Title TBD

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ABSTRACT

Due to the advancement in distributed systems and the increasing industrial demands, software systems contain multiple components with complex interactions, e.g databases and their replication, caching components, proxies and load balancers, application instances and their complex configuration parameters. The engineers in a project must thinker with many configuration parameters that change the behavior and/or structure of the system, this can cause many problems that affect the quality of the service. In other words, dealing with high dimensionality is both cognitively demanding and risky for the project.

In this work we show the design and analysis of a pragmatic machine learning based tool that aims to assist the engineering of systems that can: 1) monitor themselves, 2) Forecast workloads and performance metrics and 3) Change themselves in run-time by self-configuring and adapting for a specific scenario. After the integration of this tool with a system, it should be able to answer the question: given that we have many configuration parameters, how can we change them in order to optimize a certain metric for a given predicted workload?

We show that it can decrease the risk of changing systems' configurations in run-time and decrease the engineering effort that otherwise would be spent manually optimizing parameters, usually following a trial-and-error approach.

CCS CONCEPTS

• **TBD → TBD**;

KEYWORDS

ACM proceedings, LaTeX, text tagging

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1 INTRODUCTION

The industrial adoption of microservices has led to increasingly complex configuration schemes that are commonly fine-tuned by engineers manually. Ganek and Corbi (2003) discussed the need for autonomic computing to handle the complexity of managing software systems. They noted that managing complex systems has become too costly, prone to error, and labor-intensive, because people under such pressure make mistakes, increasing the potential of system outages with a concurrent impact on business [10]. This has driven many researchers to study self-adaptive systems over the years [4, 8, 9, 11, 16, 17]; however, the software industry still lacks practical tools to provide self-adaptation mechanisms to their systems. Thus, most of the configuring and tuning of the systems are performed manually, often in run-time, which is known to be a very time consuming and risky practice [2, 6, 10].

In this work we present an accessible tool to support the development of self-adaptive systems. One of our main goals is to provide such support requiring minimal effort from the engineers. In return our tool uses ideas from system observability, machine learning, and control theory to automatically asses the system's environment, predict the impact of changes that could potentially improve the system, and automatically make these changes.

Our approach consists of providing an API to collect relevant systems' metrics and configurations that represent the state of the system in relation to time. Then we map Service Level Objectives (SLOs) to some of these metrics, feed these into a machine learning component that is concurrently re-learning the model while analyzing and predicting the workload and the optimal configurations. As a result it provides adaptation plans that can be both 1) automatically executed, allowing the system to have self-adaptive capabilities, and 2) interpretable, allowing engineers to know the impact of a change in the configuration space before it is deployed.

In summary, our main contributions are:

- We provide a methodology to assist the development and evolution of self-adaptive systems, regardless of the presence of self-adaptability in the system's foundations. Such methodology is encapsulated in the tool described in this work.
- We show how to make the minimal necessary changes to the system, and how to model SLAs/SLOs and map them to the optimization objectives. These tasks being the development cost incurred by the engineers.
- We present a case study that shows how a software system's response time, throughput, and usage were improved by *A%*, *B%*, and *C%* respectively after integrating a self-adaptation mechanism.

The rest of this paper is structure as follows: in Section 2 we discuss some past research in the space of self-adaptive systems and provide fundamental background. In Section 3 we outline our approach, explaining the blend of ideas from different fields. In Section 4 we describe internal details and design decisions of our implementation. In Section 5 we present our case study followed by a discussion and future directions in Section 6. Finally, we conclude our findings with Section 7.

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2 RELATED WORK

Maybe related work would be better now instead of putting it in the end, since there are a lot of related work and they are very relevant to this work, it would be nice to upfront point out what has been done and what would be different in this work.

Also include background here.

3 APPROACH

3.1 Control theory and self-adaptive systems

3.2 System's configuration as an optimization problem

3.3 Providing system adaptation with machine learning

3.4 Workload simulation

3.5 System instrumentation

3.6 Machine learning architecture

3.6.1 *Features and models.*

3.6.2 *Online training.*

3.6.3 *Achieving self-adapation.*

4 IMPLEMENTATION

5 EVALUATION

To guide and evaluate our work, five research questions are used:

- **RQ1:** Can self-adaptation by learned models lead to more stable, faster, and safer software systems?
- **RQ2:** Can self-adaptation by learned models reduce the need for manually configuring and tuning systems?
- **RQ3:** Can our tool be easily integrated in software systems, requiring only small changes to the codebase?
- **RQ4:** Can our tool work with low overhead?
- **RQ5:** Which features are more relevant to predict workload and performance?

Challenges with RQ1: should we keep "stable" and "safer"? Faster is easy to quantify, stable and safer is tricky to quantify but it can be reasonably easy to infer given all the performance improvements. Thoughts?

Challenges with RQ2: same challenges as in RQ1, do we have to quantify or just inferring less need to configure/tune given that it's being done by the learned model *and* it's performing well/better is enough?

Challenges with RQ3: "Easily" sounds subjective and hard to quantify, but I believe it's possible to see that it's not a super complicated task if all it's being asked is to instrument/annotate parts of the code. But then again, I might be very biased.

Challenges with RQ5: although it might be interesting, it may not generalize to different scenarios.

6 DISCUSSION AND FUTURE WORK

7 CONCLUSIONS

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