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# An Empirical Investigation on the Relationship between Design and Architecture Smells

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**Abstract**

***Context:*** Architecture of a software system represents the key design decisions and therefore its quality plays an important role to keep the software maintainable. Code smells are indicators of quality issues in a software system and are classified based on their granularity, scope, and impact. Despite a plethora of existing work on smells, a detailed exploration of architecture smells, their characteristics, and their relationships with smells in other granularities is missing.
***Objective:*** The paper aims to study architecture smells characteristics, investigate correlation, collocation, and causation relationships between architecture and design smells.
***Method:*** We implement smell detection support for seven architecture smells. We mine 3 073 open-source repositories containing more than 118 million lines of C# code and empirically investigate the relationships between seven architecture and 19 design smells.
***Results:*** We find that smell density does not depend on repository size. Cumulatively, architecture smells are highly correlated with design smells. Our collocation analysis finds that the majority of design and architecture smell pairs do not exhibit collocation. Finally, our causality analysis reveals that design smells cause architecture smells.

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**Keywords**

Maintainability; Code quality; Code Smells; Architecture smells; Design smells; Inter-smell relationships; Collocation; Correlation; Causality, Refactoring.

## 1 Introduction

In the software development lifecycle, software design spans from low-level class design to high-level architecture design. The quality of software design, including all its facets, plays an important role in keeping a software system maintainable.

Code smells [26, 77] are indicators of software quality deterioration that make software hard to maintain. Based on granularity, scope, and impact, smells are classified as implementation [26], design [78], and architecture smells [29]. Implementation smells are confined to a limited scope, typically to a method, and require relatively less effort to refactor. Design smells have a larger scope and impact and therefore refactoring a design smell may introduce a change in a set of classes. The architecture of a software system represents the critical design decisions that span multiple components and have a system-level impact [4]. Thus, architecture smells affect a set of components and require considerable effort to refactor [56] given their relatively wider scope. Although the effort to refactor smells matches the increase in their granularity, the corresponding benefits and positive consequences also increase significantly [70].

Over the fifteen years, the software engineering community has proposed many code smell detection mechanisms [77]. These are divided into categories such as metric-based [54], rule-based [60], history-based [68], and machine learning-based [3] methods. Among these categories, metric-based mechanisms are the most widely employed. However, the existing research mainly supports implementation and some design smells. The research on architecture smells and their detection is still in a budding stage [29, 70], and requires serious attention from the community given their importance and impact on the quality of software systems.

There have been some attempts to understand the impact of code smells on architecture quality. For instance, Macia *et al.* [50] investigated the impact of nine code smells on five architecture smells and revealed that code smells are related to 78% architectural anomalies in the studied systems. Also, they found that some code smells show a higher correlation with architecture smells. Some authors [50,51,64] studied the interplay among smells at different granularities and deduced that the inter-related smells affect architecture quality negatively. Source code granularity has been found to be helpful in similar contexts such as architecture recovery [48] and defect prediction [16].

Despite these attempts to understand the impact of code smells on architecture as well as leveraging the inter-smell relationships to find optimal sequences to refactor smells [46], the relationships (such as correlation and collocation) among smells at various granularities have not been explored in detail. *Collocation* refers to a relation between a smell pair instance that is detected in the same source code element (such as a class) [85,89] whereas *correlation* measures the degree of co-occurrence in terms of number of instances detected in a source code element (such as a component) between two kinds of smells [22, 74]. Related work [50, 51, 64] suggests that there could be a *causal* relationship among smells at design and architecture smells; however, to the best of our knowledge, none of the earlier work attempts to establish causality between design and architecture smells. In addition, this work attempts to broaden the scope of the analysis both in terms of the number of smells detected and analyzed as well as the number of analyzed repositories.

This paper contributes to the current research pertaining to the field of architecture smells in the following ways:

– *Correlation and collocation analysis between code smell categories:* We analyze a large set of repositories and infer relationships among the smells belonging to two granularities (architecture and design) through correlation and collocation analysis. In particular, the analysis explores whether there are specific design smells that may act as indicators for specific architecture smells. This exploration may reveal the intricate relationships among smells at different granularities and help us glean insights from the presence or absence of explored relationships.
– *Causality analysis between design and architecture smells:* We investigate temporal relationship between smell types to figure out whether design (or architecture) smells cause architecture (or design) smells.
– *Automated architecture smell detection:* We automate the detection of a set of seven architecture smells.
– *Code smell dataset:* We build a large dataset comprising 1 232 348 instances of seven architecture and 19 design smells, extracted from 3 073 open-source C# repositories. The dataset is available online [72] for the use of software engineering research community.

The rest of the paper is structured as follows. Section 2 explains the motivation behind this work. Then we discuss the existing literature in Section 3. Section 4 outlines theoretical background describing all the design and architecture smells considered in this work along with their detection mechanism. We define and briefly explain the research questions undertaken in Section 5. We also describe the experimental study design including selection of subject systems and the overall experimental method. Results of the experiments and observations corresponding to each research question are presented in Section 6. We extend our discussion on the explored relationships along with implications to software development community in Section 7. Finally, we conclude the paper with some promising future work in Section 9.

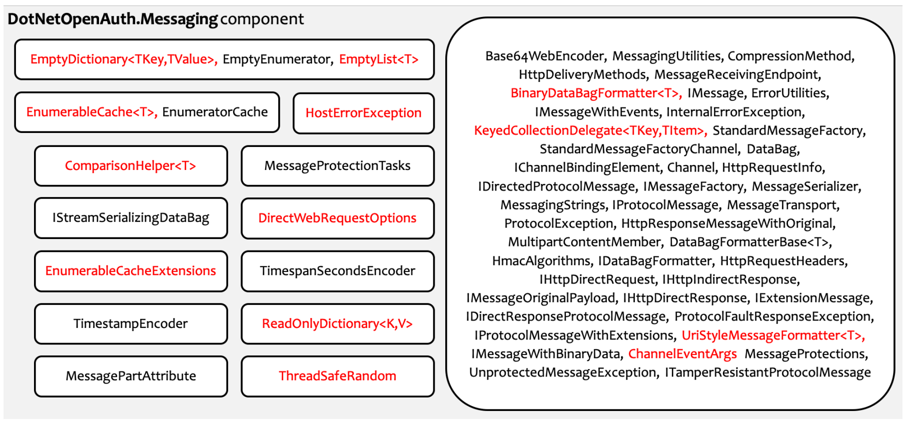

DotNetOpenAuth.Messaging component
EmptyDictionary<TKey,TValue>, EmptyEnumerator, EmptyList<T>
EnumerableCache<T>, EnumeratorCache
HostErrorException
ComparisonHelper<T>
MessageProtectionTasks
IStreamSerializingDataBag
DirectWebRequestOptions
EnumerableCacheExtensions
TimespanSecondsEncoder
TimestampEncoder
ReadOnlyDictionary<K,V>
MessagePartAttribute
ThreadSafeRandom
Base64WebEncoder, MessagingUtilities, CompressionMethod, HttpDeliveryMethods, MessageReceivingEndpoint, BinaryDataBagFormatter<T>, IMessage, ErrorUtilities, IMessageWithEvents, InternalErrorException, KeyedCollectionDelegate<TKey,TItem>, StandardMessageFactory, StandardMessageFactoryChannel, DataBag, IChannelBindingElement, Channel, HttpRequestInfo, IDirectedProtocolMessage, IMessageFactory, MessageSerializer, MessagingStrings, IProtocolMessage, MessageTransport, ProtocolException, HttpResponseMessageWithOriginal, MultipartContentMember, DataBagFormatterBase<T>, HmacAlgorithms, IDataBagFormatter, HttpRequestHeaders, IHttpDirectRequest, IHttpIndirectResponse, IMessageOriginalPayload, IHttpDirectResponse, IExtensionMessage, IDirectResponseProtocolMessage, ProtocolFaultResponseException, IProtocolMessageWithExtensions, UriStyleMessageFormatter<T>, IMessageWithBinaryData, ChannelEventArgs MessageProtections, UnprotectedMessageException, ITamperResistantProtocolMessage

Fig. 1: Motivational example—Component *DotNetOpenAuth.Messaging* has 60 classes; each box represents a disconnected sub-graph and contains related classes (via association, aggregation, composition, or inheritance). Class names written in red color show *unutilized abstractions*.

## 2 Motivation

The software engineering community has defined several code smells belonging to different granularities [77]. Many of these smells seem to be related to each other following different kinds of relationships—some smells show presence of other smells while some smells lead to other smells. Yamashita *et al.* [89] and Mantyla *et al.* [52] explore some of the relationships. In this section, we discuss a motivating example to establish a theoretical relationship between *unutilized abstraction* [78] design smell and *feature concentration* [2] architecture smell. This relationship helps in forming the basis of our research presented in this paper.

*Unutilized abstraction* design smell arises when an abstraction (e.g. class) is not used at all by other abstractions in a software system [78]. *Feature concentration* architecture smell occurs when a software component implements more than one architectural feature or concern [2]. This smell is detected by computing *Lack of Component Cohesion* (LCC) metric. LCC is computed by first identifying and grouping the related classes (by association, aggregation, composition, or inheritance) of a component in the form of a dependency graph. Dividing the number of disconnected sub-graphs by the total number of classes in the component gives us the value of the metric. A component with LCC greater than a pre-defined threshold is identified as the component suffering from *feature concentration* smell (refer to Section 4.2 for detection mechanism of *feature concentration* smell).

Figure 1 shows all 60 classes belonging to `DotNetOpenAuth.Messaging` component of `DotNetOpenAuth.Core` project in an open-source C# repository[1]. We form sub-graphs of the related classes as described above and put them in a box; therefore, each box represents a disconnected sub-graph. The grouping of classes results in 14 sub-graphs. The computed LCC is $14/60 = 0.21$ that makes the component suffering from *feature concentration* smell (assuming the threshold of LCC $= 0.20$).[2]

Interestingly, 13 classes are not used anywhere (shown in red color in Figure 1) and hence suffer from *unutilized abstraction* smell. Now, it can be observed that the reason for six sub-graphs to be detected as disconnected is rooted in the *unutilized abstraction* design smell instances (since all the classes in these sub-graphs are unutilized). These instances are contributing to the increase in the LCC value, and are, in turn introducing the *feature concentration* smell in the component. If we refactor each of these *unutilized abstraction* smell instances, the number of disconnected subgraphs reduces to eight and the total number of classes to 47. The new LCC value after the refactoring is $8/47 = 0.17$. This implies that the component no longer suffers from the *feature concentration* architecture smell. It can, therefore, be expected that a higher number of unutilized abstractions present at the design granularity in a component increases the chances of *feature concentration* smell at the architecture granularity. It also implies that if we refactor *unutilized abstraction* smell from a component, it might lead to the removal of *feature concentration* architecture smell.

Identifying architecture smells and removing them is an important yet daunting task [70]. Software development teams often hesitate to refactor architecture smells given their larger scope and risks [70]. For example, refactoring a *god component* architecture smell may result in creating another component with relevant classes from the god component. This refactoring may break the build unless all the references to classes moved to the new component are fixed accordingly. Furthermore, if some of the components are owned by different geographically dispersed teams, the need for refactoring has to be communicated to the teams and a consensus has to be built before actually carrying it out. We believe that exploring the relationships among architecture smells and smells at finer-granularity (such as design granularity) may facilitate easier adoption of architecture refactoring. This will help researchers and practitioners in understanding the role of finer-granularity code smells in introducing various architecture smells, in turn cautioning developers against the architecture degradation abilities of such smells.

## 3 Related Work

The topic of architecture smells and its impact on software development has been a subject of interest for software engineering community for many years.

[1] `https://github.com/DotNetOpenAuth/DotNetOpenAuth`

[2] In cases where there is no previous work recommending specific threshold values, we chose a value based on our experience in analyzing source code and after experimenting with various threshold values and manually analyzing the resultant set of detected smells.

We divide the literature related to this paper into four major parts: architecture smells, smells relationships, the impact of code smells on architecture degradation, and smell detection tools.

## 3.1 Architecture Smells

Garcia *et al.* [29] define an initial set of architecture smells including *ambiguous interface* and *scattered parasitic functionality*. Garcia [28] provides mathematically formal definitions of smells that help implement the smell detection tools for architecture smells. Duc Minh [42] presents an extended catalog of architecture smells along with the impacted quality attributes. A number of attempts [21,41,53,69] have been made to deliberate on introducing conceptual definitions along with the categorizations of smell relationships.

Similarly, Brown *et al.* [10] documents a set of architecture smells, among organization and process antipatterns, in enterprise settings. Andrade *et al.* [2] define a set of architecture smells for Product Line Architecture (PLA). Tamburri *et al.* [79] explore the impact of community smells on architecture quality. An open-source architecture repair model is defined by Tran *et al.* [80]. They argue that the difference between the conceptual architecture and concrete architecture is the main reason behind the occurrence of architecture smells. Behnamghader *et al.* [6] utilize ARCADE to compute change and decay metrics associated with architecture evolution.

Recently, some focused research attempts have been made to understand a specific kind of technical debt [39] *i.e., architecture technical debt* [7]. In particular, architecture debt identification has attracted considerable effort [44, 82]. Along the same lines, Mo *et al.* [59] explores the impact of refactoring on architecture debt. Similarly, Koziolek *et al.* [38] present an industrial case study to ensure the sustainability of software architecture using architecture metrics.

## 3.2 Smell Relationships

The focus of the current research that investigates the relationships among code smells has been mainly on either design or implementation granularity. The current research on smell relationships hardly involves architecture smells. Recent years have witnessed a number of empirical studies [47,87] that explore inter-smell relations. Yamashita *et al.* [88,89] empirically investigate the inter-smell relationships, termed as *collocated* and *coupled*, among 24 and 12 code smells, respectively. They explore mainly design smells and a few implementation smells. Their study reveals that the explanatory power of code smell relationships needs further investigations with complementary perspectives in order to be deemed useful. Similarly, Ma *et al.* [49] identify several coupled and some conflicting smell pairs among a set of 10 code smells.

Palomba *et al.* [67] investigate the collocation (termed as co-occurrences) among 13 design and implementation smells over multiple releases of 30 open-source software systems. In a parallel work, Walter *et al.* [85] conduct an experimental study to explore the collocation relationship among 14 design and implementation smells across 92 Java applications. They employ a variety of smell detection tools to explore the impact of tool selection on the smell relationships. Additionally, they explore the effect of the application domain on these relationships. Both of these studies foresee the importance of smell collocations in identifying classes requiring high maintenance effort and developing appropriate refactoring approaches as well as support from tools to detect smell collocation.

Fontana *et al.* [22] carry out an empirical study on the relationship between architecture and code smells. They analyze the correlation between a set of 3 architecture smells (*viz. unstable dependency, hub-like dependency,* and *cyclic dependency*) and 19 code smells including both implementation and design smells. They use Arcan and SonarQube tools to detect architecture and code smells in 111 Java subject systems. They report that the presence of architecture smells do not depend on the presence of code smells.

Sharma *et al.* [75] conduct a large-scale mining study to understand the relationships between design and implementation smells. Specifically, the study explores inter-category and intra-category correlation between smells belonging to different granularities. Bavota *et al.* [5] mine code smells in 3 Java-based programs and explore the relationship of smells with refactoring and software quality. Similarly, a study by Fontana *et al.* [20] reveals characteristics of smells such as the frequently occurring smells in various application domains.

### 3.3 Impact of code smells on architecture

It is believed that the code smells affect software architecture in a negative way. Macia *et al.* [51] present an empirical study on the relationship between code anomalies and architecture degradation. They reveal the deficiency of the present set of smell detection tools to capture the correlated architecture problems.

Oizumi *et al.* [63, 65] believe that the architecture problems are reflected in the source code through groups of code smells and study the impact of a number of code smell agglomerations on architecture problems. Guimaraes *et al.* [31, 32] conduct a controlled experiment utilizing architecture blueprints to prioritize various types of code smells based on their architectural relevance.

Martini *et al.* [56] conduct a case study on three architectural smells employing questionnaires, interviews, and code inspections on four industrial software projects. The main aim of the study is to identify and prioritize the architecture debt with the help of architecture smells. The findings of the study acknowledge the adverse effects of architecture smells and emphasize on the unavailability of automatic smell detection tools. Le *et al.* [43] perform an empirical investigation on the nature and impact of six architecture smells that most frequently appeared in a set of eight Apache Software Foundation open-source projects. They designed detection algorithms for these smells and explored relationships between issues and architecture smells under study. The outcome of the study states the negative impacts of architecture smells on maintenance effort in terms of the increased number of implementation issues and code commits.

