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Spencer: Interactive Heap Analysis for the Masses

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***Abstract*—Programming language-design and run-time-implementation require detailed knowledge about the programs that users want to implement. Acquiring this knowledge is hard, and there is little tool support to effectively estimate whether a proposed tradeoff actually makes sense in the context of real world applications.**

Ideally, knowledge about behaviour of "typical" programs is 1) easily obtainable, 2) easily reproducible, and 3) easily sharable.

We present *Spencer*, an open source web service and API framework for dynamic analysis of a continuously growing set of traces of standard program corpora. Users do not obtain traces on their own, but can instead send queries to the web service that will be executed on a set of program traces. Queries are built in terms of a set of query combinators that present a high level interface for working with trace data. Since the framework is high level, and there is a hosted collection of recorded traces, queries are easy to implement. Since the data sets are shared by the research community, results are reproducible. Since the actual queries run on one (or many) servers that provide analysis as a service, obtaining results is possible on commodity hardware.

Data in Spencer is meant to be obtained once, and analysed often, making the overhead of data collection mostly irrelevant. This allows Spencer to collect more data than traditional tracing tools can afford within their performance budget. Results in Spencer are cached, making complicated analyses that build on cached primitive queries speedy.

***Keywords*-tracing; dynamic analysis; heap analysis; tracing**

I. Introduction

Standardised program corpora are commonly used to evaluate research on run-time- and compiler optimisations – an optimisation gets implemented, and a program corpus is used to demonstrate its merit. Similarly, language abstractions and novel type systems often use the same corpora: programs from the corpus are annotated, and if it is possible to get most of the code to compile without large structural changes, this validates the utility of the type system [13], [20]. This work makes these corpora available *earlier in the research process*: we want researchers to be able to know whether – or not – the case they are optimising for exists in common programs, beyond artificial examples they have in mind. To this end, we run program corpora with comprehensive tracing, then preprocess the traces, and finally make the data available to be queried using a web interface (and an API that serves data as JSON formatted objects). Researchers can now implement queries that test whether – for instance – an optimisation they have in mind actually optimises a pattern that common programs encounter frequently.

Compared to traditional dynamic analysis, Spencer's approach strikes a *novel tradeoff*: Spencer caters explicitly to the use case where someone wants to know something about "common programs", not something about a specific program of their own. This means that Spencer's work flow is simpler than that of traditional tools: a user does not need to locally run any expensive analysis and can immediately start to work on analysing data. We hope that making program analysis *easier* will increase the chances that it is done, and improve how thoroughly it is done before research progresses. The tradeoff is that users can't easily run analyses on their own programs (they need to run Spencer locally, or work with the Spencer developers to have their data set added in this case).

Spencer is the result of scratching our own itch. As researchers in programming languages and programming language designers, we are often in search of data that can confirm or disprove hypotheses, or influence design decisions. Commonly, we end up mining existing code bases for answers, or hints at answers, which is error-prone and scales poorly. Spencer allows us to interactively explore (so far, Java) programs to find input to design processes, to gauge usefulness of designs and uncover their pain points.

While dynamic analysis oftentimes cannot produce a *sound* answer (because it is based on some particular runs of some particular programs for some particular data), the answers it gives still provide guidance and anectodal evidence that trancedes "gut feeling" and "folklore truths". The easy access to quantifiable data has changed our way of approaching programming language design.

A. Contributions

- We present Spencer, a web service to query program traces and visualise results interactively. Spencer's focus is on *heap analysis*: tracing connections between objects, studying individual objects and groups of objects throughout their lifetime, and uncovering useful invariant properties such as *uniqueness*, *immutability* and *reachability* and tying these invariants to static properties such as classes or source locations as well as dynamic properties like the span of time an object was in use.
- We introduce a query language that can be used to query the Spencer data set. Queries can easily be embedded in papers to allow readers to obtain an interactive result that is open to further exploration and refinement.
- To demonstrate its usefulness, we implement several small case studies in Spencer and show the range of queries that it can support.
- Since Spencer is a web service, traces are recorded once and

analysed often. This fact amortises the tracing overhead and makes tracing a more comprehensive data set (including the standard library) reasonable.

II. Tracing as a Service

A. Design Goals and Tradeoffs

Spencer's design goals are making knowledge of "typical" program behaviour easy to *obtain*, to *reproduce*, and to *share*.

Spencer makes one big tradeoff to meet these goals: data in Spencer is not provided by the user. Instead, the maintainers of the tool upload datasets that are deemed, by the Spencer developers, to represent a wide range of application domains, and users query those. This rules out uses of Spencer as a tool for analysing custom programs, which precludes its use as a bug-finding tool. On the other hand, all Spencer code including the tracing infrastructure is freely available as open source so nothing stops a user from running their own local Spencer service on their own data sets.

In the context of the design goals, we argue that this tradeoff is well justified. The remainder of this section will explain how.

1) Easily Obtainable Knowledge: Putting the data in a hosted repository is what makes it possible to host the tool online. Therefore, this makes knowledge available *without setting up any tool chain or configuring any tools*.

Since datasets, once uploaded, never change, query results can be cached. Running the same query again, on its own, or as a subquery of larger queries, results can be fetched from the result cache, rather than computed again. *As some datasets are large, caching is fundamentally important*. As caching also speeds up similar queries (as subexpressions of a query might be already in the cache), this mechanism is also important for *exploring data sets*: when exploring a dataset, most often a query is modified step by step. This means that the sequence of queries a user looks at commonly share subexpressions – and these are cached. Anecdotally, a query that selects all immutable objects from the `pmd` benchmark takes 65 seconds if it has never been computed before, 500–800ms if it has been computed before by any user. The speedup is between 80×–130×.

