API Misuse Detection
An Immune System inspired Approach

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Abstract—APIs are essential ingredients for developing complex software systems. However, they are difficult to learn and to use. Thus, developers may misuse them, which results in various types of issues. In this paper, we explore the use of a bio-inspired approach (artificial immune system) to detect API misuses in client code. We built APIMMUNE, a novel API misuse detector. We collect normal usages of a given APIs from the set of client programs using the APIs, especially after some API usages were fixed in those programs. The normal API usages are considered as normal body cells. We transform them into normal-usage signatures. Then, artificial detectors are randomly generated by generating artificial deviations from these usages with the objective of being different from the normal usage signatures. The generated detectors have the ability to detect risky uses of APIs exactly as the immune system detects foreign cells of the organism. Moreover, for the detection purpose, only the artificial detectors are necessary, without the need to disclose the code used to generate them. Our approach was evaluated on the misuses dataset of three APIs as well as on known misuses from a state of the art APIs misuses benchmarking dataset. APIMMUNE was also compared to four state-of-the-art API misuse detection tools. The results show that APIMMUNE has good detection accuracy and performance, and it can complement pattern-based tools for uncommon misuses detection.

Index Terms—Software libraries; Software reuse; Clustering; API Misuse; artificial immune system

I. INTRODUCTION

Nowadays, software libraries and their Application Programming Interfaces (APIs) are essential ingredients for the development of complex software systems [1]–[5]. They are supposed to provide tested and proven reusable functionality at a low cost [6]. Yet, using APIs is not always easy due to their complexity and often incomplete documentation [7]–[9]. Developers may misuse them, which results in faults difficult to debug. Preventing API misuses is not always possible due to their complexity and the many different ways they can be used. An alternative approach is to detect API misuses. The existing detection approaches for API misuses can be broadly classified into two categories: explicit and implicit detection.

Several approaches fall into the explicit detection category in which the specifications of correct API usages are determined either by the API designers or developers. The specifications are then used in the detection process where a detector assesses if a given usage is valid with respect to API specifications. However, not all libraries are well-documented for correct usages because the number of correct usages can be large.

Manually writing and maintaining specifications over time is then challenging [10], [11].

To avoid the need of writing specifications or explicitly enumerating all the potential usages, several approaches follow implicit detection in which the correct API usages are not specified before the detection. These approaches rely on the consensus principle in which an instance of an API usage is considered as a misuse if it deviates far from the frequently used ones (often called API usage patterns) [12]–[19]. While several researchers have been proposing a large number of mining techniques on API misuse detection, API misuses remain a problem in practice [20], [21].show that existing API misuse detectors have suffered high false positives due to an important issue with the use of thresholds on frequent usages (patterns) and on the deviations from those patterns. Specifically, the detectors often failed to detect misuses when they cannot relate misuses to the respective patterns because the differences between them exceed pre-defined thresholds.

To address the challenges in establishing the distinctions between correct usages and misuses or in spending efforts in writing specifications, we explore an idea from biology. A similar detection phenomenon is one from the biological immune system (BIS). The goal of this detection is to decide if an element is a normal body cell (self) or a threat that can be an antigen, e.g., bacteria, viruses, and parasites, or a malfunctioning cell, e.g., cancerous cells (non-self). The detection is done as the BIS produces among others T-cells that are created randomly and kept only if they do no match normal body cells. The number of self-elements (body cells) is very high, and the number of non-self elements is potentially infinite. Still, except for very few cases, the detection with the T-cells works very well. A key benefit of this detection mechanism in BIS is to minimize the false-positive rates, i.e., minimize the mis-identification of normal cells as non-selfs.

In this work, we explore that BIS-inspired idea to build APIMMUNE, a novel API misuse detector. The normal API
usages are considered as the normal body cells (self). We will collect normal usages of the given APIs from the set of client programs correctly using the APIs. For those API usages, APIMMUNE extracts features to be used as usage signatures. Like for the BIS, artificial detectors (equivalent of T-cells) are randomly generated with the objective of being different from the normal usage signatures. The detection is performed when APIMMUNE is used to detect API misuses in a given client program using the APIs. The API usages in the client program are extracted and compared against the detectors. Matches represent misuse risks. With this BIS-inspired mechanism, APIMMUNE avoids the establishing of the thresholds and frequencies as in the consensus-based approaches, and avoids manual writing of API specifications as in the explicit approaches. Importantly, as a consequence, as APIMMUNE creates the detectors by mutating the normal usages, we expect it to improve false positive rates over the existing approaches. Moreover, when the detectors are generated, they can be used and enhanced without the need of disclosing the clients’ code that served for the generation.

To evaluate the viability of our approach, we performed a preliminary study with three APIs. Our results show that APIMMUNE has good detection accuracy and performance, and it can complement pattern-based tools for uncommon misuses.

The rest of the paper is organized as follows. In sections II and III we introduce the principles of the artificial immune system algorithm (AIS) and discuss the parallel between the immune system and the detection of API misuse. The different steps of our approach are described in Section IV. Section V presents the results of the preliminary evaluation while providing discussions in Section VI. Section VII presents the closest related work and the novelty of our approach with respect to it. Finally, we conclude and suggest future work in Section VIII.

II. BACKGROUND

In this section, we present the background on API usages and misuses as well as on the principles of the artificial immune system (AIS), a simplified abstraction of the biological immune system (BIS).

A. API Misuses

Developers use the functionality of libraries via Application Programming Interfaces (API) to access the classes, methods, and fields that make up the APIs. Software libraries can be used in different ways. API specifications are the conditions on the usages of those API elements that a program needs to follow for the libraries to work properly [22], [23]. For example, in Java Development Kit (JDK), one could instantiate a BufferedReader Object for reading the data from a buffer, and then close the resource to guarantee data integrity.

However, not all of the usages are well documented in the official documentation and programming guides [24]. That leads to misunderstanding and, thus, incorrect usages of the APIs that violate their specifications. Those violations are called API misuses. For example, in Listing 1, the resource BufferedReader is instantiated (line 2), used to read each line (line 4) but if not closed at the end, it will be a classic example of BufferedReader misuse. This misuse is an instance of one of the 13 types of common misuses, identified by the authors of the benchmark MuBench [25], i.e., missing call.

