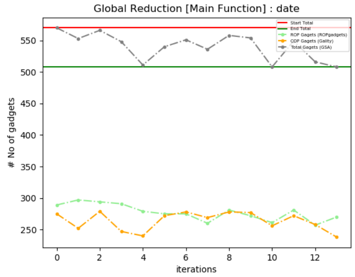


Figure 9: Gadgets plot for date

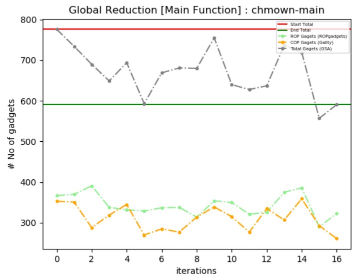


Figure 10: Gadgets plot for chown

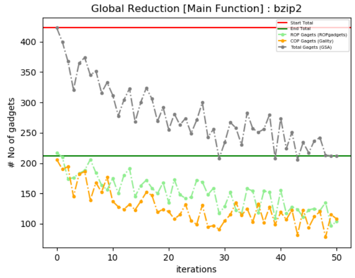


Figure 11: Gadgets plot for bzip2

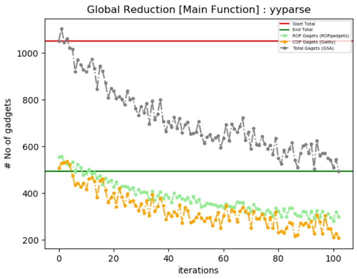


Figure 12: Gadgets plot for yyparse

VII. DeepOCCAM Tool

DeepOCCAM is an extension of OCCAM tool with new approach based on machine learning. Both OCCAM and DeepOCCAM are based on the partial evaluation approach. The major contribution of PE is to determine if the function specialization decreases the size of residual program. The function specialization increases the code size of original program but then optimization in the new function such as constant propagation can be possible after function inlining and static values substitution. So, there is an opportunity for code size reduction in the residual program after partial evaluation process.

A. *Overview*

The problem of specializing a given function at a call-site is not a trivial and thus DeepOCCAM with it's RL modelling tries to derive to a yes/no answer by learning a policy to decrease a given metric count in the final binary of the source code produced.

B. *Working Procedure*

We explain the working procedure as per our understanding of the DeepOCCAM paper, the exact working for our DeepOCCAM implementation is listed in the DeepOCCAM pipeline section of the report. **DeepOCCAM** starts by developing on top of the OCCAM tool were state modelling and metadata generation happens in the first stage, then once the metadata is generated, it is used by the RL agent to learn the rewards of function specialization action by metric count measures that come in from the GadgetSetAnalyzer. This loop repeats over and over again for each and every call-site where a function can be specialized. At each episode run the RL agent is asked to decide if specialization of a function at a given call-site is rewarding or not. Based on the `policy` learned so far and the current `encoded state`, the RL agent replies with a `yes/no` answer to the `specialization` question. The reward to the RL agent is a decrease in the count of the metric under consideration.

C. State Encoding

DeepOCCAM has been implemented with two state modelling schemes.

- Handcrafted Features `HF` from counts collected from `occam.log` file.
- LLVM IR embedding based feature vectors using Inst2Vec tool.

In `HF`, the state contains the detail (usage and feature counts) about the `caller`, `callee`, `contexts`, `loops`, `arguments to function calls` and other `call-site` details. The state in this case is a combination of the counts of these features vectors.

In `Inst2Vec` each instruction is converted to a `feature vector` using `skip gram model` similar to word embeddings. The LLVM IR of the caller, callee and calling context represented as a list of instructions are used as part of creating the feature vectors. Also, the arguments at the call site is represented as a 1-bitvector value of `0` or `1` where `Zero(0)` denotes unknown argument and `One(1)` denotes the statically known argument for the arguments list at the call site. This bitvector along with the above three vectors form a tuple of the four 2-D matrices. These tuple represents the state for the RL model.

D. Inst2Vec Usage

Inst2vec is a tool of processing the source code into the features vectors that we used for modeling the Reinforcement Learning apart from hand crafted counts collected from `occam.log` file. It follows an approach similar to skip-gram model in Natural Language Processing of pre-defined context size. The source code is first compiled into LLVM IR code. The LLVM IR is in the form of a static single assignment.As LLVM IR is independent of machine or hardware architecture and programming language , it becomes easy to train the program embeddings.The approach is similar to word2vec model.

With the LLVM IR , the contextual flow graph (XFG)is created. XFG takes into account both the data flow and control flow of the program. With these XFGs generated from LLVM IR , the consecutive statement pairs are made of pre-defined context size . These statement pairs are then checked for duplication. The XFGs pairs are made by constructing a dual graph with statement as nodes and removing duplicate edges. The process is then followed by removing statements of negligible presence. We get an inst2vec after subsampling of frequent pairs which can be optimized and trained. XFGs ensures that the semantics of statements are preserved.

We use it as an alternative in the metadata generation stage other then `HF` heuristics for feature vector representation of the state in `DeepOCCAM` pipeline.

VIII. Project Aim

As a experimental & comparison based project, our task was to run the tools on various examples to see for `static` & `dynamic` metric changes **before** & **after** the run of the tools on these examples. We setup up each tools and prepare them for metrics that we want to extract & compare in each of the runs using either statistics that are shown by the tool itself using options like `--stats` or `--opt-stats` for static analysis case or generating intermediate `binary` or `elf-section object` files for dynamic analysis.

We finally report an **overview**, **setup**, **benchmarks** & **comparision** of these tools on some same examples and also on a set of `benchmarks` used originally to test run each of the tools in the original papers.

We also implement a modification of `OCCAM` tool to run like `Trimmer` tool as per description and our understanding of the **Trimmer** original paper and a modification of base `OCCAM` tool to `DeepOCCAM` which uses a `reinforcement learning` based approach to specialization based on **DeepOCCAM** paper.

