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# How Can Subgroup Discovery Help AIOps?

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**Abstract**—The genuine supervision of modern IT systems brings new challenges as it requires higher standards of scalability, reliability and efficiency when analysing and monitoring big data streams. Rule-based inference engines are a key component of maintenance systems in detecting anomalies and automating their resolution. However, they remain confined to simple and general rules and cannot handle the huge amount of data, nor the large number of alerts raised by IT systems, a lesson learned from expert systems era. Artificial Intelligence for Operation Systems (AIOps) proposes to take advantage of advanced analytics and machine learning on big data to improve and automate every step of supervision systems and aid incident management in detecting outages, identifying root causes and applying appropriate healing actions. Nevertheless, the best AIOps techniques rely on opaque models, strongly limiting their adoption. As a part of this PhD thesis, we study how Subgroup Discovery can help AIOps. This promising data mining technique offers possibilities to extract interesting hypothesis from data and understand the underlying process behind predictive models. To ensure relevancy of our propositions, this project involves both data mining researchers and practitioners from Infologic, a French software editor.

**Index Terms**—AIOps, Data Mining, Subgroup Discovery, XAI

## I. RESEARCH PROBLEM STATEMENT

Today’s IT environments are increasingly large and complex, and therefore face significant IT operations and maintenance challenges to keep running efficiently and reliably. While classical engineering mindset focus on how to manually perform tedious tasks and resolve anomalies repetitively, rule-based solutions are not sufficient as they scarcely deal with the tsunami of data IT needs to monitor and cannot deliver predictive analysis and real-time insights and hardly respond to outages early enough [1]. These reasons have sparked the interest toward intelligent and automated platforms capable of learning accurately from large volumes of data to respond proactively to slowdowns and mitigate high-impact outages. However, the software industry is at the early stage of innovating, adopting and trusting these so-called AIOps solutions [2], [3]. A myriad of machine learning models have been proposed for the *Incident Management Procedure* to help engineers efficiently anticipate and detect outages, identify root causes, and remediate issues. Nevertheless, the best models are generally obscure as they do not convey any explanation of the internal process of making decisions, strongly limiting their adoption and deployment by practitioners. At this point, Explainable AI [4] comes into play and aims at extracting interpretable and relevant patterns from data as well as providing a transparent mechanism that explains how black box models work. In this

thesis, we address the mentioned challenges with a promising data mining technique, Subgroup Discovery [5]–[7], which seek to find interesting and interpretable patterns in data w.r.t a target problem. Particularly, we are interested in providing insights and explanations of the process that diagnose and triage incidents in the context of incident management procedure. We proposed two first contributions in that direction [8], [9]. This PhD thesis project is at the cross roads of data mining and software engineering and aim at contributing in both fields.

## II. DISCUSSION OF AIOps STATE OF THE ART

AIOps is a recent and cross-disciplinary research area. Existing contributions are scattered due to the lack of an unified terminology, rendering their discovery and comparison difficult. We carried out an in-depth bibliographic study of AIOps techniques for incident management procedure and we developed an AIOps taxonomy whose different approaches are classified with respect to a target problem. Our procedure is summarized in Fig 1, which consists of four distinct phases, with corresponding time cost to minimize. Incident reporting techniques aim first to detect performance degradation and potential anomalies and then create *tickets* to record relevant and useful information. Incidents should be prioritized according to their degree of severity [10]–[12]. Sophisticated predictive models have been proposed to detect and rank outages based on KPIs metrics, event logs [13]–[16], and execution traces [17]. Once the incident is reported, a diagnosis of the root cause is performed to locate the source problem that triggered the incident [18]–[20]. It is common for an incident to have been previously reported, hence the interest in grouping similar incidents into buckets [21]. Upon the diagnosis of an incident, the right service team should quickly engage for investigation, which is called incident triage: several approaches were proposed to successfully automate this task [22], [23]. The final step is to bring the problematic service back to a normal state by automatically suggesting appropriate healing and remedial actions based on reported historical issues and also knowledge expertise, known as incident mitigation [24], [25].

