Ruprecht-Karls-Universität Heidelberg
Institut für Informatik
Lehrstuhl für Parallele und Verteilte Systeme

Masterarbeit

Automated Checking of Clean Code Guidelines for Python

Name: Enrico Kaack
Matrikelnummer: 3534472
Betreuer: Prof. Dr. Artur Andrzejak
Datum der Abgabe: 31.10.2020

Ich versichere, dass ich diese Master-Arbeit selbstständig verfasst und nur die angegebenen Quellen und Hilfsmittel verwendet habe.

Heidelberg, dd.mm.yyyy

Zusammenfassung

Abstract auf Deutsch

Abstract

This is the abstract.

Contents

List of Figures

List of Tables

1 Introduction

This chapter contains an overview of the topic as well as the goals and contributions of your work. Description of the domain Description of the problem Summary of the approach Outline of own contributions and results

1.1 Motivation

- clean code violations can result in bad maintainable code - multiple tools exist, do not cover all clean code principles - tooling is important for productive use and for students learning clean code principles –> we therefore give an clean code overview, create a software platform to check for rules that can be expanded for teaching use and productive use and we try to use machine learning models to classify code as clean or unclean code so it may be possible for users to collect samples of unclean code and train the classifier without writing a complex rule or if a rule is not possible since the clean code rule is rather subjective

1.2 Goals

- overview of clean code principles - group CC principles into differrent abstraction levels concerning the methods used to check rule compliance (RegEx, AST-Based, Data-Flow, Dependency Graph, none (Machine learning)) - develop a software plaform that can check for rule compliance, extendable by plugins - implement some plugins plugins into the platform - analyse the use of machine learning models such as svm, gradient boosting classifier, random forest and a neural network on clean code violation detection - manipulate the code to simulate a 'noise' on the data to test if the models are able to detect the same problem in a different way, that they have not seen during training

1.3 Structure

Here you describe the structure of the thesis. For example:

2 Background and Related Work

General description of the relevant methods/techniques

What has been done so far to address the problem (closer related work)

Possible weaknesses of the existing approaches

2.1 Code Quality

The term code quality defines an evaluation of source code concerning the readability and understandability the source code. If source code is well-written and can be understood by developers easily, it is considered to be high quality.

One of the main reasons why companies and developers aim for high code quality is the maintainability of source code. With a better understandability of the source code, changing it becomes more efficient and less error-prone. Software maintenance consists mainly of those activities that involve changing source code:

1. Adding code for new features
2. Implementing changing requirements by modifying code
3. Fixing bugs to ensure correct functionality of the software.

The importance of good maintainability of source code is based on the associated cost. For project planning, different sources suggest planning 50 to 80% of the total software development costs for maintenance. A recent study from 2018 between Stripe and Harris Poll found that developers spent 42% of their time maintaining code. Increasing the effectiveness of maintaining code is consequently cost-relevant (SOURCE: `https://stripe.com/de/reports/developer-coefficient-2018`TODO). The application of agile software development paradigms is another important contributor for code to be changeable. Agile development is a software development practice of building software in increments with a running software at the end of each increment. One of the advantages is the adaptability of this model to changing requirements, since,

with the end of each increment, a requirement change can be implemented. (TODO source Manifesto for agile software development). The easiness of code changeability due to code quality becomes a business-critical requirement and can positively impact the maintainability in the following ways [3]:

1. Well-written code makes it easy to determine the location and the way source code has to be changed.
2. A developer can implement changes more efficient in good code.
3. Easy to understand code can prevent unexpected side-effects and bugs when applying a change.
4. Changes can be validated easier.

Besides the maintainability, a higher code quality makes it easier for new developers to understand the code base and be productive since it is easier to read and understand the code.

The understandability and readability of high-quality source code have implications going further than maintainability. The International Organization for Standardization provides the standard ISO/IEC 25000:2014 for "Systems and software Quality Requirements and Evaluation (SQuaRE)" [?], that measures code quality by the contribution of the following characteristic:

1. Reliability
2. Performance efficiency
3. Security
4. Maintainability

Reliability is the ability of a system to run without critical exception that would cause the system to crash, become unavailable or result in an inconsistent state. The most important factors for reliability are correct multi-threading with access to shared resources and correct memory allocation and deallocation. Performance efficiency describes an optimal use of the resources like CPU-time, memory or network bandwidth. The security aspect focus on code that does not open up as an attack vector. Especially common vulnerabilities like SQL injections shall be prevented.

To sum up, code quality is a concept to describe source code from the view of a developers ability to understand and change code. This view influence characteristics like maintainability or reliability that can be used as metrics to measure code quality.

2.2 Clean Code

In chapter 2.1, we defined the terminology of code quality. Yet the question remains, how to achieve a high code quality. One approach is the clean code concept, coined by the Robert C. Martin in its book "Clean Code: A Handbook of Agile Software Craftsmanship" [12]. Basically, source code can be seen as clean code or as non-clean chaotic code. The author describes clean code principles in the form of practical rules. Those practical rules shall result in intuitive code that is easy to understand and read, i.e. the code quality increases.

Chaotic code, on the other hand, is harder to read and understand. The author argues, developers produce chaotic code in a conflict between deadline pressure and the necessary effort to make code more intuitive and follow clean code principles [12]. The former pressure is created by deadlines that focus on the visible output like the functionality of the program, whereas the latter is not directly visible in the final product. If the success criteria are solely based on the visible output, the code quality may suffer by fast-to-write chaotic code. This behaviour is shortsighted since an accumulation of chaotic code reduces productivity over time. A larger system with chaotic code will slow down later modifications or additions of code. With the costs associated with maintainability as described in chapter 2.1, reducing the maintenance effort is a logical step. With the clean code principles, developers can read and understand code in a more intuitive way and the described costs of chaotic code will decrease [12].

The following sections explain the clean code guidelines following the book by Robert C. Martin [12].TODO give a more detailed overview of the next chapters

2.2.1 Naming

The naming section covers several rules for naming variables, functions, types and classes. Good naming can make it easier to read and understand code. "Good" naming is an opinionated topic; For Robert C. Martin, the key factor of good naming is the descriptiveness of names [12]. Descriptive names provide the reader with enough information to understand what a variable stores or what a function computes. Abbreviations or symbolic names like *a1, a2* are not descriptive and do not provide information about the meaning. Using symbolic names for mathematical expressions could be an exception to the rule if the naming mirrors the expression.

To come up with a descriptive name, it is helpful to include a verb or verb expression for function names, because functions express an action. For class names, a noun

emphasises the object character of the class.

Another helpful property of a name is an easy pronunciation since it is easier to read and to talk about the code with other developers. For reading, the pronounciation is necessary for the inner subvocalization[1]. Non-dictionary words or unusual abbreviations are harder to pronounce. Consequently, it is useful to make longer but descriptive and pronounceable names, especially since the autocomplete feature of IDEs will free the developer from typing the long name. Additionally, searching for long names works better than for short names, because long names are more likely to be unambiguous compared to shorter names. An acceptable exception to this rule are short variables in a small scope (e.g. variable i in a loop), but using i in a large scope could be ambiguous and troublesome for searching and understanding.

An old naming convention is the Hungarian naming convention. In Hungarian naming, the type is encoded as a prefix of a variable name. TODO sample and source. Nowadays, the type encoding is redundant to the automatic type inference of IDEs. The automatic type inference also prevents confusion for the reader if the type in the notation and the actual type are inconsistent. The same logic applies to a prefix for member variables and methods, since an IDE can automatically highlight those different tokens.

2.2.2 Functions

This chapter describes several rules regarding functions, that Robert C. Martin characterizes [12].

First, functions should be small in length. Exceeding 20 lines should not be necessary in most cases. If a function is small, it can be read more easily and without scrolling.