IX. Implementation Overview

We elaborate on the changes and the work we did to meet the `Project Aim`. We start with the `Chisel` tool where we did modifications to dump the reduced chunk and the original chunk sizes that are used for `markov decision` based `delta-debugging` and used it as a metric to measure the `learning rate` along with reduction in `gadgets` count for the intermediate binary produced by `Chisel` tool

For **OCCAM** tool the modification was to fix the code for running in our environment and then work on the `manifest` & `automated` make builds so that it can be run in `dockers` for final release in the project. Another modification was to dump the `counts` for `caller`, `callee`, `constant arguments`, `statically known arguments` and other `context` related details for `metadata` & `dataset` generation in the base `occam.log` file itself since **we were not able to complete the `gRPC` implementation on time** owing to build and linking related issues.

For **DeepOCCAM**, we found a **half-implemented code** repository which belongs to one of the authors for **DeepOCCAM** paper. The tool doesn't link, build or run on the current platform that we are using. It gave us insights on implementing some of the parts in the code that we are developing as an extension on **OCCAM** to develop **DeepOCCAM**.

The benchmarks we used needed modification interms of running it against updated **gllvm**, **wllvm** & **llvm-10**. There were a few other tools and frameworks that we had to install and test in-order to run the debloating tools on these benchamarks.

We compiled, build & ran the tools in `docker` containers interacting with the base `OS` via `docker volumes` & `u-tty terminal` program.

X. Pipeline Setup

We divided the task of running the `benchmark` & `motivating` examples for the `three` tools into `three` different `pipelines`. Each `pipeline` was built and deployed against different `Ubuntu OS` base `images` which was specifically required for `each` of the tools. There were some `libraries`, `python packages` and linking `object files` that conflicted when trying to run all three tools in the current base `OS` on which we were developing the tools, so we switched to using three `docker` containers one for each `tool`

We ran multiple instances of the `docker` containers for `training` and `parellel` benchmark runs so that we can cover as many as `benchmark` code examples possible. We now show `architecture` diagrams of the final `pipelines` that we intend to use for `demonstration` purposes.

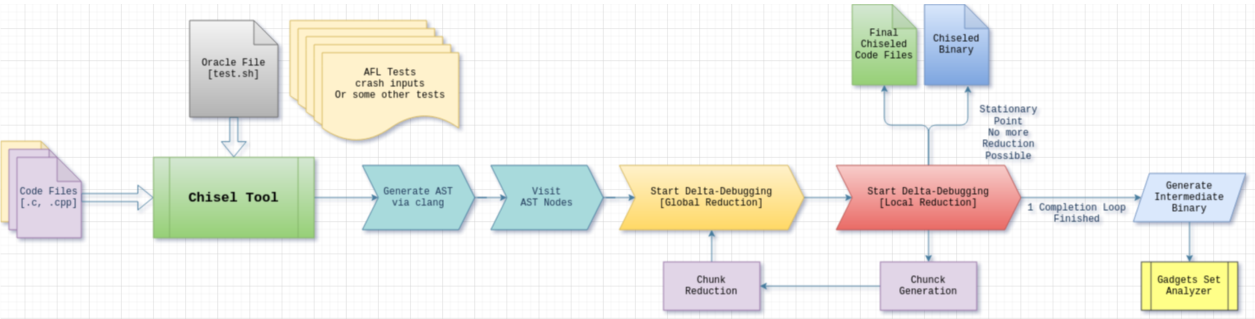


Figure 13: **Chisel Pipeline** : Setup `Chisel` runs on `Chisel-Benchmarks` & other examples

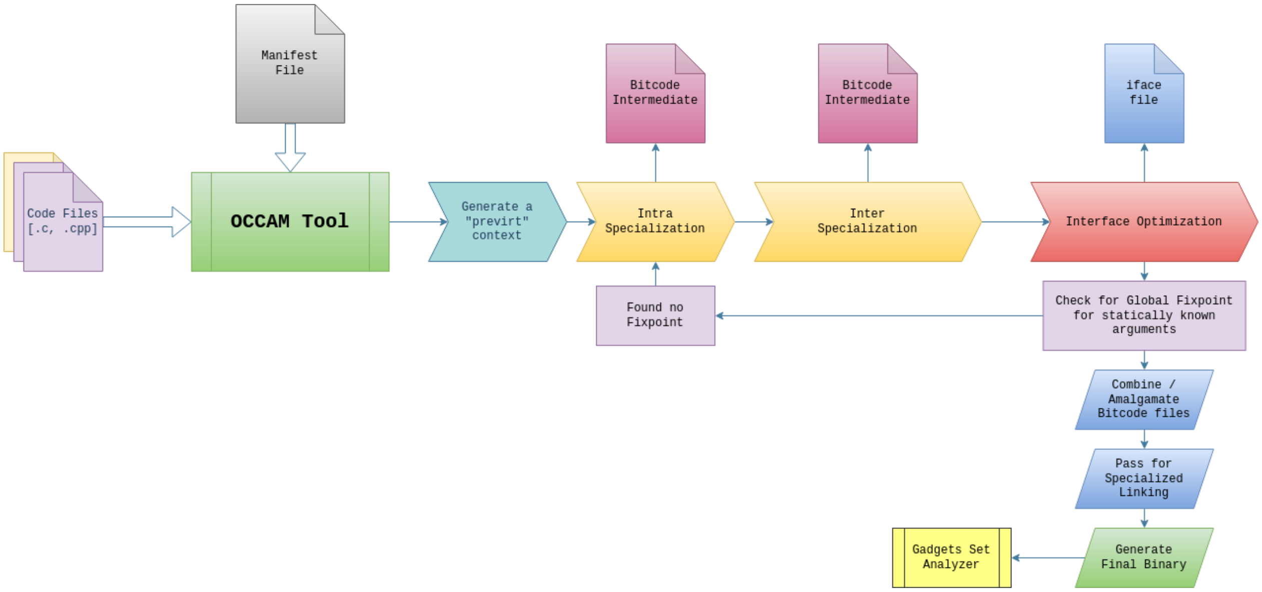


Figure 14: **OCCAM Pipeline** : Setup `OCCAM` runs on `OCCAM-Benchmarks` & other examples

