Predicting Rankings of Software Verification Competitions[*]

Anonymous Author(s)

ABSTRACT

Software verification competitions, such as the annual SV-COMP, evaluate software verification tools with respect to their effectivity and efficiency. Typically, the outcome of a competition is a *ranking* of the tools. For many applications, such as building portfolio solvers or simply choosing a verification tool for a program at hand, it would be desirable to have an idea of the (relative) performance of verification tools on a given program *beforehand*, i.e., prior to actually running all tools on the program.

In this paper, we present a machine learning approach to *predicting* rankings of tools on programs. The method builds upon so-called label ranking algorithms, which we complement with appropriate *kernels* providing a similarity measure for programs. Our kernels employ a graph representation for software source code that mixes elements of control flow and program dependence graphs with abstract syntax trees. Using data sets from SV-COMP, we demonstrate our rank prediction technique to generalize well and achieve a rather high predictive accuracy.

CCS CONCEPTS

•**Computing methodologies** →**Ranking;** *Support vector machines;* Cross-validation; •**Software and its engineering** →Software verification; Formal software verification;

KEYWORDS

Software verification, machine learning, ranking.

1 INTRODUCTION

Over the past years, software analytics [7] has become a very active research area. Software analytics is concerned with analysing software source code and its associated artefacts like code reviews, documentation and bug reports. Such data can today be found in numerous repositories and analysis can provide insights into various sorts of questions in software development, ranging from program understanding over defect prediction to power consumption.

In this paper, we employ software analytics to get an answer to the question "What software verification tool do I use for showing correctness of my program?". Software verification tools today are

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[*]Title note

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1  int i;          6  i = 0;
2  int n;          7  while (i <= n)
3  int sn;         8      sn = sn + 2;
4  n = input();    9      i = i + 1;
5  sn = 0;         10 assert (sn == n*2 || sn == 0);
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Figure 1: The verification task P_{SUM}

numerous and the past years have seen the tuning of tools to performance and precision, but still not every tool is suitable for every program and property at hand. Software verification competitions provide a comparison of tools on the basis of given benchmark verification tasks, i.e., programs together with properties. In the area of automatic verification, the most prominent competition today is the annual Competition on Software Verification SV-COMP [1]. The outcome of SV-COMP are *rankings of tools* (overall and per categories) computed by means of a scoring schema. These annually published ranking results provide data about the relative performance of tools and is readily usable for software analytics. Based on this data, a *prediction* of a likely ranking of tools on a given new verification task becomes possible. In this paper, we develop a method for performing such rank predictions.

Our method for rank prediction builds upon machine learning methods for the so-called *label ranking* problem; more specifically, we make use of *ranking by pairwise comparison* [5] using support vector machines as base learners. The key ingredient of our approach is the definition of suitable *kernel functions* [9], which act as similarity measures on verification tasks. So far, two other machine learning methods for selecting (albeit not ranking) tools or algorithms for verification have been proposed [3, 11], both of them being based on feature vectors explicitly capturing structural features of programs (like number of variables, loops, etc.). With our kernels, we take a different approach: we supply the learning algorithm with a representation of source code that enables the learner itself to identify the distinguishing patterns. We believe that our kernels are thus more readily usable for other program analysis tasks.

We have implemented our technique and carried out experimental (cross-validation) studies using data from SV-COMP 2015 and 2017. The experiments show that our technique can predict rankings with high accuracy.

2 REPRESENTING VERIFICATION TASKS

Our objective is to *predict* rankings of software verification competitions via machine learning. To this end, the learning algorithm has to be supplied with training data. We start with explaining what kind of data our rank prediction technique is supplied with, namely verification tasks and rankings.

Definition 2.1. A *verification task* (P, φ) consists of a program P (for SV-COMP written in C) and a property (also called specification) φ (typically written as assertion into the program).