2) Easily Reproducible Knowledge: Comparing the results of dynamic analyses can be tricky: different tools implemented by different researchers for different purposes commonly focus on tracing just those pieces of information those researchers need. Comparing the output of these tools can therefore be hard. One example is that most tracing tools do not record variable accesses – they are so numerous that the overhead of logging them is often deemed too high.

Spencer makes its data available to the public and hosts very comprehensive datasets: since program traces in Spencer are produced only once, but analysed often (with caching), the overhead of tracing becomes unimportant. This means that Spencer aims to record "everything" that happens. Variable loads and stores, method calls and exits, and field accesses – all with a range of meta information, such as access times, field names, calling objects and methods. We hope that this

http://spencer-t.racing/datasets	Overview of the available datasets.
http://spencer-t.racing/datasets/$\boxed{\text{dataset}}$	Specific details of one dataset.
http://spencer-t.racing/query/$\boxed{\text{dataset}}$/$\boxed{\text{query}}$	Query an existing dataset.
http://spencer-t.racing/json/select/$\boxed{\text{dataset}}$/$\boxed{\text{query}}$	Select all objects (JSON API).
http://spencer-t.racing/json/meta/$\boxed{\text{dataset}}$/$\boxed{\text{query}}$	Get object meta information (JSON API).

Figure 1: The available URLs that users can interact with.

wide range of information will allow different researchers and collaborators to compare each other's results reliably.

3) Easily Sharable Knowledge: In Spencer, every query is expressed as a URL. A query that returns all mutable objects in the dataset called "test" is expressed by this URL:

```
http://spencer-t.racing/query/test/
          MutableObj().
```

Naturally, queries can be much more complex, leading to longer URLs.

Since queries are URLs, *sharing research results is just a matter of sharing a link*; and since results are cached on the server, sharing is efficient. Because results are interactive, they serve as starting points for exploration. A reader that wants to dig deeper to verify or dispute a hypothesis that is not immediately addressed by the paper in which it appears may experiment with adding or removing one particular data set from the results, or check what objects cause a certain outlier, etc. This also makes it harder to skew results by omitting data.

B. The User Interface and Usability

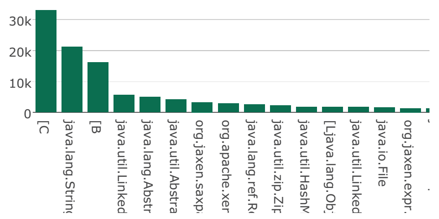
Spencer is a web service that lets users enter queries which will select sets of objects (explained in more detail in Sec. III) and see information about these selected objects. For the user, this means that they can use the tool without any installation process or even downloads of data. For developers, this makes it easy to add new visualisations, new data sets, or new primitive queries.

The user interface aims to be self documenting and the landing page, `http://spencer-t.racing`, presents links to example queries in a tutorial style. Figure 1 gives a brief overview of the sub pages that are available.

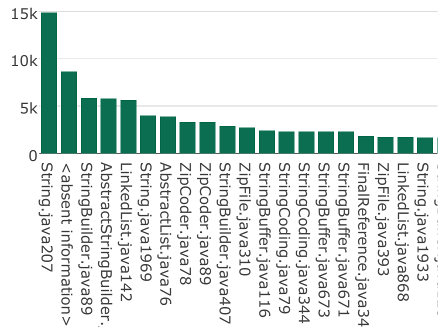
1) Visualising Selections: The ability to select objects (as covered in Section III) alone is not useful for analysis of program traces – these objects have to be tagged with meta information, and this information needs to be visualised for a user. Spencer provides a growing set of object variables:

Name	Description
`klass`	Class of an object.
`allocationSite`	Allocation site (file, line).
`thread`	Allocating thread.
`firstusage`	Allocation time.
`lastusage`	Last field access time.
`lifeTime`	Duration from allocation to `lastUsage`.

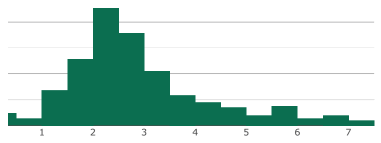
The object variables are used to visualise selection results. For instance, the classes are visualised for a selection of objects



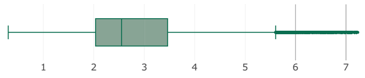
(a) The classes and number of instances (zoomed in).



(b) The allocation sites (zoomed in).



(c) The variable `log10(lifeTime)`.



(d) The variable `log10(lifeTime)` (box plot).

Figure 2: The query Obj() selects all objects. Figures (a) and (b) show visualisations of the categorical variables `klass` and `allocationSite`. Subfigures (c) and (d) show two visualisations for the numerical variable `log10(lifeTime)`. The lifetimes of objects appears to be a uni-modal distribution, with most objects being very short lived and few objects live very long.

in the form of a bar chart that shows how many objects were created from a certain class. Spencer distinguishes between categorical and numerical variables and the user interface picks visualisations accordingly.

Figure 2(a) shows an example, summarising the classes of the objects selected by the query Obj() (in other words: all objects).

III. Selection using Queries

Analyses in Spencer are written as high level queries. A query is a selection: it returns as its result a set of object IDs (a unique integral value that identifies each object).

The fact that there is a high level language of queries means that caching can be effective: if queries in Spencer would be written, for instance, in a much more expressive programming language, then many different programs could express the same query. The cache system, however, would not be able to prove that differently phrased (but equivalent) implementations of a query are in fact equivalent. Caching would therefore speed up much fewer queries. The tradeoff the design with the high level query language makes is that the queries a user can run must be supported by the system explicitly – it is possible that Spencer does not support a certain query from being run. If a query algorithm can not be expressed in Spencer, users can contribute the algorithm to the open source service and thereby make it available for other users as well.