Second, inside a function, if-, else- and while-statements should contain a function call for the condition and one function call for the body. With a descriptive naming (see 2.2.1), a function call document the condition and body in a concise and readable way. In sample TODO, reading a condition with function calls does not require the reader to decrypt the logical expression. This can also save additional comments that explain the meaning of the condition. Furthermore, if the body also contains a function call, it is fast to understand the cause-effect relation of the if expression.

Third, functions should fulfil one purpose. Since functions may have to call several functions subsequently to perform the required computation, Robert C. Martin expands the rule that functions should only operate on one abstraction level [12]. This would

[1] the internal speech when reading

result in the following structure: Functions with a low abstraction level handle data access and manipulation, e.g. string manipulation. Functions on a middle abstraction layer orchestrate the low-level operations. On the next higher level, the mid-level functions are orchestrated etc. Following this structure, a function has one purpose on the low level and one orchestration function on a higher abstraction layer.

Fourth, the number of function arguments should be three or lower. With many function arguments, it becomes harder to call a function. Simultaneously, testing becomes harder, especially if all argument combinations should be tested. Functions with none or one argument simplify testing a lot. Since testing can reveal bugs, testable code is crucial for reducing the number of bugs. If a function requires more arguments, it may be advisable to bundle those in a config object to pass multiple arguments as one. With a config object, arguments can be logically grouped that would help the reader to understand arguments.

Fifth, side-effects in a function body should be avoided. Side-effects happen if a function modifies a variable outside its scope without explicitly mentioning this in the function name. This leads to dependencies between the functions that are not obvious to a developer who checks the signature, i.e. the name, input arguments and return type, to use the function. To spot a side-effect, the developer would have to read through the function, although reading the signature should be enough to use the function. With side-effects, the function behaves unexpected and time-consuming mistakes are the consequence. Especially side-effects that initialise other objects result in a time-dependency that is hard to identify and could be overseen at all.

The next rule forbids the returning of error codes and suggests raising an exception if the programming language supports it. Raising an exception allows better separation between application logic and error handling code since the error code checking interrupts the reading flow of code. On the other hand, catching a raised exception is separated from the logic for a non-error execution and can be separated into an additional function for an even cleaner structure. TODO: see example In this case, error handling counts as the one purpose of this function.

Last, the important principle for software engineering applies directly to functions: Don't repeat yourself TODO source. Repeated code is dangerous and chaotic since it requires changes in multiple locations if it has to be modified. This makes duplicated code very prone to copy and paste errors and small mistakes that may not be obvious during development but will lead to a fatal crash at runtime. Many patterns and tools have been developed to mitigate duplicated code (TODO: some references to duplicated

code detection, etc.).

2.2.3 Comments

Comments are part of every programming language and can play an important role in code quality. Subjectively good comments clarify the meaning of the code and help to understand the code. However, comments can become outdated and wrong or provide useless information [12]. In a perfect world, the programming language and the programmer would be expressive enough that commenting is not required for clarity. Following the clean code guidelines for naming and functions makes many descriptive comments obsolete, since the function description is encoded in the function name.

Comments will not help to turn chaotic code into clean code. If a developer explains a line of code by a comment, it is often more helpful to call a function with a descriptive name to replace the comment. Since comments are not part of the program logic, if the explaining comment is not updated with the code, the comment gives misinformation to the reader like described before.

In brief, before writing a comment, the developer should think about expressing the same in code. Robert C. Martin gives some exceptions for situations, where comments can be helpful or necessary [12]:

Legal notes: Legal notes like copyright or license information and author mentions may be necessary. Although they should be short and link to an external licensing document in full extent.

Explaining comments: Some explaining comments can be helpful and are not easy to encode in normal code. For instance, an explanation of a complex regular expression may be too complicated for a function name and a comment provides the space for a sufficient explanation. This increase the readability since the developer does not need to interpret the regular expression manually.

Intention: Explaining an intention which does not become obvious by reading the source code might also be a valid use-case for a comment.

Warning for consequences: Some parts of the code can have special consequences like not being thread-safe or using many system resources. A warning can spare a developer from having trouble when using the function.

Emphasise : A comment to emphasise the importance of a seemingly unimportant part of the code prevents breaking modifications of the code.

2.2.4 Data Structures and Objects

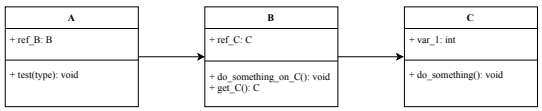
This chapter describes the rules of data structures and objects. Both store data but the way this data get exposed differ. Objects hide data behind abstractions and have functions that work with these data. Data structures expose the data and do not provide functionality.

For objects, I. Holland defined the Law of Demeter (LoD) (TODO source Assuring good style for object-oriented programs by K.J. Lieberherr ; I.M. Holland). In object-oriented programming, a method m of an object O may only call methods of the following components:

- the object O itself
- the parameters of the method
- objects that are created within m's scope
- instance variables of O

In other words, the object O only calls methods on direct "neighboors". The object does not call a method of its neighbour and subsequently calls a method on the returned object from the neighbour. By restricting the allowed method call to only direct "neighbours", the dependencies between objects are reduced and the modularity increased. As a consequence, changing methods only affects the direct neighbours and not objects in potentially different parts of the software. Figure 2.1 shows an example for the LoD. In the method *test*, a function call on B returns a reference to C. Since C is not a direct neighboor of A, the function call violates the LoD. The modularity of objects suffer, since a change of the method *do_something()* would require changes in in object A. This close coupling of an A and C is circumvented with a method *do_something_on_C* that wraps the functionality of C, so a change in C would only require a change in B. With that common layer, A and C are decoupled. Object A in this case does not know how the certain functionality is performed and it does not matter. Bad code practice like the violation of the LoD in listing 2.1 is called a train wreck, since subsequent method calls look like multiple train carriages. Such train wrecks can be improved by the described wrapping function.

Data structures are often used as Data Transfer Objects (DTO) to communicate with other processes or services. These objects do not contain any functions; instead, they only have accessible member variables. A specialisation of DTOs are Active Records that




```
def test():
    #violation of LoD
    self.B.get_C().do_something()

    #no violation of LoD
    self.B.do_something_on_C()
```

Figure 2.1: A sample illustration of the Law of Demeter. The figure on the left shows a class diagram for the classes *A*, *B* and *C*. The listing on the right shows the implmentation of the *test* method of class *A*.

contain additional methods for data storage. They are used to represent a data source like a database. For DTOs and Active Records, it is bad practice to insert business logic into this objects [12]. With business logic, the data structure becomes a hybrid between an object and a data structure. It becomes unclear, if the purpose of a hybrid is to store data or to expose methods to modify those data in a controlled way. Without the clear purpose of the object or data structure, it becomes harder to understand for developers.

2.2.5 Classes

For classes, the clean code principles describe multiple rules that improve the readability and understandability of classes.

The first rule specifies the recommended size of a class. Unlike counting lines as for functions, the size of a class is the number of responsibilities. A responsibility of a class can be manipulating data or writing data to a file. A single responsibility per class is described as Single-Responsibility-Principle and offer several advantages: First, the naming can reflect this responsibility, so the class functionality is easy to understand. Second, changing one functionality should only require changes in the one class that is responsible for this specific function. And last, we can reuse the class in different projects if we need that functionality. If the class fulfilled two responsibilities, we would have to remove the unnecessary functionality before reusing the class in a different project. Reaching back to the examples of one responsibility being data manipulation and one is writing data to a file, reusing the latter functionality would require us to strip out the data manipulation. The Single-Responsibility-Principle lead to a system of many small classes with one, clearly defined responsibility.

