# Learning a Static Analyzer from Data

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**Abstract.** To be practically useful, modern static analyzers must precisely model the effect of both, statements in the programming language as well as frameworks used by the program under analysis. While important, manually addressing these challenges is difficult for at least two reasons: (i) the effects on the overall analysis can be non-trivial, and (ii) as the size and complexity of modern libraries increase, so is the number of cases the analysis must handle.

In this paper we present a new, automated approach for creating static analyzers: instead of manually providing the various inference rules of the analyzer, the key idea is to learn these rules from a dataset of programs. Our method consists of two ingredients: (i) a synthesis algorithm capable of learning a candidate analyzer from a given dataset, and (ii) a counter-example guided learning procedure which generates new programs beyond those in the initial dataset, critical for discovering corner cases and ensuring the learned analysis generalizes to unseen programs. We implemented and instantiated our approach to the task of learning JavaScript static analysis rules for a subset of points-to analysis and for allocation sites analysis. These are challenging yet important problems that have received significant research attention. We show that our approach is effective: our system automatically discovered practical and useful inference rules for many cases that are tricky to manually identify and are missed by state-of-the-art, manually tuned analyzers.

## 1 Introduction

Static analysis is a fundamental method for automating program reasoning with a myriad of applications in verification, optimization and bug finding. While the theory of static analysis is well understood, building an analyzer for a practical language is a highly non-trivial task, even for experts. This is because one has to address several conflicting goals, including: (i) the analysis must be scalable enough to handle realistic programs, (ii) be precise enough to not report too many false positives, (iii) handle tricky corner cases and specifics of the particular language (e.g., JavaScript), (iv) decide how to precisely model the effect of the environment (e.g., built-in and third party functions), and other concerns. Addressing all of these manually, by-hand, is difficult and can easily result in suboptimal static analyzers, hindering their adoption in practice.

*Problem statement* The goal of this work is to help experts design robust static analyzers, faster, by automatically learning key parts of the analyzer from data.

We state our learning problem as follows: given a domain-specific language  $\mathcal{L}$  for describing analysis rules (i.e., transfer functions, abstract transformers), a dataset  $\mathcal{D}$  of programs in some programming language (e.g., JavaScript), and an abstraction function  $\alpha$  that defines how concrete behaviors are abstracted, the goal is to learn an analyzer  $pa \in \mathcal{L}$  (i.e., the analysis rules) such that programs in  $\mathcal{D}$  are analyzed as precisely as possible, subject to  $\alpha$ .

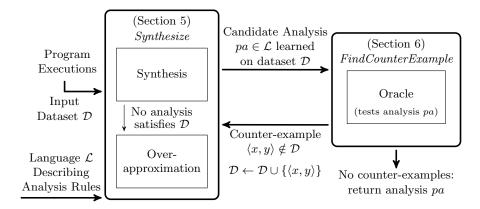
Key challenges There are two main challenges we address in learning static analyzers. First, static analyzers are typically described via rules (i.e., type inference rules, abstract transformers), designed by experts, while existing general machine learning techniques such as support vector machines and neural networks only produce weights over feature functions as output. If these existing techniques were applied to program analysis [29,25], the result would simply be a (linear) combination of existing rules and no new interesting rules would be discovered. Instead, we introduce domain-specific languages for describing the analysis rules, and then learn such analysis rules (which determine the analyzer) over these languages.

The second and more challenging problem we address is how to avoid learning a static analyzer that works well on some training data  $\mathcal{D}$ , but fails to generalize well to programs outside of  $\mathcal{D}$  – a problem known in machine learning as overfitting. We show that standard techniques from statistical learning theory [23] such as regularization are insufficient for our purposes. The idea of regularization is that picking a simpler model minimizes the expected error rate on unseen data, but a simpler model also contradicts an important desired property of static analyzers to correctly handle tricky corner cases. We address this challenge via a counter-example guided learning procedure that leverages program semantics to generate new data (i.e., programs) for which the learned analysis produces wrong results and which are then used to further refine it. To the best of our knowledge, we are the first to replace model regularization with a counter-example guided procedure in a machine learning setting with large and noisy training datasets.

We implemented our method and instantiated it for the task of learning production rules of realistic analyses for JavaScript. We show that the learned rules for points-to and for allocation site analysis are indeed interesting and are missed by existing state-of-the-art, hand crafted analyzers (e.g., Facebook's Flow [4]) and TAJS (e.g., [16]).

Our main contributions are:

- A method for learning static analysis rules from a dataset of programs. To
  ensure that the analysis generalizes beyond the training data we carefully
  generate counter-examples to the currently learned analyzer using an oracle.
- A decision-tree-based algorithm for learning analysis rules from data that learns to overapproximate when the dataset cannot be handled precisely.
- An end-to-end implementation of our approach and an evaluation on the challenging problem of learning tricky JavaScript analysis rules. We show that our method produces interesting analyzers which generalize well to new data (i.e. are sound and precise) and handle many tricky corner cases.



**Fig. 1.** Overview of our approach to learning static analysis rules from data consisting of three components – a language  $\mathcal{L}$  for describing the rules, a learning algorithm and an oracle – that interact in a counter-example based refinement loop.

## 2 Our Approach

We begin by describing components of our learning approach as shown in Fig. 1.

Obtaining training data  $\mathcal{D}$  Our learning approach uses dataset of examples  $\mathcal{D} = \{\langle x^j, y^j \rangle\}_{j=1}^N$  consisting of pairs  $\langle x^j, y^j \rangle$  where  $x^j$  is a program and  $y^j$  is the desired output of the analysis when applied to  $x^j$ . In general, obtaining such labeled training data for machine learning purposes is a tedious task. In our setting, however, this process can be automated because: (i) in static analysis, there is a well understood notion of correctness, namely, the analyzer must approximate (in the sense of lattice ordering) the concrete program behaviors, and (ii) thus, we can simply run a large amount of programs in a given programming language with some inputs, and obtain a subset of the concrete semantics for each program. We note that our learning method is independent of how the labels are obtained. For example, the labels  $y^j$  can be obtained by running static or dynamic analyzers on the programs  $x^j$  in  $\mathcal{D}$  or they can be provided manually.

Synthesizer and Language  $\mathcal{L}$  To express interesting rules of a static analyzer, we use a loop-free domain-specific language  $\mathcal{L}$  with branches (detailed description is provided in Appendix B and Appendix D). The synthesizer then takes as input the dataset  $\mathcal{D}$  with a language  $\mathcal{L}$  and produces a candidate program analysis  $pa \in \mathcal{L}$  which correctly handles the pairs in  $\mathcal{D}$ . The synthesizer we propose phrases the problem of learning a static analysis over  $\mathcal{L}$  as a problem in learning decision trees over  $\mathcal{L}$ . These components are described in Section 5.

Oracle Our goal is to discover a program analysis that not only behaves as described by the pairs in the dataset  $\mathcal{D}$ , but one that generalizes to programs beyond those in  $\mathcal{D}$ . To address this challenge, we introduce the oracle component

(FindCounterExample) and connect it with the synthesizer. This component takes as input the learned analysis pa and tries to find another program x for which pa fails to produce the desired result y. This counter-example  $\langle x,y\rangle$  is then fed back to the synthesizer which uses it to generate a new candidate analyzer as illustrated in Fig. 1. To produce a counter-example, the oracle must have a way to quickly and effectively test a (candidate) static analyzer. In Section 6, we present two techniques that make the testing process more effective by leveraging the current set  $\mathcal{D}$  as well as current candidate analysis pa (these techniques for testing a static analyzer are of interest beyond learning considered in our work).

Counter-example guided learning To learn a static analyzer pa, the synthesizer and the oracle are linked together in a counter-example guided loop. This type of iterative search is frequently used in program synthesis [32], though its instantiation heavily depends on the particular application task at hand. In our setting, the examples in  $\mathcal{D}$  are programs (and not say program states) and we also deal with notions of (analysis) approximation. This also means that we cannot directly leverage off-the-shelf components (e.g., SMT solvers) or existing synthesis approaches. Importantly, the counter-example guided approach employed here is of interest to machine learning as it addresses the problem of overfitting with techniques beyond those typically used (e.g., regularization [23], which is insufficient here as it does not consider samples not in the training dataset).

Practical applicability We implemented our approach and instantiated it to the task of learning rules for points-to and allocation site analysis for JavaScript code. This is a practical and relevant problem because of the tricky language semantics and wide use of libraries. Interestingly, our system learned inference rules missed by manually crafted state-of-the-art tools, e.g., Facebook's Flow [4].

#### 3 Overview

This section provides an intuitive explanation of our approach on a simple pointsto analysis for JavaScript. Assume we are learning the analysis from one training data sample given in Fig. 2 (a). It consists of variables a, b and b is assigned an object  $s_0$ . Our goal is to learn that a may also point to that same object  $s_0$ .

Points-to analysis is typically done by applying inference rules until fixpoint. An example of an inference rule modeling the effect of assignment is:

$$\frac{\texttt{VarPointsTo}(v_2, h) \qquad \texttt{Assignment}(v_1, v_2)}{\texttt{VarPointsTo}(v_1, h)} \quad [\texttt{Assign}]$$

This rule essentially says that if variable  $v_2$  is assigned to  $v_1$  and  $v_2$  may point to an object h, then the variable  $v_1$  may also point to this object h.

Domain specific language (DSL) for analysis rules: Consider the following general shape of inference rules:

$$\frac{\texttt{VarPointsTo}(v_2,h) \qquad v_2 = f(v_1)}{\texttt{VarPointsTo}(v_1,h)} \ [\texttt{General}]$$

```
var b = {}; // empty object s_0
                                                - ObjectExpression:{}
                                               Assignment
Expected points-to set
\mathcal{D} = \{(\mathbf{a} \to \{s_0\})\}\
                                                  Identifier:b
    (a) Training data
                               (b) Abstract syntax tree (AST) representation of (a)
  f_{desired}(x) ::=
                                            f_{overfit}(x) ::=
                                            if y is VarDeclaration: y preceding x
  if there is Assignment(x, y)
   if there is VarDeclaration: x(y)
                                             if there is VarDeclaration: x(y)
    otherwise
                                             otherwise
            (c) Learned functions to resolve points-to queries from (a)
```

Fig. 2. Example data for learning points-to analysis.

