Systematic Generation of Conformance Tests for JavaScript

BLAKE LORING, Royal Holloway, University of London, United Kingdom
JOHANNES KINDER, Bundeswehr University Munich, Germany

JavaScript implementations are tested for conformance to the ECMAScript standard using a large hand-written test suite. Not only is this a tedious approach, it also relies solely on the natural language specification for differentiating behaviors, while hidden implementation details can also affect behavior and introduce divergences. We propose to generate conformance tests through dynamic symbolic execution of polyfills, drop-in replacements for newer JavaScript language features that are not yet widely supported. We then run these generated tests against multiple implementations of JavaScript, using a majority vote to identify the correct behavior. To facilitate test generation for polyfill code, we introduce a model for structured symbolic inputs that is suited to the dynamic nature of JavaScript. In our evaluation, we found 17 divergences in the widely used core-js polyfill and were able to increase branch coverage in interpreter code by up to 15%. Because polyfills are typically written even before standardization, our approach will allow to maintain and extend standardization test suites with reduced effort.

1 INTRODUCTION

JavaScript started out as a lightweight scripting language for the web, but has grown to become a language powering large web applications, server-side backends, and embedded systems. As a result of its rushed initial development and the following rapid growth, it is also a complex and sometimes quirky language. Its growing importance as an industry standard with several competing implementations has led to it being standardized as ECMAScript, with a precise and highly complex specification document. As the language evolved, it has become common for not all implementations to support the latest language features and APIs. To make use of them but retain compatibility, developers can use polyfills, pure JavaScript libraries that simulate new language features if they are not yet supported by the interpreter.

Smooth interoperability between interpreters by different vendors and the various polyfills is ensured by the common ECMAScript standard and its test suite. While there is a formally verified reference interpreter for the core language, which closely follows the natural language specification [3], all fully-fledged implementations in browsers and other systems rely on test suites to ensure conformance. The main mechanism for validating conformance to the ECMAScript standard is Test262 [11], a manually curated test suite with the goal of covering all observable behavior of the ECMAScript specification.

Because Test262 is created manually, it is likely that it does not entirely achieve this goal. Furthermore, implementations of a specification by definition add additional implementation detail. As a consequence, we argue that interpreters contain relevant behavior that is not exercised by Test262. When corner cases remain untested, there is a potential for hidden divergences from the specification. Methods from automated test generation seem ideally suited to fill this gap and exercise hidden behavior. Techniques such as dynamic symbolic execution promise to generate high-coverage test suites fully automatically with the help of an satisfiability-modulo-theories (SMT) solver. In principle, such techniques will allow to generate test cases for implementations of ECMAScript language semantics. Full JavaScript implementations are highly complex software systems, however. There has been some success using simpler testing techniques such as fuzzing to find bugs in interpreters [15], and also using dynamic symbolic execution to test interpreters for simpler languages [5]. But so far, dynamic symbolic execution does not scale to full JavaScript
interpreters, and interpreter features such as just-in-time compilation make full support highly unlikely.

In this paper, we propose to symbolically execute straightforward implementations of JavaScript language features to generate new test cases. These are then executed on a portfolio of JavaScript interpreters, using a majority vote to decide the correct behavior. We find that polyfills are ideally suited for this task: polyfills are directly executable and provide more detail than the ECMAScript specification; at the same time, they are much more compact than implementations in an interpreter. Polyfills also have the advantage of providing a clear entry point for each supported feature, which makes directed testing possible. In interpreters, the implementation of language semantics is hidden behind parsing and translation layers, far removed from any external entry point that could be controlled by a test generation tool.

Entry points of polyfill code can require structured input such as objects and arrays, whereas dynamic symbolic execution usually only yields primitive input values returned by the SMT solver. Due to the lack of static typing in JavaScript, object and array creation cannot rely on type information as is usually done for object-oriented languages [31, 32]. Instead, we introduce a purely dynamic approach to generate structured test inputs in dynamic symbolic execution. We intercept accesses to object fields and array elements by the JavaScript program at runtime and generate test cases for each meaningful outcome, handling possible name aliasing, different field types, and the special quirks of JavaScript arrays.

We evaluate our approach in an implementation on top of ExpoSE [21], an existing dynamic symbolic execution engine for JavaScript programs. We automatically generate a rich suite of tests from the Mozilla Developer Network polyfills (mdn-polyfills) and core-js that we run against SpiderMonkey, Node.js, and QuickJS. In summary, we make the following contributions:

- We present a methodology for automated generation of conformance tests from polyfills. We employ differential testing across multiple implementations to compensate the lack of testing oracles (§3).
- We define a model for symbolic objects and symbolic arrays that dynamically synthesizes test inputs in untyped JavaScript code (§4).
- We improve the state of the art in conformance testing of ECMAScript implementations through our methodology. Using our new tests, we found 17 bugs in polyfill implementations and were able to augment the coverage of Test262 in JavaScript interpreters by up to 15% (§5).

Overall, we believe that this can lower the bar for maintaining standardization test suites like Test262 in the future. New language features are regularly implemented in polyfills before standardization, and our approach will allow to generate corresponding tests as a byproduct.

2 BACKGROUND

We begin by providing the necessary background on JavaScript (§2.1), dynamic symbolic execution (§2.2), and the particulars of applying it to test JavaScript code (§2.3).