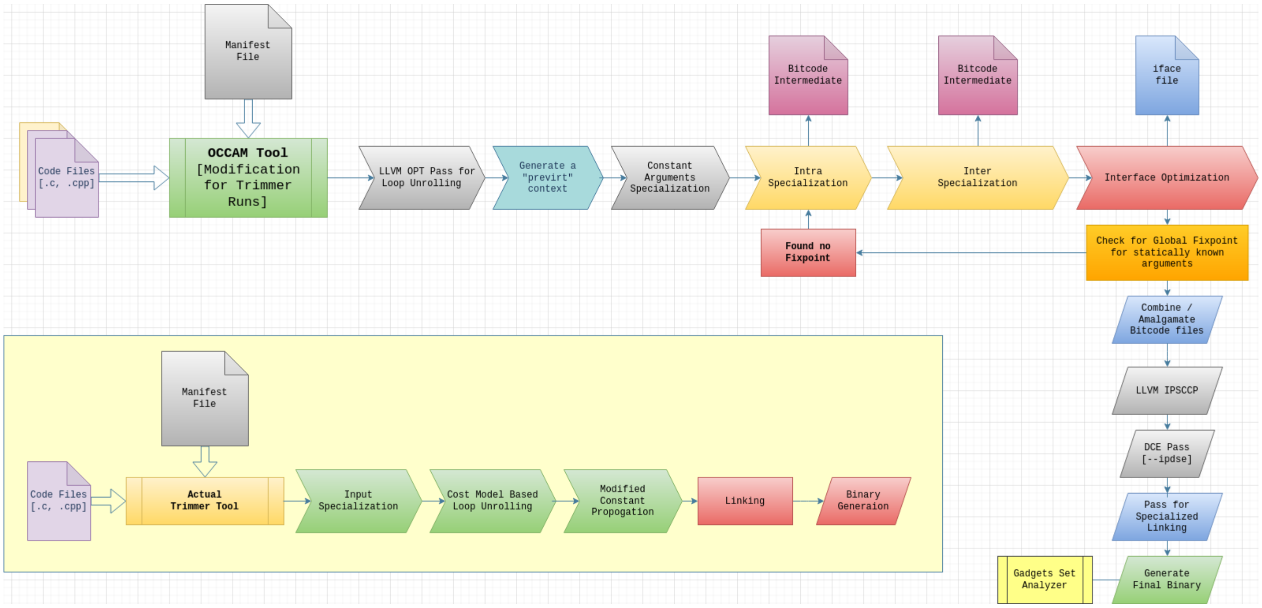


Figure 15: **Trimmer Runs** : Setup `Trimmer` runs on `OCCAM-Benchmarks` only

A. Chisel Pipeline

We give an overview of what we modified and how we setup the dockers for running the Chisel Tool. The markov model code implementation in Chisel tool is in ProbabilisticModel.cpp where we added a function to dump a few heuristics. We modified the GlobalReduction.cpp & LocalReduction.cpp code files to dump the before and after chunk sizes for plotting the learning rates. After the .reduced binary produced at each stage when the tests as per `crash_inputs` from AFL were executed, we run a `single_run()` function of the modified GadgetSetAnalyzer to get the gadgets metric counts and plot them via matplotlib. We installed all dependencies of Chisel and cloned the modified GitHub repository for the runs in a docker container running debian:buster image. We dump the plots from the data collected after the final bianry is produced. The benchmarks already contained the AFL `crash_inputs` and other tests, so we used them directly in our runs.

B. OCCAM Pipeline

We prepare the benchmarks for the `OCCAM` run. We modfied and rewrote many of the `Makefiles` and `manifests` for proper running of the benchmark examples. Some of the benchmark runs failed for `OCCAM` amalgamation (pass to combine all the bitcode files) and we only produced the static analysis metrics for these benchmark sets. We were able to run `OCCAM` for the `portfolio` benchmark runs used in the `Trimmer` paper published. We ran the scripts for `OCCAM` using different settings like `--none`, `--onlyonce`, `--aggressive`, `--nonrec-aggressive` for both `--inter-spec` and `--intra-spec policy` and dumped the metrics accordingly for each run.

The `docker` base image used for the `OCCAM` is `ubuntu:bionic`. We installed all the dependencies and other tools like `wllvm`, `gllvm`, `golang`, `llvm-10` etc for the runs. `slash` is the command line tool name for the python package `razor` that is uses the occam libraries and binary for debloating action. razor package is wrapper around the occam binary which runs the appropriate passes in `OCCAM` via `llvm-opt` tool. It links and runs the tool against the source code and the manifest file supplied.

We collect the data for each run of the benchmark for the different options of run available in the slash tool against the occam binary. We cloned the modified repository for `OCCAM`, built it from source and then ran the slash tool after the build via Makefiles and bash scripts (build.sh). We show a sample of the same below.

C. Trimmer Runs : OCCAM-T Pipeline

We didn't have the source code to Trimmer, so we modified `OCCAM` code to run with argument specialization, LLVM loop unrolling and sparse conditional constant propagation. We make a docker container from the base `OCCAM` pipeline docker image of the above. It already has all the tools and libaries needed for the build after the modifications we did to `OCCAM` source code. We added a LLVM opt pass for bounded loop unrolling, added the `LLVM` opt pass for `IPSCCP` implemeted in LLVM and set all the `specialization` decisions to true if an argument is constant specializable similar to the case of `OCCAM` running with Aggressive Poliy for inter and intra specialization passes over each function call sites.