The second rule recommends classes to have high cohesion. Cohesion is high if a method manipulates many instance variables. If all methods of a class manipulate all instance variables, the class has peak cohesion. With a high cohesion, the methods and

the class are a logical unit. A low cohesion indicates to split the class into multiple classes since the methods are not a logical unit. As a result of splitting classes into smaller logical units, will more likely comply with the Single-Responsibility-Principle. (TODO add metric for cohesion)

The last rule provides a guideline on how to handle class dependencies. If a dependency changes, the class depending on it should not change. To accomplish this decoupling from the implementation of a dependency, classes should not depend on the dependency directly but instead on an abstract class. That abstract class describe the concept of the dependency that is unlikely to change. For example, for a database dependency, the abstract class defines the concepts of string an entry and retrieving an entry. For the specific database, a concrete class implements the abstract class and provides the functionality. Changing the database only changes the implementation in the concrete class but not the concept. Therefore, there is no need to modify a class that depends on the concepts from the abstract class. This isolation of dependencies is especially useful if the dependencies are not under the developer's control and may be changed any time by a third party. But they also useful for testing, since the dependency can be replaced by a so-called mock class that only simulates the behaviour. This allows testing to be independent of the dependency and to locate potential errors in the own system or the dependency.

2.2.6 Exception Handling

This chapter covers clean code rules for error handling. Basically, the following ways are methods for handling errors: First, a function can return an error code if some exception occurred. The function caller has to check for the error code and act accordingly. Second, some programming languages support the concept of throwing and catching an exception. And last, a function can return a null value to indicate the execution failure.

In section 2.2.2, we described the clean code rule that prefers throwing an exception over returning an error code. The supporting argument of Robert C. Martin is the better separation between application logic and error handling [12]. Error codes have to be checked immediately, so the error checking interrupts the code for the application logic. By throwing and catching errors, the error handling can be completely extracted into a sperate function and can be removed from the main application logic. Furthermore, the try-catch block enforces transactional behaviour. At the end of either the try or the catch block, the application should be in a consistent state. Error codes hide this explicit transactional behaviour.

Notwithstanding the clean code rules, Go as more recent programming language[2] returns explicit error types instead of throwing an exception. This was designed to "encourage you to explicitly check for errors where thy occur", instead of "throwing exceptions and sometimes catching them" [8]. So the practical application of the clean code rule for throwing exception depends on the design of the programming language.

The third method of error handling is returning a null value. Instead of checking for a specific error code, the caller would check for a null return value. If a developer misses the check, the program will terminate with an unhandled NullPointerException at runtime. Tony Hoare introduced the null reference in 1965 and later called it his "billion-dollar mistake" [10], since it leads to many bugs and security vulnerabilities throughout the decades. Languages like Kotlin are designed with null safety enforced. Kotlin distinguishes between nullable and non-nullable references, with a compiler enforcing null checking [2]. If a language does not enforce null safety with a compiler, a special case like an empty collection or an optional type can be returned. Returning null introduce the same problems like error code handling such as mixing application and error handling logic and is additionally not explicitly marked as an error code. From a function signature, it may not be obvious that the return value may be null if the language does not support compile-time checking or optional types. Robert C. Martin describes returning null as a violation of the clean code rules [12].

Independent of the error handling method is the next rule for error handling with a third-party library. In section 2.2.5, we described wrapping dependencies like third-party libraries to decrease the coupling to the dependency. The wrapping concept also applies to error handling, since the wrapper can unify the exceptions, so the application does not check for dependency-specific error types. Changing the dependency requires only a change in the wrapper implementation but not everywhere this wrapper is used.

2.2.7 Additional Rules

Robert C. Martin describes more rules for system design, multi-threading, testing and third-party code [12]. Additionally, the author describes the concept of code smells. In theory, following these rules seems to lead to clean code. In practice, however, developers tend to violate rules in some situations. A code smell is a code characteristic that could indicate such a violation.

This work will focus on the described rules and implement a detection for some rule

[2] designed in 2007 as a response to problems with C++, Java and Python [1]

violations.

2.3 Source Code Analysis

In order to define and measure code quality, methods for analysing a program and its source code are necessary.

To analyse source code, different techniques are bundled as static code analysis. A static code analysis gathers information about the structure of the source code and program. TODO source Static Code Analysis of IEC 61131-3 Programs: Comprehensive Tool Support and Experiences from Large-Scale Industrial

The following provides a non-comprehensive overview of the most important methods for code analysis and representation. Source code itself is stored as encoded text files. This representation offers no structural information.

A first processing step is a lexical analysis, also known as tokenization. The tokenization transforms the character stream from the text file into a stream of tokens. This is possible due to the syntactic definition of a programming lanuage, that allows to split the raw text into typed tokens. A token type can be a keyword, operator or an identifier. (TODO `http://www.cs.man.ac.uk/~pjj/farrell/comp3.html`) TODO source Basics of Compiler Design by Torben Ægidius Mogensen (FOR ast, tokenizwation, data flow)

With the token stream, a parser can build an Abstract Syntax Tree (AST) that represents the abstract structure of the source code. Since the AST represents the code structure, it is possible to traverse the tree-like datastructure to analyse the source code structure.

Another method is the control flow analysis. For the control flow analysis, the program has to be represented as a control flow graph. The control-flow graph represents possible execution paths in a program and consists of nodes and edges. A node represents a basic block, i.e. a code sequence without branching. A directed edge represent jumps in the control flow; e.g. an if-statement would have two outgoing edges, one for a true condition and one for a condition evaluated as false.

Besides the control flow, it is possible to analyse the data flow in a data flow graph. With the data-flow analysis it is possible to collect information about the read and write operations to variables. In combination with the control flow graph, the data flow for different control flow can be calculated.

Last, a call graph can be computed. A call graph maps all method or function calls starting from the main method. It allows to spot dependencies between modules [15].

2.4 Clean Code Complexity Levels

We described the clean code rules in Section 2.2. This work focus on the automated checking of clean code rules. Some rules can be checked straighforward with an algorithm wheras others may be too abstract to be checked in an automated way. In this Section, we want to categorise the clean code rules into different complexity levels. The complexity levels are based on the complexity of implementing an automated rule checker.

We define three levels of complexity, based on the different source code analysis techniques and effort needed:

Basic Level The level of basic complexity covers all rules that can be checked by analysing the text, token stream or AST of the program.

Advanced Level Rules with medium complexity require a control flow, data flow, call graph analysis or more advanced, deterministic analysis techniques. Furthermore, a combination of different analysis methods from the basic complexity level will be categorized as medium complexity.

High Level The high level of complexity covers the clean code rules we think can not be checked with traditional, deterministic analysis techniques such as those described in Section 2.3. For this level, it may be indispensible to use statistical methods like machine learning approaches to create an automated checker. It is important to note that we do not proove that no deterministic algorithm exists.

TODO: simpler: low, medium, high level

Based in these levels, we categorize the clean code rules described in Section 2.2.

For naming, all rules have in common, that an algorithm would have to extract the names of entities likevaraibles, classes, functions, etc. from the source code first. The AST provides the names and entity types they describe. Extracting all names is a matter of walking over the AST. We see this in the basic complexity level.

The first important rule is the descriptiveness of names. Assesing the descriptiveness of a name is problem with high level of complexity. An algorithm would have to understand the purpose of the source code to determine if the name describes the source code. It is an ongoing research effort to use machine learning on code for different tasks. The tasks of code summarization explores the use of machine learning to generate a natural language description of source code. In a paper from 2019, Alon et. al describe a neural network to represent code as vectors and “predict a method’s name from the vector representation

of its body" (TODO: source code2vec: learning distributed representations of code). Based on that research, it may be possible to compare the summarization result with the choosen name to detect non-descriptive names. Nevertheless, it may be harder to apply such concepts to variable names, since a variable name has less context information compared to the method name with its method body.

