Scalable Software-Defect Localisation by Hierarchical Mining of Dynamic Call Graphs

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Abstract

The localisation of defects in computer programmes is essential in software engineering and is important in domain-specific data mining. Existing techniques which build on call-graph mining localise defects well, but do not scale for large software projects. This paper presents a hierarchical approach with good scalability characteristics. It makes use of novel call-graph representations, frequent subgraph mining and feature selection. It first analyses call graphs of a coarse granularity, before it *zooms-in* into more fine-grained graphs. We evaluate our approach with defects in the Mozilla Rhino project: In our setup, it narrows down the code a developer has to examine to about 6% only.

Keywords: applied data mining, call graphs, graph mining, scalability, software-defect localisation

1 Introduction

Software is rarely free from defects that cause failing behaviour. Manual debugging can be extremely expensive, and localising defects is the most time consuming and difficult activity in this context [5, 18]. Automated means to localise defects and to guide developers debugging a programme are more than desirable, for large software projects in particular. From a data mining perspective, Han and Gao identify software engineering and defect localisation in particular as a main area for *domain-specific mining* [14]. They point out that the integration of domain knowledge, i.e., specific data representations, as well as dedicated analysis techniques, are essential for the success of applied data mining.

One approach for defect localisation is to compare programme executions that are correct to executions that have failed. A variety of techniques has been proposed that mine dynamic call graphs, e.g., [4, 8, 11, 12, 21]. In such graphs, nodes typically represent methods and edges method invocations. See Figure 1(a) for an example. More specifically, the approaches try to identify patterns in programme executions that are typical for the failing case. Then they use these patterns to rank the methods being suspected to be defective. However, despite good results, the techniques proposed so far do not scale well with the size of the software project. This is caused by the NP-hard subgraph-isomorphism problem inherent to frequent subgraph mining. Various evaluations [4, 8, 11, 21] have demonstrated this effect: They deal with very small programmes such as the *Siemens Programmes* [16], with 200 to 700 lines of code (LOC).

Solving the scalability issues is challenging, as seemingly possible solutions have issues: (1) Using increased computing capabilities or distributed algorithms is not feasible due to exploding computational costs. We have experienced this effect in preliminary experiments as well. Further, spending a lot of computing time for graph mining might be inappropriate for defect localisation. (2) Solving the scalability issue with approximate graph-mining algorithms might be a solution, but might miss patterns which are important for defect localisation. For instance, [4] does not report any problems caused by the well scaling LEAP algorithm [26], but does not analyse large programmes either.

A different starting point to deal with the scalability problem in call-graph-based defect localisation is the graph representation. We investigate graph representations at coarser abstractions than the method level, i.e., the package level and the class level, and we start at such a coarse abstraction before *zooming-in* into a sus-

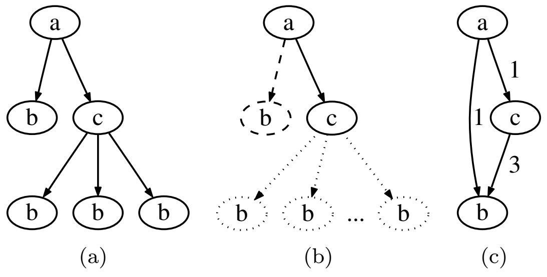


Figure 1: (a) An unreduced call graph, (b) with a structure-affecting (dashed) and a frequency-affecting bug (dotted). (c) The *total reduction* of (a) (weighted).

*Karlsruhe Institute of Technology (KIT), Germany. Email: {eichinger, ossner, klemens.boehm}@kit.edu picious region of the call graphs. These graphs are a lot smaller than conventional call graphs, and they cause scalability problems in much fewer cases. However, this idea leads to new challenges:

1. Call-graph representations have not yet been studied well for levels of abstraction higher than the method level. How do representations well-suited for defect localisation look like?
2. When *zooming-in* into defect-free regions by accident: How to design hierarchical defect localisation in a way that minimises the amount of source code to be inspected by humans?
3. It is unclear which defects can indeed be localised in coarse graph representations.

Our approach for hierarchical defect localisation builds on the *zoom-in* idea and solves these challenges. This paper makes the following contributions:

Granularities of Call Graphs. We define *call graphs at different levels of granularity*, featuring edge-weight tuples that provide further information besides the graph structure (Challenge 1). We do so by taking the specifics of defect localisation into account: We explicitly consider *API* calls as well as inter-/intra-package and inter-/intra-class method calls.

Hierarchical Defect Localisation. We describe the *zoom-in operation* for call graphs, present a *methodology for defect localisation* for the graphs at each level and describe *hierarchical procedures for defect localisation* (Challenge 2). In concrete terms, we present different variants of a depth-first search strategy to hierarchically mine a software project.

Evaluation with a Large Software Project. An essential part of our study is an evaluation featuring *real programming defects* in Mozilla Rhino (Challenge 3). To this end we use the iBUGS repository [6] and the original test suite. Rhino consists of ≈ 49k LOC, and the defects in the repository were obtained by joining information from a bug-tracking system with data and source code from a revision-control system. To our knowledge, this paper is first to demonstrate the effectiveness of call-graph-mining-based defect localisation for large programmes and real defects. In our setup, the approach narrows down the amount of code a developer has to examine to about 6% of the whole project.

Identification of New Data-Mining Research Questions. This study has uncovered several new data-mining research questions. We discuss these questions which might be relevant for many applications.

Ideas related to *zooming-in* into call graphs, namely *Graph OLAP*, have been described in [3]. The authors propose data-warehousing operations to analyse graphs, e.g., *drill-down* and *roll-up* operations, similar to our *zoom-in* proposal. However, [3] does not help in defect localisation, as it aims at interactive analyses, and it does not consider specific requirements (e.g., *API* calls).

Paper organisation: Section 2 introduces foundations. Sections 3 and 4 explain call graphs and defect localisation based on them. Section 5 contains our evaluation, Section 6 reviews related work, and Section 7 discusses threads of validity. Section 8 identifies challenges for data-mining research, Section 9 concludes.

2 Foundations

In this section we introduce the notion of defects and the basics of call-graph-based defect localisation.

