Automatic Parameter Tuning for Boogie

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Abstract

We use machine learning to predict if a certain flag must be used or not while using Boogie to check for satisfiability in a C program. The flag under consideration directly affects the overall runtime of Boogie needed to perform the check.

Keywords: Boogie, feature extraction, labeling, logistic regression, gradient descent, BFGS optimization

1. Introduction

A standard technique in verification is to transform a given program into set of verification conditions whose validity implies satisfiability of correctness property under consideration. To achieve this, practical approach is:

- 1. Transform program and proof obligations into intermediate representation
- 2. Transform intermediate representation to logical formulas

Boogie is intermediate language which can encode verification conditions for OOP. It exists for Spec#, C, Dafny, Java bytecode, Eiffel. Since Boogie is works for multiple languages, instead of building a parser for each language, we can operate directly on Boogie code and be able to perform verification on code in all these languages. Using machine learning has it's own benefits:

- Almost everyone is finding ways to incorporate it in their work.
- Machine Learning techniques to learn from failed predictions and is self-learning. It also scales well as the data size increases.
- This needs good amount of training data to generate a model (current SV-comp repository has 15,000 benchmarks)

Machine learning techniques come with their own limitations:

- No sure way to know if 15,000 benchmarks are enough for a good model.
- Figuring out good features for boogie programs and extract them is a difficult task.
- Predictions are mostly heuristics based so we still need to run the verification tools to confirm the output.
- Figure out a good ML algorithm to train is a difficult choice.

The goal of this project is to figure out the behavior of /trackAllVars (a FLAG which can be used while SMACK tool tries to verify a given property on a C program).

2. Overview

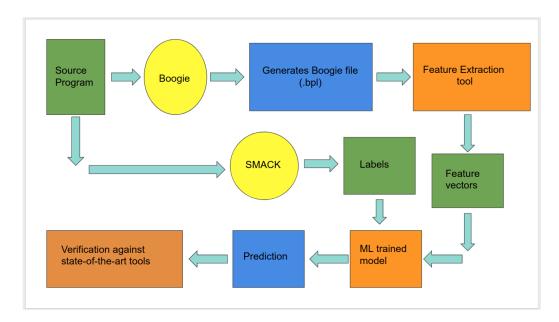


Figure 1: Architecture

The project is divided into following 3 parts:

- 1. Generate Features
- 2. Generate Labels
- 3. Machine Learning Implementation

Features are generated from Boogie files (.bpl) whereas labels are generated by running SMACK tool on SV-COMP C benhmarks (.c files). The first step for an efficient machine learning is selection of features.

For this problem, .bpl files can be generated in following 2 ways:

- 1. Run SV-COMP benchmarks on Boogie.
- 2. Run SV-COMP benchmarks on SMACK.

Since we are using SMACK to generate the labels and SMACK generates Boogie files, we used SMACK to generate the boogie files. Once all the .bpl files are generated, we use the feature extraction tool (2.1) to extract the features. The TIMEOUT for SMACK tool to verify each .c file was set to 900 seconds but waiting that long for .bpl files was time consuming. So we generate .bpl files separately with TIMEOUT set to 3 seconds without caring whether SMACK was able to verify the property or not.

2.1. Generating features

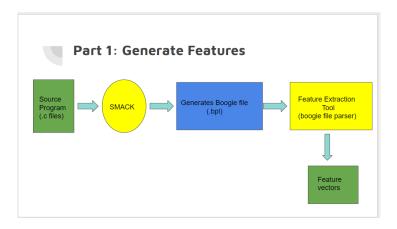


Figure 2: Feature Generation architecture

Once all the .bpl files are generated, we use the Boogie Feature Extractor to extract the features. Following is a sample of Boogie file.

```
// RUN: %boogie -typeEncoding:m "%s" > "%t"
// RUN: %diff "%s.expect" "%t"

type{:datatype} finite_map;
function{:constructor} finite_map(dom:[int]bool, map:[int]int):finite_map;

type{:datatype} partition;
function{:constructor} partition(owners:[int]int, vars:[int]finite_map):partition;

procedure P(arr:finite_map)
requires dom#finite_map(arr)[0];
ensures dom#finite_map(arr)[0];
{
}
```