Here, the function f takes a program element (a variable) and returns another program element or  $\bot$ . The rule says: use the function f to find a variable  $v_2$  whose points-to set will be used to determine what  $v_1$  points to. The Assign rule is an instance of the General rule that can be implemented by traversing the AST and checking if the parent node of x is of type Assignment and if x is its first child. In this case, the right sibling of x is returned. Otherwise f returns  $\bot$ .

Problem statement The problem of learning a points-to analysis can now be stated as follows: find an analysis  $pa \in \mathcal{L}$  such that when analyzing the programs in the training data  $\mathcal{D}$ , the resulting points-to set is as outlined in  $\mathcal{D}$ .

The overfitting problem Consider Fig. 2 (b) which shows the AST of our example. In addition to ASSIGN, we need to handle the case of variable initialization (first line in the program). Note that the dataset  $\mathcal{D}$  does not uniquely determine the best function f. In fact, instead of the desired one  $f_{desired}$ , other functions can be returned such as  $f_{overfit}$  shown in Fig. 2 (c). This function inspects the statement prior to an assignment instead of at the assignment itself and yet it succeeds to produce the correct analysis result on our dataset  $\mathcal{D}$ . However, this is due to the specific syntactic arrangement of statements in the training data  $\mathcal{D}$  and may not generalize to other programs, beyond those in  $\mathcal{D}$ .

Our solution To address the problem of overfitting to  $\mathcal{D}$ , we propose a counter-example guided procedure that biases the learning towards semantically meaningful analyses. That is, the oracle tests the current analyzer and tries to find a counter-example on which the analysis fails. Our strategy to generating candidate programs is to modify the programs in  $\mathcal{D}$  in ways that can change both the syntax and the semantics of those programs. As a result, any analysis that depends on such properties would be penalized in the next iteration of Synthesize.

As we show in the evaluation, our approach results in a much faster oracle than if we had generated programs blindly. This is critical as faster ways of finding counter-examples increase the size of the search space we can explore, enabling us to discover interesting analyzers in reasonable time.

For example, a possible way to exclude  $f_{overfit}$  is to insert an unnecessary statement (e.g., var c = 1) before the assignment a = b in Fig. 2 (a). Here, the analysis defined by  $f_{overfit}$  produces an incorrect points-to set for variable a (as it points-to the value 1 of variable c). Once this sample is added to  $\mathcal{D}$ ,  $f_{overfit}$  is penalized as it produces incorrect results and the next iteration will produce a different analysis until eventually the desired analysis  $f_{desired}$  is returned.

Correctness of the approach Our method produces an analyzer that is guaranteed to be sound w.r.t to all of the examples in  $\mathcal{D}$ . Even if the analyzer cannot exactly satisfy all examples in  $\mathcal{D}$ , the synthesis procedure always returns an *over*approximation of the desired outputs. That is, when it cannot match the target output exactly, Synthesize learns to approximate (e.g., can return  $\top$  in some cases). A formal argument together with a discussion on these points is provided in Section 5. However, our method is not guaranteed to be sound for all programs in the programming language. We see the problem of certifying the analyzer as orthogonal and complementary to our work: our method can be used to predict an analyzer which is likely correct, generalize well, and to sift through millions of possibilities quickly, while a follow-up effort can examine this analyzer and decide whether to accept it or even fully verify it. Here, an advantage of our method is that the learned analyzer is expressed as a program, which can be easily examined by an expert (we show examples of learned analyzers in Appendix E), as opposed to standard machine learning models where interpreting the result is nearly impossible and therefore difficult to verify with standard methods.

### 4 Checking Analyzer Correctness

In this section, following [3], we briefly discuss what it means for a (learned) analyzer to be correct. The concrete semantics of a program p include all of p's concrete behaviors and are captured by a function  $[p]: \mathbb{N} \to \mathcal{O}(\mathcal{C})$ . This function associates a set of possible concrete states in  $\mathcal{C}$  with each position in the program p, where a position can be a program counter or a node in the program's AST.

A static analysis pa of a program p computes an abstract representation of the program's concrete behaviors, captured by a function  $pa(p) \colon \mathbb{N} \to \mathcal{A}$  where  $(\mathcal{A}, \sqsubseteq)$  is typically an abstract domain, usually a lattice of abstract facts equipped with an ordering  $\sqsubseteq$  between facts. An abstraction function  $\alpha \colon \mathcal{O}(\mathcal{C}) \to \mathcal{A}$  then establishes a connection between the concrete behaviors and the abstract facts. It defines how a set of concrete states in  $\mathcal{C}$  is abstracted into an abstract element in  $\mathcal{A}$ . The function is naturally lifted to work point-wise on a set of positions in  $\mathbb{N}$  (used in the definition below).

**Definition 1 (Analysis Correctness).** A static analysis pa is correct if:

$$\forall p \in \mathcal{T}_{\mathcal{L}}. \ \alpha(\llbracket p \rrbracket) \sqsubseteq pa(p) \tag{1}$$

Here  $\mathcal{T}_{\mathcal{L}}$  denotes the set of all possible programs in the target programming language  $(\mathcal{T}_{\mathcal{L}})$ . That is, a static analysis is correct if it over-approximates the concrete behaviors of the program according to the particular lattice ordering.

### 4.1 Checking Correctness

One approach for checking the correctness of an analyzer is to try and automatically verify the analyzer itself, that is, to prove the analyzer satisfies Definition 1 via sophisticated reasoning (e.g., as the one found in [9]). Unfortunately, such automated verifiers do not currently exist (though, coming up with one is an interesting research challenge) and even if they did exist, it is prohibitively expensive to place such a verifier in the middle of a counter-example learning loop where one has to discard thousands of candidate analyzers quickly. Thus, the correctness definition that we use in our approach is as follows:

Definition 2 (Analysis Correctness on a Dataset and Test Inputs). A static analysis pa is correct w.r.t to a dataset of programs P and test inputs ti if:

$$\forall p \in P. \ \alpha(\llbracket p \rrbracket_{ti}) \sqsubseteq pa(p) \tag{2}$$

The restrictions over Definition 1 are: the use of a set  $P \subseteq \mathcal{T}_{\mathcal{L}}$  instead of  $\mathcal{T}_{\mathcal{L}}$  and  $[\![p]\!]_{ti}$  instead of  $[\![p]\!]_{ti} \subseteq [\![p]\!]$  denotes a subset of a program p's behaviors obtained after running the program on some set of test inputs ti.

The advantage of this definition is that we can automate its checking. We run the program p on its test inputs ti to obtain  $[p]_{ti}$  (a finite set of executions) and then apply the function  $\alpha$  on the resulting set. To obtain pa(p), we run the analyzer pa on p; finally, we compare the two results via the inclusion operator  $\sqsubseteq$ .

## 5 Learning Analysis Rules

We now present our approach for learning static analysis rules from examples.

#### 5.1 Preliminaries

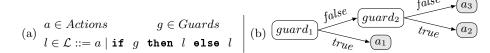
Let  $\mathcal{D} = \{\langle x^j, y^j \rangle\}_{j=1}^N$  be a dataset of programs from a target language  $\mathcal{T}_{\mathcal{L}}$  together with outputs that a program analysis should satisfy. That is,  $x^j \in \mathcal{T}_{\mathcal{L}}$  and  $y^j$  are the outputs to be satisfied by the learned program analysis.

**Definition 3 (Analysis Correctness on Examples).** We say that a static analysis  $pa \in \mathcal{L}$  is correct on  $\mathcal{D} = \{\langle x^j, y^j \rangle\}_{i=1}^N$  if:

$$\forall j \in 1 \dots N \quad y^j \sqsubseteq pa(x^j) \tag{3}$$

This definition is based on Definition 2, except that the result of the analysis is provided in  $\mathcal{D}$  and need not be computed by running programs on test inputs.

Note that the definition above does not mention the precision of the analysis pa but is only concerned with soundness. To search for an analysis that is both sound and precise and avoids obvious, but useless solutions (e.g., always return  $\top$  element of the lattice  $(\mathcal{A}, \sqsubseteq)$ ), we define a precision metric.



**Fig. 3.** (a) Syntax of a template language  $\mathcal{L}$  with branches for expressing analysis rules. (b) Example of a function from the  $\mathcal{L}$  language shown as a decision tree.

Precision metric First, we define a function  $r: \mathcal{T}_{\mathcal{L}} \times \mathcal{A} \times \mathcal{L} \to \mathbb{R}$  that takes a program in the target language, its desired program analysis output and a program analysis and indicates if the result of the analysis is exactly as desired:

$$r(x, y, pa) = \mathbf{if} (y \neq pa(x)) \mathbf{then} \ 1 \mathbf{else} \ 0$$
 (4)

We define a function cost to compute precision on the full dataset  $\mathcal{D}$  as follows:

$$cost(\mathcal{D}, pa) = \sum_{\langle x, y \rangle \in \mathcal{D}} r(x, y, pa)$$
 (5)

Using the precision metric in Equation 5, we can state the following lemma:

**Lemma 1.** For a program analysis  $pa \in \mathcal{L}$  and a dataset  $\mathcal{D}$ , if  $cost(\mathcal{D}, pa) = 0$ , then the analysis is correct according to Definition 3.

**Proof:** The proof is direct. Because  $cost(\mathcal{D}, pa) = 0$  and r is positive, then for every  $\langle x, y \rangle \in \mathcal{D}$ , r(x, y, pa) = 0. This means that y = pa(x) and so  $y \sqsubseteq pa(x)$ , which is as defined in Definition 3.