Defects in Software. In this paper, we distinguish between *defects*, *infections* and *failures* [28]: *Defects* are the positions in the source code which cause an *infection*, an *infection* is an incorrect programme state, and *failures* are an observable incorrect programme behaviour such as wrong calculation results. In our context, we use a further differentiation of ours [10]:

Occasional bugs are failures depending on the input data of the programme. Compared to *non-occasional bugs*, they are harder to localise since they require more test cases to be reproduced. *Structure-affecting bugs* are infections which affect the structure of a call graph. This is, when comparing graphs from correct and failing executions, certain graph substructures might or might not occur in either of the two variants. Figure 1(b) contains an example: a does not call b in case of an infection. There can be various reasons for this, e.g., a wrongly calculated variable value or a defective control statement, possibly within a. *Call-frequency-affecting bugs* are infections which change the call frequency of a certain substructure, rather than completely missing or adding structures. In Figure 1(b), the call frequency of b from c has changed, compared to Figure 1(a).

We focus on *occasional bugs*, as all call-graph-based defect-localisation approaches do. This requires that both correct and failing executions are available. With our approach, defects might be *structure affecting*, *call-frequency affecting*, or both.

Defect Localisation with Call Graphs. A number of call-graph-based techniques for defect localisation has been proposed [4, 8, 9, 11, 12, 21]. Their intuition is to mine for patterns in the call graphs which are characteristic for failing executions. Then they derive a defectiveness likelihood for each method. A method ranking based on such likelihoods can then guide the debugging process. The different proposals use different *call-graph representations* and *defect-localisation approaches*. We now briefly review the most important differences.

Concerning the *graph representations*, the various approaches differ with regard to the *level of granularity*, the *degree of reduction*, and the questions if *temporal* *information* is included and if the graphs are *weighted*. The first three aspects bear a trade-off between the size of the graphs and potentially more precise results on the one side and scalability on the other side.

Level of granularity: The graphs used in most approaches [4, 8, 11, 12, 21] are method-level call graphs, i.e., nodes represent methods and edges method calls. (See Figure 1(a) for an example.) [4] presents a more fine-grained basic-block-level graph representation in addition to the method level. [9] is a preliminary study of ours investigating defect localisation with class-level call graphs. It aims at a scalable solution for large software projects. However, it does not investigate a comprehensive hierarchical approach. *Degree of reduction:* In unreduced call graphs, as directly obtained from tracing, a method typically occurs several times, at various positions within a graph (see Figure 1(a)). [4, 9, 12, 21] build on call graphs where exactly one node represents a method (*total reduction*, see Figure 1(c)). [8, 11] in turn allow for more than one node. This promises more precise results, as more detailed contexts of method calls can be included in the analysis. However, this leads to larger graphs; see [10]. *Temporal information:* The graphs in [4, 8, 21] incorporate temporal information, the ones in [9, 11, 12] do not. The experiments in [10] do not lead to any results that justify the increased graph size. *Weighted graphs:* In contrast to all other representations, the graphs in [9, 11, 12] are weighted. Edge weights represent the number of corresponding method calls (see Figure 1(c)), facilitating the localisation of call-frequency-affecting bugs.

Besides different call graph representations, the various *defect-localisation approaches* localise defects in different ways. In concrete terms, they employ techniques as diverse as *support values*, *graph classification*, *discriminative subgraph mining* and *feature selection*: [8] derives defect likelihoods from *support values* of subgraph patterns in call graphs representing correct and failing programme executions. [21] builds on *graph classification* with subgraph patterns. The authors first mine frequent subgraph patterns before they use them to train a classifier. They then consider the difference in accuracy between two classifiers – one built with graph patterns including a certain method and one without them – as evidence for a defective method. [4] relies on *discriminative subgraph mining.* This technique finds subgraphs that discriminate well between correct and failing executions and thus directly identifies methods that are possibly defective. In [11], we make use of two kinds of evidence, *support values* and *feature selection* with edge weights. In [12], we target defects that affect the dataflow of a programme, by extending call graphs with abstractions referring to the dataflow.

The approaches mentioned do not scale for large software projects such as Mozilla Rhino. This paper in turn describes a scalable approach. It generalises previous work [9, 11], and it hierarchically *zooms-in* into parts of call graphs deemed problematic.

3 Dynamic Call Graphs at Different Levels

In this section, we propose and define totally-reduced call-graph representations for the method, class and package level (Sections 3.1–3.3). Then we introduce the *zoom-in* operation for call graphs (Section 3.4). Our graphs can easily be extended in either direction: More coarse-grained *meta-package-level call graphs* could rely on the hierarchical organisation of packages and would allow to analyse even larger projects. Graphs more detailed than the method level, e.g., at the level of basic blocks [4], would allow for a finer defect localisation.

On a technical level, we use AspectJ [19] to weave tracing functionality into Java programmes and to derive call graphs from programme executions. This yields an unreduced call-graph representation at the method level. (Figure 2(a) is an example.) This is the basis for all reduced representations we discuss in the following. In concrete terms, our tracing functionality internally stores unreduced call graphs in a pre-aggregated space-efficient manner. This lets us derive call-graph representations at any levels of granularity.

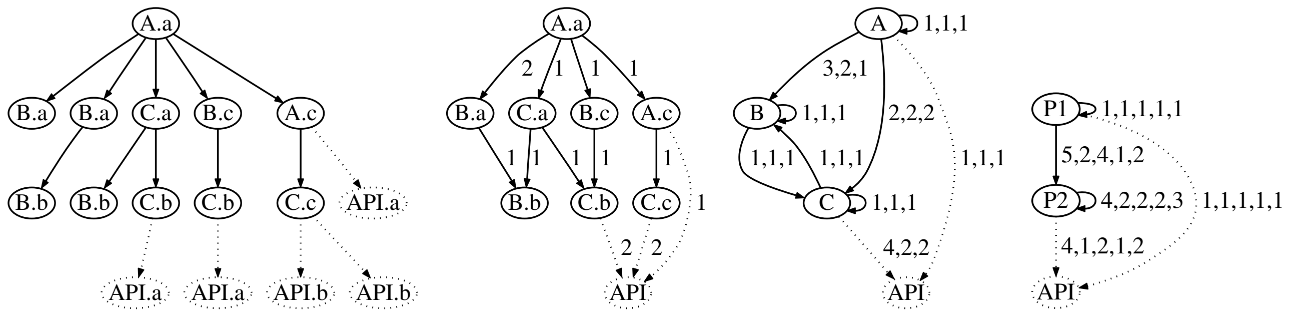
3.1 Call Graphs at the Method Level.

