DeLag: Detecting Latency Degradation Patterns in Service-based Systems

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Abstract—Performance debugging in production is a fundamental activity in modern service-based systems. The diagnosis of performance issues is often time-consuming, since it requires thorough inspection of large volumes of traces and performance indices. In this paper we present DeLag, a novel automated search-based approach for diagnosing performance issues in service-based systems. DeLag identifies subsets of requests that show, in the combination of their Remote Procedure Call execution times, symptoms of potentially relevant performance issues. We call such symptoms Latency Degradation Patterns. DeLag simultaneously search for multiple latency degradation patterns while optimizing precision, recall and latency dissimilarity. Experimentation on 700 datasets of requests generated from two microservice-based systems shows that our approach provide better and more stable effectiveness than three state-of-the-art approaches and general purpose machine learning clustering algorithms. Moreover, DeLag outperforms in terms of efficiency the second and the third most effective baseline techniques on the largest datasets used in our evaluation.

Index Terms— performance analysis, anomaly correlation, automated diagnosis, service-based systems

1 INTRODUCTION

M odern high-tech companies deliver new software in production every day [1] and perceive this capability as a key competitive advantage. In order to support this fast-paced release cycle, IT organizations often employ several independent teams that are responsible “from development to deploy” [2] of loosely coupled independently deployable services. Unfortunately, frequent software releases often hamper the ability to deliver high quality software [3]. For example, widely used performance assurance techniques, like load testing [4], are often too time-consuming for these contexts. Also, given the complexity of these systems and their workloads [5], it’s often unfeasible to proactively detect performance issues in a testing environment [6]. For these reasons, today, the diagnosis of performance issues in production is a fundamental capability for maintaining high-quality service-based systems.

Service owners are usually responsible and accountable for meeting Service Level Objectives (SLOs) on Key Performance Indicators (KPIs). Software engineers and performance analysts continuously monitor KPIs and execution traces on the run-time system to identify symptoms of potentially relevant performance issues that lead to SLOs violations. The truly identification of such symptoms is often critical: a request may involve several Remote Procedure Calls (RPC) and the number of performance traces and performance metrics to analyze can be huge. According to a recent study on microservice-based systems [7], software engineers spend days or even weeks to debug a software issue, and initial understanding, coping and localization are among the most time-consuming phases during debugging. Although several techniques have been introduced to provide automation in diagnosing performance issues in service-based systems [8], [9], [10], [11], [12], [13], [14], the reduction of the manual effort and the time needed is still critical.

Techniques for automating performance issue diagnosis rely on pattern mining to spot patterns in trace attributes (e.g., request size, response size, RPCs execution times) correlated to latency degradation of requests. The benefit provided by these techniques is threefold: 1) they provide evidences based on data on the existence of relevant performance issues, 2) they reduce the amount of traces to inspect and, 3) they provide useful information to effectively localize and debug performance issues.

Prior work on automated anomaly detection relies on association rule mining [15], [16]. These techniques extract patterns in traces that are correlated to anomalous system behaviors, but when they cause (partially or entirely) overlapping latency distributions, effectiveness may potentially decrease [12]. Other techniques suitable for detecting patterns in continuous trace attributes rely on machine learning techniques such as tree-augmented bayesian networks [8] or random forests [14], as well as on clustering approaches [19], [20].

In this paper we present DeLag (Detecting Latency Degradation Patterns): a novel approach that simultaneously searches for multiple patterns correlated with latency degradation. Some of the previous techniques work with
any types of trace attributes (either continuous or categorical) \[12, 14\], while others target only specific types of attributes such as categorical ones \[15, 21\] or execution time \[13\]. Given the relevance of Remote Procedure Call (RPC) execution time for diagnosing performance issues in service-based systems, DeLag explicitly targets this metric, as it aims at automatically identifying Latency Degradation Patterns (LDPs) \[13\], i.e. RPCs execution time behaviors that are likely to be related to relevant performance issues. DeLag searches for a whole set of patterns by maximizing precision and recall, and by simultaneously minimizing latency dissimilarity. The optimal pattern set is then selected from non-dominated Pareto-optimal solutions by using a decision making heuristic.

We evaluated DeLag on 700 datasets involving different combinations of LDPs from two service-based systems and compared DeLag to three state-of-the-art techniques for pattern detection in execution traces \[12, 13, 14\] and two general-purpose clustering algorithms. Datasets are generated by performing load testing sessions while injecting different performance issues on systems (hence different LDPs), for an overall time of ∼15 days and a half. We found that DeLag provides better and more stable effectiveness than other approaches. DeLag outperforms in terms of effectiveness all the baseline techniques in at least one case study (with \(p \leq 0.05\) and non-negligible effect size), and the effectiveness provided by DeLag is more stable than those provided by other techniques (the interquartile range for F1-scores of DeLag is smaller than those of other approaches). Additionally, we found that DeLag effectiveness is not affected by similarity of latency distributions related to different patterns (contrariwise to F1-score-based techniques), and it is also not affected by RPC execution time variation not correlated with latency degradation. Moreover, we found that DeLag is more efficient on the largest datasets used in our evaluation than the second most effective technique (by 15% in the first case study and by 22% in the second case study) and the third most effective technique (by 15% and 17% respectively).

The rest of the article is structured as follows. Section 2 describes the concept of Latency Degradation Pattern, and Section 4 describes how the problem of detecting LDPs is modeled as multi-objective optimization problem. Section 5 outlines the workflow used by DeLag to detect LDPs, and Section 3 describes how the approach can be integrated into a DevOps process. In Section 6 we present our research questions along with experimental design and results. Section 7 discusses some implications of our findings. Section 8 describes threats to validity. Section 9 presents related work, and Section 10 concludes this paper.

## 2 Latency Degradation Patterns

Services are often subject to SLO on request latency (e.g. time to load the homepage of a website). Usually, a SLO on latency defines a range of acceptable values, i.e. \(L \leq L_{SLO}\). In this paper, we name the range of latency values that do not meet SLO expectations as the targeted latency range, i.e. \(L > L_{SLO}\).

A request to a service-based system often involves several RPCs. Each request is associated to a set of execution trace attributes (i.e. RPC execution time). In this paper, we denote a request \(r\) as an ordered sequence of trace attributes \(r = (e_0, e_1, \ldots, e_m, L)\), where \(e_j\) represents the execution time of a specific RPC \(j\) triggered by the request.

Latency Degradation Patterns (LDPs) \[13\] are patterns in RPCs execution times correlated with SLO violation. They can be represented as conjunctions of predicates over RPCs execution time. Conjunctions of predicates are used, instead of single predicates, because several software issues in service-based systems lie in the interaction of multiple RPCs \[7\] rather than being rooted in the internal implementation of individual RPCs. Moreover, a single predicate alone is often not sufficient to capture the patterns of SLO violations \[8\].

An informal example of LDP could be:

![Example LDP](image)

More formally, a pattern \(P\) is denoted as a set of predicates \(\{p_0, p_1, \ldots, p_k\}\) with \(k \geq 0\). A request \(r\) satisfies \((<)\) a pattern \(P\) if every predicate \(p \in P\) is satisfied by the request \(r\):

\[
r < P \iff \forall p \in P, \quad r \prec p
\]

Each predicate targets a specific RPC \(j\) and is denoted as a triple \(p = (j, e_{min}, e_{max})\), where \(e_{min}, e_{max}\) represents a range of values on the RPC execution time. We say that a request \(r = (\ldots, e_j, \ldots)\) satisfies \(p\), denoted as \(r \prec p\), if:

\[
e_{min} \leq e_j < e_{max}
\]

Previous approaches use F1-score \[12, 13\] to measure the degree of correlation between patterns and latency degradation. The idea is to partition the set \(R\) of requests under analysis in two subsets \(R_{POS}\) and \(R_{NEG}\), namely the set of requests not meeting SLO (or positives) and the set of requests meeting SLO (or negatives)

\[
R_{pos} = \{ r \in R \mid L > L_{SLO}\}
\]

and to compute F1-score for a pattern \(P\) accordingly:

\[
F1-score = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}
\]

where precision and recall of the pattern are defined as follows:

\[
\text{precision} = \frac{|tp|}{|tp| + |fp|}
\]

\[
\text{recall} = \frac{|tp|}{|R_{pos}|}
\]

and true positives \(tp\) and false positives \(fp\) are defined as:

\[
tp = \{r \in R_{pos} \mid r \prec P\}
\]

\[
fp = \{r \in R_{neg} \mid r \prec P\}
\]

If a pattern shows high recall then it frequently appears in requests with latency falling in the targeted latency range. But, it does not provide any guarantees on its infrequency.
in requests meeting SLO. On the other hand, a high value of precision indicates that most of the requests satisfied by the pattern do not meet SLO expectations, but the number of the involved requests may be negligible and not worth to investigate. F1-score, which is the harmonic mean of precision and recall, provides a unique measure to evaluate the quality of a pattern while keeping into consideration both these aspects.

3 DELAG IN A DEVOPS CONTEXT

Our approach can be easily integrated into a DevOps process, in that DeLag is fully automated and can be executed periodically (e.g. every day) to detect symptoms of relevant performance issues in RPCs execution time. DeLag works with any type of service-based system, the only assumption is the presence of a distributed tracing infrastructure [22] (e.g. Zipkin [1], Jaeger [2], Dapper [23], etc). Given the recent widespread adoption of distributed tracing solutions [24], it seems a reasonable assumption for a modern service-based system.