#### 5.2 Problem Formulation

Given a language  $\mathcal{L}$  that describes analysis inference rules (i.e., abstract transformers) and a dataset  $\mathcal{D}$  of programs with the desired analysis results, the Synthesize procedure should return a program analysis  $pa \in \mathcal{L}$  such that:

- 1. pa is correct on the examples in  $\mathcal{D}$  (Definition 3), and
- 2.  $cost(\mathcal{D}, pa)$  is minimized.

The above statement essentially says that we would like to obtain a sound analysis which also minimizes the over-approximation that it makes. As the space of possible analyzers can be prohibitively large, we discuss a restriction on the language  $\mathcal{L}$  and give a procedure that efficiently searches for an analyzer such that correctness is enforced and cost is (approximately) minimized.

### 5.3 Language Template for Describing Analysis Rules

A template of the language  $\mathcal{L}$  for describing analysis rules is shown in Fig. 3 (a). The template is simple and contains actions and guards that are to be instantiated later. The statements in the language are either an action or a conditional **if-then-else** statements that can be applied recursively.

An analysis rule of a static analyzer are expressed as a function built from statements in  $\mathcal{L}$ . As usual, the function is executed until a fixed point [3]. The semantics of the **if** statements in pa is standard: guards are predicates (sideeffect free) that inspect the program being analyzed and depending on their truth value, the corresponding branch of the **if** statement is taken. The reason such if statements are interesting is because they can express analysis rules such as the ones of our running example in Fig. 2.

We provide a formal semantics and detailed description of how the language  $\mathcal{L}$ is instantiated for learning points-to and allocation site analysis in Appendix B and Appendix D respectively.

### ID3 Learning for a Program Analyzer

A key challenge in learning program analyzers is that the search space of possible programs over  $\mathcal{L}$  is massive as the number of possible combinations of branches and subprograms is too large. However, we note that elements of  $\mathcal{L}$  can be represented as trees where internal nodes are guards of if statements and the leafs are actions as shown in Fig. 3 (b). Using this observation we can phrase the problem of learning an analyzer in  $\mathcal{L}$  as the problem of learning a decision tree, allowing us to adapt existing decision tree algorithms to our setting.

Towards that, we extend the ID3 [27] algorithm to handle action programs in the leafs and to enforce correctness of the resulting analysis  $pa \in \mathcal{L}$ . Similarly to ID3, our algorithm is a greedy procedure that builds the decision tree in a top-down fashion and locally maximizes a metric called information gain.

Our learning shown in Algorithm 1 uses three helper functions that we define next. First, the genAction function returns best analysis  $a_{best}$  for a dataset  $\mathcal{D}$ :

$$a_{best} = genAction(\mathcal{D}) = \underset{a \in Actions}{\operatorname{arg \, min}} cost(\mathcal{D}, a)$$
 (6)

That is, genAction returns the most precise program analysis consisting only of Actions (as we will see later, an action is just a sequence of statements, without branches). If  $a_{best}$  is such that  $cost(\mathcal{D}, a_{best}) = 0$ , the analysis is both precise and correct (from Lemma 1), which satisfies our requirements stated in Section 5.2 and we simply return it. Otherwise, we continue by generating an **if** statement.

Generating branches The ID3 decision tree learning algorithm generates branches based on an information gain metric. To define this metric, we first use a standard definition of entropy. Let the vector  $\mathbf{w} = \langle w_1, ..., w_k \rangle$  consist of elements from a set C. Then the entropy H on  $\boldsymbol{w}$  is:

$$H(\boldsymbol{w}) = -\sum_{c \in C} \frac{count(c, \boldsymbol{w})}{k} \log_2 \left( \frac{count(c, \boldsymbol{w})}{k} \right)$$
 (7)

where  $count(c, \boldsymbol{w}) = |\{i \in 1 \dots k \mid w_i = c\}|$ . For a dataset  $d \subseteq \mathcal{D}$ , let  $d = \{x_i, y_i\}_{i=1}^{|d|}$ . Then, we define the following vector:

$$\boldsymbol{w}_d^{a_{best}} = \langle r(x_i, y_i, a_{best}) \mid i \in 1 \dots |d| \rangle \tag{8}$$

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\begin{array}{c|c} \mathbf{def} \; \mathit{Synthesize}(\mathcal{D}) \\ & \mathbf{Input:} \; \mathrm{Dataset} \; \mathcal{D} = \{\langle x^j, y^j \rangle\}_{j=1}^N \\ & \mathbf{Output:} \; \mathrm{Program} \; pa \in \mathcal{L} \\ & a_{best} \leftarrow \mathit{genAction}(\mathcal{D}) \\ & \mathbf{if} \; \mathit{cost}(\mathcal{D}, a_{best}) = 0 \; \mathbf{then} \; \mathbf{return} \; a_{best}; \\ & g_{best} \leftarrow \mathit{genBranch}(a_{best}, \mathcal{D}) \\ & \mathbf{if} \; g_{best} = \bot \; \mathbf{then} \; \mathbf{return} \; \mathit{approximate}(\mathcal{D}) / \! / \; \mathcal{D} \; \mathit{are} \; \mathit{noisy} \; \mathit{examples} \; ; \\ & p_1 \leftarrow \mathit{Synthesize}(\{\langle x, y \rangle \in \mathcal{D} \; | \; g_{best}(x) \}) \\ & p_2 \leftarrow \mathit{Synthesize}(\{\langle x, y \rangle \in \mathcal{D} \; | \; \neg g_{best}(x) \}) \\ & \mathbf{return} \; \; \mathit{if} \; g_{best} \; \; \mathit{then} \; p_1 \; \mathit{else} \; p_2 \\ \end{array}
```

**Algorithm 1:** Learning algorithm for programs from language  $\mathcal{L}$ .

That is, for every program in d, we record if  $a_{best}$  is a precise analysis (via the function r defined previously). Let  $g \in Guards$  be a predicate that is to be evaluated on a program x. Let  $\mathcal{D}^g = \{\langle x, y \rangle \in \mathcal{D} \mid g(x)\}$  and  $\mathcal{D}^{\neg g} = \mathcal{D} \setminus \mathcal{D}^g$ .

The information gain on a set of examples  $\mathcal{D}$  for analysis  $a_{best}$  and predicate guard g is then defined as:

$$IG^{a_{best}}(\mathcal{D}, g) = H(\boldsymbol{w}_{\mathcal{D}}^{a_{best}}) - \frac{|\mathcal{D}^g|}{|\mathcal{D}|} H(\boldsymbol{w}_{\mathcal{D}^g}^{a_{best}}) - \frac{|\mathcal{D}^{\neg g}|}{|\mathcal{D}|} H(\boldsymbol{w}_{\mathcal{D}^{\neg g}}^{a_{best}})$$
(9)

For a given predicate g, what the information gain quantifies is how many bits of information about the analysis correctness will be saved if instead of using the imprecise analysis  $a_{best}$  directly, we split the dataset with a predicate g. Using the information gain metric we define genBranch as follows:

$$g_{best} = genBranch(a_{best}, \mathcal{D}) = \underset{g \in Guards}{\arg \max} {}^{\perp} IG^{a_{best}}(\mathcal{D}, g)$$
 (10)

Here,  $\arg \max^{\perp}$  is defined to return  $\perp$  if the maximized information gain is 0, or otherwise to return the guard g which maximizes the information gain.

Back to Algorithm 1, if genBranch returns a predicate with positive information gain, we split the dataset with this predicate and call Synthesize recursively on the two parts. In the end, we return an **if** statement on the predicate g and the two recursively synthesized analysis pieces.

Approximation If the information gain is 0 (i.e.  $g_{best} = \bot$ ), we could not find any suitable predicate to split the dataset and the analysis  $a_{best}$  has non-zero cost. In this case, we define a function approximate that returns an approximate, but correct program analysis – in our implementation we return analysis that loses precision by simply returning  $\top$ , which is always a correct analysis.

In practice, this approximation does not return  $\top$  for the entire analysis, but only for few of the branches in the decision tree, for which the synthesis procedure fails to produce a good program using both genAction and getBranch.

In terms of guarantees, for Algorithm 1, we can state the following lemma.

**Lemma 2.** The analysis  $pa \in \mathcal{L}$  returned by Synthesize is correct according to Definition 3.

The proof of this lemma simply follows the definition of the algorithm and uses induction for the recursion. For our induction base, we have already shown that in case  $cost(\mathcal{D}, a_{best}) = 0$ , the analysis is correct. The analysis is also correct if approximate is called. In our induction step we use the fact that analyses  $p_1$  and  $p_2$  from the recursion are correct and must only show that the composed analysis **if**  $g_{best}$  **then**  $p_1$  **else**  $p_2$  is also correct.

## 6 The Oracle: Testing an Analyzer

A key component of our approach is an oracle that can quickly test whether the current candidate analyzer is correct, and if not, to find a counter-example. The oracle takes as an input a candidate analyzer pa and the current dataset  $\mathcal{D}$  used to learn pa and outputs a counter-example program on which pa behaves incorrectly. More formally, if  $P_{\mathcal{D}} = \{x \mid \langle x, y \rangle \in \mathcal{D}\}$ , our goal is to find a counter-example program  $p \in \mathcal{T}_{\mathcal{L}}$  such that  $p \notin P_{\mathcal{D}}$  and the correctness condition in Definition 2 is violated for the given analysis pa and program p. That is, our oracle must generate new programs beyond those already present in  $P_{\mathcal{D}}$ .

Key Challenge A key problem the oracle must address is to quickly find a counter-example in the search space of all possible programs. As we show in Section 7, finding such a counter-example by blindly generating new programs does not work as the search space of programs in  $\mathcal{T}_{\mathcal{L}}$  is massive (or even infinite).

Speeding up the search We address this challenge by designing a general purpose oracle that prioritizes the search in  $\mathcal{T}_{\mathcal{L}}$  based on ideas inspired by state-of-the-art testing techniques [10,21]. In particular, we generate new programs by performing modifications of the programs in  $P_{\mathcal{D}}$ . These modification are carefully selected by exploiting the structure of the current analysis pa in two ways: (i) to select a program in  $\mathcal{T}_{\mathcal{L}}$  and the position in that program to modify, and (ii) to determine what modification to perform at this position.

#### 6.1 Choosing Modification Positions

Given a program  $x \in P_{\mathcal{D}}$  and analysis pa, we prioritize positions that are read while executing the program analysis pa and changing them would trigger different execution path in the analyzer pa itself (not the analyzed program). Determining these positions is done by instrumenting the program analyzer and recording the relevant instructions affecting the branches the analyzer takes.

For example, for Fig. 2 (a), we defined the analysis by the function  $f_{overfit}$ . For this function, only a subset of all AST nodes determine which of the three cases in the definition of  $f_{overfit}$  will be used to compute the result of the analysis. Thus, we choose the modification position to be one of these AST nodes.

#### 6.2 Defining Relevant Program Modifications

We now define two approaches for generating interesting program modifications that are potential counter-examples for the learned program analysis pa.

Modification via Equivalence Modulo (EMA) Abstraction The goal of EMA technique is to ensure that the candidate analysis pa is robust to certain types of program transformations. To achieve this, we transform the statement at the selected program position in a semantically-preserving way, producing a set of new programs. Moreover, while the transformation is semantic-preserving, it is also one that should not affect the result of the analysis pa.

More formally, an EMA transformation is a function  $F_{ema}: \mathcal{T}_{\mathcal{L}} \times \mathbb{N} \to \mathcal{O}(\mathcal{T}_{\mathcal{L}})$  which takes as input a program p and a position in the program, and produces a set of programs that are a transformation of p at position n. If the analysis pa is correct, then these functions (transformations) have the following property:

$$\forall p' \in F_{ema}(p, n).pa(p) = pa(p') \tag{11}$$

The intuition behind such transformations is to ensure stability by exploring local program modifications. If the oracle detects the above property is violated, the current analysis pa is incorrect and the counter-example program p' is reported. Examples of applicable transformations are dead code insertion, variable names renaming or constant modification, although transformations to use can vary depending on the kind of analysis being learned. For instance, inserting dead code that reuses existing program identifiers can affect flow-insensitive analysis, but should not affect a flow-sensitive analysis. The EMA property is similar to notion of algorithmic stability used in machine learning where the output of a classifier should be stable under small perturbations of the input as well as the concept of equivalence modulo inputs used to validate compilers [21].

Modification via Global Jumps The previous modifications always generated semantic-preserving transformations. However, to ensure better generalization we are also interested in exploring changes to programs in  $P_{\mathcal{D}}$  that may not be semantic preserving, defined via a function  $F_{gj}: \mathcal{T}_{\mathcal{L}} \times \mathbb{N} \to \mathcal{P}(\mathcal{T}_{\mathcal{L}})$ . The goal is to discover a new program which exhibits behaviors not seen by any of the programs in  $P_{\mathcal{D}}$  and is not considered by the currently learned analyzer pa.

Overall, as shown in Section 7, our approach for generating programs to test the analysis pa via the functions  $F_{gj}$  and  $F_{ema}$  is an order of magnitude more efficient at finding counter-examples than naively modifying the programs in  $P_{\mathcal{D}}$ .

## 7 Implementation and Evaluation

In this section we provide an implementation of our approach shown in Fig. 1 as well as a detailed experimental evaluation instantiated to two challenging analysis problems for JavaScript: learning points-to analysis rules and learning allocation site rules. In our experiments, we show that:

 The approach can learn practical program analysis rules for tricky cases involving JavaScript's built-in objects. These rules can be incorporated into existing analyzers that currently handle such cases only partially.

**Table 1.** Program modifications used to instantiate the oracle (Section 6) that generates counter-examples for points-to analysis and allocation site analysis.

Program Modifications				
$F_{ema}$	$F_{gj}$			
Adding Dead Code	Adding Method Arguments			
Renaming Variables	Adding Method Parameters			
Renaming User Functions Side-Effect Free Expressions	Changing Constants			

- The counter-example based learning is critical for ensuring that the learned analysis generalizes well and does not overfit to the training dataset.
- Our oracle can effectively find counter-examples (orders of magnitude faster than random search).

These experiments were performed on a 28 core machine with 2.60Ghz Intel(R) Xeon(R) CPU E5-2690 v4 CPU, running Ubuntu 16.04. In our implementation we parallelized both the learning and the search for the counter-examples.

Training dataset We use the official ECMAScript (ECMA-262) conformance suite (https://github.com/tc39/test262) – the largest and most comprehensive test suite available for JavaScript containing over 20 000 test cases. As the suite also includes the latest version of the standard, all existing implementations typically support only a subset of the testcases. In particular, the NodeJS interpreter v4.2.6 used in our evaluation can execute (i.e., does not throw a syntax error) 15 675 tests which we use as the training dataset for learning.

Program modifications We list the program modifications used to instantiate the oracle in Table 4. The semantic preserving program modifications that should not change the result of analyses considered in our work  $F_{ema}$  are inserted dead code and renamed variables and user functions (together with the parameters) as well as generated expressions that are side-effect free (e.g, declaring new variables). Note that these mutations are very general and should apply to almost arbitrary property. To explore new program behaviours by potentially changing program semantics we use program modifications  $F_{gj}$  that change values of constants (strings and numbers), add methods arguments and add method parameters.

#### 7.1 Learning Points-to Analysis Rules for JavaScript

We now evaluate the effectiveness of our approach for the task of learning a points-to analysis for the JavaScript built-in APIs that affect the binding of this. This is useful because existing analyzers currently either model this only partially [11,4] (i.e., cover only a subset of the behaviors of Function.prototype APIs) or not at all [24,15], resulting in potentially unsound results.

We illustrate some of the complexity for determining the objects to which this points-to within the same method in Fig. 4. Here, this points-to different