The next rule covers the easy pronunciation of names. A rule violation would be the use of abbreviations or non-dicitonary words in variable names that are hard to pronounce. An approach with basic level of complexity could be a minimum number of characters for every name. A more advanced approach could utilize naming conventions such as camel case or underscore seperated words to extract the single words of a name and compare it with a dictionary. While it would help to prevent spelling mistakes and should ensure pronounceability, a dictionary may not contain all words. Especially with domain-specific words, this could lead to false alarms.

Variable names in a small, lcoal scope are excepted from the rule of pronounceability and thus longer names. To determine the scope of a variable, the data-flow analysis could be used. With the analysis, the previous rule could include this exception. Due to the data-flow analysis, we categorize this rule into the advanced level of complexity.

Detecting hungarian notation could be accomplished with regular expressions on the variable names, since the hungarian notation follows predefined notation strategies. Therefore, such a rule checker would be basic level of complexity.

For functions, the clean code principles define multiple rules. First, functions should be smaller than 20 lines of code. A checker for this rule would be at the basic level of complexity, since the AST contains all the necessary information about the function body. If the metadata such as line number are retained during AST construction, a checker can calculate the lines of code for the function body.

The next rule covers the function call in the condition and body part of a conditional such as an if-statement. An algorithm can scan the AST to check the condition and body nodes of the conditional statement.

Regarding the purpose of a function, the clean code rules suggest a function to have one purpose and to operate on one abstraction level. Counting the number of purposes requires an understanding of the meaning of the code. Similar understanding would be necessary for the level of abstraction. We argue such a checker would be in the high level of complexity category, since the understanding of code could only be achieved with machine learning. The aforementioned research field of code summarization could be beneficial for this task, too. A natural language description of a function may require the

model to "understand" the purpose and task in orer to articulate it in natural language. It may be possible to use work in this field to detect functions with multiple purposes or abstraction levels.

The rule that limits the number of function arguments is on a basic level of complexity. The AST contains the information about the code structure and therefore all function arguemnts. Counting those requires the algorithm to search for function nodes in the AST and count the number of arguemnts.

The next rule forbids side-effects of a function. Detecting side-effects can be broken down into a two step process. First, tracing the data manipulation of a functions is at the advanced level of complexity. With a data-flow analysis and call graph, it is possible to check what varaibles a function manipulates. Second, the classification wether an effect of a function is a side-effect requires an understanding of the intended effect of a function that is described in the name. We argue the understanding of the intended effect is at the high level of complexity.

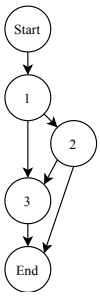
The clean code rules discourage the use of error code to indicate exceptions. If the error codes are not part of the programming lanuage specification (as they are not for Python), it could be hard for an automated checker to distinguish between returned error codes and non-error values. There may be indicators such as an early return of a constant value or comparing a returned value with a constant value.This indicators as a heuristic may be good enough for practical use. We would classify such a checker at the high level of complexity.

The automated checking for repeated code is an active research topic. As described in Section 2.2.2, efforts are made with several tools to detect repeated code. We therefore categorize a code duplication checker to be in the high level of complexity.

2.5 Quantitative Metrics for Code Quality

To define the quality of a software product, it is necessary to have methods to express the code quality as quantitative units. This has multiple advantages:

- A metric sums up the quality of a project in a single unit.
- A quantitative approach tracks the changes in code quality over time. Therefore, it is obvious if code quality improves or not. In case the quality undercuts a threshold, special measures like mandatory refactoring can be undertaken.




```
def function(a,b):
    if a < b: # (1)
        if b < 10: #(2)
            a = a + b
        else:
            return b #(end)
    a = a * 2 #(3)
    return a #(end)
```

Figure 2.2: Control-flow graph visualisation for a code sample. The graph has 6 edges, 5 nodes and one connected component. The cyclomatic complexity is 3.

- A developers performance can be evaluated based on the code quality. Since the maintainability and reliability of the software depends on the code quality, this is a good incentive to enforce high-quality work.
- A certain level of code quality may be required by a contract. As a result, a customer may have fewer bugs and a smaller maintenance effort.

Metrics for code quality are a subset of general software metrics. The following sections describe common software metrics that express code quality.

2.5.1 Cyclomatic Complextiy

Cyclomatic Complexity is a metric for the complexity of a section of code. It was introduced by Thomas McCabe. It measures the complexity by counting the number of linearly independent execution paths [13].

An execution path is the subsequent execution of instructions. With control flow structures such as if statements, two execution paths are possible, depending on the evaluation of the if condition. An execution path is linearly independent if it includes one subpath that is not part of any other path. A control flow graph represents all possible control flows as described in 2.3. Figure 2.2 shows a control flow graph for a sample function.

The cyclomatic complexity on a control-flow graph as the number of linearly independent execution paths is defined as:

$$M = E - N + 2P \tag{2.1}$$

E is the number of edges, N the number of nodes and P the number of connected components. A connected graph is a subgraph, in which all nodes are connected to each

other by a path. Following this definition, the cyclomatic complexity can be calculated. Figure 2.2 shows a visualisation of a sample python function. The control-flow graph has six edges, five nodes and is one connected component. Using equation 2.1, the cyclomatic complexity is 3.

MacCabe recommends limiting the cyclomatic complexity to 10. NIST confirms this recommendation in TODO. A lower cyclomatic complexity improves testability since the complexity represents the number of execution paths that need to be tested. Therefore, M is the upper bound for the number of test cases for full branch coverage. Furthermore, studies suggest a positive correlation between cyclomatic complexity and defects in functions. TODO source Software that has to comply to safety standards like ISO 26262 (for electronics in automobiles) or IEC 62304 (for medical devices) are mandated to have a low cyclomatic complexity [11, **?**].

Although cyclomatic complexity is used throughout the industry, several shortcomings are under critique. First, complexity from data flow is ignored. Working with a larger number of variables and operations, the code becomes more complex, but the cyclomatic complexity does not take this into account. Second, nested code structures are not considered by the metric, although it adds additional difficulty for understanding. TODO source as Halstead critique.

2.5.2 Halstead Complexity Measures

Maurice Halstead introduced the Halstead complexity measures (HCM) in 1977 [9]. Halstead approached the complexity measure with an empirical approach by defining observable and measurable properties and put them into relations.

The measurable properties are operators and operands. Operators are symbols in expressions like an addition, subtraction or multiplication symbol. Operands are the values and variables that are manipulated by the operators.

The sum and number of distinc operators and operands are counted as:

- η_1 as the number of distinct operators
- η_2 as the number of distinct operands
- N_1 is the sum of all operators
- N_2 is the sum of all operands

From these base properties, Halstead derrived additional properties:

- Program vocabulary size:

$$\eta = \eta_1 + \eta_2$$

- Program length as the sum of all operators and operands:

$$N = N_1 + N_2$$

- The volume of a program in terms of program length and program vocabulary is defined as:

$$V = N * \log_2 \eta$$

Based on those properties, code metrics can be calculated. First, the difficulty of understanding a program is calculated as:

$$D = \frac{\eta_1}{2} * \frac{N_2}{\eta 2}$$

The major contributors to difficulty are the number of distinct operators η_1 and the sum of all operands N_2.