## 3.4 Smell Detection Tools

A plethora of smell detection tools has been developed by the community using various techniques. The prominent techniques used to detect smells are metrics-based [54, 83, 84], rules-based (or heuristics) [60], machine learning-based [36], and history-based [66]. However, most of the present tools support the detection of a very scanty kind of smells and target mainly Java programming language. Moreover, the existing tools mainly focus on implementation and a limited set of design smells.

There have been some attempts to detect architecture smells. Titan toolset [86] detects modularity violations such as cyclic dependencies. Similarly, Arcan [23] detects two architecture (*cyclic dependency* and *unstable dependency*) and one design smells (*hub-like dependency*). Mo *et al.* [58] identify a set of hotspot patterns (recurring architecture problems) based on a combination of historical and architectural information of software systems. Hochstein *et al.* [34] describe a method of diagnosing architectural degeneration using an architecture evaluation tool. Nam *et al.* [62] present a method to visualize the evolution of software architecture that may lead a manual observer to spot architecture smells. ARCADE [6] allows architecture recovery and computing of architecture decay and change metrics to observe and track architecture evolution. Despite the above-mentioned attempts, to the best of our knowledge, none of the existing publicly available tools can detect a decent number of architecture smells in large software systems.

There are a few commercial tools such as Lattix[3], Sotoarc[4], and Structure101[5] that support architecture comprehension and conformance. Although some architecture smells (such as *cyclic dependency*) could be detected using these tools, they do not support architecture smell detection natively and explicitly. For design smells, tools such as NDepend[6] and JArchitect[7] help users identify quality issues. The analysis provided by these tools may aid the users in spotting some specific design smells (such as *unutilized abstraction*, *insufficient modularization*, and *cyclically-dependent modularization*). However, the tools lack explicit support for design smells. Table 1 provides a brief overview of the features supported by various commercial tools.

To summarize, the presented study provides a useful tool for practitioners and researchers to detect architecture and design smells. but also explores the relationships among them by analyzing a large number of repositories. The

[3] `https://lattix.com/`

[4] `https://www.hello2morrow.com/products/sotograph/sotoarc`

[5] `https://structure101.com/`

[6] `https://www.ndepend.com/`

[7] `https://www.jarchitect.com`

Table 1: Comparison of commercial tools for design/architecture analysis

| **Tools** | **Design/Architectu smells natively supported** | **Design/Architectu smells indirectly supported** | **Other features** |
|---|---|---|---|
| NDepend | Insufficient modularization, multifaceted abstraction, unutilized abstraction, deep hierarchy | Code quality metrics, dependency matrix, complexity analysis, code query | Quality gate, trend monitoring, continuous integration reporting |
| JArchitect | Insufficient modularization, multifaceted abstraction, unutilized abstraction, deep hierarchy | Code quality metrics, dependency matrix, code query | Quality gate, trend monitoring |
| Lattix Architect | | Dependency matrix | Architecture compliance, continuous monitoring |
| SotoArc | | Interactive dependency visualization | Architecture compliance, refactoring simulation |
| Structure101 | | Interactive dependency visualization, complexity analysis | Architecture compliance |
| Designite | 19 design and 7 architecture smells | Code quality metrics, dependency matrix | Trend analysis |

study presented in this paper is different from the existing research in a variety of ways. Firstly, we explore the relationships (through correlation, collocation, and causality analysis) between architecture- and design-level smells, whereas the previous studies focused on identifying predominantly the collocation of design smells. We believe that studying smell relationships horizontally (*i.e.,* smells belonging to the same granularity) as well as vertically (*i.e.,* smells belonging to different granularities) will complement the existing literature and reveal new insights. Secondly, where a number of previous studies [1, 67, 85] infer that the collocation of code smells complicates source code comprehension and maintenance, the collocation of smells at different design granularities might serve as a blessing in disguise as an occurrence of design granularity smell may indicate the occurrence of an architecture granularity smell, providing useful pointers to the developers for design optimization through effective refactoring. Thirdly, this is a mining study involving a relatively large set of more than three thousand open-source C# repositories including 26 design and architecture smells, which is expected to make the findings more generalizable. To the best of our knowledge, none of the existing research attempts targets to explore the temporal causality as well as correlation and collocation relationships between individual architecture and design smells.

## 4 Theoretical Background

In this section, we provide definitions of the considered architecture and design smells. Our presentation of the considered seven architecture and 19 design smells is based on the existing, considerable, coverage by the research and practitioner communities. Further, we elaborate on the detection mechanism of architecture and design smells that we use in our implementation.

### 4.1 Smell granularities and terminology

*Code smell* is an umbrella term used to describe indicators of poor quality that may occur in source code. Smells are classified based on various criteria [77] such as domain, granularity, and artifact. In the traditional source code context, software smells are classified based on their scope and impact in the following three granularities: implementation, design, and architecture. Implementation smells are confined to typically a method. For instance, *long method*, *long parameter list*, or *complex conditional* [26] are implementation smells that can be detected just by observing the source code of a method. The granularity of design smells is higher than implementation smells where we observe classes, their properties, and their relationships with other classes to detect them. Examples of design smells include *insufficient modularization*, *multifaceted abstraction*, and *deep hierarchy* [78]. Architecture smells occur at the highest granularity. We see source code in the form of components and their interactions with other components. *Feature concentration*, *god component*, and *dense structure* are examples of architecture smells [29]. In this study, a component refers to a *namespace* or an *assembly* in C# (equivalent to a *package* construct in Java) and a *type* or an *abstraction* refers to a *class* or an *interface*. Though the above discussion applies to object-oriented context, it can be generalized to apply on non-object oriented source code.

Many smells belonging to different granularities have similar names or causes. Despite the similarity, these smells are different because their scope and impact vary significantly. For example, *cyclic-dependency modularization* and *cyclic dependency* arise at design and architecture granularities, respectively. Although their names are almost the same, their semantics differ. Cycles (either directly or indirectly) among classes lead to *cyclically-dependent modularization* smell at design granularity whereas a cycle formed by two or more components introduces *cyclic dependency* architecture smell. The difference between the two lies in the granularity and the level of abstraction. Similarly, though *multifaceted abstraction* and *feature concentration* smells share the cause *i.e.,* poor cohesion, they arise at design and architecture granularities respectively. Despite the same cause, their scope and impact differ significantly—*multifaceted abstraction* is the result of poor cohesion in a class whereas *feature concentration* shows poor cohesion among a set of classes belonging to a component. Apart from the differences arising from scope and impact, their detection mechanism also differ. For instance, *multifaceted abstraction* gets detected by computing Lack of Cohesion among Methods (LCOM), which takes into account the commonalities (such as common field access) among the methods of a class. On the other hand, *feature concentration* architecture smell is detected by computing Lack of Component Cohesion (LCC) which considers similarity among classes (refer to Sections 4.2 and 4.3).

In this study, we restricted the scope of the analysis to source code; thus, we are analyzing source code to detect smells at different granularities. A set of architecture smells can also be detected by comparing design artifacts, such as architecture diagrams or design specifications, with the source code. However, it is not feasible to find architecture diagrams or specifications for open-source projects. Moreover, even if they are available, they significantly differ in notation as well as form and format that makes it practically infeasible to consider them for the purpose.

## 4.2 Architecture Smells

The architecture smells selected for this study represent anomalies related to a variety of internal software quality aspects. For instance, *feature concentration* smell represents *cohesion*, *scattered functionality* represents *coupling*, *god component* captures *size*, and *dense structure* represents *complexity* aspects. We implemented the support to detect architecture smells in Designite for this study. We also considered the automation feasibility of smell detection while choosing these smells and hence did not pick architecture smells that are infeasible or too complex to be automated. One example of such a smell is *stovepipe system* architecture smell [10] which is detected when subsystems of an application are integrated in a temporary manner using multiple integration strategies and mechanisms.

The architecture smells considered in this paper along with their detection mechanisms are explained below. The detection mechanism used in the tool is in-line with the existing literature. For instance, *unstable dependency* smell gets detected by computing instability metric of each component, which is proposed by Martin *et al.* [55] and used by Fontana *et al.* [23, 24]. Some of the smells are implemented for the first time in the software engineering literature as far as we know; hence, for them we not only provide detection mechanisms but also discuss the rationale used to decide any threshold they use. Taking a deeper look at the thresholds reveals that there are two kinds of thresholds; apart from the key metric thresholds, sometimes additional conditions are imposed to reduce the possibilities of false-positives. For instance, ambiguous interface smell gets detected when a component has only one public method. However, this heuristic will lead to many small components to be detected as the components suffering from this smell. Hence, to avoid this, we apply an additional check to ensure we don't detect too small components as smelly components.

### *4.2.1 Cyclic Dependency*

This smell arises when two or more architecture-level components depend on each other directly or indirectly [45, 58].

***Detection mechanism:***

- We compute a dependency list for each component. Therefore, such a list for component $A$ represents the components on which component $A$ depends. Component $A$ depends on component $B$ if at least one of the classes in $A$ refer (by association, aggregation, or composition) to at least one of the classes in component $B$.
- We construct a directed graph using the above information where *nodes* refer to components and *edges* refer to their dependencies.
- We then apply depth-first search algorithm to detect cycles in the graph for each component. For large graphs, we stop the exploration after a threshold (currently set to 5 hops) to avoid extraneous computation.

### *4.2.2 Unstable Dependency*

This smell arises when a component depends on other less stable components [24]. Stable Dependencies Principle (SDP) [55] states that the dependencies between packages should be in the direction of the stability of packages. Hence, a package should only depend on packages that are more stable than itself. An *unstable dependency* architecture smell occurs when this principle is not followed.

***Detection mechanism:***

- Instability of a component is computed as follows:

$$I = \frac{C_e}{C_e + C_a} \tag{1}$$

  Here, $I$ represents the degree of instability of the component, $C_a$ represents the afferent coupling (or incoming dependencies), and $C_e$ represents the efferent coupling (or outgoing dependencies).
- We compare the computed metric value of each component against its dependent components, and detect the smell when the dependent component is more stable.

### *4.2.3 Ambiguous Interface*

This smell arises when a component offers only a single, general entry-point into the component [29]. This smell typically appears in event-based publish-subscribe systems where interactions are not explicitly modeled and multiple components exchange event messages via a shared event bus.

***Detection mechanism:***

We detect this smell when we find a component containing only one *public* or *internal* method. An *internal* method in C# has the visibility inside the assembly; hence, other components within the assembly may access it. We detect the smell only when the component has at least 5 classes to avoid small components from getting reported as ambiguous interfaces. This additional check is applied to avoid false-positives derived from reported false-positive cases from users of Designite.

### *4.2.4 God Component*

This smell occurs when a component is excessively large either in terms of Lines Of Code (LOC) or the number of classes [45].

***Detection mechanism:***

We detect this smell when a component has more than 30 classes or 27 000 LOC following the recommendations by Lippert *et al.* [45].

### *4.2.5 Feature Concentration*

This smell occurs when a component realizes more than one architectural concerns or features [2]. In other words, the component is not cohesive.

***Detection mechanism:***

– The software engineering literature has relied on metrics such as Lack of Cohesion of Methods (LCOM) [11] to identify diverse features or responsibilities realized by a class. We have extended the same concept for detecting the feature concentration smell. We compute Lack of Component Cohesion (LCC) to measure a component's cohesion.
– To compute LCC, we identify related classes in a component, prepare a dependency graph, and identify the number of disconnected sub-graphs. Two classes are related if they share any of the association, aggregation, composition, or inheritance relationships.

$$LCC = \frac{\text{Number of disconnected sub-graphs}}{\text{Total number of classes}} \tag{2}$$

– We detect this smell if LCC is more than a pre-defined threshold. We currently use 0.2 as the LCC threshold to detect this smell. We chose this threshold after experimenting with various threshold values and analyzing the resultant set of detected smells manually. Since this smell has never been detected in software engineering literature, we derive the metric threshold by the following heuristic. If all the classes are connected to other classes in a component, the resultant dependency graph would be a connected graph and we will get LCC = 0. Hence, any component having LCC >0 can be considered as a candidate for this smell. However, it would be a very stringent threshold. We experimented with a few options (0, 0.1, 0.2, and 0.3) to find out a suitable threshold by comparing the results with these options and found 0.2 as the optimal threshold. However, we allow other users and researchers to change the threshold in the tool as per their needs.

#### *4.2.6 Scattered Functionality*

This smell arises when multiple components are responsible for realizing the same high-level concern [29]. It is an indication that possibly classes or methods must be moved from one component to another in order to reduce coupling among components and enhance cohesion within each component.

***Detection mechanism:***

- We determine the accesses to at least two external components that occur from a method.
- When two or more components are accessed from one method, it becomes a possible case of scattered functionality smell. However, to ensure that we are not reporting the one-off instances (and thus false-positives), we identify the smell when such accesses occur more than one.

#### *4.2.7 Dense Structure*

This smell arises when components have excessive and dense dependencies without any particular structure [74].

***Detection mechanism:***

- This smell occurs when components form a very dense dependency graph. In order to detect this smell, a dependency graph involving all the components is formed and the average degree of the graph is computed. The average degree of a graph can be computed as follows:

$$\text{Average degree} = \frac{2 \times |E|}{|V|} \tag{3}$$

  Where $E$ is the set of all edges and $V$ is the set of all vertices belonging to the graph.
- We detect the smell when the average degree is greater than a pre-defined threshold. To choose an appropriate threshold, we started with the $7\pm2$ rule of psychology [57]. We experimented with values 5 to 9 for the threshold value and analyzed the resultant set of detected smells manually. We found the threshold value 5 as the most appropriate.
- Since the dependency graph is formed by considering all the components present in a repository, at most only one instance of this smell can occur for a source code repository.

### 4.3 Design Smells

Suryanarayana *et al.* [78] proposed a mechanism to classify design smells identified in the literature based on four major object-oriented principles (*i.e., abstraction*, *encapsulation*, *modularization*, and *hierarchy*). We detect 19 smells, all that is feasible to implement without detecting too many false-positives, out of 25 smells proposed in the catalog. This set of supported smells covers all the commonly known and studied design smells. Though, the design smells detection support in Designite has been discussed in earlier work [75, 76], we elaborate on the detection mechanism for all the considered design smells. As the case with architecture smells, we provide rationale for choosing certain threshold where the smells are not commonly detected and their corresponding thresholds are not known.

#### *4.3.1 Duplicate Abstraction*

This smell arises when two or more abstractions have identical names or identical implementations. Duplicate code is difficult to maintain. Often, a change in one of the clones needs to be reflected across all the other duplicates. Overlooking this implied overhead may lead to difficult to trace bugs. This smell can be refactored by identifying and extracting a common implementation in the duplicates into a common class or method [78].

***Detection mechanism:*** We detect this smell when we find code clones (type-1) [37] of size greater than 20 lines. The size is chosen as 20 lines to avoid detecting smaller auto-generated code snippets as clones.

#### *4.3.2 Imperative Abstraction*

This smell arises when an operation is turned into a class. If operations are turned into classes, the design suffers from an explosion of one-method classes and complexity of the design increases. This smell can be refactored by creating an appropriate abstraction to host the method existing within the imperative abstraction [78].

***Detection mechanism:*** If a class has only one public method and the size of the class (in terms of LOC) is greater than the pre-defined threshold (*i.e.,* 100), we detect this smell. We applied this threshold to avoid detecting smaller classes which contain only one method but do not justify the rationale of getting converted the class into a method.

#### *4.3.3 Multifaceted Abstraction*

This smell arises when an abstraction has more than one responsibility — contract or obligation [9, p. 53] — assigned to it. When an abstraction includes multiple responsibilities, it implies that the abstraction will be affected and needs to be changed for multiple reasons. The smell can be refactored by applying "extract class" refactoring on a subset of methods to form more cohesive classes [78].

We clarify now in the manuscript that term 'responsibility' (which is coming from object-oriented parlance) means the abstraction's contract or obligation. It also reflects in Single responsibility principle. Software engineering literature is using the LCOM metric to measure the (lack of) cohesion that essentially captures the interactions among the source code elements of the class and identifies the degree of cohesiveness.