```
global.length = 4;
var dat = [5, 3, 9, 1];
function isBig(value) {
  return value >=
    this.length;
}

// this points to global
dat.filter(isBig); // [5, 9]
// this points to boxed 42
dat.filter(isBig, 42); // []
// this points to dat object
dat.filter(isBig, dat); // [5, 9]
```

Fig. 4. JavaScript code snippet illustrating subset of different objects to which this can point to depending on the context method isBig is invoked in.

**Table 2.** Dataset size, number of counter-examples found and the size of the learned points-to analysis for JavaScript APIs that affect the points-to set of this.

Function Name	Dataset Size	Counter-examples Found	Analysis Size*
Function.prototype			
call()	26	372	97 (18)
apply()	6	182	54 (10)
Array.prototype			
map()	315	64	36 (6)
some()	229	82	36 (6)
forEach()	604	177	35 (5)
every()	338	31	36 (6)
filter()	408	76	38 (6)
find()	53	73	36 (6)
<pre>findIndex()</pre>	51	96	28 (6)
Array			
from()	32	160	57 (7)
JSON			
<pre>stringify()</pre>	18	55	9 (2)

<sup>\*</sup> Number of instructions in  $\mathcal{L}_{pt}$  (Number of **if** branches)

objects depending on how the method is invoked and what values are passed in as arguments. In addition to the values shown in the example, other values may be seen during runtime if other APIs are invoked, or the method <code>isBig</code> is used as an object method or as a global method.

Language  $\mathcal{L}$  To learn points-to analysis, we use a domain-specific language  $\mathcal{L}_{pt}$  with if statements (to synthesize branches for corner cases) and instructions to traverse the JavaScript AST in order to provide the specific analysis of each case. We provide a detailed list of the instructions with their semantics in Appendix B and Appendix C.

Learned analyzer A summary of our learned analyzer is shown in Table 2. For each API we collected all its usages in the ECMA-262 conformance suite, ranging from only 6 to more than 600, and used them as initial training dataset for the learning. In all cases, a significant amount of counter-examples were needed to refine the analysis and prevent overfitting to the initial dataset. On average, for

Fig. 5. Illustration of program locations (underlined) for which the allocation site analysis should report that a new object is allocated.

each API, the learning finished in 14 minutes, out of which 4 minutes were used to synthesise the program analysis and 10 minutes used in the search for counter-examples (cumulatively across all refinement iterations). The longest learning time was 57 minutes for the Function.prototype.call API for which we also learn the most complex analysis – containing 97 instructions in  $\mathcal{L}_{pt}$ . We note that even though the APIs in Array.prototype have very similar semantics, the learned programs vary slightly. This is caused by the fact that different number and types of examples were available as the initial training dataset which means that also the oracle had to find different types of counter-examples. We provide an example of the learned analysis in Appendix E.

### 7.2 Learning Allocation Site Analysis for JavaScript

We also evaluate the effectiveness of our approach on a second analysis task – learning allocation sites in JavaScript. This is an analysis that is used internally by many existing analyzers. The analysis computes which statements or expressions in a given language result in an allocation of a new heap object.

We illustrate the expected output and some of the complexities of allocation site analysis on a example shown in Fig. 9. In JavaScript, there are various ways how an object can be allocated including creating new object without calling a constructor explicitly (for example by creating new array or object expression inline), creating new object by calling a constructor explicitly using new, creating a new object by calling a method or new objects created by throwing an exception. In addition, some of the cases might further depend on actual values passed as arguments. For example, calling a new Object(obj) constructor with obj as an argument does not create a new object but returns the obj passed as argument instead. The goal of the analysis is to determine all such program locations (as shown in Fig. 9) at which new object is allocated.

Consider the following simple, but unsound and imprecise allocation site analysis:

$$f_{alloc}(x) = \begin{cases} true & \text{if there is } \texttt{Argument:x or NewExpression:x} \\ false & \text{otherwise} \end{cases}$$

which states that a location x is an allocation site if it is either an argument or a new expression. This analysis is imprecise because there are other ways to

allocate an object (e.g., when creating arrays, strings, boxed values or by calling a function). It is also unsound, because the JavaScript compiler might not create a new object even when NewExpression is called (e.g., new Object(obj) returns the same object as the given obj).

Instead of defining tricky corner cases by hand, we use our approach to learn this analyzer automatically from data. We instantiate the approach in a very similar way compared to learning points-to analysis by adjusting the language and how the labels in the training dataset are obtained (details provided in Appendix D). For this task, we obtain 134 721 input/output examples from the training data, which are further expanded with additional 905 counter-examples found during 99 refinement iterations of the learning algorithm. For this (much higher than in the other analyzer) number of examples the synthesis time was 184 minutes while the total time required to find counter-examples was 7 hours.

The learned program is relatively complex and contains 135 learned branches, including the tricky case where NewExpression does not allocate a new object. Compared to the trivial, but wrong analysis  $f_{alloc}$ , the synthesized analysis marks over twice as many locations in the code as allocation sites ( $\approx 21 \text{K vs} \approx 45 \text{K}$ ).

#### 7.3 Analysis Generalization

We study how well the learned analyzer for points-to analysis works for unseen data. First, we manually inspected the learned analyzer at the first iteration of the *Synthesize* procedure (without any counter-examples generated). We did that to check if we overfit to the initial dataset and found that indeed, the initial analysis would *not* generalize to some programs outside the provided dataset. This happened because the learned rules conditioned on unrelated regularities found in the data (such as variable names or fixed positions of certain function parameters). Our oracle, and the counter-example learning procedure, however, eliminate such kinds of non-semantic analyses by introducing additional function arguments and statements in the test cases.

Overfitting to the initial dataset was also caused by the large search space of possible programs in the DSL for the analysis. However, we decided not to restrict the language, because a more expressive language means more automation. Also, we did not need to provide upfront partial analysis in the form of a sketch [32].

Oracle effectiveness for finding counter-examples We evaluate the effectiveness of our oracle to find counter-examples by comparing it to a random ("black box") oracle that applies all possible modifications to a randomly selected program from the training dataset. For both oracles we measure the average number of programs explored before a counter-example is found and summarize the results in Table 3. In the table, we observe two cases: (i) early in the analysis loop when the analysis is imprecise and finding a counter-example is easy, and (ii) later in the loop when hard corner cases are not yet covered by the analysis. In both cases, our oracle guided by analysis is orders of magnitude more efficient.

**Table 3.** The effect of using the learned analysis to guide the counter-example search.

Difficulty	Programs explored "Black Box"	d until first counter-example is found Guided by Analysis
Easy ( $\approx 60\%$ ) Hard ( $\approx 40\%$ )		13 130

Is counter-example refinement loop needed? Finally, we compare the effect of learning with a refinement loop to learning with a standard "one-shot" machine learning algorithm, but with more data provided up-front. For this experiment, we automatically generate a huge dataset  $\mathcal{D}_{huge}$  by applying all possible program modifications (as defined by the oracle) on all programs in  $\mathcal{D}$ . For comparison, let the dataset obtained at the end of the counter-example based algorithm on  $\mathcal{D}$  be  $\mathcal{D}_{ce}$ . The size of  $\mathcal{D}_{ce}$  is two orders of magnitude smaller than  $\mathcal{D}_{huge}$ .

An analysis that generalizes well should be sound and precise on both datasets  $\mathcal{D}_{ce}$  and  $\mathcal{D}_{huge}$ , but since we use one of the datasets for training, we use the other one to validate the resulting analyzer. For the analysis that is learned using counter-examples (from  $\mathcal{D}_{ce}$ ), the precision is around 99.9% with the remaining 0.01% of results approximated to the top element in the lattice (that is, it does not produce a trivially correct, but useless result). However, evaluating the analysis learned from  $\mathcal{D}_{huge}$  on  $\mathcal{D}_{ce}$  has precision of only 70.1% with the remaining 29.1% of the cases being unsound! This means that  $\mathcal{D}_{ce}$  indeed contains interesting cases critical to analysis soundness and precision.

Summary Overall, our evaluation shows that the learning approach presented in our work can learn static analysis rules that handle various cases such as the ones that arise in JavaScript built-in APIs. The learned rules generalize to cases beyond the training data and can be inspected and integrated into existing static analyzers that miss some of these corner cases. We provide an example of both learned analyses in Appendix E.

### 8 Related Work

Synthesis from examples Similar to our work, synthesis from examples typically starts with a domain-specific language (DSL) which captures a hypothesis space of possible programs together with a set of examples the program must satisfy and optionally an oracle to provide additional data points in the form of counterexamples using CEGIS-like techniques [32]. Examples of this direction include discovery of bit manipulation programs [18], string processing in spreadsheets [12], functional programs [6], or data structure specifications [8]. A recent work has shown how to generalize the setting to large and noisy datasets [28].

Other recent works [14,17] synthesize models for library code by collecting program traces which are then used as a specification. The key differences with our approach are that we (i) use large dataset covering hundreds of cases and (ii) we synthesize analysis that generalizes beyond the provided dataset.

Program analysis and machine learning Recently, several works tried to use machine learning in the domain of program analysis for task such as probabilistic type prediction [19,29], reducing the false positives of an analysis [25], or as a way to speed up the analysis [26,13,1] by learning various strategies used by the analysis. A key difference compared to our work is that we present a method to learn the static analysis rules which can then be applied in an iterative manner. This is a more complex task than [19,29] which do not learn rules that can infer program specific properties and [25,26,13,1] which assume the rules are already provided and typically learn a classifier on top of them.