Simalar to `OCCAM`, we ran the modified benchmark scripts using `--ipdse` (for -Pipsccp), `--unroll-loop` (in `passes.py` in razor) and dumped along with `LLVM` the metrics accordingly for each run. The **green** column in the static analysis tables in for `OCCAM-T` (we call this modification to `OCCAM` as `OCCAM-T` instead of Trimmer).

A word on **Trimmer**, **OCCAM** also uses partial evaluation concept like **Trimmer** for specializing functions at call-sites but it is less aggressive compared to the **Trimmer** because it does not include **`specialized loop unrolling`** and the modified **`constant propagation`** implementation in Trimmer Tool

D. DeepOCCAM Pipeline

We found a **half-implemented code** repository which belongs to one of the authors for **DeepOCCAM** paper. The tool doesn't link, build or run on the current platform that we are using. It gave us insights on implementing some of the parts in the code that we are developing as an extension on **OCCAM** to develop **DeepOCCAM**.

- Modified code in base **OCCAM** tool to collect **RL** related features in the `occam.log` file.
- Implemented a **deep reinforcement learning model** from the insights we got from the **half-implemented code**. We were stuck on how to do the rewards implementation and the above repository helped us in implementating the same.
- We setup a **docker** based container pipeline to build, run and debloat an example **code repository**. The **training** part happened outside the docker, we just saved and extracted the model for later use in container.
- We had to modify the way the tool was plotting and processing some the feature vectors. We used **`Adam Optimization`**, **`ReLU`** functions, **`Softmax`**, **`torch.nn GRU`** neural net for **`inst2vec`** & **`Linear fully-connected`** layers etc. for implementing the **`ML`** part of **DeepOCCAM** tool.
- Used `bzip` code & `tree` for inst2vec features creation in **deep reinforcement learning model**. We essentially have two ways to generate and represent the states in this implementation one for handcrafted features from the data in `occam.log` file and the other from `inst2vec`. We strore this in `metadata.json` files for training and evalutation purpose.
- Generated embeddings for bzip from inst2vec and used the same embeddings for debloating bzip in `DeepOCCAM` runs. Unlike pretrained embeddings, this new embeddings did work well for bzip run but not for other runs.

In sumamry, for the RL implementation we first have a `metadata` generation stage from feature vectors be it either `HF` or from `Inst2Vec` tool, then we have a `learning` & `training` episodes stage where we use these features and train a RL agent to follow a policy to decide a `yes/no` for specialization problem. The learning lags one `time stage` behind the current `OCCAM` running stage, since we are not using `gRPC`.

Once the training of the `RL` model is over or we have some considerable number of good episode runs (excluding the broken runs), we use it in evaluation mode where given a state representation from `OCCAM` it can tell whether to `specialize` or `not specialize` the function at the `call-site`.We next present the `architecture` digrams for our `DeepOCCAM` pipeline and the actual `DeepOCCAM` implementation based on our understanding of the paper. Finally we show the plots for `DeepOCCAM` learning stages, `gadget counts` versus `training cycles` for `bzip` program from `OCCAM` benchmark set.