2.1 JavaScript

JavaScript has a dynamic type system, so program source code contains no type annotations and no type checking is performed during preprocessing. Instead, type information (tags) is attached to values when they are created and rules are enforced at runtime. All values are in the same form, a structure consisting of data and a tag that indicates the value type. Whenever the interpreter executes an instruction, it first inspects the type of operands. If the operands are not in the desired type, then a series of type coercion rules are applied to convert them to usable types or a type error is thrown. For example, "Hello " + 5 results in the string "Hello 5". Automatic type coercions
can have unintuitive semantics. For example, in contrast to the previous expression, "Hello" - 5 evaluates to NaN, since a string added to a number coerces the number to a string, but a string subtracted from a number attempts to coerce the string to a number. The combination of dynamic typing and automatic type coercion can make bugs in programs hard to track, since applying operations on incompatible types will not cause an immediate error and instead propagate through the program. For example, the following program will produce the result "NaNHello10". If y is not fixed, it will be difficult to identify where first error occurs:

```javascript
function doTask(y) {
    let j = y + 10;
    let q = 4 - y + j;
    return q;
}
doTask('Hello');
```

Objects are maps from string property names to values. Objects are constructed dynamically and have no pre-set structure. `let x = { a: 'H' };` constructs a new object with a single property, a and assigns it to the variable x. After executing `x.b = 'Q';`, x will have two properties set, a, and b. Values of any type can be assigned to object properties, including other objects, arrays, and functions. For example, the following code will create a new function and assign it to the property `printA` on x:

```javascript
x.printA = function() {
    console.log(this.a);
}
```

When a function attached to an object is executed, the containing object is passed as the `this` argument to the function call. For example, `x.printA();` will print H, since this refers to x.

The language also allows object-oriented programming. Classes are constructed dynamically through constructor functions and the `new` keyword. When `new` is used, a fresh object will be created and the constructor is executed with the `this` value equal to the new object. The resulting object is returned after construction. For example, the following code defines a new class and then creates an instance of it with the argument "Hello":

```javascript
function A(arg) {
    this.arg = arg;
}
let a = new A("Hello");
```

Note that there is no distinction between class constructors and other functions. In our example, since A is a function, we are also allowed to execute it without the `new` keyword. This allows created objects to call other class constructors to simulate inheritance. For example, the following code will create a class constructor B, and use the A constructor to make sure it has the same properties:

```javascript
function B(arg) {
    A.call(this, arg);
}
```

Assigning all properties of a new object in the constructor can make managing code difficult, so the language also includes object prototypes. If we want a value to be added to every instance of A, then we can add it to the prototype object which exists as a property of every function. For example, once we execute `A.prototype.q = 'bye';`, the property q will exist in any new instance of A. These prototypes can be chained together, forming inheritance chains. For example, the
following code defines B an extension of A, and will print bye since it inherits q from the chained prototype:

```javascript
function B() {
  B.prototype.constructor.call(this, "Hello");
}
B.prototype = Object.create(A.prototype);
console.log((new B()).q);
```

Prototype chaining and prototypal inheritance are core to object abstractions in JavaScript. While later revisions to the standard add support for the class keyword, this is just syntactic sugar for prototypes.

### 2.2 Dynamic Symbolic Execution

Dynamic symbolic execution (DSE) is an automated test generation approach based on constraint solving and has been shown to be effective at bug-finding [4, 6, 13]. DSE generates new test cases for a program through repeat executions. In DSE, some inputs to a program are marked as symbolic while others are fixed. The DSE engine then generates a series of assignments for symbolic values which each exercise a unique control flow path through the program. For example, when analyzing the following program, we begin by replacing the input x with the symbol X:

```javascript
var x = X;
var y = x + x;
if (x > 10) {
  if (y < 20) {
    ...
  }
}
```

When executing the program we maintain a symbolic state in addition to the concrete state. The concrete state drives test execution, while the symbolic state tracks constraints on the symbols in the program. To begin analysis, we execute the test harness with an initial concrete assignment for the symbolic inputs. For our example, we pick the initial assignment x = 5.

With our test setup and our initial test case selected, we are now ready to symbolically execute the program. When operations involve symbolic operands, we compute the concrete result using the concrete value of the operand and use a symbolic interpreter to generate the resulting symbol. We see this on line 2, where execution with our initial test case will yield a concrete value of y = 10, and a symbolic value of $y = X + X$. We now reach line 3, the first branching condition in the program. In DSE, we use the concrete state to decide which branch to follow for the current test execution and we also develop a symbolic path condition (PC), a symbolic representation of the conditional operations which drove us down the branches we followed. On line 3 we follow the else branch, and do not enter the if condition since the concrete value of x is 5. We use the ← operator to denote updates to the symbolic path condition. At this step we update our path condition with $PC ← PC ∧ X < 10$. After this, our first test case terminates.

Upon termination, the DSE engine uses the PC and an SMT solver in order to find alternate assignments for the symbolic inputs. We find these alternate assignments by negating the conditional operations in the PC so that the next test case will take the opposite route at that branching point. We now try and find an alternative assignment for x which will follow the true branch on line 3. We query the SMT solver to decide there is any assignment for x where $x > 10$, and the SMT solver gives us the input $x = 25$, our new test case.
Since we have identified a new test case, we now re-execute our program with the new concrete assignment for $X$. During this execution we follow the true path on line 3, and each line 4 with the path constraints $PC = X > 20$. On line 4, we check if $y < 20$. In this test case, $y$ has a concrete value of 50, and a symbolic value of $X + X$. Since 50 is greater than 20, we take the else path and update the PC with $PC ← PC ∧ X + X > 20$, leading to test case termination.

We now use the SMT solver to decide if there is an assignment for $X$ which explores the true branch on line 4. We take the PC and negate the last constraint, resulting in a query asking the SMT solver if there is a feasible assignment for $X$ such that $X > 10 ∧ X + X < 20$. Here, the SMT solver tells us that there is no feasible assignment for $X$, so we know that the true branch on line 4 is unreachable. Since there are no new test cases for our program our DSE is now complete and we have explored all feasible control flows contingent on our symbolic $X$. In general, there will be an impractical (possibly infinite) number of test cases to execute. So instead of exhausting all test cases, we repeatedly execute new test cases until we reach a time limit or a predefined coverage goal. Therefore, DSE can in general not be used for software verification, but it is ideally suited to generate high-coverage test suites fully automatically.