Learning invariants In an orthogonal effort there has also been work on learning program invariants using dynamic executions. For recent representative examples of this direction, see [7,20,30]. The focus of all of these works is rather different: they work on a per-program basis, exercising the program, obtaining observations and finally attempting to learn the invariants. Counter-example guided abstraction refinement (CEGAR) [2] is a classic approach for learning an abstraction (typically via refinement). Unlike our work, these approaches do not learn the actual program analysis and work on a per-program basis.

Scalable program analysis Another line of work considers scaling program analysis in hard to analyse domains such as JavaScript at the expense of analysis soundness [5,24]. These works are orthogonal to us and follow the traditional way of designing the static analysis components by hand, but in the future they can also benefit from automatically learned rules by techniques such as ours.

## 9 Conclusion and Future Work

We presented a new approach for learning static analyzers from examples. Our approach takes as input a language for describing analysis rules, an abstraction function and an initial dataset of programs. Then, we introduce a counterexample guided search to iteratively add new programs that the learned analyzer should consider. These programs aim to capture corner cases of the programming language being analyzed. The counter-example search is made feasible thanks to an oracle able to quickly generate candidate example programs for the analyzer.

We implemented our approach and applied it to the setting of learning a points-to and allocation site analysis for JavaScript. This is a very challenging problem for learning yet one that is of practical importance. We show that our learning approach was able to discover new analysis rules which cover corner cases missed by prior, manually crafted analyzers for JavaScript.

We believe this is an interesting research direction with several possible future work items including learning to model the interfaces of large libraries w.r.t to a given analysis, learning the rules for other analyzers (e.g., type analysis), or learning an analysis that is semantically similar to analysis written by hand.

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## Appendix

Here we provide a detailed description of how we instantiated the learning approach presented in our work to the tasks of learning points-to and allocation site analysis for JavaScript. In particular, the appendix contains following sections:

- A: Instantiation of the learning points-to analysis
- B: Description of  $\mathcal{L}_{pt}$  language for points-to analysis
- C: Formal semantics of  $\mathcal{L}_{pt}$  language
- D: Instantiation of the learning for allocation site analysis
- E: Examples of learned program analyses
- F: Implementation details of our approach

## A Points-to Analysis

In this section we present an instantiation of our approach to the task of learning transformers/rules for points-to analysis. The goal of points-to analysis is to answer queries of the type  $q: V \to \mathcal{P}(H)$ , where V is a set of program variables and H is a heap abstraction (e.g., allocation sites). That is, the goal is to compute the set of (abstract) objects to which a variable may point-to at runtime. Similar to the example illustrated in Section 3, to answer such queries a common line of work [31,11,24] uses a declarative approach where the program is abstracted as a set of facts and the analysis is defined declaratively (e.g., as a set of Datalog rules) using inference rules that are applied until a fixed point is reached.

Our goal Our goal is to learn the inference rules that define the analysis, from data, as described in our approach so far. In particular, we would like to infer rules of the following general shape:

$$\frac{\texttt{VarPointsTo}(v_2,h) \qquad v_2 = f(v_1)}{\texttt{VarPointsTo}(v_1,h)} \ [\texttt{General}]$$

where the goal of learning is to find a set of functions f that, when used in the points-to analysis, produce precise results (as defined earlier). However, we focus our attention not on learning the standard and easy to define rules, as the one for assignment, but on rules that are hard and tricky to model by hand and are missed by existing analyzers. In particular, consider the following subset of inference rules that capture the points-to sets for the this variable in JavaScript. This rule has the following shape:

$$\frac{\texttt{VarPointsTo}(v_2,h) \qquad v_2 = f(\texttt{this})}{\texttt{VarPointsTo}(\texttt{this},h)} \quad [\texttt{THIS}]$$

which is an instantiation of the general rule for the this variable by setting  $v_1 = \text{this}$ . In JavaScript, designing such rules is a challenging task as there are many corner cases and describing those precisely requires more inference rules than the rest of the (standard) analysis rules. Further, because assigning

**Table 4.** Program modifications used to instantiate the oracle (Section 6) that generates counter-examples for points-to analysis and allocation site analysis.

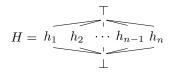
Program Modifications			
$F_{ema}$	$F_{gj}$		
Adding Dead Code	Adding Method Arguments		
Renaming Variables	Adding Method Parameters		
Renaming User Functions Side-Effect Free Expressions	Changing Constants		

a value to the this object is not allowed (i.e., using this as a left-hand side of an assignment expression), the value of this at runtime is not observed at the program level, yet assignments do occur internally in the interpreter and the runtime. Complicating matters, the actual values of the this reference can depend on the particular version of the interpreter.

### A.1 Instantiating our Learning Approach

We now define the necessary components required to instantiate the learning approach described so far. Most of the instantiations are fairly direct except for the language  $\mathcal{L}$ , described separately in Appendix B.

Lattice of abstract heap locations Fig. 6 shows the lattice  $(\mathcal{H}, \sqsubseteq)$  used to represent the abstract domain of heap locations H. The abstraction function  $\alpha \colon O \to H$  maps the concrete objects seen at runtime to abstract heap locations represented using a context-insensitive allocation site abstraction H. The lattice is quite simple and consists of the standard elements  $\top$ ,  $\bot$  and elements corresponding to individual heap locations  $h_1 \cdots h_n$  that are not comparable.



**Fig. 6.** Lattice of context-insensitive abstract heap locations H for points-to analysis.

Concrete and abstract program semantics The concrete properties we are tracking and their abstract counterpart as described in Section 4 are instantiated by setting  $\mathcal{C} := O$ ,  $\mathcal{A} := H$  and  $\mathbb{N} := \langle V, \mathbb{I}^* \rangle$ . That is, all concrete program behaviors are captured by a function  $\llbracket p \rrbracket \colon \langle V, \mathbb{I}^* \rangle \to \mathcal{O}(O)$  that for each program variable V sensitive to the k-most recent call sites I computes a set of possible concrete objects seen at runtime O. The abstract semantics are similar except that we instantiate the abstract domain to be the lattice describing heap-allocated objects H. We discuss how we obtain the concrete behaviors  $\llbracket p \rrbracket_{ti}$  after running the program on a set of test inputs ti in Appendix F.1.

*Program modifications* We list the program modifications used to instantiate the oracle in Table 4. The semantic preserving program modifications that should

not change the result of points-to analysis  $F_{ema}$  are inserted dead code and renamed variables and user functions (together with the parameters) as well as generated expressions that are side-effect free (e.g, declaring new variables). To explore new program behaviours by potentially changing program semantics we use program modifications  $F_{gj}$  that change values of constants (strings and numbers), add methods arguments and add method parameters.

## B Language for Points-To Inference Rules

We now provide a definition of our domain specific language  $\mathcal{L}_{pt}$ , an instantiation of the template language  $\mathcal{L}$  shown in Fig. 3. Our main goal was to design a language  $\mathcal{L}_{pt}$  that is fairly generic: (i) it does not require the designer to provide specific knowledge about the analysis rules, and (ii) the language can be used to describe rules beyond those of points-to analysis. Point (i) is especially important as specifying tricky parts of the analysis rules by hand requires substantial effort, which is exactly the process we would like to automate. Indeed, we aim at a language that is expressive enough to capture complex rules which use information from method arguments, fields, assignments, etc., yet can be automatically discovered during the learning.

To achieve this, the main idea is to define  $\mathcal{L}_{pt}$  to work over Abstract Syntax Tree (AST) by providing means of navigating and conditioning on different parts of the tree. Further, we do not require the analysis to compute the results directly (e.g., a concrete points-to set for a given location). Instead, we allow the results to be specified indirectly by means of navigating to an AST position that determines the result. For example, such locations in the AST correspond to program positions with the same points-to set for points-to analysis, or to declaration sites for scope analysis or to program positions with the same type for type analysis. Next, we discuss the syntax and semantics of  $\mathcal{L}_{pt}$ .

Syntax The syntax of  $\mathcal{L}_{pt}$  is summarized in Fig. 7 and consists of two kinds of basic instructions – Move instructions that navigate over the tree and Write instructions that accumulate facts about the visited nodes. We split the Move instructions into three groups where  $\text{Move}_{\text{core}}$  include language and analysis independent instructions that navigate over trees,  $\text{Move}_{\text{js}}$  include instructions that navigate to a set of interesting program locations that are specific to the JavaScript language. Finally we include  $\text{Move}_{\text{call}}$  which allows learning of a call-site sensitive analysis. Using the Move and Write instructions we then define an action to be a sequence of Move instructions and a guard to be a sequence of both Move and Write instructions.

Semantics Programs from  $\mathcal{L}_{pt}$  operate on a state  $\sigma$  defined as follows:  $\sigma = \langle t, n, ctx, i \rangle \in States$  where the domain  $States = AST \times X \times Context \times \mathbb{I}^*$ . In a state  $\sigma = \langle t, n, ctx, i \rangle$ , t is an abstract syntax tree, n is the current position in the tree, ctx is the currently accumulated context and i is the current call trace. The accumulated context  $ctx \in Context = (N \cup \Sigma \cup \mathbb{N})^*$  by a  $\mathcal{L}_{pt}$  program

