

# Generic Sensitivity: Generics-Guided Context Sensitivity for Pointer Analysis

Haofeng Li, Tian Tan, Yue Li, Jie Lu, Haining Meng, Liqing Cao, Yongheng Huang, Lian Li, Lin Gao, Peng Di, Liang Lin, and ChenXi Cui

**Abstract**—Generic programming has found widespread application in object-oriented languages like Java. However, existing context-sensitive pointer analyses fail to leverage the benefits of generic programming. This paper introduces *generic sensitivity*, a new context customization scheme targeting generics. We design our context customization scheme in such a way that generic instantiation sites, i.e., locations instantiating generic classes/methods with concrete types, are always preserved as key context elements. This is realized by augmenting contexts with a type variable lookup map, which is efficiently generated in a context-sensitive manner throughout the analysis process. We have implemented various variants of generic-sensitive analysis in WALA and conducted extensive experiments to compare it with state-of-the-art approaches, including both traditional and selective context-sensitivity methods. The evaluation results demonstrate that generic sensitivity effectively enhances existing context-sensitivity approaches, striking a new balance between efficiency and precision. For instance, it enables a 1-object-sensitive analysis to achieve overall better precision compared to a 2-object-sensitive analysis, with an average speedup of 12.6 times (up to 62 times).

**Index Terms**—pointer analysis; generic programming; context sensitivity;



## 1 INTRODUCTION

Pointer analysis statically computes the possible run time values (abstract memory locations) of pointer variables in a program, and it provides a foundation for a variety of applications, such as bug detection [1], [2], [3], compiler optimization [4], security analysis [5], [6], [7], [8], etc. The effectiveness and precision of those client applications directly depend on the precision of the underlying pointer analysis results.

There is a rich literature optimizing the efficiency and precision of pointer analysis [9], [10], [11], [12], [13], and one of the key mechanism to improve precision is *context-sensitivity* [14], [15], [16], [17], [18], [19]. Context-sensitive pointer analyses differ values of a pointer variable under different calling contexts, effectively reducing spurious results introduced by infeasible inter-procedural control flow paths and drastically improving precision. In general, a context is represented by a sequence of  $k$  context elements, where context elements can be call-sites ( $k$ -call-site-sensitivity), allocation sites of receiver objects ( $k$ -object-sensitivity), types of receiver objects or types that contain the methods which allocate receiver objects (two strategies

of  $k$ -type-sensitivity defined by Smaragdakis et al. [18]). For object-oriented programs, object-sensitivity is believed to be better than call-site-sensitivity in achieving precision and efficiency [14], [15], and type-sensitivity is regarded as a more efficient, but less precise alternative to object-sensitivity [18].

Under  $k$ -limiting, the most recent  $k$  context-elements are picked to represent a context. For instance,  $k$ -object-sensitive pointer analysis analyzes a method  $m$  with its context  $[O_k, \dots, O_1]$ , where  $O_1$  is a receiver object of  $m$  and  $O_{i+1}$  is an *allocator* of  $O_i$ , i.e., a receiver object of a method allocating  $O_i$ . In practice,  $k$  is often limited to 1 or 2 in analyzing large real-world applications [20], [21].

This paper, for the first time, proposes a new context customization scheme for *generics*. Generic programming allows to write generic algorithms for different data representations using *type variables*, and has been widely adopted and used in modern programming languages including C++, Java, C#, etc. For instance, the previous study [22] over a large corpus of open-source projects demonstrated that generics, since its introduction to Java in 2004, is one of the most frequently used features in Java. With generics, we can define classes or methods with type variables as parameters, and later instantiate those classes or methods by giving them specific actual types. And type variables can also serve as type arguments at instantiation sites. Taking the following code snippet as an example, type variable  $K$

```

1 class C1<K> ... {
2     void foo() {
3         C2<K> c = new C2<>();
4     }
5 }
6 class C2<V> {}

```

is used as type argument when instantiating generic class  $C2$  at line 3. Therefore, both of type variables  $K$  and  $V$  represent the same concrete type. In this case, the concrete type

(Corresponding authors: Lian Li, Haofeng Li.)

- Haofeng Li, Jie Lu, Haining Meng, Liqing Cao, Yongheng Huang and Lian Li are with SKLP, Institute of Computing Technology, CAS, Beijing 100049, China.
- Tian Tan and Yue Li are with State Key Laboratory for Novel Software Technology, Nanjing University, China.
- Lian Li is with Zhongguancun Laboratory, China.
- Haining Meng, Liqing Cao, Yongheng Huang, Lian Li are with University of Chinese Academy of Sciences, China.
- Lin Gao is with TianqiSoft Inc, China.
- Peng Di is with Ant Group, China.
- Liang Lin and ChenXi Cui are with Alibaba Group, China.

E-mail: lianli@ict.ac.cn, lihaofeng@ict.ac.cn

(corresponding to type variables  $\kappa$  and  $\nu$ ) can distinguish different contexts of the methods constrained by  $\kappa$  and  $\nu$  (i.e., the methods or their declaring classes declared with the information of generic types).

Our context customization scheme for generics is based on the observation that *generic instantiation sites*, i.e., locations instantiating generic with concrete types, can be served as key context elements, but not preserved in existing context-sensitive analyses, and thereby often leading to poor efficiency and precision. As a result, we propose *generic sensitivity*: instead of always picking the most recent traditional context elements (i.e., call-sites, objects, types), we keep generic instantiation sites as part of contexts and propagate such information within generic classes and generic methods. This may sound trivial but can be challenging, since type variables are propagated across generic classes (e.g., inner generic classes/objects defined within other generic classes) or generic methods (by calling other generic methods). So, the biggest challenge lies in accurately determining the generic instantiation sites of type variables. In our approach, we address this challenge by augmenting contexts with generic instantiation information, and propagate it along type variables efficiently. It should be noted that regarding the elements that form the contexts, both generic sensitivity and object sensitivity utilize allocation sites to build their respective contexts. Nevertheless, the approaches these two techniques adopt to create the contexts differ significantly. According to [14], [15], object sensitivity builds its contexts using the receiver objects at the call sites, whereas generic sensitivity builds its contexts using the sites of generic instantiation.

We have implemented our approach in WALA [23] and evaluated it against a set of 18 real-world applications, including the DCAPO benchmark suite [24] and another 7 popular open-source applications. We conduct comprehensive experiments to compare generic sensitivity with state of the arts, including both traditional and selective context-sensitivity approaches. The evaluation results show that generic sensitivity effectively facilitates existing context-sensitivity approaches in achieving a new trade-off between efficiency and precision. For examples, it enables a 1-object-sensitive analysis to achieve overall better precision than a 2-object-sensitive analysis, with an average speedup of  $12.6\times$  (up to  $62\times$  for `chart`). Additionally, it can also contribute to enhancing the efficiency and precision of selective context-sensitivity approaches like ZIPPER [25] and ZIPPER-E [26], which are widely recognized as the state-of-the-art selective context-sensitive pointer analysis.

To summarize, the paper makes the following contributions:

- We present generic sensitivity, a new context customization scheme targeting generics. To the best of our knowledge, this is the first attempt to optimize context-sensitive pointer analysis for generic programming.
- We explain how to apply generic sensitivity to two mainstream context-sensitive variants: k-object-sensitivity and k-type-sensitivity.
- We have implemented different variants of generic sensitive pointer analysis in WALA [23] and evaluated our implementations against a large set of 18 popular real-world applications, including the DCAPO bench-

mark suite and 7 popular open-source applications. Experimental results show that generic sensitivity effectively enhances both traditional and selective context-sensitivity approaches, striking a new trade-off between efficiency and precision.

This article extends and improves upon the paper authored by Li et al. [27], which was presented at the Proceedings of the 30th ACM Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering (ESEC/FSE 2022). In comparison, this article includes significant extensions, expanding the content by approximately six additional pages in a two-column format. The key enhancements are summarized as follows:

- We introduced a local analysis which can infer actual type parameter corresponding to generic type (Section 3.1).
- We presented k-generic-sensitivity which extends original 1-generic-sensitivity to support arbitrary depth of context (Section 4.3).
- We evaluated generic sensitivity with or without applying ZIPPER and ZIPPER-E (Section 5.7).
- We additionally implemented k-generic-sensitivity in WALA and evaluated its precision and efficiency in our benchmarks (Section 5.8).

The rest of the paper is organized as follows. Section 2 motivates our approach with an example and highlights its key challenges. Section 3 formalizes context representation of generic sensitivity. Section 4 formally describes generic sensitivity and explains how it can be adapted to object-sensitivity and type-sensitivity. Section 4.3 illustrates how to extend our generic sensitivity when the depth of context is more than 1. We evaluate the effectiveness and efficiency of generic sensitivity in Section 5. Section 6 reviews related work and Section 7 concludes this paper.

## 2 MOTIVATION

We first give a brief introduction on context-sensitive pointer analysis (Section 2.1). Then we illustrate the limitations of existing context-sensitive pointer analysis in analyzing generics with an example (Section 2.2). Finally, we motivate generic sensitivity, and discuss its main challenges (Section 2.3).

### 2.1 Context Sensitivity

Pointer analysis computes the points-to sets of program variables, i.e., set of *abstract locations* that can be pointed to by a variable  $v$  (denoted as  $pts(v)$ ). Typically, abstract locations are represented as allocation sites (instructions allocating objects, e.g., `new` in Java), denoting all dynamic object instances allocated by the instruction at run time. In context-sensitive analysis, both variable  $v$  and abstract location  $o$  are qualified with a context, effectively distinguishing their different dynamic instances. Hence, instead of computing whether  $o \in pts(v)$  as in context-insensitive analysis, context-sensitive analysis computes the relation  $(c_o, o) \in pts(c_v, v)$ , where  $c_o$  and  $c_v$  are the context for abstract location  $o$  and variable  $v$ , respectively.

Call-site sensitivity, object sensitivity, and type sensitivity are three main variants of context sensitivity, where call-sites, allocation sites of receiver objects, and types of receiver

objects are considered as context elements, respectively. To ensure termination, *k-limiting* is applied to bound the number of context elements to  $k$ . In practice,  $k$  is often set to no larger than 2 for scalability.

Among the above three variants, object sensitivity and type sensitivity (as a cheaper alternative) are considered to be more suitable in analyzing object-oriented programs. In particular, object sensitivity is more precise and efficient than call-site sensitivity and is considered as the most precise context-sensitivity variant for Java [28], [29]. In  $k$ -object-sensitivity, an object  $o_0$  is cloned multiple times, each with a different context of length  $k - 1$ , referred to as the *heap context*. A heap context is in the form of  $[o_{k-1}, \dots, o_1]$ , where  $o_i$  ( $1 < i \leq k - 1$ ) is an allocator of  $o_{i-1}$ , i.e.,  $o_{i-1}$  is allocated in a method with  $o_i$  being a receiver object. Thus, method  $o_0.m$  (with  $o_0$  be a receiver object) will be analyzed context-sensitively multiple times: for each distinct heap context  $c_o$ , the method is analyzed once under the *method context*  $[c_o, o_0]$ . In type sensitivity, contexts are constructed in the same fashion, except that the context element  $o_i$  (in object-sensitivity) is replaced with its type. As a result, multiple object-sensitive contexts will be merged and analyzed together in type-sensitive analysis, yielding less precise results.

## 2.2 A Motivating Example

Let us study context-sensitive pointer analysis with an example in Figure 1. The example uses generic class `java.util.HashMap`. Hereafter, we only discuss the two main stream context-sensitive variants for object-oriented programs: object-sensitivity and type-sensitivity.

In the `main` method, there are two `HashMap` objects:  $O_1$  (line 2) and  $O_2$  (line 7). Object  $O_A$  is created and put into  $O_1$  at line 3, then retrieved back via the `get` method at line 4. Similarly, object  $O_B$  is created and put into  $O_2$  at line 8, then retrieved back at line 9. As a result, the two cast operations (line 5 and 10) will never fail.

The simplified code snippet of `HashMap` is given in lines 13 - 38. `HashMap` stores data in `table`, an array of `Node` objects (line 15). The `put` method creates a `Node` object and stores it in `table` (lines 16-19). The `get` method retrieves the corresponding `Node` object from `table`, then returns its value via the `getValue` interface (lines 20-23). Note that the `Node` class (lines 24-38) is implemented as an inner generic class, and it is instantiated with the type variables (i.e.,  $K$  and  $V$ ) of its outer class `HashMap` when creating a `Node` object.

*k-Object Sensitivity.* In 1-object sensitive analysis (abbreviated as 1-obj), the receiver object of the call to `put/get` method at line 3/4 and line 8/9 are  $O_1$  and  $O_2$ , respectively. Hence, the call to `put/get` methods at different call-sites can be distinguished using contexts  $[O_1]$  and  $[O_2]$ . In `put` (line 17), with 1-obj analysis, we get  $pts([O_1], n) = \{O_4\}$  and  $pts([O_2], n) = \{O_4\}$ . Then in the constructor of `Node` (lines 27-30), since  $O_4$  is the only receiver object, we get  $pts([O_4], key) = \{A, B\}$  and  $pts([O_4], value) = \{O_A, O_B\}$ . As a result, call to  $O_1.get$  and  $O_2.get$  will return a value pointing to both  $O_A$  and  $O_B$ , leading to cast-may-fail false alarms at line 5 and line 10.

This example can only be precisely analyzed when the context depth is set to more than 1. In `put` (line 17),

```

1 public static void main(String[] args) {
2   HashMap<String, A> map1 = new HashMap<>(); //O1
3   map1.put("A", new A()); //OA
4   Object v1 = map1.get("A");
5   A a = (A) v1; //cast may fail?
6
7   HashMap<String, B> map2 = new HashMap<>(); //O2
8   map2.put("B", new B()); //OB
9   Object v2 = map2.get("B");
10  B b = (B) v2; //cast may fail?
11 }
12
13 class HashMap<K,V> ... {
14
15   Node<K,V>[] table = new Node[16]; //O3
16   public void put(K k, V v, ...) {
17     Node<K,V> n = new Node<>(k, v, ...); //O4
18     table[hash(k)] = n;
19   }
20   public final V get(K k) {
21     Node<K,V> n = table[hash(k)];
22     return n.getValue();
23   }
24   class Node<M,N> ... {
25     M key;
26     N value;
27     Node(M k, N v, ...) {
28       key = k;
29       value = v;
30     }
31     public final M getKey() {
32       return key;
33     }
34     public final N getValue() {
35       return value;
36     }
37   }
38 }

```

Fig. 1: Simplified code example of `java.util.HashMap`.

with 2-obj analysis, we get  $pts([O_1], n) = \{(O_1, O_4)\}$  and  $pts([O_2], n) = \{(O_2, O_4)\}$ , where object  $O_4$  is qualified with a heap context. Hence, the constructor of class `Node` (lines 27-30) is analyzed twice with 2 distinct contexts:  $[O_1, O_4]$  and  $[O_2, O_4]$ . Thus, we can precisely compute the pointer values of key and value as  $pts([O_1, O_4], key) = \{A\}$ ,  $pts([O_2, O_4], key) = \{B\}$ ,  $pts([O_1, O_4], value) = \{O_A\}$ , and  $pts([O_2, O_4], value) = \{O_B\}$ . Finally, we can correctly analyze that  $pts(v1) = \{O_A\}$  and  $pts(v2) = \{O_B\}$ , avoiding false cast-may-fail alarms.