2.3 Dynamic Symbolic Execution for JavaScript

The complex dynamic type system, dynamic nature of programs, and rapid pace of change in the language make JavaScript programs challenging to symbolically execute. Additionally, programs use a lot of high level features, such as objects, arrays, strings and regular expressions which can be tricky to reason about symbolically.

Saxena et al. [28], Li et al. [20], and Fragoso Santos et al. [12] built custom symbolic interpreters for JavaScript, but the language changes frequently and these engines target older versions of the standard, making them impractical for current real-world analysis. Sen et al. [29] took an alternate approach when developing Jalangi, a symbolic framework which uses program instrumentation to embed the symbolic engine directly into a program. By instrumenting the program source code maintenance cost is reduced, but it is harder to segregate the symbolic state from the running program. Jalangi does not support symbolic regular expressions, and only includes a limited support for strings. The engine is also no longer supported, but can still be run on ES5 programs.

To generate our conformance tests we use ExpoSE. ExpoSE is a open-source DSE engine for modern JavaScript [21] designed for practical symbolic execution. The engine separates test case scheduling, SMT solving, and test execution which allows for concurrent executions. In ExpoSE, test executions are isolated to avoid artifacts from asynchronous events impacting subsequent executions. ExpoSE uses Jalangi2 [30] to instrument programs, embedding the symbolic execution engine into the code. To propagate symbolic values, ExpoSE uses concolic values, where a symbolic value includes both a symbolic expression and a concrete value for that test case. These values are propagated through the program instead of standard JavaScript values. When performing operations, the instrumented program will first check if operands are symbolic. When symbolic, the instrumentation will call a symbolic interpreter to develop the symbolic expression before directly evaluating the concretely portion. ExpoSE uses the Z3 constraint solver to find alternate test cases, and includes support for strings and ES6 regular expressions out of the box [22].

*Modifications to ExpoSE.* In addition to adding support for symbolic objects (§4.2), we made additions to ExpoSE so that it can treat type-coercions we observed in existing polyfills. In JavaScript, numeric values may be either integers or floating point values and there is no idiomatic way to ensure that a value is an integer. If a developer wants to force a number to be an integer they often use a bitwise operation to force the coercion, since bitwise logic truncates operands to integers. To illustrate this, the $\text{targetLength} = \text{targetLength} >> 0$ ensures that the length is an integer
with a bitshift by 0. ExpoSE did not accurately model bitwise operations and other esoteric behaviors of the type system, but these are used often in built-in implementations, so we modified the engine to support them.

3 CONFORMANCE TESTING USING POLYFILLS

We generate new implementation conformance tests for JavaScript interpreters through symbolic execution of polyfills; implementations of built-in methods in JavaScript. Existing supplementary test suites like Test262, the official ECMA test suite [11], are created by exploring conditions in the specification. Since they are manually curated, bugs may be missed—particularly when treating edge cases. Here, we use a DSE engine to automatically explore the subtleties of built-in implementations in polyfills, and then apply the generated tests to other implementations, since they should all behave identically.

3.1 Polyfills

With each evolution of JavaScript there is a period of time where new feature support will not be ubiquitous, since each vendor will take time to update their implementation. To remedy this, polyfills, short programs which implement built-in methods, have become common. A polyfill will inject a built-in into the standard library at runtime if it is not already supported by the host interpreter.

In this paper we use two polyfill packages, core-js [26] and mdn-polyfills [16], to test our approach. These libraries contain polyfill implementations of standard library methods added in the ES6 standard. core-js is the de-facto standard for polyfills with 78,000,000 monthly downloads. mdn-polyfills is less highly depended on, with 72,000 monthly downloads on NPM, the largest JavaScript package repository.

3.2 Architecture

We generate new test cases by dynamic symbolic execution of polyfills. Analysis of these polyfills will generate inputs that explore the intricacies of built-in specifications, but we do not have a ground-truth for the correct behavior of a test case. To solve this problem we use a suite of interpreters and have them vote on the correct answer. This acts an oracle to identify when an implementation is incorrect, and only requires manual intervention when two or more implementations diverge.

We split our implementation into two components, the test case generator, and the test case executor. The test case generator uses ExpoSE to generate new test cases. The test case executor executes a test suite extracted from the symbolic executions and checks that each of our selected interpreters is implemented correctly.

3.3 Test Case Generation

We generate new test cases by symbolically executing polyfills using ExpoSE. Figure 1 provides an overview of the architecture. We begin by supplying the test apparatus with a target built-in and the number of arguments the method expects. The apparatus then constructs a series of symbolic inputs to use as arguments, including a symbolic value for this. ExpoSE then analyzes the generated test harness and begins to output a series of test cases. We also execute each new test case in Node.js to mitigate any errors in ExpoSE. We forward the result of the concrete and symbolic executions to the path verifier, a tool that double-checks that the concrete and the symbolic result are identical. If they are not, then the test case is discarded. Otherwise, we add the test case to the generated test case suite, and the symbolic path condition is used to generate
new test cases. We use an object-aware type encoding when finding alternate test cases to explore more of our target polyfills (§4).

### 3.4 Test Case Executor

The second component in our design is the test case executor. Our automatically generated test cases do not have a predetermined expected result because the result found during symbolic execution may be from a flawed implementation. Instead of using predetermined test case results, we use a consensus-based approach to detect incorrect implementations, illustrated in Figure 2. We execute each test case in several different interpreters. Each interpreter has a different interface so we generate a compatible test through a test translator that takes a test input and returns a program compatible with a specific engine. For polyfills, we inject the target method into a Node.js instance, replacing any existing implementation. We then execute each of these programs and collect the output.