B. Artificial Immune System Detection

A detailed presentation of the biological immune system and Artificial Immune Systems can be found in [26], [27]. Let us summarize the principles of the artificial immune system algorithm (AIS) that interests us for our work.

To protect the organism from potential pathogens, the immune system follows a 3-step cycle: (1) discovery, (2) identification and (3) elimination. The discovery step detects potential pathogens, such as viruses and bacteria. When such an element is detected, the identification step is responsible for checking if the identified element is known (immune memory).

Finally, in the elimination step, the adequate response is selected depending on the identification step. Discovery is the phase that interests us in particular as we are concerned with the detection of API misuses. Therefore, we explain its principle in the following paragraphs.

There is no central organ that fully controls the immune system. Instead, detectors wander in the body searching for harmful elements. Any element that can be recognised by the immune system is called an antigen. The cells that originally belong to our body and are harmless to its functioning are termed self (for self antigens) while the disease-causing elements are named non-self (for non-self antigens). The immune system classifies cells that are present in the body as self and non-self cells.

The immune system produces a large number of randomly created detectors T-cells that can be used to detect non-self elements. The T-cells are created randomly and exposed to normal cells. If a T-cell matches a normal cell, it is removed from the repertoire of immune cells to avoid the body attacking itself. This is called negative selection. When using the AIS metaphor, it is not possible to create a large number of T-cells. Hence, it is important to ensure a maximum coverage while keeping minimal the number of T-cells.

The next important notion of an AIS is the affinity computation between a detector and an encountered cell. The affinity is a similarity function that assesses if the encountered cell belongs to self or not.

Figure 1 gives a simplified overview of how the presented AIS concepts will be used in our approach. The normal API usages are considered as the normal body cells (equivalent of the self). We will collect normal usages of the given APIs from the set of client programs correctly using the APIs. Artificial detectors (equivalent of the T-cells) will be randomly generated with the objective of being different from the normal usage of APIs. The detection is performed on tested methods using the APIs, that will be compared against the detectors to estimate the misuse risks.

III. BIS-INSPIRED API MISUSE DETECTION FORMULATION

In this section, we present our formulation of the API misuse detection problem by the adaptation of the BIS.
```java
StringBuffer strbuf = new StringBuffer();
BufferedReader in = new BufferedReader(new FileReader(file));
String str;
while ((str = in.readLine()) != null) {
    strbuf.append(str);
}
if (strbuf.length() > 0) {
    outMessage(strbuf.toString());
}
in.close();
```

**Listing 1: BufferedReader usage example**

*Figure 1: AIS concepts applied to the API misuse detection*

**Definition 1 (API Usage):** An API usage is a fragment of client code that involves the API classes and/or methods for a given library.

The code fragment in Listing 1 is an example of usage of APIs in JDK library with classes such as `StringBuffer`, `BufferedReader`, and `FileReader`, and method calls such as `BufferedReader.readLine()`, `StringBuffer.append(...)`, and `StringBuffer.length()`.

When a client method is considered as an API usage, not all its statements are relevant to this usage. To capture the specific usage, we extract a *groum*, a graph-based representation for the API usage [28].

**Definition 2 (API Usage Graph):** An API Usage Graph (GROUM) is a directed graph representing an API usage in which nodes represent API objects constructor calls, method calls, field accesses, and branching points of the control structures, and edges represent temporal usage orders and data dependencies among them.

For example, the API usage of Listing 1 will lead to the *groum* shown in Figure 2.

As mentioned in Section II in a BIS, the notion of Self refers to what is normal by contrast to what is risky. In the API misuse detection problem, the Self is the correct use of the API.

**Definition 3 (API Usage as Self):** The self for an API is a set of API usage methods that are known to be correct.

The Self for an API can be extracted from the set of client programs that correctly use the APIs. Identifying correct usages can be done manually based on history data (e.g., issue tracking systems). In our experiments (see Section V), we used an automated approach to extract the Self. We included in this set versions of methods using the API that were fixed after a bug was declared in them. We retain a fixed version if its *groum* differs from one of the corresponding buggy version.

Another important concept in BIS is the mutations of T-cells to detect the anomaly cells. Roughly speaking, the immune system generates T-cells from the stem cells and keep only those that do not match body cells (negative selection). When transposing the principle of the negative selection to the detection of API misuses, it is necessary to generate detectors (equivalent to T-cells) by randomly mutate the Self API usages. As the goal is to generate a limited number of detectors with a maximum coverage of the deviations from the Self, the generation process can be viewed as a *multi-objective optimization* problem. If we fix the number of detectors for performance consideration, the goal is, therefore, to find the set of detectors that deviate from the normal use situations in the Self, but also are as much as possible different from one another to avoid duplications.

**Definition 4 (Detector Generation):** The generation process aims to produce a fixed number of detectors that deviate from the normal API usages in correct client programs, and that are different as much as possible from one another.

**Definition 5 (A Mutation):** A mutation of an API usage is the *groum* of the API usage after the application of a mutation operation.

**Definition 6 (Mutation Operators):** Mutation operators are respectively: adding an edge to or removing an edge from the *groum*, adding a node (a random API method call), removing a node, replacing a node (changing a method call by another), moving (changing the position of) a node in the *groum*, and adding, removing and moving an exception.

For example, a mutation of the correct usage from Figure 2 is the graph without the node `BufferedReader.close` and the inducing edges to that node.

The next important notion to instantiate in our formulation is the affinity computation that assesses the similarity between a T-cell (detector) and an encountered cell (an evaluated client method) to determine if the cell is part of the Self or not.

**Definition 7 (Affinity of APIs):** In the API misuse detection context, the similarity between a detector graph and an API usage in a client program is measured by the graph editing distance between the respective groums.

The basic mapping between a BIS and our detection prob-
lem is not enough to fully tackle the complexity of the API misuse problem. In this section, we present the additional features that complement the BIS-inspired detection.