In Spencer, there are primitive queries, a set of basic selections that the backend implements, and query combinators that users can use to combine queries into more fine grained selections. Table I shows an overview of the available queries. For example, the query MutableObj() returns a set of object IDs that were mutated during a particular program's run. The query ReachableFrom(q) returns the set of objects that *are reachable* (via the heap, or via stack variables) from any object returned by the query q. The query CanReach(q) returns all objects that *reach* an object returned by q. Combined, the query CanReach(ImmutableObj()) returns all objects that are "indirectly mutated", meaning all objects that are either mutated themselves, or objects that have fields referring to indirectly mutated objects. The variants HeapReachableFrom(q) and CanHeapReach(q) only consider reachability through fields, *i.e.,* it excludes stack variables.

The Deeply(q) selects all objects that are *dominated* by the objects selected by q in the object graph. For example, if o is in q, and o' is an object which can only be reached from o (directly or indirectly), and o'' is an object which can be reached from o by also from outside of o, then o' will be selected by Deeply(q) but not o''. Similarly, HeapDeeply(q) only considers fields, not stack variables. Sec. V-B has an example for its usage.

IV. Comparisons and Query Refinement

We have, so far, shown how to use queries that select objects. When exploring data sets, it is often useful to interactively compare several queries with each other and see whether – or not – the objects selected by several queries have large overlaps. Several subqueries, separated by a slash form a composite query: ImmutableObj()/HeapUniqueObj()/TinyObj(). The result of this query shows – amongst other things – the percentage of all objects in a particular data set that satisfied each query, but also the intersections of the queries, *e.g.,* all objects which are both immutable and tiny. Figure 3(a) shows this information in form of a matrix.

A. Exploring Selections

All information that the matrix of a query shows could have been obtained using the And query combinator. However, query compositions are useful because they form the starting point of exploration of data. A user can execute operations on either of the subqueries. These operations are exposed by the user interface as hyperlinks, facilitating speedier interaction with the system. Being able to modify these queries, in our experience,

Primitive Query	Selects all objects that are...
Obj()	Any object.
MutableObj()	mutated outside the constructor.
ImmutableObj()	not mutated outside the constructor.
InstanceOf(c)	instances of the given class c.
StationaryObj()	never written to after being read the first time.
TinyObj()	never referring to any other objects.
UniqueObj()	never aliased.
HeapUniqueObj()	referred to from two fields at the same time.

Query Combinator	Selects all objects that are...
RefersTo(q)	All objects that ever have a variable or field referring to an object in q.
HeapRefersTo(q)	All objects that ever have a field referring to an object in q.
ReferredFrom(q)	All objects that are ever referred to from a variable or field of an object in q.
HeapReferredFrom(q)	All objects that are ever referred to from a field of an object in q.
ReachableFrom(q)†	All objects selected by q, and all objects that are referred to from fields or variables of objects that are ReachableFrom(q).
HeapReachableFrom(q)†	All objects selected by q, and all objects that are referred to from fields of objects that are HeapReachableFrom(q).
CanReach(q)†	All objects selected by q, and all objects that held variables or fields pointing at objects that CanReach(q).
CanHeapReach(q)†	All objects selected by q, and all objects that held fields pointing at objects that CanHeapReach(q).
Deeply(q)†	All objects in q that CanReach only objects also in q.
HeapDeeply(q)†	All objects in q that CanHeapReach only objects also in q.
Not(q)	All objects that are not in q.
And($q_1 \ldots q_N$)	All objects that are in all queries.
Or($q_1 \ldots q_N$)	All objects that are in at least one query.

Table I: Queries and their Meaning. See Section III for detailed descriptions. †these queries are recursively defined, this means that these selections effectively "walk the memory graph".

improves user experience and the browser's browsing history makes it natural to go back and revisit queries that a user has seen before.

1) Focusing on a Subquery: To focus on a subquery means to constrain the other subqueries to only select a subset of the focused query's selection. Given the composite query InstanceOf(java.lang.String)/HeapUniqueObj(), then to focus on the query for the heap unique objects would produce the resulting query that selects all strings that *are also* heap-unique: And(HeapUniqueObj() InstanceOf(java.lang.String)).

Figure 3(a) shows a query that consists of three subqueries, and subfigure (b) illustrates the effects of focusing on one of them. Table II depicts the focus operation's transformation of composite queries.

2) Hiding a Subquery: To hide a subquery means to constrain the other subqueries to *never* select objects in the subquery's selection. It can be thought of set subtraction. Given the same composite query as before, InstanceOf(java.lang.String)/HeapUniqueObj(), to hide the subquery for the heap unique objects would produce the resulting query that selects all strings that *are not* heap-unique: And(Not(HeapUniqueObj()) InstanceOf(-java.lang.String)).

Hiding a query q is equivalent to negating the query first – Not(q) – and then focusing on the negated query.

Figure 3(a) shows a query that consists of three subqueries, and subfigure (c) illustrates the effect of hiding one of them.

3) Splitting a Subquery: For a number of composed queries with a subquery q_N, a common question is often whether the queries $q_1 \ldots q_{N-1}$ yield different results for objects that are selected by q_N and objects that are not – a case analysis of sorts. To *split a subquery* q_N means to first, eliminate this query from a query comparison, and to replace each of the other subqueries q by *two new subqueries* And(q q_N) and And(q Not(q_N)), see Table II.

To give an example, consider age ordering of objects. An object is age-ordered if it is younger than all objects it has field references to. An object is reverse age-ordered if it is older than all objects it has field references to.

Starting with the query comparison AgeOrderedObj()/ReverseAgeOrderedObj()/InstanceOf(j.l.String), and splitting on InstanceOf(java.lang.String) gives the resulting query comparison:

And(InstanceOf(j.l.String) AgeOrderedObj()) /
And(InstanceOf(j.l.String) ReverseAgeOrderedObj()) /
And(Not(InstanceOf(j.l.String)) AgeOrderedObj()) /
And(Not(InstanceOf(j.l.String)) ReverseAgeOrderedObj())[1]

This comparison makes it evident that strings are more commonly reverse age-ordered than other classes.