Following the example of DeCaf [14], patterns derived by DeLag can be stored into a database along with their F1-scores (see Equation (2)) to build historical knowledge and to automatically diagnose different categories of potential performance issues:

1) New: A new LDP is identified that has never appeared in the past.
2) Regressed: F1-score of the LDP is substantially increased compared to the past.
3) Known: F1-score of the LDP is similar to the recent one.
4) Improved: F1-score of the LDP is substantially decreased compared to the past.
5) Resolved: LDPs that were previously detected do not appear anymore.

The description of each category is intentionally broad. Their concrete definition highly depends on the context (e.g. system characteristics and service owners needs), hence they are reported to provide the intuition on how DeLag can be integrated into a DevOps process.

4 MULTI-OBJECTIVE OPTIMIZATION MODEL

Existing approaches based on F1-Score optimization [12], [13] search for optimal partitions of the targeted latency range while considering a single optimal pattern for each sub-interval. The sum of F1-scores is maximized in order to get the optimal set of patterns. Although this technique works properly in situations where different performance issues lead to clearly distinguishable latency behaviors, its effectiveness decreases when latency degradations introduced by different issues are similar. For example, Fig. 1a shows a scenario with two performance issues leading to two clearly separated latency distributions. This is the ideal scenario for F1-score-based approaches, since the targeted latency range can be divided in a way that clearly separates the LDPs (e.g. pattern 2 for the (460ms, 550ms) sub-interval and pattern 1 for (550ms, 750ms)). However, there may be cases where it is difficult to partition the targeted latency range so that patterns are clearly separated (e.g. Fig. 1b). This limitation was also highlighted in the work of Krushevskaja and Sandler [12] by showing that, the more latency distributions (related to different patterns) are close one to another, the more the effectiveness of the approach decreases.

Our approach overcomes the latter problem by simultaneously searching multiple LDPs for the entire targeted latency range.

In this section, we describe how we model the problem of detecting LDPs as a multi-objective optimization problem. First, we define the search space of our optimization problem. Then, we describe our optimization objectives.

4.1 Search Space

DeLag simultaneously searches multiple patterns for the entire targeted latency range, therefore each possible set of patterns \( S = \{P_1, P_2, ..., P_n\} \) is considered as a solution. As described in Section 2, a pattern is a set of predi-

1. https://zipkin.io
2. https://www.jaegertracing.io
cates $P = \{p_1, p_2, ..., p_m\}$ and each predicate is a triple $p = (j, e_{\min}, e_{\max})$ where $e_{\min}$ and $e_{\max}$ define the execution time range for the RPC $j$. RPC execution time is a continuous value, thus $e_{\min}$ and $e_{\max}$ can assume a wide range of possible values. In order to exclude, from our search space, solutions with near-similar predicates as well as irrelevant predicates (i.e. related to rare execution time behaviors), we identify (through clustering method), for each RPC $j$, a set of eligible values $E_j$. Therefore, each predicate $p = (j, e_{\min}, e_{\max})$ in the solution space must be such that $e_{\min} \in E_j$, $e_{\max} \in E_j$, for a given RPC $j$, is defined by selecting values in the RPC execution time range that separate dense regions of the execution time distribution. For example, a plausible set for the execution time of the RPC Auth, showed in Fig. 2a could be $E_{\text{Auth}} = \{25, 175, 250, 350\}$.

The key intuition of this search space reduction is that it allows to consider only patterns related to relevant RPC execution time behaviors, while excluding from the search space those patterns related to rare transient execution time behaviors, as well as patterns that are similar in terms of RPC execution time behavior.

4.2 Optimization Objectives

DeLag optimizes pattern sets by simultaneously maximizing precision and recall, and by minimizing latency dissimilarity.

In Section 2, we defined precision and recall to measure the quality of a single pattern, and in the following we adapt these measures to a whole pattern set.

We say that a request $r$ satisfies a pattern set $S$ if at least one pattern $P$ in $S$ is satisfied by $r$:

$$ r \ll S \iff \exists P \in S, \ r \ll P $$

It is worth noting that a request $r$ can satisfy multiple patterns in the set $S$. Nevertheless, we minimize the number of requests satisfied by multiple patterns by minimizing latency dissimilarity, as it will be detailed later in this section.

True positives and false positives for the pattern set $S$ can be defined as follows:

$$ tp = \{ r \in R_{\text{pos}} \mid r \ll S \} $$

$$ fp = \{ r \in R_{\text{neg}} \mid r \ll S \} $$

\hspace{1cm} (6)

Precision measures the proportion of requests satisfied by $S$ having latency above $L_{\text{SLO}}$ (i.e. $R_{\text{pos}}$), as described in Equation (5).

Recall, instead, measures the proportion of requests that do not meet SLO (i.e. $R_{\text{pos}}$) and satisfy $S$, as described in Equation (4).

However, only maximizing precision and recall may not be enough. In the following we describe an exemplificative scenario, where requests affected by two distinct performance issues can be satisfied by a single pattern while reaching both the maximum precision and recall. Fig. 2a shows the bivariate distribution of the latency for loading the homepage of a website and the execution time of an invoked RPC, namely Auth. Requests not meeting SLO (i.e. $R_{\text{pos}}$) and satisfy $S$, as described in Equation (4).

while keeping the same precision and recall, $S_2$ provides a more informative view on the nature of the latency degradation. Indeed, $P_1$ and $P_2$ identify two clusters of requests with different performance behaviors. In order to avoid shallow solutions like $S_1$, we penalize pattern sets where latencies of requests within each cluster are diverse, by minimizing latency dissimilarity.

Latency dissimilarity is the sum of the average squared
distance of latencies from the mean value, within each cluster of requests. Each pattern \( P \in S \) identifies a set of requests \( C_P = \{ r \in R \mid r < P \} \). Latency dissimilarity, for a given pattern set \( S \), can be computed as follows:

\[
\sum_{P \in S} \sum_{r \in C_P} (L_r - \mu_P)^2 \tag{7}
\]

where \( L_r \) is the latency for the request \( r \) and \( \mu_P \) is the average latency for requests satisfied by \( P \):

\[
\mu_P = \frac{\sum_{r \in C_P} L_r}{|C_P|} \tag{8}
\]

Furthermore, the minimization of latency dissimilarity reduces the chance that the same request satisfies multiple patterns in \( S \). Indeed, if the same request satisfies multiple patterns then latency dissimilarity tends to increase as the same request \( r \) will contribute multiple times to the summation in Equation (7).

Our optimization model involves three orthogonal objectives, i.e. maximizing precision and recall while minimizing latency dissimilarity. We use Pareto optimality to plot the set of non-dominating solutions.

5 The DeLag Approach

DeLag workflow is depicted in Fig. 3. Firstly, DeLag starts by constructing the search space of the optimization problem (Search Space Construction). Secondly, it precomputes results of inequality checks and stores them in lookup tables that will be then used to avoid repeated computation in fitness evaluation (Precomputation). Thirdly, it generates as set of non-dominated Pareto-optimal patterns sets through a multi-objective evolutionary algorithms (Genetic Algorithm). Finally, it employs a heuristic to select a single pattern set from the set of Pareto-optimal solutions as the final solution (Decision Maker).

In the following we describe details of each workflow component. Section 5.1 describes Search Space Construction. Section 5.2 describes the main components of the Genetic Algorithm, while Section 5.3 describes how Precomputation improves the efficiency of the evolutionary process. Finally, Section 5.4 outlines the Decision Maker.

5.1 Search Space Construction

The key step for shaping the search space of our problem involves the identification of highly dense regions of the RPC execution time. Basically, a set \( E_j \) of eligible values must be identified for each RPC \( j \). As in our previous work [13], DeLag employs a Mean shift algorithm [25] to automatically identify high density intervals of the RPC execution time range. Mean shift is a feature-space analysis technique for locating maxima of a density function [26], and its application domains include cluster analysis in computer vision and image processing [25]. We use the implementation provided by scikit-learn [27]. For each RPC \( j \), Mean shift algorithm clusters requests according to their corresponding execution time. We then infer split points \( E_j \) according to the highly dense identified regions. We discard clusters with size less than \( |R_{pos}| \cdot 0.05 \) to exclude execution time values rarely occurring in requests (further discussion on this point can be found in Section 8).

Since eligible values selection for RPCs are independent one by another, DeLag selects \( E_j \) for each RPCs \( j \) in parallel to speed-up the process.

5.2 Genetic Algorithm

Algorithm 1 presents the genetic algorithm that solves the optimization problem defined in Section 5.2. DeLag uses NSGA-II [28] to build (successively-improved) Pareto-optimal solutions, while seeking new non-dominating pattern sets. NSGA-II is a widely-used multi-objective genetic algorithm in the context of Search Based Software Engineering [29]. The algorithm first generates a random initial population \( P \). Then, it performs \( g_{\text{max}} \) generations while keeping track of the best individuals ever lived in the evolutionary process, namely Pareto front \( PF \). At each generation, a new population \( Q \) is generated by performing crossover, mutation or reproduction on randomly selected individuals. The population for the subsequent generation is then obtained by using the NSGA-II selection operator [28] on the original population \( P \) joined with the newly generated population \( Q \). At the end of the search, the algorithm returns the set of generated solutions found to be non-dominating \( PF \).