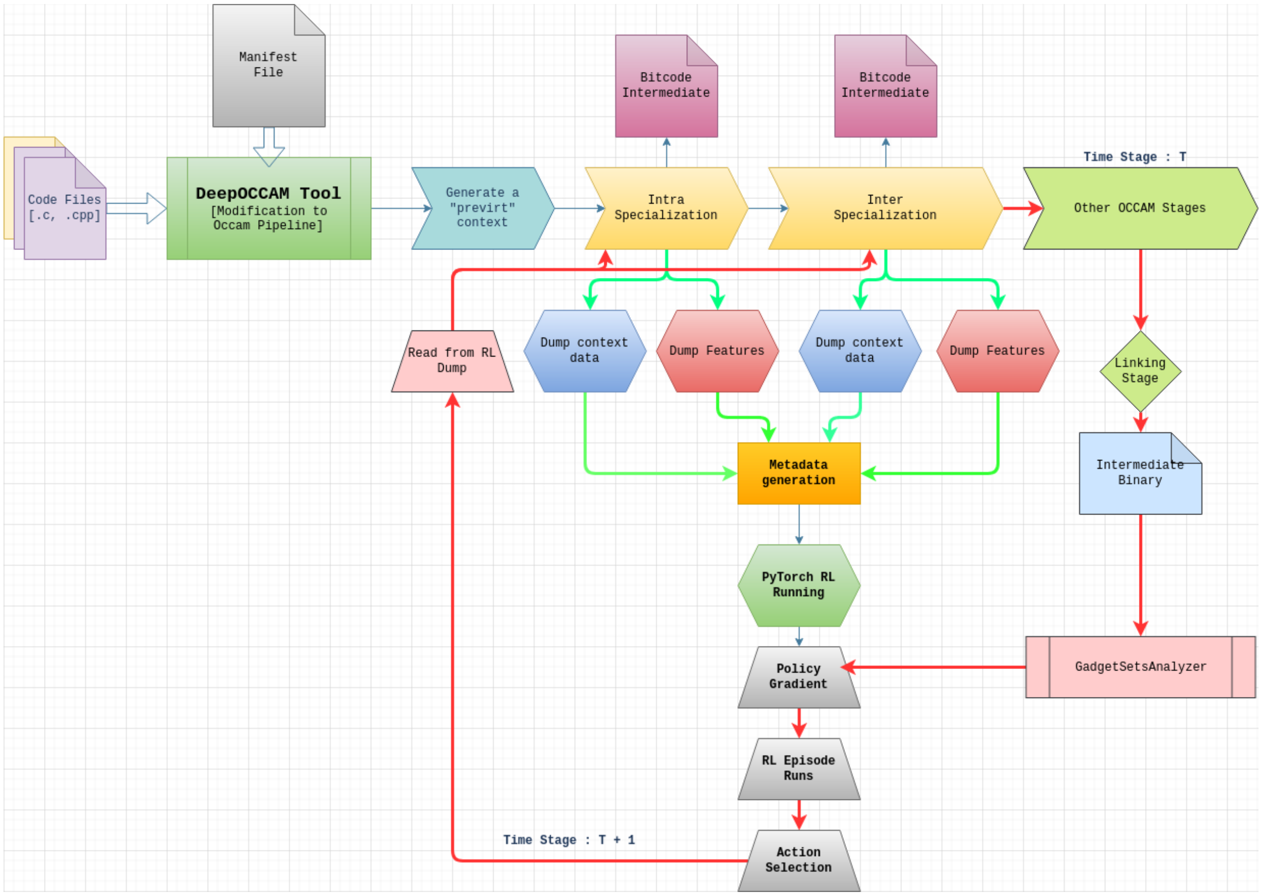


Figure 16: **DeepOCCAM Pipeline**

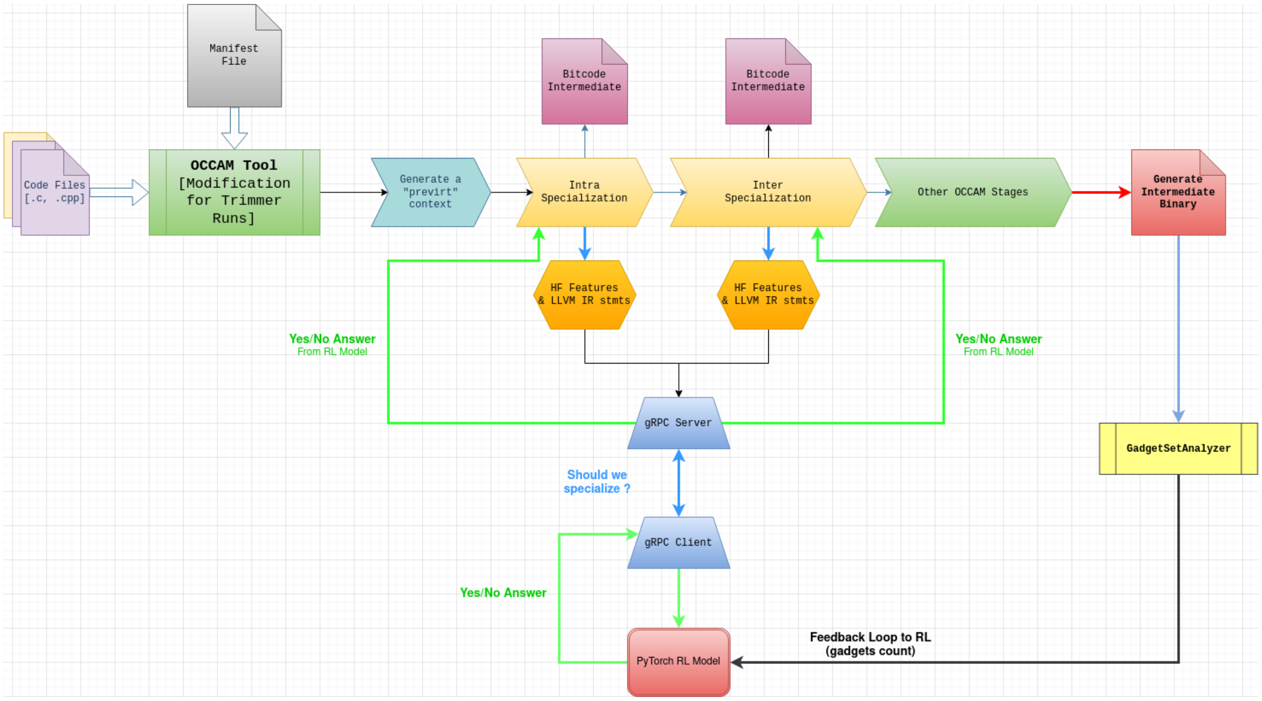


Figure 17: **DeepOCCAM : From our understanding of the Paper**

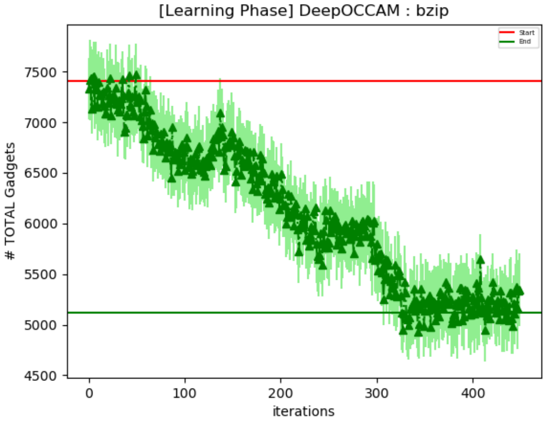


Figure 18: **DeepOCCAM Total**

450 iterations bzip - HF

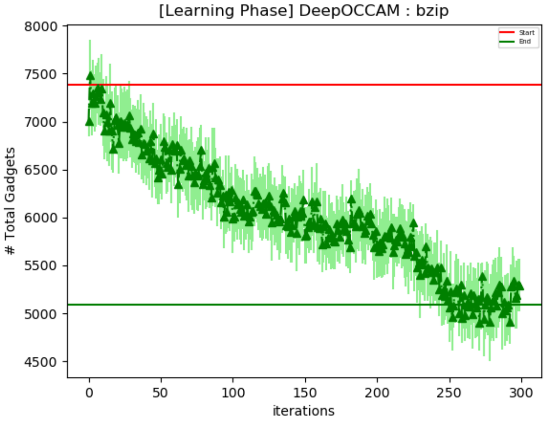


Figure 19: **DeepOCCAM Total**

300 iterations bzip - inst2vec bzip embedding

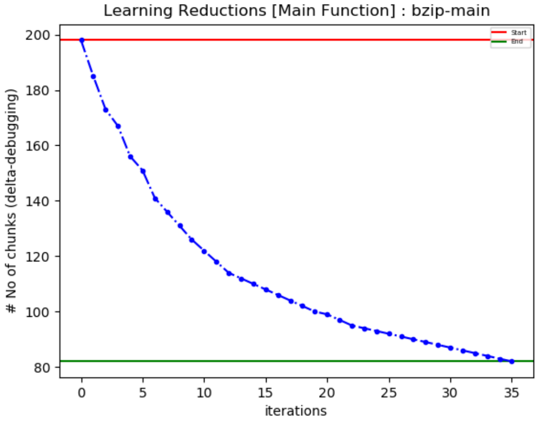


Figure 20: **Chisel** Learning bzip `main()`

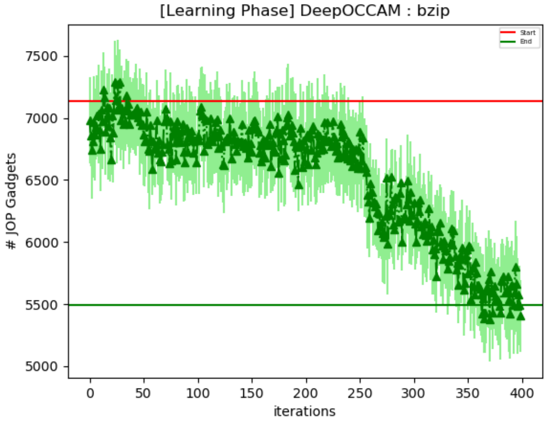


Figure 21: **DeepOCCAM JOP**

400 iterations bzip - HF

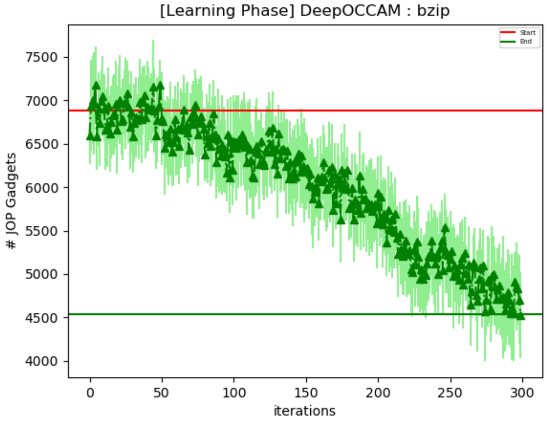


Figure 22: **DeepOCCAM JOP**

300 iterations bzip - inst2vec bzip embedding

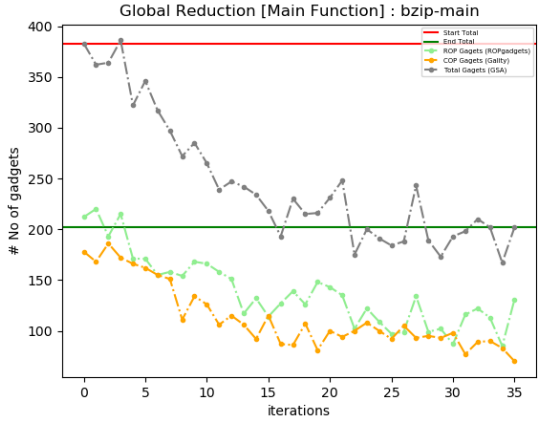


Figure 23: **Chisel** Gadgets Count `main()`

XI. Comparision & Analysis Metrics

We divide our analysis and comparision into two parts where the Static Analysis covers all the AST level modifications and reductions done by the tools are measured and comapred via CFG Analysis. The static analysis metrics are already provided by the tools. In some cases we modified it to get as much as details as possible from the static transforamtions that were happening in the tools. The second part is Dynamic Analysis where we compare only the final binary produced by the tools using `ROPgadgets` tool and `GadgetsSetAnalyzer` for `ROP`, `JOP`, `COP`, `SYS` & `Total Unique Gadgets` count.

A. Comparision : Static Analysis

We get static analysis details from the tools after all the reduction and elimination passes have been completed. `OCCAM`. `OCCAM-T (Trimmer)` & `DeepOCCAM` all implement a final `rewrite` pass (this is a major part of the OCCAM tool to write the final bitcode, and these tools have been developed from `OCCAM`) after which they dump the static analysis details . The metrics against which we show the comparision are `Function counts`, `Instruction counts`, `External call counts`, `Direct Call counts` etc.