Figure 3: Sample Boogie code

For this project, we deal with basic counting features like counting number of functions, variables, constant type declarations, number of functions with implementations

Lemma 1: A singular matrix is a matrix with no inverse i.e. the matrix is not invertible (mostly caused when 2 rows are similar). Lets say that r1, r2 are 2 rows of a matrix A and r1 = c * r2 where c is some constant then A has no inverse.

The features need to be selected carefully to avoid creating a singular matrix. In Boogie, number of functions and number of implementations of functions can be different because they are declared and implemented separately and some functions don't have an implementation (body). The pattern above is

```
vers--net--phy--davicom.ko-ldv_main0_sequence_infinite_withcheck_stateful.cil.out.bpl,16,1355,87,103,1,0

vers--net--phy--davicom.ko-ldv_main0_sequence_infinite_withcheck_stateful.cil.out.bpl,16,1355,87,103,0,0

rivers--watchdog--iTCO_vendor_support.ko-ldv_main0_sequence_infinite_withcheck_stateful.cil.out.bpl,46,1355,123,106,1,0

rivers--watchdog--iTCO_vendor_support.ko-ldv_main0_sequence_infinite_withcheck_stateful.cil.out.bpl,46,1355,123,106,0,0

rivers--platform--x86--mxm-wmi.ko-ldv_main0_sequence_infinite_withcheck_stateful.cil.out.bpl,16,1355,94,69,1,0

rivers--platform--x86--mxm-wmi.ko-ldv_main0_sequence_infinite_withcheck_stateful.cil.out.bpl,16,1355,94,69,0,0

rivers--hwmon--gpio-fan.ko-ldv_main0_sequence_infinite_withcheck_stateful.cil.out.bpl,21,1355,175,726,1,0

rivers--rhwmon--gpio-fan.ko-ldv_main0_sequence_infinite_withcheck_stateful.cil.out.bpl,21,1355,175,726,0,0

vers--auxdisplay--cfag12864bfb.ko-ldv_main0_sequence_infinite_withcheck_stateful.cil.out.bpl,16,1355,109,166,1,0

vers--auxdisplay--cfag12864bfb.ko-ldv_main0_sequence_infinite_withcheck_stateful.cil.out.bpl,16,1355,109,166,0,0
```

Figure 4: Sample of feature vectors

{Filename} {no. of implementations} {no. of variables} {no. of constants} {no. of type declarations} {no. of functions} {/Trackallvars status}.

/Trackallvars status is a special feature not extracted from the .bpl files. It is a Flag which affects the runtime for SMACK to verify property for a given .c

file. I experiment with both, Keeping the Flag=ON (0) and Flag=OFF (1). This approach was primarily used because when a new .c file is encountered, we don't know if to keep the Flag On or Off.

2.2. Generating Labels

In the previous section, we saw that /TrackAllVars was a special feature that we added. In this section, we explain in detail how the value of this feature was set and how the final labels were generated. From the dia-