The DeLag genetic algorithm is implemented on top of the DEAP evolutionary computation framework [30]. In the following we describe the “key ingredients” of our genetic algorithm: representation, crossover, mutation, selection and fitness.

5.2.1 Representation

The genetic algorithm simultaneously searches multiple LDPs, thus each individual corresponds to a whole pattern set. The representation of an individual is illustrated in Fig. 4. Our approach generates a set of of these individuals, which corresponds to a population of individuals in the evolutionary algorithm. Each individual consists of several chromosomes (patterns \{ \( P_1, P_2, \ldots, P_n \) \}), and each chromosome contains multiple genes (predicates \{ \( p_1, p_2, \ldots, p_m \) \}), which consist of random combinations of
Algorithm 1: Genetic Algorithm

Data: max generation \( g_{\text{max}} \), crossover probability \( p \), mutation probability \( q \)
Result: Pareto front \( P_F \)

1. initialise population \( P \);
2. evaluate fitness of \( P \) and update \( P_F \);
3. for \( i \) in range(0, \( g_{\text{max}} \) do
   4. for \( j \) in range(0, |\( P_j \)|) do
      5. if \( r < p \) then \( \triangleright \) apply crossover
         6. randomly select \( S_1 \) and \( S_2 \) from \( P \);
         7. \( S' \leftarrow \text{crossover}(S_1, S_2) \);
      8. else if \( r < p + q \) then \( \triangleright \) apply mutation
         9. randomly select \( S \) from \( P \);
        10. \( S' \leftarrow \text{mutation}(S, q) \);
      11. else \( \triangleright \) apply reproduction
         12. randomly select \( S \) from \( P \);
         13. \( S' \leftarrow S \);
        14. \( Q \leftarrow Q \cup \{S'\} \);
      15. evaluate fitness of \( Q \) and update \( P_F \);
     16. \( P' \leftarrow \text{sorted}(Q \cup P, \prec_c) \); \( \triangleright \) see Equation (9) for \( \prec_c \)
     17. \( P \leftarrow P' \cup \{Q\} \); \( \triangleright \) new population

return \( P_F \);

Algorithm 2: Mutation

Data: individual \( S \), mutation probability \( q \)
Result: mutant \( S' \)

1. \( r \sim U(0, 1) \);
2. if \( r < \frac{1}{1} \) then \( \triangleright \) apply remove mutation (individual)
    3. randomly select one pattern \( P \) from \( S \);
    4. \( S' \leftarrow S \setminus \{P\} \);
3. else if \( r < \frac{2}{2} \) then \( \triangleright \) apply add mutation (individual)
    4. generate a new random pattern \( P \);
    5. \( S' \leftarrow S \cup \{P\} \);
4. for each pattern \( P \) in \( S' \) do
   5. \( r \sim U(0, 1) \);
   6. if \( r < q \) then
      7. if \( r < \frac{q}{2} \) then \( \triangleright \) apply remove mutation (chromosome)
         8. randomly select one predicate \( p \) from \( P \);
         9. \( P \leftarrow P \setminus \{p\} \);
      10. else \( \triangleright \) apply add mutation (chromosome)
           generate a new random predicate \( p \);
           \( P \leftarrow P \cup \{p\} \);
   11. return \( S' \);

5.2.3 Mutation

Algorithm 2 illustrates the mutation operator, which is performed with probability \( q \) at each new generation on a randomly selected individual \( S \). Mutation is performed at two levels: individual and chromosome.

First, mutation is applied at individual level by performing one among three possible types of mutation with equal probability: add, remove or split. The add mutation randomly adds a newly generated chromosome. The remove mutation removes a randomly chosen chromosome from the individual. The split mutation splits a randomly selected chromosome \( P \) within \( S \) in two novel chromosomes \( P_1 \) and \( P_2 \). The latter operator first randomly selects a RPC \( j \) and a threshold \( t \in E_j \). Then, \( P_1 \) and \( P_2 \) are created by partitioning requests that satisfy the randomly chosen \( P \) in two parts (those having \( e_j < t \) and those having \( e_j \geq t \)). Finally, \( P \) is replaced by \( P_1 \) and \( P_2 \) in \( S \). The detailed steps performed by the split mutation operator are outlined in Algorithm 3.

Then, chromosome level mutation is performed on each chromosome, in turn, with probability \( q \). Similarly to individual level mutation, chromosome mutation applies one between two possible types of mutation with equal probability: add or remove. The add mutation randomly adds a newly generated gene, while the remove mutation removes a randomly chosen gene from the chromosome.

5.2.4 Selection

We employed the widely used elitism method defined in NSGA-II [28]. This method defines a comparison operator \( \prec_c \) based on rank and crowding-distance. The rank is a measure of level of non-domination of the individual, while the crowding-distance is a measure of density of individuals in the neighborhood.
Algorithm 3: splitPattern

Data: pattern P
Result: pattern P_1, pattern P_2
Randomly select a RPC j;
select a predicate \( p = \langle k, e_{\text{min}}, e_{\text{max}} \rangle \) with \( k = j \);
if \( p \) exists then
   \( e_\text{min} = e_{\text{min}} \);
   \( e_\text{max} = e_{\text{max}} \);
   \( P' \leftarrow P \setminus \{ p \} \);
else
   \( e_\text{min} \leftarrow \min(E_j) \);
   \( e_\text{max} \leftarrow \max(E_j) \);
   \( P' \leftarrow P \);
Randomly select \( t \in E_j \) s.t. \( e_\text{min} < t < e_\text{max} \);
\( p_1 \leftarrow \langle j, e_{\text{min}}, t \rangle \);
\( p_2 \leftarrow \langle j, t, e_{\text{max}} \rangle \);
\( P_1 \leftarrow P \cup \{ p_1 \} \);
\( P_2 \leftarrow P \cup \{ p_2 \} \);
return \( P_1, P_2 \);

For two pattern sets \( S_1 \) and \( S_2 \), we say \( S_1 \prec_c S_2 \) if and only if:
\[
S_1^{\text{rank}} < S_2^{\text{rank}} \vee (S_1^{\text{rank}} = S_2^{\text{rank}} \wedge S_1^{\text{dist}} > S_2^{\text{dist}})
\]  
(9)

This selection policy favors individuals with smaller non-domination rank and, when the rank is equal, it favors the one with greater crowding distance (less dense region).

5.2.5 Fitness

The individual fitness value is recorded as a triple: precision, recall and latency dissimilarity. In order to avoid overfitting, solutions containing patterns with recall \( \leq 0.05 \) are penalized by assigning them the worst fitness, i.e. \( \{0,0,0\} \) (further discussion on this point can be found in Section 6).

Fitness evaluation can be time consuming, but it is also easily parallelizable [31]. Therefore, for sake of efficiency, DeLag supports parallel fitness evaluation by assigning individuals to multiple fitness evaluators, which may run on distributed machines (a single multicore machine was used in our experimental evaluation, when comparing DeLag with other techniques).

In our experimental evaluation the initial population was created by generating 30 random individuals, crossover and mutation probability were fixed to 0.6 and 0.4, respectively, and the evolutionary process terminates after 300 generations.

5.3 Precomputation

The identification of true positives and false positives for a pattern set \( S \) (see Equation (3)) is the key operation for computing precision and recall. This operation requires to verify, for each request \( r \in R \), whether \( r \prec S \). This verification involves several inequality checks, which are likely to be repeated several times during the evolution process. DeLag reduces the fitness evaluation effort by precomputing inequality check results, thus avoiding redundant computation. Inequality checks are denoted as pairs \( \langle j, t \rangle \), where \( j \) is a RPC and \( t \in E_j \) is an eligible value, hence an execution time threshold. Inequality check results are denoted as ordered sequences of booleans \( B_{\langle j,t \rangle} = \langle b_0^{\langle j,t \rangle}, b_1^{\langle j,t \rangle}, ..., b_n^{\langle j,t \rangle} \rangle \), where \( b_i^{\langle j,t \rangle} \) refers to the check result for the request \( r_t \) in \( R \).

A check result \( b_i^{\langle j,t \rangle} \) for a given inequality check \( \langle j, t \rangle \) and a request \( r_t = (..., e_j, ...) \) is defined as:
\[
b_i^{\langle j,t \rangle} = \begin{cases} 
    \text{True} & \text{if } e_j \geq t \\
    \text{False} & \text{otherwise}
\end{cases}
\]

Two boolean sequences (namely \( B_i^{\text{pos}} \) and \( B_i^{\text{neg}} \)) are precomputed for every pair \( \langle j, t \rangle \), which represent inequality check results, respectively, for positive and negative requests (i.e., \( R_{\text{pos}} \) and \( R_{\text{neg}} \)). Boolean sequences are encoded as bitstrings and stored in two lookup tables, one for positives requests \( H_{\text{pos}} \) and another one for negative requests \( H_{\text{neg}} \) as shown in Fig. 5. The length of each bitstring in \( H_{\text{pos}} \) (resp. \( H_{\text{neg}} \)) is equal to the number of requests in \( R_{\text{pos}} \) (resp. \( R_{\text{neg}} \)). A bitstring can be retrieved by lookup tables using the corresponding index, i.e. \( \langle j, t \rangle \). Fig. 6 shows the process used to create \( H_{\text{pos}} \) and \( H_{\text{neg}} \).