Second, the combination of difficulty and volume is the required effort for understanding or changing code follows:

$$E = D * V$$

Third, the effort for changes translates into real time following the relation:

$$T = \frac{E}{18} s.$$

Last, the number of bugs correlates with the following relation TODO cite: A survey on metric of software complexity:

$$B = \frac{V}{3000}$$

HCM focus on the complexity introduced by data manipulation but ignores complexity from the control-flow. Since the cyclomatic complexity focus on the control-flow complexity but not on the data-flow complexity, it is practical to use both together to supplement each drawback (TODO source: A survey on metric of software complexity). Additionally, the correlation with the number of bugs is based on the programmer's skill estimation with a fixed value of 3000. Since this varies between projects, such an experiential and fixed number is doubtable (TODO source as before).

2.5.3 Software Maintainability Index

The software maintainability index was developed by Dan Coleman and Paul Oman in 1994. 16 HP engineers evaluated 16 software systems and scored it in a range from 0 to 100, with 100 representing best maintainability [6]. Following a regression analysis, they identified the following equation to match the maintainability of the evaluated systems:

$$MI = 171 - 5.2 * \ln \overline{V} - 0.23 * \overline{M} - 16.2 * \ln \overline{LOC} + 50 * \sin \sqrt{2.4 * C}$$

$\overline{V}$ is the average Halstead Volume, $\overline{M}$ the average cyclic complexity, LOC the lines of code and C as fraction of comments.

The software maintainability index was defined many years ago with a limited sample size of developers and projects. Additionally, programming languages have changed significantly over time. A study by Sjøberg et al. suggest no correlation between the software maintainability index and actual maintenance effort in a controlled environment [18]. Although the study only analysis four software projects and lacks generalisation, they find a strong anti-correlation with different maintainability metrics. Only the code size seems to correlate with the actual maintainability. The former seems to be consistent with a systematic review on software maintainability predictions and metrics by Riaz et. al [17].

2.6 Tools for Code Quality Analysis

It is good practice to use static code analysis tools to improve code quality. A static code analysis examines a program by analysing an abstract syntax tree, the control or data flow, a pointer analysis or an abstract (approximated) execution. In comparison to dynamic analysis, the code is not executed. The result of static analysis can be based on approximations, so there might be false-positive results. An expert has to examine the result and correct results if necessary [15].

Besides the use of static code analysis for compiler and optimisations, it is also helpful for analysing the code quality. Different categories of code quality-related principles can be analysed:

Code Guidelines: A static code analysis can ensure compliance to structural, naming and formatting code guidelines.

Standard Compliance: A requirement for a software may be compliance to an

industry-standard like IEC 61508 or ISO 26262 [**?**, 11]. Static code analysis can ensure or at least assist with the compliance.

Code Smells: Some code smells follow a known pattern and a static code analysis can detect those smells. Since code smells can be an indication for chaotic code, it is best if these smells are detected and removed early on.

Bug Detection: Although bug detection with static analysis can not detect all bugs, every detected bug before a software release is important. Examples for detected bugs are unhandled expressions or concurrency issues [7].

Security Vulnerability Detection: Static code analysis tools can detect some security vulnerabilities like SQL Injection Flaws, buffer overflows and missing input validation with high confidence. Since these are some common, easy to exploit vulnerabilities, an analysis for security vulnerabilities can increase the security of the overall software [19].

The following sections provide an overview of a few static code analysis tools with a focus on code quality and maintainability. We selected them based on popularity and if the projects are still maintained.

2.6.1 PyLint

PyLint is a code analysis tool for the Python programming language. It is open-source and licensed under the GNU General Public License v2.0 and available for all common platforms. PyLint can be executed as a standalone program or can be integrated into common IDEs like Eclipse. A continuous integration pipeline may include PyLint as well to ensure an analysis on every build.

With PyLint, the developer can make sure the code complies to the PEP8 (TODO) style guide for python coding. This includes name formatting, line length and more. It does not calculate a metric for the code but instead warns about violated principles. Additionally, PyLint can detect common errors like missing import statements that may cause the program to crash at the start or later at runtime. To support refactoring, PyLint can detect duplicated code and will suggest refactoring the code.

PyLint can be configured to ignore some checks and to disable specific rules. To expand the ruleset, a developer can write a "checker", an algorithm to check for a specific rule. The algorithm can analyse the raw file content, a token stream of the source code or an AST representation. The checker can raise a rule violation by providing the location

information and the problem type to the PyLint framework and it will be included in the PyLint analysis report.

2.6.2 PMD Source Code Analyzer Project

PMD is an "extensible cross-language static code analyser" for Java, JavaScript and more. As an open-source project, it is licensed under a BSD-style license and is available for macOS, Linux and Windows-based systems. It integrates into build systems like Maven and Gradle as well as into common IDEs like Eclipse and IntelliJ. PMD can run as part of a continuous integration pipeline and is included in the automated code review tool Codacy (see TODO).

Depending on the target language, PMD supports different rules. For Java, PMD has ruled in the following categories:

Best practices: Best practices include rules like one declaration per line or using a logger instead of a *System.out.print()* in production systems.

Coding Style and Design Several rules to improve the readability of the code like naming conventions, ordering of declarations and design problems like a violation of the law of Demeter, Cyclomatic complexity calculation and detection of god classes.

Multihtreading: Rules to mainly prevent the use of not thread-safe objects or methods. Due to the nature of multi-threading and unpredictable scheduling of threads, problems like unpredictable values of variables or deadlocks may occur. Since they may not occur in every execution, they are hard to spot and to debug. Consequently, warnings of using non-thread-safe code may save hours of debugging.

Performance: These rules flag known operations that have hidden performance implications. For example, string concatenation with the plus operator in Java causes the Java Virtual Machine to create an internal String buffer. This can slow down the program execution if numerous String concatenations are performed.

Security: Security-wise, PMD only checks for hardcoded values for cryptographic operations like keys and initialisation vectors.

Error Prone Code: PMD checks for several known code structures that will or may cause a bug at execution. Some rules are part of the clean code principles described in 2.2 and some rules are specific to the target language.

A user can expand the PMD ruleset in two ways: A XPath expression can be specified and will be validated against the AST by the PMD framework. For more control, it is possible to write a Java-based plugin that implements a custom AST traverser. The latter allows for more sophisticated rules and checks.

2.6.3 Codacy

Codacy is a software to "automate your code quality" (TODO source) for more than 30 programming languages. It is available as a cloud-based subscription service with a free tier for open-source projects and a self-host option for enterprise customers. Codacy runs as cloud software and a user can connect a GitHub, GitLab or Bitbucket repository that will be scanned automatically on every push or trigger a scan of local files with a command-line program. Additionally, a badge can be added to the readme page to show off the analysis results.

Codacy can be seen as a platform that runs multiple different "analysis engines". These analysis engines combine multiple tools depending on the language. For Python, Codacy uses PyLint, Bandit (a scanner for security issues) and a metric plugin. Due to the licensing of those analysis engines, the engines are open-sourced, whereas the Codacy platform is proprietary.

Depending on the language, Codacy supports scanning for common security and maintainability issues. The later is faced with scanning for Code Standardization, Test Coverage and Code Smells to reduce technical debt.

Codacy allows customisation by disabling certain rules and changing rule parameters like the pattern to fit the rules to the project.

2.6.4 Sonarqube

Sonarqube is an analysis tool to maintain high code quality and security. It supports 15 programming languages in the open-source version licensed under the GNU Lesser General Public License, Version 3.0. In the Developer Edition, Sonarqube supports 22 languages and 27 languages in the enterprise edition. Sonarqube is a self-hostable server application with a SonarScanner client module that can be integrated into build pipelines like Gradle and Maven as well as a command-line tool for other build pipelines. The SonarScanner reports the result to the server, that serves a website to review the results. With the Developer Edition, branch and pull request analysis are possible and a pull request will be annotated with the analysis results.