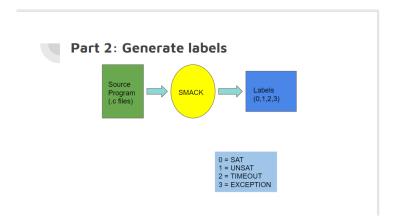


Figure 5: Label Generation architecture

gram, we can see that we use the .c files from SV-COMP repository to run SMACK. We run 2 instances of SMACK for each input file, one with /track-AllVars=ON and other with /track-AllVars=OFF. The TIMEOUT=900 seconds i.e. SMACK will either verify the property to be SAT/ UNSAT in 900 seconds or return a label TIMEOUT. We then merge the features with labels by comparing the filename. In this step, we also add an extra feature /track-AllVars depending on which file it was merged from. So, for each input file, we had 2 feature vectors only differing in the column for /track-AllVars. After the correct encoding for labels, we achieve the following where the last entry on each row is the label. It can be noted that 2 rows are same except for the /track-AllVars status and label. For some files, setting the flag=ON/OFF didn't matter and they resulted in same label.

```
|/proj/SMACK/sv-benchmarks/c/recursive/recHanoi02_true-unreach-call_true-no-overflow_true-termination.c SAT |/proj/SMACK/sv-benchmarks/c/recursive/Ackermann03_true-unreach-call_true-no-overflow.c SAT |/proj/SMACK/sv-benchmarks/c/recursive/Ackermann03_true-unreach-call_true-no-overflow.c SAT |/proj/SMACK/sv-benchmarks/c/recursive/Ackermann03_true-unreach-call_true-no-overflow.c SAT |/proj/SMACK/sv-benchmarks/c/recursive/McCarthy91_true-unreach-call_true-no-overflow.c SAT |/proj/SMACK/sv-benchmarks/c/recursive/McCarthy91_true-unreach-call_true-no-overflow_true-termination.c SAT |/proj/SMACK/sv-benchmarks/c/recursive/McCarthy91_true-unreach-call_true-no-overflow_true-termination.c SAT |/proj/SMACK/sv-benchmarks/c/truivers-simplified/floppy_simpl4_false-unreach-call_true-valid-memsafety_true-termination.cil.c SAT |/proj/SMACK/sv-benchmarks/c/tremination-memory-alloca-todo/a.07-alloca_false-no-overflow.c EXCEPTION |/proj/SMACK/sv-benchmarks/c/tremination-memory-alloca-todo/b.07-alloca_false-no-overflow.c EXCEPTION |/proj/SMACK/sv-benchmarks/c/termination-memory-alloca-todo/b.07-alloca_false-no-overflow.c EXCEPTION |/proj/SMACK/sv-benchmarks/c/termination-memory-alloca-todo/b.07-alloca_false-no-overflow.c EXCEPTION |/proj/SMACK/sv-benchmarks/c/termination-memory-alloca-todo/b.07-alloca_false-no-overflow.c EXCEPTION |/proj/SMACK/sv-benchmarks/c/termination-memory-alloca-todo/b.07-alloca_false-no-overflow.c EXCEPTION |/proj/SMACK/sv-benchmarks/c/termination-memory-alloca-todo/b.07-alloca_false-no-overflow.c EXCEPTION |/proj/SMACK/sv-benchmarks/c/seq-pthread/cs_fib_longer_false-unreach-call.c INTEOUT |/proj/SMACK/sv-benchmarks/c/seq-pthread/cs_fib_longer_false-unreach-call.c INTEOUT |/proj/SMACK/sv-benchmarks/c/seq-pthread/cs_fib_true-unreach-call.c INTEOUT |/proj/SMACK/sv-benchmarks/c/demination-restricted-15/a.09_assume_true-termination_true-no-overflow.c EXCEPTION |/proj/SMACK/sv-benchmarks/c/termination-restricted-15/a.09_assume_true-termination_true-no-overflow.c EXCEPTION |/proj/SMACK/sv-benchmarks/c/termination-r
```

Figure 6: Sample of Labels

2.3. Machine Learning implementation

Since the possible labels are 0,1,2,3, we use a well known classification algorithm in machine learning known as logistic regression. We treat this problem as multi-class classification problem and use the algorithm known as **one vs all classification algorithm**. **Notations:** FeatureMatrix = X, Labelsvector = Y Since we have 5 features, we generate a vector

$$\theta = [\theta_0 \theta_1 ... \theta_4 \theta_5]$$

These are our parameters.