These data structures enable fast identification of true positives and false positives across multiple requests through bitwise operations. A bitwise operation works on one or more bit strings at the level of their individual bits. We use three common bitwise operators: and (\&), or (\lor) and not (\neg). A predicate \( p = \langle j, e_{\text{min}}, e_{\text{max}} \rangle \), with \( e_{\text{min}}, e_{\text{max}} \in E_j \) (see Section 5.1), can be efficiently evaluated on positive requests as well as on negative requests by performing the following steps. First, boolean sequences associated to inequality checks \( \langle j, e_{\text{min}} \rangle \) and \( \langle j, e_{\text{max}} \rangle \) are retrieved by lookup tables \( H_{\text{pos}} \) and \( H_{\text{neg}} \). We denote them as \( B_i^{\text{pos}}_{\langle j, e_{\text{min}} \rangle} \) and \( B_i^{\text{neg}}_{\langle j, e_{\text{min}} \rangle} \), and \( B_i^{\text{pos}}_{\langle j, e_{\text{max}} \rangle} \) and \( B_i^{\text{neg}}_{\langle j, e_{\text{max}} \rangle} \).

Then, positive and negative requests that satisfy predicate \( p \) are derived through bitwise operations:
\[
B_i^{\text{pos}} = B_i^{\text{pos}}_{\langle j, e_{\text{min}} \rangle} \land \neg B_i^{\text{neg}}_{\langle j, e_{\text{max}} \rangle}
\]
\[
B_i^{\text{neg}} = B_i^{\text{neg}}_{\langle j, e_{\text{min}} \rangle} \land \neg B_i^{\text{pos}}_{\langle j, e_{\text{max}} \rangle}
\]

Hence \( b_i^{\langle j,t \rangle} \in B_i^{\text{pos}} \) (resp. \( b_i^{\langle j,t \rangle} \in B_i^{\text{neg}} \)) is equal to \( \text{True} \) if the request \( r_t \) in \( R_{\text{pos}} \) (resp. \( r_t \) in \( R_{\text{neg}} \)) satisfies the predicate \( p \), i.e. \( r_t \prec p \), and is equal to \( \text{False} \) otherwise.

The same approach is also applied to check whether a request satisfies a pattern or not, \( r_t \prec P \):
\[
B_i^{\text{pos}} = \bigwedge_{p \in P} B_i^{\text{pos}}_p
\]
\[
B_i^{\text{neg}} = \bigwedge_{p \in P} B_i^{\text{neg}}_p
\]
And to verify whether a request satisfies the whole pattern set, \( r_i \subset S \):

\[
B_S^{pos} = \bigvee_{p \in S} B_p^{pos} \quad B_S^{neg} = \bigvee_{p \in S} B_p^{neg}
\]

Number of true positives and false positives for a given pattern set \( S \) are obtained by counting \( \text{True} \) booleans (i.e. number of 1 in the bit string) in both \( B_S^{pos} \) and \( B_S^{neg} \):

\[
|tp| = |\{b \in B_S^{pos} \mid b = \text{True}\}| \quad |fp| = |\{b \in B_S^{neg} \mid b = \text{True}\}|
\]

Finally, precision and recall can be derived through a simple numerical computation (see Equations (3) and (4)).

### 5.4 Decision Maker

The manual identification of a relevant single pattern set from the Pareto-optimal set \( \mathcal{PF} \) can be complex. DeLag employs a heuristic to avoid this manual process, thus enabling full automation. The decision making heuristic uses the generalized form of the F1-score formula:

\[
F_{\beta}\text{-score} = (1 + \beta^2) \cdot \frac{\text{precision} \cdot \text{recall}}{(\beta^2 \cdot \text{precision}) + \text{recall}} \quad (10)
\]

The \( F_{\beta}\text{-score} \) is a generalization of the F1-score that adds a configuration parameter called beta. The F1-score uses a beta value of 1.0, which gives the same weight to both precision and recall. A beta value less than 1 gives more weight to precision and less to recall, whereas a larger beta value gives less weight to precision and more weight to recall. Maximizing precision implies the minimization of false positives, whereas maximizing recall implies the minimization of false negative.

We argue that minimization of false positives is likely to be more relevant than minimization of false negatives in the context of LDPs detection. Indeed, patterns with non-negligible amounts of false positives are likely to be less meaningful (whatever the amount of false negatives is), since they are not peculiar to requests not meeting SLO. Conversely, patterns with non-negligible amount of false negatives can still be relevant if the number of false positives is low, because they are peculiar to a portion of requests in \( R_{pos} \), therefore they are likely to be potential symptoms of performance issues. For these reasons, the decision-making heuristic sacrifices recall in favor of precision if this implies a gain in terms of latency dissimilarity. Algorithm 4 outlines the decision making heuristic. The heuristic selects pattern sets with maximum \( F_{\beta}\text{-score} \) while \( \beta \) ranges from 0.1 (precision is weighted 10 times as much as recall) to 1 (equally weighted). Then, it chooses among the selected solutions the one with minimum latency dissimilarity.

In order to speed up the process, the heuristic leverages lookup tables \( H_{pos} \) and \( H_{neg} \) generated in the precomputation phase.

# 6 Evaluation

We evaluated DeLag by performing a set of experiments aimed at answering the following research questions.

**RQ₁** Can DeLag effectively detect LDPs? In this RQ, the LDPs detected by DeLag are compared to the ones detected by prior work and general purpose clustering algorithms. The effectiveness of the methods are compared on precision \( (Q_{prec}) \), recall \( (Q_{rec}) \) and F1-score \( (Q_{F1}) \), as they will be defined in Section 6.3.

**RQ₂** How do overlapping patterns affect DeLag effectiveness? F1-score-based techniques are less effective when distinct patterns lead to partially (or entirely) overlapping latency distributions. With this RQ, we want to check whether DeLag overcomes this limitation. We evaluate how proximity of latency distributions (related to distinct LDPs) affects our effectiveness. The approach is experimented on a variety of scenarios while controlling the proximity of latency distributions related to different patterns.

**RQ₃** How non-critical RPC execution time variation affects DeLag effectiveness? Not all execution time variations of RPCs produce effect on latency (e.g. RPCs outside the critical path). With this RQ, we want to determine whether deviations of execution times on non-critical RPCs decrease the effectiveness of DeLag. The approach is experimented on a variety of scenarios while controlling the magnitude of increment of execution times on non-critical RPCs.

**RQ₄** What is the DeLag efficiency? Modern service-based systems collect thousands of traces per day (or even more), therefore efficiency is a major concern for DeLag. In our last RQ, we evaluate the efficiency of DeLag on datasets by different sizes.

In order to assess the generality of DeLag, we carried out our experiments on two case studies based on open-source microservice-based systems. The first one relies on E-Shopper, an e-commerce web application, while the second one on Train Ticket, a web-based booking system. Both case studies are introduced in Section 6.1. In Section 6.2, we describe the techniques used as baselines. The methodology used for the evaluation is described in 6.3, followed by descriptions of experiments carried out to address each research question, respectively, in Sections 6.4, 6.5, 6.6, and 6.7.

### 6.1 Case studies

#### 6.1.1 E-Shopper

The first case study is based on E-Shopper, a small-size microservice-based system, already used in the evaluation. 3. https://github.com/SEALABQualityGroup/E-Shopper
of our previous works [13], [32]. E-Shopper is a typical e-commerce application, which is developed as a suite of small services, each running in its own Docker container. It is designed using microservice design principles. Microservices are developed in Java and interactions among them are based on RESTful APIs. The application produces execution traces that are reported and collected by Zipkin, i.e. a popular distributed tracing system [24], and stored in Elasticsearch. We focus our experimentation on requests loading the homepage, which involve a number of 25 invocations of 7 unique RPCs spread across 5 microservices.

### 6.1.2 Train Ticket

The second case study is based on Train Ticket which is the largest and most complex open source microservice-based system (within our knowledge at the time of writing). The system was already used in previous software engineering studies [7], [33]. Train Ticket provides typical train ticket booking functionalities such as ticket enquiry, reservation, payment, change, and user notification. It is designed using microservice design principles and covers different interaction modes such as synchronous and asynchronous invocations, and message queues. The application produces execution traces that are reported and collected by Jaeger, and stored in Elasticsearch. The system contains 41 microservices related to business logic (uses four programming languages Java, Python, Node.js, and Go) with each service running in its own Docker container. Our experimentation focuses on requests devoted to the ticket searching process, which involve a number of 48 invocations of 14 unique RPCs spread across 9 microservices.

### 6.2 Baselines techniques

We compare DeLag against both domain-specific state-of-the-art approaches and general-purpose clustering algorithms. The latter were considered because of their straightforward application to the subject problem, i.e. the identification of clusters of requests that shows similar behavior in terms of RPCs execution time. We considered two widely popular clustering algorithms, i.e. K-Means [34] and Hierarchical clustering [35], and for both of them we used the implementation provided by scikit-learn [27].

As domain-specific baselines we considered both F-score-based methods (i.e., our previous work [13] and the one proposed by Krushevskaja and Sandler [12]), and a recently proposed random-forest-based approach [14]. Unfortunately, only our previous work provides publicly available source code, therefore we have re-implemented both the approach of Krushevskaja and Sandler [12] and the one of Bansal et al. [14], which are now publicly available in the replication package [36].