```
\begin{split} m \in \mathsf{Move}_\mathsf{core} &::= \mathsf{Up} \mid \mathsf{Left} \mid \mathsf{Right} \mid \mathsf{DownFirst} \mid \mathsf{DownLast} \mid \mathsf{Top} \\ m \in \mathsf{Move}_\mathsf{js} &::= \mathsf{GoToGlobal} \mid \mathsf{GoToUndef} \mid \mathsf{GoToNull} \mid \mathsf{GoToThis} \mid \mathsf{UpUntilFunc} \\ m \in \mathsf{Move} &::= \mathsf{Move}_\mathsf{core} \cup \mathsf{Move}_\mathsf{call} \cup \mathsf{Move}_\mathsf{js} & m \in \mathsf{Move}_\mathsf{call} ::= \mathsf{GoToCaller} \\ w \in \mathsf{Write} &::= \mathsf{WriteValue} \mid \mathsf{WritePos} \mid \mathsf{WriteType} \mid \mathsf{HasLeft} \mid \mathsf{HasRight} \mid \mathsf{HasChild} \\ & a \in Actions_{pt} ::= \epsilon \mid \mathsf{Move} \; ; \; a \\ & g \in Guards_{pt} ::= \epsilon \mid \mathsf{Move} \; ; \; g \mid \mathsf{Write} \; ; \; g \\ & ctx \in Context ::= (N \cup \Sigma \cup \mathbb{N})^* \\ & l \in \mathcal{L}_{pt} ::= \epsilon \mid a \mid \mathsf{if} \; g = ctx \; \mathsf{then} \; l \; \mathsf{else} \; l \end{split}
```

Fig. 7. Language  $\mathcal{L}_{pt}$  for expressing the result of points-to query by means of navigating over an abstract syntax tree.

is a sequence of observations on the tree where each observation can be a non-terminal symbol N from the tree, a terminal symbol  $\Sigma$  from the tree or a natural number in  $\mathbb{N}$ . Initially, execution starts with the empty context  $[] \in Context$  and the AST t, initial node n and current call trace i supplied as arguments.

For a program  $p \in \mathcal{L}_{pt}$ , a tree  $t \in AST$ , and a position  $n \in X$  in the tree, we say that program p computes a position  $n' \in X$ , denoted as p(t, n, i) = n', iff there exists a sequence of transitions from  $\langle p, t, n, [], i \rangle$  to  $\langle \epsilon, t, n', [], i \rangle$ . That is, n' is the last visited position by executing the program p on a tree t starting at position n. The context is empty both at the beginning and at the end of execution as it is used only to evaluate the **if** condition when deciding which branch to take. We provide the small-step semantics of Move and Write instructions as well as the **if-then-else** statement, in the Appendix C.

Example Consider the following program in  $\mathcal{L}_{pt}$  that encodes the Assign rule illustrated in Section 3:

$$f(t,n,i) = \begin{cases} \texttt{Right} & \text{if WritePos Up WriteType = 1 Assignment} \\ \texttt{Top} & \text{else} \end{cases}$$

When executed on a tree t in Fig. 2 (b) starting at position n = Identifier:a, the program f first executes the guard WritePos Up WriteType which starts by writing value 1 as the node at current position is the first child, then navigates to the position of parent node and writes its type Assignment. This collected context 1 Assignment is then compared to the one specified in the condition. The equality is satisfied and the program takes the if branch, resets the current position back to the position n before executing the context inside the if branch, and then continues executing the code inside the if, Right, which navigates to its right sibling. This sibling is also the output of executing program f(t, n, i).

## C Formal Semantics of $\mathcal{L}_{pt}$ Language

Here, we provide the semantics of all Move and Write instructions as presented in Appendix B. Further, we provide small-step semantics of  $\mathcal{L}_{pt}$  language.

### C.1 $\mathcal{L}_{pt}$ : Semantics of Instructions

The semantics of the write instructions are described by the [WRITE] rule in Fig. 8. Each write accumulates a value c to the context ctx according to the function wr:

$$wr \colon \mathtt{Write} \times AST \times X \times \mathbb{I}^* \to N \cup \Sigma \cup \mathbb{N}$$

defined as follows:

- wr(WriteType, t, n, i) returns x where  $x \in N$  is the non-terminal symbol at node n
- -wr(WriteValue, t, n, i) returns the terminal symbol at node n if one is available or a special value 0 otherwise, and
- wr(WritePos, t, n, i) returns a number  $x \in \mathbb{N}$  that is the index of n in the list of children kept by the parent of n.
- wr(HasLeft, t, n, i) and wr(HasRight, t, n, i) return 1 if the n has a left (right) sibling and 0 otherwise.
- wr(HasChild, t, n, i) returns 1 if the n has at least one children and 0 otherwise.
- wr(HasCaller, t, n, i) returns 1 if the call trace is non-empty (i.e., |i| > 0) and 0 otherwise.

Move instructions are described by the [Move] and [Move-Fail] rules in Fig. 8 and use the function mv:

$$mv \colon \mathtt{Move} \times AST \times X \times \mathbb{I}^* \to X \times \mathbb{I}^*$$

defined as follows:

- $-mv(Up, t, n, i) = n' \times i$  where n' is the parent node of n in t or  $\bot$  if n has no parent node in t. Note that the [MOVE] rule updates the node at the current position to be the parent.
- $mv(\texttt{Left}, t, n, i) = n' \times i$  where n' is the left sibling of n in t or  $\bot$  if n has no left sibling. Similarly, mv(Right, t, n) produces the right sibling or  $\bot$  if n has no right sibling.
- $mv(\mathtt{DownFirst}, t, n, i) = n' \times i$  where n' is the first child of n in t or  $\bot$  if n has no children. Similarly,  $mv(\mathtt{DownLast}, t, n, i)$  produces the last child of n or  $\bot$  if n has no children.
- $-mv(GoToGlobal, t, n, i) = n' \times i$  where n' is a node corresponding to the global JavaScript object in the t. For this and other GoTo operations the value of n' is independent of the starting node n.

$$\begin{array}{lll} t \in AST & n \in X & ctx \in Context & i \in \mathbb{I}^* & s \in \mathcal{L}_{pt} \\ \hline op \in \texttt{Move} & n' \times i' = mv(op,t,n,i) & n' \notin \{\bot,\top\} \\ \hline \langle op :: s,t,n,ctx,i\rangle \to \langle s,t,n',ctx,i'\rangle & [\texttt{MOVE}] \\ \hline \hline op \in \texttt{Move} & n' \times i' = mv(op,t,n,i) & n' \in \{\bot,\top\} \\ \hline \langle op :: s,t,n,ctx,i\rangle \to \langle \epsilon,t,n',ctx,i\rangle & [\texttt{MOVE-FAIL}] \\ \hline \hline & op \in \texttt{Write} & c = wr(op,t,n,i) \\ \hline \langle op :: s,t,n,ctx,i\rangle \to \langle s,t,n,ctx\cdot c,i\rangle & [\texttt{WRITE}] \\ \hline & op \in \textbf{if} & g = ctx & \textbf{then} & l_{true} & \textbf{else} & l_{false} \\ \hline \langle g,t,n,[],i\rangle \to \langle \epsilon,t',n',ctx',i'\rangle & ctx = ctx' \\ \hline \langle op,t,n,ctx,i\rangle \to \langle l_{true},t,n,ctx,i\rangle & [\texttt{IF-TRUE}] \\ \hline & op \in \textbf{if} & g = ctx & \textbf{then} & l_{true} & \textbf{else} & l_{false} \\ \hline \langle g,t,n,[],i\rangle \to \langle \epsilon,t',n',ctx',i'\rangle & ctx \neq ctx' \\ \hline \langle op,t,n,ctx,i\rangle \to \langle l_{false},t,n,ctx,i\rangle & [\texttt{IF-FALSE}] \\ \hline \end{array}$$

Fig. 8.  $\mathcal{L}_{pt}$  language small-step semantics. Each rule is of the type:  $\mathcal{L}_{pt} \times States \rightarrow \mathcal{L}_{pt} \times States$ .

- $mv(\texttt{GoToThis}, t, n, i) = n' \times i$  where n' is a node corresponding to the object to which this keyword points-to in the top-level scope. In a web browser this would be window object while in Node.js application it is module.exports.
- $mv(\texttt{GoToUndefined}, t, n, i) = n' \times i$  where n' is a node corresponding to the undefined JavaScript object in the t. Similarly, for  $mv(\texttt{GoToNull}, t, n, i) = n' \times i$  the n' is the null value.
- $mv(\texttt{GoToCaller}, t, n, i \cdot i') = n' \times i'$  where n' is the node corresponding to call site of the top method i from call trace and i' is the call trace with the method i removed. If the call trace is empty then  $n' = \bot$ .
- $mv(\mbox{UpUntilFunc},t,n,i) = n' \times i$  navigates recursively to the first n' using the  $\mbox{Up}$  operation such that the parent of n' is a function declaration or root of the tree is reached.
- $-mv(\text{Top},t,n,i) = \top \times i$  denotes that the analysis approximates the result to the  $\top$  element in the lattice.

### C.2 $\mathcal{L}_{pt}$ : Small-step Semantics of $\mathcal{L}_{pt}$ language.

Recall from Appendix B that  $\mathcal{L}_{pt}$  programs operate on a state  $\sigma$  defined as follows:  $\sigma = \langle t, n, ctx, i \rangle \in States$  where the domain States is defined as  $States = AST \times X \times Context \times \mathbb{I}^*$ . Initially, execution starts with the empty context  $[] \in Context$  and for a program  $p \in \mathcal{L}_{pt}$ , a tree  $t \in AST$ , and a position  $n \in X$  in the tree, we say that program p computes a position  $n' \in X$ , denoted as p(t, n, i) = n', iff there exists a sequence of transitions from  $\langle p, t, n, [], i \rangle$  to  $\langle \epsilon, t, n', [], i \rangle$ . The small-step semantics of executing a  $\mathcal{L}_{pt}$  program are shown in Fig. 8.

Fig. 9. Illustration of program locations (underlined) for which the allocation site analysis should report that a new object is allocated.

## D Allocation Site Analysis

In this section we describe the instantiation of our approach to the task of learning allocation site analysis. The goal of allocation site analysis is to answer queries of the type  $q: L \to \{true, false\}$ , where L is a set of program locations. That is, for each program location the analysis returns a boolean value denoting whether the location is an allocation site or not.

Our Goal Our goal is to learn an inference rules from data in the following shape:

$$\frac{f(l) = true}{\texttt{AllocSite}(l)} \ [\texttt{ALLOC}]$$

Example We illustrate the expected output and some of the complexities of allocation site analysis on a small example shown in Fig. 9. The goal of the analysis is to determine all the program locations at which new object is allocated. In JavaScript there are various ways how an object can be allocated, some of which are shown in Fig. 9. These include creating new object without calling a constructor explicitly (for example by creating new array or object expression inline), creating new object by calling a constructor explicitly using new, creating a new object by calling a method or new objects created by throwing an exception. In addition, some of the cases might further depend on actual values passed as arguments. For example, calling a new Object (obj) constructor with obj as an argument does not create a new object but returns the obj passed as argument instead.

### D.1 Instantiating our Learning Approach

We now define the necessary components required to instantiate the learning approach described in our work.

Abstract Lattice Fig. 10 shows the lattice  $(\mathcal{H}_a, \sqsubseteq)$  used to represent the abstract domain for allocation site analysis. The abstraction function  $\alpha \colon L \to H_a$  maps the concrete program locations to elements true and false which denote whether the program location is an allocation site or not.

$$H_a = true \int_{\perp}^{\top} false$$

Fig. 10. Lattice used for allocation site analysis.