Loop	loop	If	conditional
Decl	variable declaration	Assign	variable assignment
Incr	variable increment	Assert	assertion
Ref	variable reference	Int_Literal_Small	integer literal in [0,10]
Function_Call	function call	Int_Literal_Medium	integer literal in [10,100]
Function_Return	function return	Int_Literal_Large	integer literal > 100

Table 1: Some node identifiers and their meaning

Figure 1 shows our running example P_{SUM} of a verification task (computing n times 2 via addition). In a verification run, a verification tool is run on a verification task in order to determine whether the program fulfills the specification. The outcome of such a verification run is a pair (TIME, ANSWER), where TIME is the time in seconds from the start of the verification run to its end, and ANSWER is either TRUE, FALSE or UNKNOWN. The ranking is done via a scoring schema which gives positive and negative points to outcomes. When the scores of two tools are the same, the runtimes (of successful runs) determine the ordering.

The purpose of the machine learning algorithm is to learn from the provided ranking how tools will perform on specific verification tasks. Our machine learning technique is based on *kernel methods* (see e.g. [9]). In general, a kernel can be interpreted as a similarity measure on data instances (in our case verification tasks), with the idea that similar results (in our case rankings) are produced for similar instances. While kernel-based learning algorithms are completely generic, the kernel function itself is application-specific.

The simplest way of defining a kernel is via the inner product of *feature vectors*, i.e., vectorial representations of data objects. In the two approaches existing so far [3, 11], corresponding features of programs, such as number of loops, are defined in an explicit way. Our approach essentially differs in that features are specified in a more indirect way, namely by systematically extracting (a typically large number of) generic features from a suitable representation of the verification task. Selecting the useful features and combining them appropriately is then basically left to the learner.

But how to represent the verification tasks? The first idea is to use the source code itself (i.e., strings). However, the source code of two programs might look very different although the underlying program is actually the same (different variable names, while instead of for loops, etc.). What we need is a representation that abstracts from such issues but still represents the structure of programs, in particular dependencies between elements of the program. These considerations (and some experiments comparing different representations) have led to a *graph* representation of programs combining concepts of three existing program representations:

Control flow graphs: CFGs record the control flow in programs and thus the overall structure with loops, conditionals etc.; these are needed, for example, to see loops.
Program dependence graphs: PDGs [4] represent control and data dependencies between elements in programs. This information is important, e.g., to detect a loop boundary depending on an input variable (as in program P_{SUM}).
Abstract syntax trees: ASTs reflect the syntactical structure of programs according to a given grammar and can for instance help to reveal the complexity of expressions.

Unlike CFGs and PDGs but (partly) alike ASTs, we abstract from concrete names occuring in programs. Nodes in the graph will thus not be labelled with statements or variables as occuring in the program, but with abstract identifiers. We let *Lab* be the set of all such labels. Table 1 lists some identifiers and their meaning.

Definition 2.2. Let P be a verification task. The *graph representation* of P is a graph $G = (N, E, s, t, \rho, \tau, \eta)$ with

- N a set of nodes (basically, we build an AST for every statement in P, and use the nodes of these ASTs),
- E a set of edges, with $s : E \rightarrow N$ denoting the start and $t : E \rightarrow N$ the end node of an edge,
- $\rho : N \rightarrow Lab$ a labelling function for nodes,
- $\tau : E \rightarrow \{CD, DD, SD, CF\}$ a labelling function for edges reflecting the type of dependence: *CD* (control dependency) and *DD* (data dependency) origin in PDGs, *SD* (syntactical dependence) is the "consists-of" relationship of ASTs and *CF* (control flow) the usual control flow in programs,
- $\nu : E \rightarrow \{T, F\}$ a function labelling control dependence edges according to the valuation of the conditional they arise from. All other edges are labelled true.

We let $\mathcal{G}_V$ denote the set of all verification task graphs.

Figure 2 depicts the graph representation of the verification task P_{SUM}. The rectangle nodes represent the statements in the program and act as root nodes of small ASTs. For instance, the rectangle labelled Assert at the bottom, middle represents the assertion in line 10. The gray ovals represent the AST parts below the root nodes. We define the *depth* of nodes n, $d(n)$, as the distance of a node to its root node. As an example, the depth of the Assert-node itself is 0, the depth of both ==-nodes is 2.

3 PREDICTING RANKINGS

This section starts with a short description of label ranking and the method of ranking by pairwise comparison. Moreover, we introduce our kernel functions on verification tasks.