B. Comparision : Dynamic Analysis

We use the final binary that we get from the runs of these tools to extract information regarding runtime behaviour and check for metrics that define an active attack surface. These metrics are mainly `ROP`, `JOP`, `COP`, `SYS` & `Total Unique Gadgets` counts. We modified the source code for `GadgetSetAnalyzer` to enable a easier `single_run()` function to get the `counts` as a `JSON` dump from the the tool directly. Each of the `docker` containers used for building the pipeline have `ROPgadgets`, `gality`, `angr` & `GadgetSetAnalyzer` installed for easy use. A sample dump would look like as below.

```
{
  "COP gadgets": 146,
  "JOP gadgets": 1951,
  "ROP gadgets": 567,
  "Total unique gadgets": 2664
}
```

C. Why Gadgets Count?

Call Oriented programming (COP),**Jump Oriented programming (JOP)** and **Return Oriented Programming (ROP)** are **computer security exploitation** techniques. The hacker uses the binary instructions to combine some sort of short sequences of instructions which are commonly called **gadgets** using return section code in the stack and make **unwanted** stack sections directly **executable**. The gadgets like COP, ROP & JOP **hijack** the actual control flow of the program and once the control is disturbed, hacker can make use of this **opportunity** to attack the system. Therefore, it is necessary to keep these gadgets as minimum as possible. While **debloating** the program **reduces** the number of gadgets, it is still not guaranteed that the attack is prevented but it **minimizes** the attack surface to a certain extent.