*k-Type Sensitivity.* Type-sensitive analysis is less precise than object-sensitive analysis. Hence, 1-type analysis cannot distinguish the pointer values of  $v1$  and  $v2$ , yielding the same false alarms. Moreover, the standard 2-type analysis cannot distinguish the context in analyzing the constructor (and other methods) of `Node` either, since both  $O_1$  and  $O_2$  have type `HashMap` (for efficiency, the actual type parameters of generic-typed local variables are often omitted in the byte code). The default type-sensitive analysis can be extended with a simple analysis as illustrated in Section 5.1, to infer the actual parameters for variables with generic types. Thus, 2-type analysis can then distinguish the context using the distinct generic types `HashMap<String, A>` and `HashMap<String, B>`.

For clarity, we simplify the example in Figure 1 so that it can be precisely analyzed by a 2-obj analysis. The real

```

1 public static void main(String [] args) {
2     G<A> g = new G<A> (); // O1
3     B b = new B (); // O2
4     g.foo(b);
5 }
6 public class G<T> {
7     public void <E> foo(E e) {
8         M<T> m = new M<T> (); // O3
9         m.bar();
10        M<E> n = new M<E> (); // O4
11        n.bar();
12    }
13 }
14 public class M<K> {
15     public void bar() { }
16 }

```

Fig. 2: Example of generics.

implementation of `HashMap` is much more complicated and may require a deeper context. Various algorithms and design patterns wrap generic classes inside other generic classes, which can be precisely analyzed only with a very deep context. For instance, `HashSet` is implemented by encapsulating `HashMap` and it can only be precisely analyzed with at least 3-object-sensitivity. Existing work [25], [30] also summarized numerous scenarios where a deeper context ( $\geq 3$ ) is required. However, as the number of contexts grows exponentially with the depth, it is often infeasible to scale 3-obj analysis to real-world applications [21], [31], [32].

### 2.3 Generic Sensitivity

Generics enable us to create standardized algorithms for processing various types of data to enhance the reusability of algorithms. Many sophisticated algorithms necessitate encapsulating and integrating numerous classes and methods for practical deployment. So these classes and methods are constrained by identical generic types within each call stack. In Figure 1, `Node` offers support for `HashMap` and consistently upholds the equivalent generic type constraint as `HashMap`. Hence, the key to ensure precision is to keep the *instantiation location*, i.e., location instantiating generic type parameters with concrete types, as part of context for generics. As such, distinct pointer values flow into/from generic methods and generic objects can be effectively identified.

In our example in Figure 1, line 2 and line 7 instantiate the generic class `HashMap` with actual types. So, *generic instantiation locations* of `HashMap` are  $O_1$  and  $O_2$  respectively. Therefore the *generic instantiation locations* of the call to `put/get` method at line 3/4 and line 8/9 are  $O_1$  and  $O_2$ , respectively. Hence, the call to `put/get` methods at different call-sites can be distinguished using contexts  $O_1$  and  $O_2$ . And then actual types are passed as type variables:  $\langle K, V \rangle$  of `HashMap` to instantiate `Node` at line 17. So, *instantiation locations*  $O_1$  and  $O_2$  can not only differentiate the methods in class `HashMap` under different call-stack but also can distinguish the methods in `Node`. In other words, *generic instantiation locations* of the call to constructor/`getValue` of `Node` at line 17/22 are  $O_1$  and  $O_2$  respectively. Hence, the call to constructor/`getValue` of `Node` at different call-stacks can be distinguished only using contexts  $O_1$  and  $O_2$ . As a result, with generic-sensitivity, we can compute the same

precise result as 2-obj analysis, but with less cost by avoid computing points-to information under potentially more contexts:  $pts(O_1, key) = \{ "A" \}$ ,  $pts(O_2, key) = \{ "B" \}$ ,  $pts(O_1, value) = \{ O_A \}$ , and  $pts(O_2, value) = \{ O_B \}$ , where  $O_1$  and  $O_2$  serve as the generic instantiation locations in this case.

Someone may wonder if we can discard the receiver objects of generic classes and use their heap contexts as the contexts of target methods when the current methods are within generic classes? It seems feasible for the code in Figure 1. For example, when we analyze the code at line 22 in `get` method whose declaring class is generic class `HashMap`, we discard the receiver object  $O_4$  and use its heap contexts  $[O_1]$  and  $[O_2]$  as contexts. However, this approach does not work for generic methods. As shown in Figure 2, the generic method `foo` (with type parameter `E`) is defined in generic class `G` (lines 6 - 13) with type parameter `T`. At line 8, we create a new generic object with type variable `T`, whose actual type is instantiated (to `A`) at line 2. Hence, we should pick  $O_1$  as the context in analyzing the method call `m.bar` at line 9. On the other hand, line 10 instantiates the generic class `M` with type variable `E`. In our generic-sensitivity approach, the instantiation location of `E`, represented by  $O_2$  at line 3, is chosen as the context for analyzing the method call `n.bar` at line 11. However, if we were to adopt the previously mentioned approach of omitting receiver objects of generic classes, the context for `n.bar` would be determined as  $O_1$ . As a result, it would be the same context as `m.bar`, failing to distinguish between contexts.

To effectively analyze the above example, we need to precisely identify the actual instantiation location of type variables under different contexts. This may require a context-sensitive pointer analysis to compute, as will be explained in Section 3.

## 3 PRELIMINARIES

In generic sensitivity, we precisely track propagation of type variables by augmenting context with generic instantiation locations, which are generated context-sensitively during the analysis. This section will formalize the standard context sensitivity and offer necessary extensions for generics.

### 3.1 Context Customization

The traditional context  $c$  is extended to a tuple  $\langle c, G \rangle$ , where  $G$  records all instantiation sites for available type variables. For non generic-related methods,  $G$  is  $\emptyset$ . The size of  $G$  is bounded to the number of available type variables.

For object-sensitive analysis,  $G$  maps a type variable to its instantiate location (more precisely, to the abstract object created at the instantiate location). For type-sensitive analysis,  $G$  maps a type variable to its instantiated concrete type. In Java, developers can instantiate a generic class with explicit types (Figure 3(a)), or without giving any actual type arguments. In the later case, the generic class is by default instantiated with type `Object`. For instance, in Figure 3 (b), `s` is created at line 3 with type `HashSet<Object>`. At line 4, an object with type `A` is firstly created and implicitly cast to `Object`, before it is put in `s`.

| With Actual Type Arguments  | Without Actual Type Arguments   |
|---|---|
| <pre> 1 class C { 2   void foo() { 3     Set&lt;A&gt; s = new HashSet&lt;&gt;(); 4   } 5 } </pre> | <pre> 1 class C { 2   Set foo() { 3     Set s = new HashSet(); 4     s.add(new A()); 5     return s; 6   } 7 } </pre> |
| (a)   | (b)   |

Fig. 3: Generic instantiation in Java.

Since type-sensitive analysis relies on concrete type information, it will fail to distinguish different contexts when generic classes are instantiated without giving actual type parameters, leading to imprecise results. We can employ a precise inter-procedural pre-analysis to infer actual type arguments of generics as [33], [34], [35]. However, the cost of such a pre-analysis may offset the benefits brought by more precise type information. Hence, we apply a simple analysis to infer actual instantiated types of a generic object by examining its local usages, as follows.

In code of Java, actual type parameters are only declared in the signatures of formal parameters (i.e.,  $foo(Set \langle A \rangle x)$ ), the signatures of fields (i.e.,  $Set \langle A \rangle f;$ ) and type signature of partial local variables (i.e.,  $Set \langle A \rangle x = \dots$ ). However, there are cases where it is not always possible to obtain the actual type parameters directly at the instantiation sites of generic classes or generic methods. Taking the following code snippet as an example, to get the concrete type corresponding to type variable  $T$  at line 4, we need to infer the actual type

```

1 void main() {
2   C<A> v1 = new C<>();
3   C v2 = v1;
4   foo(v2);
5 }
6 void <T> foo(C<T> p){}

```

parameter of variable  $v_2$  which can only be found at signature of variable  $v_1$ . To infer the actual type parameters, we designed a local analysis. Table 1 shows the constraints of our local inference. We use  $foo(Set \langle A \rangle x)$  to represent method  $foo$  with formal parameter  $x$  whose signature is  $Set \langle A \rangle$ . For clarity, we define method  $foo$  with one parameter only. Similarly, field signature and variable signature are defined at the rules of FIELD DECLARATION and VARIABLE DECLARATION respectively. We use  $R(x)$  to represent the inferred results (the mappings from type variables to actual type parameters) where  $x$  represents variable or field used in the current method. It is forbidden to assign several actual type parameters to a type variable. So,  $R(x)$  is singleton. Without loss of generality, we consider a simplified subset of Java with six canonical statements in Table 1:

- FORMAL PARAMETER, FIELD DECLARATION and VARIABLE DECLARATION. Actual type parameters can be captured directly by parsing the method signature, field signature or variable type signature if they are declared in these signatures.
- ASSIGN. If a variable can be assigned to another, both of them should contain the same actual type parameter. Otherwise, compilation errors will occur.
- STORE and LOAD. The actual type parameter can be

propagated to local variables by field access statements, so, we maintain consistent actual type parameter on both sides of the statement.

According to the constraints in Table 1, actual type parameters can be inferred if they are declared. However, not all actual type parameters will be explicitly declared in the Java code. To handle such conditions, we designed a local analysis to infer type parameters (Definition 3.1).

TABLE 1: Actual type parameter inference. The generic type of class Set is E.

| Kind                 | Statements in method:<br>$foo(Set \langle A \rangle x)$ | Constraints        |
|----------------------|---|--------------------|
| FORMAL PARAMETER     | $x$   | $R(x) = \{E : A\}$ |
| FIELD DECLARATION    | $Set \langle A \rangle f;$                              | $R(f) = \{E : A\}$ |
| VARIABLE DECLARATION | $Set \langle A \rangle x = \dots$                       | $R(x) = \{E : A\}$ |
| ASSIGN               | $x = y;$  | $R(x) = R(y)$      |
| STORE                | $y.f = x;$  | $R(x) = R(f)$      |
| LOAD                 | $x = y.f;$  |                    |

**Definition 3.1.** Type parameter inference: if generic object  $O$  instantiating generic class with formal type parameter  $T$  does not escape its declared scope and all its usages of  $T$  can be resolved to type  $C$ , we can safely regard  $C$  as the actual type parameter instantiating  $T$ .

We perform a simple conservative escape analysis where a variable escapes a scope if 1) it is accessible outside the scope, 2) it returns from the scope, or 3) it is stored to another escaping variable. As in Figure 3(b), if  $s$  is not returned (i.e., does not escape its declared scope  $foo$ ), we can infer that  $s$  instantiates  $HashSet$  with type  $A$ , i.e.,  $s$  has type  $HashSet \langle A \rangle$ .

Finally, if we fail to resolve the actual type parameters instantiating a generic class, we use the instantiation location as a pseudo type. In the example Figure 3 (b), the actual type parameter of variable  $s$  at line 3 cannot be inferred (due to an escaped/returned variable). In such scenario, we use a pseudo type  $T_3$  to instantiate  $s$ , i.e., the statement at line 3 is regarded as  $Set \langle T_3 \rangle s = new HashSet()$ . This allows us to label this generic context for potential context distinction. In this way, the pseudo type  $T_3$ , denoted for the current instantiation site, can be seen as a form of object sensitivity, and is employed when inferring the actual type parameters is not feasible. As such, we are effectively applying object-sensitivity-like approach in analyzing generics since each instantiation location is regarded as a distinct type even

| Kind   | Statements  |
|--------|---|
| NEW    | $l : x = \text{new } C \langle \mathcal{T} : A \rangle$ |
| ASSIGN | $l : x = y;$  |
| LOAD   | $l : x = y.f;$  |
| STORE  | $l : x.f = y;$  |
| CALL   | $l : x = v_0.m' \langle \mathcal{T} : A \rangle (v_1)$  |

Fig. 4: Five types of statements analyzed by context-sensitive pointer analyses.

though sometimes it is not possible to deduce the actual type parameters.

### 3.2 A Simplified Java Language

Without loss of generality, we consider a simplified subset of Java, with five types of labeled statements in Figure 4. We write " $x = \text{new } C \langle \mathcal{T} : A \rangle$ " for object allocation. If  $C$  is a generic class,  $\mathcal{T}$  is its formal type parameter, and  $A$  is the actual type parameter instantiating  $\mathcal{T}$ . Otherwise, both  $\mathcal{T}$  and  $A$  is  $Nil$ . Similarly, a generic method call " $x = v_0.m' \langle \mathcal{T} : A \rangle (v_1)$ " instantiates its formal type parameter  $\mathcal{T}$  with actual type parameter  $A$ . Both  $\mathcal{T}$  and  $A$  are  $Nil$  for non-generic method invocations. For clarity, our formalization considers NEW and Call statements with one type parameter only. The general forms of NEW and Call statements with multiple parameters can be analyzed in the same fashion.

The statement " $x = \text{new } C(\dots)$ " in Java is modeled as " $x = \text{new } C; x.\langle \text{init} \rangle(\dots)$ ", where  $\langle \text{init} \rangle(\dots)$  is the corresponding constructor invoked. Control flow statements are irrelevant for context-sensitive flow-insensitive analysis hence skipped. Accesses to array elements are modeled by collapsing all the elements into a special field of the array. In addition, every method is assumed to return via the variable  $ret$ . Since we formalize a method call with only one actual parameter, each method also has only one formal parameter  $p$ .

Given a program, let  $\mathbb{M}, \mathbb{F}, \mathbb{H}, \mathbb{V}, \mathbb{L}, \mathbb{T}$  be its sets of methods, fields, allocation sites, local variables, statement labels and types, respectively. We use the symbol  $\mathbb{C}$  for the universe of contexts. The following auxiliary functions are used in our rules:

- **methodOf**:  $\mathbb{L} \mapsto \mathbb{M}$
- **methodCtx**:  $\mathbb{M} \mapsto \wp(\mathbb{C})$
- **dispatch**:  $\mathbb{M} \times \mathbb{H} \mapsto \mathbb{M}$
- **pts**:  $(\mathbb{V} \cup \mathbb{H} \times \mathbb{F}) \times \mathbb{C} \mapsto \wp(\mathbb{H} \times \mathbb{C})$
- **typeOf**:  $\mathbb{V} \mapsto \mathbb{T}$

where **methodOf** gives the containing method of a statement, **methodCtx** maintains the contexts used for analyzing a method, **dispatch** resolves a call to a target method, **pts** records the context-sensitive points-to information for a variable or field, and **typeOf** returns the declared type of a variable.