Once the test case has been executed by each implementation, we pass the results to a voting mechanism. The voting mechanism looks for implementations where behavior diverges from the others. If the outcome of a built-in call diverges either in exception type or result then we say that the interpreters disagree and raise an error. Specifically, we say that an implementation disagrees if either of the following two conditions are violated:

1. If a test case throws an exception and others do not, or the exception type differs from other implementations.
2. If a test case has output different from the others.

We do not compare the exact text of exceptions because it is not specified by the ECMAScript specification. If a single implementation disagrees then it is marked as incorrect. When multiple implementations disagree, we cannot make any conclusion about correct behavior and mark the test case for manual review.

### 4 REPRESENTING SYMBOLIC DATA STRUCTURES IN JAVASCRIPT

To allow automated generation of structured test inputs for built-in methods, we require a method for maintaining symbolic objects and arrays. We developed new encodings for untyped symbolic objects, i.e., symbolic objects with no pre-specified property names or types (§4.2), arrays of mixed types (§4.3), and for homogeneously typed arrays (§4.4).
4.1 Motivation

Support for symbolic objects is key to the exploration of built-ins because it allows thorough exploration of object and array-centric built-ins. More subtly, support allows the DSE engine to consider esoteric type-checking in built-in methods. The specification includes precise but unintuitive rules on how input values are to be interpreted and when type contract violations should raise an error.

To highlight how an object encoding can improve coverage of these edge cases, we now consider `Array.prototype.find`.

Usually, this method is given an array as its base argument and a predicate. The array is then searched, left to right, until a value satisfying the predicate is found. If no values satisfy the predicate then `undefined` is returned. For example, `[11, 23, 20].find((x) => x % 2 == 0)` would yield 20, the first even number in the array. If we look at the method specification, we see that there is a quirk to this method contract. The method accepts any object which looks like an array (i.e., any object with a length property). Because of this, `Array.prototype.find.call({0: 11, 1: 23, 2: 20, length: 3}, (x) => x % 2 == 0)` behaves equivalently to the previous example, but `Array.prototype.find.call({0: 11, 1: 23, 2: 20}, (x) => x % 2 == 0)` will yield `undefined`, since the object does not specify a length.

One further quirk is the coercion of `length` to an integer. The specification does not reject non-integer length properties, leading to a coercion that resolves `Array.prototype.find.call({0: 20, length: true}, (x) => x % 2 == 0)` to 20, but `Array.prototype.find.call({0: 20, length: false}, (x) => x % 2 == 0)` to `undefined`, as `true` is coerced to 1.

In mdn-polyfills these checks are implemented by `var o = Object(this)`, which ensures the value is either an array or an object, followed by `var len = o.length >>> 0`, which selects the length of the object and ensures it is an integer using type coercion. In this case, if the length property is not an integer then it is first coerced to a number and subsequently truncated to an integer. Through our encoding of objects, we can synthesize useful test cases for such behavior.

4.2 Symbolic Objects

Representing JavaScript objects in DSE engines is challenging due to the dynamic type system. Existing SMT solvers do not support a “theory of objects.” Recreating a dynamic datatype in SMT and implementing the required reasoning would complicate solver-side logic and effectively move much language-specific reasoning into the SMT solver, which is designed to be language-agnostic.

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1https://github.com/msn0/mdn-polyfills/blob/master/src/Array.prototype.findIndex/findIndex.js
So instead we opt to translate the reasoning about symbolic objects into a form that can be represented as an SMT problem over primitive types. We develop an intermediate encoder that outputs typed SMT problems directly in the DSE engine. The intermediate encoder does not require solver extensions, instead simulating symbolic objects by following every object operation along a program trace and exploring feasible alternatives.

We model symbolic objects by tracking property lookups and updates to objects. For this, we rewrite all property lookups to use the common interface `getProperty(object, propertyName)` and all property updates to use `setProperty(object, propertyName, value)`. In both cases, `object` is the object operated on and `propertyName` is a string indicating which property is being accessed. For `setProperty`, `value` is the new value of the given property. With this instrumentation, we can keep track of all object operations during execution, updating the symbolic state when appropriate. We instrument arrays similarly, with `getProperty` and `setProperty` interfaces for all property lookups. They differ in the typing of property names, where they also accept integer values, since arrays can contain integer and string property names.

The root of our encoding is the creation of new symbolic values for properties we have not seen before while returning the value stored in a state for properties that we have previously set. Our encoding for objects is illustrated in Figure 3. Here we see how a symbolic object behaves under various typical operations.

The first step in Figure 3 shows how symbolic objects support fully concrete operations. Here, we record the concrete value supplied to be returned on subsequent lookups. When we perform a lookup for a property that we have not encountered before, we introduce a new symbolic value to the program and set it to the appropriate property. The created symbol does not have a fixed type, and instead uses existing support in the DSE engine to explore the program as if it were any of the supported symbolic types. In the case of ExpoSE, the DSE engine we use in this paper, the symbolic types supported are undefined, null, boolean, number, string and through our encoding also objects and arrays. The second operation illustrates this process on `objA` in Figure 3, where the new symbol `Z` is introduced and assigned to the property `z`.

Next, we want to set a property with a concrete property name but a symbolic value. As with a fully concrete set property, we record the supplied property value to the object state; here, it makes no difference if the supplied properties are concrete or symbolic.

The last matter that we address in this example is how we approach setting and getting of properties with symbolic property names. Here, we attempt to create new test cases for each of the previously recorded properties of an object - even if they are subsequently deleted. The final operation illustrates this in the figure, where we write a concrete value with a symbolic property name, leading to two new paths. One where the property `r` is replaced with 5, and another where the property `z` is replaced with 5. This final step causes under-approximation in our encoding: We

Fig. 3. Illustration of symbolic object modeling.
Algorithm 1: Symbolic object encoder – getProperty(base, property).