In this paper, we propose total graph reductions that are weighted, where exactly one node represents a method. We do not make use of any temporal information. All this leads to a compact graph representation [10].

As an innovation, we consider calls of methods belonging to the Java class library (API) in all graphs. We do so as we believe that some defects might affect the calls of such methods. To our knowledge, no previous study has considered such method calls. However, to keep the instrumentation overhead to a minimum, we do not consider API-internal method calls. In the graph representation, we use one node (API) to represent all methods belonging to the class library.

Notation 1. *A* method-level call graph *is a graph where every method is represented by exactly one node, directed edges represent method invocations, and edge weights stand for the frequencies of the calls represented by the edges. The API node represents all methods of the class library and does not have any outgoing edges.*

Example. Figure 2(b) is a method-level call graph. It is the reduced version of the graph in Figure 2(a). The API nodes in Figure 2(a) represent two API methods, a and b, represented by one node in Figure 2(b).



(a) unreduced (b) method level (c) class level (d) package level

Figure 2: An unreduced call graph and its total reduced representations at the method level, class level and package level. Notation: *class.method*; class *A* forms package *P1*, classes *B* and *C* form package *P2*.

3.2 Call Graphs at the Class Level. We now propose class-level call graphs with tuples of weights. The rationale is to include some more information, which would otherwise be lost by the rigorous compression.

NOTATION 2. *In* class-level call graphs*, every class is represented by exactly one node, and edges represent inter-class method calls (or intra-class calls in case of self-loops). The API node is as in the method-level call graphs. An edge is annotated with a tuple of weights:* (t, u, v)*. t refers to the total number of method calls represented by the edge (as in method-level call graphs), u is the number of different methods invoked, and v is the number of different methods that invoke methods.*

Example. Figure 2(c) is a class-level call graph, it is the compression of the graphs in Figures 2(a) and (b). Class-level call graphs may include self-loops (except for the *API* node), even if there is no recursion.

3.3 Call Graphs at the Package Level. The reduction for this level is analogous to the previous ones, but to capture more information, we extend the edge-weight tuples by two elements:

NOTATION 3. *In* package-level call graphs*, there is one node for each package, and there is an additional API node. The edge-weight tuples are as follows:* $(t_m, u_c, u_m, v_c, v_m)$*, where* u_c *is the number of different classes called,* v_c *the number of different classes calling, and* t_m, u_m, v_m *are as* t, u, v *in Notation 2. ('m' stands for method, 'c' for class.)*

Example. We assume that class *A* in Figure 2 forms package *P1*, that classes *B* and *C* are in package *P2*, and that methods *API.a* and *API.b* belong to the same class. Figure 2(d) then is a package-level call graph, representing the call graphs from Figures 2(a)–(c).

3.4 The *Zoom-In* Operation for Call Graphs. Before we discuss the *zoom-in* operation for call graphs, we first define an auxiliary function:

DEFINITION 1. *The* generate function *is of the following type:* $generate_{level} : (\mathbb{G}_{unreduced}, \mathbb{V}) \rightarrow \mathbb{G}_{level}$*, where* $\mathbb{G}_{unreduced}$ *stands for unreduced call graphs,* $\mathbb{G}_{level}$ *for call graphs of the level specified by level* $\in \{method, class, package\}$ *and* $\mathbb{V}$ *for sets of vertices.* $A \in \mathbb{V}$ *specifies the area to be included in the graph to be generated, by means of a set of vertices of the package level (package names) in case 'level = class' or of the class level (class names) in case 'level = method'. In case 'level = package',* $A = \star$ *selects all packages.*

From a given unreduced graph, the function generates a subgraph at the level specified, containing all nodes contained in A (all nodes if $A \neq \star$*) and edges connecting these nodes. If* $A = \star$*, the function introduces a new node labelled 'Dummy' in the subgraph generated that stands for all nodes not selected by A.*

In the *generate function*, we treat the *API* nodes separately from other nodes. They do not have to be explicitly contained in *A*, but are contained in the resulting graphs by default, as described in Notations 2 and 3. As the *generate function* selects certain areas of the graph, it obviously omits other areas. This is a conscious decision, as small graphs tend to make graph mining scalable. As calls of methods in the omitted areas might indicate defects nevertheless, the *generate function* introduces the *Dummy* nodes to keep some information about these methods.

To *zoom-in* to a finer level of granularity, say into a certain package $p \in V(G_{\mathrm{p}})$ (*V* denotes the set of vertices of a graph) of a package-level call graph G_{p} to obtain a class-level call graph G_{c}, one calls the *generate function* as follows: $G_{\mathrm{c}} := generate_{class}(G_{\mathrm{u}}, \{p\})$, where G_{u} is the unreduced call graph of G_{p}. Zooming from a class-level call graph to a method-level call graph is analogous.

4 Hierarchical Defect Localisation

We now describe our hierarchical approach for defect localisation. At first, we introduce defect localisation without considering the hierarchical procedure, i.e., we describe how defect localisation works for call graphs at any selected level of granularity (Section 4.1). We then present different approaches for turning this technique into a hierarchical procedure (Section 4.2).

4.1 Defect Localisation in General. We now discuss defect localisation with call graphs at arbitrary levels of granularity. After a short overview, we describe subgraph mining and defect localisation based on edge-weight tuples. Finally, we discuss the incorporation of information from static source-code analysis.

Overview. Algorithm 1 works with unreduced call graphs U, representing programme executions. More specifically, it deals with graphs at a user-defined *level*, describing a certain subgraph of the graphs (parameter A). For the time being, we consider the package level ($A = ☆$), i.e., without restricting the area. The algorithm first assigns a $\mathit{class} \in \{\mathit{correct}, \mathit{failing}\}$ to every graph $u \in U$ (Line 3), using a test oracle. Such oracles are typically available [18]. Then the procedure generates reduced call graphs, from every graph u (Line 4). Next, the procedure derives frequent subgraphs of these graphs, which provide different contexts (Line 5). The last step calculates a likelihood of containing a defect, for every software entity e at the *level* specified (i.e., a package, class or method; Line 6). We do so by deriving a discriminativeness measure for the edge-weight-tuple values, in each context separately. The P values for all entities of a certain *level* form a ranking of the entities, which can be given to software developers. They would then review the suspicious entities manually, starting with the one which is most likely to be defective. Alternatively, this result can be the basis for a *zoom-in* into a finer level of granularity, as described in Section 4.2.