For Python, Sonarqube offers more than 170 rules. These rules are in the following categories:

Code Smells: Code Smells like duplicated String literals are flagged with four different levels of severity (from higher to lower severity): Blocker, Critical, Major, Minor. Explanations and examples are accessible for the developer to understand and fix the issue. The analysis is more in-depth than AST-based solutions since it additionally uses control and data-flow analysis.

Bug: Multiple rules cover bugs that would definitively result in a runtime exception and program termination. As an example, calling a function with the wrong number of arguments will be flagged with the highest severity, since it will raise a TypeError during runtime. Although programmers may notice issues like this during coding and testing, the issue can remain hidden if it only triggers a special execution path of the system.

Security Hotspot: The Security Hotspot analysis unfolds pieces of code that may be a real vulnerability and requires a human review. The scanning has a hotspot detection for seven out of the OWASP Top Ten Web Application security risks (TODO src). A flagged hotspot contains a detailed explanation of the reason for being flagged and a guide on how to review this hotspot. The recommendation to double-check a piece of code can help to prevent a security vulnerability from being deployed to production.

Security Vulnerabilities: A security vulnerabilities analysis reveal code that is at risk of being exploited and has to be fixed immediately. Especially misconfiguration of cryptographic libraries can be revealed easily and future damage prevented.

Additionally, Sonarqube offers several metrics like test coverage and a custom derivate of Cyclomatic Complexity named Cognitive Complexity [5]. The authors see several shortcomings in the original Cyclomatic Complexity model:

- Parts of code with the same Cyclomatic Complexity do not necessarily represent an equal difficulty for maintenance.
- Cyclomatic Complexity does not include modern language features like try/catch and lambdas. Therefore, the score can not be accurate.
- Cyclomatic Complexity lacks useability on a class or module level. Since the minimum complexity of a method is one and a high aggregated Cyclomatic Complexity

for a class is measured for small classes with complex methods or large classes with low complexity per method (e.g. a domain class with just getter/setter).

Cognitive Complexity addresses these points, especially the incorporation of modern language features and meaningfulness on class and module level.

The calculation is based on three rules [5]:

Ignore Shorthand Structures : Method calls condense multiple statements into one easy to understand the statement. Therefore, method calls as shorthand are ignored for the score. Similarly, shorthand structures like the null-coalescing operator reduce the Cognitive Complexity compared to an extensive null check and are therefore ignored for score calculation.

Break in the linear control flow : A break in the expected linear control flow by loop structures and conditionals adds to Cognitive Complexity as to Cyclomatic Complexity. Additionally, Catches, Switches, sequences of logical operators, recursion and jumps also adds to Cognitive Complexity, since these structures break the linear control flow.

Nested flow-breaking strcutures : Flow-breaking structures that are nested additionally increase the Cognitive Complexity, since it is harder to understand than non-nested structures.

The method-level Cognitive Complexity score represents a relative complexity difference between methods that would have the same Cyclomatic Complexity. Furthermore, the aggregated Cognitive Complexity on a class or module level now differentiate between classes with many, simple methods and classes with a few, but complex methods. As a result, domain classes (containing mainly getters/setters) have a lower score compared to classes with complex code behaviour [5].

Developers can extend Sonarqube similarly to PMD. They can write a Java plugin that can access the AST but also a semantic model of the code. Additional, extensions can be created that provide the functionality to other extensions. The Java plugin is compiled into a .jar file and placed into the plugin dir of the Sonarqube installation. For simpler rules, XPath expressions are possible through the web interface and allow a quick extension. For instance, if developers observe bad code style during a pull request review, they can quickly write a rule to enforce this rule in all subsequent pull requests automatically.

Integration in continuous integration, manual review

Tools review for all tools that check different stuff
Single Responsible principle, Open-Closed principle

3 Approach

Approach(es) without the quantitative results (or only selected results to motivate the choices/the problems)

What has possibly failed (short)

What has worked and why

What could be possible method extensions/improvements

This section is divided into the approach for the Clean Code Analysis Plattform and the Clean Code classification.

3.1 Clean Code Analysis Plattform

The goal of the design and implementation of the Clean Code Analysis Plattform (CCAP) is a tool for software developers to improve the code quality of existing and new code. The tool accepts a directory containing source code files as input and analyses the input for snippets of improvable code quality. If the analysis classifies a code snippet as problematic, it should help the developer to improve the snippet by providing information about the problem. Ultimately, this should train the developer to spot problematic code by its own and to write clean code by default, so the number of alerts should decrease. At the same time, the overall software quality of a project increases immediately at rewriting a marked snippet and in the long term at training the developer to write code with higher quality.

In order to use the tool effectively, the design and implementation should cover the following requirements:

Useability : The CCAP should be an easy-to-use tool. Developers shall be able to install and run the tool. The extra effort of using this tool should be small, and the developer should use the tool in his day-to-day workflow without additional friction. The developers can interpret the issue and localise the problematic code spot immediately.

Expandability : The extension of the detected code problems should be easy. A clear defined interface for extensions is required so an extension developer would not need specific knowledge about the internal architecture of the tool. The expandability allows the desired workflow of a developer finding problematic code in an, e.g. peer-review, formalising it into an extension and sharing this extension with the team. With each iteration, the code quality of all team members would increase.

Integration : The tool should be easy to integrate into different systems. These systems include local workflows like git pre-commits or build systems and remote continuous integration/delivery/deployment pipelines.

A more specific requirement is Python as an input language and the expansion language. After JavaScript, Python is the second most popular programming language 2019 according to the Github statistics (`https://octoverse.github.com/#top-languages`). Besides the general popularity, Python is heavily used in the scientific community for machine learning and universities for teaching programming. These groups are part of the potential target audience, and students in specific can benefit from automated reporting of low-quality source code.

3.1.1 Architecture

The CCAP architecture is divided into a static part and two extension possibilities: An extension with analysis plugins adds more rules that are validated by the system. Adding an output plugin allows specifying the output format to fit custom workflow needs. The static part consists of four components: A core component to act as an orchestration unit, a component for handling the source code input and a component for handling the analysis plugins as well as output plugins. The design follows the requirements and goals for the platform. (TODO: High-level architecture schematic diagram)

The core component contains the main function and handles argument validation and parsing. Furthermore, it orchestrates other components by initialising and executing those. This process is divided into the argument parsing, initialisation and execution phase: In the argument parsing phase, the command line arguments are parsed and validated. It validates the existence of the required input directory argument and the optional plugin path configuration for the analysis plugins and the output plugins. Additionally, the logging level and the output format can be defined. The latter determines, which output plugin will be used, although the existence of the specified plugin is not

validated in this phase. A parsing or validation error will cause a program termination without further processing. The initialisation phase instantiates all components and the analysis plugin handler will scan the specified directories for plugins and keeps an index of all found plugins in memory. The output plugin manager scans for an output plugin, that satisfies the specified argument. If no plugin matches the output argument, the program will terminate with a one exit code and a failure message to indicate the problem. In the execution phase, the input handling component scans the input directory for files ending with *.py* and parses the source code into an Abstract Syntax Tree (AST) per file. In the next step, the core passes the parsed data to the analysis plugin handler. The latter will execute all plugins for all files and collects the results. Afterwards, the core component calls the output plugin component to output the results. If no exceptions occur during the execution phase, the program will be terminated with a zero exit code indicating the successful run.

The input component scans the given input directory for all Python source code files and parse the source code into an AST. For scanning the input directory, an algorithm will walk recursively over all folders and files. The detection of Python source code files is based on the file ending *.py*. The algorithm will return a list of file paths and the corresponding file content. Next, the AST parser is called and will add a parsed AST object to the list besides the file path and content. This list will be passed to the analysis plugins by the analysis plugin handler. An alternative approach would be to not read and parse the code in the input component, but instead, let the plugins read and parse the file content if needed. With many files to scan, the latter approach would have a lower memory footprint since the file content and the AST will not be held in memory. Consequently, every analysis plugin has to perform an expensive read operation from disk and the performance scales with the number of files and the number of analysis plugins. If the input component reads all files, the information is held in the main memory and the performance only scales with the number of files. Since the files are text-based, the number of files needed to exceed the main memory is expected to be high enough to fit most projects. (TODO sample calculation?).