The first feature is the clustering of the API usages before the generation of the detectors. Many APIs can be used in different ways by different clients. To ensure addressing all these different usage variations, we apply a clustering process to the API usages in the Self to group similar API usages in clusters. Each cluster corresponds to a usage scenario. Then the generation process will take into account the representativeness of the generated detectors with respect to the obtained clusters.

The second feature is to replace the boolean detection results (Self/non-Self) by a risk score that allows to rank the evaluated methods according to the estimated risk. This helps client-program developers dedicating their available effort to the methods with the higher risk scores.

IV. APIMMUNE: BIS-inspired API Misuse Detection

This section presents our algorithms to realize APIMMUNE, an BIS-inspired API misuse detection tool.

Our approach to detect API misuses is depicted in Figure 2. We begin with the extraction of usage signatures (groums) that represent the usage scenarios from the methods of a given client code corpus (Self). As the API can be used in different ways, the next step is to cluster the signatures depending on which API methods are involved. Then, starting from the clusters, a set of detectors is generated. The final step is the actual detection, in which all the generated detectors are used to assess the misuse risk of each new client method. Note that the obtained detectors will have their own independent life cycles. They can be reused/shared, enhanced with new detectors when new safe clients are considered and destroyed if they detect false positive(s).

A. Usage Signature Extraction

The goal of this step is to produce, for each method in the safe clients’ code, a signature that captures the API usage independently from the client behavior. To this end, we use the tool GrouMiner [28] to extract a groum as defined in Section III. The initial groum contains all the elements in the considered-method body. Then, this groum is pruned by removing all the nodes and edges that are not concerned with the API calls. Let us consider again the code fragment of Listing I the initial groum is the one of Figure 2. Now if only the BufferedReader class is considered as part of the API the pruning process will produce the groum depicted in Figure 4.
B. Signature Clustering

An API can offer different functionalities and then expose different sets of methods to use them. It is, then, important to target different families of misuses without enumerating them explicitly. A good way to handle this variety of API usages is to identify similar usage scenarios. In this context, the second step of our approach is to derive clusters of usage-signatures, which define families of API usage scenarios. The clustering allows targeting different usage scenarios during the detector generation and taking into account those that are not very common. Moreover, if the detectors are generated without clustering, redundant detectors will be derived for similar usage scenarios that were not clustered. Figure 5 shows the clustering process.

In a first step, We cluster API methods that are co-used together by the client methods. To this end, we use DBSCAN, a density-based clustering algorithm [29]. DBSCAN constructs clusters of API methods by grouping those that are close to each other (i.e., similar methods) form a dense region. Two API methods are close to each other (short distance) if they have a high co-occurrence frequency, thus, they will share a large set of common usage. Moreover, with DBSCAN we don’t need to specify the number of clusters, and DBSCAN is also very robust to outliers which in our case will occur for utility methods that are frequently co-used with domain-specific methods. The algorithm has two parameters: The first parameter is the minimum number of methods in a cluster. We set it at two so that a cluster includes at least two methods of the API. The second parameter is epsilon, the maximum distance within which two points can be considered as neighbor, each to other. In other words, epsilon value controls the minimal density that a clustered region can have. The shorter is the distance between methods within a cluster the denser is the cluster. We set it at 0.8 to minimize the noisy points, i.e., two methods are clustered together if they share at least 20% of their client calling methods.

In a second step, we derive the families of API usage scenarios. For each API-method cluster inferred in the first step, we identify its corresponding client methods, i.e., the client methods using the API methods in the cluster.

C. Detector Generation

To allow the detection of API misuses, we use a genetic algorithm to generate detectors mimicking the T-cells. The objective is to generate a fixed number of detectors that represent artificial signatures that are different from those of the safe code (random alterations of the good-usage signatures). The genetic-based generation algorithms start from a population of randomly alterations of the good-usage signatures. The genetic-based generation algorithms start from a population of randomly generated detector sets, each having a fixed size. Each set is a candidate solution. Then the algorithm evolves these sets through a given number of generations.

In each generation, the algorithm create a new population of candidate detector sets by modifying the detectors in the sets (production of new genetic material by the mutation operator) and/or by combining detectors coming from different sets (recombination of the existing genetic material by the crossover operator).

After the clustering step, we experimented with two alternative generation process. The first, call it parallel evolution, consists in having a separate detector generation process (Figure 6). The second, call global evolution, uses the clusters to seed the generation process by producing an initial set of detector that are globally refined later on (Figure 7).

Parallel evolution: The detector generation is performed specifically for each cluster in a parallel mode. Detectors are generated by mutating client-method groums. We evolve detectors separately for each cluster, using a genetic algorithm, and we merge the best final solutions (set of detectors) at the end of the process. If the number of clusters is high, merging all the detectors may results in a large set of detectors. Thus, we use another optimization process to reduce the number of the merged detectors to a minimal set. To this end, we use a proportionate selection, also known as roulette wheel selection, to generate a population of random combinations of detectors with each combination having a fixed size. The probability of a detector to be included in any of the combinations is proportional to its fitness (see below for the fitness calculation). Then the generated population evolves through genetic recombination. Note that this last process does not generate new detectors. It only searches for the best combination of a fixed number of detectors.
Global evolution: In this alternative, the genetic algorithm is allied only once. We seed the initial population of detectors candidate sets with detectors coming from each cluster using the roulette wheel selection to have a representation of individuals conforming to the cluster size. The larger client-method groums are in a cluster, the more candidate detectors are likely to be generated from this cluster. Then, the genetic-basic generation process runs on this initial population regardless of the clusters that served to generate the initial population.

For all the alternatives, the evolution is guided by the two objectives of having a set of detectors that is different from the normal signatures while being diverse. Additionally, the evolution of solutions is performed using genetic operators, i.e., elitism, crossover, and mutation. The details of the most important elements of the algorithm are as follows.

Elitism: When creating the next generation of candidate detector sets, a small subset of the current-generation sets having the highest fitness values is automatically added. The elitism ensures to keep the best solutions during the evolution.