Algorithm 1 Procedure of defect localisation.

```
Input: a set of unreduced call graphs $U$,
    a $\mathit{level} \in \{\mathit{package}, \mathit{class}, \mathit{method}\}$, an area $A$
Output: a ranking based on each software entity $e$'s
    likelihood to be defective $P(e)$
1: $G = \varnothing$ // initialise a set of call graphs
2: for all graphs $u \in U$ do
3:     check if $u$ refers to a correct execution,
       and assign a $\mathit{class} \in \{\mathit{correct}, \mathit{failing}\}$ to $u$
4:     $G = G \cup \{\mathit{generate}_{\mathit{level}}(u, A)\}$
5: $SG = \mathit{frequent\_subgraph\_mining}(G)$
6: calculate $P(e)$ for all software entities $e$ at the $\mathit{level}$
   specified, based on $SG$
```

Subgraph Mining. The frequent-subgraph-mining step (Line 5 in Algorithm 1) mines the pure graph structure and ignores the edge-weight tuples for the moment. This is as conventional graph-mining algorithms do not take weights into account. Later steps will make use of them. We use the subgraphs obtained as different *contexts* and perform all further analyses for every subgraph context separately. This aims at a higher precision than an analysis without such contexts and allows localising defects that only occur in a certain context.

Example. A failure might occur when method a is called from method b, only when method c is called as well. Then, the defect might be localised only in the context of call graphs containing all methods mentioned, but not in graphs without method c.

We rely on the ParSeMiS implementation [24] of CloseGraph [27] for frequent subgraph mining. CloseGraph has successfully been used in related studies [9, 11, 12, 21]. In a set of graphs G, it discovers subgraphs with a user-defined minimum support. For this value, we use $\min(|G_{\mathrm{corr}}|, |G_{\mathrm{fail}}|)/2$, where G_{corr} and G_{fail} are the sets of call graphs of correct and failing executions, respectively ($G = G_{\mathrm{corr}} \cup G_{\mathrm{fail}}$). This ensures that no structure occurring in at least half of all executions belonging to the smaller class is missed. Preliminary experiments have shown that this minimum support allows for both short runtimes and good results.

The *API* and *Dummy* nodes as well as *self-loops* (↻) require a special treatment during subgraph mining. *API nodes:* As almost all methods call *API* methods, almost every node in a call graph has a connection to the *API* node. This increases the number of edges in a call graph significantly, compared to a graph without *API* nodes, possibly leading to scalability issues. At the same time, as almost every node has an edge to an *API* node, these edges usually are not interesting for defect localisation. We therefore omit these edges during graph mining, but keep the edge-weight tuples for the subsequent analysis step. This is, only nodes and edges drawn with solid lines in Figure 2 are considered. *Dummy nodes:* We treat *Dummy* nodes in the same way as we treat *API* nodes, as their structural analysis with subgraph mining does not seem to be promising. *Dummy* nodes tend to be connected to many other nodes as well, leading to unnecessarily large graphs. *Self-loops:* Such edges result from recursion at the method level. However, at the package and class level, a self-loop represents calls within the same entity, which happens frequently. Therefore, self-loops enlarge the graph significantly while not bearing much information. We therefore treat self-loops at the package and class level as *API* and *Dummy* nodes: We omit them

exec.	sg_1																					sg_2				···	*class*
	$A{\rightarrow}B$			$A{\rightarrow}C$			$A\circlearrowleft$			$B\circlearrowleft$			$C\circlearrowleft$			$A{\rightarrow}API$			$C{\rightarrow}API$			$B{\rightarrow}C$			···		
	t	u	v	t	u	v	t	u	v	t	u	v	t	u	v	t	u	v	t	u	v	t	u	v	$(\circlearrowleft, API)$		
g_1	3	2	1	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	4	2	2	1	1	1	···	···	*correct*
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋱	⋱	⋮
g_n	9	1	1	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	4	2	2	-	-	-	···	···	*failing*

Table 1: Example feature table for class-level call graphs.

during graph mining and keep the edge-weight tuples for subsequent analysis.

Edge-Weight-Based Defect Localisation. When graph mining is completed, we calculate the likelihood that a method contains a defect (Line 6 in Algorithm 1). The rationale is to identify methods which call other methods with discriminative edge-weight-tuple values, i.e., method calls whose frequencies vary in correct and failing executions. As mentioned, we analyse every edge weight in the call graphs in the context of every subgraph mined. This aims at a high probability to reveal a defect, as every edge weight is typically investigated in many different contexts. To this end, we assemble a feature table as follows:

Notation 4. *A* feature table *for defect localisation has the following structure: The rows stand for all programme executions. For every edge in every frequent subgraph, there is one column for every edge-weight-tuple element (i.e., a single call frequency t or tuples of values, depending on the granularity level of the call graph considered, see Section 3). For all edges leading to API and Dummy nodes as well as for all self-loops ($\circlearrowleft$), there are further columns for the edge-weight-tuple elements; again, for each subgraph separately. The table cells contain the edge-weight-tuple values, except for the very last column, which contains the class $\in$ {correct, failing}. If a subgraph is not contained in a call graph, the corresponding cells have a null value ('-').*

We do not include *Dummy* nodes in the tables when considering the method level, as preliminary experiments have shown that this does not lead to any benefit. However, we include *API* nodes at all levels.

Example. Table 1 is a feature table corresponding to class-level call graphs, such as the one in Figure 2(c). (This graph is execution g_1 in the table.) Suppose that the preceding graph-mining step has found two subgraphs, sg_1 ($B{\leftarrow}A{\rightarrow}C$) and sg_2 ($B{\rightarrow}C$). The very first column lists the call graphs $g \in G$. The next column corresponds to sg_1 and edge $A{\rightarrow}B$ with the total call frequency t. The following two columns correspond to the remaining two edge-weight tuple elements u and v (see Notation 2). Then follows the second edge in the same subgraph ($A{\rightarrow}C$) with its edge-weight tuple (t, u, v). Next, all self-loops ($A\circlearrowleft$, $B\circlearrowleft$, $C\circlearrowleft$) and *API* calls ($A{\rightarrow}API$, $C{\rightarrow}API$) in sg_1 are listed. (*Dummy* nodes would be listed here as well, but do not exist in this example.) The same columns for subgraph sg_2 and finally the class of the execution follow. Graph g_n does not contain sg_2, which is indicated by '-'.