***Detection mechanism:*** Software engineering literature is using the Lack of Cohesion among Methods (LCOM) metric to measure the (lack of) cohesion that essentially captures the interactions among the source code elements of the class and identifies the degree of cohesiveness. To detect the smell, we compute (LCOM) metric for each type. If the value of the metric is greater than a threshold (*i.e.,* 0.80) and the type is not very small —number of fields and methods are greater than or equal to a threshold (*i.e.,* 7), we detect the smell. The threshold on LCOM is inspired by existing work [19] and a popular code quality tool NDepend[8].

#### *4.3.4 Unnecessary Abstraction*

Each abstraction has two essential elements—data (*i.e.,* fields) and behavior (*i.e.,* methods). If an abstraction does not have associated methods but only fields, then that abstraction is not needed. This smell occurs when an abstraction that is actually not needed (and thus could have been avoided) gets introduced in software design. Having needless abstractions in the design increases its complexity unnecessarily and affects the understandability of the overall design. This smell is eliminated by removing the unnecessary abstraction or by applying "inline class" refactoring to merge the class with another class [78].

***Detection mechanism:*** If a type (except enumerations) has no methods and the number of fields and properties are less than a threshold (*i.e.,* 5), we detect this smell. We derive this threshold because the number of fields and properties less than the threshold are commonly declared as a part of enumeration types or can be easily placed in the classes where they are getting used.

#### *4.3.5 Unutilized Abstraction*

This smell arises when an abstraction is left unused (either not directly used or not reachable). Unused abstractions pollute the design space and increase cognitive load. In addition, such abstractions may lead to reliability issues by getting invoked accidentally. An unused abstraction can be refactored by eliminating it from the code [78].

***Detection mechanism:*** A type is unutilized if the fan-in metric of the type is zero *i.e.,* there are no classes that depend on this type and the type has no supertype. In case, the type has supertype, the type suffers from this smell if fan-in for both the type and its supertype is zero.

#### *4.3.6 Deficient Encapsulation*

Public fields are accessible across the software system and hence they make software design complex and debugging difficult. This smell occurs when the

[8] `https://www.ndepend.com/docs/code-metrics#LCOM`

declared accessibility of one or more members of an abstraction is more permissive than actually required. Presence of this smell indicates that the internal implementation details are exposed for the abstraction leading to reduced understandability due to the complex interface. Also, the clients of the abstraction may depend directly upon the implementation details of the abstraction making it difficult to change and extend the abstraction. It can be refactored by applying "encapsulate field" refactoring [78].

***Detection mechanism:*** If a type has at least one public field or global field (declared as *public static*), we detect this smell.

### *4.3.7 Unexploited Encapsulation*

This smell arises when explicit type checks are performed (using chained if-else or switch statements that check for the type of the object) instead of exploiting the variation in types already encapsulated in the form of an inheritance hierarchy. A hierarchy facilitates variations in an encapsulation; however when type-based switches are performed, the client code needs to be changed whenever an existing abstraction is changed. Hence changeability and extensibility of the software system are impacted. This smell can be refactored by replacing the type-based switches to an inheritance hierarchy and polymorphic methods [78].

***Detection mechanism:*** We retrieve the list of types that are being explicitly checked in a method. We find the number of checked types that belong to the same inheritance hierarchy. If the number is greater than one, we detect this smell. The threshold value is chosen as greater than one because it doesn't make sense to detect the smell when there is only one subtype.

### *4.3.8 Broken Modularization*

This smell arises when data and/or methods that ideally should have been localized into a single abstraction are separated and spread across multiple abstractions. When members that should be put together are scattered across different abstractions, understanding all the methods and their functionality is no longer easy. Furthermore, introducing changes and feature enhancements becomes difficult because modifications may need to be made across several abstractions. To eliminate the smell, it is required to put together the data members and corresponding methods into a single abstraction by using a series of "move method" or "move field" refactorings [78].

***Detection mechanism:*** There are two variants of this smell [78]—classes that are used as a holder of data members without corresponding methods and methods in a class more interested in members of another class. We only detect the first variant of the smell.

If a type doesn't have any methods and count of fields and properties is greater than a certain threshold (*i.e.,* 5), we detect this smell. The additional threshold (5) is applied to ensure that we don't tag small classes as broken modularization.

#### *4.3.9 Cyclically-dependent Modularization*

This smell arises when two or more abstractions depend on each other directly or indirectly creating a tight coupling between the abstractions. When a set of abstractions are coupled together in a tangle, a change in one of these abstractions may lead to a ripple effect across all the coupled classes. Hence, it is difficult to understand as well as introduce new features or changes to the classes belonging to the tangle. This smell can be refactored by breaking the cycle by moving some of the fields or methods to another class [78].

***Detection mechanism:*** We prepare a dependency graph of types from their incoming and outgoing dependencies. We use this dependency graph to detect direct or indirect cycles.

#### *4.3.10 Hub-like Modularization*

This smell arises when an abstraction has dependencies (both incoming and outgoing) with a large number of other abstractions. Any change to an abstraction, on which many other abstractions depend, is difficult to change because the change in the abstraction may lead to changes in the abstractions that depend on this abstraction. Due to this reason, a hub class can be affected by numerous other abstractions, and can, in turn, affect abstractions that depend on that hub class. This coupling pattern makes the design with hub classes prone to ripple effects impacting the changeability and extensibility of the design. The smell can be refactored either by splitting the hub class using "extract class" or in some cases by applying "chain of responsibility" pattern [78].

***Detection mechanism:*** If both fan-out and fan-in metrics of a type are greater than a threshold (*i.e.,* 20), the type suffers from this smell. This threshold is selected based on the recommended threshold by Ferreira et al. [18].

#### *4.3.11 Insufficient Modularization*

This smell arises when an abstraction exists that has not been completely decomposed, and a further decomposition could reduce its size, implementation complexity, or both. A large and complex implementation is difficult for developers to comprehend and change. A bloated interface, which is often the case in this smell, is difficult to use by the client abstractions. Often, multiple kinds of clients access the abstraction and hence a change in this abstraction leads to breaking many of the client classes. The smell can be refactored by segregating related members and extracting them into separate classes using "extract class" refactoring [78].

***Detection mechanism:*** There are three forms of this smell; hence, we report this smell when even one of the below case is true.

– If the count of public methods in a type crosses a threshold (*i.e.,* 20), the type is suffering from *insufficient modularization.*

– If the total methods in a type are more than a threshold (*i.e.,* 30), we detect this smell. We extrapolated the suggestion of Lippert et al. [45] of number of classes in a component to the number of maximum desired methods in a class.
– We compute Weighted Methods per Class (WMC) for each type. We detect this smell if the value of the metric is more than a threshold (*i.e.,* 100). The threshold is chosen based on the recommendation by Herbold et al. [33].

### *4.3.12 Broken Hierarchy*

This smell arises when a supertype and its subtype conceptually do not share an "IS-A" relationship resulting in broken substitutability. When a supertype and its subtypes do not honor "IS-A" relationship, clients of the abstractions may attempt to assign objects of subtype to supertype references and may expose to unexpected behavior. For example, invoking a method that is not honored by a subtype object may lead to a runtime failure. This smell can be refactored by applying "replace inheritance with delegation" refactoring [78].

***Detection mechanism:*** The relation "IS-A" means that a type is a specialized version of its supertype. It implies that a subtype implements one or more methods in a more specific way. Our detection mechanism uses this implication to form the following heuristic. For each class that has at least one super class with at least one public method, we check whether the class satisfies the condition of *broken hierarchy* smell. If the class doesn't have any method overridden or "leniently" overridden from its super classes, we detect the smell. A method is leniently overridden when the method name matches (but not necessarily the parameter types) with any of the public methods in the super classes; it is akin to method overloading within an inheritance hierarchy.

### *4.3.13 Cyclic Hierarchy*

This smell arises when a supertype in a hierarchy depends on any of its subtypes. In the presence of this smell, any modification in subtypes may affect supertypes that may, in turn, affect other subtypes of the hierarchy. Refactorings such as "move method" and "extract class" could be utilized to break the cycle. Also, in some cases, it is feasible to merge both the subtype and supertype into one type to remove the smell [78].

***Detection mechanism:*** If a type accesses any of its subtypes, then we detect this smell.

### *4.3.14 Deep Hierarchy*

This smell arises when an inheritance hierarchy is excessively deep. With the increase in the depth of a hierarchy, it gets difficult to predict the behavior of the leaf classes since such classes inherit a large number of public and protected methods. Refactorings such as “collapse hierarchy” and “split hierarchy” could be used to remove the smell [78].

***Detection mechanism:*** We measure the Depth of Inheritance Tree (DIT) metric for each type. If the metric value crosses a threshold (*i.e.,* 6), as recommended by Suryanarayana et al. [78], we detect this smell.

### *4.3.15 Missing Hierarchy*

This smell arises when a code fragment uses conditional logic (typically in conjunction with “tagged types”) to explicitly manage variation in behavior where a hierarchy could have been created and used to encapsulate those variations. It is easy to modify existing types and add support for new types within the hierarchy when a hierarchy is encapsulating variation. However, with type-based switches, the client code needs to undergo a change whenever an existing type is changed. This smell can be refactored by applying “extract hierarchy” refactoring [78].

***Detection mechanism:*** We get a list of types checked explicitly in a method, for example, by using *instanceof* operator. Then, if more than one of the types in this list are not belonging to an inheritance hierarchy then we conclude that an inheritance hierarchy is missing.

### *4.3.16 Multipath Hierarchy*

This smell arises when a subtype inherits both directly as well as indirectly from a supertype leading to unnecessary inheritance paths in the hierarchy. Redundantly inherited supertype complicates the hierarchy leading to confusion and in turn impacts readability and understandability quality attributes. The smell can be refactoring simply by removing the unnecessary inheritance paths in a hierarchy [78].

***Detection mechanism:*** We derive a list of the direct super classes of a class. We also retrieve all the ancestors of all the parents. If there is any type common between these two lists, we conclude the presence of this smell.

### *4.3.17 Rebellious Hierarchy*

This smell arises when a subtype rejects the methods provided by its supertype(s). Rejecting methods from supertypes indicates that the subtype cannot be safely replaced with a reference of supertype and hence violates the Liskov substitution principle [55]. When the smell is present, the client of the abstraction may be surprised why the subtype objects do not behave as expected. Furthermore, with this smell, clients cannot freely substitute supertype references with subtype objects. This constraint leads to the tight coupling of client code with the concrete types of the hierarchy and impacts the changeability of the design [78].

***Detection mechanism:*** We check all the non-private methods in a class. If any method is overridden and either the method is empty or has only statement that throws an exception, we detect this smell.

### *4.3.18 Unfactored Hierarchy*

This smell arises when there is unnecessary duplication among types in a hierarchy. In the presence of this smell, a change in the clone code needs to be replicated across all the associated clones. This constraint not only impacts changeability of the system but also reliability (when the same change is not done in other associated clones). This smell can be refactored by "pull-up method" refactoring to remove the duplicates within a hierarchy [78].

***Detection mechanism:*** We detect this smell when we find code clones in sibling types (where the classes share supertype).

### *4.3.19 Wide Hierarchy*

This smell arises when an inheritance hierarchy is too wide indicating that intermediate types may be missing. In the absence of intermediate abstractions, the sibling classes are not the same level of abstraction. That makes it difficult for programmers to understand the sibling classes since some classes are too high-level while others are at a low-level of abstraction. Furthermore, the smell affects the extensibility of the hierarchy due to missing "hook points" facilitated by a properly designed hierarchy. A common strategy to remove the smell is to apply "extract superclass" refactoring to introduce intermediate abstractions [78].

***Detection mechanism:*** We compute the Number of Children (NC) metric for each type. If the value of the metric crosses a threshold (*i.e.,* 10), as recommended by Suryanarayana et al. [78], we detect this smell.

## 5 Study Design

We define five research questions exploring the relationship between architecture and design smells. In order to provide answers to the research questions, we specify a protocol to select and download open-source repositories. We analyze the downloaded repositories using Designite [71,76]—our smell detection tool that we use in this study.

### 5.1 Research Questions

Building on the motivation and the background, we compose five research questions to explore the relationships between architecture and design smells. Figure 2 puts together the research questions pictorially.

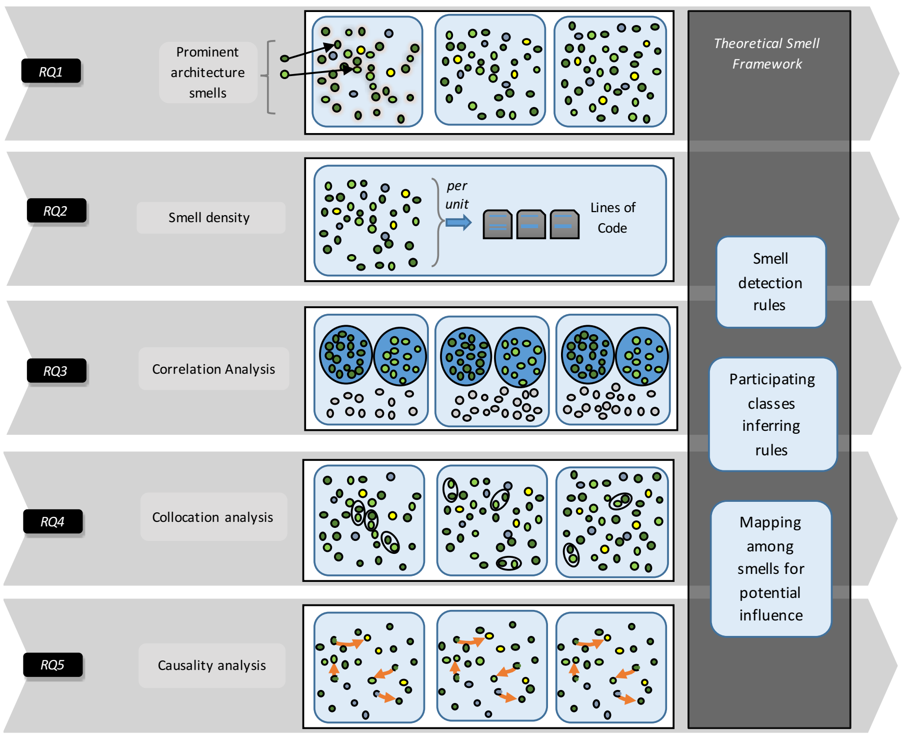

RQ1
Prominent architecture smells
RQ2
Smell density
per unit
Lines of Code
RQ3
Correlation Analysis
RQ4
Collocation analysis
RQ5
Causality analysis
Theoretical Smell Framework
Smell detection rules
Participating classes inferring rules
Mapping among smells for potential influence

Fig. 2: Overview of the research questions

**RQ1.** ***Which architecture smells are more prominent in open-source C# repositories?***
RQ1 aims to identify whether a specific sub-set of considered architecture smells is more prevalent in the analyzed open-source software repositories. The answer to RQ1 may caution the developers about a set of architecture smells expected to have more chances of occurrence and prompts them to take precautionary measures.

**RQ2.** ***Is architecture smell density affected by the size of the repositories?***
It is commonly believed that the complexity of a software system increases with the size of the system. In this research question, we aim to analyze whether the density of architecture smells increases or decreases with the increase in the system size. Smell density [74, 75] is a normalized metric that represents the average number of smells identified per thousand lines of code.

**RQ3.** ***Are detected architecture smell instances correlated with design smells instances?***
RQ3 explores how the architecture smells correlate with design smells. First, we consider the cumulative values of both kinds of smells (architec-

ture and design). A strong correlation between kinds of code smells would encourage us to understand the occurrence patterns and provide valuable insights into the similarity between these pairs.
Further, we also investigate the correlation between individual design smells and architecture smells. This would help us to find out whether there exist specific types of design smells that are strongly correlated to specific types of architecture smells.

**RQ4.** ***Are architecture smells collocated with design smells?***
RQ4 aims to explore whether architecture and design smell occur at the same location (*i.e.,* classes) within the source code. A positive result of the collocation analysis would establish a strong relationship between architecture and design smells.
Apart from exploring collocation cumulatively between both kinds of smells, the question investigates the collocation relationships between individual pairs of design smells and architecture smells. This would help us to figure out whether and to what extent specific design smells show collocation with architecture smells.