In the following we provide descriptions of each baseline technique:

**K-Means.** The K-Means algorithm [34] clusters data by trying to separate samples in k groups, while minimizing a criterion known as within-cluster sum-of-squares. K-Means requires the number of clusters to be specified. In our experimentation, we execute the algorithm with k ranging from 2 to 10 and we pick the best solution among them.

**Hierarchical clustering (HC).** Hierarchical clustering [35] is a general family of clustering algorithms that build nested clusters by progressively merging or splitting them. We use an implementation based on a bottom-up approach: each observation starts in its own cluster, and clusters are successively merged together. Also hierarchical clustering requires the number of clusters to be specified, therefore we employed the same approach used for the K-Means algorithm.

**Krushevskaja and Sandler (KrSa).** This approach [12] models the problem of detecting patterns as a binary optimization problem and uses a branch-and-bound algorithm combined with a dynamic programming algorithm to maximize the sum of the F1-scores achieved by the patterns. The approach requires the encoding of trace attributes to binary features and the selection of a set of split points to divide the targeted latency range. Similarly to what has been done here in the search space construction phase (Section 5.1), our re-implementation of this approach uses Mean shift algorithm [25] for both encoding and split points selection. In order to avoid overfitting, we force the Mean Shift algorithm to discard clusters of requests with size less or equal to \(|R_{POS}| \cdot 0.05\). We used the implementation of this approach already used in our previous work [13].

**Cortellessa and Traini (CoTr).** Similarly to KrSa, our previous algorithm [13] searches for the optimal set of patterns that maximize the sum of the F1-scores. The main difference relies on the technique used to search the optimal pattern for each sub-interval, which is based on a genetic algorithm. More details on the approach can be found in [13]. We used the same experimental setup used for KrSa for both encoding step and split point selection, while the size of population of the genetic algorithm is set to 30. The genetic algorithm performs 300 iterations with mutation and crossover probability set to 0.4 and 0.6, respectively. In the experiments, we used the original implementation of the approach [13].

**DeCaf.** DeCaf [14] trains a random forest model [37] and then infers predicates correlated with anomalous behavior. We used the implementation of the random forest algorithm based on classification trees provided by scikit-learn [27]. Predicates extraction and deduplication were re-implemented in Python. In order to avoid overfitting, the minimum number of training data in a leaf is set to \(|R_{POS}| \cdot 0.05\). The number of trees and features sampling ratio are set to 50 and 0.6, respectively, as in the original paper [14]. The output of the algorithm is a ranking of predicates based on their correlation scores. In our evaluation we considered the top 10 scored predicates.

### 6.3 Methodology

In order to evaluate the effectiveness of DeLag, we run DeLag on a variety of datasets of requests containing different combinations of LDPs for both case studies. In a nutshell, each dataset used in our evaluation was generated as follows. Firstly, we altered the source code of the system to introduce delays on certain RPCs with certain probabilities, thus reproducing performance issues that lead to LDPs.
Then, we performed load testing on the altered system to simulate user traffic, thus producing a dataset of requests.

Delays simulate performance issues that repeatedly occur on the system and cause latency degradation for relevant portions of requests, thus producing LDPs. We call these simulated performance issues Artificial Delay Combinations (ADCs). ADCs are designed to simulate both performance issues that are rooted in the internal implementation of individual RPCs (i.e. a single RPC is involved), and performance issues that arises from the interaction of multiple services [7] (i.e. multiple RPCs are involved). Specifically, each ADC involves from a minimum of one RPC to a maximum of three RPCs, and it is defined by a set of pairs \((j, d)\), where \(d\) denotes the delay in milliseconds that is introduced in RPC \(j\).

We evaluated DeLag using a variety of scenarios from both case studies, where each scenario involves two randomly generated ADCs (hence two LDPs). We developed a process that enables us to automatically alter the source code of the system by injecting delays according to the generated ADCs. Each request to the altered system is randomly assigned to one of the two ADCs with probability 0.1 (hence, with 0.8 probability is not subject to any delay) and delays are automatically introduced to the corresponding RPCs according to the ADC. For each scenario, we perform a load testing session involving 20 synthetic users simulated by Locust\(^7\) where each user makes a request to the system and randomly waits 1 to 3 seconds for the next request. At the end of each session, the operational data collected by distributed tracing tools (i.e. Jaeger and Zipkin) are processed and transformed into tabular format, thus producing a dataset. Fig. 7 shows an example of dataset, where each row represents a request and each column contains the cumulative execution time of a RPC. It is cumulative because it represents the whole contribution, in terms of execution time, of the RPC to the whole request. In other words, if a request involves multiple invocations of the same RPC, then the cell contains the sum of all invocation execution times. The Latency column contains the overall request latency, while the ADC column reports whether the request is assigned to an ADC \((A_1\) or \(A_2\)) or not (-). Each dataset contains approximately 10% of requests assigned to the first ADC \(A_1\) (we denote this subset of requests as \(R_{A_1}\)), 10% assigned to \(A_2\) (resp. \(R_{A_2}\)) and 80% of requests showing the non-altered RPCs execution times behavior. For each scenario, \(L_{SLO}\) is defined as the smallest latency for requests assigned to one of the two ADCs.

We measure the effectiveness of DeLag on a given scenario (i.e. dataset) by using three quality measures: precision, recall and F1-score. DeLag outputs a pattern set \(S^* = \{P_1, ..., P_n\}\) which identifies a set of clusters of requests \(C^* = \{C_{P_1}, ..., C_{P_n}\}\), where each cluster \(C_P \in C^*\) identifies the set of requests satisfied by \(P\), i.e. \(C_P = \{r \in R \mid r \in P\}\). In order to evaluate DeLag, we intend to verify whether there are two patterns in \(S^*\) that identify \(R_{A_1}\) and \(R_{A_2}\), respectively. To this aim, we first identify the best matching patterns \(P_{A_1}, P_{A_2} \in S^*\), where \(P_{A_1}\) (respectively \(P_{A_2}\)) is chosen by selecting the pattern that maximizes F1-score while considering requests in \(R_{A_1}\) (respectively \(R_{A_2}\)) as positives and all other requests as negatives. Once \(P_{A_1}\) and \(P_{A_2}\) are identified, precision, recall and F1-score can be derived as follows:

\[
Q_{prec} = \frac{|C_{P_{A_1}} \cap R_{A_1}| + |C_{P_{A_2}} \cap R_{A_2}|}{|C_{P_{A_1}}| + |C_{P_{A_2}}|} \tag{11}
\]

\[
Q_{rec} = \frac{|C_{P_{A_1}} \cap R_{A_1}| + |C_{P_{A_2}} \cap R_{A_2}|}{|R_{A_1} \cup R_{A_2}|} \tag{12}
\]

\[
Q_{F1} = 2 \cdot \frac{Q_{prec} \cdot Q_{rec}}{Q_{prec} + Q_{rec}} \tag{13}
\]

These measures can be also applied to evaluate baseline techniques, since F1-score-based techniques and DeCal return set of patterns which identify clusters of requests (similarly to DeLag), while clustering algorithms directly return clusters of requests.

Both DeLag and baselines involve randomness (except for KrSa which uses a deterministic algorithm), thus to mitigate effectiveness variability we execute these techniques on each dataset 20 times.

The generation of datasets and the experimentation of techniques are performed on a dual Intel Xeon CPU E5-2650 v3 at 2.30GHz, totaling 40 cores and 80GB of RAM.

### 6.4 RQ1: Effectiveness

In order to answer RQ1, we generated 50 random scenarios for each case study. Each ADC \(A\) is randomly generated as follows. Firstly, a total delay \(\vartheta\) associated with \(A\) is chosen; that is, every request assigned to \(A\) will have an overall slowdown of \(\vartheta\). Secondly, 1 to 3 RPCs are randomly selected among those executed in the critical path (i.e. 5 for E-Shopper and 13 for Train Ticket). We explicitly chose RPCs in the critical-path to ensure that every delay introduced by \(A\) causes latency degradation. Thirdly, the total delay \(\vartheta\) is evenly split among selected RPCs. Note that if the RPC \(j\) is called a number of \(i_j\) times in the request, then the whole delay assigned to \(j\) is divided by \(i_j\). At the end of this process, the ADC \(A\) is composed by a set of pairs \((j, d)\), where \(d\) denotes the delay in milliseconds that is introduced in each execution of RPC \(j\), and it is such that:

\[
\vartheta = \sum_{(j, d) \in A} i_j \cdot d
\]

The total delay \(\vartheta\) is randomly chosen in the \([L_\mu \cdot 0.2, L_\mu \cdot 0.4]\) range, where \(L_\mu\) is the average request latency for the system without any ADCs. \(L_\mu\) is equal to 116ms for Train ticket and to 395ms for E-Shopper; these values are derived by performing load testing sessions on the non-altered systems using the setup defined in Section 6.3.