After assembling the feature table, we employ the *information-gain feature-selection algorithm* (*InfoGain*, [25]) in its Weka implementation [13] to calculate the discriminativeness of the columns and thus of the different edge-weight-tuple values. The *InfoGain* is a measure from information theory and builds on *entropy.* Values of *InfoGain* are in the interval $[0, 1]$. High values indicate a table column affected by a defect. For this step, we could choose from various feature-selection algorithms available. However, previous work [11, 12] has shown that entropy-based measures are well-suited for defect localisation.

So far, we have derived defect likelihoods for every column in the table. However, we are interested in likelihoods for software entities (i.e., packages, classes or methods), and every software entity corresponds to more than one column in general. To obtain the defect likelihood $P(e)$ of software entity e, we assign every column to the calling software entity. We then calculate $P(e)$ as the maximum of the *InfoGain* values of the columns assigned to e. By doing so, we identify the defect likelihood of a software entity by its most suspicious invocation. The call context of a likely defective software entity and suspicious columns are supplementary information which we report to software developers to ease debugging.

Example. The graphs g_1 (see Figure 2) and g_n in Table 1 display similar values, but refer to a correct and a failing execution. Suppose that method $A.a$ contains a defect with the implications that (1) method $B.c$ will not be called at all, and (2) that method $B.a$ will be called nine times instead of twice. This is reflected in columns 2–4, referring to (t, u, v) of $A{\rightarrow}B$ in sg_1. t increases from three ($1 \times B.c$, $2 \times B.a$) to nine ($9 \times B.a$), u decreases from two ($B.c$, $B.a$) to one ($B.a$), and v stays the same – in class A, only method a invokes other methods. The *InfoGain* measure will recognise fluctuating values of t and u, leading to a high ranking of class A.

Incorporation of Static Information. The edge-weight and *InfoGain*-based ranking procedure sometimes has the minor drawback that two or more entities (i.e., packages, classes or methods) have the same ranking position. In such cases, we fall back to a second ranking criterion: We sort such entities decreasingly by their size in (normalised) lines of code (LOC) derived with LOCC [17]. The rationale is that the size frequently correlates with the defectiveness likelihood [23]. This is, large methods tend to be more defective.

4.2 Hierarchical Procedures.

The defect-localisation procedure described in Section 4.1 can already guide a manual debugging process: A developer can first do defect localisation at the package level. She or he can then decide to *zoom-in* into certain suspicious packages. The developer would continue with our defect-localisation technique at the class level, proceeding with the method level etc. However, it might happen that the developer *zooms-in* into an area where no defect is located. In this case, the developer would backtrack and *zoom-in* elsewhere etc. This manual process, guided by our technique, bears the potential that important background knowledge known to the developer can be easily included.

In this section, we say how to turn the manually-guided debugging process into semi-automatic procedures for defect localisation. We present a depth-first-search-based (DFS-based) procedure and a so-called merge-based variant. We also propose a technique that partitions large packages and classes.

DFS-Based Defect Localisation. Our DFS-based procedure follows the idea to manually investigate the most suspicious method in the most suspicious class in the most suspicious package first. If this first method turns out to not be defective, we go to the second most suspicious method in the same class. If all methods in this class are investigated, we backtrack to the next class etc. We further propose the parameters k, l, m. They limit the number of software entities to be investigated at each stage, to k packages, l classes and m methods. Algorithm 2 formalises this approach. The parameters k, l, m can be set to infinity in order to obtain a parameter-free algorithm; at the end of this section we also present a means to set these parameters.

Algorithm 2 DFS-Based Defect Localisation.

```
Input: a set of classified (correct, failing) unreduced
    call graphs $U$, parameters $k, l, m$
Output: a defective method
 1: $SG = \mathit{frequent\_subgraph\_mining}(\{\mathit{generate}_{\mathit{package}}(u, \star) | u \in U\})$
 2: calculate $P(\mathit{package})$, based on $SG$
 3: for all $\mathit{package} \in \mathit{top}_k(P(\mathit{package}))$,
    ordered decreasingly by $P(\mathit{package})$ do
 4:   $SG = \mathit{frequent\_subgraph\_mining}(\{\mathit{generate}_{\mathit{class}}(u, \{\mathit{package}\}) | u \in U\})$
 5:   calculate $P(\mathit{class})$, based on $SG$
 6:   for all $\mathit{class} \in \mathit{top}_l(P(\mathit{class}))$,
      ordered decreasingly by $P(\mathit{class})$ do
 7:     $SG = \mathit{frequent\_subgraph\_mining}(\{\mathit{generate}_{\mathit{method}}(u, \{\mathit{class}\}) | u \in U\})$
 8:     calculate $P(\mathit{method})$, based on $SG$
 9:     for all $\mathit{method} \in \mathit{top}_m(P(\mathit{method}))$,
        ordered decreasingly by $P(\mathit{method})$ do
10:       present method to the user
11:       if method is defective then
12:         return method
```

Algorithm 2 iterates through three loops, one for packages, one for classes and one for methods (Lines 3, 6 and 9). In each loop, the algorithm calculates a defectiveness likelihood P for the respective software entities. This is, Lines 1–2, 4–5 and 7–8 comprise the graph-mining step (Line 5 in Algorithm 1) and the step that calculates P (Line 6 in Algorithm 1), as described in Section 4.1. These lines make use of the *generate function* (see Definition 1), each with the area selection based on the currently selected software entity at the respective coarser level. Ultimately, the algorithm presents suspected methods to the user and terminates in case the user has identified a defect (Lines 10–12).

The DFS-based procedure described works interactively. This is, the potentially expensive graph-mining step as well as the calculation of P are done only when needed – the algorithm might terminate before all packages and classes have been analysed. The suspected methods are presented to the user in an on-line manner. This avoids long runtimes before a developer actually can start debugging. However, it is of course possible to skip Lines 10–12 in Algorithm 2 and to save the current *method* to an ordered list of suspected methods. This leads to a ranking as described in Section 4.1. To ease experiments, we follow this approach in our evaluation.

