Quality Attributes in AI-ML-Based Systems: Differences and Challenges

Bachelor Thesis

# Organization

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# Context & Motivation

Software systems with machine learning or artificial intelligence components (AI-ML-based systems [1]) share a lot of software engineering concerns with traditional systems, but their specialized nature also leads to several new challenges [2]. One important aspect of software engineering and architecture are quality attributes (QAs) [3], which are also referred to as non-functional or cross-functional requirements. The importance of existing QAs such as functional correctness, performance efficiency, or maintainability may be perceived differently in AI-ML-based systems or they may be more challenging to assure. Additionally, such systems also come with new QAs like explainability [4][5], fairness [6], or trainability [7]. While some general publications exist on this topic [8][9][10], it is still difficult to get an overview of the role of QAs in AI-ML-based systems, especially from the perspective of software professionals.

# Objectives

The goal of this study is therefore to analyze practitioners’ perception of QAs in the context of AI-ML-based systems. Interesting notions could be the perceived criticality of QAs (i.e. does AI/ML change this or are the domain or context of the system still more important?), what QAs are most challenging to assure, or how prevalent the influence of “new” QAs actually is. More fine-grained research questions should be defined by the student.

# Methods

Select one or more fitting methods to analyze the state of practice like a survey, interviews, a grey literature review, or the mining of Q&A forums like StackOverflow. Design a detailed study protocol to answer the selected research questions.

# References

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[4] L. Chazette, O. Karras, and K. Schneider, “Do End-Users Want Explanations? Analyzing the Role of Explainability as an Emerging Aspect of Non-Functional Requirements,” in *2019 IEEE 27th International Requirements Engineering Conference (RE)*, 2019, pp. 223–233.

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