## III. HOW CAN SUBGROUP DISCOVERY HELP AIOps?

We briefly illustrate Subgroup Discovery (SD) as follows, considering a dataset where objects are described by attributes, one of which is a class. The goal is to discover interesting patterns or object generalizations such as numerical attribute ranges, that strongly characterize a given class. This basic idea also called *supervised descriptive rule discovery* [7]: it

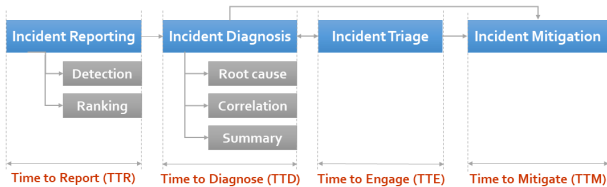


Figure 1. The proposed Incident Management Procedure

produces rules of the form  $pattern \Rightarrow target$  as well as many metrics to assess the quality of the rule. Since then, SD has been developed on three axes. First, the languages on which the patterns are defined are diverse and heterogeneous (itemsets, numerical vectors, graphs, etc.). Second, since the number of possible patterns is exponential w.r.t. input data, smart enumeration techniques are required with exhaustive search [26], but more and more with heuristic search taking into account an exploration/exploitation trade off [27] and to produce a small set of interesting patterns [28]. Finally, the notion of interestingness is probably the most important. An important step has been made with the introduction of Exceptional Model Mining [29], a generalization of SD where subgroups of objects with a *deviant behavior* are sought for, i.e., inducing a local model that differ from a global one. Successfully using SD for a given application requires to consider jointly and smartly the three axes which is not trivial. In what follows, we briefly present our first proposals where SD can help AIOps takes in a COPILOTE environment [30].

#### A. Targeting suspect query fragments in large SQL Workloads

In this work [8], we addressed SQL workload analysis, a crucial task for database administrators to identify schema issues and improve performances. Although DBAs can easily identify queries repeatedly causing performance issues, it remains challenging to automatically identify subsets of queries that share some properties only and foster at the same time some target measures, such as execution time. This perfectly falls to an instance of SD. After efficiently parsing queries to extract important attributes (e.g., tables, fields, predicates), we augment queries with other relevant information such as performance metrics, environment features, and anomaly alerts. Then, we define a suitable pattern language: we opted for a numerical representation for each single observation in the workload. We then integrate a diverse set of interestingness measures whose choice is made by the end-user, e.g. one is interested in a set of queries whose execution time distribution is significantly higher and deviant from the "norm". We provide exact and heuristic algorithms to identify subgroups of interest. Furthermore, we integrate a visual tool that enables the user to interact with the framework and iteratively learn from the obtained results. The experiments were conducted on an SQL workload that contains more than 140K queries run on our production-environment servers. Through the provided results, we were able to pinpoint query properties that are always correlated with performance degradation (e.g., missing indexes, concurrency issues, etc.).

#### B. Interpretable summaries of opaque incident triaging

In this work [9], we addressed the problem of incident triage aiming to assign incidents to the right maintenance service team to mitigate anomalies quickly and effectively. We first motivate the need of automatically triage the large number of incidents reported on our ERP product maintenance platform at Infologic. Then, we propose an efficient black box model trained on 170K user reported incidents. This motivates our main contribution consisting in an original approach that summarizes local explanations of black box predictions. Indeed, recent developments in explainable AI help in providing global explanations of the model, but also, and most importantly, with local explanations for each model prediction. Unfortunately, providing a human with an understandable explanation for each outcome is not conceivable when dealing with an important number of daily predictions. To address this problem, our original method rooted in SD propose to conceptualize the predicted model outcomes into subgroups according to both (1) a common description and (2) the ability to locally mimic the black box model with a white box one. More precisely, we group objects into a controlled number of subgroups, and for each subgroup we provide an explanation that holds for all of its objects. Each of these subgroups is also described with a description (pattern) that separates it exactly from the rest of the dataset. The proposed solution allows the user to not only interpret the black box outcome for each subgroup, but also to understand the nature of the objects that a subgroup contains. Experiments show that the identified subgroup imitate very well the black box decisions while providing interpretable and meaningful explanations that help practitioners understanding why a given incident were assigned to a specific service team.

#### IV. PERSPECTIVES

The aforementioned contributions are two first practical steps on the research question of this PhD thesis started in December 2020. Indeed, it is too ambitious, probably unrealistic, to directly approach AIOps in a top-down fashion for a full automation of Incident Management. We learned from these two analyses two main lessons. First, subgroup discovery has some limitations, which are actually research challenges: although it has become a mature technique, there is still room for improvement and new applications are particularly good at identifying these limitations. For example, dealing with multi-objective SD [31] and with labels from a hierarchy [32] is difficult. Second, experimenting with real data of our company with the goal to use our data-centric approaches in production revealed us several insights on why/how it is difficult to make adopt techniques such as Subgroup Discovery, it requires a perfect combination of the three SD axis, along with interactivity, prior knowledge and feedback integration, visualization tools, etc. We already started working on other applications linked to the incident management procedure, namely, crash deduplication [21] and early detection of JVM memory leaks [33]. These are two critical problems for Infologic and here again, we believe that Subgroup Discovery has a high potential w.r.t. the state of the art.

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