Crossover: After performing the elitism, the remaining slots for the next generation are filled using the crossover between detector sets of the current generation. The crossover consists of selecting two sets and producing two offsprings by exchanging subsets of detectors as illustrated in Figure 5. The selection favors the fittest detector sets while keeping a certain degree of randomness. When selecting two detector sets, the crossover is performed under a probability (set to 0.9).

Mutation: After each crossover, the offsprings (or the parents if the crossover is not performed) are candidates for mutation with a certain probability (set to 0.2). When a decision is made to mutate a detector set, a subset of its detectors is randomly selected and one of the nine types of mutations is randomly selected to apply on each of these detectors. API M M U N E considers the types of mutation operators as explained in Section III. Figure 9 shows the add node mutation.

Fitness function: Both the elitism and selection for the crossover use a fitness function to favor the fittest detector sets. For a detector set $S$, the fitness function is the average of the fitness scores of each detector $d_i \in S$. To ensure a maximum coverage with a limited set of detectors, the fitness function of each detector should consider two aspects: the dissimilarity with the safe usage signatures $C$ and the dissimilarity with the other detectors of $S$. Consequently, the fitness score of a detector $d_i$ is the linear combination of two dissimilarity functions:

$$\text{fitness}(d_i) = \alpha \cdot \text{clientDis}(d_i) + \beta \cdot \text{detectorDis}(d_i)$$  \hspace{1cm} (1)$$

Both client distance $\text{clientDis}(d_i)$ and detector distance $\text{detectorDis}(d_i)$ are based on the similarity function $\text{sim}(d_i, y)$ between two groums: $d_i$ for the detector and $y$ for either another detector or a Self API usage. It is defined as the proportion of shared elements (nodes, edges, exceptions and control structures) between the compared groums.

To derive $\text{clientDis}(d_i)$, we start by calculating $\text{minDis}(d_i)$, the minimal distance between $d_i$ and any of the API usages in the Self $C$.

$$\text{minDis}(d_i) = 1 - \max_{s_j \in C}(\text{sim}(d_i, s_j))$$  \hspace{1cm} (2)$$

To capture the fact that deviation from the normal usages are in general different but not that distant from the normal usages, we give a perfect distance score $\text{clientDis}(d_i) = 1$ when the $\text{minDis}(d_i)$ is in a certain interval $[l, h]$ where $l$ is close to 0 and $h$ is a maximum tolerated deviation. We considered the interval $[0.01, 0.33]$ in our experiments. For values outside this interval, we assign to $\text{clientDis}(d_i)$ a value between 0 and 0.75 proportionably to how far we are from the interval. This value is 0 if $\text{minDis}(d_i)$ equals 0 or 1.

The distance with the other detectors $\text{detectorDis}(s_i)$ is calculated as follows:

$$\text{detectorDis}(s_i) = 1 - \frac{\sum_{d_k \in C, k \neq i} \text{sim}(d_i, d_k)}{|C| - 1}$$  \hspace{1cm} (3)$$
Figure 6: Detectors generation process with clustering. Process with merging after evolution

Figure 7: Detectors generation process with clustering. Process with merging before evolution on the bottom
Regardless of detector generation alternative, the best detector set $R$ is used in the future to assess new client code.

D. Misuse Detection

The actual detection consists in measuring the similarity between the signature $a_t$ of each new client method $m_t$ with each detector $d_j \in R$ using the $\text{sim}(a_t,d_j)$ function. For a given $m_t$, the risk score is derived by aggregating similarities with the individual detectors.

The obvious strategy is to assign to the risk score the maximum similarity found between $m_t$ and the detectors in $R$. Alternatively, rather than looking at the detector that best matches the method being evaluated, we assign higher risk scores to methods that are close to multiple detectors. The closer the method is to different detectors with high similarities, the more it will be considered at risk. In our metaphor with the immune system, this would mean that a cell that tends to match several T-cells would be qualified as pathogenic. To implement this idea, we use the logical function of *Noisy or*. The risque score according to the *Noisy or* aggregation is calculated as follows and as illustrated in Figure 8:

$$\text{risk}(m_t) = 1 - \left( \prod_{d_k \in R} 1 - \text{sim}(d_j, a_t) \right)$$

V. Empirical Evaluation

The objective of this section is to evaluate the performance of our approach in detecting API misuses in practice and in comparison with existing techniques. We formulated the research questions of our evaluation as follows:

**RQ1.** What is the impact of different detector generation strategies on the misuse detection accuracy?

**RQ2.** What is the execution cost of our approach in term of required execution time and storage?

**RQ3.** How well does our approach perform compared to existing approaches?

For each experiment in this section, we present the research question to answer, the research methodology to address it, followed by the obtained results.

A. Training Data Collection

As explained in Section IV, our approach generates misuse detectors for a specific API of interest. In our experiments, we evaluate our approach on APIs providing different functionality from three different packages of JDK:

1. **java.util.Iterator**
2. **javax.crypto.***
3. **java.util.Iterator**
4. **javax.crypto.*”}

1. [https://docs.oracle.com/javase/8/docs/api/java/util/Iterator.html](https://docs.oracle.com/javase/8/docs/api/java/util/Iterator.html)
2. [https://docs.oracle.com/javase/8/docs/api/javax/crypto/package-summary.html](https://docs.oracle.com/javase/8/docs/api/javax/crypto/package-summary.html)
To train the detectors, we need to collect a large samples of good usages of these APIs in their client code. We did that by looking at the changes to client methods that fixed the uses of these APIs in the histories of open source projects hosted on GitHub. We consider the client methods before the changes (buggy ones) as misuses and those after the changes (fixed ones) as good uses of these APIs.