Given a list of context element  $c = [e_1, \dots, e_n]$  and a context element  $e$ , we use the notation  $e ++ c$  for  $[e, e_1, \dots, e_n]$  and  $c_k$  for  $[e_1, \dots, e_k]$  where  $k < n$ .

## 4 GENERIC SENSITIVITY

In this section, we will illustrate context customization scheme formally.

$$\begin{array}{l}
 \frac{l : x = \text{new } C \quad m = \text{methodOf}(l) \quad \text{ctx} \in \text{methodCtx}(m) \quad \text{hctx} = \text{ctx}_{k-1}}{(O_l, \text{hctx}) \in \text{pts}(x, \text{ctx})} \quad \text{[NEW]} \\
 \\
 \frac{l : x = y \quad m = \text{methodOf}(l) \quad \text{ctx} \in \text{methodCtx}(m)}{\text{pts}(y, \text{ctx}) \subseteq \text{pts}(x, \text{ctx})} \quad \text{[ASSIGN]} \\
 \\
 \frac{l : x = y.f \quad m = \text{methodOf}(l) \quad \text{ctx} \in \text{methodCtx}(m) \quad (O, \text{hctx}) \in \text{pts}(y, \text{ctx})}{\text{pts}(O.f, \text{hctx}) \subseteq \text{pts}(x, \text{ctx})} \quad \text{[LOAD]} \\
 \\
 \frac{l : x.f = y \quad m = \text{methodOf}(l) \quad \text{ctx} \in \text{methodCtx}(m) \quad (O, \text{hctx}) \in \text{pts}(x, \text{ctx})}{\text{pts}(y, \text{ctx}) \subseteq \text{pts}(O.f, \text{hctx})} \quad \text{[STORE]} \\
 \\
 \frac{l : x = a_0.f(a_1) \quad m = \text{methodOf}(l) \quad (O_0, \text{hctx}) \in \text{pts}(a_0, \text{ctx}) \quad \text{ctx}' = O_0 ++ \text{hctx} \quad m' = \text{dispatch}(f, O_0)}{\text{ctx}' \in \text{methodCtx}(m') \quad (O_0, \text{hctx}) \in \text{pts}(\text{this}^{m'}, \text{ctx}') \quad \text{pts}(a_1, \text{ctx}) \subseteq \text{pts}(p^{m'}, \text{ctx}') \quad \text{pts}(ret^{m'}, \text{ctx}') \subseteq \text{pts}(x, \text{ctx}')} \quad \text{[CALL]}
 \end{array}$$

Fig. 5: Rules for object sensitivity.

### 4.1 Customizing Object Sensitivity

Let  $\mathbb{G} := \overline{\mathbb{T}} \mapsto \overline{\mathbb{H}}$  maps a type variable  $\mathcal{T} \in \mathbb{T}$  to an allocation site  $O_l \in \mathbb{H}$  (identified by label  $l$ ). The universe context is  $\mathbb{C} = \mathbb{H}^* \times \mathbb{G}$ . We define the following three functions:

$$\text{Gen}(G, \mathcal{T}, A, O_l) = \begin{cases} \emptyset & \mathcal{T} = Nil \\ [\mathcal{T} \rightarrow O_l] & \mathcal{T} \neq Nil \wedge A \notin G \\ [\mathcal{T} \rightarrow G(A)] & \mathcal{T} \neq Nil \wedge A \in G \end{cases}$$

$$\text{Append}(G, G_m, \mathcal{T}, A, O_l) = \begin{cases} G & \mathcal{T} = Nil \\ G \uplus [\mathcal{T} \rightarrow O_l] & \mathcal{T} \neq Nil \wedge A \notin G \uplus G_m \\ G \uplus [\mathcal{T} \rightarrow G \uplus G_m(A)] & \mathcal{T} \neq Nil \wedge A \in G \uplus G_m \end{cases}$$

$$\text{Ctx}(\text{ctx}, O_0, G) = \langle O_0 ++ \text{ctx}, G \rangle$$

where the function  $G(A)$  looks up the mapped allocation site of type variable  $A$ .

The first two functions are used to generate  $G$  for NEW and CALL statements, and the last function is used to construct contexts by combining standard context and generic context. Figure 6 gives the rules for analyzing NEW and CALL statements in Figure 4. Except for [NEW] and [CALL], the other 3 rules are same as standard k-obj analysis (in Figure 5). We only list [NEW] and [CALL], since the other 3 rules are same as in Figure 5

In [NEW], an abstract heap object  $O_l \in \mathbb{H}$  is created. Given the method context  $\text{ctx} = \langle c, G \rangle$ ,  $O_l$ 's heap context  $\text{hctx}$  is constructed as  $\langle c_{k-1}, G' \rangle$ , where  $c_{k-1}$  selects the first  $k-1$  context elements from  $c$  as in standard k-obj analysis and  $G'$  is generated by the **Gen** function, as follows.

- If  $O_l$  is a non-generic object, i.e., formal type parameter  $\mathcal{T}$  is  $Nil$ ,  $G'$  is set to  $\emptyset$ . Thus, method calls with non-generic objects as their receiver objects are analyzed same as in standard object-sensitive analysis.
- If  $O_l$  is instantiated with a concrete type, i.e.,  $\mathcal{T} \neq Nil \wedge A \notin G$ ,  $G'$  is set to  $[\mathcal{T} \rightarrow O_l]$ . As a result, the instantiate location  $l$  is regarded as part of context in analyzing a method call with  $O_l$  being a receiver object.

$$\begin{array}{l}
l : x = \text{new } C(\mathcal{T} : A) \quad m = \text{methodOf}(l) \\
\quad \quad \quad \text{ctx} = \langle c, G \rangle \in \text{methodCtx}(m) \\
\hline
G' = \text{Gen}(G, \mathcal{T}, A, O_l) \quad \text{hctx} = \langle c_{k-1}, G'_{n-1} \rangle \quad \text{[NEW]} \\
\quad \quad \quad (O_l, \text{hctx}) \in \text{pts}(x, \text{ctx}) \\
\\
l : x = a_0.f(\mathcal{T} : A)(a_1) \quad m = \text{methodOf}(l) \\
\quad \quad \quad \text{ctx} = \langle c_m, G_m \rangle \in \text{methodCtx}(m) \\
(O_0, \text{hctx}) \in \text{pts}(a_0, \text{ctx}) \quad (O_1, -) \in \text{pts}(a_1, \text{ctx}) \\
\text{hctx} = \langle c, G \rangle \quad G' = \text{Append}(G, G_m, \mathcal{T}, A, O_1) \\
\quad \quad \quad \text{ctx}' = \text{Ctx}(c, O_0, G') \quad m' = \text{dispatch}(f, O_0) \quad \text{[CALL]} \\
\hline
\text{ctx}' \in \text{methodCtx}(m') \quad (O_0, \text{hctx}) \in \text{pts}(\text{this}^{m'}, \text{ctx}') \\
\quad \quad \quad \text{pts}(a_1, \text{ctx}) \subseteq \text{pts}(p^{m'}, \text{ctx}') \\
\quad \quad \quad \text{pts}(\text{ret}^{m'}, \text{ctx}') \subseteq \text{pts}(x, \text{ctx})
\end{array}$$

Fig. 6: Rules for k-Obj/k-type analysis with generic customization.

- At last, if  $O_l$  is instantiated with a type variable, i.e.,  $\mathcal{T} \neq \text{Nil} \wedge A \in G$ , we identify the actual instantiate location of  $A$  by looking up the context of  $l$ 's containing method.  $G'$  is set to  $[\mathcal{T} \mapsto G(A)]$ , enforcing that the actual generic instantiation location is always part of the context.

Note that the **Gen** function does not preserve existing mapping of type variables in  $G$ . Since those type variables are invisible in analyzing method calls where  $O_l$  is the receiver object, there is little benefit to preserve them in the heap context of  $O_l$ .

In **[CALL]**, let  $O_0$  be a receiver object of the method call with heap context  $\text{hctx} = \langle c, G \rangle$  and let  $\text{ctx} = \langle c_m, G_m \rangle$  be a context of  $m$ . Similar to **[NEW]**, a context  $\text{ctx}' = \langle O_0 ++ c, G' \rangle$  is constructed by **Ctx** function in analyzing  $m'$ , where  $O_0 ++ c$  appends the receiver object  $O_0$  with  $O_0$ 's heap context in a standard manner and  $G'$  is generated by the **Append** function, as follows.

- If  $f$  is a non-generic call, i.e.,  $\mathcal{T} = \text{Nil}$ ,  $G$  remains unchanged.
- If  $f$  is a generic call instantiated with a concrete type, i.e.,  $\mathcal{T} \neq \text{Nil} \wedge A \notin G \uplus G_m$ ,  $G'$  is generated by adding the new mapping  $\mathcal{T} \mapsto O_l$  to  $G$ .
- If  $f$  is a generic call instantiated with a type variable, i.e.,  $\mathcal{T} \neq \text{Nil} \wedge A \in G \uplus G_m$ ,  $G'$  is generated by introducing to  $G$  a mapping: from  $\mathcal{T}$  to its actual instantiate site  $G \uplus G_m(A)$ . Note that available type variables can be propagated from the receiver object (in which case  $A \in G$ ), or from the caller method (in which case  $A \in G_m$ ).

One may wonder whether the same type variable  $A$  may exist in both  $G$  and  $G_m$ . In that case, by construction,  $A$  must be introduced at the allocation site of generic object  $O_0$ , by the **Gen** function. Such information may be further propagated to contexts of method  $m$ . In that case, both  $G(A)$  and  $G_m(A)$  are resolved to the same location instantiating  $A$ .

In the conclusion of the rule,  $\text{ctx}' \in \text{methodCtx}(m')$  shows how the context of a method are introduced. Initially, we have  $\text{methodCtx}(\text{main}) = \{\langle \square, \emptyset \rangle\}$ .

Let us revisit the example in Figure 2. A generic object  $O_1$  is created at line 2. Hence, we have  $(O_1, \langle \square, \top \mapsto O_1 \rangle) \in \text{pts}(g, \langle \square, \emptyset \rangle)$  (**[NEW]**). Line 4 invokes the generic method  $f_{\text{oo}}(\mathbb{E})$  where  $O_1$  is the receiver object and  $O_2$  is the actual

parameter, i.e.,  $g.f_{\text{oo}}\langle \mathbb{E} : \mathbb{B} \rangle(b)$ . Hence, we analyze the target method  $f_{\text{oo}}$  with context  $\langle [O_1], [\top \mapsto O_1, \mathbb{E} \mapsto O_2] \rangle$  (**[CALL]**). In  $f_{\text{oo}}$ , the object created at line 8 ( $O_3$ ) is instantiated with type variable  $\top$ . Hence, it has the generated heap context  $\langle [O_1], \kappa \mapsto O_1 \rangle$ . Similarly,  $O_4$  at line 10 has the heap context  $\langle [O_1], \kappa \mapsto O_2 \rangle$ . The two method call at line 9 and 10 are then analyzed with distinct contexts. To summarize,  $G$  always maps an available type variable to its actual instantiation location, to encode actual instantiation location of generics as part of context.

## 4.2 Customizing Type Sensitivity

The k-type-sensitivity is a coarse approximation of the k-object-sensitivity, with a trade-off between precision and efficiency in favor of the latter. Similarly, we customize k-type-sensitivity to improve efficiency with sacrificing some precision.

For type-sensitive analysis,  $\mathbb{G} := \overline{\mathbb{T} \mapsto \mathbb{T}}$  maps a type variable  $\mathcal{T} \in \mathbb{T}$  to an actual type  $T \in \mathbb{T}$ . The **Gen**, **Append** and **Ctx** functions are defined as follows.

$$\text{Gen}(G, \mathcal{T}, A, O_l) = \begin{cases} \emptyset & \mathcal{T} = \text{Nil} \\ [\mathcal{T} \mapsto A] & \mathcal{T} \neq \text{Nil} \wedge A \notin G \\ [\mathcal{T} \mapsto G(A)] & \mathcal{T} \neq \text{Nil} \wedge A \in G \end{cases}$$

$$\text{Append}(G, G_m, \mathcal{T}, A, O_l) = \begin{cases} G & \mathcal{T} = \text{Nil} \\ G \uplus [\mathcal{T} \mapsto A] & \mathcal{T} \neq \text{Nil} \wedge A \notin G \uplus G_m \\ G \uplus [\mathcal{T} \mapsto G \uplus G_m(A)] & \mathcal{T} \neq \text{Nil} \wedge A \in G \uplus G_m \end{cases}$$

$$\text{Ctx}(c, O_0, G) = \langle \text{typeOf}(O_0) ++ c, G \rangle$$

Compared to object-sensitivity, the object allocation site is not used by the three functions.

Let us study the example in Figure 2 again. A generic object  $O_1$  is instantiated with actual type  $A$  at line 2. Hence, we have  $(O_1, \langle \square, \top \mapsto A \rangle) \in \text{pts}(g, \langle \square, \emptyset \rangle)$  (**[NEW]**). At line 4, we have the generic method call  $g.f_{\text{oo}}\langle \mathbb{E} : \mathbb{B} \rangle(b)$  where  $O_1$  is the receiver object. Since  $O_1$  has the declared type  $G$ , we analyze the target method  $f_{\text{oo}}$  with context  $\langle [G], [\top \mapsto A, \mathbb{E} \mapsto B] \rangle$  (**[CALL]**). In  $f_{\text{oo}}$ , the object created at line 8 ( $O_3$ ) is instantiated with type variable  $\top$ . Hence, it has the generated heap context  $\langle [G], \kappa \mapsto A \rangle$ . Similarly,  $O_4$  at line 10 has the heap context  $\langle [G], \kappa \mapsto B \rangle$ . Finally, the method  $\text{bar}$  is analyzed under two contexts  $\langle [M], \kappa \mapsto A \rangle$  and  $\langle [M], \kappa \mapsto B \rangle$ . It is worth noting that in our extended type analysis, the generic type and the recorded actual instantiated types form the complete instantiated type signatures for generics.