**RQ5.** ***Do design smells cause architecture smells (or vice-versa)?***
This research question extends the relationship analysis beyond correlation and collocation and explores whether design smells "cause" architecture smells or vice-versa. A smell $d$ causes smell $a$ if predictions of the values of $a$ based on its own past values and on the past values of $d$ are better than the predictions of $a$ calculated only using its own past values [30].
It would reveal the degree of influence that design smells have on architecture smells (and vice versa). A high influence would hint that by carrying out a suitable refactoring early during the evolution of the software may lead to fewer smells at the different granularity.

To address the research questions defined above, we design an experimental setup, perform the experiments, extract the required data, and document our inferences and observations.

## 5.2 Downloading Subject Systems

We used the following protocol to identify our subject systems.

– We use RepoReapers [61] to filter out low-quality and too small repositories among the abundant repositories present on Github. RepoReapers analyzed a huge number of GitHub repositories and evaluated each of the repositories on eight dimensions providing a fair idea about their quality characteristics. These dimensions are architecture (as evidence of code organization), continuous integration and unit testing (as evidence of quality), community and documentation (as evidence of collaboration), history, issues (as evidence of sustained evolution), and license (as evidence of accountability). A repository scoring low on these dimensions are indeed of low quality compared to a repository scoring high on the same dimensions. RepoReapers assigns a score corresponding to each dimension.

– We select all the repositories containing C# code where at least six out of eight RepoReapers' dimensions have suitable scores. We consider a score suitable if it has a value greater than zero. Values of some of the dimensions (architecture, documentation, issues, and unit test) range between 0 and 1, some other dimensions (license and continuous integration) may take either 0 or 1. Only dimensions history and community may take values minimum 0 to more than 1. Our goal was to filter out poor quality repositories and hence we selected the criteria where we consider values greater than zero as favorable values. Our choice of C# is motivated by the fact that a large part of the academic literature focuses on subject systems written in the Java programming language. It is desirable that we, as the research community, diversify our explorations and generalize our research. Our choice of C# is an attempt to fill the gap as empirical studies in programming languages other than Java.
– Next, we sort the repositories based on the number of assigned stars. We select repositories tagged with more than 10 stars.
– Following these criteria, we download and analyze more than 3 400 repositories using Designite (version 3.4.0). We could not analyze some of the repositories due to either missing external dependencies or custom build mechanisms (*i.e.,* missing standard C# project files). We successfully analyze 3 073 repositories.
– Software test code contains different types of smells (*i.e.,* test smells [17]) which is not in the scope of this paper. Hence, we exclude the test code belonging to the selected software repositories from our empirical analysis.

A complete list of the selected C# repositories along with their analyzed results can be found online [72]. Table 2 presents some key characteristics of the selected subject systems.

Table 2: Characteristics of the Analyzed Repositories

| **Attributes** | **Values** |
|---|---:|
| Repositories | 3 073 |
| Components | 114 706 |
| Types | 1 120 960 |
| Methods | 5 545 197 |
| Lines of code (C# only) | 118 699 236 |

## 5.3 Tool Support—Designite

Designite [71, 76] is a software design quality assessment tool for software systems written in C# programming language. The tool supports detection of 19 design and 11 implementation smells. For the purpose of this study, we implemented support to detect seven architecture smells within the tool. Apart from its GUI-based desktop application, Designite also offers a console application which is particularly useful for analyzing a large number of repositories automatically. Customization is one of the major features of the tool—a user can customize the way input source code is provided to the tool, certain smells to skip in an analysis session, or change thresholds that are used to detect certain smells. The tool offers free *Academic* licenses for all academic purposes.

The selection of smells to support is based on the commonality of these smells in the software engineering literature. Specifically, many authors have defined, discussed, and detected commonly occurring design smells; a mature consolidated catalog is proposed by Suryanarayana *et al.* [78]. Designite implements 19 out of the 25 design smells presented in the catalog. Similarly, we implemented architecture smells commonly discussed by the software engineering community [2, 8, 24, 45, 74].

### *5.3.1 Manual validation*

We conducted a manual validation to establish the accuracy of the tool. We chose a project `DotNetOpenAuth.Core` from a well-known open-source repository `DotNetOpenAuth`[9] for the purpose. The selected project contains 16 663 LOC, 136 types, and 7 components. We sought help from two volunteers to carry out manual validation—one volunteer works in a software development company (three years of industry experience) and another volunteer is a Ph.D. student with one year of industry experience. Both the volunteers did not work of the analyzed repository in advance; however, they have hands-on experience on working with complex industrial solutions and have a fair idea of software architecture and code smells.

We enforced the following protocol for the validation.

– Each volunteer carried out the initial manual analysis individually without discussing it with another volunteer.
– Given their industry experience, they were aware of the basic concept of code smells and commonly known smells. Each volunteer picked all the considered design and architecture smells one by one and understood the semantics of the smell. We provided additional material to make their learning faster.
– Both the individuals went through all source code files one by one and checked the existence of each smell following the definition of each smell.
– While identifying smells, they were allowed to use IDE features such as *go to definition* and *list all references* as well as metrics generated from other tools.
– Once both the volunteers completed the analysis, the volunteers discussed their results, sorted out differences, and prepared a consolidated mutually agreed results. The consolidated results had 52 design and 18 architecture smells.
– At this point, they used Designite and analyzed the considered project and obtained a list of design and architecture smells.

[9] `https://github.com/DotNetOpenAuth/DotNetOpenAuth`

– They compared the results obtained from the tool with their set of smells and tagged them as true-positive, false-positive, and false-negative. During this categorization, they observed that a subset of smells is identified by the tool which was not revealed by their manual analysis. They analyzed each of the smells in the subset and categorized them as well similar to the rest of the smells.

Table 3 presents the result of the manual validation showing smell instances detected by Designite and the consolidated set of smells identified by the volunteers. The table also shows number of false-positives and false-negatives that we found in this validation. The detailed report showing individual smells along with the names of each component or class where they occur along with corresponding classification can be found online [73].

Interestingly, volunteers could not find all the legitimate smells manually; though, when the tool reported these instances, they classified them as true-positive. The highest number of smells that were missed by the volunteers are *cyclically-dependent modularization* and *cyclic dependency*. In this context, the volunteers found only unit-cycles *i.e.,* cycles involving only two classes or components. However, the tool reported cycles with different lengths. Volunteers verified all of these non-unit cycles and found them as true-positive. It implies that many smells go unnoticed even one actively looks for them; this observation emphasizes the importance of using tools.

The tool reported two false-positive instances of *unutilized abstraction*. Both of the instances are reported for exception types *i.e.,* classes that define custom exceptions. The tool could not resolve such instances of the types when they are thrown from a return statement.

The tool also failed to detect one instance of *broken modularization* smell. The volunteers classified the smell because the class only has a few data members and an empty constructor. However, due to the presence of the constructor, the tool did not identify the smell.

We compute precision and recall exhibited by the tool in the following way.

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

Here, TP, FP, and FN refer to true-positive, false-positive, and false-negative instances. Based on the above analysis, we obtain precision = $117/(117+4) = 96.6\%$ and recall = $117/(117+1) = 99.1\%$.

## 5.4 Overview of the Method

Figure 3 presents an overview of our experimental setup. The software repositories selected using RepoReapers are downloaded from GitHub. These repositories are then fed to Designite to identify smells that are exported in the form

Table 3: Results of Manual Validation

| Smells | Designite | Manual | TP | FP | FN |
|---|---|---|---|---|---|
| Broken Hierarchy | 2 | 1 | 1 | 1 | 0 |
| Broken Modularization | 2 | 3 | 2 | 0 | 1 |
| Cyclically-dependent Modularization | 34 | 34 | 34 | 0 | 0 |
| Duplicate Abstraction | 9 | 9 | 9 | 0 | 0 |
| Hub-like Modularization | 1 | 1 | 1 | 0 | 0 |
| Imperative Abstraction | 9 | 9 | 9 | 0 | 0 |
| Insufficient Modularization | 5 | 5 | 5 | 0 | 0 |
| Multipath Hierarchy | 1 | 1 | 1 | 0 | 0 |
| Rebellious Hierarchy | 2 | 2 | 2 | 0 | 0 |
| Unnecessary Abstraction | 20 | 19 | 19 | 1 | 0 |
| Unutilized Abstraction | 5 | 3 | 3 | 2 | 0 |
| Wide Hierarchy | 4 | 4 | 4 | 0 | 0 |
| Cyclic Dependency | 13 | 13 | 13 | 0 | 0 |
| Unstable Dependency | 4 | 4 | 4 | 0 | 0 |
| God Component | 1 | 1 | 1 | 0 | 0 |
| Feature Concentration | 5 | 5 | 5 | 0 | 0 |
| Scattered Functionality | 3 | 3 | 3 | 0 | 0 |
| Dense Structure | 1 | 1 | 1 | 0 | 0 |
| | **121** | **118** | **117** | **4** | **1** |

of CSV files. We perform statistical analysis—specifically, correlation analysis (Spearman), Granger causality, and phi-coefficient using contingency matrix to answer the addressed research questions on the detected instances of architecture and design smells. We then infer, document, and present observations based on the results of our analysis.

## 6 Results

This section presents the results along with our observations corresponding to each research question addressed in this study.

**RQ1.** ***Which architecture smells are more prominent in open-source C# repositories?***

**Approach:** Designite offers a console application along with its GUI-based application to enable large-scale analysis. We use the console application and analyze each downloaded repository. The tool provides detected design and architecture smells in separate CSV files for each analyzed repository. We summarize the detected smells and compute the total number of detected smell instances for all the architecture smells.

**Results:** Table 4 lists the total number of architecture smells in all the analyzed repositories. The table reveals that the *cyclic dependency* is the most frequently occurring architecture smell followed by *feature concentration* smell. One potential reason for *cyclic dependency* to occur in a high volume is the permutations of the cycles due to one dependency that is mainly responsible for introducing a cycle. For example, Figure 4 shows dependencies among four components viz. `Documentation` (D), `Semantics` (S), `TypeSystem` (T),

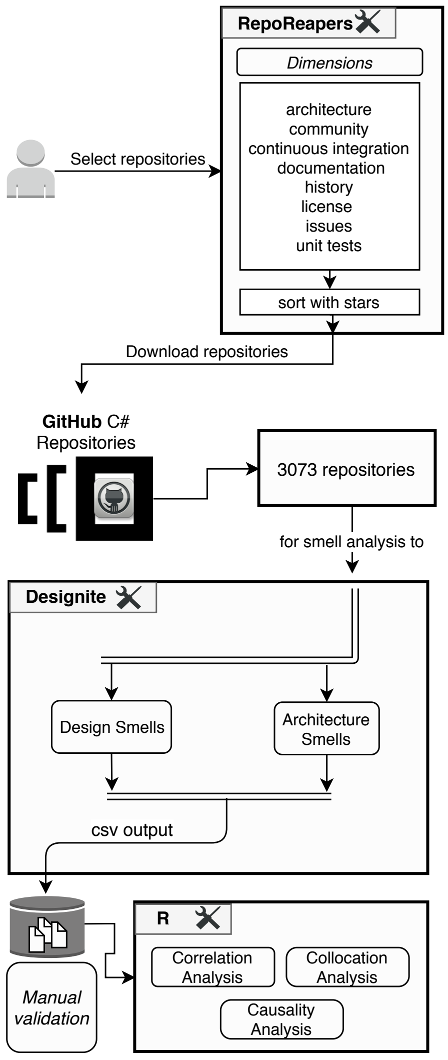


Fig. 3: Overview of the Method

and `TypeSystem.Implementation` (I) of `ICSharpCode.NRefactory` project[10]. These four components have four unit cycles *i.e.,* cycles containing exactly two components; however, permutations of components forming a cycle having more than two components lead the tool to report eight *cyclic dependency* architecture smell instances in this project. The tool discards repeating subsequences and cycles more than the length of five.

[10] `https://github.com/icsharpcode/NRefactory`

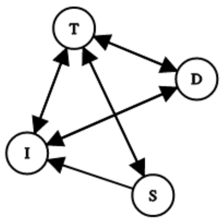


Fig. 4: Dependencies among four components of NRefactory

Table 4: Number of detected instances and smell density (per KLOC) of architecture smells in the analyzed repositories

| Architecture smell | #Instances | Smell density |
|---|---|---|
| Cyclic Dependency | 47 270 | 0.398 |
| Feature Concentration | 23 483 | 0.198 |
| Scattered Functionality | 20 170 | 0.170 |
| Unstable Dependency | 11 823 | 0.099 |
| God Component | 6 758 | 0.057 |
| Ambiguous Interface | 1 223 | 0.010 |
| Dense Structure | 144 | 0.001 |

The *dense structure* smell has been detected the least number of times among the detected smells. This can mainly be attributed to the fact that, by definition, the smell can be detected at most once in a repository while all other architecture smells can be spotted multiple times in a repository. Along the same lines, the *ambiguous interface* smell occurs occasionally because often a component has multiple interfacing points and extra effort is required to make a component offer only one entry-point.

Apart from the number of detected instances of architecture smells, we present the total detected instances of design smells in the analyzed repositories in Table 5. At design granularity, *cyclically-dependent modularization* and *unutilized abstraction* are the most frequently occurring smells.

Both *feature concentration* and *multifaceted abstraction* capture the cohesion aspect. The difference between them is that *feature concentration* happens when a set of classes within an architectural component do not follow the single responsibility principle (SRP) whereas *multifaceted abstraction* smell arises due to the violation of the same principle among the methods of a class. **Surprisingly, *feature concentration* smell occurs more often at architecture granularity (20% of the components) than its design granularity counterpart —*multifaceted abstraction* (0.3% of all the types).** This indicates that components are more prone to violate the single responsibility principle than the classes at design granularity. Therefore, the software developers must pay attention to the component composition and cohesion when they extend a component.

Similarly, *god component* and *insufficient modularization* smells violate the principle of modularization at architecture and design granularity respectively.

Table 5: Number of detected instances and smell density (per KLOC) of design smells in the analyzed repositories

| Design smell | #Instances | Smell density |
|---|---:|---:|
| Cyclically-dependent Modularization | 224 218 | 1.888 |
| Unutilized Abstraction | 194 852 | 1.641 |
| Duplicate Abstraction | 165 558 | 1.394 |
| Unnecessary Abstraction | 157 619 | 1.327 |
| Deficient Encapsulation | 73 591 | 0.619 |
| Insufficient Modularization | 57 698 | 0.486 |
| Broken Hierarchy | 48 485 | 0.408 |
| Broken Modularization | 45 771 | 0.385 |
| Unfactored Hierarchy | 41 387 | 0.348 |
| Rebellious Hierarchy | 40 848 | 0.344 |
| Imperative Abstraction | 20 023 | 0.168 |
| Cyclic Hierarchy | 16 260 | 0.136 |
| Unexploited Encapsulation | 13 463 | 0.113 |
| Wide Hierarchy | 6834 | 0.057 |
| Multipath Hierarchy | 6 269 | 0.052 |
| Missing Hierarchy | 3 296 | 0.027 |
| Multifaceted Abstraction | 3 166 | 0.026 |
| Hub-like Modularization | 1 509 | 0.012 |
| Deep Hierarchy | 630 | 0.005 |

We observe that both of these smells show similar occurrence frequency; 6% and 5% of the components and types respectively suffer from *god component* and *insufficient modularization* smells.

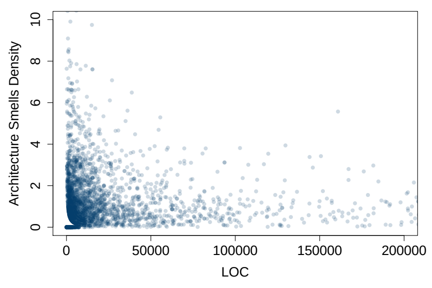
**In summary, *cyclic dependency* and *feature concentration* are the two most frequently occurring architecture smells. It is recommended for developers to avoid cycles among components and make components cohesive to increase maintainability of their software systems.**

**RQ2.** ***Is architecture smell density affected by the size of the repositories?***

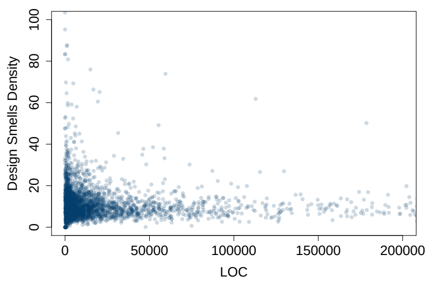
**Approach:** Smell density [74, 75] is a normalized metric that represents the average number of smells identified per thousand lines of code. We obtain a total number of lines of code as well as total number of architecture smells for each repository from the results produced by the tool. Using this information, we compute architecture smell density for all the analyzed repositories individually. We also compute the Spearman correlation coefficient between the architecture smell density and the repository size (in LOC).