#### Table:

| RPC 1 | RPC 2 | RPC 3 | Latency | ADC |
|-------|-------|-------|---------|-----|
| 300   | 220   | 51    | 490     | -   |
| 330   | 250   | 55    | 520     | A1  |
| 320   | 235   | 52    | 495     | -   |
| 321   | 229   | 55    | 494     | -   |
| 340   | 230   | 52    | 525     | A2  |
| ...   | ...   | ...   | ...     | ... |

Fig. 7: Example of dataset

---

\(^7\)https://locust.io/
Modern service-based systems involve many asynchronous interactions \(^2\), therefore many RPCs execution times variations could not produce any degradation on request latency. In order to reproduce this behavior, we also inject a random delay \(\hat{d}\) in one non-critical RPC that doesn’t produce any effect on request latency. We selected, for each case study, one asynchronous RPC whose execution time degradation doesn’t cause any slowdown to requests. \(\hat{d}\) is injected in both non-altered requests and in requests assigned to ADCs (with probability 0.5). Thus 50% of requests on each scenario will manifest execution time variations on the selected non-critical RPC. Similarly to \(\hat{d}\), \(\hat{d}\) is randomly chosen, for each scenario, in the \([L_\mu \cdot 0.2, L_\mu \cdot 0.4]\) range. In order to ensure that \(\hat{d}\) doesn’t produce any effect on request latency, we performed load testing sessions on each case study while altering each system with \(\hat{d} = L_\mu \cdot 0.4\) and \(\hat{d} = 0\), and we verified that the observed average latency of requests doesn’t show notable deviation from \(L_\mu\).

Datasets for every scenario and case study are generated by performing load testing sessions by 20 minutes each. The generation of the 50 datasets for both case studies took \(~\sim 47\) hours, while experimentation of DeLag and baselines on the generated datasets lasted \(~\sim 61\) hours, which leads to an overall time of \(~\sim 4.5\) days spent for RQ1 experiments.

**Results**

For each scenario, we calculated the mean value of each quality measure, namely precision \((Q_{pre})\), recall \((Q_{rec})\) and F1-score \((Q_{F1})\), over 20 runs for each technique. Note that a single run is performed for KrSa, given its deterministic behavior. Fig. 8 shows the distribution of these values, where each boxplot contains the mean values obtained from all scenarios of a given case study for a particular technique. From a bird’s eye view of Fig. 8 we can observe that the effectiveness provided by DeLag is more “stable” compared to those provided by other techniques. The \(Q_{F1}\) first and third quartile are 0.86 and 0.93 respectively for E-Shopper, and 0.85 and 0.95 for Train Ticket, thus leading to an interquartile range (IQR) smaller than any other technique in the Train Ticket case study, and smaller than three out of the five baselines in the E-Shopper case study. The plot shows that the variation of F1-score provided by DeLag is smaller, compared to other approaches, not only within each case study, but also across them. For example, precision and recall of clustering algorithms (i.e. K-means and HC) show tiny dispersions in the E-Shopper case study, but their distributions are completely different in the Train Ticket case study, but also across them. For example, box plots for KrSa, whose F1-score comparison with DeLag reports \(p > 0.05\) in the Train Ticket case study, show higher variability with respect to DeLag, especially in terms of recall. Another example is the comparison with HC, since it provides more stable effectiveness both within the same case study and across them. For example, box plots for KrSa, whose F1-score comparison with DeLag reports \(p > 0.05\) in the Train Ticket case study, show higher variability with respect to DeLag, especially in terms of recall. Another example is the comparison with HC, since it provides a similar effectiveness to DeLag in the Train Ticket case study, but F1-scores provided by HC are clearly worse \((Q_{F1} < 0.7)\) than those provided by DeLag for most of the E-Shopper scenarios.

Summing up, we answer RQ1 as follows: DeLag can effectively detect LDPs, since it provides a (very often) improved and always more stable effectiveness compared to those of baseline techniques.

### 6.5 RQ2: Overlapping Patterns

In order to answer RQ2, we generated datasets (for both case studies), while varying the distance between the total delay introduced by \(A_1\) and the one introduced by \(A_2\). We defined 5 different experimental setups of delays assigned to \(A_1\) and \(A_2\) respectively. Table 2 reports these setups, which range from scenarios where latency distributions related to ADCs completely overlap (i.e. \(Distance = L_\mu \cdot 0\)) to scenarios where distributions are clearly separated (i.e. \(Distance = L_\mu \cdot 0.2\)). For each setup, we generated 20 scenarios (i.e. datasets), where total delays introduced by \(A_1\) and \(A_2\) are fixed by the setup, but RPCs involved in each scenario are different. Then, we avoid influence on ef-

| Case study | Technique | \(Q_{pre}\) | \(Q_{rec}\) | \(Q_{F1}\) |
|------------|-----------|-------------|-------------|-------------|
| E-Shopper  | K-means   | 1.000(0.47) | <0.001(0.84) | <0.001(0.83) |
|            | HC        | 1.000(0.51) | <0.001(0.84) | <0.001(0.83) |
|            | KrSa      | 0.966(0.34) | 0.028(0.15)  | 0.045(0.17)  |
|            | CoTr      | 0.016(0.10) | 0.036(0.06)  | 0.026(0.09)  |
|            | DeCaf     | <0.001(0.92) | <0.001(0.75) | <0.001(0.95) |
| Train Ticket | K-means  | 0.011(0.19) | 0.853(0.46)  | 0.002(0.22)  |
|             | HC        | 0.306(0.16) | 0.975(0.60)  | 0.384(0.07)  |
|             | KrSa      | 0.764(0.10) | 0.083(0.04)  | 0.186(0.03)  |
|             | CoTr      | <0.001(0.58) | <0.001(0.53) | <0.001(0.61) |
|             | DeCaf     | <0.001(0.88) | <0.001(0.59) | <0.001(0.92) |

**TABLE 1: RQ1. Results of the Wilcoxon test (Cliff’s delta effect size in brackets) performed on the precision \((Q_{pre})\), recall \((Q_{rec})\) and F1-score \((Q_{F1})\), provided by DeLag compared to those provided by baseline methods.**

| \(\delta_1\) | \(\delta_2\) | Distance |
|-------------|-------------|----------|
| \(L_\mu \cdot 0.3\) | \(L_\mu \cdot 0.3\) | \(L_\mu \cdot 0\) |
| \(L_\mu \cdot 0.275\) | \(L_\mu \cdot 0.325\) | \(L_\mu \cdot 0.05\) |
| \(L_\mu \cdot 0.25\) | \(L_\mu \cdot 0.35\) | \(L_\mu \cdot 0.1\) |
| \(L_\mu \cdot 0.225\) | \(L_\mu \cdot 0.375\) | \(L_\mu \cdot 0.15\) |
| \(L_\mu \cdot 0.2\) | \(L_\mu \cdot 0.4\) | \(L_\mu \cdot 0.2\) |

**TABLE 2: RQ2. Experimental setups. Each row represents a particular setup, where \(\delta_1\) and \(\delta_2\) denote total delays introduced by \(A_1\) and \(A_2\) respectively, and Distance denotes expected distance between average request latency of \(R_{A_1}\) and the one of \(R_{A_2}\).**
effectiveness due to non-critical RPC execution time variation by fixing $\delta$ to $L_\mu \cdot 0.3$ in all the generated scenarios. In order to avoid extremely long experimentation time, we decreased the duration of load testing sessions to 5 minutes. Nevertheless, we expect that this does not affect the validity of our results, as the number of requests involved in each dataset is still relevant (more than 2.5k requests), and dataset size mainly affects efficiency of techniques (see RQ3) rather than their effectiveness. Overall, the duration for experiments related to RQ2 took $\sim$5 days. The dataset generation process lasted $\sim$43 hours, while the execution of DeLag and baseline techniques on the 200 generated datasets took $\sim$74 hours.

Results

We calculated the mean F1-score ($Q_{F1}$) among 20 runs for each technique (except for KrSa). Fig. 9 depicts the distributions of these means for DeLag, CoTr and KrSa under different experimental setups. For completeness, results for other techniques (K-means, HC and DeCaf) are reported in our online appendix. Fig. 9 shows that both KrSa and CoTr are less effective as far as the distance between total delays introduced by $A_1$ and $A_2$ decreases (i.e., from right to left on the x-axis). The mean, the median, the first and the third quartile for KrSa and CoTr always decrease starting from $\text{Distance} = L_\mu \cdot 0.10$ until $\text{Distance} = L_\mu \cdot 0.0$. This confirms the evidence provided by [12] about the inadequacy of F1-score-based approaches on patterns leading to similar latency behaviors. The same behavior cannot be observed on DeLag, which instead seems to improve for the same range of setups in Train Ticket and doesn’t show a relevant decrease in those in E-Shopper. From Fig. 9 we can assert that the F1-score provided by DeLag is more stable across different setups than those of F1-score-based methods. This finding is further confirmed by Fig. 10, which shows mean F1-scores provided on each scenario as function of the distance between the observed average latency of requests in $R_{A_1}$ and the one of those in $R_{A_2}$. Logarithmic regression lines in plots clearly show a trend towards lower effectiveness for both KrSa and CoTr when distance between latency related to different patterns decreases. The same trend does not show up in DeLag.

Summing up, we answer RQ3 as follows: closeness of latency distributions related to different patterns does not affect the effectiveness of DeLag, therefore our approach overcomes this limitation of F1-score-based methods.