The analysis plugin handler manages all analysis plugins. This component finds all plugins, executes the plugin and collects the reported results. During the initialisation phase of the core component, the analysis plugin handler will scan the plugin directory for all Python files. It imports all Python files and scans those for classes, that inherit from an abstract *AbstractAnalysisPlugin* class. The abstract class defines all methods that need to be implemented in the concrete plugin subclass. The analysis plugin handler

instantiates all found classes. During the core execution phase, the core receives a list with the file name, file content and the parsed AST. All plugins are called on a specific entry point method that is defined in *AbstractAnalysisPlugin* with the aforementioned list. The plugin will return an instance of *AnalysisReport* with the plugins metadata and a collection of problems. The report is collected for every plugin into an *FullReport*. Additionally, the report contains information about the overall plugin execution time and run arguments. After all plugins have been executed for all files, the analysis plugin handler returns the *FullReport* to the core component.

The last component in the execution chain is the output plugin handler that will pass the *FullReport* to the specified output plugin. It implements the same algorithm as the analysis plugin handler to find all plugins that inherit from *AbstractOutputPlugin*. Instead of keeping track of all plugins, only the plugin that corresponds to the output format argument is instantiated. The output plugin has an entry point as defined in *AbstractOutputPlugin* that is called with all the collected results.

Analysis Plugins

Analysis plugins provide the easy extendability of the platform by developers. All users of the tool can expand the set of problems it can detect by implementing a plugin Python and placing it into the plugin directory of the tool. In order to be compatible with the core components, a plugin has to be a class that inherits from the *AbstractAnalysisPlugin* class. Firstly, the abstract class introduces a class member variable *metadata* of the class *PluginMetaData*. A concrete plugin class sets this class member in the constructor to provide a plugin name, author and optional website. This metadata is used in the output to show more information about the plugin that reported a problem. Secondly, *AbstractAnalysisPlugin* specifies a *do_analysis* method that serves as a entry point that the platform will call. It accepts a list of *ParsedSourceFile* objects that contains the file path, the file content and the corresponding AST for all input files. With this information, the plugin can implement any logic to detect problems. For example, the plugin can traverse the AST to look for specific node types, it can use a tokeniser on the content of the files and analyse the token stream or it can run sophisticated machine learning algorithms on the source code. The plugin can even import third-party libraries, although they have to be installed by the user on the system. After detecting all problems, the plugin returns an *AnalysisReport*. The report contains the plugins metadata and a list of found problems. These problems are instances of a problem class inheriting from *AbstractAnalysisProblem*. The abstract class expects a

file path and line number as constructor arguments and requires the plugin developer to override the problem name and description (see listing **??** for an example). The problem name and description will be shown in the final output and should follow the following guidelines:

```
class ReturnNoneProblem(AbstractAnalysisProblem):
    def __init__(self, file_path, line_number):
        self.name = "Returned None"
        self.description = "Returning None is dangerous since the caller has to check for None.
    Otherwise, a runtime exception may occur."
        super().__init__(file_path, line_number)
```

Listing 3.1: Example for overwriting the *AbstractAnalysisProblem* with a concete implmentation. The problem name and description are overwritten.

- Have a proper name that allows the experienced developer to recognise the problem quickly.
- Explain what code construct is problematic.
- Give reasons why this code is seen as problematic.
- Show guidance and examples on how to fix the problem and improve the code.

Although it is possible to use one plugin for multiple, different problem types, having one plugin for one problem type helps to reuse and share the plugin. Additionally, it can be disabled easily by removing the plugin from the plugin folder.

Steps to create an analysis plugin In order to expand the CCAP with an analysis plugin, the following steps are required for a developer:

1. Create a *.py* file with a class inheriting from *AbstractAnalysisPlugin*.
2. Instanziate *PluginMetaData* and assign it to the metadata member.
3. Define a problem class inheriting from *AbstractAnalysisProblem* and set the problem name and description following the guidelines above.
4. Implement the *do_analysis* method with a *ParsedSourceFile* parameter. Return an *AnalysisReport* instance with all found problems.
5. Place the *.py* file into the analysis plugin directory of the tool.

Whereas these are the minimum required steps to implement the plugin, the developer is free to add additional methods, classes or import libraries as necessary. Furthermore, it is advisable to implement several tests to ensure the plugins correctness. CCAP uses pytest [1] for testing, implementing a test is as easy as writing a function with a "test_" prefix and running the *pytest* command. The plugin can be tested by simulating a call from the CCAP core with a mocked *ParsedSourceFile*.

Return None Plugin A rather simple analysis plugin demonstrates the capabilities of the CCAP: The Return None Plugin scans the source code for functions that return the None value. Returning None may result in runtime exceptions if the function caller does not expect and handle a potential None return. Although the None can be returned directly or as a value of the returning variable, this plugin only focus on the explicit *return None* statement to showcase the options for the developer to analyse the source code.

Detecting *return None* is possible in multiple ways. The following shows the possibilities for developer to implement such a detector:

Regular Expression : In the *do_ analysis* method, a developer has access to the source code as a string. Therefore, it is straitforward to use a regular expression to detect a *return None* statement.

```
import re
matches = re.finditer(r"return None", source_file.content, re.MULTILINE | re.DOTALL)
```

Since the regex library only returns the start and end index of matches, these have to be converted to line numbers. Afterwards a *ReturnNullProblem* instance can be created for every match and added to the *AnalysisReport* for this plugin.

This approach uses regular expressions to match patterns in a string without utilising the structures of the code. It is a simple but powerful way and most developers are familiar with regular expression. On the flip-side, source code may have various ways syntactic ways to express a semantic. Consequently, the regular expressions have to be designed carefully to cover all variations. For instance, it is possible to encounter a doubled whitespace, that would break the aforementioned regular expression. Additionally, regular expressions do not operate on the structure of the code; therefore, they can not detect high-level patterns on the code structure.

[1] `https://docs.pytest.org/en/stable/`

Tokenisation : The process of dividing a character stream into a sequence of tokens is called tokenisation (also known as lexical analysis). With the Python tokeniser, a token can contain multiple characters and has a token type like name, operator or indentation. A token sequence provides more information about the code structure that can be used to detect problematic patterns. A token sequence for a *return None* statement would be the following:

```
[...( type: NAME, value: return), (type: NAME, value: None)...]
```

A simple algorithm would scan the sequence for two subsequent name tokens with the values "return" and "None". The abstraction level of a token sequence is higher than of a character sequence. Since the whitespace between "return" and "None" provide no semantic meaning, it is removed on this abstraction level. Whereas the regular expression based approach would have to deal with problems as the doubled whitespace, the token-based approach profits from the higher abstraction level and can access meaningful tokens directly.

Abstract Syntax Tree : After tokenisation, a parser takes the token stream and prases it into a hierarchical data structure like an Abstract Syntax Tree. With an AST the code is represented structurally and it is possible to traverse the tree following the structure of the code. The AST consists of nodes with different type and children, for example, a node representing an if statement. It is possible to access the condition and the body of the if statement as descendant nodes in the AST. Analysing an AST allows a higher abstraction level then analysing the token string since the code structure is represented. Therefore, more abstract rules that analyse the code structure are possible.