The proposed approach obviously has the drawback that the user has to set the parameters k, l, m. When the values are too low, the technique might miss a defect. Based on our experience, it is not hard to set appropriate parameters based on empirical values derived from debugging other defects in the same project. Furthermore, we will present an automated choice of optimal parameter values in the following paragraphs.

Merge-Based Variant of DFS-Based Defect Localisation. This technique is an alternative to the DFS-based one. Instead of presenting the results to the user in an on-line manner, it replaces Lines 10–12 in

Algorithm 2 with code that saves all methods processed (along with their likelihood P) in a result set. Then, right after Line 12 in Algorithm 2, it sorts all methods decreasingly by their defect likelihood.

The drawback of this procedure is that the algorithm has to terminate before one can actually start debugging. On the other side, we hypothesise that the defect localisations obtained by this merge-based variant are better than the ones with the first approach. We evaluate this hypothesis in Section 5.

Concerning the parameters k, l, m, the merge-based variant is more robust. As the merged result set is sorted at the very end, large parameter values usually do not lead to worse localisation results. They only affect the runtime. As yet another variant, we propose *parameter-free defect localisation*. Here we set the parameters k, l, m to infinity. This promises to not miss any defective method. In addition, if one uses this variant several times with a certain software project, one can use it to empirically set the parameter values. This allows for an efficient usage of the interactive (online) DFS-based procedure without parameters that are too high or to speed up the regular merge-based variant.

Partitioning Approach. The hierarchical procedures investigated in this paper analyse small *zoomed-in* call graphs at several granularities. However, a number of software projects – especially large ones and those with a long history – have imbalanced sizes of packages and classes. This might lead to large graphs that cause scalability issues, even if we are considering a *zoomed-in* subgraph only. It is an open research question how to overcome such situations. For now, we present a sampling-based partitioning approach for such cases.

Whenever a certain call graph at the package or class level is too large to be handled, we partition the graph into two (or, if needed more) partitions. We do so by randomly sampling nodes from the graph. We keep the edges connecting two nodes within the same partition. As not all edges connect nodes belonging to the same partition, we would lose a lot of information. To compensate for this effect, we introduce a dummy node $Dummy_{\text{part}}$ in each partition, representing all nodes in other partitions. We treat $Dummy_{\text{part}}$ nodes in exactly the same way as *Dummy* nodes, i.e., we omit them during graph mining and include the edge-weight-tuple values in the feature tables.

When graph partitions are generated and $Dummy_{\text{part}}$ nodes are inserted, we do defect localisation as described before with each partition separately. Then, similarly to the merge-based variant, we merge the rankings obtained from the different partitions and obtain a defectiveness ranking ordered by the P values of the software entities. This lets us proceed with any manual or automated hierarchical defect localisation procedure, as described before.

This partitioning approach for large packages and classes has worked well in preliminary experiments. However, there might be cases where a loss of relevant information exists, and defect localisation might not work. For instance, think of a defect which occurs in a certain subgraph context that is distributed over several partitions. In such situations, the defect-localisation procedure can be repeated with a different partitioning, either based on the expertise of a software developer or by using another seed for random partitioning.

5 Evaluation with Real Software Defects

We now evaluate our defect-localisation techniques in order to demonstrate their effectiveness and usefulness for large software projects. After a description of the target programme and the defects (Section 5.1) we explain the evaluation measures used (Section 5.2). Then we focus on defect localisation at the different levels in isolation (Section 5.3). Finally, we evaluate the hierarchical defect-localisation approaches (Section 5.4).

5.1 Target Programme and Defects: Rhino.

For our evaluation we rely on Mozilla Rhino, as published in the iBUGS project [6]. Rhino is an open-source JavaScript interpreter, consisting of nine packages, 146 classes and 1,561 methods or ≈ 49k LOC (normalised 37k LOC). iBUGS provides a number of original defects that were obtained by joining information from the bug-tracking system of the project with data and source code from its revision-control system. Furthermore, it contains the original test cases along with the test oracles. See [7] for details on how the data was obtained. All in all, Rhino from the iBUGS repository provides a realistic test scenario for defect localisation in a large software project, at least compared to programmes used in related evaluations that are two orders of magnitude smaller, e.g., [4, 8, 11, 21].

Concretely, we make use of 14 defects (Table 2 lists the defect numbers) from the iBUGS Rhino repository which have associated test cases and represent *occasional bugs*. These defects represent different real programming errors, and they are hard to localise: They occur occasionally and have been checked-in into the revision-control system before a failing behaviour has been discovered. See the iBUGS repository [6] for more details. In addition, iBUGS provides about 1,200 test cases consisting of some JavaScript code to be executed by Rhino, together with the corresponding oracles. As in many software projects, there are only a few failing test cases for each defect, besides a lot of passing cases. To obtain a sufficient number of failing cases, we have gen-

level\defect	85880	114491	114493	137181	157509	159334	177314	179068	181654	181834	184107	185165	191668	194364	∅
package	2	1	1	4	2	1	1	1	3	1	3	1	3	2	1.9
class	1	8	8	16	20	1	2	15	5	1	1	2	3	3	6.1
method	1	2	2	-	1	1	1	10	3	3	9	10	1	2	3.5

Table 2: Defect-ranking positions for the three levels separately.

erated new ones by varying existing ones. In concrete terms, we have merged JavaScript code from correct and failing test cases.

5.2 Evaluation Measures. In order to assess the precision of our techniques, we consider the ranking positions of the actual defects. These positions quantify the number of software entities (i.e., packages, classes and methods) a software developer has to investigate in order to find the defect. (Smaller numbers are preferred.) As the sizes of methods can vary significantly, we deem it more adequate to assess the hierarchical approaches by considering the normalised LOC rather than only the number of methods involved. We therefore provide the percentage of LOC to examine in addition to the ranking position. We calculate the percentage as the ratio of methods that has to be examined in the software project, i.e., the sum of LOC of all methods with a ranking position smaller than or equal to the position reported, divided by the total LOC.