In order to do that, we first collected high-quality repositories. To eliminate toy or experimental repositories, we used GitHub APIs to search for Java repositories that had been given at least 5 stars by individual GitHub users. This gave us 21,745 repositories. Then, for each repository, we identified the commits that had potentially fixed bugs by applying string pattern matching on the contents of the commit messages against keywords fix, bug, issue, error, problem, exception and fail. For each potential fixing commit, we mapped the methods before and after the change from the set of changed files. For each modified method, we used the abstract syntax tree (AST) differencing algorithm in [30] to identify the changed AST nodes. If a changed method does not contain any changed AST nodes whose resolved type is java.util.Iterator or belongs to package javax.crypto or javax.servlet.http, we disregard it. To make sure that a changed method actually fixes the usage of the APIs of interest, we construct and compare the groums with respect to the three APIs of interest of the methods before and after the change. If the groums are different, we add the method before the fix to the set of misuses and the method after the fix to the set of good uses of the corresponding API. We keep the misuses for the validation experiment. The numbers of projects, fixing commits, pairs of misuses and good uses of API groums generated for each API in our dataset are shown in Table I.

Table I: Statistics of the Training Dataset.

| API             | Projects | Commits | Uses   | API groums |
|-----------------|----------|---------|--------|------------|
| Iterator        | 832      | 1,560   | 1,833  | 3,641      |
| javax.crypto    | 74       | 132     | 201    | 271        |
| javax.servlet.http | 968 | 4,672   | 6,607  | 957        |

B. Accuracy Analysis

In the first experiment, we aim to answer **RQ1. What is the impact of different detector generation strategies on the misuse detection accuracy?**

As explained in Section [IV] API misuse detectors can be generated using different strategies. We evaluate the detection accuracy with respect to the following factors in detector generation strategies:

- **Detector generation strategies**: How to generate detectors after the clustering step. As mentioned in Section [IV]
we have two strategies to exploit the clusters for the detector generation: (1) parallel evolution or (2) global evolution.

- **GROUM complexity**: groms abstract the API usage and capture different aspects of the source code, which may lead to complex groms and a significant overhead for detector generation and groms comparison. We are interested in evaluating whether we can achieve the same detection accuracy with simpler groms in which we don’t consider data dependencies.

- **Clustering**: One of the enhanced features introduced into our approach is the clustering. It helps to handle the variety of API usages, and it avoids the generation of a huge yet redundant number of detectors. We are interested in evaluating the impact of the clustering on the detection accuracy and what would be the effect of omitting the clustering from our approach.

1) **Analysis method**: To answer (RQ1), we performed a 10 fold cross-validation on each of the three APIs java.util.Iterator, javax.crypto, and javax.servlet.http. We generated misuse detectors according to three generation configurations based on the previously mentioned variation factors: parallel vs. global evolution, simple vs. complex groms and with vs. without clustering. We then identified which configuration achieves the best accuracy.

For the 10 fold cross-validation, we created 10 folds that contain each 10% of the good API usages collected (as explained in Section V-A). Then for each fold, we generate the detectors using the good uses from nine folds. The tenth fold, not used in the detector generation, is used in the test set. This test set is completed with the same number of bad usages, to have a balanced test set with the same number of good and bad usages. The detectors are then applied on each good and bad use case contained in this test set, to calculate their risk score (c.f., Section IV-D). The cases are then sorted by their
scores. This allows to compute the accuracy on the top-ranked use cases since we expect the API misuse to have the highest risk scores. We compute the accuracy as the number of true positives (misuses) over the number of considered top-k use cases. We calculate the accuracy for both top 10% and top 30% use cases.

2) Results and Analysis for RQ1: Tables II, III, and IV present the accuracy results for the three detector generation configurations.

**Study 1.A: parallel vs. global evolution.**

The global evolution (Table III) allows achieving in general better accuracy than the parallel evolution (Table III). We conjecture that the global evolution introduces more diversity during the generation. Conversely, parallel evolution forces the individual generation of the detectors for clusters having different sizes, which in some cases limits the exploration possibilities. For example, we obtained 8 clusters of sizes 2, 2, 5, 6, 24, 44, 46, and 95 for crypto. In the small clusters, we do not have enough examples of good usage to generate accurate detectors. In other words, if we want to generate 50 different detectors from two groums, we have to find 50 different mutations of these two groums, which is difficult when the groums are small graphs with few nodes. The same observation holds for http, with slightly less difference between the two strategies. http has 3 clusters of sizes 17, 51 and 61 and then has less small clusters than crypto. Note that the results for Iterator are exactly the same for the two strategies for the simple reason that a unique cluster was obtained (the API has only 4 methods), and then both strategies behave the same.

**Study 1.B: simple vs. complex groums.**

Using simple groums is slightly better than using complex groums. For Iterator, the accuracy increases by 2% when we use simple groums. For crypto, the use of simple groums increases the accuracy for both parallel and global process. In particular, for parallel process (Table III), the accuracy increases from 40% to 50% on the top 10% of ranked methods. The exception is for http where the accuracy slightly decreases for the parallel evolution but stays high (70%) with the global evolution.

These results could be explained by the fact that the data dependency edges in the groums are not obvious for the API usage comprehension and take an important weight during the similarity computation between a method and a detector. If we look at the Figure 4 and we remove the data dependency edges in blue, we have a groums with 7 elements instead of 10. So, the simple groums give implicitly more weight to each node and the other edge which are more important for API usage comprehension.

Note that the simplification of the groums was done after the detector generation. During the generation process, we consider the data dependencies.

**Study 1.C: with vs. without clustering.**

The clustering allows achieving much better accuracy than without clustering. The clustering benefits the detection accuracy as we can observe on the top 10% an increase of 3.33% with the parallel evolution and an increase of 20% with global evolution on http whereas crypto sees an increase of 10% with the global evolution to obtain 60% of accuracy (Table IV Table III and Table II).

As we conjectured, the clustering allows to target specifically different usage scenarios during the detector generation. When the detectors are generated without clustering, some usage scenarios can be partially ignored in the random generation of detectors, especially those that are not very common, i.e., the probability to generate a detector from this rare usage scenarios is low.

In conclusion With this first study, we first show that global evolution is more beneficial than parallel evolution because of the presence of small clusters. Second, simple groums are slightly more efficient because they give more weight to important information about the API usages. Finally, not performing the clustering is detrimental to the detection accuracy and confirms the intuition that grouping the API usages to generate the detectors is beneficial.

C. Efficiency Analysis

In this experiment, we aim to answer RQ2. What is the execution cost of our approach in term of required execution time and storage?