**Results:** We would like to observe how architecture smell density changes with the repository size. Figure 5a shows a scatter plot between architecture smell density and LOC of repositories. A Spearman correlation ($\rho$) value of 0.2140 (with p-value $< 2.2e-16$) shows no correlation between architecture smell density and LOC. Similarly, analyzing the correlation between design smell density and LOC gives us a value of $-0.0758$ (with p-value $< 2.2e-16$) (refer to Figure 5b).

**The results indicate that the size of a project has no impact on the smell density of the project.**



(a)



(b)

Fig. 5: Architecture/design smell density vs LOC

**RQ3.** ***Are detected architecture smell instances correlated with design smells instances?***

**Approach:** We compute the total number of smell instances belonging to each smell type individually—let us say $A$ (total architecture smell instances) and $D$ (total design smell instances) for each repository. We then find the Spearman correlation between the series of $A$ and $D$. Further, we computed the total number of smell instances for each architecture (referred to as $A_i$ where $i$ may take values from 1 to 7 representing each architecture smell analyzed) and design (referred to as $D_j$ where $j$ may take values from 1 to 19 representing each design smell analyzed) smell. We calculate the Spearman coefficient between the individual pairs of architecture and design smells, *i.e.*, between each pair of $A_i$ and $D_j$ for all possible values of $i$ and $j$, to observe the fine-grained correlation between architecture and design smell pairs.

**Results:** The number of detected instances of architecture and design smells exhibit a very high Spearman correlation coefficient ($\rho$) value of 0.8494 (with p-value $< 2.2e - 16$). Figure 6 shows a scatter plot between total detected instances of architecture and design smells in each repository. **This indicates that architecture smells exhibit strong positive correlation with design smells.** Therefore, it can be inferred that a large population of design smell instances present in a repository is associated with the presence of a high number of architecture smell instances and vice-versa. These observations might encourage a software developer to find and refactor architecture smells when she finds a large number of design smells in her software system.

To find deeper and fine-grained relationships, we compute Spearman correlation coefficients between individual design smells and architecture smells.

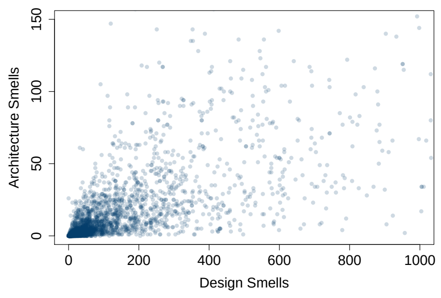


Fig. 6: Scatter plot between number of architecture smells and design smells

Figure 7 presents Spearman correlation coefficient values for all 133 architecture-design smell pairs in a heatmap. The darker color of a cell in the heatmap shows a stronger correlation. A cell with coefficient value in the red color shows statistically insignificant values (p-value $\geq 0.005$).

The heatmap shows strong correlation for many smell pairs. *Feature concentration* and *unutilized abstraction* show the strongest individual correlation (0.83). We discussed a real-world example discussing the relationship between the two smells in Section 2. Smell pair *feature concentration* and *unnecessary abstraction* also shows a high correlation as the presence of *unnecessary abstraction* instances increases the chance of detecting *feature concentration* smell. Similarly, other pairs of smells that show high correlation are: *god component* and *insufficient modularization* and *cyclic dependency* and *cyclically-dependent modularization*. On the other hand, *ambiguous interface* and *dense structure* at architecture granularity and *deep hierarchy* at the design granularity show the least correlation with other smells.

**The high correlation between cumulative as well as individual pairs of design and architecture smells indicates that a software developer must pay attention to the quality at architecture (or design) granularity if she perceives high number of smells at design (or architecture) granularity.**

## RQ4. *Are architecture smells collocated with design smells?*

**Approach:** Architecture and design smells differ in granularity, hence they get reported in a set of components and a set of classes, respectively. To analyze whether both kinds of smells are collocated, we identify a set of *participating classes* for each architecture smell. A participating class contributes non-trivially to the occurrence of an architecture smell instance. Specifically, a design smell instance $d$ and architecture smell instance $a$ are considered to be "collocated" if a class reported by the instance $d$ participates in instance $a$.

We created a table containing all the classes belonging to all the analyzed repositories with their corresponding total architecture and design smell in-

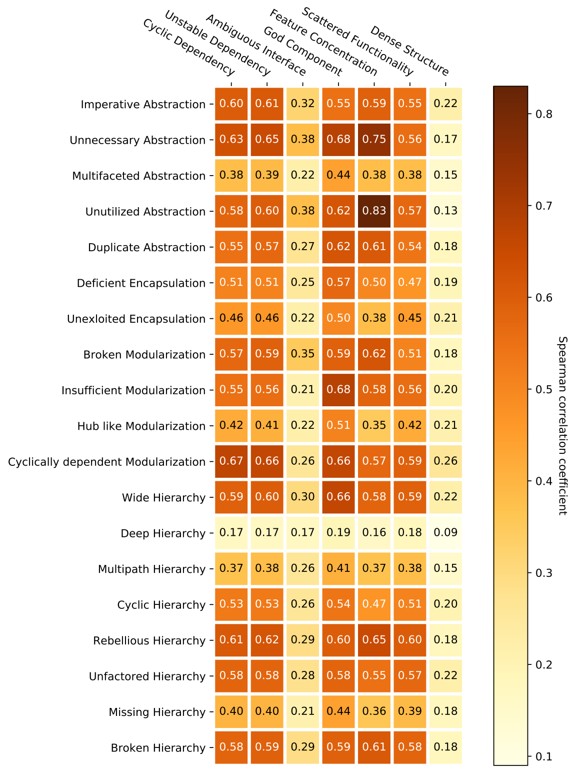


Fig. 7: Spearman correlation coefficients between individual architecture and design smells

stances. We created 2 × 2 contingency matrices for both the smell categories and compute phi-coefficient. The value of phi-coefficient measure the degree of association between two variables [15].

We analyzed cumulative instances of both smell categories as well as 133 individual smell pairs. Naturally, the frequency of architecture and design smells are not the same due to the difference in granularity and scale; thus the number of architecture smells is significantly lower than the number of design smells instances. We have to normalize both the numbers for semantically correct analysis and therefore we normalize the number of design smells by multiplying the ratio of specific design and architecture smells.

Table 6: Contingency matrix for a design and architecture smell

| | | Design smell | |
|---|---|---|---|
| | | 1 | 0 |
| Architecture smell | 1 | a | b |
| | 0 | c | d |

Table 6 shows the contingency matrix for a design and architecture smell pair. The values of variables *a, b, c,* and *d* are used to compute the phi-coefficient [15]. However, as described above, we normalize the number of design smells instances *i.e., c*.

$$c' = c \times \frac{\text{Number of architecture smells}}{\text{Number of design smells}} \tag{6}$$

We compute phi-coefficient using the following equation.

$$\phi = \frac{a \times d - c' \times b}{\sqrt{(a+b) \times (c'+d) \times (a+c') \times (b+d)}} \tag{7}$$

**Inferring participating classes:**
To perform the collocation analysis between architecture and design smell instances, we identify participating classes for each architecture smell. A participating class contributes to the architecture smell non-trivially. We formulated and implemented the following rules to infer participating classes for each architecture smell.

*Cyclic dependency:* For each identified cycle, we find the classes (belonging to each component contributing to the formation of the cycle) that participate in the cycle. We include all these classes to the participating classes list.

*Unstable dependency:* This smell occurs when a component depends on another component which is less stable than itself. In this case, all the classes that refer to classes of a less stable component are the participating classes for this smell.

*Ambiguous interface:* We detect the smell when a component has only one public or internal method. We assign the class that has the public or internal method as the participating class for the architecture smell.

*God component:* The tool detects two variants of this smell. First, using LOC-based detection where LOC of the component crosses a threshold and second, using NOC-based detection where the number of classes in the component crosses a threshold. We include all the classes of the component as the participating classes.

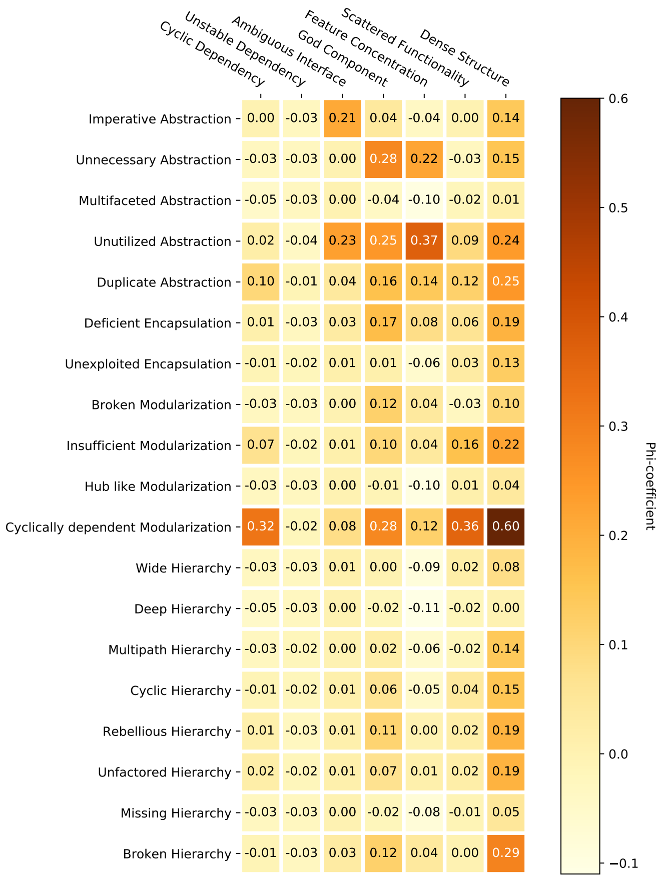
*Feature concentration:* We detect the smell when a component is realizing more than one responsibility. We include all the classes of the component as the participating classes for the smell.

*Scattered functionality:* In this smell, classes scattered in multiple components realize the same architectural concern. We identify all these classes and tag them responsible for this architecture smell.

*Dense structure:* We identify all classes that refer to at least one class belonging to another component (hence contributing to the degree of the host component). We include all of the identified classes as the participating classes for the architecture smell.

**Results:** We obtained $\phi = -0.14$ as the value of phi-coefficient computed for cumulative values of design and architecture smells for each type. The value of phi-coefficient indicates that design and architecture smells do not collocate.

We also compute phi-coefficients for individual architecture and design smell pairs. Figure 8 shows collocation analysis heatmap of architecture and design smells. Each cell shows the computed phi-coefficient for an architecture-design smell pair.



| | Cyclic Dependency | Unstable Dependency | Ambiguous Interface | God Component | Feature Concentration | Scattered Functionality | Dense Structure |
|---|---|---|---|---|---|---|---|
| Imperative Abstraction | 0.00 | -0.03 | 0.21 | 0.04 | -0.04 | 0.00 | 0.14 |
| Unnecessary Abstraction | -0.03 | -0.03 | 0.00 | 0.28 | 0.22 | -0.03 | 0.15 |
| Multifaceted Abstraction | -0.05 | -0.03 | 0.00 | -0.04 | -0.10 | -0.02 | 0.01 |
| Unutilized Abstraction | 0.02 | -0.04 | 0.23 | 0.25 | 0.37 | 0.09 | 0.24 |
| Duplicate Abstraction | 0.10 | -0.01 | 0.04 | 0.16 | 0.14 | 0.12 | 0.25 |
| Deficient Encapsulation | 0.01 | -0.03 | 0.03 | 0.17 | 0.08 | 0.06 | 0.19 |
| Unexploited Encapsulation | -0.01 | -0.02 | 0.01 | 0.01 | -0.06 | 0.03 | 0.13 |
| Broken Modularization | -0.03 | -0.03 | 0.00 | 0.12 | 0.04 | -0.03 | 0.10 |
| Insufficient Modularization | 0.07 | -0.02 | 0.01 | 0.10 | 0.04 | 0.16 | 0.22 |
| Hub like Modularization | -0.03 | -0.03 | 0.00 | -0.01 | -0.10 | 0.01 | 0.04 |
| Cyclically dependent Modularization | 0.32 | -0.02 | 0.08 | 0.28 | 0.12 | 0.36 | 0.60 |
| Wide Hierarchy | -0.03 | -0.03 | 0.01 | 0.00 | -0.09 | 0.02 | 0.08 |
| Deep Hierarchy | -0.05 | -0.03 | 0.00 | -0.02 | -0.11 | -0.02 | 0.00 |
| Multipath Hierarchy | -0.03 | -0.02 | 0.00 | 0.02 | -0.06 | -0.02 | 0.14 |
| Cyclic Hierarchy | -0.01 | -0.02 | 0.01 | 0.06 | -0.05 | 0.04 | 0.15 |
| Rebellious Hierarchy | 0.01 | -0.03 | 0.01 | 0.11 | 0.00 | 0.02 | 0.19 |
| Unfactored Hierarchy | 0.02 | -0.02 | 0.01 | 0.07 | 0.01 | 0.02 | 0.19 |
| Missing Hierarchy | -0.03 | -0.03 | 0.00 | -0.02 | -0.08 | -0.01 | 0.05 |
| Broken Hierarchy | -0.01 | -0.03 | 0.03 | 0.12 | 0.04 | 0.00 | 0.29 |

Fig. 8: Collocation analysis between individual architecture and design smell pairs

Phi-coefficient between *cyclically-dependent modularization* and *dense structure* shows the highest collocation. It is logical because cycles between classes increase the complexity of software's dependency graph and degree of components that in turn leads to *dense structure* smell. Similarly, the phi-coefficient between *feature concentration* and *unutilized abstraction* shows relatively high collocation. This collocation makes sense because the presence of one or more unutilized abstractions increases the value of LCC for a component. This increased value of LCC, in turn, leads to *feature concentration* smell as discussed in the detection mechanism for the smell (Section 4.2). We discussed a concrete example of collocation between *feature concentration* and *unutilized abstraction* in Section 2. Along the expected lines, *cyclically-dependent modularization* design smell shows relatively higher collocation with *cyclic dependency* architecture smell.

**Apart from a few smell pairs, rest of the smells pairs show low values of collocation coefficient. The low collocation values suggest that majority of architecture and design smells do not collocate with each other.**

We present an example of collocation of *feature concentration* architecture smell and *cyclically-dependent modularization* design smell. The component `ICSharpCode.NRefactory` in NRefactory[11] project contains ten classes/interfaces. As explained in Section 4.2, we identify disconnected dependency graphs within a component and compute LCC. Figure 9 shows the identified disconnected dependency graph where each box encapsulates a set of related classes. The computed LCC is 0.5 that makes the component suffering from *feature concentration* smell. This component also reports a *cyclically-dependent modularization* design smell between `TextLocation` and `TextLocationConverter` classes (shown with red background).

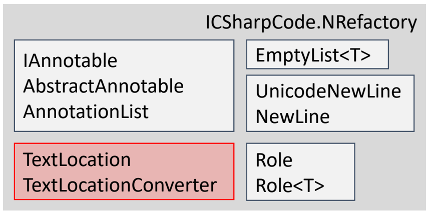


Fig. 9: Feature concentration smell identified for the `ICSharpCode.NRefactory` component; the smell is collocated with *cyclically-dependent modularization* design smell (between `TextLocation` and `TextLocationConverter` classes)

**RQ5.** ***Do design smells cause architecture smells (or vice-versa)?***

**Approach:** To further expand the analysis exploring the relationship between architecture and design smells, we explore the causality relationship between them.