5.3 Experimental Results (Different Levels). We now present the defect-localisation results for the three different levels. This is, we consider complete package-level call graphs and call graphs at the class and method level, *zoomed-in* into the correct package (and class). We do so in order to assess the defect-localisation abilities for every level in isolation.

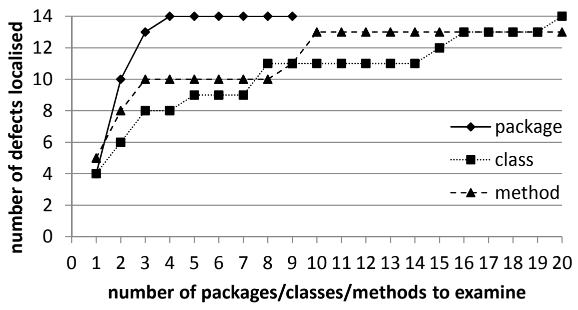


Figure 3: The numbers of defects localised when examining a certain number of packages/classes/methods.

Table 2 contains the experimental results, the ranking positions for all defects investigated, separately for the three levels. Figure 3 provides a graphical representation of the same data. It plots the number of defects localised when a developer examines a certain number of the top-ranked entities. For example, the third triangular point from the left means that 10 out of 14 defects are localised when examining up to three methods.

At the *package level*, the defective package is ranked at position one or two in 10 out of 14 cases, i.e., localisation is precise. The explanation for such good results at the coarsest level is the small number of nine packages in Rhino. At the *class level*, the results look a little worse at first sight. However, eight defects can be localised when examining three classes or less (out of 146). Only three defects are hard to localise, i.e., a developer has to inspect 15 or more classes. At the method level, 13 of the defects can be localised by examining 10 methods or less (out of 1,561), 10 of them with three methods or less. Only one defect, no. 137181, cannot be localised at all. This defect does not affect the call-graph structure nor the call frequencies.

All in all, the call-graph representations at the different levels – as well as the localisation technique – localise most defects with a high precision. However, when using package-level graphs to manually *zoom-in* into a package, packages ranked at position three or four might be misleading. This is not unexpected, as it is well known that many defects have effects only in their close neighbourhood [7]. This might not affect a package-level graph at all. The hierarchical approaches, in particular the merge-based ones, try to overcome this effect by investigating several packages systematically.

We use the results from this section to set the parameters k, l, m for the hierarchical approaches. The maximum localisation precision in Figure 3 is reached at four packages, 20 classes or 10 methods. When using these values as parameters, the hierarchical approaches do not miss any defects they could actually localise while avoiding to examine more source code than necessary.

5.4 Experimental Results (Hierarchical). We now present the results from three experiments with the different hierarchical approaches (see Section 4.2): E1 – DFS-based defect localisation; E2 – merge-based variant thereof; E3 – parameter-free defect localisation. Table 3 contains the numerical results in two variants: the ranking positions at the method level and the corresponding percentage of source code. As before, Figure 4

exp.\defect	85880	114491	114493	137181	157509	159334	177314	179068	181654	181834	184107	185165	191668	194364	∅
E1	3	9	56	-	170	3	5	120	64	3	54	29	55	15	45.1
E2	52	12	3	-	46	1	1	68	9	3	100	154	8	25	37.1
E3	54	18	3	-	49	1	1	77	14	5	155	210	8	31	48.2
E1	1.2%	4.5%	10.3%	-	20.6%	2.6%	1.6%	9.8%	5.1%	4.4%	7.5%	3.1%	11.6%	1.5%	6.4%
E2	6.7%	2.6%	5.4%	-	10.3%	2.6%	1.3%	7.5%	0.3%	4.4%	10.4%	15.2%	5.9%	6.7%	6.1%
E3	8.2%	3.4%	5.4%	-	10.5%	2.6%	1.3%	8.1%	1.9%	4.5%	17.8%	20.1%	5.9%	8.3%	7.5%

Table 3: Hierarchical defect localisation results. E1: DFS-based defect localisation; E2 merge-based variant thereof; E3: parameter-free defect localisation. Top: method-ranking position; bottom: LOC to examine.

is a graphical representation of this data. Similarly to related work (e.g., [18, 20]), it represents the percentage of defects localised versus the percentage of source code that does not need to be examined.

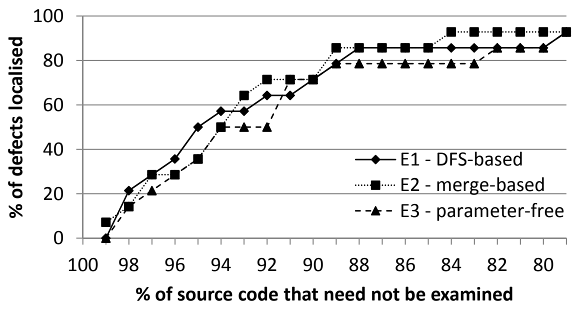


Figure 4: The percentage of defects localised when not examining a certain percentage of source code.

In line with our hypothesis (see Section 4.2), the merge-based variant (E2) performs better than the pure DFS-based approach (E1) in all but four data points in Figure 4. The average values in Table 3 reflect this as well. With the merge-based variant (E2), one finds a defect by examining 6.1% of the source code on average. Not surprisingly, parameter-free defect localisation (E3) always performs worse than or equal to the parameterised variant (E2). However, it still allows a developer to find defects by inspecting 7.5% of the code on average, without having to set any parameters.

Focusing on the best approach, the merge-based variant (E2), two defects are pinpointed directly, and six defects can be localised by investigating less than 10 methods. Only one defect cannot be localised at all (as before), and for only two defects 100 or more methods need to be inspected. All in all, we deem these results very helpful: On average, almost 94% of the source code can be excluded from manual debugging, and to find 86% of all defects, one can skip 89% of the code.

6 Related Work

Dynamic defect-localisation techniques analyse instrumented programme runs, while *static* techniques investigate the source code only. We now briefly review some work apart from call-graph mining (see Section 2).

Static Analysis. *Mining software repositories* maps post-release failures from a bug database to defects in source code. For example, [23] derives code metrics and builds regression models which then predict possible post-release failures. Such approaches rather give hints on code quality issues than pinpointing actual defects. FindBugs [2] is an approach complementary to ours. Its static code analysis for Java works well when identifying certain typical patterns of defect-prone programming, but cannot identify all sophisticated defects.