V. Case Studies

This section describes two cases that highlight how Spencer can be used. Unless otherwise noted, all graphs that are shown here are renderings that the web user interface produces.

A. Case 1: Exploring the Layout of Strings

Our first case study highlights how Spencer can be used to explore a data set with a potential run-time optimisation in mind. The goal here is not to propose a run-time optimisation, but to show how a researcher could leverage the platform in practise.

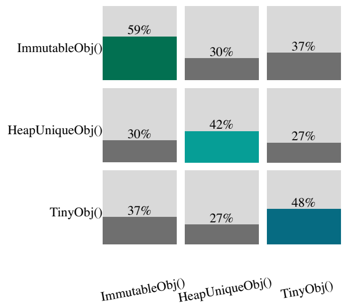
Strings (and the character arrays that store their data) are the class with the highest memory usage in many Java programs [14]. As the page for the `java.lang.String` class code[2] shows, Strings in Java are objects with only one reference type field: the field `value` holds a reference to an array of characters that contains the string's data. Listing 1 shows an excerpt of the pretty printed Java bytecode that a user can find on this page.

A Spencer query that selects the arrays that are reachable from Strings can be written thus:

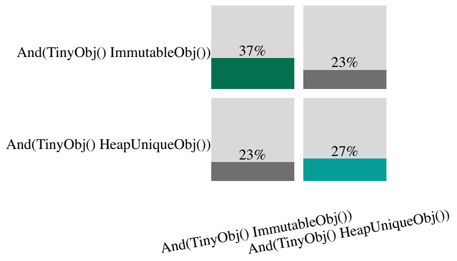
A1: HeapReferredFrom(InstanceOf(j.l.String))

[1]A reader running this composite query might notice that some objects are both age ordered and reverse age ordered. The objects that are selected by both are tiny objects, which can be verified by filtering out tiny objects, which yields the empty set.

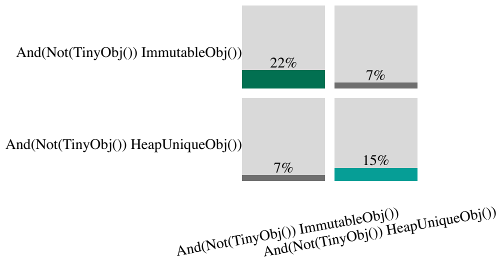
[2]http://spencer-t.racing/source/test/java.lang.String



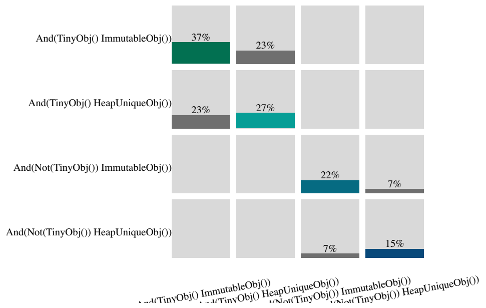
(a) No query focused, no query hidden.



(b) After focusing on tiny objects.



(c) After hiding tiny objects.



(d) After splitting by tiny objects. The top-left group of values contains tiny objects, the bottom right group contains non-tiny objects. The information here is the combination of subfigures (b) and (c).

Figure 3: Comparing the three queries ImmutableObj()/HeapUniqueObj()/TinyObj(), we modify this composite query by: focusing (b); hiding (c); or splitting (d)—the tiny objects.

	q_1 / ... /		q_{N-1}	/ q_N	
	`And(Not(`q_N`)` q_1`)` / ... /		`And(Not(`q_N`)` q_{N-1}`)`		hiding q_N
	`And(`q_N q_1`)` / ... /		`And(`q_N q_{N-1}`)`		focusing on q_N
`And(`q_N q_1`)` /	`And(Not(`q_N`)` q_1`)` / ... /	`And(`q_N q_{N-1}`)` /	`And(Not(`q_N`)` q_{N-1}`)`		splitting on q_N

Table II: Refining a composite query $q_1/\ldots/q_n$ by focusing or hiding q_N.

```
public final class java/lang/String
  implements
    java/io/Serializable
    java/lang/Comparable
    java/lang/CharSequence {
  // ...
  private final [C value
  private I hash
  // ...
}
```

Listing 1: An excerpt of the definition of the class `java.lang.String`, reachable under the view `http://spencer-t.racing/source/test/java.lang.String`. `[C` in Java bytecode denotes an array of primitive characters and `I` denotes a primitive integer.

Strings in Java are, according to the documentation, immutable [1]. Arrays, however, are typically not immutable since they are constructed empty and must be populated with values. Arrays in strings could however be *stationary*, meaning that they are fully initialised before being read. To test whether this intuition is true, we add a new sub query to compare stationary objects versus the character arrays from before:

A1.1: ⟨A1⟩/StationaryObj() [3]

The matrix visualisation of this composite query (shown in Fig. 4) shows that 75% of objects are stationary, that 16% of objects are heap-referred from strings (top left), and that also 16% of objects are both heap-referred from strings and stationary (top right, bottom left). This suggests that all objects referred to from fields in string objects are also stationary – as a sanity check, we hide stationary objects and confirm that this selection indeed returns *no* objects:

A1.2: And(Not(StationaryObj()) ⟨A1⟩)

The query A1.2 returns no instances, meaning that these arrays are all stationary. Thus the the trace data on which these queries are run indicate a strong possibility of a static invariant that these arrays are stationary. This might be verifiable from the source code (available directly from Spencer), but it may not be the case that Java is able to express this, or that the actual classes involved in an aggregate are known statically.

Stationary data is safe to share from many objects. To detect whether this fact is leveraged by the string class we can go

[3]For clarity we use the abbreviation ⟨A1⟩ to stand in for its definition above. Actual Spencer query syntax would repeat the query A1 there.