1 if property is symbolic then
2   for knownProp in base do
3     // Attempt to generate a test case for each known property
4       if Concrete(property) = knownProp then
5         PC ← PC ∧ property = knownProp;
6       else
7         PC ← PC ∧ property ≠ knownProp;
8     return base[property];
9   else
10      if property not in base then
11         base[property] = fresh symbol;
12      return base[property];

Algorithm 2: Symbolic object encoder – setProperty(base, property, value).

1 if property is symbolic then
2   for knownProp in base do
3     // Attempt to generate a test case for each known property
4       if Concrete(property) = knownProp then
5         PC ← PC ∧ property = knownProp;
6       else
7         PC ← PC ∧ property ≠ knownProp;
8     return base[property] = value;
9   else
10      // Record the new value for property
11     return base[property] = value;

do not enumerate on properties that we have not seen previously. We could, in principle, support this through the enumeration of all possible property names, but this would lead to an infeasible number of paths to explore.

To implement our encoding we instrument the getProperty and setProperty operations executed by a program with our object encoder, detailed in Algorithm 1 and Algorithm 2. We send any portions of the program trace involving symbolic objects to these intermediate encoders. The distinction between known and unknown properties is core to our symbolic object encoding, with the symbolic object keeping track of any properties that it has encountered before. Each symbolic object is created with an initial map of known properties. A setProperty operation with a concrete property name marks that property as known, and it will then on return the supplied value to preserve JavaScript semantics. The complementary getProperty operation on a fixed property has normal behavior, returning the (potentially symbolic) known value from the object. So far, this encoding is straightforward and preserves standards semantics, returning known property values for an object. However, in order to explore the program symbolically, we need a special approach to treating unknown property lookups. Whenever a program performs a getProperty on an unknown property we return a new, untyped, symbolic variable rather than undefined (the standard behavior). The specified property of the symbolic object is then marked as known and fixed to this
new symbolic value. When a test case terminates, new tests will be created to explore the program for each supported symbolic type.

There are a number of advanced features which can change the behavior of `getProperty` and `setProperty` operations, such as `defineProperty`, which can trigger the execution of a function instead of map lookup. Methods can also be used to change the enumerability of properties within an object. We concertize the symbolic objects when handling these cases, and so our encoding is under-approximate when modeling these behaviors.

### 4.3 Mixed Type Arrays

We have described an approach to model objects, which are in essence maps between string property names and values of any type. We now show the same approach can be applied to arrays as well. Conceptually, arrays are very similar to objects, mapping integer or string property names to values. The most significant differences between arrays and objects are the custom behaviors of the length property, enumeration, and accompanying methods (e.g., `push` and `pop`). In JavaScript, it is valid to also write to non-integer properties to arrays, with the array acting as an object in these cases. For example, `let arr = [1, 2, 3]; arr['dst'] = '/home';` would yield `[0: 1, 1: 2, 2: 3, length: 3, dst: '/home']`.

We intercept reads and writes to array length, which is a reserved property name in arrays. The array length property will always be one higher than the largest element index in the array. This point is important because arrays do not need to be contiguous (i.e., there may be gaps between two indices). This design choice has an impact on enumeration, where looping on the array length will include all indices `0 <= index < arrayLength`, but using the `of` or `in` operators will only include those which have been set, since these operators will only include properties which are marked as enumerable. For example, examine the following program:

```javascript
let arr = []
arr[0] = 1;
arr[4] = 2;
```
Here, the interpreter will yield the array \([0: 1, 4: 2, \text{length}: 5]\). If we enumerate using the \texttt{of} or \texttt{in} operators we would see 1 and 2 enumerated upon, however if we enumerate and print all properties through the array length then we would see 1, \texttt{undefined}, \texttt{undefined}, 2 printed.

When a program writes to the array length property, the array will be truncated or expanded to the new length. If the value is less than the current array length, any values in the indices \(\text{newLength} \leq \text{index} < \text{oldLength}\) will be deleted from the array. If the value is greater than the current array length, then the array will be extended with \texttt{undefined} values. To illustrate this, see the following program:

```javascript
let x1 = [1,2,3]
let x2 = [1,2,3]
x1.length = 100;
x2.length = 0;
```

In this example the variable x1 would have a length of 100 with all values after 3 being \texttt{undefined}, while x2 will be empty.

We illustrate these changes in behavior through Figure 4. To ensure we accurately model array length, we create a separate symbolic integer to represent it. This value is initially unbounded and has constraints applied as the program executes. As we fetch property 5, we explore two paths, one where the existing length property is large enough to accommodate the new value and one where it is not. In the case where it is not the value of the property will be undefined, and in the other case it will return a new symbol using the same approach as our symbolic objects. The second step illustrates what happens when an array lookup occurs on an array that is longer than our property index. Here, a second path is infeasible because the array length cannot be less than six. Direct writes to an array fix the symbolic length; writing a length of zero to the array truncates it, removing all properties. Subsequent property lookups will all return undefined. A write of length 100 expands the array to a fixed length but does not fix any properties. Here, a property lookup creates a fresh symbol because the previous one was erased. The new symbol is given a unique name in the path condition, and can interact with the symbol that used to occupy this property.