1) Analysis method: We measure the execution times for different steps of the approach as well as the average required storage for the 3 APIs when serializing the detectors’ groums. We run with the best detector generation strategy which uses simple groums (without data dependencies), clustering and global evolution of detectors for each API to compute the average performances. For each execution we compute the time at each step of the detectors generation and risk-score computation. For memory usage, we use JVM Monitor to obtain realtime data. And for storage, we look at the Windows explorer properties of the output folders. To measure the performance of our approach, we use the benchmark MuBench.

APIMMUNE works in 2 steps, the detector generation and the risk evaluation. The first step takes relatively a long time with in average 33 minutes to generate the detectors for the 3 APIs. The generation of detectors consists of 3 steps: extracting API groums from source code, clustering usages and generating the detectors. The extraction of APIs groums takes less than 10 minutes and varies among APIs depending on the number of methods provided as input. Clustering takes less than 15 seconds. As for the detectors, the generation exceeds 15 minutes to produce 50 detectors per API. Note that the detector generation process is performed once and the generated detectors can be used several time to evaluate different clients using the API for which the detectors were generated. The minutes magnitude can be acceptable.

We measured the execution time of the risk estimation only for Iterator and crypto because MuBench has not client code and misuses for http. The risk estimation is also divided into 3 steps which are listed in Table 5. The first step is the extraction of API groums from client code under evaluation.

4http://jvmmonitor.org/index.html
Table II: Detection accuracy for \textit{Global} evolution.

| Complex groups | Simple groups |
|----------------|---------------|
| Mean accuracy 10% data (%) | 52.7% | 70% |
| Mean accuracy 30% data (%) | 54.6% | 57.8% |

Table III: Detection accuracy for \textit{Parallel} evolution

| Complex groups | Simple groups |
|----------------|---------------|
| Mean accuracy 10% data (%) | 52.7% | 40% |
| Mean accuracy 30% data (%) | 54.6% | 51.4% |

Table IV: Detection accuracy for the generation without clustering and \textit{simple} groums.

| Mean accuracy 10% data (%) | 54.3% | 30% |
| Mean accuracy 30% data (%) | 55.7% | 55.5% |

This step takes less than 23s for \textit{Iterator} and less than 10s for \textit{crypto}. This difference in time is explained by the fact that \textit{Iterator} clients compose a corpus of more than 21,000 methods and produce 2,175 uses. In contrast, \textit{crypto} has only 20 different uses in 120 methods. The second step is to load the trained detectors to use them for the detection. This takes about 10s for 50 detectors for each of the two APIs. Finally, there is the sorting time which are less than 9 seconds for \textit{Iterator} and about a tenth of a second for \textit{crypto}. This is explained by the difference in the number of methods to sort, 100 times more for \textit{Iterator}.

For memory measurement, we ran the experiment for the 3 APIs with clustering and global evolution on a laptop under Windows 10 with an OS architecture amd64, 8 processors and 6 GB of RAM. On average, an API \textit{groum} is stored on 26 MB of memory and a detector on 2.5 MB. It is, therefore, necessary to provide more than 125 MB of memory to save 50 detectors. In terms of heap memory the maximum is 3,695 MB and on average it is used 1,109 MB.

In conclusion, API\textsc{immune} requires more time to generate the detectors, but this is done only once. It requires much less time to evaluate client programs and assign risk scores to their methods. This short time allows potential integration into IDEs.

Table V: Evaluation time in seconds on MUBench clients.

| API groums building data | 24.64 | 9.41 |
| Detectors deserialization | 10.34 | 10.15 |
| Ranking time | 8.81 | 0.16 |
| Total time | 43.80 | 10.31 |

\textbf{D. Comparative Analysis}

In this experiment, we aim to answer \textbf{RQ3. How well does our approach perform compared to existing approaches?}

1) \textit{Analysis method:} To answer this research question, we run API\textsc{immune} to detect misuses in MuBench dataset \cite{25} and compare the result with those of the misuse detection tools in MuBenchPipe \cite{31}. MuBench provides a benchmark of API misuses from real-world projects, which have been manually verified. MuBenchPipe provides a pipeline for running existing detectors on the misuses in MuBench. In the current version, MuBenchPipe supports four Java API misuse detectors: DMMC \cite{32}, GROUMiner \cite{28}, Jadet \cite{33}, and Tikanga \cite{34}, all of which mine patterns from each subject project and detect misuses as violations of the patterns at the same time. MuBench contains misuses from a wide range of APIs including \textit{Iterator} and \textit{javax.crypto}. However, it does not contain misuses from \textit{javax.servlet.http}. Therefore, in this experiment, we compare the detectors on only misuses of \textit{Iterator} and \textit{javax.crypto}. MuBench has 13 and 7 misuses for respectively \textit{Iterator} and \textit{javax.crypto}. Using the detectors trained from our dataset collected from GitHub, we detected misuses in the methods of the projects in the benchmark and ranked the analyzed methods according to their risk scores. For \textit{Iterator} uses, we only considered the top-13 ranked methods, since MuBench just flagged 13 misuses of \textit{Iterator}. And for the same reason, we considered the top-7 ranked methods for \textit{javax.crypto}. To compare the tools we calculate the recall as the number of misuses detected by a tool over the total number of known misuses in MuBench. We also went through the identified misuses to qualitatively and conceptually compare our approach and the considered tools to show how they could complement each other.

2) \textit{Results for RQ3:} As shown in \textbf{Table VI}, API\textsc{immune} performs better than the others four tools for \textit{crypto} and less good than two out of the four tools for \textit{Iterator}. What is interesting in the results of our approach is the diversity of misuse revealed. For \textit{crypto} we detect 3 misuses of different types, a missing call, a missing exception handling and a missing condition value or state. For \textit{Iterator}, all misuses are missing condition value or state. Three considerations may explain the good performance for \textit{crypto}.

The first important point is that we do not mine and use usage patterns. Using patterns restrict the detection to specific scenarios. That focus on specific usages and do not take into account the diversity of API utilization, especially rare usages.