```
m \in {\tt Move_{core}} ::= {\tt Up \mid Left \mid Right \mid DownFirst \mid DownLast \mid Top} m \in {\tt Move_{alloc}} ::= {\tt PrevNodeValue \mid PrevNodeType} m \in {\tt Move} ::= {\tt Move_{core} \cup Move_{alloc}} w \in {\tt Write} ::= {\tt WriteValue \mid WritePos \mid WriteType \mid HasPrevNodeValue} {\tt NewAlloc \mid NoAlloc}
```

Fig. 11. Language  $\mathcal{L}_{alloc}$  for expressing the result of allocation site query by means of navigating over an abstract syntax tree.

Concrete and abstract program semantics The concrete properties we are tracking and their abstract counterpart as described in Section 4 are instantiated by setting  $\mathcal{C} := \{true, false\}, \mathcal{A} := H_a \text{ and } \mathbb{N} := L$ , where L is a set of all program locations (nodes in an AST). That is, all concrete program behaviors are captured by a function  $[p]: \langle L \rangle \to \{true, false\}$  that for each program location L computes whether it is an allocation site. The abstract semantics are similar except that we instantiate the abstract domain to be the lattice  $(\mathcal{H}_a, \sqsubseteq)$ . We discuss how we obtain the concrete behaviors  $[p]_{ti}$  after running the program on a set of test inputs ti in Appendix F.1.

*Program modifications* We use the same set of program modification as used to learn points-to analysis (described in Appendix A).

Language for allocation site analysis The DSL language  $\mathcal{L}_{alloc}$  used to instantiate the learning of allocation site analysis is very similar to the  $\mathcal{L}_{pt}$  used for points-to analysis. The syntax of the language is shown in Fig. 11 and is based on the same idea of navigating over the abstract syntax tree of a given program. It contains two additional instructions NewAlloc and NoAlloc used to denote whether a given location is an allocation site. These two instructions are used in the leafs of the learned analysis. Additionally, it defines two general instructions used to navigate over the AST – PrevNodeValue and PrevNodeType. The formal semantics of these instructions are following:

- mv(PrevNodeValue, t, n) = n' where n' is the position of the most recent AST node with the same value as the current node, i.e., the maximal n' such that n' < n and wr(WriteValue, t, n) = wr(WriteValue, t, n'). Further, to enable modular learning we require that both nodes n and n' are defined within the same function or in the top level scope of the program. If no such value n' exists in the t then a  $\bot$  is returned.
- mv(PrevNodeType, t, n) = n' has the same semantics as PrevNodeValue except that we require that the types at given nodes are the same, i.e., wr(WriteType, t, n) = wr(WriteType, t, n').

Finally, we note that the formal semantics of the  $\mathcal{L}_{alloc}$  are the same as presented for  $\mathcal{L}_{pt}$  except that for  $\mathcal{L}_{alloc}$  we do not include the information about current call trace. That is, the program state  $\sigma$  is defined as follows:  $\sigma = \langle t, n, ctx \rangle \in States$  where the domain  $States = AST \times X \times Context$ .

```
Array.prototype.filter ::=

if caller has one argument then

points-to global object

else if 2nd argument is Identifier then

if 2nd argument is undefined then

points-to global object

else

points-to 2nd argument

else if 2nd argument is This then

points-to 2nd argument

else if 2nd argument is null then

points-to global object

else //2nd argument is a primitive value

points-to new allocation site
```

Fig. 12. Learned analysis for JavaScript API Array.prototype.filter.

## E Learned Program Analyses

### E.1 Points-to Analysis

To illustrate the complexity of the learned program analysis and the fact that it is easy for it to be interpreted by a human expert, we show the learned analysis for the API Array.prototype.filter in Fig. 12. By inspecting the programs in the branches we can see that the analysis learns three different locations in the program to which the this object can point-to: the global object, a newly allocated object, or the second argument provided to the filter function. The analysis also learns the conditions determining which location to select. For example, this points to a new allocation site only if the second argument is a primitive value, in which case it is boxed by the interpreter. Similarly, this points-to the second argument (if one is provided), except for cases where the second argument is null or undefined.

For better readability we replaced the sequence of instructions in  $\mathcal{L}_{pt}$  used as branch conditions and branch targets with their informal descriptions. For example, the learned sequence that denotes the second argument of the calling method is GoToCaller DownFirst Right Right. It is important to note that that we were not required to manually provide any such sequences in the language but that the learning algorithm discovered such relevant sequences automatically.

#### E.2 Allocation Site Analysis

Here we provide details and the learned program for allocation site analysis. We start by describing a subset of the learned program that corresponds to handling of statements that allocate objects using NewExpression. Then we describe the full analysis.