6.6 RQ3: Non-critical RPCs

Here, we intend to evaluate whether the effectiveness of DeLag is affected by execution time variations on non-critical RPCs, i.e. RPCs whose execution time variations do not cause latency degradation. Basically, they can be considered as background noise. We generated datasets for different scenarios while controlling the magnitude of delay introduced on these RPCs. Similarly to Section 6.4, one asynchronous RPC is selected for each case study. We used different experimental setups, where each setup is defined by a different value assigned to $\delta$, that is the amount of delay introduced in the non-critical RPC. We used 5 different experimental setup that are defined by the following values of $\delta$: $L_\mu \cdot 0.0$, $L_\mu \cdot 0.1$, $L_\mu \cdot 0.2$, $L_\mu \cdot 0.3$ and $L_\mu \cdot 0.4$. For each setup we generated 20 different scenario. A delay of $\delta$ is introduced in the non-critical RPC with 0.5 probability on each request performed to the altered system. Complementarily to what we have done for RQ2, in order to avoid influence on the effectiveness due to closeness of latency distributions related to distinct ADCs, here we fix delays introduced by $A_1$ and $A_2$ to $L_\mu \cdot 0.25$ and $L_\mu \cdot 0.35$ respectively. Datasets are generated by performing load testing sessions of 5 minutes, as done for RQ2.
Fig. 9: RQ2. F1-scores ($Q_{F1}$) for KrSa, CoTr and DeLag under different experimental setups (see Table 2). The x-axis labels report the expected distance between the average latency of requests in $R_{A_1}$ and the one of those in $R_{A_2}$.

Fig. 10: RQ2. F1-scores provided by KrSa, CoTr and DeLag as function of the distance (in milliseconds) between the observed average latency of requests in $R_{A_1}$ and the one of those in $R_{A_2}$. Each point of the plot represents the mean F1-score for the method on a particular scenario.

Fig. 11: RQ3. F1-scores ($Q_{F1}$) for K-means, HC and DeLag under different experimental setups. The x-axis labels report the amount of delay introduced in non-critical RPCs ($\hat{d}$) for each experimental setup.

Overall, the duration for experiments related to RQ3 took $\sim$5 days. The dataset generation process lasted $\sim$44 hours. The execution of DeLag and baseline techniques on the 200 generated datasets took $\sim$74 hours.

Results

Fig. 11 shows distributions for F1-scores provided by K-Means, HC and DeLag for each experimental setup. For completeness, results for other techniques (KrSa, CoTr and DeCaf) are reported in our online appendix [36]. Fig. 11 does not suggest a correlation between $\hat{d}$ and DeLag effectiveness. For example, in the E-Shopper case study, both median and mean of F1-scores decrease from scenarios with $\hat{d} = L_{\mu} \cdot 0.0$ to scenarios with $\hat{d} = L_{\mu} \cdot 0.1$, but they both slightly increase in all the subsequent setups. In the Train Ticket case study, instead, both mean and median of F1-scores show an alternating behavior when $\hat{d}$ increases. On the contrary, the effectiveness of some other techniques seems to be monotonically affected by execution time variation on non-critical RPCs. For example, both K-Means and HC provide near-optimal effectiveness when $\hat{d} = L_{\mu} \cdot 0.0$, i.e. there is no execution time variation on non-critical RPC, but their F1-scores significantly decrease as far as $\hat{d}$ increases.

Summing up, we answer RQ3 as follows: the effectiveness of DeLag is not monotonically affected by execution time variations in non-critical RPCs. This is a fundamental step towards the adoption of DeLag in real world settings, since asynchronous interactions are pervasive in today’s service-based systems.

6.7 RQ4: Efficiency

In order to analyze the efficiency of DeLag and baseline approaches, we record the elapsed time to complete the entire end-to-end pattern detection process on different datasets with varying sizes. We generated datasets of different sizes
for both case studies by using 5 different experimental setups, which control the duration of load testing sessions for each scenario (see Table 3).

Longer sessions obviously lead to higher number of requests to analyze, thus to more computationally expensive runs. For each setup we considered 20 different scenarios, which are randomly generated by using the same approach as for RQ1. Note that datasets generated for Train Ticket are more computationally expensive than those of E-Shopper, since the number of RPCs under analysis is higher in the former case (25 unique RPCs compared to 7).

Unlike for effectiveness assessment, we don’t expect that efficiency of techniques is influenced by randomness, therefore we perform a single run of each technique on each dataset to reduce the time effort.

The overall data generation process for RQ4 took ~10 days, while the execution of DeLag and baseline techniques took ~4 days and a half.

Results
Table 4 shows the average execution time of each technique for each experimental setup. DeCaf, K-means and HC severely outperform DeLag in terms of efficiency. DeCaf is 531.9 times (E-Shopper) and 580.3 times (Train ticket) more efficient than DeLag on datasets generated by 160 minutes load testing sessions, i.e., the largest datasets in our evaluation. On the same datasets, K-means and HC outperform DeLag by 479.3 and 19.3 times, respectively, in the E-Shopper case study, and by 457.4 and 8.3 times in the Train ticket case study. Despite their efficiency, these techniques have been shown to be less effective when compared to others. For example, Fig. 12 showed that both the mean and the median F1-score provided by DeCaf are below 0.7 in both case studies, while the mean and the median F1-score provided by clustering methods are below 0.7 in one out of the two case studies. Moreover, even KrSa and CoTr provide a mean F1-score above 0.7 and a median F1-score above 0.8 in both case studies, therefore overall they provide better effectiveness when compared to DeCaf and general-purpose clustering algorithms.

Fig. 13 shows execution times in minutes of each technique on the largest datasets used in our evaluation (~80.2k requests for E-Shopper and ~90.4k requests for Train Ticket). The mean execution time of DeLag is 35 minutes on E-Shopper and 59 minutes on Train Ticket. DeLag outperforms KrSa in efficiency by 0.15 times (E-Shopper) and by 0.22 times (Train Ticket), while CoTr is outperformed by 0.15 times on E-Shopper and by 0.17 times on Train Ticket.

Summing up, we answer RQ4 as follows: DeLag is consistently less efficient than DeCaf and general-purpose clustering algorithms. Nevertheless, these techniques provide lower effectiveness on the majority of considered scenarios when compared to DeLag. DeLag is also less efficient than the second and the third most effective technique when dealing with smaller datasets, but the efficiency of DeLag improves (when compared to these baselines) as the size of dataset increases. Moreover, DeLag clearly outperforms both KrSa and CoTr on the largest datasets used in our evaluation.

7 Discussion
We found that clustering algorithms (K-means and HC) are significantly more efficient than DeLag. Nevertheless,
DeLag also outperforms in terms of effectiveness CoTr in the E-Shopper case study ($p < 0.001$ and large effect size), as well as in the Train Ticket case study ($p \leq 0.05$ and small effect size). When compared to KrSa, instead, DeLag provide better effectiveness in the E-Shopper case study ($p \leq 0.05$ and negligible effect size) while statistical test returns $p > 0.05$ in the Train Ticket study. Moreover, we found that effectiveness provided by F1-scores-based techniques (KrSa and CoTr) is less stable than the one provided by DeLag (IQRs for $Q_{F1}$ provided by DeLag are significantly smaller than those of KrSa and CoTr). In addition, these techniques are less effective when distinct patterns lead to partially (or entirely) overlapping latency distributions, while DeLag overcomes this limitation. Our approach also outperforms in terms of efficiency F1-score-based techniques on largest datasets used in our evaluation. We conclude that the use of DeLag is preferable over F1-score-based techniques.

Overall, DeLag provides better and more stable effectiveness than other techniques. Moreover, DeLag is more efficient than the second and the third most effective techniques on the largest datasets used in our evaluation. However, when higher efficiency is required, fastest techniques such as clustering algorithms or DeCaf could be preferable. Nevertheless, practitioners have to take into account the limitations of these latter techniques.

8 Threats to Validity

8.1 Internal validity

Both DeLag and baseline techniques are subject to overfitting, i.e. patterns involving negligible numbers of requests. In order to deal with this behavior, each technique provides one or more configurable parameters. The use of different configurations may lead to different results, thus causing unfair comparison among the effectiveness provided by different techniques. On the other hand, the experimentation of techniques for different combinations of parameter values can be impractical due to extremely long execution times. In order to minimize this threat, we set parameters across different techniques with “similar policies”. Namely, we used a reasonable threshold across different techniques such that each detected pattern must involve at least $|R_{pos}| \cdot 0.05$
requests (i.e. 5% of requests not meeting SLO expectations). For example, we forced the Mean Shift algorithm, used by KrSa and CoTr for encoding and split point selection, to discard clusters of requests with sizes less or equal to \(|R_{pos}| \cdot 0.05\). Similarly, the Mean Shift algorithm used in the Search Space Construction phase of DeLag is forced to discard clusters smaller than \(|R_{pos}| \cdot 0.05\). The same threshold (i.e. \(|R_{pos}| \cdot 0.05\)) is also used in the Genetic Algorithm of DeLag to penalize solutions with patterns involving small numbers of requests. Finally, we used the same value to define the minimum number of training data in a leaf node [37] for the random-forest model of DeCaf.

DeLag and baselines use randomized algorithms, therefore each execution may potentially lead to different results. Guidelines to assess randomized techniques [38] recommend to perform a high number of repeated runs (e.g. 1000 repetitions). However, using such a high number of repetition in our experiments would be unfeasible due to extremely long execution times. In order to have statistically significant results in a reasonable time, we performed 20 runs per technique.

8.2 Construct validity

We generated several scenarios to test the effectiveness of DeLag in LDPs detection. A potential threat to our work is that ADCs do not represent relevant causes of latency degradation within each scenario, i.e. they do not generate LDPs. In order to minimize this threat, we plot latencies distribution for each scenario and we check that requests assigned to ADCs are prevalent in requests showing degraded latency, i.e. \(L > L_{SLO}\).