We use the mechanism proposed by Granger [30] to figure out whether two random variables are associated with a causality relationship. We chose Granger's method to analyze causality relationship because the method has been used by other similar studies [12,13]. Specifically, Palomba et al. [67] have

[11] `https://github.com/icsharpcode/NRefactory`

used the same method in their exploration to study co-occurrences among code smells.

Equation 8 presents Granger's method mathematically. Architecture and design smell instances computed over a period of time represent two time-series $A$ and $D$ respectively. A variable $d$, representing design smell instances at time $t$, causes variable $a$, representing architecture smell instances at time $t$, if the predictions of variable $a$ with the past values of both $a$ as well as $d$ are better than the predictions using only the past values of $a$. The following equation expresses the above intuition mathematically.

$$a(t) = \sum_{j=1}^{k} f(a(t-j)) + \sum_{j=1}^{k} f(d(t-j)) \tag{8}$$

To carry out the causality analysis, we required time-series data of design and architecture smell instances detected for many versions belonging to a repository. We chose five repositories from our selected collection of repositories (refer to Section 5.2) with the highest number of commits. These repositories were chosen to maximize the chances of getting a sufficiently long time-series to carry out the analysis.

It is prohibitively resource-intensive to analyze all commits of a repository (one of the repositories contains close to 65 thousand commits). To select a subset of these commits, a naive way could have been to select a predefined number of commits equally divided on the temporal dimension. For instance, Couto et al. [12] select commits at every two-weeks temporal distance. However, this mechanism would result in a set of commits that missed some commits with many changes and included commits that are superfluous *i.e.,* very similar to other commits. We propose a new mechanism to identify commits that need to be analyzed to produce a time-series for our causality analysis, based on a divide and conquer strategy.

Algorithm 1 presents the pseudo-code that we employed to select a set of commits for the analysis. It starts with the first and the last commit by including them in the selected commits. It then checks whether the commit in the middle of both the start and end commits should be included for the analysis. The algorithm includes the middle commit if the commit is significantly different than the start or end commit. A commit is significantly different than another commit if the number of classes that are different from one commit to another crosses a threshold (we used 20% as the threshold value). We decide a class in a commit is different than the class with the same name in another commit if both of these classes have different values for at least one of these metrics: weighted methods per class (WMC), number of children (NC), lack of cohesion in methods (LCOM), Fan-in, and Fan-out. If the algorithm finds a commit significant, then it looks for other commits that need to be included recursively by finding the next middle commit. We verified implementation of the algorithm by manually checking the produced results at each intermediary step to ensure the correctness of the algorithm.

```
Input: Path of a repository
Output: Selected commits
begin
    allCommits = GetAllCommitHash(repositoryPath)
    selectedCommit.Add(0)
    AnalyzeCommit(allCommits[0])
    lastCommitIndex = allCommits.Size − 1
    selectedCommit.Add(lastCommitIndex)
    AnalyzeCommit(AllCommits[lastCommitIndex])
    FindIntermediateCommits(allCommits, 0, lastCommitIndex, ‘f’)
end

FindIntermediateCommits()
Input: all commits, startIndex, endIndex, direction
Output: Selected commits
begin
    if endIndex ≤ startIndex then
        return
    end
    nextCandidate = (startIndex + endIndex) / 2
    if nextCandidate ≤ startIndex or nextCandidate ≥ endIndex then
        return
    end
    AnalyzeCommit(allCommits[nextCandidate])
    if direction = ‘f’ then
        isSignificant = IsDifferenceSignificant(allCommits[startIndex],
          allCommits[nextCandidate])
    else
        isSignificant = IsDifferenceSignificant(allCommits[nextCandidate],
          allCommits[endIndex])
    end
    if isSignificant then
        selectedCommits.Add(nextCandidate)
        FindIntermediateCommits(allCommits, startIndex, nextCandidate, ‘f’)
        FindIntermediateCommits(allCommits, nextCandidate, endIndex, ‘b’)
    end
end

IsDifferenceSignificant()
Input: commit1, commit2, threshold
Output: True/False
begin
    changedClasses = 0
    for each class c in commit1 and commit2 do
        metrics1, metrics2 = ReadMetrics(GetClass(c, commit1), GetClass(c,
          commit2))
        if metrics1 ≠ metrics2 then
            changedClasses += 1
        end
    end
    changeRatio = changedClasses/totalClasses
    if changeRatio ≥ threshold then
        return True
    else
        return False
    end
end
```

**Algorithm 1:** The proposed algorithm to select commits for analysis

We analyzed each of the five repositories and present here the results from one repository, RavenDB,[12] with the largest number of significant commits.

It is mandatory to ensure the *stationary* property of a time-series before analyzing it and drawing conclusions based on that. A time-series is stationary if its statistical properties such as mean, variance, and autocorrelation are constant over time [14]. If a time-series is non-stationary, it shows seasonal effects, trends, and fluctuating statistical properties changing over time. Such effects are undesired for the causality analysis and thus a time-series must be made stationary before we perform the causality analysis. We carried out the augmented Dickey-Fuller unit root test [27] to check the stationary property of our time-series. Initially, our time-series was non-stationary. There are a few techniques to make a non-stationary time-series a stationary one [40]. We addressed this issue by applying a *difference* transformation, *i.e.,* subtracting the previous observation from the present observation for all columns. Techniques such as *differencing*, that we applied, help stabilize the mean of a time series by removing changes in the time series, and therefore eliminate or reduce the non-stationary nature of the series. This transformation resulted in a stationary time-series that we confirmed by performing the augmented Dickey-Fuller unit root test again. We carried out the causality analysis on the cumulative sum of all design and architecture smells for each analyzed commit as well as on individual types of design and architecture smells.

**Results:** We first compute the Granger causality between cumulative values of design and architecture smells. Table 7 presents the results of the causality test. The p-values shown in each cell show the causality from column to row. The table shows that design smells cause architecture smells with significant p-value (*i.e.,* less than 0.005). Time-series obtained from analyzing other repositories also confirm the observation. For instance, causality analysis on Umbraco-CMS[13] repository also shows that design smells cause architecture smells with p-value 0.0036 while cumulative architecture smells do not decisively cause design smells with p-value 0.3593.

Table 7: Causality test results (p-values) between cumulative values of design and architecture smells

| | Architecture smells | Design smells |
|---|---|---|
| Architecture smells | 1 | 0.0001 |
| Design smells | 0.2669 | 1 |

We also carried out causality analysis at individual smell granularity. Table 8 shows p-values corresponding to the causal effect of individual design smells on architecture smells, where the blue-colored cells indicate a significant causal relationship. It is interesting to note that *cyclically-dependent modularization* appears to cause all architecture smells. Also, smells such as *hub-like*

[12] `https://github.com/ravendb/ravendb`

[13] `https://github.com/umbraco/Umbraco-CMS`

Table 8: Causality test results (p-values) showing individual design smells causing architecture smells

| | Imperative Abstraction | Unnecessary Abstraction | Multifaceted Abstraction | Unutilized Abstraction | Duplicate Abstraction | Deficient Encapsulation | Unexploited Encapsulation | Broken Modularization | Insufficient Modularization | Hub-like Modularization | Cyclically-dependent Modularization | Wide Hierarchy | Deep Hierarchy | Multipath Hierarchy | Cyclic Hierarchy | Rebellious Hierarchy | Unfactored Hierarchy | Missing Hierarchy | Broken Hierarchy |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Cyclic Dependency | 0.001 | 0.630 | 0.143 | 0.086 | 0.078 | 0.059 | 0.000 | 0.053 | 0.313 | 0.003 | 0.000 | 0.709 | — | 0.000 | 0.752 | 0.108 | 0.222 | 0.064 | 0.893 |
| Unstable Dependency | 0.003 | 0.376 | 0.403 | 0.128 | 0.069 | 0.069 | 0.000 | 0.048 | 0.827 | 0.003 | 0.000 | 0.726 | — | 0.000 | 0.205 | 0.264 | 0.121 | 0.123 | 0.714 |
| Ambiguous Interface | 0.004 | 0.019 | 0.181 | 0.323 | 0.044 | 0.144 | 0.353 | 0.026 | 0.027 | 0.011 | 0.001 | 0.001 | — | 0.943 | 0.192 | 0.285 | 0.509 | 0.384 | 0.231 |
| God Component | 0.565 | 0.003 | 0.064 | 0.337 | 0.001 | 0.757 | 0.583 | 0.007 | 0.046 | 0.070 | 0.000 | 0.741 | — | 0.765 | 0.050 | 0.504 | 0.114 | 0.001 | 0.305 |
| Feature Concentration | 0.323 | 0.013 | 0.128 | 0.611 | 0.001 | 0.318 | 0.329 | 0.004 | 0.407 | 0.226 | 0.000 | 0.841 | — | 0.650 | 0.027 | 0.325 | 0.174 | 0.005 | 0.222 |
| Scattered Functionality | 0.608 | 0.200 | 0.416 | 0.672 | 0.182 | 0.010 | 0.002 | 0.234 | 0.083 | 0.003 | 0.000 | 0.151 | — | 0.588 | 0.393 | 0.258 | 0.922 | 0.017 | 0.171 |
| Dense Structure | 0.253 | 0.105 | 0.404 | 0.058 | 0.217 | 0.275 | 0.138 | 0.416 | 0.644 | 0.208 | 0.001 | 0.000 | — | 0.000 | 0.095 | 0.061 | 0.180 | 0.002 | 0.004 |

Table 9: Causality test results (p-values) showing individual architecture smells causing design smells

| | Cyclic Dependency | Unstable Dependency | Ambiguous Interface | God Component | Feature Concentration | Scattered Functionality | Dense Structure |
|---|---|---|---|---|---|---|---|
| Imperative Abstraction | 0.724 | 0.649 | 0.737 | 0.882 | 0.479 | 0.875 | 0.000 |
| Unnecessary Abstraction | 0.000 | 0.000 | 0.549 | 0.834 | 0.952 | 0.255 | 0.041 |
| Multifaceted Abstraction | 0.007 | 0.144 | 0.387 | 0.121 | 0.237 | 0.086 | 0.025 |
| Unutilized Abstraction | 0.000 | 0.000 | 0.273 | 0.844 | 0.732 | 0.207 | 0.641 |
| Duplicate Abstraction | 0.024 | 0.000 | 0.543 | 0.889 | 0.826 | 0.314 | 0.722 |
| Deficient Encapsulation | 0.001 | 0.115 | 0.164 | 0.317 | 0.379 | 0.200 | 0.702 |
| Unexploited Encapsulation | 0.001 | 0.006 | 0.058 | 0.728 | 0.701 | 0.631 | 0.002 |
| Broken Modularization | 0.110 | 0.006 | 0.285 | 0.889 | 0.701 | 0.197 | 0.297 |
| Insufficient Modularization | 0.001 | 0.050 | 0.244 | 0.740 | 0.926 | 0.336 | 0.005 |
| Hub-like Modularization | 0.000 | 0.061 | 0.092 | 0.429 | 0.584 | 0.841 | 0.792 |
| Cyclically-dependent Mod. | 0.700 | 0.085 | 0.001 | 0.334 | 0.233 | 0.171 | 0.000 |
| Wide Hierarchy | 0.185 | 0.203 | 0.217 | 0.644 | 0.446 | 0.284 | 0.435 |
| Deep Hierarchy | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Multipath Hierarchy | 0.002 | 0.001 | 0.177 | 0.600 | 0.335 | 0.362 | 1.000 |
| Cyclic Hierarchy | 0.895 | 0.090 | 0.004 | 0.728 | 0.123 | 0.053 | 0.305 |
| Rebellious Hierarchy | 0.000 | 0.002 | 0.385 | 0.865 | 0.824 | 0.231 | 0.214 |
| Unfactored Hierarchy | 0.450 | 0.492 | 0.003 | 0.430 | 0.562 | 0.013 | 0.966 |
| Missing Hierarchy | 0.523 | 0.245 | 0.038 | 0.837 | 0.175 | 0.030 | 0.001 |
| Broken Hierarchy | 0.873 | 0.171 | 0.000 | 0.898 | 0.852 | 0.009 | 0.966 |

*modularization* and *multipath hierarchy* also contribute towards causing three kinds of architecture smells each. On the other hand, many smells such as *deficient encapsulation*, *multifaceted abstraction*, and *unutilized abstraction* do not cause any architecture smell. *Deep hierarchy* smell was not detected in the repository and hence its degree of involvement in causing architecture smells cannot be determined.

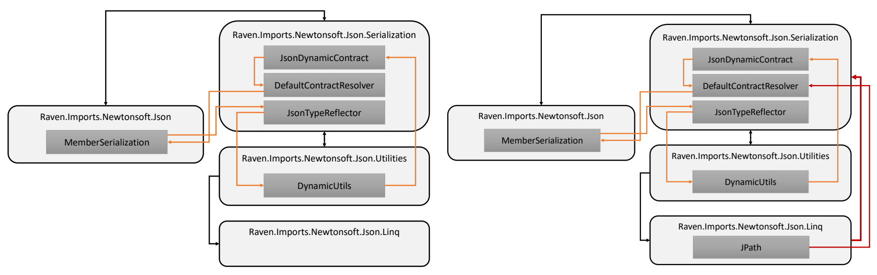
We also performed causality analysis in the opposite direction *i.e.,* exploring whether architecture smells cause design smells at the individual level. Table 9 shows the results of the analysis. Unsurprisingly, the *cyclic dependency* causes eight kinds of design smells. *God component, feature concentration,* and *scattered functionality* architecture smells do not contribute at all towards causing design smells. It is interesting to note that only *multifaceted abstraction* smell neither causes any architecture smell nor is it caused by any architecture smell.

**In summary, we found that design smells cumulatively cause architecture smells. This implies that the current set of architecture smells in software systems are present due to smells at both design and architecture granularity in the previous versions of the software.**

Next, we present couple of examples demonstrating design smells causing architecture smells as a software system evolves. Both the examples presented below are observed from the RavenDB repository; we analyzed many commits of the repository for the causality analysis.

As Table 8 shows, *cyclically-dependent modularization* exhibits the highest causality on architecture smells among all analyzed design smells. The following example shows how an instance of *cyclically-dependent modularization* that arose in one version leads to *cyclic dependency* architecture smell in a subsequent version of the software system. Figure 10 shows a design fragment where rounded-corner rectangles represent components and rectangles inside them represent classes belonging to the components. Orange arrows show dependencies between classes and black arrows show dependencies between components.

We observe that in a commit (ending with commit-hash `bfacefcb`), a *cyclically-dependent modularization* design smell has been detected among five classes. In this commit, components `Serialization, Utilities`, and `Linq` are not forming a cycle and hence no *cyclic dependency* architecture smell involving these components is reported. However, in the next commit (ending with commit-hash `8cd11cff`), a class `JPath` in `Linq` component refers to a class in `Serialization` component and hence introduces a dependency between the components (shown by a red arrow in Figure 10b). It is important to note that source code changes carried out specifically in this commit do not introduce a cycle among architecture components. However, due to an existing cycle among other classes and components that was created in the last commit, a new cycle among the three components (*i.e.,* `Serialization, Utilities,` and `Linq`) is formed and reported in this commit. In other words, *cyclically-dependent modularization* design smell detected in the previous version **caused** a *cyclic dependency* architecture smell in this version.


Raven.Imports.Newtonsoft.Json.Serialization
JsonDynamicContract
DefaultContractResolver
JsonTypeReflector
Raven.Imports.Newtonsoft.Json
MemberSerialization
Raven.Imports.Newtonsoft.Json.Utilities
DynamicUtils
Raven.Imports.Newtonsoft.Json.Linq
Raven.Imports.Newtonsoft.Json.Serialization
JsonDynamicContract
DefaultContractResolver
JsonTypeReflector
Raven.Imports.Newtonsoft.Json
MemberSerialization
Raven.Imports.Newtonsoft.Json.Utilities
DynamicUtils
Raven.Imports.Newtonsoft.Json.Linq
JPath

(a) (b)

Fig. 10: cyclically-dependent modularization smell in version k leading to cyclic dependency architecture smell in version k+1. Dependencies between classes are shown by using orange arrows; black arrows show dependencies between components. Red arrow shows a new dependency that completes a cycle among three components.