```
if WriteType == NewAllocation then
 if constructor for given object was used before then
 else if last argument is LiteralNumber then
  NewAlloc
 else if last argument is LiteralString then
  NewAlloc
 else if constructor with no arguments then
  NewAlloc
 else if last argument is LiteralBoolean then
  NewAlloc
 else if last argument is UnaryExpression then
  NewAlloc
 else if last argument is ArrayExpression then
  NewAlloc
 else if last argument is null then
  NewAlloc
 else
  if last argument has been used before then
   Top
  else
   Top
```

Fig. 13. Learned analysis for object allocation by invoking the constructor explicitly.

Program learned for object allocation using NewExpression As illustrated in Fig. 9, calling new in a JavaScript program does not necessarily lead to allocation of a new object. The exception are the semantics of the built-in Object class that are defined as follows<sup>1</sup>:

"The Object constructor creates an object wrapper for the given value. If the value is null or undefined, it will create and return an empty object, otherwise, it will return an object of a Type that corresponds to the given value. If the value is an object already, it will return the value."

— Object constructor

By inspecting the learned program shown in Fig. 13 we can see that it learns the above semantics by checking the type of the argument passed to the constructor. If the argument is one of the primitive types or a null value then it will be always wrapped in an new object (marked by returning NewAlloc as the leaf program). The program also learns that in case the constructor has no arguments it always allocates a new object. In case the argument was used before then the analysis chooses to conservatively approximate the result.

Full learned analysis The summary of the full allocation site analysis learned for JavaScript is shown in Fig. 14. We can see that the analysis iteratively refines the dataset by conditioning on various types of predictions.

<sup>1</sup> https://developer.mozilla.org/en-US/docs/Web/JavaScript/Reference/Global\_Objects/Object

First, the analysis checks whether the given value was used before in the program. This case typically applies to global objects for which their first reference in the program is considered an allocation site. Therefore, if the object was seen before (i.e., HasPrevNodeValue returns true) it is very likely that it is not an allocation site. However this might not be always the case and therefore the learning algorithm chooses to approximate this branch (as it cannot find a further refinement). A counter-example for using NoAlloc program inside this branch is for example a program that uses new Map() and then Map.prototype. Here, even though the Map is used before in the program, it is considered a new allocation site at the time the prototype field is accessed. This is because the instrumentation does not track the read of object Map when calling a constructor.

Subsequently, the analysis identifies that calling some methods might return a new object and learns to model such cases. Here an interesting first branch that is learned is to check whether the call is used in an ExpressionStatement, i.e., as a single statement. In this case the return value is not used in the program and therefore is unlikely to be an allocation site. However, similar to the previous case, this is not guaranteed and therefore the algorithm learns to approximate this branch.

Next, an analysis or accessing elements in an array is learned. Note that this analysis is quite complex as the elements in the array might alias with other variables which makes it difficult for the analysis to precisely determine a simple model for this case.

Further, a simple model is learned for the standard allocation site locations such as the arguments and implicit constructors. Finally, the analysis also learns that the left hand side of an assignment cannot be an allocation site.

## F Implementation

In this section we describe the implementation details of our approach.

#### F.1 Obtaining Programs's Concrete Behaviors $[p]_{ti}$

We extract the relevant concrete behaviours of the program p by instrumenting the source code (not the interpreter) such that when executed, p produces a trace  $\pi$  consisting of all object reads, method enters, method exits and call sites. Additionally, at each method entry, we record the reads of all the parameters and the value of this. Further, every element in the trace contains a mapping to the location in the program (in our case to the corresponding node in the AST) and object reads record the unique identifier of the object being accessed.

Training dataset for points-to analysis Given such a trace  $\pi$ , we create a dataset  $\mathcal{D}_{pt}$  used for points-to analysis by generating one input/output example for each position in the trace  $\pi$  at which the **this** variable was read. Further, we select only the first read of **this** in each scope as all such references point to the same object. An input/output example is a pair  $\langle AST \times X \times \mathbb{I}^*, O \rangle$ , where  $t \in AST$  is

```
if HasPrevNodeValue then
 Top
else if WriteType == CallExpression then
 if Up WriteType == ExpressionStatement then //return value not assigned
  Top
 else
else if WriteType == ArrayAccess then
else if Up WriteType == CatchClause|FunctionExpression then
 NewAlloc //arguments
else if WriteType == ObjectExpression|ArrayExpression|LiteralRegExp then
 NewAlloc //implicit constructors
else if WriteType == NewExpression
else if Up WriteType == AssigmentExpression
 if left hand side of the assigment then
  NoAlloc
 else
  . . .
else
 . . .
```

Fig. 14. Summary of learned allocation site analysis for JavaScript.

an abstract syntax tree corresponding to the input program,  $n \in X$  is a position in the tree where a given read was performed,  $i \in \mathbb{I}^*$  is a call trace and  $o \in O$  is the identifier of the concrete object seen during execution.

Training dataset for allocation site analysis Given such a trace  $\pi$ , we create a dataset  $\mathcal{D}_{alloc}$  used for allocation site analysis by generating one input/output example for each position in the trace  $\pi$  as follows:

- 1. select all positions in the trace  $\pi$  where an object was read.
- 2. for each position select only the first read in the trace, i.e., first loop iteration or first method invocation.
- 3. filter reads of this object and field access.

An input/output example is a pair  $\langle AST \times X, O \rangle$ , where  $t \in AST$  is an abstract syntax tree corresponding to the input program,  $n \in X$  is a position in the tree where a given read was performed. From a trace  $\pi$  we determine the correct label  $O \in \{true, false\}$  by assigning label true for all positions in  $\pi$  for which the corresponding identifier of the object being accessed was not seen previously within the same method call (or global scope) and false otherwise. That is, intuitively we say that program location is an allocation site if the object being read was not seen before. We consider method call boundaries to make the analysis modular an independent of the current program call trace.

#### F.2 Checking Analysis Correctness

Points-to analysis For a program analysis pa and a dataset  $\mathcal{D}$ , we are interested in checking whether the analysis results computed for program p are correct with respect to the concrete values seen during the execution of p. Recall (from Appendix B) that executing the analysis  $pa \in \mathcal{L}_{pt}$  on an input example  $\langle t, n, i, o \rangle$  (as defined above) produces a position n' = pa(t, n, i) in the program or the element  $\top$ . If the analysis returns  $\top$  then it is trivially correct, otherwise we distinguish between two cases. If n' = n, we say that the analysis is correct if the value o has not been seen in the trace  $\pi$  before position n. This is true when position n is a new allocation site. If  $n' \neq n$ , we say that the analysis is correct if the value o has been seen previously in the trace at position n'.

Allocation site analysis Checking the correctness of the allocation site analysis is trivial as executing the analysis  $pa \in \mathcal{L}_{alloc}$  on an input example  $\langle t, n, o \rangle$  produces one of the labels NewAlloc, NoAlloc or Top which can be directly compared to the expected output  $o \in \{true, false\}$ .

### F.3 Synthesising $\mathcal{L}_{pt}$ and $\mathcal{L}_{alloc}$ Programs

We instantiate the learning described in Section 5 using the following two program generators genAction and genBranch for the  $\mathcal{L}_{pt}$  and  $\mathcal{L}_{alloc}$  languages. For  $\mathcal{L}_{pt}$  we instantiate genAction using an enumerative search that considers all programs up to size 5. For  $\mathcal{L}_{alloc}$  the genAction simply tries two possible programs NewAlloc and NoAlloc.

We instantiate the genBranch using the same procedure for both  $\mathcal{L}_{pt}$  and  $\mathcal{L}_{alloc}$  languages. In particular, we use enumerate search that considers as conditions all programs up to size 6 (with up to 5 move and 1 write instruction). To determine the concrete value used as a right-hand side of the condition, we collect the top 10 most common values observed when executing the condition and pick one that maximizes the information gain metric as defined in Section 5.4. For the dataset sizes used in our work such simple generators proved to be effective in practice. To scale for larger datasets one could use the idea of representative sampling [28] that was shown to work well for the domain of programs.

### F.4 Regularization

The purpose of regularization is to select simpler programs from language  $\mathcal{L}$ . In particular, we use the following regularized cost function  $cost_{reg}(\mathcal{D}, pa) = cost(\mathcal{D}, pa) + \lambda \cdot \Omega(pa)$ , where  $\lambda$  is a regularization constant empirically set to 0.01 and  $\Omega(pa)$  is a regularization that penalizes more complex programs. We instantiate  $\Omega(pa)$  to return number of instructions in pa. Additionally, for programs that use WritePos and WriteValue we multiply the regularization  $\Omega(pa)$  by a factor of two as these values are less stable under program modification. We note that using such regularized cost function directly in the learning is a useful extension of our approach that allows controlling the amount of approximation (by setting the value of  $\lambda$ ).

## F.5 JavaScript Restrictions

Finally, we remove from the training data programs that use the eval function, dynamic function binding using Function.prototype.bind and Function object constructor. These are language features that require combination of analyses to handle precisely and are therefore typically ignored by static analyzers [22]. We also filter accesses to arguments object for the allocation site analysis. This is a limitation of our instrumentation that instruments reads and methods calls by means of wrapper functions that affect the binding of arguments object.