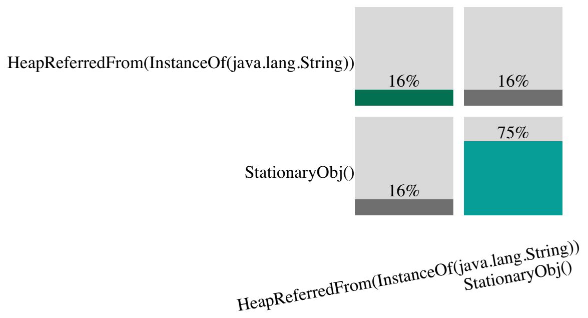


Figure 4: Objects that are heap reachable from strings vs. stationary objects. The coloured cells on the main diagonal show the percentage of objects that are selected by the query, the objects off the main diagonal show the percentage that fulfill both queries.

back to query A1, and add a subquery to look for objects that have at most one reference from the heap:

A2: ⟨A1⟩/HeapUniqueObj())

The matrix visualisation of this composite query is shown in Fig. 6 and tells us that there are 14% of objects that are heap reachable from strings *and also* heap unique, meaning a 1:1 mapping from string objects to character arrays. This means there are *shared* character arrays in the program, but we do not yet know whether they are shared by strings. To investigate, we want to focus on the remaining 2% of objects reachable from strings, but that are not unique: hiding the heap unique objects does precisely that, yielding the query:

A3: And(Not(HeapUniqueObj()) ⟨A1⟩)

To see if all of these objects are strings, we select the objects that hold field references to shared objects by applying the HeapRefersTo query combinator (Fig. 5 shows an illustration of what it means to nest a HeapReferredFrom query inside a HeapRefersTo query.):

A4: HeapRefersTo(⟨A3⟩)

To further select the objects (if any) that are not strings, we add a composite query to select all strings, and hide those:

A5: And(Not(InstanceOf(java.lang.String)) ⟨A4⟩)

We can inspect the class of the objects that are now selected and find that these objects are instances of the class `java.lang.StringBuffer`.

If we want to know where those arrays were allocated, we can go back to query A3, and click inspect on the allocation sites. This reports that all of them were allocated in file `StringBuffer.java`, on line 671. inspecting the source code of the class `StringBuffer` (link: `StringBuffer`), we find that this line corresponds to the method `toString()` (see Listing 2).

B. *Case 2: Uncovering Safety Properties of Objects*

The advent of multicore has renewed the interest in immutability, and caused mutable state to be criticised. Mutable state that is shared across threads is a risky programming pattern, and immutable state is suggested as a safe alternative. A reasonable question then is to investigate how easy it might be to retrofit

```
// access flags 0x21
public synchronized toString()Ljava/lang/
  String;
 L0
  LINENUMBER 670 L0
  ALOAD 0
  GETFIELD java/lang/StringBuffer.
 toStringCache : [C
  IFNONNULL L1
 L2
  LINENUMBER 671 L2
  ALOAD 0
  ALOAD 0
  GETFIELD java/lang/StringBuffer.value : [
 C
  ICONST_0
  ALOAD 0
  GETFIELD java/lang/StringBuffer.count : I
  INVOKESTATIC java/util/Arrays.copyOfRange
   ([CII)[C
  PUTFIELD java/lang/StringBuffer.
 toStringCache : [C
 L1
```

Listing 2: Instances of the class `ShallowImmutable` can never be changed, yet it is still not safe to share `ShallowImmutable` instances accross threads – the heap-reachable `Mutable` instance could cause data races.

abstractions like immutability or uniqueness (references that can never be aliased) into object-oriented programming as realised in Java. In order to make such a judgement, we will construct a query that selects all safe objects, and then analyse the objects that are *not* thread-safe.

We start with immutability:

B1: ImmutableObj()

In our trace data, we find a large number of immutable objects (59%). Our notion of immutability is however shallow, and although an object stays the same, if its aggregate values change, it is arguably not immutable. Listing 3 illustrates this.

```
final class ShallowImmutable {
  private final Mutable m;
  public ShallowImmutable(Mutable m) {
    assert(m != null);
    this.m = m;
  }
  public Mutable getMutable() {
    return this.m;
  }
}
```

Listing 3: Instances of the class `ShallowImmutable` can never be changed, yet it is still not safe to share `ShallowImmutable` instances across threads – the heap-reachable `Mutable` instance could cause data races.

In order to only select objects whose transitive closure of reachable state is immutable, we modify the query:

B2: HeapDeeply(⟨B1⟩)

Instances of the class `ShallowImmutable` in Listing 3

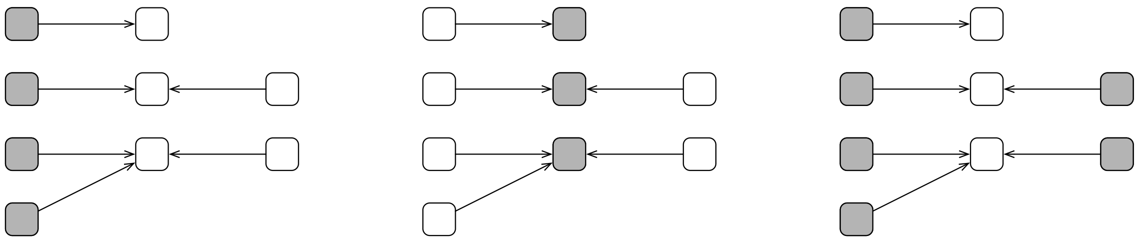

(a) Some query q's selection. (b) HeapReachableFrom(q)). (c) HeapRefersTo(HeapReachableFrom(q)).

Figure 5: *Gray objects are selected.* HeapRefersTo and HeapReferredFrom are not inverse operations, as this example shows. Case study A in Sec. V-A uses such i similar query to find all objects that have a reference to non-unique character arrays in strings to find which objects have reference to these arrays (these figures were not created using Spencer).