## 4.3 K-Limiting

Just like three mainstream variants of context-sensitivity (k-object sensitivity, k-type sensitivity and k-call-site sensitivity), the generic can be wrapped by another generic. So, we have to limit the depth of generic contexts to avoid unbearable number of contexts. However, we cannot increase the depth at every generic allocation since generic instantiation is less prevalent than traditional contexts in Java programs. Taking Figure 1 as an example, the context depth of the constructor (line 17) of `Node` cannot be increased because the actual types ( $K, V$ ) of `Node` are type variables, and

```

1 public static void main(String[] args) {
2   Q<A> q1 = new Q<>(); //O1
3   q1.putOrCreate("A", null);
4   Object v1 = q1.get("A");
5   A a = (A) v1; //cast may fail?
6
7   Q<B> q2 = new Q<>(); //O2
8   q2.putOrCreate("B", new B()); //OB
9   Object v2 = q2.get("B");
10  B b = (B) v2; //cast may fail?
11 }
12
13 class Q<E> ... {
14
15  private InnerQ<E> inner=new InnerQ(); //OIQ
16  public void putOrCreate(String key, E e) {
17    return inner.putOrCreate(key, e);
18  }
19  public Object get(String key) {
20    return inner.get(key);
21  }
22  class InnerQ<E> ... {
23    private HashMap<String, Object> map = new
      HashMap<>(); //OHM
24    public void putOrCreate(String key, E e) {
25      if (e == null) {
26        map.put(key, new A()); //OA
27      } else {
28        map.put(key, e);
29      }
30    }
31    public Object get(String key) {
32      return map.get(key);
33    }
34  }
35 }

```

Fig. 7: Code example for k-generic sensitivity.

actual instantiate locations can be retrieved according to heap context and context of current method. We will discuss how to extend our generic sensitivity when the depth of context is more than 1 by using an example in Figure 7.

In Figure 7, we defined a class  $Q$  with a generic type  $E$  (line 13-35). In class  $Q$ , there is a field `inner` which points to the `InnerQ` object  $O_{IQ}$  created at line 15. there are two methods `putOrCreate`(line 16-18) and `get`(line 19-21), both of which just invoke the methods in class `InnerQ`. There is a `HashMap` object  $O_{HM}$  being created at line 23 and assigned to field `map`. The object  $O_{HM}$  is instantiated with type arguments: `String` and `Object`. In method `putOrCreate`, an `A` object  $O_A$  (line 26) is created and putted in  $O_{HM}$  when the parameter `e` is `null`, otherwise parameter `e` is putted in  $O_{HM}$ . The `get` method retrieves the corresponding object from `map`, then returns it(line 31-33).

Similar with the `main` method in Figure 1, in the `main` method of Figure 7, there are two  $Q$  objects:  $O_1$  (line 2) and  $O_2$ (line 7). Because the second actual parameter of invoke `putOrCreate` at line3 is `null`, object  $O_A$  is putted into  $O_1$  and then retrieved back via the `get` method at line 4. Similarly, object  $O_B$  is created and put into  $O_2$  at line 8, then retrieved back at line 9. Because the second actual parameter of invoke `putOrCreate` at line 8 is not `null`,  $O_2$  will not contain object  $O_A$ . As a result, the two cast operations (line 5 and 10) will never fail. Because object  $O_A$  is created in a condition branch, we can distinguish it by using path-sensitivity.

Similar with the example in Figure 1, line 2 and line 7 instantiate the generic class  $Q$  with actual types. Those actual types are passed as type variables of  $Q$  to instantiate `InnerQ` at line 15. Hence, the corresponding location ( $O_1$  and  $O_2$ ) should be regarded as the context in analyzing methods of class `InnerQ`. So, with 1-object-sensitivity, we can distinguish  $O_{HM}$  with different contexts at line 23, meanwhile, we can also distinguish  $O_A$  with different contexts at line 26. However, the type variables of  $O_{HM}$  are `String` and `Object`, the outermost corresponding location ( $O_1$  and  $O_2$ ) cannot be propagated into `HashMap` continuously. As a result,  $O_A$  and  $O_B$  will be confused in  $O_{HM}$ , if the depth of context is set to 1.

If we set the context depth to 2, we combine the outer corresponding location ( $O_1$  and  $O_2$ ) and the inner corresponding location ( $O_{HM}$ ), and then propagate it into class `Node` in Figure 1, then we can distinguish the field value. As a result, we can compute a precise results:  $pts(v1) = \{O_A\}$ , and  $pts(v2) = \{O_B\}$ .

If we use object sensitivity to analyze the example in Figure 7, we have to set the context depth more than 4: 2-layer contexts can distinguish the methods in `InnerQ`, another 2-layer contexts to distinguish the methods in `Node`.

In section 3.2, we have formalized the representation and propagation of generic context. In this section, we will extend  $\mathbb{G}$  and revise functions **Gen** and **Append** to adapt k-generic sensitivity where  $k > 1$ .

#### 4.3.1 Customizing Object Sensitivity

We change  $\mathbb{G}$  into a array  $[G_k, \dots, G_1]$ , where  $G_i := \overline{\mathbb{T}} \mapsto \overline{\mathbb{H}}$  maps a type variable  $\mathcal{T} \in \mathbb{T}$  to an allocation site  $O_l \in \mathbb{H}$  (identified by label  $l$ ). Meantime, the **Gen** and **Append** functions are changed as follows.

$$\mathbf{Gen}(G, \mathcal{T}, A, O_l) = \begin{cases} G & \mathcal{T} = Nil \\ [\mathcal{T} \rightarrow O_l] ++ G & \mathcal{T} \neq Nil \wedge A \notin G_1 \\ G_1[\mathcal{T}] \rightarrow G_1(A) & \mathcal{T} \neq Nil \wedge A \in G_1 \end{cases}$$

$$\mathbf{Append}(G, G_m, \mathcal{T}, A, O_l) = \begin{cases} G & \mathcal{T} = Nil \\ G_1 \uplus [\mathcal{T} \rightarrow O_l] & \mathcal{T} \neq Nil \wedge A \notin G_1 \uplus G_{m_1} \\ G_1 \uplus [\mathcal{T} \rightarrow G_1 \uplus G_{m_1}(A)] & \mathcal{T} \neq Nil \wedge A \in G_1 \uplus G_{m_1} \end{cases}$$

For **Gen** functions, the changes are listed as follows.

- If formal type parameter  $\mathcal{T}$  is `Nil`, we just return the generic context of current method.
- If formal type parameter  $\mathcal{T} \neq Nil$  and actual type parameter  $A \notin G$ , the generics propagation is stopped. So, we create a new generic mapping  $[\mathcal{T} \mapsto O_l]$  and append to the current generic context by using “+” operator.
- At last, if  $O_l$  is instantiated with a type variable, i.e.,  $\mathcal{T} \neq Nil \wedge A \in G$ , we identify the actual instantiate location of  $A$  by looking up the context of  $l$ 's containing method. We can generate the innermost generic mapping  $G_1$  of current generic context array to  $[\mathcal{T} \mapsto G(A)]$ .

For **Append** functions, we just generate the innermost generic mapping by following the constraints in Section 4.

As showing in Figure 6, we limit the depth of generic-context by  $G'_{n-1}$ . In order to distinguish from  $k$  which



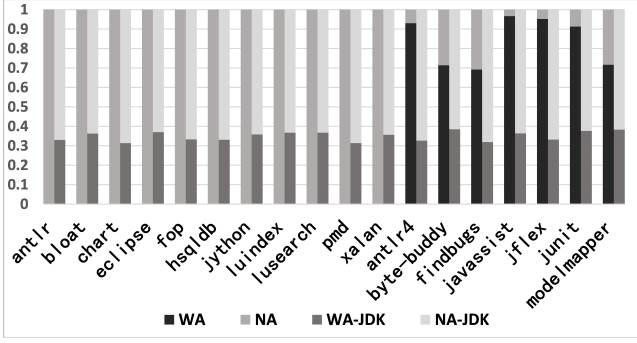


Fig. 8: Percentages of generic object allocations with actual types. WA is with actual types, NA is without actual types, WA-JDK and NA-JDK are generic object allocations in JDK with or without actual types.

represents the limited depth of traditional context, we use  $n$  to represent the limited depth of generic context.

Let us revisit the example in Figure 7. We create generic objects  $O_1$  (line 2) and  $O_2$  (line 7) respectively. Hence, we construct generic mappings  $[E \mapsto O_1]$  and  $[E \mapsto O_2]$  respectively. And then the same generic mappings can be generated for object  $O_{IQ}$  at line 15. At line 23, we create generic mappings  $[K \mapsto O_{HM}, V \mapsto O_{HM}]$  and append the generic mappings above to generate two generic context array:  $[[E \mapsto O_1], [K \mapsto O_{HM}, V \mapsto O_{HM}]]$  and  $[[E \mapsto O_2], [K \mapsto O_{HM}, V \mapsto O_{HM}]]$ . Finally, we can distinguish the methods of Node in Figure 1 according to the generic context arrays above.

#### 4.3.2 Customizing Type Sensitivity

For type-sensitive analysis,  $G_i := \overline{T} \mapsto \overline{T}$  maps a type variable  $T \in \mathbb{T}$  to an actual type  $T \in \mathbb{T}$ . The **Gen** and **Append** functions are revised as follows.

$$\text{Gen}(G, T, A) = \begin{cases} G & T = Nil \\ [T \rightarrow A] ++ G & T \neq Nil \wedge A \notin G_1 \\ G_1[T] \rightarrow G_1(A) & T \neq Nil \wedge A \in G_1 \end{cases}$$

$$\text{Append}(G, G_m, T, A) = \begin{cases} G & T = Nil \\ G_1 \uplus [T \rightarrow A] & T \neq Nil \wedge A \notin G_1 \uplus G_{m_1} \\ G_1 \uplus [T \rightarrow G_1 \uplus G_{m_1}(A)] & T \neq Nil \wedge A \in G_1 \uplus G_{m_1} \end{cases}$$

Let us revisit the example in Figure 7. We create generic objects  $O_1$  (line 2) and  $O_2$  (line 7) respectively. Hence, we construct generic mappings  $[E \mapsto A]$  and  $[E \mapsto B]$  respectively. And then the same generic mappings can be generated for object  $O_{IQ}$  at line 15. At line 23, we create generic mappings  $[K \mapsto String, V \mapsto Object]$  and append the generic mappings above to generate two generic context array:  $[[E \mapsto A], [K \mapsto String, V \mapsto Object]]$  and  $[[E \mapsto B], [K \mapsto String, V \mapsto Object]]$ . Finally, we can distinguish the methods of Node in Figure 1 according to the generic context arrays above.

## 5 IMPLEMENTATION AND EVALUATION

We evaluate generic sensitive pointer analysis by applying and comparing our context customization scheme to an

TABLE 2: Number of generic object allocations (abbreviated as GC) and generic method invocations (GM). #S is the number of instantiate locations, and #A is the number of actual type arguments.

| Programs    | Application  |              | JDK          |              |
|-------------|--------------|--------------|--------------|--------------|
|             | GC<br>#S(#A) | GM<br>#S(#A) | GC<br>#S(#A) | GM<br>#S(#A) |
| antlr       | 21(37)       | 1(1)         | 503(701)     | 262(397)     |
| bloat       | 304(376)     | 8(8)         | 342(472)     | 217(348)     |
| chart       | 198(277)     | 39(39)       | 532(741)     | 280(420)     |
| eclipse     | 74(97)       | 32(32)       | 349(479)     | 222(353)     |
| fop         | 128(195)     | 4(4)         | 586(810)     | 293(431)     |
| hsqldb      | 102(126)     | 4(4)         | 626(851)     | 342(483)     |
| jython      | 101(138)     | 5(5)         | 346(476)     | 221(352)     |
| luindex     | 54(70)       | 8(8)         | 452(620)     | 254(399)     |
| lusearch    | 54(70)       | 8(8)         | 452(620)     | 254(399)     |
| pmd         | 187(249)     | 9(9)         | 590(810)     | 308(445)     |
| xalan       | 35(56)       | 1(1)         | 348(482)     | 217(348)     |
| antlr4      | 345(450)     | 1,213(1,225) | 610(846)     | 324(466)     |
| byte-buddy  | 342(430)     | 257(261)     | 380(523)     | 244(376)     |
| findbugs    | 455(617)     | 93(102)      | 570(794)     | 295(432)     |
| javassist   | 60(74)       | 13(13)       | 341(470)     | 218(349)     |
| jflex       | 21(28)       | 0(0)         | 509(704)     | 265(400)     |
| junit       | 46(52)       | 55(56)       | 393(537)     | 251(383)     |
| modelmapper | 335(416)     | 206(210)     | 379(522)     | 244(376)     |

array of pointer analyses at different precision. In total, there are 11 variants of standard pointer analyses. For illustration, we mainly compare two groups of them in this section: object-sensitive group (GenO, 1-obj, Gen+1-obj, 2-obj) and type-sensitive group (GenT, 1-type, Gen+1-type, 2-type). Additionally, We compare the precision and efficiency of generic sensitivity with or without applying ZIPPER [25] and ZIPPER-E [26], the state-of-the-art selective context-sensitivity approaches provided by TAI-E [36].

Hereafter, we use GenT as the customization scheme for type-sensitivity and GenO as the customization scheme for object-sensitivity. By default, GenT and GenO are our context customization schemes applied to the insensitive Andersen’s analysis [37]. In this case, only generic objects/methods are analyzed context-sensitively. The notation Gen+k-obj represents the GenO scheme applied to k-obj analysis, and Gen+k-type represents the GenT scheme applied to k-type analysis. In other words, Gen+k-obj scheme uses both generic information and allocation sites of receiver objects as contexts for generic-related methods and uses allocation sites of receiver objects as contexts for the remaining methods. The same principle applies to other variants of context-sensitivity as well. The notations ending in Z represent applying ZIPPER to the target analysis, e.g., 1-objZ represents applying ZIPPER to 1-obj analysis, which means that only the methods selected by ZIPPER are analyzed by 1-obj. Similarly, The notations ending in ZE represent applying ZIPPER-E to the target analysis, e.g., 1-objZE represents applying ZIPPER-E to 1-obj analysis. Note that ZIPPER-E is able to achieve significantly better efficiency than ZIPPER with comparable precision [26].