3.1 Label Ranking

In the setting of label ranking (see e.g. [5]), we are interested in predicting rankings (total orders) $\succ$ on a finite set of K alternatives identified by *class labels* $\mathcal{Y} = \{y_1, \ldots, y_K\}$; in our case, the alternatives correspond to the verification tools to be compared. Formally, a total order $\succ$ can be identified with a permutation π of the set $[K] = \{1, \ldots, K\}$. Preferences on $\mathcal{Y}$ are "contextualized" by instances $x \in \mathcal{X}$, where $\mathcal{X}$ is an underlying instance space; in our case, instances are programs to be verified. Thus, each instance x is associated with a ranking $\succ_x$ of the label set $\mathcal{Y}$.

The goal in label ranking is to learn a "label ranker", that is, a model $\mathcal{M} : \mathcal{X} \rightarrow \mathbb{S}_K$, where $\mathbb{S}_K$ denotes the class of permutations
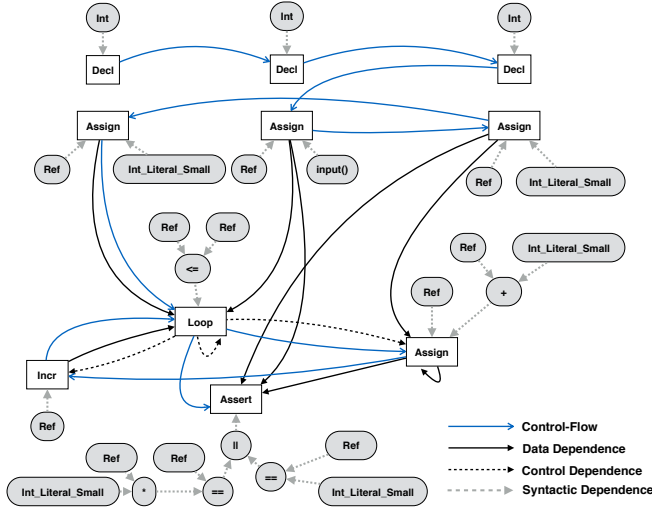
Figure 2: Graph representation of P_{SUM} eliding labelling v

of $[K]$. The predictions $\hat{\pi} = \mathcal{M}(x)$ produced by such a model for an instance x are evaluated in terms an accuracy measure such as the *Spearman rank correlation*:

$$S(\pi, \hat{\pi}) = 1 - \frac{6 \sum_{i=1}^{K} (\pi(i) - \hat{\pi}(i))^2}{K(K^2 - 1)} \in [-1, 1]$$

As training data $\mathbb{D}$, a label ranker uses a set $\{(x_n, \pi_n)\}_{n=1}^{N}$ of instances with associated rankings.

3.2 Ranking by Pairwise Comparison

We tackle the label ranking problem using the method of *ranking by pairwise comparison* (RPC), a meta-learning technique that reduces a label ranking task to a set of binary classification problems [5]. More specifically, the idea is to train a separate model (base learner) $\mathcal{M}_{i,j}$ for each pair of labels $(y_i, y_j) \in \mathcal{Y}$, $1 \leq i < j \leq K$, and to combine the predictions of these models into an overall ranking.

The models $\mathcal{M}_{i,j}$ can be trained by any binary classifier as base learner. In our approach, we use support vector machines [9] for this purpose. SVMs are so-called "large margin" classifiers separating positive from negative training instances in $\mathbb{R}^m$ by means of a linear hyperplane. They can be turned into more flexible, nonlinear classifiers using the idea of "kernelization". To this end, a kernel function on $\mathcal{X}$ is needed.

Definition 3.1. A function $k : \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}$ is a *positive semidefinite kernel* iff k is symmetric, i.e., $k(x, x') = k(x', x)$, and

$$\sum_{i=1}^{N} \sum_{j=1}^{N} c_i c_j k(x_i, x_j) \geq 0$$

for arbitrary N, arbitrary instances $x_1, \ldots, x_N \in \mathcal{X}$ and arbitrary $c_1, \ldots, c_N \in \mathbb{R}$.