Second, our groums capture various control structures,
including exceptions, which allows to better represent the API good usage and the potential deviances. This is why we were able to detect a missing exception.

The last benefit of our approach is the edge typing of groums. This allows, among others, to define the scopes in which the API methods are called. For example, with the loop inclusion edge, it is possible to distinguish between an API method call inside a loop and the same call after a loop. This bring more precise information about the usage scenario. In conclusion, APIMMUNE can complement the pattern-based detection tools. These are good in detecting specific cases of misuses as it was the case for Iterator. However, for diverse misuses, as for crypto, APIMMUNE is better suited as it learns various deviations from normal uses rather than encoding a fixed set of patterns.

| Tool    | Iterator | crypto |
|---------|----------|--------|
| APIMMUNE| 8% (1)   | 43% (3) |
| DMMC    | 14% (2)  | 0% (0) |
| GROUMiner| 0% (0)   | 0% (0) |
| Jadet   | 0% (0)   | 0% (0) |
| Tikanga | 23% (3)  | 0% (0) |

VI. DISCUSSION AND THREATS TO VALIDITY

It is widely recognized that several factors can bias the validity of empirical studies. We will discuss the different threats that may affect our study. External Validity concerns the possible biases related to the choice of experimental subjects/objects. Although we have analyzed a large-scale dataset of 4,869 API groums with 8,641 API uses, collected from 6,364 commits of 1,874 projects selected in an initial set of 21,745 repositories. We cannot claim that our results can be generalized beyond the three APIs for which the dataset was collected. Regarding the Internal validity, we did not fine-tune the other detectors our self, we rather used the results reported in MUBench with the configurations reported in their respective publications of the different detectors. Probably a better fine-tuning would have lead to different results. Another threat to internal validity can be related to the knowledge and expertise of the human evaluators who compared the groums of the methods before and after the bug fixing commit; To add the method before the fix to the set of misuses and the method after the fix to the set of good uses of the corresponding API. However, it is only the expertise of the human evaluators that guaranty that the result of the fix itself is a good use of the API. Threats to construct validity can be related to the measurements performed to address the research questions. In our study, we measured the risk score for each evaluated method. The misuse detectors are applied to each good and bad use case contained in the test set. The cases are then sorted by their risk scores. This allows computing the accuracy on the top-ranked cases. We computed the accuracy as the number of true positives (misuses) over the number of considered top-k use cases. While the adoption of these measurements is popular to assess the efficiency of algorithms and to conduct comparative studies we cannot neglect the existence of a slight bias related to the set of ground truth used to calculate accuracy, as the good and bad use case were manually validated. Moreover, the experimenter expectancy effect is another possible threat. Indeed, the manual inspection was performed by two of the authors.

Our approach does not outperform others in all cases. We have rather developed an approach to complement existing work. Existing misuse detection techniques are mainly based on usage patterns. This strategy is effective in detecting specific cases of misuses in particular on APIs similar to the Iterator where the uses are easy to characterize and patterns are easy to infer. Our approach brings a new way of addressing the API misuse problem. While the vast majority of existing detectors consider the deviation from perfection as a criterion to identify API misuses, we rather decided to opt for the closeness to evil as a criterion to detect the API misuses. Instead of measuring how far from right behavior (i.e. the patterns) is the evaluated method, we look at how similar is an evaluated method to bad behaviors (i.e. the detectors). Moreover, in our metaphor with the immune system, a cell that tends to match several T-cells would be qualified as pathogenic. Thus, we made the choice to assign higher risk scores to methods that are close to multiple detectors through the logical function of Noisy or, rather than looking at the detector that best matches the method being evaluated. To improve APIMMUNE in detecting specific cases of misuses, as it was the case for Iterator, a different strategy to measure the risk score could be investigated, for instance the maximum similarity between the evaluated method and each of the detectors. However, for diverse misuses, as for crypto, APIMMUNE can complement the pattern-based detection tools. as it learns various deviations from normal uses rather than encoding a fixed set of patterns.

In our approach, we generate only fifty detectors for each API, this could be considered a low number and we could consider producing a larger number of detectors. However, if we generate a high number of detectors this will bring into the picture the detectors diversity issue. When the detectors are not as diverse as expected, the misuse detection step will be impacted. If a method (a cell) tends to match several detectors (T-cells) it would be qualified as misuse (pathogenic). Thus, we assign higher risk scores to methods that are close to multiple detectors through the logical function of Noisy or. As a consequence, if the detectors are not different from each other we will assign higher risk scores to methods that are similar to the same redundant detectors. Moreover, our choice to limit the number of detectors is also motivated by performance concern. The genetic-based generation of detectors is a heavy process during which thousands of detectors are generated and are compared to the training data set as well as to each other, to finally come up with a limited set of best and most diverse detectors. Despite all those reasons, we have to admit that fixing the number of detectors to allow number for all the evaluated APIs, is a strategy that needs to be improved. in our future work, we will investigate the impact of correlating the number of detectors to some characteristics of the API such as the number of public methods or the number of inferred clusters (usage scenarios of the APIs)."
of the safe code. However, the fact that a detector deviates from the normal API usages in the learning dataset, doesn’t guarantee that the detector actually represents by itself a misuse of the API. Moreover, in a very extreme case, we may consider the risk that the detector generation could end up producing signatures that are good or efficient usage of the API. Even though this case is almost impossible, our approach has the features that allow avoiding it. What actually makes a detector deviate from the good usage of an API is the mutation operator. Each detector undergoes one or multiple mutations among nine types of mutations. Moreover, we replace the boolean detection results (Self/non-Self) with a risk score that allows ranking the evaluated methods according to the estimated risk. We assign higher risk scores to methods that are close to multiple detectors through the logical function of Noisy or, rather than looking at the detector that best matches the method being evaluated. Thus even though a bad detector ends up in the list of used detectors, its impact will be reduced through the comparison with other detectors. In addition, the obtained detectors will have their own independent life cycles. They can be reused/shared, enhanced with new detectors when new safe clients are considered and destroyed if they detect false positive(s).