### 5.1 Implementation

We have implemented our generic customization scheme in WALA and applied it to several pointer analysis variants: object-sensitive analysis, type-sensitive analysis, and insen-

TABLE 3: Efficiency and precision metrics of different analyses on DaCapo benchmarks

| Program  | Metrics        | CI     | obj    |        |           |         |           | type   |        |            |         |            |
|----------|----------------|--------|--------|--------|-----------|---------|-----------|--------|--------|------------|---------|------------|
|          |                |        | GenO   | 1-obj  | Gen+1-obj | 2-obj   | Gen+2-obj | GenT   | 1-type | Gen+1-type | 2-type  | Gen+2-type |
| antlr    | Time (s)       | 5.8    | 7.0    | 26.9   | 14.3      | 58.8    | 65.8      | 9.9    | 9.3    | 11.3       | 16.6    | 14.5       |
|          | #cast-may-fail | 833    | 495    | 729    | 408       | 414     | 386       | 507    | 739    | 412        | 723     | 408        |
|          | #poly-call     | 1,513  | 1,248  | 1,374  | 1,184     | 1,167   | 1,166     | 1,252  | 1,418  | 1,211      | 1,275   | 1,178      |
|          | #reach-methods | 7,324  | 7,020  | 7,171  | 6,953     | 6,962   | 6,935     | 7,020  | 7,201  | 6,966      | 7,142   | 6,936      |
|          | #call-edge     | 42,111 | 36,667 | 39,795 | 35,803    | 35,808  | 35,723    | 36,691 | 39,987 | 35,942     | 38,100  | 35,763     |
| bloat    | Time (s)       | 11.9   | 12.9   | 242.8  | 178.0     | -       | -         | 12.9   | 26.7   | 26.0       | 274.5   | 183.4      |
|          | #cast-may-fail | 2,018  | 1,459  | 1,890  | 1,300     | -       | -         | 1,471  | 1,903  | 1,303      | 1,884   | 1,297      |
|          | #poly-call     | 2,223  | 1,693  | 1,999  | 1,608     | -       | -         | 1,697  | 2,118  | 1,639      | 1,719   | 1,584      |
|          | #reach-methods | 9,207  | 8,934  | 9,066  | 8,835     | -       | -         | 8,934  | 9,095  | 8,845      | 9,018   | 8,798      |
|          | #call-edge     | 66,992 | 58,397 | 64,060 | 56,775    | -       | -         | 58,421 | 64,464 | 56,913     | 61,173  | 56,203     |
| chart    | Time (s)       | 11.4   | 12.9   | 282.6  | 33.5      | 2,087.6 | 1,855.8   | 12.9   | 27.7   | 15.0       | 191.5   | 42.0       |
|          | #cast-may-fail | 1,795  | 1,175  | 1,668  | 982       | 979     | 913       | 1,210  | 1,691  | 998        | 1,661   | 979        |
|          | #poly-call     | 2,010  | 1,637  | 1,869  | 1,535     | 1,503   | 1,498     | 1,646  | 1,939  | 1,585      | 1,715   | 1,542      |
|          | #reach-methods | 11,804 | 11,420 | 11,647 | 11,284    | 11,282  | 11,241    | 11,420 | 11,684 | 11,339     | 11,619  | 11,310     |
|          | #call-edge     | 65,360 | 56,387 | 62,180 | 53,928    | 53,780  | 53,603    | 56,522 | 62,696 | 54,651     | 61,112  | 54,313     |
| eclipse  | Time (s)       | 7.9    | 9.8    | 28.8   | 14.7      | 97.4    | 92.4      | 9.9    | 11.4   | 10.8       | 27.8    | 16.3       |
|          | #cast-may-fail | 1,037  | 720    | 909    | 579       | 568     | 540       | 732    | 928    | 592        | 906     | 578        |
|          | #poly-call     | 1,268  | 1,013  | 1,123  | 936       | 920     | 919       | 1,017  | 1,169  | 977        | 1,053   | 932        |
|          | #reach-methods | 7,731  | 7,474  | 7,572  | 7,345     | 7,347   | 7,320     | 7,474  | 7,612  | 7,410      | 7,545   | 7,326      |
|          | #call-edge     | 44,320 | 38,293 | 41,838 | 36,150    | 36,068  | 35,983    | 38,297 | 42,127 | 37,225     | 39,742  | 36,203     |
| fop      | Time (s)       | 8.0    | 8.8    | 17.6   | 12.1      | 68.1    | 70.6      | 9.4    | 10.5   | 10.1       | 17.1    | 14.9       |
|          | #cast-may-fail | 812    | 485    | 708    | 397       | 411     | 383       | 497    | 718    | 400        | 702     | 396        |
|          | #poly-call     | 1,136  | 861    | 990    | 790       | 773     | 772       | 865    | 1,034  | 817        | 885     | 784        |
|          | #reach-methods | 6,847  | 6,547  | 6,709  | 6,480     | 6,489   | 6,462     | 6,547  | 6,739  | 6,493      | 6,674   | 6,463      |
|          | #call-edge     | 37,230 | 32,077 | 35,198 | 31,204    | 31,208  | 31,123    | 32,100 | 35,380 | 31,333     | 33,476  | 31,164     |
| hsqldb   | Time (s)       | 7.8    | 8.6    | 19.2   | 11.7      | 53.2    | 61.1      | 8.1    | 9.1    | 9.1        | 17.3    | 12.3       |
|          | #cast-may-fail | 775    | 453    | 677    | 371       | 385     | 357       | 465    | 687    | 374        | 671     | 370        |
|          | #poly-call     | 1,104  | 839    | 965    | 775       | 760     | 759       | 843    | 1,012  | 805        | 868     | 771        |
|          | #reach-methods | 6,604  | 6,311  | 6,468  | 6,243     | 6,253   | 6,226     | 6,311  | 6,498  | 6,256      | 6,440   | 6,227      |
|          | #call-edge     | 36,324 | 31,237 | 34,312 | 30,366    | 30,375  | 30,290    | 31,260 | 34,498 | 30,499     | 32,640  | 30,330     |
| jython   | Time (s)       | 9.3    | 13.3   | 103.6  | 78.1      | -       | -         | 11.8   | 17.0   | 17.1       | 4,322.3 | 3,996.9    |
|          | #cast-may-fail | 1,284  | 908    | 1,178  | 812       | -       | -         | 920    | 1,191  | 815        | 1,176   | 811        |
|          | #poly-call     | 1,604  | 1,338  | 1,455  | 1,262     | -       | -         | 1,342  | 1,507  | 1,297      | 1,366   | 1,260      |
|          | #reach-methods | 8,852  | 8,548  | 8,714  | 8,453     | -       | -         | 8,548  | 8,741  | 8,464      | 8,688   | 8,437      |
|          | #call-edge     | 52,026 | 44,891 | 49,603 | 43,588    | -       | -         | 44,895 | 49,809 | 43,847     | 47,378  | 43,654     |
| luindex  | Time (s)       | 8.2    | 9.3    | 22.7   | 13.1      | 49.0    | 54.8      | 9.6    | 10.0   | 9.5        | 16.4    | 14.2       |
|          | #cast-may-fail | 811    | 468    | 709    | 375       | 389     | 361       | 480    | 719    | 379        | 702     | 375        |
|          | #poly-call     | 1,142  | 869    | 992    | 802       | 787     | 786       | 873    | 1,046  | 831        | 895     | 798        |
|          | #reach-methods | 6,924  | 6,635  | 6,789  | 6,568     | 6,577   | 6,550     | 6,635  | 6,818  | 6,580      | 6,760   | 6,551      |
|          | #call-edge     | 37,493 | 32,349 | 35,454 | 31,460    | 31,467  | 31,382    | 32,372 | 35,643 | 31,596     | 33,775  | 31,430     |
| lusearch | Time (s)       | 8.3    | 10.1   | 26.0   | 14.2      | 71.8    | 70.0      | 8.6    | 10.2   | 10.6       | 20.4    | 15.3       |
|          | #cast-may-fail | 917    | 517    | 811    | 417       | 399     | 371       | 529    | 823    | 420        | 772     | 386        |
|          | #poly-call     | 1,334  | 1,055  | 1,181  | 983       | 966     | 965       | 1,059  | 1,233  | 1,010      | 1,078   | 977        |
|          | #reach-methods | 7,596  | 7,287  | 7,463  | 7,212     | 7,221   | 7,194     | 7,287  | 7,492  | 7,224      | 7,431   | 7,195      |
|          | #call-edge     | 40,787 | 35,267 | 38,706 | 34,328    | 34,333  | 34,248    | 35,290 | 38,893 | 34,454     | 36,878  | 34,288     |
| pmd      | Time (s)       | 8.4    | 10.5   | 27.8   | 14.9      | 78.6    | 77.0      | 10.2   | 13.0   | 11.6       | 24.5    | 16.5       |
|          | #cast-may-fail | 1,260  | 822    | 1,149  | 727       | 744     | 712       | 834    | 1,161  | 730        | 1,143   | 725        |
|          | #poly-call     | 1,204  | 912    | 1,062  | 844       | 826     | 825       | 916    | 1,109  | 872        | 941     | 835        |
|          | #reach-methods | 8,337  | 8,021  | 8,198  | 7,955     | 7,955   | 7,928     | 8,021  | 8,229  | 7,968      | 8,168   | 7,929      |
|          | #call-edge     | 44,572 | 38,754 | 42,490 | 37,873    | 37,870  | 37,778    | 38,777 | 42,690 | 38,016     | 40,624  | 37,821     |
| xalan    | Time (s)       | 6.6    | 8.2    | 19.6   | 12.4      | 54.3    | 56.6      | 9.1    | 10.2   | 9.3        | 15.0    | 13.5       |
|          | #cast-may-fail | 779    | 461    | 676    | 374       | 388     | 360       | 473    | 686    | 377        | 670     | 373        |
|          | #poly-call     | 1,106  | 841    | 964    | 774       | 759     | 758       | 845    | 1,010  | 803        | 867     | 770        |
|          | #reach-methods | 6,619  | 6,332  | 6,483  | 6,265     | 6,274   | 6,247     | 6,332  | 6,513  | 6,278      | 6,454   | 6,248      |
|          | #call-edge     | 36,019 | 30,979 | 34,008 | 30,109    | 30,116  | 30,031    | 31,002 | 34,190 | 30,238     | 32,338  | 30,071     |

sitive analysis. There is a default implementation of  $k$ -obj analysis in WALA. However, instead of setting the heap context depth to  $k-1$ , it sets both method context and heap context to the same depth  $k$ . Hence, we revised the default implementation to be consistent with the standard  $k$ -obj definition [14], [15], [18]. We also implemented in WALA a new  $k$ -type analysis according to its original definition [18].

Sometimes, generic instantiation information may be wiped out in Java bytecode. For instance, Java tends to erase the actual instantiation type of a local variable if it is assigned from another generic typed variable. Hence, we apply simple type inference based on the rule that the LHS and RHS of an assignment must have identical generic types.

We disable the exclusion option in WALA which can exclude some packages of JDK because those packages in the exclusion are wildly used in all benchmarks. For native

code, we use the summaries provided by WALA. We disable the reflection option in WALA since it fails to analyze most benchmarks even with insensitive pointer analysis.

## 5.2 Setting

We evaluate the 18 Benchmarks in Table 2, including the popular DAcapo suite (top half of the table) and 7 popular open source programs (bottom half of the table). All experiments are conducted on an Intel Core(TM) i5-10210U laptop (1.6GHz) with 40 GB of RAM, running Ubuntu 20.04.01. As in previous work [20], [21], [25], [30], the JDK version is JDK1.6 (1.6.0\_30) and we set a time budget of 90 minutes in analyzing each benchmark. We run each benchmark 5 times and report the average analysis time of the 5 runs.

Our evaluation answers the following research questions:

TABLE 4: Efficiency and precision metrics of different analyses on applications

| Program     | Metrics        | CI      | obj     |         |           |         |           | type    |         |            |         |            |
|-------------|----------------|---------|---------|---------|-----------|---------|-----------|---------|---------|------------|---------|------------|
|             |                |         | GenO    | 1-obj   | Gen+1-obj | 2-obj   | Gen+2-obj | GenT    | 1-type  | Gen+1-type | 2-type  | Gen+2-type |
| antlr4      | Time (s)       | 23.1    | 45.1    | -       | 3,566.9   | -       | -         | 36.9    | 154.8   | 165.6      | -       | -          |
|             | #cast-may-fail | 3,608   | 2,779   | -       | 2,156     | -       | -         | 2,899   | 3,245   | 2,364      | -       | -          |
|             | #poly-call     | 3,507   | 2,888   | -       | 2,695     | -       | -         | 2,980   | 3,359   | 2,813      | -       | -          |
|             | #reach-methods | 21,029  | 20,545  | -       | 20,430    | -       | -         | 20,548  | 20,900  | 20,453     | -       | -          |
|             | #call-edge     | 166,399 | 152,186 | -       | 149,833   | -       | -         | 152,479 | 163,145 | 150,304    | -       | -          |
|             | Time (s)       | 14.0    | 21.4    | 1,197.3 | 202.1     | -       | -         | 18.0    | 63.0    | 30.2       | 2,393.1 | 752.7      |
| byte-buddy  | #cast-may-fail | 1,715   | 1,095   | 1,582   | 829       | -       | -         | 1,119   | 1,599   | 856        | 1,549   | 798        |
|             | #poly-call     | 3,527   | 3,084   | 3,357   | 2,921     | -       | -         | 3,096   | 3,435   | 2,992      | 3,220   | 2,853      |
|             | #reach-methods | 11,773  | 11,305  | 11,646  | 11,121    | -       | -         | 11,309  | 11,685  | 11,155     | 11,606  | 11,072     |
|             | #call-edge     | 70,635  | 58,776  | 67,552  | 55,848    | -       | -         | 59,443  | 67,866  | 56,511     | 64,337  | 55,459     |
|             | Time (s)       | 9.5     | 11.8    | 65.4    | 15.4      | 193.8   | 148.1     | 11.9    | 16.0    | 11.7       | 47.8    | 18.8       |
|             | #cast-may-fail | 1,223   | 734     | 1,112   | 566       | 600     | 547       | 757     | 1,125   | 578        | 1,105   | 572        |
| findbugs    | #poly-call     | 1,626   | 1,229   | 1,414   | 1,144     | 1,109   | 1,107     | 1,234   | 1,525   | 1,182      | 1,277   | 1,139      |
|             | #reach-methods | 9,242   | 8,852   | 9,082   | 8,685     | 8,693   | 8,662     | 8,852   | 9,113   | 8,703      | 9,024   | 8,673      |
|             | #call-edge     | 51,887  | 42,600  | 48,520  | 40,639    | 40,636  | 40,476    | 42,641  | 48,789  | 40,842     | 45,582  | 40,642     |
|             | Time (s)       | 6.5     | 8.3     | 16.5    | 11.8      | 50.5    | 59.2      | 7.6     | 8.4     | 8.7        | 14.3    | 12.3       |
|             | #cast-may-fail | 765     | 448     | 671     | 370       | 384     | 356       | 460     | 681     | 373        | 665     | 369        |
|             | #poly-call     | 1,089   | 824     | 956     | 766       | 751     | 750       | 828     | 1,003   | 796        | 859     | 762        |
| javassist   | #reach-methods | 6,519   | 6,229   | 6,381   | 6,159     | 6,168   | 6,141     | 6,229   | 6,413   | 6,174      | 6,352   | 6,142      |
|             | #call-edge     | 35,379  | 30,328  | 33,396  | 29,486    | 29,493  | 29,408    | 30,351  | 33,580  | 29,617     | 31,726  | 29,448     |
|             | Time (s)       | 10.4    | 12.2    | 116.8   | 35.0      | 1,445.8 | 1,411.0   | 11.9    | 23.2    | 16.8       | 326.1   | 135.0      |
|             | #cast-may-fail | 1,545   | 1,087   | 1,414   | 907       | 920     | 881       | 1,131   | 1,443   | 923        | 1,416   | 909        |
|             | #poly-call     | 2,004   | 1,631   | 1,854   | 1,547     | 1,532   | 1,507     | 1,673   | 1,923   | 1,602      | 1,783   | 1,563      |
|             | #reach-methods | 10,708  | 10,356  | 10,544  | 10,265    | 10,247  | 10,206    | 10,364  | 10,577  | 10,286     | 10,522  | 10,254     |
| jflex       | #call-edge     | 56,310  | 49,154  | 53,737  | 47,763    | 47,285  | 47,129    | 49,390  | 54,204  | 48,110     | 53,181  | 47,831     |
|             | Time (s)       | 6.8     | 13.1    | 36.8    | 17.5      | 73.2    | 79.2      | 12.9    | 12.1    | 14.6       | 39.0    | 22.8       |
|             | #cast-may-fail | 962     | 633     | 862     | 473       | 502     | 452       | 648     | 875     | 489        | 850     | 470        |
|             | #poly-call     | 1,303   | 1,016   | 1,180   | 930       | 925     | 909       | 1,020   | 1,233   | 960        | 1,094   | 921        |
|             | #reach-methods | 8,008   | 7,771   | 7,891   | 7,630     | 7,639   | 7,610     | 7,773   | 7,910   | 7,649      | 7,843   | 7,613      |
|             | #call-edge     | 41,715  | 36,473  | 39,663  | 34,867    | 34,905  | 34,764    | 36,530  | 39,839  | 35,030     | 38,021  | 34,817     |
| modelmapper | Time (s)       | 13.0    | 19.8    | 899.5   | 158.4     | -       | -         | 17.7    | 51.8    | 27.0       | 3,058.6 | 843.6      |
|             | #cast-may-fail | 1,678   | 1,094   | 1,546   | 821       | -       | -         | 1,119   | 1,563   | 847        | 1,513   | 789        |
|             | #poly-call     | 3,529   | 3,102   | 3,364   | 2,933     | -       | -         | 3,114   | 3,444   | 3,010      | 3,229   | 2,864      |
|             | #reach-methods | 11,732  | 11,283  | 11,605  | 11,073    | -       | -         | 11,287  | 11,644  | 11,107     | 11,565  | 11,018     |
|             | #call-edge     | 69,389  | 58,014  | 66,347  | 55,040    | -       | -         | 58,684  | 66,669  | 55,716     | 63,237  | 54,633     |