Dynamic Analysis. Tarantula [18] is a *coverage-analysis technique.* To localise defects, it generates a ranking of statements which are executed more often in failing executions. While this technique is relatively simple, it produces good results. In the evaluation [18], it has outperformed five competing approaches. However, it does not take into account how often a statement is executed within one programme run. This tends to miss certain defects such as *call-frequency affecting bugs.* AMPLE [5] analyses sequences of method calls. The authors demonstrate that the temporal order of calls is more promising to analyse than statement coverage only. However, AMPLE only derives relatively coarse-grained class-level localisations. [22] also deals with sequences, but presents a *failure-detection approach.* This is, it does not localise defects, but decides whether an execution is correct or not. In general, the usage of call sequences instead of statement coverage is a generalisation which takes more structural information into account. Call-graph-based techniques in turn cover more complex structural information than sequences.

SOBER [20] is a *statistical defect-localisation technique.* It makes use of more detailed information than *coverage analysis* and instruments predicates on condition statements and return values. It then calculates defect likelihoods: Predicates yield high values when their evaluations differ significantly in correct and failing executions. SOBER has outperformed Tarantula in most situations [20]. Opposed to our approach, it does not analyse structural properties of call graphs. Hence, detecting *structure-affecting bugs* is more difficult.

7 Threads to Validity

No defect-localisation technique can localise any kind of defect – nor does ours. A direct comparison to other approaches is difficult: Many of them work on the granularity of lines instead of methods, or do not rank their results, but present unordered sets of warnings. FindBugs [2], for instance, has both of these characteristics. As many *static* approaches, it can identify standard defect patterns, but was not able to detect any of the more complicated real defects in Rhino. One of the best *dynamic* approaches, Tarantula [18], generates a ranking of lines suspected to be defective. When comparing the amount of code a developer has to examine, the Tarantula evaluation only counts the actual lines listed in its ranking instead of counting all lines of all methods, as done by our approach. Another dynamic approach, SOBER [20], generates a ranking of condition predicates. This is not directly comparable to our method ranking, too.

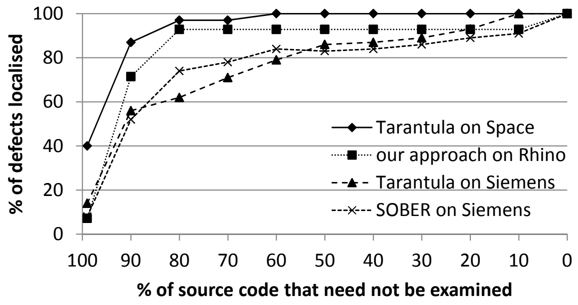


Figure 5: Assessment of the results by comparing related evaluations (values taken from [18, 20]).

When looking at Tarantula and our approach from a theoretical perspective, our approach considers more data than code coverage (but at the coarser method level). This includes (1) call frequencies, (2) subgraph contexts and (3) the information which method has called another one. This data is potentially relevant for defect localisation, e.g., to localise frequency-affecting bugs (1) and structure-affecting bugs (2, 3).

To show that our approach delivers results with about the same or even better precision as others, we compare some values in Figure 5. It contains the original data values from the Tarantula [18] and SOBER [20] evaluations with the *Siemens Programmes* [16] and a not publicly available programme called *Space* (Tarantula only). The figure shows that our merge-based technique performs almost always better on Rhino than Tarantula and SOBER on *Siemens* and a little worse than Tarantula on *Space*. It is difficult to come up with further conclusions, as the other evaluations do not deal with real defects. Furthermore, the *Siemens Programmes* (<1k LOC) as well as *Space* (≈ 6k LOC) are a lot smaller than Rhino (≈ 49k LOC), and it is not known how well Tarantula and SOBER scale for this size.

8 Challenges for Data-Mining Research

The techniques developed in this study raise a number of general data-mining research questions. These questions are relevant for many applications, and we discuss them in the following:

Graph Clustering. Caused by the class hierarchy of a grown software project, class and package sizes frequently are very imbalanced. This leads to scalability issues. Furthermore, the manual assignment of software entities to larger units, as typically done by the software developer (e.g., of a class to a package), is often arbitrary. To overcome such problems, it would be helpful to have natural and balanced hierarchies. This could be done by means of *(weighted) graph clustering* [1] on call graphs, for instance, similarly to hierarchical mining of community structures in (social) networks [15]. From a general data-mining perspective, this is interesting, because our setting would provide an objective evaluation framework for graph clustering. 'Objective' means that clusterings of different quality are expected to yield results with different localisation precision as well. This is in contrast to numerous evaluations where domain experts have decided how good the various results are.

Integrated Hierarchical Search on Graphs. Our approach processes graphs at different levels, one after the other. Although these graphs are related (by *zoom-in*), the analysis at the different levels is currently done separately, without benefiting from the hierarchical procedure. This is, we have not tried to identify any synergy from that relationship so far. It would be interesting to investigate how an integrated hierarchical search procedure could look like that makes use of previous results and speeds up the process. Such results might be of interest for graph mining in other application domains as well.

Weighted Subgraph Mining. In this study we analyse *weighted call graphs* by means of a two-step approach: *frequent subgraph mining* followed by *feature selection*. To our knowledge, alternative approaches for an integrated analysis of weighted graphs have never been studied systematically. However, we expect that an integration would allow for much faster analyses. Furthermore, algorithms for *weighted subgraph mining* could be used in many domains where weighted graphs are present. The algorithms envisioned should be able to analyse tuples of numerical weights and might exploit correlations between the tuple elements.

9 Conclusions

Defect localisation is essential in software engineering. We have presented a hierarchical call-graph-based approach, building on newly proposed graph representations of different levels of granularity. To localise defects, it hierarchically analyses graphs of a coarse granularity before it *zooms-in* into more fine-grained graphs. This allows for the analysis of relatively large software projects. Our evaluation features defects from the field in such a project, Mozilla Rhino. The result is that the amount of source code a developer has to examine manually can be reduced to about 6% in our setup. To our knowledge, this is the first study applying call-graph mining to a project of this size. Besides our contributions in domain-specific data mining for software engineering, we have identified new general data-mining research questions relevant for many domains.

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