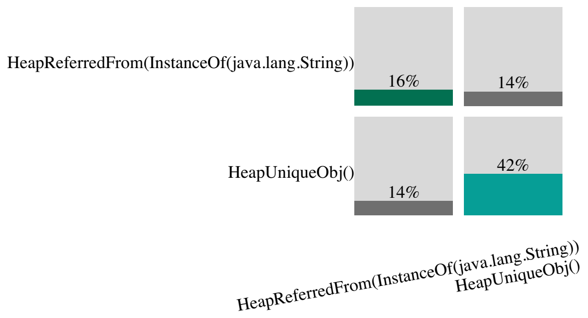


Figure 6: Query A2: Most objects that are heap-referred to from strings are heap unique, but not all (16% are heap-referred to from strings, but 14% are both heap-referred to and heap unique).

would not be selected by B2 because they contain a heap reference to mutable objects of the class `Mutable`. In our dataset, the fraction of deeply immutable objects is 53% – most objects that are immutable (B1) are also deeply immutable (B2), only 6% of objects are immutable but not heap-deeply so.

We can investigate those 6% of objects by constructing a composite query of B1 and B2, and hiding B2. This yields:

B2.1: And(Not(⟨B2⟩) ⟨B1⟩)

According to the classes of the selected objects, strings are by far the most common objects of those that are not deeply immutable, but immutable. But in the previous case study in Sec. V-A, we have learned that strings are – even though they do not fulfill the requirements of the MutableObj() query – "morally immutable". We account for this fact by including them, and their `value` arrays:

```
B3:   Or(InstanceOf(j.l.String)
        HeapReferredFrom(InstanceOf(j.l.String))
        ⟨B2⟩
      )
```

Stackbound objects (objects that are never referenced from fields) are also thread safe, as in order to share an object across threads, it needs to pass through a field at some point (threads can not access each other's stacks directly). Similarly, unique objects are safe even if they are touched by several threads – after all, the objects can not be touched by several threads at the same time, as there is only one active reference at each time:

B4: Or(StackBoundObj() UniqueObj() ⟨B3⟩))

In programming language design, a possible pitfall is to design abstractions that fit simple cases well but that are not able to support real world use cases. Imagining we're implementing a type system for a Java-like language that has type abstractions for stack-boundedness, uniqueness, and immutability (there are many such works in the literature *e.g,*. [11], [5], [6], [16], [18], [9]). We would like to understand what are the objects that are not "safe", – to see the potential usefulness of our type system, and also understand the objects that are unlikely to fit our abstractions:

B5: Not(⟨B4⟩)

Looking at the classes of these "unsafe objects", we see the bar chart in Fig. 7. It tells us, for instance, that Nodes of linked data structures are problematic for such a type system design: the class `java.util.LinkedList$Node` is the most commonly used unsafe class. This result is correct: nodes are aliased from the heap and nodes are referenced both from the previous *and* from the following node (linked lists in Java are doubly linked [2]). Nodes are also mutable, as building a list requires changing the `next` field of the nodes. And, since it is a linked data structure, these objects are not stackbound either. Were we developing such a type system, we would now have identified a possible shortcoming that we would need to address, given how central linked lists are to many programs.

VI. Internal Details

Spencer, the web based tool requires a tool chain behind the scenes to function. This tool chain includes three key programs:

1) A tool, called `spencer-trace`, to modify all code loaded in a running Java virtual machine to emit event logs (see Sec. VI-A).
2) A tool, called `spencer-load`, to load these event logs into a data base (see Sec. VI-B).

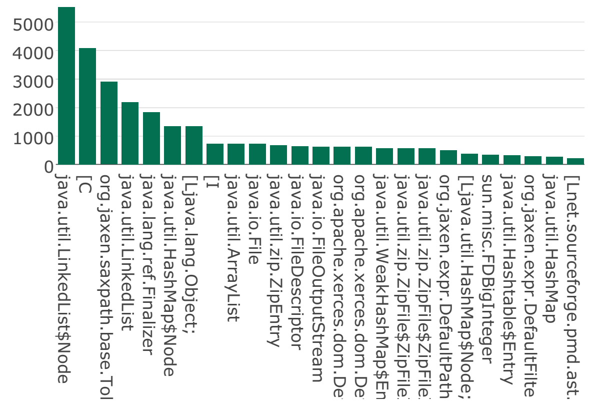


Figure 7: Query B5: Classes of objects that are “unsafe”, a programming language design that deals with the abstractions in case study B (Sec. V-B) must be careful to be able to express these classes.

3) Spencer, the web application that has been presented above.

A. Tracing with `spencer-trace`

The `spencer-trace` tool is a wrapper for the Java HotSpot™ VM. It is intended to understand all arguments that HotSpot™ understands and therefore to serve as a drop-in replacement for it. When `spencer-trace` runs a compiled program, additionally to executing Java bytecode, it will intercept loading of any bytecode (whether from disk, or dynamically generated, or via other sources), and transform the loaded code. The implementation of this is backed by a JVMTI (JVM Tool Interface[4]) agent. JVMTI makes it possible to intercept loading of classes by implementing a handler. In this handler implementation, `spencer-trace` sends the code of the class to a code transformation library that modifies the code as shown in Listing 4. The transformation inserts calls to methods into the code that will write events in a standardised format to disk. The tool takes care to not instrument data that are used during instrumentation (like the code that instruments classes itself) by doing the transformation and logging in native (C-code) implementations and by running the class transformation in a separate JVM process. Listing 4 shows a description of the inserted instrumentation. From this listing, it is easy to see that the overhead the tracing incurs is substantial. This is a problem for programs who have built-in time outs, but our experience with generating trace data is that albeit slow, it works solidly. The fact that the data from one trace can be used to perform many analyses also mitigates the slowdown.