- RQ1. How extensively is generics used in real-world applications?
- RQ2. Can generic sensitivity improve precision over existing context-sensitive approaches?
- RQ3. Can generic sensitivity improve efficiency over existing context-sensitive approaches?
- RQ4. Does generic sensitivity offer a better trade-off than standard context-sensitive analyses?
- RQ5. Can generic sensitivity improve precision and efficiency over state-of-the-art selective context-sensitivity approaches, ZIPPER and ZIPPER-E?
- RQ6. How the precision and efficiency of k-generic sensitivity change as k increases?
- RQ7. Can local analysis improve precision of generic sensitivity?

### 5.3 RQ1. Generic Usages

Table 2 summarizes the generic usages in each benchmark. We separate the usages in application code with those in JDK libraries which are transitively invoked by applications. As shown in Table 2, there are extensive usages of generics: `findbugs` has the largest number of generic object allocations (455) and `antlr4` has the largest number of generic method invocations (1,213). Although some application, e.g., `antlr`, uses generics infrequently. Its underlying JDK library makes extensive usages of generics, suggesting the necessity of an optimized context-sensitive pointer analysis targeting generics.

Figure 8 depicts the percentages of generic usages with actual type arguments, including those usages where our simple conservative type inference analysis (Section 3) can infer actual type arguments. The `WA` is the percentage of

cases that our local analysis can deal with, and the `NA` represents the other cases. The number of actual types inferred is small. As shown in Figure 8, the percentages are quite low for `DACAPO` Benchmarks. The reason is that `DACAPO` is released only a few years after generics being introduced into Java, and many Java applications at that time did not use the new generic feature (i.e., instantiating generics with actual type parameters). The percentage is much higher (>70%) for the 7 open-source applications, showing that new applications commonly use modern generic features supported by the language.

Comparing `antlr4` to its earlier version `antlr`, there are much more generic usages in `antlr4`, confirming that Java generics is widely adopted in modern Java applications.

Generics is extensively used in modern Java applications and the underlying JDK library, suggesting the necessity to develop customized context-sensitive pointer analysis for generics.

### 5.4 RQ2. Precision

Following [30], [31], [32], we measure the precision of context-sensitive analyses using four basic metrics: `#call-edges` (number of call graph edges), `#reach-methods` (number of reachable methods), `#poly-call` (number of polymorphic calls discovered), and `#cast-may-fail` (number of cast operations that may fail). As their names suggest, these metrics are obtained by different client applications of context-sensitive pointer analyses. All client applications are sound. Hence, for all the metrics, lower is better.

Since our approach introduces extra context-elements on top of standard `k-obj` or `k-type` analyses, `Gen+k-obj` (`Gen+k-type`) is always more precise than `k-obj` (`k-type`) analysis.

TABLE 5: Efficiency and precision metrics of different analyses combined with ZIPPER and ZIPPER-E on DaCapo benchmarks

| Program  | Metrics        | 1-objZ | Gen+1-objZ | 2-objZ | Gen+2-objZ | 1-objZE | Gen+1-objZE | 2-objZE | Gen+2-objZE |
|----------|----------------|--------|------------|--------|------------|---------|-------------|---------|-------------|
| antlr    | Time (s)       | 8.3    | 9.8        | 27.4   | 35.6       | 7.7     | 11.1        | 9.5     | 12.0        |
|          | #cast-may-fail | 777    | 687        | 708    | 681        | 794     | 723         | 728     | 722         |
|          | #poly-call     | 1,393  | 1,262      | 1,269  | 1,255      | 1,433   | 1,306       | 1,319   | 1,302       |
|          | #reach-methods | 7,212  | 7,154      | 7,176  | 7,135      | 7,248   | 7,201       | 7,226   | 7,198       |
|          | #call-edge     | 40,395 | 38,118     | 38,644 | 38,040     | 40,793  | 38,857      | 39,412  | 38,843      |
| bloat    | Time (s)       | 89.0   | 101.3      | -      | -          | 19.5    | 29.7        | 25.2    | 30.6        |
|          | #cast-may-fail | 1,936  | 1,690      | -      | -          | 1,955   | 1,739       | 1,755   | 1,737       |
|          | #poly-call     | 2,033  | 1,708      | -      | -          | 2,075   | 1,776       | 1,784   | 1,768       |
|          | #reach-methods | 9,093  | 9,023      | -      | -          | 9,127   | 9,066       | 9,091   | 9,063       |
|          | #call-edge     | 64,599 | 61,174     | -      | -          | 65,107  | 62,134      | 62,369  | 62,015      |
| chart    | Time (s)       | 27.7   | 44.8       | 247.1  | 229.0      | 20.4    | 37.5        | 42.3    | 67.0        |
|          | #cast-may-fail | 1,732  | 1,500      | 1,525  | 1,472      | 1,746   | 1,538       | 1,551   | 1,537       |
|          | #poly-call     | 1,898  | 1,679      | 1,681  | 1,669      | 1,921   | 1,714       | 1,745   | 1,710       |
|          | #reach-methods | 11,674 | 11,570     | 11,607 | 11,534     | 11,689  | 11,600      | 11,637  | 11,600      |
|          | #call-edge     | 62,902 | 60,879     | 61,229 | 60,164     | 63,313  | 61,431      | 61,779  | 61,427      |
| eclipse  | Time (s)       | 10.7   | 18.6       | 44.6   | 54.6       | 9.7     | 16.4        | 12.0    | 18.0        |
|          | #cast-may-fail | 979    | 882        | 899    | 872        | 995     | 917         | 918     | 912         |
|          | #poly-call     | 1,148  | 1,030      | 1,037  | 1,023      | 1,188   | 1,074       | 1,085   | 1,068       |
|          | #reach-methods | 7,612  | 7,552      | 7,574  | 7,533      | 7,647   | 7,598       | 7,623   | 7,595       |
|          | #call-edge     | 42,401 | 40,159     | 40,700 | 40,051     | 42,826  | 41,296      | 41,861  | 41,261      |
| fop      | Time (s)       | 8.3    | 14.3       | 27.2   | 35.1       | 8.1     | 12.2        | 8.7     | 12.4        |
|          | #cast-may-fail | 756    | 667        | 687    | 661        | 773     | 702         | 707     | 701         |
|          | #poly-call     | 1,024  | 884        | 893    | 879        | 1,056   | 920         | 933     | 916         |
|          | #reach-methods | 6,734  | 6,669      | 6,691  | 6,650      | 6,769   | 6,715       | 6,740   | 6,712       |
|          | #call-edge     | 35,518 | 33,356     | 33,812 | 33,282     | 35,905  | 34,329      | 34,553  | 34,315      |
| hsqldb   | Time (s)       | 8.8    | 11.3       | 25.7   | 31.8       | 7.7     | 11.6        | 8.5     | 11.5        |
|          | #cast-may-fail | 724    | 634        | 655    | 628        | 741     | 670         | 675     | 669         |
|          | #poly-call     | 991    | 860        | 869    | 855        | 1,024   | 897         | 910     | 893         |
|          | #reach-methods | 6,493  | 6,434      | 6,457  | 6,416      | 6,528   | 6,480       | 6,506   | 6,478       |
|          | #call-edge     | 34,627 | 32,493     | 32,936 | 32,421     | 35,014  | 33,201      | 33,669  | 33,189      |
| jython   | Time (s)       | 45.4   | 51.5       | -      | -          | 12.4    | 15.6        | 15.1    | 20.5        |
|          | #cast-may-fail | 1,234  | 1,129      | -      | -          | 1,241   | 1,159       | 1,163   | 1,157       |
|          | #poly-call     | 1,503  | 1,345      | -      | -          | 1,518   | 1,366       | 1,375   | 1,358       |
|          | #reach-methods | 8,750  | 8,674      | -      | -          | 8,762   | 8,700       | 8,726   | 8,697       |
|          | #call-edge     | 50,092 | 46,605     | -      | -          | 50,504  | 48,287      | 49,310  | 48,264      |
| luindex  | Time (s)       | 9.7    | 13.0       | 26.0   | 32.3       | 8.2     | 12.4        | 8.7     | 12.1        |
|          | #cast-may-fail | 755    | 661        | 682    | 655        | 772     | 697         | 702     | 696         |
|          | #poly-call     | 1,018  | 887        | 896    | 882        | 1,050   | 923         | 936     | 919         |
|          | #reach-methods | 6,813  | 6,755      | 6,777  | 6,736      | 6,848   | 6,801       | 6,826   | 6,798       |
|          | #call-edge     | 35,763 | 33,618     | 34,068 | 33,544     | 36,150  | 34,332      | 34,807  | 34,318      |
| lusearch | Time (s)       | 11.2   | 14.0       | 34.7   | 42.3       | 9.1     | 13.7        | 12.2    | 16.6        |
|          | #cast-may-fail | 858    | 754        | 763    | 736        | 876     | 791         | 786     | 780         |
|          | #poly-call     | 1,210  | 1,075      | 1,084  | 1,070      | 1,242   | 1,111       | 1,124   | 1,107       |
|          | #reach-methods | 7,485  | 7,426      | 7,448  | 7,407      | 7,520   | 7,472       | 7,497   | 7,469       |
|          | #call-edge     | 39,023 | 36,682     | 37,184 | 36,608     | 39,411  | 37,425      | 37,952  | 37,411      |
| pmd      | Time (s)       | 11.5   | 15.6       | 37.7   | 46.9       | 10.5    | 15.1        | 17.8    | 21.1        |
|          | #cast-may-fail | 1,196  | 1,049      | 1,073  | 1,043      | 1,210   | 1,083       | 1,090   | 1,082       |
|          | #poly-call     | 1,092  | 928        | 937    | 923        | 1,115   | 955         | 968     | 951         |
|          | #reach-methods | 8,225  | 8,162      | 8,184  | 8,143      | 8,251   | 8,199       | 8,224   | 8,196       |
|          | #call-edge     | 42,815 | 40,264     | 40,781 | 40,190     | 42,935  | 40,748      | 41,292  | 40,734      |
| xalan    | Time (s)       | 9.1    | 12.0       | 25.1   | 30.1       | 7.8     | 11.3        | 8.8     | 11.3        |
|          | #cast-may-fail | 723    | 632        | 653    | 626        | 740     | 668         | 673     | 667         |
|          | #poly-call     | 994    | 863        | 872    | 858        | 1,026   | 899         | 912     | 895         |
|          | #reach-methods | 6,508  | 6,450      | 6,472  | 6,431      | 6,543   | 6,496       | 6,521   | 6,493       |
|          | #call-edge     | 34,323 | 32,199     | 32,635 | 32,125     | 34,709  | 32,904      | 33,365  | 32,890      |

Table 3 and Table 4 compare precision metrics in 2 groups: object-sensitive group (GenO, 1-obj, Gen+1-obj, 2-obj) and type-sensitive group (GenT, 1-type, Gen+1-type, 2-type). Column 4-8 in both tables show results for object-sensitive group, and results of type-sensitive group are given in Column 9-13 of both tables.

Under the given 90 minutes budget, 2-obj analysis fails to process five benchmarks: bloat, jython, antlr4, byte-buddy, and modelmapper. Both 1-obj and 2-type analyses timeout on antlr4. Those timeout cases are outlined with “-” in both of tables.

*Object-Sensitivity Group.* GenO, where only generic ob-

jects and methods are analyzed context-sensitively, is noticeably more precise than 1-obj for all metrics across all benchmarks. 2-obj is more precise than GenO in those benchmarks that it is able to finish running: for #cast-may-fail, #poly-call, #reach-methods, and #call-edge, the ratio of the number reported by GenO against that reported by 2-obj is 120.34%, 109.65%, 101.14%, and 103.53%, respectively. Gen+1-obj successfully analyzes all benchmarks without timeouts, and it achieves slightly better precision than 2-obj, reporting 97.87%, 101.85%, 99.92%, and 100.10% of the number reported by 2-obj for the 4 metrics, respectively.

