Using a Semantic Knowledge Base to Improve the Management of Security Reports in Industrial DevOps Projects

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ABSTRACT
Integrating security activities into the software development lifecycle to detect security flaws is essential for any project. These activities produce reports that must be managed and looped back to project stakeholders like developers to enable security improvements. This so-called Feedback Loop is a crucial part of any project and is required by various industrial security standards and models.

However, the operation of this loop presents a variety of challenges. These challenges range from ensuring that feedback data is of sufficient quality over providing different stakeholders with the information they need to the enormous effort to manage the reports. In this paper, we propose a novel approach for treating findings from security activity reports as belief in a Knowledge Base (KB).

By utilizing continuous logical inferences, we derive information necessary for practitioners and address existing challenges in the industry. This approach is currently evaluated in industrial DevOps projects, using data from continuous security testing.

CCS CONCEPTS
• Security and privacy → Software security engineering; • Theory of computation → Automated reasoning.

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1 INTRODUCTION
Automating security activities like periodic testing for vulnerabilities and flaws is essential in industrial projects utilizing DevOps techniques [3, 8] to produce software products in domains with high security-related demand. As a result, new data about the software security is continuously generated, informing about shortcomings of the software and new requirements. In order to improve the product, reports must be fed back into the development cycle and be addressed by developers [11]. This so-called Feedback Loop is demanded by various standards and industry best practices [1, 7].

In practice, however, the task of implementing the Feedback Loop presents various challenges. The first challenge is the quality of the reports. The vast amount of data produced by security activities varies in format, content, perspective, assumptions, and evaluation [14], which necessitates data processing. Issues like False Positives are common in reports [9], reducing their reliability. The second challenge is how the data is utilized. The correct interpretation of the security activity data is essential for the subsequent actions, as data itself fuels project decisions and represents the software’s security level. Moreover, each project has its own demands, e.g., regarding standards compliance. Consequently, a high-quality demand applies to the produced information and must be customized project-wise. Our third challenge is that data from security activities is only half of what is needed. Inputs by security experts, customer opinion, or vulnerability databases are essential to correctly estimate the impact of findings and present a valid representation of reality. Finally, performing the management manually to collate actionable information is neither feasible in industrial software development projects nor conforming with the DevOps mindset, where automation of tasks is crucial [6]. Hence, we see a necessity to address the question:

How can the Feedback Loop for security reports in industrial DevOps projects be optimized?

The optimization should include the process being faster, customizable, with the least manual effort, more automation, highly reliable, and comprehensible for the project team.

2 USING A SEMANTIC KNOWLEDGE BASE

2.1 Theory
We propose the usage of a semantic KB to address the challenges identified above. A KB comprises primary information, logically interconnected by database semantics and stored free of constraints in a metasstructural database. In contrast to a database, a KB has primary methods of data processing, which allow the continuous generation of new information based on existing data [4, 5]. KBs have been applied in various areas, including management of sensor data [10], the elicitation of high-quality requirements [2], and even vulnerability management [13]. In contrast to existing approaches, we apply KBs to the domain of secure software engineering to manage security reports. However, this implies multiple changes to existing concepts to ensure a successful function in this use case. Initially, we consider the content of the KB as belief instead of knowledge due to the lack of data reliability. This particularly includes contradictory information from our data sources. Consequently, belief must be revisable, including the explicit belief (provided from outside the KB) and derived belief (derived by the KB). Moreover, the inference procedure must be customized to each
This implies that each KB has to deal with belief and inference rules being incrementally added or changed throughout the project. As each KB is unique to its project, a traditional approach using a static ontology is not feasible for our use case, especially when considering changing inference rules. Instead, we enable the incremental creation of a KB for each project. To ensure a consistent KB, we monitor all changes to the KB and identify contradictory information. If conflicting data is identified, it is resolved by considering external human input as more reliable (e.g., False Positive identification). Any belief derived from the formerly contradictory information is revised and re-calculated.

With this approach, we address various challenges of the industrial security report management with a semantic KB. The automated generation of data with pre-written inference rules ensures high reliability, high comprehensibility, project customization and reduces the scope for human errors. The automation of the report management reduces the manual effort and speeds up processing.

2.2 Practice

In order to test our theoretical concept, we implemented it for industrial software development projects. We realized our concepts of belief, inference rules, continuous inference, and metastructural data storage in the components depicted in Figure 1.

The Data Storage component, which comprises rules and belief, is implemented using the Elasticsearch search engine, which allows us to perform advanced queries on the data. Belief is stored in entities of Elasticsearch documents. Inference rules, however, are written in Python code. The step where our inference rules are applied to the current content of the KB to derive new information is implemented by the Inference Engine. With the Logical Core, we ensure consistency between new beliefs being added or existing beliefs being revised. These components are implemented in Python, using a self-developed logic to ensure consistency within the KB. Investigating the connections to incremental logic programming approaches, such as Differential Datalog [12], is an interesting direction for future work.

In practice, each project has to customize the information contained in the KB by writing documents for belief and inference rules. Based on our experience, specific inference rules are necessary for any project. These include a parser for security reports, a deduplication between findings, a validation of findings using human expertise, and a prioritization of the resulting issues. In most cases, these inference rules are streamlined, meaning that they build upon each other in a pipeline-like manner. To avoid the artificial inflation of the KB, we restrict new inferences solely to those that might be invalidated by external input (e.g., incorrect deduplication).

Deduplication, e.g., works on findings that have been parsed before from the original reports. During the execution of this rule, findings with similar values for title or description are summarized. If conflicting data is identified, it is resolved by considering external human input (e.g., False Positive identification). Any belief derived from the formerly contradictory information is revised and re-calculated.

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3 CONCLUSION AND FUTURE

The management of reports produced by security activities in industrial DevOps projects is essential in every domain. In this paper, we suggest a novel approach of using a semantic KB for this use case. We indicate necessary changes to existing KB concepts and introduce our concept implementation. We believe that utilizing logical inferences in combination with the reliability of a KB is a promising approach for usage in industrial software engineering projects. Substantiating this belief with a long-term evaluation in a realistic setting will be the core activity of future work.

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