$$h_{\theta}(x) = g(\theta^T x)$$

$$h_{\theta}(x) = g(\theta_0 + \theta_1 x_1 + \theta_2 x_2 + \dots + \theta_5 x_5)$$

Where g(z) is the sigmoid function defined as:

$$g(z) = \frac{1}{1 + e^{-z}}$$

We experiment with 700 .c files from SV-benchmarks so X is a 700x6 matrix and Y is 700x1 vector. From this we create our training data of size 500 i.e. \hat{X} is 500x6 matrix and \hat{Y} is 500x1 matrix and test data of size 200 i.e. \bar{X} is

```
16,1355,87,103,1,0

16,1355,87,103,0,0

46,1355,123,106,0,0

46,1355,123,106,0,0

16,1355,94,69,1,0

16,1355,94,69,0,0

21,1355,175,726,1,0

21,1355,175,726,0,0

16,1355,109,166,1,0

16,1355,109,166,0,0
```

Figure 7: Final matrix X[1:6],Y

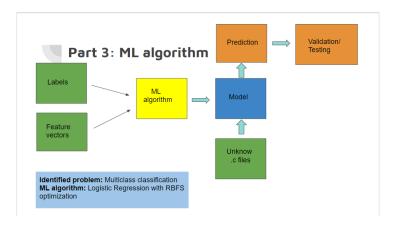


Figure 8: ML architecture

200x6
matrix and \bar{Y} is 200x1 matrix. The cost function for logistic regression is:

$$J(\theta) = \frac{-1}{m} \sum_{i=1}^{m} -y * log(h_{\theta}(x)) - (1-y) * log(1-h_{\theta}(x))$$

We want to compute the vector θ such that we $\min_{\theta} J(\theta)$ We can gradient descent performing simultaneous updates to vector θ in the following way:

$$\theta_j := \theta_j - \alpha \sum_{i=1}^m (h_\theta(x^{(i)}) - y^{(i)}) x_j^{(i)}$$

The problem with performing gradient descent is that it depends on the parameter α which controls how slow or quick we converge to the local min-

imum. Instead of gradient descent, we use BFGS optimization to compute the θ which computes $\min_{\theta} J(\theta)$

We obtain 95% accuracy on our test data when we compare the results of our predictions to that of the original labels.

Example: For an unknown test file: We run the above model for /track-AllVars=0 and /trackAllvars=1, and let's say we obtain foollowing combinations: If both predictions result into TIMEOUT/ EXCEPTION then we

0	1	Choice
SAT/UNSAT	TIMEOUT/ EXCEPTION	0
TIMEOUT/ EXCEPTION 2	SAT/UNSAT	1
TIMEOUT/ EXCEPTION 3	TIMEOUT/ EXCEPTION	Ø
SAT/ UNSAT	SAT/ UNSAT	1,0

Table 1: Table caption

need not run SMACK and thus, we can save overall runtime of SMACK. Whereas if one of the 2 results into SAT/ UNSAT then we activate the FLAG accordingly and still save runtime by not exploring all combinations. The worst case for this technique would be when both settings result into opposite results i.e. one results into SAT and other results into UNSAT. In that case, we have no choice but to try out both settings.

3. Conclusion

The θ we received was [-0.000001-0.000023-0.001635-0.0001450.000068-0.000001] and we achieved a 95% success in predicting the labels correctly. With the results from this report, we can see some hope in incorporating Machine Learning techniques to Software Verification tools to not necessarily perform the verification itself, but to optimize the parameters for verification tools to reduce the runtime significantly by not exploring over all possible parameter combinations for each input file. The reduction in number of TIMEOUT is a sign of a good verification tool.

The source code can be found at

 $https://github.com/ankit--agrawal/SV_course/tree/master/Project/source_code$ The results are reproducible and only the .bpl files are not available on the Github repository because they were huge

4. References

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