*Type-Sensitivity Group.* Gen+1-type is by far the most

TABLE 6: Efficiency and precision metrics of different analyses combined with ZIPPER and ZIPPER-E

| Program     | Metrics        | 1-objZ  | Gen+1-objZ | 2-objZ | Gen+2-objZ | 1-objZE | Gen+1-objZE | 2-objZE | Gen+2-objZE |
|-------------|----------------|---------|------------|--------|------------|---------|-------------|---------|-------------|
| antlr4      | Time (s)       | 829.8   | 1,516.3    | -      | -          | 104.2   | 453.1       | 3,342.4 | 3,824.7     |
|             | #cast-may-fail | 3,240   | 3,025      | -      | -          | 3,261   | 3,062       | 3,087   | 3,061       |
|             | #poly-call     | 3,312   | 2,997      | -      | -          | 3,353   | 3,062       | 3,111   | 3,062       |
|             | #reach-methods | 20,834  | 20,655     | -      | -          | 20,853  | 20,731      | 20,793  | 20,730      |
|             | #call-edge     | 160,391 | 156,775    | -      | -          | 160,862 | 157,928     | 158,552 | 157,918     |
| byte-buddy  | Time (s)       | 227.2   | 452.2      | -      | -          | 30.0    | 43.4        | 71.9    | 76.8        |
|             | #cast-may-fail | 1,630   | 1,416      | -      | -          | 1,657   | 1,456       | 1,473   | 1,439       |
|             | #poly-call     | 3,399   | 3,083      | -      | -          | 3,427   | 3,149       | 3,164   | 3,139       |
|             | #reach-methods | 11,666  | 11,495     | -      | -          | 11,684  | 11,574      | 11,623  | 11,569      |
|             | #call-edge     | 67,953  | 62,197     | -      | -          | 68,336  | 63,997      | 66,308  | 63,937      |
| findbugs    | Time (s)       | 16.0    | 23.8       | 55.1   | 69.0       | 12.0    | 15.8        | 17.7    | 24.2        |
|             | #cast-may-fail | 1,162   | 956        | 979    | 952        | 1,172   | 974         | 995     | 972         |
|             | #poly-call     | 1,443   | 1,242      | 1,229  | 1,216      | 1,462   | 1,263       | 1,275   | 1,255       |
|             | #reach-methods | 9,109   | 8,996      | 9,018  | 8,975      | 9,120   | 9,021       | 9,051   | 9,019       |
|             | #call-edge     | 48,855  | 44,845     | 45,050 | 44,707     | 49,188  | 45,609      | 45,923  | 45,559      |
| javassist   | Time (s)       | 8.0     | 11.8       | 22.3   | 28.7       | 8.6     | 10.1        | 10.3    | 12.9        |
|             | #cast-may-fail | 714     | 624        | 645    | 618        | 722     | 642         | 655     | 641         |
|             | #poly-call     | 976     | 845        | 854    | 840        | 997     | 868         | 881     | 864         |
|             | #reach-methods | 6,408   | 6,349      | 6,371  | 6,330      | 6,427   | 6,379       | 6,404   | 6,376       |
|             | #call-edge     | 33,682  | 31,557     | 31,993 | 31,483     | 34,035  | 32,203      | 32,679  | 32,189      |
| jflex       | Time (s)       | 23.5    | 33.3       | 207.2  | 185.8      | 12.5    | 20.2        | 20.3    | 27.1        |
|             | #cast-may-fail | 1,468   | 1,309      | 1,332  | 1,300      | 1,484   | 1,336       | 1,352   | 1,335       |
|             | #poly-call     | 1,883   | 1,693      | 1,720  | 1,692      | 1,909   | 1,726       | 1,756   | 1,726       |
|             | #reach-methods | 10,575  | 10,462     | 10,498 | 10,445     | 10,593  | 10,504      | 10,531  | 10,503      |
|             | #call-edge     | 54,146  | 52,335     | 52,663 | 51,837     | 54,554  | 52,852      | 53,140  | 52,848      |
| junit       | Time (s)       | 9.7     | 21.7       | 34.0   | 51.8       | 11.9    | 17.1        | 14.7    | 21.8        |
|             | #cast-may-fail | 911     | 799        | 818    | 789        | 924     | 824         | 839     | 821         |
|             | #poly-call     | 1,200   | 1,019      | 1,032  | 1,010      | 1,230   | 1,055       | 1,064   | 1,047       |
|             | #reach-methods | 7,917   | 7,854      | 7,866  | 7,834      | 7,936   | 7,874       | 7,902   | 7,870       |
|             | #call-edge     | 39,941  | 38,057     | 38,879 | 37,931     | 40,308  | 38,447      | 39,329  | 38,395      |
| modelmapper | Time (s)       | 103.6   | 139.5      | -      | -          | 29.2    | 43.8        | 54.1    | 77.5        |
|             | #cast-may-fail | 1,595   | 1,396      | -      | -          | 1,620   | 1,436       | 1,454   | 1,419       |
|             | #poly-call     | 3,406   | 3,104      | -      | -          | 3,433   | 3,173       | 3,186   | 3,163       |
|             | #reach-methods | 11,626  | 11,474     | -      | -          | 11,643  | 11,552      | 11,598  | 11,547      |
|             | #call-edge     | 66,764  | 61,353     | -      | -          | 67,145  | 63,161      | 65,279  | 63,101      |

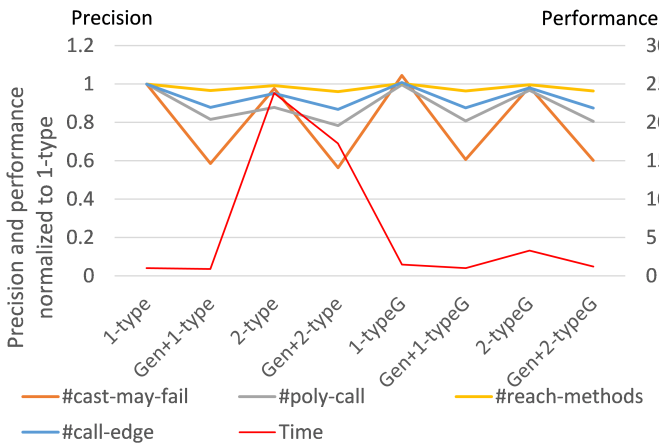


Fig. 9: Efficiency and precision metrics of different strategies of type sensitivity. Lower is better along all axes.

precise variant in the group, reporting 59.1%, 92.7%, 97.3%, and 92.1% of the number reported by 2-type for the above 4 metrics, respectively. Surprisingly, GenT also achieves better precision than 2-type, reporting 72.98%, 96.81%, 98.27%, and 94.90% of the number reported by 2-type, respectively. This may suggest again the benefit of applying generic instantiation locations to distinguish contexts, especially for the cases where coarse context elements (like types) do not work effectively.

The context elements of type-sensitivity in Table3 and Table4 are types of receiver objects (we use “bad strategy” to represent this strategy). To validate the robustness of generic sensitivity on different strategies of type-sensitivity [18], Figure 9 shows the precision and efficiency of different analyses against 1-type-sensitivity in Table3 and Table4. We use  $k$ -typeG to represent  $k$ -type-sensitivity, the context elements of which are types that contain the methods which allocate receiver objects (we use “good strategy” to represent this strategy). The precision on all metrics of the two strategies are similar, and generic sensitivity can significantly enhance the precision of both strategies on average.

### 5.5 RQ3. Efficiency

As shown in Table 3 and Table 4, 2-obj timeouts for 5 benchmarks: bloat, jython, antlr4, byte-buddy and modelmapper. Comparing Gen+1-obj to 1-obj, Gen+1-obj achieves an average speedup of 1.8  $\times$ , despite the fact that it is simultaneously much more precise. Compared to 2-obj with similar precision, Gen+1-obj achieves a speedup of 62  $\times$  for chart, with an average speedup of 12.6  $\times$  for the 13 applications that 2-obj run to completion. Similarly, Gen+1-type also achieves noticeably better efficiency than 1-type, with an average efficiency improvement of 20%. As Figure 9 shows, comparing with the “bad strategy”, the “good strategy” is slightly slower when  $k=1$  on average, and much faster under  $k=2$ . And generic sensitivity can generally improve the efficiency of both strategies.

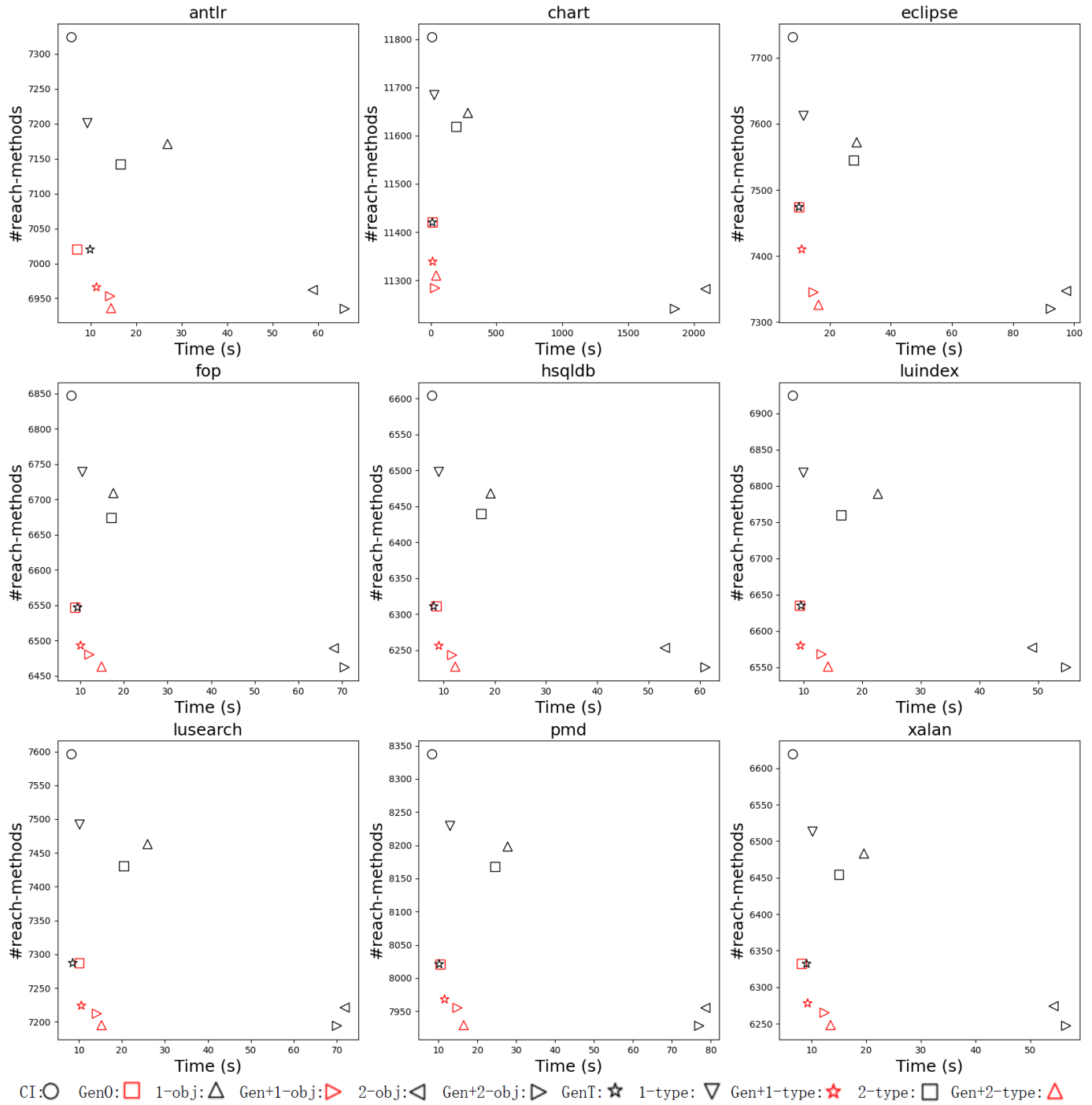


Fig. 10: Precision(#reach-methods)/Efficiency spectrum for DACAPO benchmarks. Lower is better along both axes.

Although  $Gen+k-obj$  ( $Gen+k-type$ ) introduces extra context elements to  $k-obj$  ( $k-type$ ) analysis, the efficiency gain brought by more precise results can often compensate for the cost of introduced extra context elements. As an evidence, the two generic sensitive approaches  $Gen+1-obj$  and  $Gen+1-type$  outperforms  $1-obj$  and  $1-type$ , respectively.

### 5.6 RQ4. Precision and Efficiency Trade-off

Figure 10 depicts the efficiency and precision spectrum for an array of 11 pointer analysis variants. The figure plots precision in #reach-methods metric (with other precision

metrics showing similar results) against analysis time over a set of 9 benchmarks in DACAPO. The other 2 benchmarks, *bloat* and *python*, are not included in the graph since both  $2-obj$  analysis and  $Gen+2-obj$  analysis fail to analyze them.

In Figure 10, lower numbers are better on both axes. Hence, analyses in the bottom left corner are superior in both precision and efficiency. As shown in the graph, the 3 variants  $Gen+1-obj$ ,  $Gen+1-type$ , and  $Gen+2-type$  achieve overall best trade-offs between precision and efficiency. The most precise analysis is  $Gen+2-obj$ . However, its efficiency is similar to  $2-obj$  and both are significantly slower

than the other variants. For `#reach-methods`, `Gen+2-type` achieves similar precision to `Gen+2-obj`, with significant efficiency improvements. Let us compare `Gen+1-obj` with `2-obj`, `Gen+1-obj` is much faster and it is also more precise than `2-obj` for all benchmarks, except for `hsqldb`. Between `Gen+1-type` and `Gen+1-obj`, `Gen+1-type` is slightly faster for all benchmarks but incur significant precision loss for `luindex`.

Generic sensitivity offers a good solution in balancing precision and efficiency. The three variants `Gen+1-obj`, `Gen+1-type`, and `Gen+2-type` achieve overall best precision and efficiency trade-offs.

## 5.7 RQ5. Comparing with Selective Context Sensitivity

Table5 and Table6 compare precision and efficiency of `k-obj` and `Gen+k-obj` with or without applying ZIPPER and ZIPPER-E (two state-of-the-art selective context-sensitivity approaches) on our benchmarks. Consistent with the conclusion in [25], [26], both of ZIPPER and ZIPPER-E can achieve substantial speedup with slight loss of precision than standard `k-object-sensitivity`. Generic Sensitivity and selective context-sensitivity approaches complement each other, as they are able to further enhance the precision and efficiency when combined.

For examples, ZIPPER-E can significantly improve the efficiency of generic-sensitivity, i.e., `Gen+2-objzE` can analysis all benchmarks under the given time budge while `Gen+2-obj` fail to analysis five benchmarks: `bloat`, `jython`, `antlr4`, `byte-buddy` and `modelmapper`. Comparing with `1-objz`, `Gen+1-objz` is significant more precise: for `#cast-may-fail`, `#poly-call`, `#reach-methods`, and `#call-edge`, the ratio of the number reported by `Gen+1-objz` against that reported by `1-objz` is 88.03%, 87.94%, 99.06%, and 94.21% respectively. The conclusion is similar for ZIPPER-E, the ratio of the number reported by `Gen+1-objzE` against that reported by `1-objzE` is 89.83%, 88.72%, 99.26%, and 95.30%, respectively. Comparing with `2-objz`, `Gen+1-objz` is already able to achieve an average speedup of 2.8× with slight improvement of precision, the ratio of the number reported by `Gen+1-objz` against that reported by `2-objz` is 97.54%, 99.23%, 99.70%, and 98.79% for `#cast-may-fail`, `#poly-call`, `#reach-methods`, and `#call-edge` respectively.

## 5.8 RQ6. Precision/Efficiency of K-Generic Sensitivity

Same with other variants of context sensitivity, the precision will increase as the depth of context increases. Figure 11 compares the precision of `1-obj`, `Gen+1-obj`, `2-Gen+1-obj` and `3-Gen+1-obj`. The four metrics of precision are normalized to `1-obj`. Compared to `1-obj`, `Gen+1-obj`, `2-Gen+1-obj` and `3-Gen+1-obj` are noticeably more precise. For `#cast-may-fail` metric, `2-Gen+1-obj` achieves slightly better precision than `Gen+1-obj`. For other metrics, the precision improvements are insignificant. For `chart`, `3-Gen+1-obj` achieves slightly better precision than `2-Gen+1-obj` on `#cast-may-fail` and `#call-edge` metrics. For other benchmarks, both of `3-Gen+1-obj` and `2-Gen+1-obj` have the same precision on all metrics.