Similarly, we discuss below how *unnecessary abstraction* design smell detected in a version caused *god component* architecture smell in the following versions of the software system. In a commit (ending with commit-hash `77ee97d8`), component `Newtonsoft.Json.Utilities` gets detected with four instances of *unnecessary abstraction* design smells; the component contains a total of 29 classes in the commit. However, in the following commit (ending with commit-hash `ece305f5`), the component introduces a few classes and the total number of classes reaches 32. Due to this increase, a *god component* architecture smell is detected in the component. However, we can infer that this instance of *god component* would not arise if the *unnecessary abstraction* smell instances were not detected in the previous commit. In summary, *unnecessary abstraction* smell instances detected in the previous commit **caused** the *god component* architecture smell instance in this commit.

## 7 Discussion and Implications

In this section, we provide interpretations of our findings. Our results reveal the individuality of smells at the explored granularities. In our context, individuality refers to the uniqueness of the smells showing differentiating characteristics than other smells. We also discuss the scope of each of the relationships examined in this work and the interplay among themselves. In the implication section, we emphasize that smells often occur independently at each granularity and software development teams must address them at all granularities.

### 7.1 Interpretations of results

We explore correlations between architecture and design smells cumulatively as well as between individual pairs. Very high correlations may indicate that a given smell is *superfluous*. For example, tracking humans' left-eye and right-eye colors will show an extremely high correlation between the two, and consequently storing only eye color is enough. Our analysis shows a very strong correlation between the high and low granularity smells when considered cumulatively; however, the fine-grained correlation analysis reveals varying degrees of correlation. This result demonstrates that each smell provides value-adding information. Furthermore, interestingly, even similar (by definition) smells at different granularities show varying degrees of correlation. Five architecture smells have similar corresponding smells at design granularity; it means that these smells represent and capture the same concept at different granularities. These smell pairs with their corresponding correlations are *cyclic dependency—cyclically-dependent modularization* ($\rho = 0.67$), *feature concentration—multifaceted abstraction* ($\rho = 0.38$), *scattered functionality—broken modularization* ($\rho = 0.51$), *god component—insufficient modularization* ($\rho = 0.68$), and *ambiguous interface—imperative abstraction* ($\rho = 0.32$). The varying degree of correlations—from low to moderate and strong—indicates the non-monotonic relationship between these smell pairs and further emphasizes the individuality and uniqueness of these smells.

We examine the collocation relationship between architecture and design smells; the results show that they exhibit collocation only for some smell pairs. It implies that though architecture smells arise from code and implementation choices made during the software development, the factors that cause them go beyond these choices and they have their individuality unique from smells at design granularity.

Our temporal analysis to explore the causality between design and architecture smells clearly shows that design smells cause architecture smells. In other words, the cause of the present set of detected architecture smells can often be traced back not only to the architecture smells in previous versions but also to the design smells.

## 7.2 Understanding the interplay between correlation, collocation, and causation

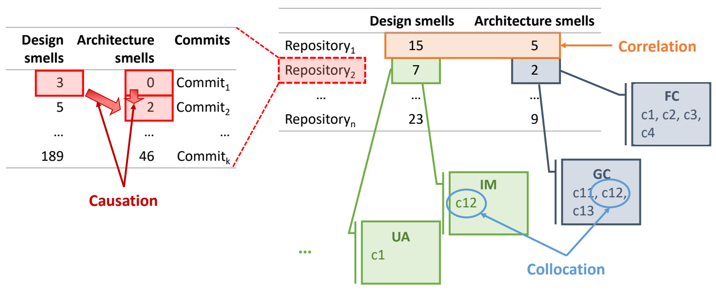


Fig. 11: Understanding correlation, collocation, and causation. IM and UA are examples of design smell instances and GC and FC are examples of architecture smell instances. $c_i$ refers to involved class in a smell instance.

Let us recap the correlation, collocation as well as causation between design and architecture smells (see Figure 11).

**Correlation** analysis is performed at the unit-scope of a repository *i.e.*, we measure the total number of detected instances for design and architecture smells for each repository and perform correlation analysis between the obtained series. This implies that the high correlation that our results exhibit is applicable at the repository or project level.

**Collocation** is calculated per class for each pair of design and architecture smell instance. We determine if the considered pair of architecture and design smell instance is occurring in the same set of classes. Architecture smells are by default reported at the component granularity and hence we map each instance of architecture smell to a set of classes by computing participating classes for the smell.

**Causation** is a temporal relationship that we measure by analyzing many commits of a repository and performing Granger's causality on the obtained time-series.

All this means is that correlation and collocation analysis differ significantly on their unit-scope. Given a confined unit-scope *i.e.,* type, collocation represents a stricter relationship compared to correlation. The source of the weaker collocation can be traced back to the stricter relationship.

## 7.3 Implications of Reported Findings

We infer the following implications for the software development community.

*Software development teams must detect, analyze, and refactor smells at all granularities.* This implication is derived from our correlation analysis for smells arising at different granularities. Our results show that the presence of a high volume of design smells is associated with the presence of a high number of architecture smells and vice versa. Existing tools (such as NDepend[14] and SonarQube[15]) mainly detect implementation and some design issues. Due to this limitation, a software development team using these tools perceives only a limited set of quality issues and thus issues at higher granularities may go unnoticed.

*Developers must avoid cycles among classes as well as among components* to keep the structure of the software easy to understand. Our results show that cyclic dependencies at both design and architecture granularities occur most frequently in open-source C# repositories compared to other smells (refer to RQ1 results). A higher number of cycles in software introduce tangles and make the software difficult to comprehend.

*The smell density of a software system does not depend on the size of the software.* Actively used software systems grow; however, whether the software evolves with the focus on code quality or not defines the long-term maintainability of the software. For example, in our analysis, the *dense structure* smell has been detected in fewer than 5% of the analyzed repositories. We observed that the median of LOC computed for all the analyzed repositories is 7 394 while it is 42 405 for the repositories where the smell has been detected. This indicates that the smell is less prone to occur in small repositories. However, the large size of a repository is not the only deciding factor. We found that 72 repositories are larger than the median LOC 42 405 where the smell does not occur. This implies that the evolution of a software system focused on quality may result in a more maintainable software system.

[14] `http://www.ndepend.com/`
[15] `https://www.sonarqube.org/`

### 7.4 Secondary Contributions of this Work

We have added support to detect seven architecture smells in the Designite tool. The software development community may use this tool to analyze their source code and improve the maintainability of their code. The research community may utilize the tool to carry out studies concerning code smells. The tool is available online[16] and free for all academic purposes.

We analyzed more than 3000 repositories to prepare a dataset containing the detected smells at architecture, design, and implementation granularities for each of the analyzed repositories. We used this dataset to answer the research questions addressed in this paper. We have made the dataset available online [72]. The software engineering research community may utilize it in many ways including bench-marking and comparison as well as exploring other dimensions of source code suffering from smells.

## 8 Threats to Validity

*Construct validity* concerns the appropriateness of observations and inferences made on the basis of measurements taken during the study. Static code analysis is typically prone to false-positives and false-negatives. To mitigate this concern, we employed a comprehensive set of tests for the smell detection tool used in this study to rule out obvious deficiencies. Additionally, we found the results of manual validation of the detected instances by the tool very satisfactory (Section 5.3.1).

Designite uses various metric thresholds to detect smells. It is a known and accepted fact that there is no one globally accepted threshold set for various metrics [25,35]. We chose the thresholds that are commonly used by the software engineering community. Moreover, we made many of the thresholds customizable within the tool to let users choose a set of appropriate thresholds based on their organization's preferences.

The higher the abstraction, the more important the context of a software system becomes. Context and domain knowledge play an important role while detecting and refactoring, especially, design and architecture smells. Given the sheer scale, it was not possible to carry out a qualitative analysis for all the repositories. Considering a large number of repositories mined in this study, we believe that the results are still relevant and generalizable.

While computing causality relationship between design and architecture smell instances over a period of time, there could be some confounding factors [81] that influence both design and architecture smell instances time-series. Randomization is often used to reduce the effects of confounding factors that we also adopted in the study.

*External validity* concerns the generalizability and repeatability of the produced results. The study analyzes only open-source C# repositories as subject

[16] `https://www.designite-tools.com`

systems. Given the fact that most of the current literature focuses only on subject systems written in Java programming language, our study complements the existing literature. Furthermore, we have considered a large set of 3 073 C# repositories of varied sizes and contexts, making this work the largest mining study (by scale) so far for software smells.

## 9 Conclusions

Architecture smells are the design degradation indicators at architecture granularity spanning multiple software components. Combining finer-grained code smells with the coarse-grain smells could make the task of maintaining a high quality of a software product easier. This work carries out correlation, collocation, and causation analysis to identify relationships among design and architecture smells. We implemented seven architecture smells in our code smell detection tool Designite and mined seven architecture and 19 design smells from a large set of 3 073 C# repositories downloaded from GitHub. A total of 1 232 348 architecture and design smell instances are made available to the software engineering research community in the form of a smell dataset.

The results of this study indicate that *cyclic dependency* is the most frequently occurring architecture smell. This may prompt developers to pay additional attention to avoid cycles among the components. The co-occurrence analysis shows that the architecture smells exhibit a strong positive correlation ($\rho = 0.85$) with design smells. This implies that a project containing a high number of design smells also exhibit a higher number of architecture smells and vice-versa. We perform fine-grained correlation analysis between individual smell pairs. The results reveal the varying degree of correlation between the smell-pairs belonging to different granularities.

Our collocation analysis reveals that both kinds of smells show selective collocation and the majority of smell pairs do not collocate with each other. Furthermore, our exploration to understand the causal relationship between architecture and design smells shows that design smells cause architecture smells. It implies that refactoring design smells early in a software development lifecycle may result in fewer architecture smells in the future versions of the software system.

In the future, we intend to extend our supported set of architecture smells and carry out more detailed analysis such as patterns of smell introduction and removal with time along with their relationships. Further, a comprehensive catalog of architecture smells containing examples, causes, appropriate thresholds, and remedies would be of great use to the software practitioners.

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## References

1. Abbes, M., Khomh, F., Gueheneuc, Y., Antoniol, G.: An empirical study of the impact of two antipatterns, blob and spaghetti code, on program comprehension. In: 2011 15th European Conference on Software Maintenance and Reengineering, pp. 181–190 (2011). DOI 10.1109/CSMR.2011.24
2. de Andrade, H.S., Almeida, E., Crnkovic, I.: Architectural bad smells in software product lines: An exploratory study. In: Proceedings of the WICSA 2014 Companion Volume, WICSA '14 Companion, pp. 12:1–12:6. ACM (2014). DOI 10.1145/2578128.2578237
3. Arcelli Fontana, F., Mäntylä, M.V., Zanoni, M., Marino, A.: Comparing and experimenting machine learning techniques for code smell detection. Empirical Software Engineering **21**(3), 1143–1191 (2016)
4. Bass, L., Clements, P., Kazman, R.: Software Architecture in Practice, 3rd edn. Addison-Wesley Professional (2012)
5. Bavota, G., De Lucia, A., Di Penta, M., Oliveto, R., Palomba, F.: An experimental investigation on the innate relationship between quality and refactoring. Journal of Systems and Software **107**, 1–14 (2015)
6. Behnamghader, P., Le, D.M., Garcia, J., Link, D., Shahbazian, A., Medvidovic, N.: A large-scale study of architectural evolution in open-source software systems. Empirical Softwate Engineering **22**(3), 1146–1193 (2017). DOI 10.1007/s10664-016-9466-0. URL `https://doi.org/10.1007/s10664-016-9466-0`
7. Besker, T., Martini, A., Bosch, J.: Managing architectural technical debt: A unified model and systematic literature review. Journal of Systems and Software **135**, 1 – 16 (2018). DOI https://doi.org/10.1016/j.jss.2017.09.025. URL `http://www.sciencedirect.com/science/article/pii/S0164121217302121`
8. Bloch, J.: Effective Java (2nd Edition) (The Java Series), 2 edn. Prentice Hall PTR (2008)
9. Booch, G., Rumbaugh, J., Jacobson, I.: The Unified Modeling Language User Guide. Addison-Wesley, Reading, MA (1999)
10. Brown, W.J., Malveau, R.C., McCormick, H.W.S., Mowbray, T.J.: AntiPatterns: Refactoring Software, Architectures, and Projects in Crisis, 1 edn. John Wiley & Sons (1998)
11. Chidamber, S.R., Kemerer, C.F.: A metrics suite for object oriented design. IEEE Trans. Softw. Eng. **20**(6), 476–493 (1994). DOI 10.1109/32.295895
12. Couto, C., Pires, P., Valente, M.T., Bigonha, R.S., Anquetil, N.: Predicting software defects with causality tests. Journal of Systems and Software **93**, 24 – 41 (2014). DOI https://doi.org/10.1016/j.jss.2014.01.033. URL `http://www.sciencedirect.com/science/article/pii/S0164121214000351`
13. Couto, C., Pires, P., Valente, M.T., da Silva Bigonha, R., Hora, A.C., Anquetil, N.: Bugmaps-granger: A tool for causality analysis between source code metrics and bugs (2013)
14. Cox, D., Miller, H.: The Theory of Stochastic Process, 1 edn. Chapman and Hall, London (1965)
15. Cramer, H.: Mathematical Methods of Statistics, 1 edn. Princeton University Press (1946)
16. Cui, D., Liu, T., Cai, Y., Zheng, Q., Feng, Q., Jin, W., Guo, J., Qu, Y.: Investigating the impact of multiple dependency structures on software defects. In: Proceedings of the 41st International Conference on Software Engineering, ICSE '19, pp. 584–595. IEEE Press, Piscataway, NJ, USA (2019). DOI 10.1109/ICSE.2019.00069. URL `https://doi.org/10.1109/ICSE.2019.00069`

17. Deursen, A.v., Moonen, L., Bergh, A.v.d., Kok, G.: Refactoring test code. In: M. Marchesi (ed.) Proceedings of the 2nd International Conference on Extreme Programming and Flexible Processes (XP2001), pp. 92–95. University of Cagliari (2001)
18. Ferreira, K.A., Bigonha, M.A., Bigonha, R.S., Mendes, L.F., Almeida, H.C.: Identifying thresholds for object-oriented software metrics. Journal of Systems and Software **85**(2), 244 – 257 (2012). DOI https://doi.org/10.1016/j.jss.2011.05.044. URL `http://www.sciencedirect.com/science/article/pii/S0164121211001385`. Special issue with selected papers from the 23rd Brazilian Symposium on Software Engineering
19. Filó, T.G.S., da Silva Bigonha, M.A.: A catalogue of thresholds for object-oriented software metrics (2015)
20. Fontana, F.A., Ferme, V., Marino, A., Walter, B., Martenka, P.: Investigating the Impact of Code Smells on System's Quality: An Empirical Study on Systems of Different Application Domains. In: 2013 IEEE International Conference on Software Maintenance (ICSM), pp. 260–269. IEEE (2013)
21. Fontana, F.A., Ferme, V., Zanoni, M.: Towards assessing software architecture quality by exploiting code smell relations. In: Proceedings of the 2015 IEEE/ACM 2Nd International Workshop on Software Architecture and Metrics, SAM '15, pp. 1–7. IEEE Computer Society, Washington, DC, USA (2015). DOI 10.1109/SAM.2015.8
22. Fontana, F.A., Lenarduzzi, V., Roveda, R., Taibi, D.: Are architectural smells independent from code smells? an empirical study. Journal of Systems and Software **154**, 139 – 156 (2019). DOI https://doi.org/10.1016/j.jss.2019.04.066. URL `http://www.sciencedirect.com/science/article/pii/S0164121219301013`
23. Fontana, F.A., Pigazzini, I., Roveda, R., Tamburri, D., Zanoni, M., Nitto, E.D.: Arcan: A Tool for Architectural Smells Detection. In: 2017 IEEE International Conference on Software Architecture Workshops (ICSAW), pp. 282–285. IEEE (2017)
24. Fontana, F.A., Pigazzini, I., Roveda, R., Zanoni, M.: Automatic detection of instability architectural smells. In: Software Maintenance and Evolution (ICSME), 2016 IEEE International Conference on, pp. 433–437. IEEE (2016)
25. Fourati, R., Bouassida, N., Abdallah, H.B.: A Metric-Based Approach for Anti-pattern Detection in UML Designs. In: Computer and Information Science 2011, pp. 17–33. Springer Berlin Heidelberg (2011)
26. Fowler, M.: Refactoring: Improving the Design of Existing Programs, 1 edn. Addison-Wesley Professional (1999)
27. Fuller, W.A.: Introduction to Statistical Time Series, 1 edn. John Wiley and Sons New York (1976)
28. Garcia, J.: Technical report: Architectural Smell Definitions and Formalizations. `http://csse.usc.edu/TECHRPTS/2014/reports/usc-csse-2014-500.pdf` (2014). [Online; accessed 16-June-2017]
29. Garcia, J., Popescu, D., Edwards, G., Medvidovic, N.: Toward a catalogue of architectural bad smells. In: Proceedings of the 5th International Conference on the Quality of Software Architectures: Architectures for Adaptive Software Systems, QoSA '09, pp. 146–162. Springer-Verlag (2009). DOI 10.1007/978-3-642-02351-4_10
30. Granger, C.W.J.: Investigating causal relations by econometric models and cross-spectral methods. Econometrica **37**(3), 424–438 (1969). URL `http://www.jstor.org/stable/1912791`
31. Guimaraes, E., Garcia, A., Cai, Y.: Exploring blueprints on the prioritization of architecturally relevant code anomalies – a controlled experiment. In: 2014 IEEE 38th Annual Computer Software and Applications Conference, pp. 344–353 (2014). DOI 10.1109/COMPSAC.2014.57
32. Guimarães, E., Vidal, S., Garcia, A., Diaz Pace, J.A., Marcos, C.: Exploring architecture blueprints for prioritizing critical code anomalies: Experiences and tool support. Software: Practice and Experience **48**(5), 1077–1106. DOI 10.1002/spe.2563. URL `https://onlinelibrary.wiley.com/doi/abs/10.1002/spe.2563`
33. Herbold, S., Grabowski, J., Waack, S.: Calculation and optimization of thresholds for sets of software metrics. Empirical Software Engineering **16**, 812–841 (2011)
34. Hochstein, L., Lindvall, M.: Diagnosing architectural degeneration. In: 28th Annual NASA Goddard Software Engineering Workshop, 2003. Proceedings., pp. 137–142 (2003)