Additionally, `spencer-trace` stores both the original and the transformed version of the class file into a log directory. The transformed version of the class file permits running programs with only some classes of interest being instrumented which boosts performance considerably.

[4]http://docs.oracle.com/javase/8/docs/platform/jvmti/jvmti.html

One issue `spencer-trace` faces is actions taken by methods implemented natively – these methods not be instrumented currently. One such method is `System.arraycopy`, a native implementation that copies a range from one array into another array. One effect this has is that character arrays of strings often will appear to be immutable, when in fact they were not – because the writes that `arraycopy` generates are missing in the data. We are considering wrapping the most common native methods to overcome this problem.

```
public int hashCode() {
+ try {
+   NI.methodEnter(.."hashCode"..);
+   NI.read(.."hash"..);
    int h = this.hash;

+   NI.loadFieldA(..this, "value",
                     this.value,..);
    if (h == 0 && this.value.length > 0) {
+     NI.storeVar(..2, this.value..);
      char val[] = this.value;

+     NI.loadFieldA(..this, "value"..);
      for (int i=0;
           i<this.value.length;
           i++) {
+       NI.loadArray(..val, i, this..);
        h = 31 * h + val[i];
      }
+     NI.modify(..this, "hash"..);
      this.hash = h;
    }
+   NI.methodExit(.."hashCode"..)
    return h;
+ } catch (Throwable t) {
+   NI.methodExit(.."hashCode"..);
+   throw t;
+ }
}
```

Listing 4: The instrumentation adds calls to record what a method was doing. This listing shows the effect of code transformation on the method `hashCode` of the class `java.lang.String`. The transformation works on Java bytecode, not Java code, this presentation in Java is therefore just for illustration. Lines that start with + are added by the transformation. Variables of reference type (classes, arrays) are instrumented, primitive variables are currently not. The `NativeInterface` interface (abbreviated as `NI`) is added by `spencer-trace`, the method implementations write the data to disk.

The tracefiles are written in a standardised format, using a specification compatible with the Cap’n Proto tool. Cap’n Proto accepts record-like specifications as input and generates libraries in a number of languages (the supported languages include C, C++, Java, C#, Go, OCaml, Ruby, Javascript, and others) that can be used to write these records to disk or read them back. Using this approach, users could implement their own tools that generate trace files (perhaps for languages that are not running on the JVM at all) and spencer could then host these traces just as well.

```
struct VarStoreEvt {
  callermethod  @0 :Text;
  callerclass   @1 :Text;
  callertag     @2 :Int64;
  newval        @3 :Int64;
  oldval        @4 :Int64;
  var           @5 :Int8;
  threadName    @6 :Text;
}
```

Listing 5: A specification for an event that represents a variable assignment in the Cap'n Proto's input language. Cap'n Proto can use such specifications to generate optimised libraries in a range of languages that will write these events to disk or read them back into memory.

B. Loading Traces with `spencer-load`

Program traces can be loaded into a local database using the `spencer-load` tool. The tool reads the logs from a file produced by `spencer-trace` (Sec. VI-A) and loads them into a PostgreSQL database.

This database contains tables to track: objects (identified by a unique ID) containing the object's class, the event number of their first appearance in the trace, and the event number of their last appearance; references between objects (including when the reference was established; whether stored in a variable or in a field; when the reference ended), and method calls (including which object was being called, name and signature of the method, when the method was called, and when the call returned).

C. Available Data

Spencer currently hosts traces of 9 of the programs in the DaCapo program corpus version 9.12 [4] (*c.f.* http://www.spencer-t.racing/datasets) comprising more than 3 billion events and over 2.000 loaded classes including libraries. The selection of programs currently only features Java programs but will eventually grow to include programs in other languages (like Scala, Clojure, and Ruby), too. The number of current programs is limited by the hard drive capacity that the current server has and we are working on increasing the available space and their size is limited by available RAM[5]. In principle, Spencer can instrument any application running on the JVM. A common problem, however, is asynchronously communicating software that puts bounds on reply latencies. The slowdown of Spencer can, in such cases, cause time-outs to happen. Such software may – where possible – need to be run with changed parameters in order to account for the slowdown.

[5]To reviewers: The current server provides only 16GB of RAM, which is not sufficient to run some queries on the larger benchmarks like `avrora` and `h2`, but we hope that the amount of RAM will be at least doubled in the next few weeks. Additionally, we will implement optimisations that conserve memory.

Name	Objects	Log
`luindex`	81,158	5.8GB
`pmd`	131,462	2.7GB
`fop`	521,789	10GB
`batik`	526,945	21GB
`xalan`	1,133,391	48GB
`lusearch`	1,212,743	61GB
`sunflow`	2,419,900	91GB
`h2`	6,655,852	207GB
`avrora`	932,085	236GB
Total:	13,615,325	≈680GB

Table III: Currently loaded benchmarks, a similar list can be found in the tool: http://spencer-t.racing/datasets.

VII. Related Work

Many tools for dynamic analysis have been developed in the past. The JVM, historically has been a good basis, due to tools like JVMTI that we also rely on.

What sets Spencer apart from the previous work is that Spencer is – mostly – a collection of data with tools to analyse them in ways that makes it easy to explore data, unearth knowledge about a running program, and share the results or collaborate. Previous work on dynamic tracing focus on collecting the data. In this regard, Spencer contributes the inclusion of variable events in traces, which previous state-of-the-art tools like RoadRunner [10] does not do.

A. Snapshotting for Heap Analysis

Snapshotting is a sampling-based dynamic analysis technique that regularly stops a running program and writes all contents of the heap to disk. The snapshots can then be analysed offline.