VII. RELATED WORK

In this section, we focus on presenting the related work on API misuse detection approaches that use the consensus principle. Those approaches typically follow two steps: mining the (good) usage patterns from a given code corpus and considering uses deviating from the patterns as misuses. Amann et al. [31] have recently conceptually compared the capabilities of existing API-misuse detection approaches, and conducted several empirical studies to evaluated and compared four well-known detectors using a benchmark infrastructure called MUBench [25]. The authors reported the existing API misuse detectors have suffered high false positives due to an important issue with the use of thresholds on frequent usages (patterns) and on the deviations from those patterns.

JADET is a misuse detector for Java [33] that focuses on API call order and call receivers in usages. It derives a pair of calls for each call order. The sets of these pairs are the inputs to the mining to identify API patterns, in term of sets of pairs of API calls. JADET is capable of detecting missing method calls and missing loops as a missing call-order relation from a method call in the loop header to itself. Tikanga [34] is built up on JADET, and extends it to general Computation Tree Logic formulae on object usages with the use of model checking on those. Tikanga applies Formal Concept Analysis [35] to mine patterns and misuses at the same time.

Tapir [36], [37] considers the recovery of temporal API usage patterns as an optimization problem and solves it using a genetic-programming algorithm. API temporal constraints are mined from execution traces of client programs using the API, and Linear Temporal Logic (LTL) formulas, representing candidate usage patterns are recovered. Tapir alert the user of potential API misuse of when LTL formulas, are violated.

Nguyen et al. [28] propose a graph-based object usage model (groum) for their misuse detector in GrouMiner. It uses sub-graphs mining to mine patterns as frequent usage sub-graphs. GrouMiner can detect misuses with missing API elements compared to patterns. In our work, we do not abstract-learn usage patterns from historical data to use them for the detection. The novelty of our approach is in generating new artificial data, i.e., detectors, that diverge from the historical data, following the negative selection principle. By doing this, we create new artifacts (detectors) that can be shared among development groups without disclosing the clients’ code.

DMMC [32], [38] aims to detect misuses in API method calls with exactly one missing one. It focuses on type usages, i.e., sets of methods called on a given receiver type of a given method. The assumption is that violations should have only few exactly similar usages, but many near-similar ones. Alatin [39] mine alternative patterns for condition checking. It applies frequent-itemset mining on the set of rules on pre- and post-condition checks on the receiver, the arguments, and the return value of a method call. It detects missing null checks and missing value or state conditions that are ensured by checks. CAR-Miner [40] aims to detect API misuses in error handling. To detect a misuse, it extracts the normal call sequence and the exception call sequence for a method call. It learns the association rules and then determines the expected exception-handling as well as missing method calls among error-handling functions. AX09 [41] also detects incorrect error handling. It uses model checking to generate error handling paths as sequences of method calls and applies frequent-subsequence mining to detect patterns. It then uses push-down model checking to verify the consistency to these patterns and identify respective misuses.

PR-Miner [42] encodes API usages as a set of all function names in a function in C, and uses frequent-itemset mining to detect patterns. Misuses are the subset that occurred at least 10 times less frequently than the pattern. It focuses on detecting missing method calls. Chronicler [43] aims to detect patterns in frequent call orders in inter-procedural control-flow graphs. The orders hold at least 80% of all execution paths are patterns and otherwise, they are violations. Chronicler detects missing method calls. Since loops are unrolled exactly once, it cannot detect missing iterations. DroidAssist [44] detects misuses in Java bytecode. It learns the call sequences to build a Hidden Markov Model. If a likelihood of a given call sequence is too small, it is considered as a misuse. MUDETECT [45] increases the level of details found in identified patterns, in order to increase the accuracy and recall of API misuse detection. MUDETECT uses a new graph representation of API usages that captures different types of API misuses and it devised a systematically designed ranking strategy that effectively improves precision. More recently Ren et al. [46] devised a text mining technique that extracts Android API misuses and patches from StackOverflow answers. The method produces a natural language report from these code fragments, explaining how to use the API.

As we can see in table VII, in the majority of the cases the misuse detection is not specific to a single API and thus it fails in identifying different types of misuses related to that API.
More broadly, the learning step is dependent on the considered client systems that generally focus on specific usages and do not take into account the diversity of API utilization, especially rare usages.

VIII. Conclusion

In this work, we propose API-MMUNE, an approach to detect API misuses using the immune-system metaphor. The normal API usages are considered as self normal body cells. Whereas API misuses are considered as the non-self antigens. We use a genetic algorithm to generate detectors mimicking the T-cells that can be used to detect non-self API misuses. This approach has the advantage of generating the detectors once, and then, they can be used and enhanced without the need of disclosing the clients’ code, nor abstracting good use patterns. Moreover, the detectors can be produced for different versions of the programming interface, which brings more flexibility to the detection process. The evaluation of API-MMUNE shows that it can detect various types of misuses, however, our approach does not outperform others in all cases. We have rather developed an approach to complement existing work. Existing misuse detection techniques are mainly based on usage patterns. This strategy is effective in detecting specific cases of misuses in particular on APIs where the uses are easy to characterize and patterns are easy to infer. Moreover, pattern-based approaches are heavily dependent on the frequency of good usage in the learning data set. API-MMUNE can complement the pattern-based detection tools that are limited to fixed sets of misuse patterns. For diverse misuses, API-MMUNE is better suited as it learns various deviations from normal uses rather than encoding a fixed set of patterns. API-MMUNE may require some time to generate the detectors, but this is done only once. It requires much less time to evaluate client programs and assign risk scores to their methods. This short time encourages potential integration into IDEs. Despite the encouraging results, there is still some exploration to be done with API-MMUNE the approach has multiple parameters that had to be set. It could be interesting to explore the results with different threshold parameters to see their impact on detection efficiency. For instance, we could increase the number of generated detectors while taking into account the potential redundancy of generated detectors. In the future, we plan to experiment with larger datasets involving many APIs. This will help us customize the detection process to the characteristics of these APIs (number of public methods, the number of distinct functionalities, etc.). Another area for improvement is to explore the combination of our approach with pattern-based detection.

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