Next, we address the question of how to define appropriate kernel functions on verification tasks.

Algorithm 1 relabel (Graph relabelling)

Input: $G = (N, E, s, t, \rho, \tau, v)$ graph
    $z : \Sigma^* \rightarrow \Sigma$ injective compression function
    $\eta : N \rightarrow 2^E$ neighbour function
    m iteration bound
Output: relabelled graph G
1: **for** $i = 1$ to m **do**
2:     **for** $n \in N$ **do**
3:         $Aug(n) := \langle z(\rho(s(e)) \oplus \tau(e) \oplus v(e)) \mid e \in \eta(n) \rangle$
4:         $Aug(n) := sort(Aug(n))$
5:         $str(n) := concat(Aug(n))$
6:         $str(n) := \rho(n) \oplus str(n)$
7:         $\rho(n) := z(str(n))$
8: **return** G

3.3 Graph Kernels for Verification Tasks

Verification tasks are represented by specific graphs, whence our kernel needs to operate on graphs. As our graphs are representations of programs with several thousands lines of code, we have chosen to proceed from our own kernel development based on *Weisfeiler-Lehman subtree kernels* [10], which are known to scale well to large graphs.

Weisfeiler-Lehman (WL) kernels are extensions of the WL test of isomorphism between two discretely labelled, undirected graphs [12]. This test basically compares graphs according to their node labels. For taking edges into account, node labels are extended with information about neighbouring nodes in three steps: Concatenate label of node n with labels of its neighbours (Augmentation), sort this sequence according to predefined order on labels (Sorting), compress thus obtained sequences into new labels (Compression). These steps are repeated until the node label sets of the two graphs differ or a predefined bound on the number of iterations is exhausted.

For making this WL test act as a kernel for verification tasks, we made three adaptations to the graph relabelling, giving rise to Algorithm 1: (1) extension to directed multigraphs, (2) customization to specific neighbours of nodes, and (3) integration of edge labels. In Algorithm 1, we use the notation $\langle \ldots \mid \ldots \rangle$ for list comprehensions, defining a sequence of values. We let $\Sigma = \mathbb{N}$ with the usual ordering $\leq$ and map all node identifiers and edge labels to $\mathbb{N}$. The functions *sort* and *concat* sort sequences of labels (in ascending order) and concatenate sequences, respectively.

Definition 3.2. Let $G_i = (N_i, E_i, s_i, t_i, \rho_i, \tau_i, v_i)$, $i = 1, 2$ be graph representations of verification tasks, $z : \Sigma^* \rightarrow \Sigma$ a compression function, $m \in \mathbb{N}$ an iteration bound, $d \in \mathbb{N}$ a depth for subtrees and $\eta_i : N_i \rightarrow 2^{E_i}$ neighbour functions. The *verification graph kernel* $k_{\eta_1, \eta_2, z}^{(d, m)} : \mathcal{G}_V \times \mathcal{G}_V \rightarrow \mathbb{R}$ is defined as

$$k_{\eta_1, \eta_2, z}^{(d, m)}(G_1, G_2) = \sum_{i=1}^{m} k^d \begin{pmatrix} relabel(G_1, z, \eta_1, m), \\ relabel(G_2, z, \eta_2, m) \end{pmatrix}$$

with

$$k^d(G, G') = \sum_{n \in N} \sum_{n' \in N'} k_\delta^d(n, n') \text{ and}$$

$$k_\delta^d(n, n') = \begin{cases} \delta(\rho_1(n), \rho_2(n')) & \text{if } d(n) \leq d \wedge d(n') \leq d \\ 0 & \text{else} \end{cases},$$

Table 2: SV-COMP 2017 – Prediction accuracy (mean and standard deviation) in terms of the Spearman rank correlation

Kernel / Data Set	SAFETY	TERMINATION	MEMSAFETY
k_{CF} (CFG)	**.635 ± .003**	.657 ± .007	.755 ± .004
k_{DD} (data dependency)	.618 ± .003	.635 ± .006	.754 ± .007
k_{CD} (control dependency)	.627 ± .002	.637 ± .006	.756 ± .005
$k_{CD,DD}$ (PDG)	.630 ± .005	.644 ± .003	**.757 ± .007**
$k_{CF,CD,DD}$ (PDG + CFG)	.632 ± .004	.658 ± .009	.756 ± .003
weighted combination	.634 ± .003	**.664 ± .010**	.756 ± .003
features of [3]	.560 ± .004	.560 ± .006	.717 ± .001
default predictor	.452 ± .003	.339 ± .004	.668 ± .001

where δ is a Dirac kernel defined as $\delta(u, w) = 1$ if u equals w and 0 otherwise.