### 4.4 Optimized Support for Homogeneously Typed Arrays

The final component of our encoding is a direct translation to SMT for homogeneously typed arrays. This encoding enables symbolic property names in homogeneously typed arrays. As motivated previously, directly encoding JavaScript arrays in SMT is too expensive for DSE, since we would need to encode potentially recursive values in SMT. Our generic array and object encoding overcome this by on-demand symbol generation, but this strategy cannot reason about property indices symbolically. For example, in the following program, we will not exercise the error:

```javascript
let i = I with initial vale 0;
let arr = A with initial value [];
if (arr[0] == 5 && arr[i] != 5) {
  throw 'Error';
}
```

In this program, we do not exercise the error because we concretize symbolic property names. Thus, \(\text{arr}[i]\) will resolve to \(\text{arr}[0]\), leading to an infeasible constraint of \(\text{arr}[0] = 5 \land \text{arr}[0] \neq 5\), and will not consider any paths where \(i\) is not 0 due to concretization. If we set \(i\) to 1, then this error would be found. We provide an encoding for homogeneously typed arrays directly in SMT to explore portions of a program where property name concretization is limiting analysis. Since the encoding is directly in SMT, we no longer need to concretize property names, allowing us to reason about property names symbolically.
Algorithm 3: Homogeneous Array – getProperty(base, index).

```plaintext
1 if 0 ≤ index < base.length then
2   PC ← PC ∧ 0 ≤ index < base.length;
3   return select(base, index);
4 else
5   PC ← PC ∧ (index < 0 ∨ index > base.length);
6   return undefined;
```

Algorithm 4: Homogeneous Array – setProperty(base, index, value).

```plaintext
1 if index > 0 then
2   base.length = index + 1 if index ≥ base.length otherwise base.length;
3   base = store(base, index, value);
4 return value
```

Algorithm 5: Homogeneous Array – downgrade(array)

```plaintext
1 knownValues = [];
2 for i in Concrete(base.length) do
3   knownValues[i] = select(base, i);
4 return GenericArray(knownValues, base.length)
```

Our encoding uses existing SMT solver support to represent arrays. A typed array has two symbolic components, the array data and array length. The array base is a symbolic mapping of integer property names to symbolic values of the array’s type. The symbolic length property is used to represent the current constraints on array length, which is necessary to test out-of-bounds array element access. A symbolic getProperty can explore two paths, one where the array is shorter than the index resulting in undefined, the second where the array includes the index, resulting in a value of the array type. setProperty operations update the symbolic length to accommodate the new value and then inserts it into the base. This is illustrated in Algorithm 3 and Algorithm 4. In these algorithms, the methods select and store map directly to SMT. We downgrade when a setProperty is given a value that is not the array base type.

The process for downgrading a homogeneously typed array to a mixed-type array is detailed in Algorithm 5. Array downgrading converts a homogeneously typed array into a generic array to allow mixed types. We do this by using the concrete array length to derive the initial mapping for the mixed-type array. We copy the homogeneously typed array’s length into the new array so that we respect existing length constraints.

5 EVALUATION

We now set out to show the effectiveness of our approach on a subset of JavaScript built-in functions introduced with the ES6 specification. Here, we set out to answer the following research questions:

RQ1: Is our approach able to cover the logic of built-in functions?
RQ2: Can our approach find any bugs in built-in methods?
RQ3: Does the addition of our test cases improve coverage of Test262?
### 5.1 Test Case Generation

In our first experiment we answer RQ1 through an evaluation on two popular ES6 built-in method implementations found on NPM. We extracted our surrogate implementations from core-js and mdn-polyfills. Overall, we collected 96,470 new unique test cases. We show that we achieve high coverage of the built-in implementations during symbolic execution, suggesting that a large portion of the implementation is covered.

#### 5.1.1 Methodology.

Our test harness loads the portions of the library we wish to test and selects a target method. The method is then executed with symbolic arguments for both the `this` argument and each of the method arguments. We analyze this harness with ExpoSE. Each method is tested in isolation, through a single analysis using ExpoSE with a timeout of one hour on a 64 core machine. After analysis, the generated test cases are combined and duplicates are removed.

#### 5.1.2 Results.

We generated 129,960 new test cases overall, which was reduced to 96,470 after removal of duplicate tests. Table 1 presents the results of our evaluation, providing coverage information from the analysis of the core-js and mdn-polyfills variant if the method was supported by that library. Overall, we found that our prototype is more capable of generating test cases for

| Function         | Test Cases | core-js Coverage | mdn-polyfill Coverage |
|------------------|------------|------------------|-----------------------|
| Array.from       | 13122      | 90%              | 84%                   |
| Array.of         | 162        | 84%              | 82%                   |
| Array.fill       | 2645       | 89%              | 85%                   |
| Array.filter     | 81         | 88%              | N/A                   |
| Array.findIndex  | 162        | 72%              | 51%                   |
| Array.forEach    | 81         | 78%              | N/A                   |
| Array.reduce     | 729        | 76%              | N/A                   |
| Array.some       | 162        | 84%              | 35%                   |
| String.endsWith  | 64179      | 86%              | 82%                   |
| String.includes  | 15957      | 93%              | 91%                   |
| String.padStart  | 13220      | 94%              | 94%                   |
| String.padEnd    | 13220      | 94%              | 94%                   |
| String.repeat    | 2066       | 96%              | 83%                   |
| String.startsWith| 4215       | 91%              | 88%                   |
| String.trim      | 2025       | 95%              | 83%                   |

Table 1. Automatically generated test cases by built-in method.
string methods than array methods. These results are inline with our expectations, as the string support in ExpoSE is mature. Further improvements in ExpoSE modeling and SMT solvers could improve this support even further. In particular, our encoding currently does not include symbolic models for array methods other than push, pop, includes, indexOf, which may lower overall performance.

5.2 Executing Our Test Cases

We have now generated a suite of test cases for our selected methods and are ready to test built-ins. In this section we set out to answer RQ2 by executing our tests on five JavaScript built-in implementations. We execute each of our generated test cases on three interpreters and two polyfill implementations. To analyze the output of these test cases, we construct the voting mechanism outlined in §3.4 from our selected interpreters. Each test case is executed once per interpreter, and after they finish they vote on the correct output. We found 17 unique bugs in mdn-polyfills, showing that our approach is effective in generating useful test cases for conformance testing. We did not find bugs in any other implementations but this was expected as the methods tested are from a mature standard. We found zero cases which required manual intervention during voting.