Figure 13 compares analysis times for `1-obj`, `Gen+1-obj`, `2-Gen+1-obj` and `3-Gen+1-obj`. As shown in Figure 13,

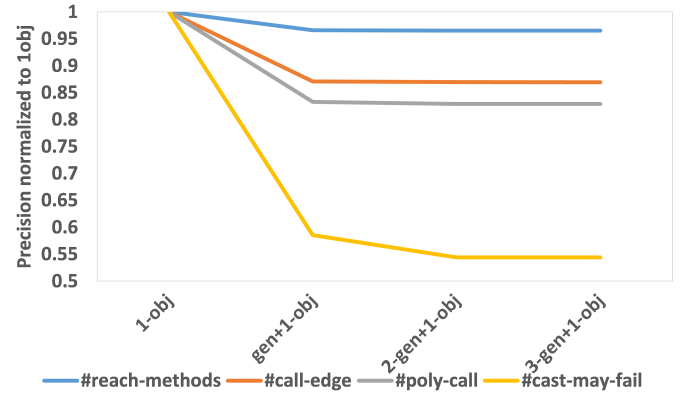


Fig. 11: Precision of k-generic sensitivity.

compared to `Gen+1-obj`, `2-Gen+1-obj` and `3-Gen+1-obj` slow down 0.85× and 6.18× on average, respectively. Still, `2-Gen+1-obj` is still faster than `1-obj` on average. If we disable the limitation of the depth of generic context, it will timeout on all benchmarks as other context-sensitivity approaches.

## 5.9 RQ7. Performance of Local Analysis

Section 3.1 introduces a local analysis that can detect actual type parameters. Additionally, we defined a degradation strategy that employs pseudo types as actual type parameters in instances where the local analysis is deemed invalid. However, this strategy may influence the precision. Taking Figure 1 as an example, without local analysis, we cannot infer the actual type parameters of `Node` at line 17 and use  $T_{17}$  to replace them. So, the contexts of the constructor of class `Node` will be  $[V \mapsto T_{17}]$  rather than  $[V \mapsto O_1]$  and  $[V \mapsto O_2]$  where we omit the context mapping of formal type parameter `K`. Figure 12 shows the precision of `Gen0` with or without local analysis for `#cast-may-fail`, `#poly-call`, `#reach-methods`, and `#call-edge`. On average, the ratio of the number reported by `Gen0` with local analysis against that reported by `Gen0` without local analysis is 93.31%, 96.78%, 99.26%, 98.06%, respectively. Meantime, both strategies take similar time for all benchmarks.

## 6 RELATED WORK

Context-sensitive pointer analysis for Java has been extensively studied in the literature. There are three mainstream variants of context sensitivity: `k-object` sensitivity, `k-type` sensitivity and `k-call-site` sensitivity. In addition to the above three variants, the work [20] proposes a hybrid approach which applies object sensitivity to instance method invocations and call-site sensitivity to static method invocations. The hybrid approach is superior to pure object-sensitivity since static methods don't have receiver objects. Jonas and Welf [38] use the points-to set of receiver object to approximate a context [38]. In [39], the cartesian product of the points-to sets of all arguments (including this) are used to symbolically represent a context. Our generic customization scheme can be adapted to the above context-sensitive variants as well.

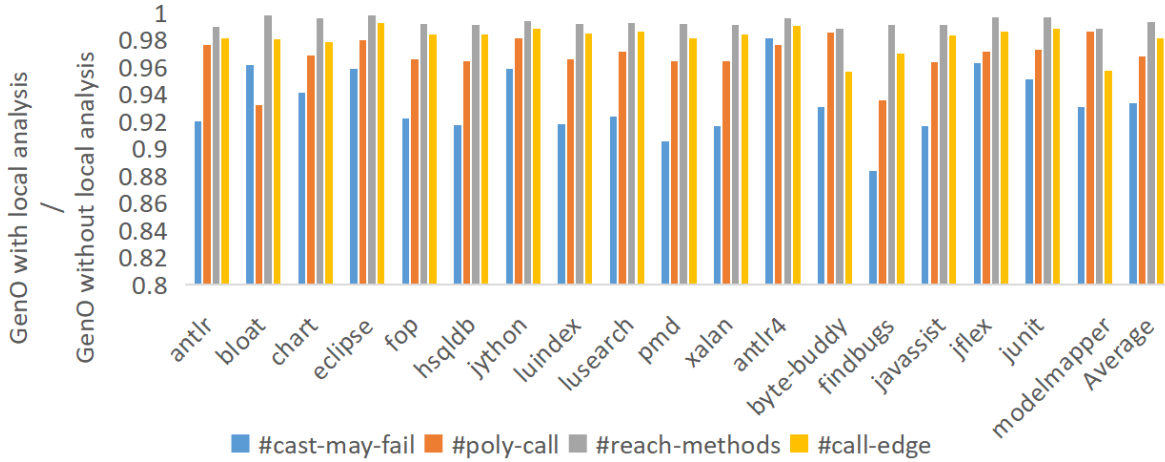


Fig. 12: The precision of GenO with local analysis against GenO without local analysis.

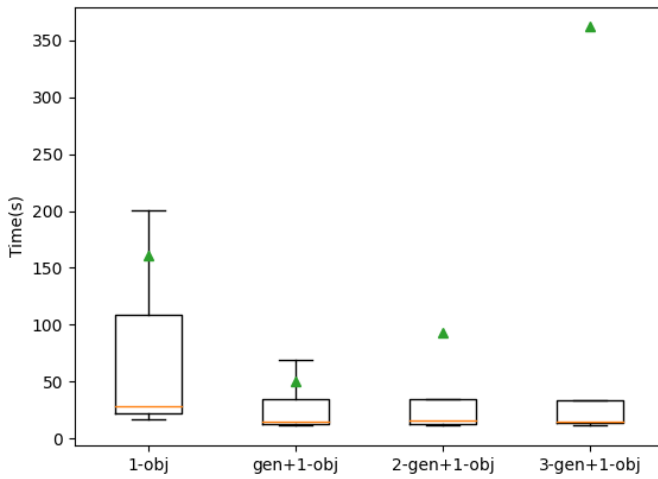


Fig. 13: Efficiency of k-generic sensitivity. The triangle represents means.

Selective context-sensitivity has gained much attention recently since it may offer a better trade-off between precision and efficiency, where methods can be analyzed with different context elements and depths. Researchers have applied manually-selected metrics and heuristics [40], [41], [42], or learning-based approaches [43], [44], [45], [46], [47] to selectively analyze a subset of methods context-sensitivity. SCALER [21] determines whether to analyze a method context-sensitively or not based on an estimation of its potential memory consumption. ZIPPER [25] introduces three kinds of value-flow patterns to identify precision-critical methods, and those patterns can be computed by solving a graph reachability problem on a precision flow graph. As a result, most precision can be preserved while achieving noticeable speedup. The later ZIPPER-E [26], as a new variant of Zipper, is able to significantly accelerate Zipper with comparable precision. EAGLE [30] performs a CFL-reachability-based pre-analysis to enable selective context-sensitivity in k-obj, while guaranteeing precision. TURNER [48] finds a sweet spot between ZIPPER and EAGLE, which enables k-obj analysis to run significantly faster than EAGLE while achieve better precision

than ZIPPER. CONCH [48] finds context-dependent objects, avoiding contexts bloating. BATON [31] proposes a Unit-Relay framework by collectively integrating different context selectors. Instead of selecting which methods to be context-sensitive analyzed, BEAN [49] makes k-obj sensitive analysis more precise by skipping those unhelpful context elements. In [32], Tan et al. apply a pre-analysis to selectively apply type-based abstractions to heap objects, provided that such approximation does not affect the precision of type-based clients, e.g., call graph construction. Compared to the above selective sensitive approaches, we propose a context customization scheme targeting generics and our approach can be applied together with the above optimization techniques, to further improve precision or efficiency, or both. Generic sensitivity can also be applied with call-site sensitivity by augmenting contexts with call-sites and propagating mappings from type variables to call-sites along type variables, similar to the methodology in the paper. OBJ2CFA introduces an innovative context-tunneled k-call-site sensitive analysis which may outperform object sensitivity in a general k-limiting setting by selecting critical call-sites as contexts. Generic sensitivity and OBJ2CFA may complement each other, akin to combining generic sensitivity with Zipper. Recently, the CUT-SHORTCUT approach [50] has made significant strides in accelerating context-sensitivity-like pointer analysis without employing context sensitivity. This achievement is accomplished by leveraging various patterns within its graph manipulation principle. In light of these advancements, we anticipate that our generic-sensitivity approach can provide new insights into the identification of novel generics-related patterns within this principle. This, in turn, can facilitate the exploration of new trade-offs between precision and efficiency.

There have been numerous approaches leveraging efficient data structure implementation to scale context-sensitive pointer analysis, e.g., using bit vectors or bit sets [51], [52], using binary decision diagrams (BDDs) [53], [54], [55], using geometric encoding techniques [56], or graph systems [57]. The work [58], [59] investigated on how to manually model semantics of data structures, to effectively speed up an analysis by omitting their complicated



implementation details. Compared to the above approaches, we target a different problem on how to effectively analyze generics in a context-sensitive manner and our approach can also benefit from the above optimization techniques.

## 7 CONCLUSION

We introduce generic-sensitive pointer analysis, a new context customization scheme designed for generics. To the best of our knowledge, this is the first context-sensitive pointer analysis targeting generics. Our scheme is built upon the insight that generic instantiation locations can serve as crucial context elements for effectively distinguishing contexts in Java programs. Leveraging this observation, we have established formal rules and outlined the application of generic customization to two prominent context-sensitive variants: object sensitivity and type sensitivity. Extensive experimental evaluations have been conducted, demonstrating the effectiveness of generic sensitivity in improving both traditional and selective context-sensitivity approaches. Our results highlight the potential for a new trade-off between efficiency and precision in Java pointer analysis, and we expect this work to pave the way for further exploration of generics for more precise pointer analysis.

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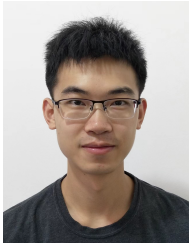
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**Haofeng Li** Haofeng Li received his BS degree from Shandong University in 2017 and his PhD degree from the Institute of Computing Technology, Chinese Academy of Sciences in 2023. He is currently an assistant professor in the Institute of Computing Technology, Chinese Academy of Sciences. His research interests include program analysis, pointer analysis and bug detection.



**Yongheng Huang** Yongheng Huang received his BS degree in information security at Huazhong University of Science and Technology, China, in 2020. He is currently working toward the PhD degree at the Institute of Computing Technology, Chinese Academy of Sciences. His research interests include program analysis and web security.

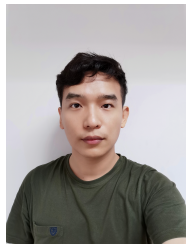


**Tian Tan** Tian Tan received his Ph.D. degree in Computer Science from University of New South Wales in 2017, and B.Eng. degree in Software Engineering from Northwestern Polytechnical University in 2013. He was a postdoc working at Aarhus University, Denmark (2017 - 2019). He is currently an associate research professor at the Department of Computer Science and Technology, Nanjing University. His research interests include program analysis and programming languages.

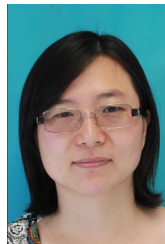


**Lian Li** Lian Li received his BSc degree in Engineering physics from Tsinghua University in 1998 and his PhD degree from University of New South Wales in 2007. He is currently a professor in the Institute of Computing Technology, Chinese Academy of Sciences, where he leads the Program Analysis Group.

Lian Li's main research interest focuses on program analysis, more specifically, on program analysis techniques and practical tools for improving software safety and security.



**Yue Li** Yue Li received his PhD degree in Computer Science from University of New South Wales (UNSW Sydney) in 2016, and B.Eng degree in Software Engineering and M.Eng degree in Computer Science from Northwestern Polytechnical University in 2010 and 2012, respectively. He was a postdoc working at Aarhus University, Denmark (2017 - 2019) and UNSW Sydney (2016 - 2017). He is currently an associate professor at the Department of Computer Science and Technology, Nanjing University. His research interests include program analysis and programming languages.



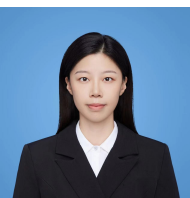
**Lin Gao** Lin Gao received her BS degree from Peking University in 1998 and her PhD degree from University of New South Wales in 2009. She is currently CTO of Beijing ZhongKe TianQi Information Technology Co., Ltd.



**Jie Lu** Jie Lu received his BS degree in Computer Science from Sichuan University in 2014 and his PhD degree from the Institute of Computing Technology, Chinese Academy of Sciences in 2020. He is currently an associate professor in the Institute of Computing Technology, Chinese Academy of Sciences. His research interests include program analysis, log analysis and distributed systems.

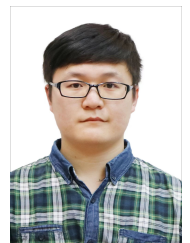


**Peng Di** Peng Di received his PhD degree in computer science and engineering from the University of New South Wales in 2013. He is a professor-level senior engineer at Ant Group where he leads the Program Analysis Group. He is also an adjunct academic staff at UNSW Sydney and Zhejiang University. His research spans programming languages, compiler technology and software engineering. He played a key role in co-founding several open-source projects, including SVF, MindSpore, CodeFuse, and others.



**Haining Meng** Haining Meng received her BS degree in Software Engineering from Northwest University, China, in 2017. She is currently working toward the PhD degree at the Institute of Computing Technology, Chinese Academy of Sciences. Her research interests include program analysis.

**Liang Lin** Liang Lin is collaborating author in the Database Products Business Unit of Alibaba's Cloud Intelligence Group. Liang Lin is a researcher at Alibaba Group and also serves as the head of the AnalyticDB MySQL team. The Alibaba Cloud AnalyticDB MySQL team actively participates in industry research, continuously improves product capabilities, and is dedicated to providing the market with more agile, efficient, and secure real-time high-concurrency online analytical cloud computing services.



**Liqing Cao** Liqing Cao received his BS degree in information security from Huazhong University of Science and Technology, China, in 2019. He is currently working toward the PhD degree at the Institute of Computing Technology, Chinese Academy of Sciences. His research interests include program analysis.

**Chenxi Cui** Chenxi Cui is collaborating author in the Database Products Business Unit of Alibaba's Cloud Intelligence Group. Chenxi Cui is a member of the AnalyticDB MySQL Engineering Efficiency&Quality team.