The advantages of snapshotting include that the amount of data generated generally is lower; the disadvantages include that it is unknown what happened to an object in between snapshots. Having continuous data about an object's execution permits Spencer to provide convincing results in cases where snapshots would not be able to do this: if many object have only one incoming reference in a heap snapshot, that does not mean that unique variables are a useful type abstraction – because they might be aliased before and after the snapshot. Temporary violations of uniqueness, or ABA-style updates to objects will be invariable by caught by spencer, and this is part of the implementation of uniqueness and immutability. An advantage of snapshotting is its ability to deal with native code.

Potanin et. al's Fox [17] relies on snapshotting and also uses a query language. Potanin et. al used Fox to look for uniqueness in the heap of Java programs. The proportion of aliased objects found in their corpus was 13.6% on average. This is roughly in line with values that we observe for the query Not(HeapUnique() but, as stated above, the measuring methodology differs as Spencer is able to track all events on an object. While the results are similar, it is unclear whether the objects reported as *e.g.,* unique are the same across both tools.

Interestingly, the case study about strings in Section V-A is similar to approaches used in real world development of programming language run-times: heap snapshots (also called heap dumps) have been used to gain insights into run-time optimisations – before implementing. One example is work by Oracle on compressed strings in Java (strings can only use one byte per character, rather than two, in case they only contain ASCII characters). There, heap dumps of strings have been used to estimate how much application memory could be saved by implementing such an optimisation (*"We have a large corpus of heap dumps [..] that can be used to estimate the heap occupancies for some frequent classes. So, we have crafted a simple simulator that introspected what Strings are there, [..] and how compressible those characters are."* [3])[6]. Spencer can, right now, not deal with this case, as we do not store what primitive values are assigned into arrays. As noted in the section on future work (Sec. VIII), we plan to extend tracing of primitive values, and also record sizes of arrays to support such use cases.

Chis et al. analyse heap snapshots, focusing on memory bloat in Java programs and identifies common problems that are specific to Java programs [7]. These problems include implementation-specific issues: for example, they find many empty `java.util.ConcurrentHashMap` objects that contain few or no elements but use considerable amounts of memory each and suggest practical fixes to get rid of this overhead. Mitchell et al. [15], summarises heap snapshots in ways that programmers may comprehend with a different goal than ours—to identify memory bloat.

B. Trace-Based Tools

The ROADRUNNER tracing framework [10] is a state-of-the-art tracing tool developed by Flanagan et. al. The goal of ROADRUNNER to simplify obtaining trace data by facilitating rapid prototyping of dynamic analyses for concurrent Java programs. ROADRUNNER is in this respect similar to the `spencer-tracing` tool, but does not have any counterparts to the remaining Spencer tool-chain. ROADRUNNER and `spencer-tracing` export a similar feature set, but the latter importantly include variable events in its traces.

One similarity that Spencer and ROADRUNNER have is extensibility: ROADRUNNER supports combining several analyses using analyses as a "chain of filters" where each filter reduces the number of objects that the subsequent filter has to analyse. Spencers query combinators are more powerful than that, one example being the ability to walk the heap using query combinators like $\mathsf{CanReach}(q)$.

C. Static Analysis

Hackett and Aiken use static analysis on C programs [12]. They are able to uncover some static invariants of C programs, but are not able to gauge *e.g.,* how common certain kinds of objects are at run-time. Following their static analysis approach is less feasible in Java programs because of the additional problems that must be solved, such as dealing with dynamic dispatch and dynamic code generation.

Unkel and Lam [18] use static analysis on Java benchmarks and open source programs to detect the number of stationary fields. Nelson et. al later study the same property using dynamic analysis [16]. They find the number of stationary fields to be in the range of 55–82% in a variety of programs (the static analysis giving the lower bound and the dynamic analysis giving the upper bound). Spencer measures a stronger property – stationary *objects*, which are objects with only stationary fields.

Vanciu et al. [19] use static analysis on hand-annotated programs to extract Object Ownership Graphs (OOG). It is a conservative whole-program analysis that shows all possible objects and all possible communication between objects. These graphs do not scale well to large programs.

VIII. Future Work

Future work on Spencer can be divided into four main categories. First, extending the data sets with more programs and more traces of single programs with varying inputs. Second, the Spencer feature set will be extended by more queries, including thread-locality, access patterns, etc. Third, we will use Spencer to validate designs, both our own, and those of others. For example, there exist many proposals (*e.g.,* [6], [8], [11], [9]) for type system designs to rule out certain classes of errors that include unique references, immutable objects, etc. It would be interesting to see the extent to which such systems could describe the shapes of existing programs. Fourth, improsed user interface, improved visualisation and object interaction. For example, a currently missing feature is the ability to select objects from the visualisations. For example, we are often interested in the outliers of a statistic – where are the objects that live the longest allocated? What are their classes? To answer such questions, one must download Spencer data dumps and write one's own analyser. This is suboptimal.

IX. Conclusion

We have presented Spencer, a web based tool for easy, reproducible heap analysis for programs running on the JVM. Spencer, we believe, will be useful for researchers in the field of programming languages like ourselves, who want input to design decisions, and rule out ideas on an early stage, and for researchers who wish to understand and quantify Java heaps. What sets Spencer aside from previous work is its aim to simplify exploration of a particular kind of data set to answer a more narrow set of questions, rather than provide a tracing solution that "fits all". This limits its usefulness as a general-purpose tool, but greatly simplifies the user experience.

The nine programs that make up the Spencer tool-chain comprise approximately 10,000 LOC in a mixture of Java, C++, and Scala. They are all open-source and available on GitHub, but more imprortantly Spencer is provided as a free service hosted by Uppsala University. The continously growing data set currently weights in at 680GB.

[6]In general, it is hard to translate application memory savings to virtual memory savings, as JVMs use sophisticated memory optimisations, that depend on runtime settings. We do not know of runtime optimisations that can automatically reduce the size of arrays, so savings obtained by using smaller arrays are likely to translate directly to virtual memory savings.

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