5.2.1 Methodology. We selected QuickJS 2019-10-27, SpiderMonkey 68 (through the standalone interpreter), Node.js v8.12.0, core-js v3.1.4 and mdn-polyfills v5.17.1 for testing. We tested each of the test-cases identified in §5.1. We executed each test case once with each competing implementation and stored the output. Next, we examined the result of each test case for divergence between the tested implementations. If there is any divergence then we used the outlined voting mechanism to resolve the failing case. Test cases were each executed with a maximum time of 10 minutes on each interpreter, though no test cases hit this boundary. Tests which crashed or exceeded the timeout are terminated with a failure.

5.2.2 Results. Table 2 presents a summary of test case executions for the 5 built-in implementations. Unique Exceptions gives the number of unique exceptions identified across the executions of all test cases (i.e, where an exception text has not been seen before after test specific details are removed). Test Case Failure details the total number of test cases where the interpreter failed to give a result due to crash or timeout. The final column, Bugs gives the number of bugs found in each implementation.

| Implementation       | Unique Exceptions | Test Case Failure | Bugs |
|----------------------|-------------------|-------------------|------|
| mdn-polyfills [16]   | 34                | 200               | 17   |
| core-js [26]         | 63                | 125               | 0    |
| SpiderMonkey [24]    | 72                | 66                | 0    |
| Node.js [10]         | 56                | 122               | 0    |
| QuickJS [2]          | 24                | 141               | 0    |

Table 2. Test case summaries for 5 built-in implementations.

Our test case executor found 17 bugs automatically, all within mdn-polyfills. We were able to confirm these bugs through manual analysis. For example, in one test case we observed that String.prototype.includes.apply([0,0], [[]]) should yield true, but in mdn-polyfills the built-in returns false. We found this divergence occurs because the implementation does not coerce the [0,0] to a string. The identified bugs show that a consensus based test executor can be used to verify the correct behavior of built-in JavaScript methods. Manual analysis found that
the bugs identified were all triggered by unconsidered type coercions in string and array methods. In some cases, this led to the method producing output when it should have thrown an error. In others, the method produced an incorrect output, such as `Array.includes`, which would return `true` when it should have returned `false` on some inputs.

In addition to finding some bugs, we exercised many unique exceptions in interpreters. The high number of unique exceptions suggests that our test suite is exploring many interesting corner cases of implementation. Interestingly, we do not see the same number of unique exceptions across interpreters. We found that some implementations have much more verbose error messages for built-ins than others. While the exception messages are not standardized, and so this is not an implementation error, the lack of verbosity could make errors harder to debug.

We experienced some test case failure for each of the implementations tested. We observed zero cases of failure due to test timeouts or interpreter error; instead, all observed failures were due to interpreter memory limits. Most of these errors occur in `String.repeat`, where many of the test inputs are large values which hit interpreter memory limits. We examined our surrogates to understand why the DSE engine is generating such extreme cases. We find that in one of our surrogate implementations there is an upper limit on string size through a boundary condition `if (str.length * count >= 1 << 28)`. The condition drives ExpoSE to generate a series of test cases supplying large arrays or strings as input. The specification does not specify interpreter memory limits, so the different number of failing cases is not an error. In particular, we observed that SpiderMonkey avoids test case failure in these cases by having stricter limits on bounds for `repeat`. As an example, at the time of writing, Node.js will execute `'h'.repeat(1 << 28)` but SpiderMonkey will not. In the specification, ECMAScript does not add any constraints to the range of strings, so long as they are positive integers. In practice, the reason we see these memory errors in QuickJS and Node, but not SpiderMonkey, is because string boundaries are explicit in SpiderMonkey method implementations. So these errors manifest as exceptions without crashing the interpreter.

Our study has shown that we can detect faults in a real built-in implementation with 35,000 weekly downloads at time of writing. The ability to detect real bugs using our approach shows that a consensus based approach for test case evaluation can be effective. In addition, our approach generated a large number of unique exceptions in the tested cases and covered an obscure difference in string length constraints between interpreters, demonstrating that our test cases explore interesting paths through the implementations.

5.3 Test Suite Coverage

To ensure that our new approach generates novel test cases, we now compare the branch coverage of the new test cases to Test262. We show that the addition of our test cases leads to an increase in overall branch coverage in QuickJS, demonstrating that our approach is generating novel test cases.

To test our approach we built a version of the QuickJS interpreter with support for gcov so we could collect internal code coverage metrics. QuickJS is a complete ES6 implementation of JavaScript [2]. We selected this interpreter because it executes the code in a purely interpreted manner, without JIT or other runtime optimization, and it has built-ins implemented directly in its source code. This is important as many prominent engines, including Node.js [10] and SpiderMonkey [24], do not implement language built-ins directly in source code. Instead, these engines implement a small subset of JavaScript in their native language and then implement the remaining built-ins in JavaScript. Implementing built-ins in JavaScript allows these engines to take advantage of JIT optimizations and reduce engine development time, but, this makes it challenging to collect coverage metrics as built-in functions do not have a clear instrumentation point.
In our study, we found that our automatically generated conformance test suite improves branch coverage by up to 15%. We see coverage improvements in almost every tested function, demonstrating that the approach is versatile. Our results show that we can use automatically generated test cases to supplement the Test262 suite to provide greater overall coverage of JavaScript interpreters.

5.3.1 Methodology. We modified the QuickJS build process to include support for branch coverage output via gcov, a tool which collects coverage information through compile time instrumentation. For each built-in method, we then executed all of our generated test cases and the relevant portion of the Test262 suite. Once each had finished, we extracted the covered branches, using a manual analysis to identify the appropriate function names in the QuickJS source code.