It is extremely important to keep track of the metrics of **gadgets** as these metrics when used to learn a RL policy will help in maximizing the rewards which in turn reduces the **code attack** surface. So while testing **DeepOCCAM**, these gadgets counts need to be tracked. We use the **number** of **gadgets** we get by running each tool namely **Chisel**, **OCCAM-T (Trimmer)**, **OCCAM** or our implementation of **DeepOCCAM** as a reasonably important metric of comparision.

nettest__bsd

Libraries/Tools	Before	None	Aggressive	DeepOCCAM	Non-rec	Only once	IPDSE/IPSCCP
				RL Model	Aggressive		Loop Unrolling
Functions	33	23	24	24	24	24	24
Basic Blocks	979	553	573	573	573	573	573
Instructions Count	6301	3045	3140	3140	3140	3140	3140
Direct Calls	862	402	412	412	412	412	412
External Calls	794	369	377	377	377	377	377
Memory Instructions Load/Store	2859	1350	1396	1396	1396	1396	1396

Table I: Comparison of `DeepOCCAM` with other `OCCAM` Run settings and `OCCAM-T Run (Trimmer)`

httpd

Libraries/Tools	Before	None	Aggressive	DeepOCCAM	Non-rec	Only once	IPDSE/IPSCCP
				RL Model	Aggressive		Loop Unrolling
Functions	1083	477	428	430	444	416	441
Basic Blocks	12943	11615	12563	13562	12999	11401	12652
Instructions Count	83238	62428	65842	66521	70773	61667	65252
Direct Calls	22603	5279	5152	5259	5932	5175	5869
External Calls	20712	4152	4563	4628	4787	4116	4625
Memory Instructions Load/Store	17071	16334	18345	17056	18347	16188	17854

Table II: Comparison of `DeepOCCAM` with other `OCCAM` Run settings and `OCCAM-T Run (Trimmer)`

GNU Tree

Libraries/Tools	Before	None	Aggressive	DeepOCCAM	Non-rec	Only once	IPDSE/IPSCCP
				RL Model	Aggressive		Loop Unrolling
Functions	52	40	41	44	44	40	42
Basic Blocks	1458	1845	1850	1891	1891	1845	1850
Instructions Count	7442	8957	9152	9286	9286	8957	9365
Direct Calls	1051	1257	1150	1290	1290	1257	1362
External Calls	845	1167	1147	1200	1200	1167	1058
Memory Instructions Load/Store	1944	2362	2344	2344	2344	2222	2452

Table III: Comparison of `DeepOCCAM` with other `OCCAM` Run settings and `OCCAM-T Run (Trimmer)`

airtun_ng-airtun-ng

Libraries/Tools	Before	None	Aggressive	DeepOCCAM	Non-rec	Only once	IPDSE/IPSCCP
				RL Model	Aggressive		Loop Unrolling
Functions	4	4	3	3	3	4	3
Basic Blocks	451	445	450	450	450	445	448
Instructions Count	2521	2481	2523	2523	2523	2481	2523
Direct Calls	328	327	330	330	330	327	330
External Calls	322	321	326	326	326	321	325
Memory Instructions Load/Store	671	658	672	672	672	658	675

Table IV: Comparison of `DeepOCCAM` with other `OCCAM` Run settings and `OCCAM-T Run (Trimmer)`

bzip2

Libraries/Tools	Before	None	Aggressive	DeepOCCAM	Non-rec	Only once	IPDSE/IPSCCP
				RL Model	Aggressive		Loop Unrolling
Functions	61	35	54	54	54	35	54
Basic Blocks	2776	2538	3137	3137	3137	2538	3137
Instructions Count	24412	20540	23769	23769	23769	20540	23769
Direct Calls	4714	621	1011	1011	1011	621	1011
External Calls	4575	515	835	835	835	515	835
Memory Instructions Load/Store	5144	5209	5989	5989	5989	5209	5989

Table V: Comparison of `DeepOCCAM` with other `OCCAM` Run settings and `OCCAM-T Run (Trimmer)`

curl

Libraries/Tools	Before	None	Aggressive	DeepOCCAM	Non-rec	Only once	IPDSE/IPSCCP
				RL Model	Aggressive		Loop Unrolling
Functions	124	59	62	62	52	59	57
Basic Blocks	2823	2764	4256	4375	3369	2764	3369
Instructions Count	11870	11777	17965	18106	14512	11777	15854
Direct Calls	1786	1696	2423	2500	2005	1696	2145
External Calls	1234	1250	1911	1911	1519	1250	1975
Memory Instructions Load/Store	2503	2511	3698	3858	3048	2511	3625

Table VI: Comparison of `DeepOCCAM` with other `OCCAM` Run settings and `OCCAM-T Run (Trimmer)`

NET UUID Program							
Libraries/Tools	**Before**	**None**	**Aggressive**	**Machine Learning**	**Non-rec Aggressive**	**Only once**	**IPDSE/IPSSCP Loop Unrolling**
Functions	10	9	9	9	9	9	9
Basic Blocks	38	34	34	34	34	34	34
Instructions Count	349	304	304	304	304	304	304
Direct Calls	23	20	20	20	20	20	20
External Calls	12	9	9	9	9	9	9
Memory Instructions Load/Store	141	128	128	128	128	128	128

Table VII: Comparison of `DeepOCCAM` with other `OCCAM` Run settings and `OCCAM-T Run (Trimmer)`

netsh Program Program							
Libraries/Tools	**Before**	**None**	**Aggressive**	**Machine Learning**	**Non-rec Aggressive**	**Only once**	**IPDSE/IPSSCP Loop Unrolling**
Functions	12	11	13	13	13	11	11
Basic Blocks	313	312	332	332	332	312	312
Instructions Count	1319	1315	1417	1417	1417	1315	1315
Direct Calls	195	194	196	196	196	194	194
External Calls	172	171	173	173	173	171	171
Memory Instructions Load/Store	433	431	481	481	481	431	431