In order to have quantitative measures on the effectiveness of techniques, we chose, among the returned set of patterns, two patterns \((P_{A_1}, P_{A_2})\) that seems to be related to the targeted ADCs. Selecting different patterns may result in different effectiveness measures \((Q_{precision}, Q_{recall}, Q_{F1})\). One option we considered was to select them manually, but this approach has two cons: it takes significant human effort and it can leave room for subjectivity. Therefore we opted for an automated approach which selects, for each ADC \(A\), the pattern with maximum F1-score while considering requests assigned to \(A\) as positives and all other requests as negatives. We are aware that patterns selected using this strategy can be suboptimal, and that there may be other patterns among those returned by each technique that can provide higher effectiveness, but overall we expect that our selection strategy is reasonable enough to evaluate the effectiveness of DeLag, and to compare it with the baseline.

Another threat to our work is that we evaluated DeLag only on scenarios where two LDPs are involved, therefore the effectiveness of techniques may change when considering more patterns. Nevertheless, we showed that our approach is more effective than those of baselines techniques when two distinct LDPs are involved.

8.3 External validity

DeLag achieves a high effectiveness in our evaluation. We cannot ensure that DeLag can achieve the same effectiveness on other datasets outside our experimental setup (e.g. real world scenarios). Nevertheless, through an evaluation on 700 randomly generated scenarios for two case studies, we showed that our approach is more effective than three state-of-the-art approaches and two general-purpose clustering algorithms. Datasets for scenarios are generated in laboratory since, at best of our knowledge, there are no publicly available datasets suitable to validate our work. Moreover, it is challenging to find industries that are willing to share their operational data. We limited our evaluation to these two systems since we were not able to identify other open-source service-based systems with non-trivial number of RPCs involved within each request. Nevertheless we evaluated DeLag on two systems with different characteristics and number of RPCs involved.

We evaluated the efficiency of DeLag on datasets of different sizes, ranging from 4.9k requests to 80.2k requests for E-Shopper and ranging from 5.6k requests to 90.4k requests for Train Ticket. LDPs detection in real world service-based systems may involve higher number of requests. Nevertheless, we showed that the efficiency of DeLag improves, when compared to the second and the third most effective technique, as the number of requests increases. Moreover, DeLag outperforms both these techniques on the largest datasets used in our evaluation.

9 RELATED WORK

In this section we summarize prior work on automated diagnosis of software systems. These techniques can be classified into two broad categories: (1) those that detect patterns in time-series metrics and (2) those that detect patterns in traces. Time series metrics are operational data measured over intervals of time (e.g. average response time per minutes of a particular RPC), while traces contain data about causally related events of individual end-to-end requests (e.g. RPC execution time for a particular request). Our approach, DeLag, falls in the second category, since it detects patterns in distributed traces related to individual end-to-end requests of a service-based system.

Cohen et al. [8] devised the first technique for automated diagnosis of performance issues in software systems. They used a class of probabilistic models (Tree-Augmented Bayesian Networks) to identify combinations of time-series metrics and threshold values that correlate with compliance with SLOs for average-case response time. Duan et al. introduced Fa [19], an automated diagnosis technique that uses anomaly-based clustering to clusters time-series metrics based on how they differ from those related to failure and pinpoints metrics linked to failure. MonitorRank [16] uses the historical and current time-series metrics, along with the call graph of the service-based system to build an unsupervised model for ranking. This technique identifies metrics correlated to system anomalies by using an adaptation of the PageRank algorithm [59]. Farshchi et al. [20] adopts regression-based analysis to find the correlation between operation’s activity logs and the operation activity’s effect on cloud resources. Other techniques for detecting patterns in time series metrics relies on association rule mining [15], hierarchical detectors [11] or pairwise-correlation analysis [9].

The first work that falls in the second category (i.e. the one based on traces) is the one introduced by Chen et al.,
which uses decision trees [40] to identify causes of failures. In this technique, decision trees are trained on traces, and combinations of trace attributes are ranked according to their degree of correlation with failure. Han et al. introduced StackMine [16], a technique that mines callstack traces to help performance analysts to effectively discover costly callstack patterns. StackMine identifies callstack patterns correlated with poor performance by using an adaptation of a classic association rule mining algorithm [41]. Unfortunately, these techniques [16, 40] are unsuitable to identify patterns in continuous attributes (e.g., execution time), since they specifically target categorical trace attributes. For example, StackMine specifically targets function names within callstack traces, while the technique proposed by Chen et al. [40] targets categorical request trace attributes such as host machine names, request types and thread ids. At the best of our knowledge, the first automated diagnosis technique suitable for pattern detection in continuous trace attributes is the one proposed by Krushevskaja and Sandler [12]. In this technique, the pattern detection problem is modeled as a binary optimization problem and solved using combinatorial search algorithms (i.e., dynamic programming combined with branch-and-bound algorithm or forward feature selection). Although this approach works with continuous trace attributes, a non-automated encoding step is required to transform continuous trace attributes to binary features. In our recent work [13], we introduced few advancement on top of the work of Krushevskaja and Sandler: (1) an automated approach to discretize continuous attributes based on the Mean Shift algorithm [26], (2) the approach search on a wider search space using a genetic algorithm, and (3) according to our preliminary experimental evaluation [13], it is faster and more effective. Both the approach of Krushevskaja and Sandler [12] and ours [13] are based on a similar technique. The latency range considered as degraded is divided through a set of split points, and for each sub-interval the pattern with the best F1-score is considered; the algorithm searches for the split of the latency range that maximizes the sum of the F1-scores. Recently, Bansal et al. introduced DeCaf [14], a technique based on random forests, which can be applied both on categorical and continuous attributes. Similarly to [40], this technique first trains a random forest model and then ranks predicates extracted by the model according to their correlation with system anomalies. Bansal et al. demonstrated that DeCaf can be applied on traces with categorical attributes with up to 1M cardinality, by evaluating their approach in two large scale services.

In this paper we specifically focus on Latency Degradation Patterns [13] (i.e., RPC execution time patterns correlated with latency degradation), therefore we compared the effectiveness and efficiency of DeLag to those of techniques suitable to this problem, i.e., automated diagnosis techniques that can be applied for pattern detection in continuous trace attributes [12, 13, 14].

Other studies on software diagnosis rely on visualization techniques. Beschastnikh et al. [42] introduced ShiViz, which presents distributed system executions as interactive time-space diagrams to help diagnosis and debugging of software issues. Zhou et al. [7] used ShiViz to conduct an empirical study to investigate the effectiveness of existing industrial debugging practices compared to those of state-of-the-art tracing and visualization techniques for distributed systems, thus showing that the current industrial practices of debugging can be improved by employing proper tracing and visualization techniques. The study of Sambavisan et al. [43] compares three well-known visualization approaches in the context of presenting the results of one automated performance root cause analysis approach [44]. Visualization techniques are time consuming, as they require human intervention and are more useful when performing fine-grained analysis, while DeLag automatically detect patterns in RPCs execution times to identify potential relevant performance issues.

DeLag detects patterns in traces collected by a distributed tracing infrastructure, therefore distributed tracing research [22] is related to our work. Dapper [23] was the pioneering work in this space, Canopy [45] processes traces in real-time, derives user-specified features, and outputs performance datasets that aggregate across billions of requests. Pivot Tracing [46] gives users the ability to define traced metrics at runtime, even when crossing component or machine boundaries. Related to our work are also studies on automated log parsing as they extract run-time operational data which can be then exploited by automated diagnosis techniques. These techniques focus on analyzing raw service logs to extract meaningful events and run-time information. LogCluster [47] proposed an approach that automatically parses log messages by mining the frequent tokens in the log messages. Logram [48] leverages n-gram dictionaries to achieve efficient log parsing, while other techniques formulated log parsing as a clustering problem and used various approaches to measure the similarity/distance between two log messages [49, 50, 51]. A systematic literature review on automated log parsing can be found elsewhere [52].

10 Conclusion

In this work, we propose DeLag, an automated approach to diagnose performance issues in service-based systems. Our approach leverages a search-based algorithm to detect patterns in RPC execution time behaviors correlated with latency degradation of requests, namely Latency Degradation Patterns. DeLag simultaneously search multiple patterns while optimizing precision, recall and latency dissimilarity, and it uses a heuristic algorithm to select the optimal pattern set from the set of non-dominated solutions.

Through an evaluation of DeLag on 700 datasets with different combinations of LDPs from two case study systems, we demonstrated that DeLag provides (very often) better and (always) more stable effectiveness than three state-of-the-art techniques and two general purpose clustering algorithms. We also demonstrate that, contrarily to other techniques, the effectiveness of DeLag is affected neither by the proximity of latency distributions related to different patterns, nor by execution time variations in non-critical RPCs. Finally, we demonstrate that DeLag is more efficient than the second and the third most effective baseline techniques when a high number of requests is involved.

As future work, we plan to put effort on the improvement of the efficiency of our approach, and to extend the
The data and scripts used in our study are publicly available.

ACKNOWLEDGMENTS
Luca Traini’s work was supported by the project “Software Performance in Agile/DevOps context” funded within Programma Operativo Nazionale Ricerca e Innovazione 2014-2020.

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