AI Assisted/Automated code refactoring

How the development of AI may impact the future of code refactoring

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***Abstract*—This Paper aims to shed light onto developments in AI Assisted/Automated Code refactoring, how it can help the indtustry and which models work most efficiently to tackle different challenges code refactoring brings. This will be done by going over various literature describing first the challenges at hand and afterwards discussing several possible solutions that have been tested to gain a greater understanding and to generate an informed outlook into further developments of this technology.**

***Index Terms*—machine learning algorithms, software code refactoring, deep neural network**

I. Introduction

Refactoring, as defined by Fowler [8], is "the process of changing a software system in such a way that does not alter the external behavior of the code yet improves its internal structure". More and more empirical studies have since established a positive correlation between refactoring operations and code quality metrics. All this evidence hints at refactoring being a high-priority concern for software engineers. [1].
However, deciding when and how to refactor can prove to be a challenge for developers. Refactoring in an early stage may be cost too much for what youre getting out of it, and refactoring too late may cause the refactor to be an even bigger time comittment. [11]
Tools have been in the hands of many developers to make this process more streamlined for years now. Analytics tools to sniff out bugs or give hints on how to improve code quality such as PMD, ESLint, and Sonarqube can be integrated in different stages of a developers' workflow, e.g. inside IDEs, during code review or as an overall quality report. [1]
Taking a closer look at these tools, however, reveals that they commonly have a lot of false positives, making developers lose their confidence in them. Often, the detection strategies are based on hard threshholds of just a handfull of metrics, such as lines of code in a file (e.g. PMD's famous "problematic" classification occuring once a method reaches 100 lines per default). These simplistic ways of detection simply aren't able to capture the full complexity of modern software systems. Manually analyzing hundreds of metrics and figuring out which ones are the cause of technical dept is very hard and almost impossible for tool-developers, which is where machine learning-based solutions come into play. We will take a closer look at how exactly different ML-Models go about this task in section III

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