Table VIII: Comparison of `DeepOCCAM` with other `OCCAM` Run settings and `OCCAM-T Run (Trimmer)`

Chisel Tool (Final)	**bzip**		**date**		**mkdir**		**rm**		**tree**	
Binary Metrics	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**	**Before**	**After**
ROP Gadgets	646	313	408	166	210	84	485	111	567	405
COP Gadgets	97	55	39	8	7	5	44	5	50	9
JOP Gadgets	6728	1562	5214	877	2282	176	4476	190	2126	775
Total Unique Gadgets (Excluding SYS & Chain)	7374	1930	5626	1046	2492	260	4965	301	2693	1187

Table IX: Dynamic Binary Analysis results for `Chisel` for **Gadgets Count**

Bzip2 Program	Original	Chisel Tool	OCCAM-T (Trimmer)	DeepOCCAM RL Model	OCCAM Aggressive	OCCAM None
ROP Gadgets	646	313	1311	1395	1336	1455
COP Gadgets	97	55	208	226	205	236
JOP Gadgets	6872	1562	3784	3722	3848	4585
Total Unique Gadgets (Excluding SYS & Chain)	7374	1930	5284	5117	5185	6345

Table X: Dynamic Binary Analysis : Gadgets Count comparision for Bzip2

GNU Tree	Original	Chisel Tool	OCCAM-T (Trimmer)	DeepOCCAM RL Model	OCCAM Aggressive	OCCAM None
ROP Gadgets	567	405	483	567	713	515
COP Gadgets	50	9	19	146	39	83
JOP Gadgets	2126	775	2774	1951	1951	2564
Total Unique Gadgets (Excluding SYS & Chain)	2693	1189	3258	2664	2664	3162

Table XI: Dynamic Binary Analysis : Gadgets Count comparision for GNU Tree

XII. Observations & Fails

For `DeepOCCAM` tool, using `bzip` & `tree` source code files for generating the `inst2vec` embeddings worked out well in debloating `bzip` & `tree` but it does defeat the purpose that we can't generate the embeddings in inst2vec first and then use it for feature vector creation in metadata stage, each time that we want to run `DeepOCCAM`. Using prembedded `inst2vec` embeddings, we got too many `broken` runs.

For some of the tools and libraries, `OCCAM` or any variant of `OCCAM` say `OCCAM-T` or `DeepOCCAM` did no significant reduction of the attack surface nor did it decrease static analysis metric counts, reason for that could failure in proper specialization of the function at the call-site or rewrite passes failling due to ammalgamation pass not working correctly. The exact reason for this observation is unknown to us.

A. *Insights*

The way we encode the states heavily depends on the metrics that can directly help in reducing the final comparision metric we are using for comparision of two tools. It is not a trivial task to decide as to whether we should specialize a function at a call-site or not. We ran `OCCAM` and `DeepOCCAM` under a random specialization policy where we took the decision to specialize or not at random and found that in some cases, the `global fixed point` computation took a huge time (1 2) days to terminate. We definitely need a proper understanding of what are the effects of `specializing` at a call-site and also on what counts to choose for a good `hand crafted` heuristics based feature vector, `HF` in short.

XIII. Conclusion (Finally, Who won?)

It may appear from the data we shared and the plots we showed in the `Project` that `Chisel` tool works the best in-terms of deblaoting `C` or `C++` based software projects, but it isn't scalable since, it long time for the `Chisel` tool to run on each benchmark set and debloat it. For `bzip` it took 14 hours to complete the run with training enabled, however, `DeepOCCAM` took just 5 hours to finish and reach a stead state on the gadgets count.

Each tool we used in our project shines in some contexts but lags in the other. The `Chisel` tool has one added advantage over all other tools since it does `source-to-source` transformation, which can help a developer to identify certain code pieces directly with a tool like `diff` to know what is `undesired` in the current execution context and further feature developement or enhancement of that piece of code is no more required in the settings that the end user would use the final tool.

Unlike `OCCAM` tool or it's other variants `OCCAM-T` or `DeepOCCAM` which are easy to run and setup for a given `C` or `C++` based software projects, `Chisel` tool requires more work from the developer/end-user since writing the `test.sh` oracle script that executes the tests for the given project is harder to write compared to a just a `manifest` file for the former, thus the former tools shine in this aspect. Moreover it may not be possible for developers to write good enough tests for the `Chisel` tool oracle specification. Using `fuzzing` or `EGT based Symbolic Execution` along with `Chisel` may work out great but that is for future works.

There is no clear winner amongst `debloating` tools and it completely depends of the purpose and the intention of the developer as to what all needs to be removed from the code yet guaranteeing soundness and completeness up-to certain extent.

XIV. Other Tools

We used many other tools for completing the project especially related to multiple runs, builds and execution of the tools. We list the most important ones below:

- `GNU Parallels` tool for multiple runs and execution of both `Chisel` tool and `OCCAM` in dockers.
- `gllvm & wllvm` to generate whole-library LLVM bitcode files from multiple files `C` or `C++` source files.
- `PyTorch` : For `DeepOCCAM` RL implementation.
- `MLPack` : `Chisel` Probabilistic model code. (Markov Process Modelling).

XV. Project Assets

We share below a list of the `docker` images and `GitHub` repositories that we used either directly or used with modification in the source code.

A. *GitHub Repositories*

- OCCAM Tool : `https://github.com/lahiri-phdworks/OCCAM`
- OCCAM Test & Benchmarks : `SRI-CSL OCCAM Benchmarks`
- Chisel-Bench : `Modified Chisel Benchmarks`
- Chisel Tool : `Chisel Tool`
- Inst2Vec : `Modified Inst2Vec tool`
- Binary GSA Testing Tool : `GadgetSetAnalyzer Repository`
- DeepOCCAM : `DeepOCCAM Implementation which we used to get insights to develop on top of OCCAM`

B. *Docker Images : Repository Links*

- Docker Images : `Docker Images [use the recent ones]`

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