THEOREM 3.3. *The kernel $k_{\eta_1, \eta_2, z}^{(d, m)}$ is positive semi-definite.*

Our kernels can now be used in a support vector machine within the ranking by pairwise composition approach outlined above.

4 EXPERIMENTAL EVALUATION

We have implemented the above described technique as to evaluate the performance of our method for rank prediction. Here, we report on SV-COMP 2017 data. We compared six variants of our kernel with respect to prediction accuracy, each of which focuses on different aspects of a program. Such kind of customization of kernels becomes possible thanks to the two neighbouring functions η_1 and η_2. In our case, neighbours are chosen according to the type of edge connecting them. We define $\eta_\ell, \ell \in \{CD, DD, SD, CF\}$ to be $\eta_\ell(n) = \{e \mid \tau(e) = \ell \wedge t(e) = n\}$, and let $\eta_L(n) = \bigcup_{\ell \in L} \eta_\ell(n)$ for a node n. For our kernels, we always use the same neighbouring function on both graphs. Hence, we will just use the edge labels employed in neighbouring functions as indizes for kernels. Our experiments include kernels $k_{\{CF\}}, k_{\{CD\}}, k_{\{DD\}}, k_{\{CD,DD\}}$, and $k_{\{CF,CD,DD\}}$. In addition, we included an equally weighted linear combination k_{lin} of some of our kernels, which is defined as

$$k_{lin}(G_1, G_2) = \tfrac{1}{3} k_{\{CF\}}(G_1, G_2) + \tfrac{1}{3} k_{\{CD\}}(G_1, G_2) + \tfrac{1}{3} k_{\{DD\}}(G_1, G_2)$$

To get an insight on how the prediction accuracy performs compared to state-of-the-art approaches, we also included the accuracy achieved by using the feature vectors from Demyanova et al. [3]. In addition, we constructed a *default predictor* for comparison: the default predictor takes all rankings of the data set used for learning, determines the ranking which minimizes the distance (wrt. Spearman rank correlation) to these rankings and always predicts this default ranking without any learning.

We constructed the following data sets for our experiments: SAFETY, TERMINATION, and MEMSAFETY. Each data set consists of several verification tasks (up to 500) and participating tools (up to 11) and is taken from the SV-COMP 2017 benchmark sets. To examine the prediction accuracy for each configuration, we performed a 10-fold cross-validation. The overall *accuracy* is then the average over all the accuracies encountered in each step.

In Table 2, we report the average prediction accuracies (and standard deviations) in terms of the Spearman rank correlation; note that an average accuracy of 0 would be obtained by guessing rankings at random, while +1 stands for predictions that perfectly coincide with the true ranking (and −1 for completely reversing that ranking). As can be seen, our approach shows a rather strong

predictive performance. Depending on the verification task, different kernels achieve the best results, though the differences in performance are statistically non-significant. More importantly, our approach significantly outperforms the one of [3] as well as the default predictor on all tasks.

5 CONCLUSION

In this paper, we have proposed a method for predicting rankings of verification tools on given programs. Our rank prediction technique builds on existing methods for label ranking via pairwise comparison. To this end, we have developed an expressive representation of source code, capturing various forms of dependencies between program elements.

Our approach can be seen as a tool for *algorithm selection*, a problem that has also been tackled by other authors [3, 11, 13]. The use of Weisfeiler-Lehman kernels has been studied in [6, 8]. A machine learning approach to software verification itself has recently been proposed in [2]. However, to the best of our knowledge, the use of machine learning for predicting *rankings* of verification tools has never been tried so far.

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