35. Kessentini, W., Kessentini, M., Sahraoui, H., Bechikh, S., Ouni, A.: A Cooperative Parallel Search-Based Software Engineering Approach for Code-Smells Detection. IEEE Transactions on Software Engineering **40**(9), 841–861 (2014)
36. Khomh, F., Vaucher, S., Guéhéneuc, Y.G., Sahraoui, H.: A Bayesian Approach for the Detection of Code and Design Smells. In: QSIC '09: Proceedings of the 2009 Ninth International Conference on Quality Software, pp. 305–314. IEEE Computer Society (2009)
37. Koschke, R.: Survey of research on software clones. In: R. Koschke, E. Merlo, A. Walenstein (eds.) Duplication, Redundancy, and Similarity in Software, no. 06301 in Dagstuhl Seminar Proceedings. Internationales Begegnungs- und Forschungszentrum für Informatik (IBFI), Schloss Dagstuhl, Germany, Dagstuhl, Germany (2007). URL `http://drops.dagstuhl.de/opus/volltexte/2007/962`
38. Koziolek, H., Domis, D., Goldschmidt, T., Vorst, P.: Measuring architecture sustainability. IEEE Softw. **30**(6), 54–62 (2013). DOI 10.1109/MS.2013.101. URL `https://doi.org/10.1109/MS.2013.101`
39. Kruchten, P., Nord, R.L., Ozkaya, I.: Technical debt: From metaphor to theory and practice. IEEE Software **29**(6), 18–21 (2012). DOI 10.1109/MS.2012.167
40. Kwiatkowski, D., Phillips, P.C., Schmidt, P., Shin, Y.: Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? Journal of Econometrics **54**(1), 159 – 178 (1992). DOI https://doi.org/10.1016/0304-4076(92)90104-Y. URL `http://www.sciencedirect.com/science/article/pii/030440769290104Y`
41. Lanza, M., Marinescu, R., Ducasse, S.: Object-Oriented Metrics in Practice. Springer-Verlag, Berlin, Heidelberg (2005)
42. Le, D.M., Carrillo, C., Capilla, R., Medvidovic, N.: Relating architectural decay and sustainability of software systems. In: 2016 13th Working IEEE/IFIP Conference on Software Architecture (WICSA), pp. 178–181 (2016). DOI 10.1109/WICSA.2016.15
43. Le, D.M., Link, D., Shahbazian, A., Medvidovic, N.: An empirical study of architectural decay in open-source software. In: 2018 IEEE International Conference on Software Architecture (ICSA), pp. 176–17609 (2018). DOI 10.1109/ICSA.2018.00027
44. Li, Z., Liang, P., Avgeriou, P.: Architectural technical debt identification based on architecture decisions and change scenarios. In: 2015 12th Working IEEE/IFIP Conference on Software Architecture, pp. 65–74 (2015). DOI 10.1109/WICSA.2015.19
45. Lippert, M., Roock, S.: Refactoring in large software projects: performing complex restructurings successfully. John Wiley & Sons (2006)
46. Liu, H., Ma, Z., Shao, W., Niu, Z.: Schedule of bad smell detection and resolution: A new way to save effort. IEEE Transactions on Software Engineering **38**(1), 220–235 (2012). DOI 10.1109/TSE.2011.9
47. Lozano, A., Mens, K., Portugal, J.: Analyzing code evolution to uncover relations. In: 2015 IEEE 2nd International Workshop on Patterns Promotion and Anti-patterns Prevention (PPAP), pp. 1–4 (2015). DOI 10.1109/PPAP.2015.7076847
48. Lutellier, T., Chollak, D., Garcia, J., Tan, L., Rayside, D., Medvidović, N., Kroeger, R.: Measuring the impact of code dependencies on software architecture recovery techniques. IEEE Transactions on Software Engineering **44**(2), 159–181 (2018). DOI 10.1109/TSE.2017.2671865
49. Ma, W., Chen, L., Zhou, Y., Xu, B., Zhou, X.: Are anti-patterns coupled? an empirical study. In: 2015 IEEE International Conference on Software Quality, Reliability and Security, pp. 242–251 (2015). DOI 10.1109/QRS.2015.43
50. Macia, I., Arcoverde, R., Garcia, A., Chavez, C., von Staa, A.: On the relevance of code anomalies for identifying architecture degradation symptoms. In: 2012 16th European Conference on Software Maintenance and Reengineering, pp. 277–286 (2012)
51. Macia, I., Garcia, J., Popescu, D., Garcia, A., Medvidovic, N., von Staa, A.: Are automatically-detected code anomalies relevant to architectural modularity? In: the 11th annual international conference, pp. 167–178. ACM Press (2012)
52. Mantyla, M., Vanhanen, J., Lassenius, C.: A taxonomy and an initial empirical study of bad smells in code. In: International Conference on Software Maintenance, 2003. ICSM 2003. Proceedings., pp. 381–384 (2003). DOI 10.1109/ICSM.2003.1235447

53. Mantyla, M., Vanhanen, J., Lassenius, C.: A taxonomy and an initial empirical study of bad smells in code. In: International Conference on Software Maintenance, 2003. ICSM 2003. Proceedings., pp. 381–384 (2003). DOI 10.1109/ICSM.2003.1235447
54. Marinescu, R.: Detection strategies: Metrics-based rules for detecting design flaws. In: Proceedings of the 20th IEEE International Conference on Software Maintenance, ICSM '04, pp. 350–359. IEEE Computer Society (2004)
55. Martin, R.C.: Agile software development: principles, patterns, and practices. Prentice Hall (2002)
56. Martini, A., Fontana, F.A., Biaggi, A., Roveda, R.: Identifying and prioritizing architectural debt through architectural smells: A case study in a large software company. In: 12th European Conference on Software Architecture (ECSA 2018) (2018). DOI 10.1109/ICSA.2018.00027
57. Miller, G.A.: The magical number seven plus or minus two: some limits on our capacity for processing information. Psychological review **63 2**, 81–97 (1956)
58. Mo, R., Cai, Y., Kazman, R., Xiao, L.: Hotspot Patterns: The Formal Definition and Automatic Detection of Architecture Smells. In: WICSA, pp. 51–60. IEEE Computer Society (2015). DOI 10.1109/WICSA.2015.12
59. Mo, R., Cai, Y., Kazman, R., Xiao, L., Feng, Q.: Architecture anti-patterns: Automatically detectable violations of design principles. IEEE Transactions on Software Engineering pp. 1–1 (2019). DOI 10.1109/TSE.2019.2910856
60. Moha, N., Guéhéneuc, Y., Duchien, L., Meur, A.L.: DECOR: A method for the specification and detection of code and design smells. IEEE Trans. Software Eng. **36**(1), 20–36 (2010). DOI 10.1109/TSE.2009.50
61. Munaiah, N., Kroh, S., Cabrey, C., Nagappan, M.: Curating github for engineered software projects. Empirical Software Engineering **22**(6), 3219–3253 (2017). DOI 10.1007/s10664-017-9512-6. URL `https://doi.org/10.1007/s10664-017-9512-6`
62. Nam, D., Lee, Y.K., Medvidovic, N.: Eva: A tool for visualizing software architectural evolution. In: 2018 IEEE/ACM 40th International Conference on Software Engineering: Companion (ICSE-Companion), pp. 53–56 (2018)
63. Oizumi, W., Garcia, A., da Silva Sousa, L., Cafeo, B., Zhao, Y.: Code anomalies flock together: Exploring code anomaly agglomerations for locating design problems. In: Proceedings of the 38th International Conference on Software Engineering, ICSE '16, pp. 440–451. ACM, New York, NY, USA (2016). DOI 10.1145/2884781.2884868. URL `http://doi.acm.org/10.1145/2884781.2884868`
64. Oizumi, W.N., Garcia, A.F., Colanzi, T.E., Ferreira, M., v. Staa, A.: When code-anomaly agglomerations represent architectural problems? an exploratory study. In: 2014 Brazilian Symposium on Software Engineering, pp. 91–100 (2014). DOI 10.1109/SBES.2014.18
65. Oizumi, W.N., Garcia, A.F., Colanzi, T.E., Ferreira, M., Staa, A.V.: On the relationship of code-anomaly agglomerations and architectural problems. Journal of Software Engineering Research and Development **3**(1), 11 (2015). DOI 10.1186/s40411-015-0025-y
66. Palomba, F., Bavota, G., Di Penta, M., Oliveto, R., Poshyvanyk, D., De Lucia, A.: Mining version histories for detecting code smells. IEEE Transactions on Software Engineering **41**(5), 462–489 (2015)
67. Palomba, F., Bavota, G., Penta, M.D., Fasano, F., Oliveto, R., Lucia, A.D.: A large-scale empirical study on the lifecycle of code smell co-occurrences. Information and Software Technology **99**, 1 – 10 (2018). DOI https://doi.org/10.1016/j.infsof.2018.02.004
68. Palomba, F., Bavota, G., Penta, M.D., Oliveto, R., Lucia, A.D., Poshyvanyk, D.: Detecting bad smells in source code using change history information. In: 2013 28th IEEE/ACM International Conference on Automated Software Engineering (ASE), pp. 268–278 (2013). DOI 10.1109/ASE.2013.6693086
69. Pietrzak, B., Walter, B.: Leveraging code smell detection with inter-smell relations. In: P. Abrahamsson, M. Marchesi, G. Succi (eds.) Extreme Programming and Agile Processes in Software Engineering, pp. 75–84. Springer Berlin Heidelberg, Berlin, Heidelberg (2006)
70. Samarthyam, G., Suryanarayana, G., Sharma, T.: Refactoring for software architecture smells. In: Proceedings of the 1st International Workshop on Software Refactoring, pp. 1–4. ACM (2016). DOI 10.1145/2975945.2975946

71. Sharma, T.: Designite - A Software Design Quality Assessment Tool. http://www.designite-tools.com (2018). [Online; accessed 31-Mar-2018]
72. Sharma, T.: A dataset of code smells (2019). DOI 10.5281/zenodo.2538646. URL https://doi.org/10.5281/zenodo.2538646
73. Sharma, T.: Designite validation data (2019). DOI 10.5281/zenodo.2538655. URL https://doi.org/10.5281/zenodo.2538655
74. Sharma, T., Fragkoulis, M., Spinellis, D.: Does your configuration code smell? In: Proceedings of the 13th International Workshop on Mining Software Repositories, MSR'16, pp. 189–200 (2016). DOI 10.1145/2901739.2901761
75. Sharma, T., Fragkoulis, M., Spinellis, D.: House of cards: Code smells in open-source c# repositories. In: 2017 ACM/IEEE International Symposium on Empirical Software Engineering and Measurement (ESEM), pp. 424–429 (2017). DOI 10.1109/ESEM.2017.57
76. Sharma, T., Mishra, P., Tiwari, R.: Designite — A Software Design Quality Assessment Tool. In: Proceedings of the First International Workshop on Bringing Architecture Design Thinking into Developers' Daily Activities, BRIDGE '16. ACM (2016). DOI 10.1145/2896935.2896938
77. Sharma, T., Spinellis, D.: A survey on software smells. Journal of Systems and Software **138**, 158 – 173 (2018). DOI https://doi.org/10.1016/j.jss.2017.12.034. URL http://www.sciencedirect.com/science/article/pii/S0164121217303114
78. Suryanarayana, G., Samarthyam, G., Sharma, T.: Refactoring for Software Design Smells: Managing Technical Debt, 1 edn. Morgan Kaufmann (2014)
79. Tamburri, D., Kazman, R., Van Den Heuvel, W.J.: Splicing community and software architecture smells in agile teams: An industrial study. In: Agile and Lean: Organizations, Products and Development (2019). DOI 10.24251/HICSS.2019.843
80. Tran, J.B., Godfrey, M.W., Lee, E.H.S., Holt, R.C.: Architectural repair of open source software. In: Proceedings IWPC 2000. 8th International Workshop on Program Comprehension, pp. 48–59 (2000). DOI 10.1109/WPC.2000.852479
81. VanderWeele, T.J., Shpitser, I.: On the definition of a confounder. The Annals of Statistics **41**(1), 196–220 (2013). DOI 10.1214/12-aos1058. URL http://dx.doi.org/10.1214/12-AOS1058
82. Verdecchia, R., Malavolta, I., Lago, P.: Architectural technical debt identification: The research landscape. In: Proceedings of the 2018 International Conference on Technical Debt, TechDebt '18, pp. 11–20. ACM, New York, NY, USA (2018). DOI 10.1145/3194164.3194176. URL http://doi.acm.org/10.1145/3194164.3194176
83. Vidal, S., Vazquez, H., Díaz-Pace, J.A., Marcos, C., Garcia, A., Oizumi, W.: JSpIRIT: A flexible tool for the analysis of code smells. In: Proceedings - International Conference of the Chilean Computer Science Society, SCCC, pp. 1–6. Universidad Nacional del Centro de la Provincia de Buenos Aires, Tandil, Argentina, IEEE (2016)
84. Vidal, S.A., Marcos, C., Díaz-Pace, J.A.: An approach to prioritize code smells for refactoring. Automated Software Engineering **23**(3), 501–532 (2016)
85. Walter, B., Fontana, F.A., Ferme, V.: Code smells and their collocations: A large-scale experiment on open-source systems. Journal of Systems and Software **144**, 1 – 21 (2018)
86. Xiao, L., Cai, Y., Kazman, R.: Titan: a toolset that connects software architecture with quality analysis. In: FSE 2014: Proceedings of the 22nd ACM SIGSOFT International Symposium on Foundations of Software Engineering, pp. 763–766. Drexel University, ACM (2014)
87. Yamashita, A., Moonen, L.: Exploring the impact of inter-smell relations on software maintainability: An empirical study. In: 2013 35th International Conference on Software Engineering (ICSE), pp. 682–691 (2013). DOI 10.1109/ICSE.2013.6606614
88. Yamashita, A., Moonen, L.: To what extent can maintenance problems be predicted by code smell detection? – an empirical study. Information and Software Technology **55**(12), 2223 – 2242 (2013)
89. Yamashita, A., Zanoni, M., Fontana, F.A., Walter, B.: Inter-smell relations in industrial and open source systems: A replication and comparative analysis. In: 2015 IEEE International Conference on Software Maintenance and Evolution (ICSME), pp. 121–130 (2015)