When evaluating the coverage of a function within a program, we present both shallow and deep metrics for combined coverage increases, and follow calls to a depth of 3 when presenting absolute branch coverage. If we only present shallow coverage metrics (i.e., we do not follow function calls), then we may under-represent coverage improvements as logic for built-ins is often spread across many methods. Conversely, including all reachable functions may make our results less insightful by including large amounts of indirectly related code, such as utility methods, which may also be called by other methods during execution. By presenting our combined coverage improvements at different call depths, the reader can see how branch coverage changes as we follow an implementation deeper into the methods it calls.

In our coverage metrics we only include methods defined in the core QuickJS implementation and do not include library calls.

5.3.2 Results. Table 3 details total number of branches, branches covered by our systematically generated conformance tests (ExpoSE), and branches covered by Test262. We selected a call depth of 3 as following calls further included many utility methods, making results less insightful. Here, tests generated by our approach achieve reasonable branch coverage, but do not exceed the coverage of Test262 which is already very high for every method. When we combine the branches
covered by automatically generated conformance tests and Test262 we see an overall coverage improvement over Test262 for every tested function, demonstrating that generated conformance tests are exploring new routes through the implementation.

Table 4 shows the results of our coverage study at various call depths. The function names in the table are the internal function names in QuickJS. QuickJS sometimes implements optimized methods for typed arrays, which is why there may be two methods for the same feature. We see branch coverage improvements in many of the methods we test, in some cases seeing a 15% improvement overall. Our results demonstrate that our automatically generated test cases do explore further into built-in method behavior than Test262 answering RQ3. In most functions, we see notable coverage increases, even at a call depth of 0 (i.e., not including the coverage impact of any called methods). These results highlight that our approach is exploring untraveled paths through built-in function implementations login, and not just expanding coverage in utility methods. The coverage increases at low call depths show that built-in specific edge cases are being exercised, as these expressed near the surface of the call-tree.

Our study of interpreter coverage achieved between automatically generated conformance tests and Test262 shows that supplementing Test262 with automatically generated test cases will improve the test suite. We found that our approach would improve branch coverage of the test suite by up to 15% in a complete ES6 JavaScript engine. These improvements demonstrate that our method can improve conformance testing for JavaScript interpreters using only automatically generated test cases. Such coverage improvements in the testing suite raise the likelihood that implementation errors will be detected before they cause problems in the wild.

### 6 RELATED WORK

We now briefly review related work in the space of dynamic symbolic execution, with a particular emphasis on memory models and handling of symbolic reads and writes to objects and arrays.
Mayhem [8] is a dynamic symbolic execution engine for compiled programs that represents a 32-bit address space symbolically to model program memory. In this work a symbolic memory model improved the effectiveness of DSE by 40%, showing that supporting symbolic memory is crucial. To make their solution feasible, they limit the symbolic representation to reads and do not consider writes symbolically. EXE [7] supports a single-object model, where pointers are concretized and only a single address is considered. The approaches are similar to our own when treating symbolic field names, where ExpoSE concretizes the field name to avoid exploring an unbounded number of inputs.

S2E [9] models system memory symbolically in a symbolic machine emulation, achieved through instrumentation of memory reads and writes. Modeling memory interactions in low level applications is very different from JavaScript, since memory is fixed type and the DSE engine does not need specific encodings for language structures.

The DSE engine KLEE [6] supports multiple memory models, including a forking approach where one path is created to explore each symbolic memory region, and a flat approach which reasons about memory as a single continuous block. Recent approaches split memory regions into segments to allow more efficient analysis [17]. These approaches are highly tailored to reasoning about systems memory with C style pointers and are not directly applicable to JavaScript object modelling.

Bucur et al. [5], found that useful symbolic execution of JavaScript interpreters and their programs is out of reach of current binary symbolic execution engines. This work highlights the need for symbolic dynamic language interpreters, where knowledge of the language structure can make symbolic execution feasible.

There has been work to enable automated testing for Java [1, 14, 27]. Symbolic encodings for Java classes are insufficient for JavaScript as they rely upon a known structures and typing [18, 31, 32]. Our approach is similar to previous symbolic representations of maps, but does not require fixed type fields.

Kristensen and Møller [19] use TypeScript type specifications and feedback directed random fuzzing to identify mismatches between type specifications and observed behaviors. Through this approach the authors identify many inconsistencies, motivating the use of dynamic analysis for specification testing.

Marinescu and Cadar [23] symbolically execute test suites to find bugs. A symbolic execution runs on the existing harnesses used by a program for unit testing, replacing concrete values with symbolic ones in order take advantage of interesting test conditions. Unlike our approach, only simple error conditions are considered because the tool cannot deduce the expected output after a charge in input.

Palikareva et al. [25] use DSE to automatically discover differences in behavior between program versions. The authors test versions of the same software, while our approach tests differences between many implementations of the same specification. As versions of the same software are tested but program specifications are not static, it is difficult to decide whether changes in behavior between two versions are desired. This differs from our approach, where the behavior of compliant implementations is fixed and divergence is an error.

7 CONCLUSIONS

We have presented a new approach to automated generation of conformance tests for the ECMA Script language specification based on dynamic symbolic execution of polyfills. To adapt symbolic execution to this setting, we introduced a new model for generating structured inputs in the presence of dynamic types. We evaluate our method on selected functions from JavaScript built-in implementations, generating 96,470 new conformance test cases from two packages of polyfills.
Using majority voting in place of usual test oracles, we found 17 pre-existing bugs in JavaScript built-in implementations. Our new test cases improve branch coverage of the Test262 implementation conformance test suite by up to 15%.

Overall, our approach promises to make JavaScript conformance testing more thorough and simpler to set up in the future. Given that often polyfills are written before standardization to experiment with new language features, our method can derive corresponding conformance tests directly from these implementations.

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