To detect a *return None* statement in the abstract syntax tree, an algorithm would traverse all AST nodes looking for a return-typed node. If found, the value descendant contains the statement part after the return keyword. A *None* value would be represented as a node of type constant or name constant (depending on the parser version). The value descendant of the constant node may then be checked for equality to *None*. All AST nodes contain the corresponding line number, that are necessary for creating a problem message. See listing 3.2 for a Python implementation.

Analysing the AST is best for problems in the code structure since the AST represents the code structure in a well-defined, traversable data structure. Although

simpler patterns like the *return None* could be detected using regular expressions, a detection on AST level allows detecting the semantic meaning instead of the syntactic representation of a problem. For more complex problems, it is inevitable to use the AST most of the time.

```
for node in ast.walk(a.ast):
    if isinstance(node, ast.Return):
        return_value = node.value
        if isinstance(return_value, ast.Constant) or isinstance(return_value, ast.
NameConstant):
            if return_value.value is None:
                problems.append(ReturnNullProblem(a.file_path, return_value.lineno))
```

Listing 3.2: Detecting RETURN NONE problems by analsing the AST data structure.

This implementation covers only the simple case, in which *return None* is written explicitly. Of course, several modifications are possible, that would not be detected by this plugin and would require more sophisticated algorithms. Evaluating, if machine learning models trained on this simple rule can also detect such modifications is part of the second part in research question 3 (TODO: check, jump link).

Since detection alone is not a great help for the user, a useful description of the problem is necessary. As described in section 2.2.6, there are some alternatives to returning none. If none happens due to an error, it is better to raise an exception and provoke an explicit error handling, which prevents runtime errors. If the standard return type is a collection, an empty list is more appropriate, since the function caller will most likely write the logic for an unknown amount of list items. However, if the standard return type is a single object, it is not apparent what to return. With PEP484 (TODO source), an optional type was introduced for type hints in Python 3. Using a static type checker for Python like mypy (TODO source) outputs a warning if a developer forgets to check an optional for not being none.

Condition with Comparison The second plugin detects a direct comparison in a conditional statement. For better readability and understandability, it is suggested to use a function call with an appropriate name that evaluates to true or false. This function call allows a natural reading of the conditional statement without deciphering the meaning of the boolean logic.

An if-statement consists of a condition and body part. If the condition evaluates to true, the body is executed. For the condition, any logical expression will be evaluated. A simple algorithm would take the AST, search for if nodes and check if the condition part

is a compare node. However, negation and logic AND/OR would not be detected by the simple approach. Consequently, a recursive algorithm has to follow logic operators and checks the expressions for comparison nodes. The simple approach does not provide value for the CCAP but we use if for the machine learning evaluation with the problem type name CONDITION COMPARISON SIMPLE.

Following these considerations, an advanced algorithm would scan for if nodes in the AST. The conditional part as a boolean expression is evaluated in a recursive function that returns true if a direct comparison is made anywhere in a boolean expression. The conditional part can be a boolean operation (like AND/OR) or a unary operator (like NOT). In these cases, the recursive function will be called again with the respective expressions. If the conditional part is neither a boolean operation nor a unary operator, a true is returned if the conditional part is not a method call. The last case would be the base case in the recursion. Listing 3.3 shows the Python implementation of the recursion.

```
def _check_if_direct_comparison(self, node):
    if isinstance(node, ast.BoolOp):
        violated = False
        #check all expressions of the boolean operator
        for value in node.values:
            if self._check_if_direct_comparison(value):
                violated = True
        return violated
    elif isinstance(node, ast.UnaryOp):
        return self._check_if_direct_comparison(node.operand)

    return not isinstance(node, ast.Call)
```

Listing 3.3: Recursive function to analyse an if statement for direct comparisons. Since a condition should contain a method call, the function returns False if this is not the case.

Output Plugins

With output plugins, CCAP adds additional flexibility towards the output format. Depending on environmental requirements, the output can be adapted with custom logic by defining an output plugin. For instance, running the tool locally could write the results to the standard output in a human-readable way or create a formatted HTML file to be displayed in the browser. A machine-readable JSON output may be preferred

when running inside an automated workflow.

Output plugins follow similar concepts as analysis plugins. A plugin class inherits from *AbstractOutputPlugin*. The abstract class introduces the metadata member of the *PluginMetaData* class to encapsulate plugin name and author information. Additionally, a second member variable *output_format* has to be defined with a short abbreviation for the output format. This field is used by the output plugin handler to select the output plugin by the run arguments. Consequently, it should be unique; otherwise, the first found plugin with a matching *output_format* field is selected by the output plugin handler. Therefore, using a custom prefix string is recommended.

As entry point method, the method *handle_report* has to be implemented. The method provides an instance of *FullReport* as its argument. The *report* field holds a collection of *AnalysisReport* for every analysis plugin that has been executed. With metadata and problem information, the output plugin has access to all required information to produce the desired output.

Steps to create an output plugin To expand the output capabilities of the CCAP, the following steps are, similiar to analysis plugins, required:

1. Create a *.py* file with a class inheriting from *AbstractOutputPlugin*.
2. Instanziate *PluginMetaData* and assign it to the metadata member.
3. Set the *output_format* field with a unique abbreviation for this output format. Since it should be unique, a custom prefix prevents a name collision with preexisting plugins.
4. Implement the *handle_report* method with a *ParsedSourceFile* parameter.
5. Place the *.py* file into the output plugin directory of the tool.

Standard Output Plugin The Standard Output Plugin writes the formatted output to the stdout stream. It is enabled if no output plugin is explicitly specified.

The output is divided into a general part and the problem list. The former contains the input path, all executed plugins, a total runtime and a summary field with the numbers of problems in total. The latter displays the list with problems, grouped by analysis plugin. For each problem, the problem name, file path, line number and description is printed. A colon separates the file path and line number. Some terminals parse the path

and line number so that a user can click the path and it opens the default editor with the cursor in the correct line. Sample output is shown in listing 3.1.1.

```
Analysis Report on /Users/d064518/MA_CleanCodeAnalyser/test_programs.
Analyse Plugins: Condition Method Call Plugin, Simple Condition Method Call Plugin, Return None
    (Null) Plugin, Sample Plugin.
Total time: None
Summary: Found 16 problem(s)
  ----------------------------------------
PROBLEMS:
  PLUGIN NAME: Condition Method Call Plugin by Enrico Kaack <e.kaack@live.de>
    Found: Explicit comparison in condition in /Users/d064518/MA_CleanCodeAnalyser/
    test_programs/return_none.py:18
      Explicit comparisons in conditions should be replaced by method call for better readability
...
PLUGIN NAME: Return None (Null) Plugin by Enrico Kaack <e.kaack@live.de>
    Found: Returned None in /Users/d064518/MA_CleanCodeAnalyser/test_programs/
    return_none.py:4
      Returning None is dangerous since the caller has to check for None. Otherwise, a runtime
    exception may occur.
```

HTML Output Plugin For larger projects, the Standard Output Plugin may not be sufficient to get an overview of the project or to generate a report. Therefore, the HTML Output Plugin creates a *report.html* file, that can be opened in every browser and provides a cleaner overview. It has similar general data at the top as the Standard Output Plugin, but it moves the problem description into a tooltip to offer a more compact overview. See figure **??** for an example screenshot.

3.1.2 Extensions

While the core functionality exists, extensions for the CCAP would aim for improved useability for the user. One important improvement in useability would be an IDE integration for common IDEs like Visual Studio Code. A good starting point would be the Langauge Server Protocol[2]. This IDE integration requires a language client as a Visual Studio Code extension and a protocol-compliant language server. The latter would wrap the CCAP and modify it slightly to process a single, changed document and return the results. Since the CCAP architecture is modular, this is possible without larger modifications.

[2] `https://microsoft.github.io/language-server-protocol/`

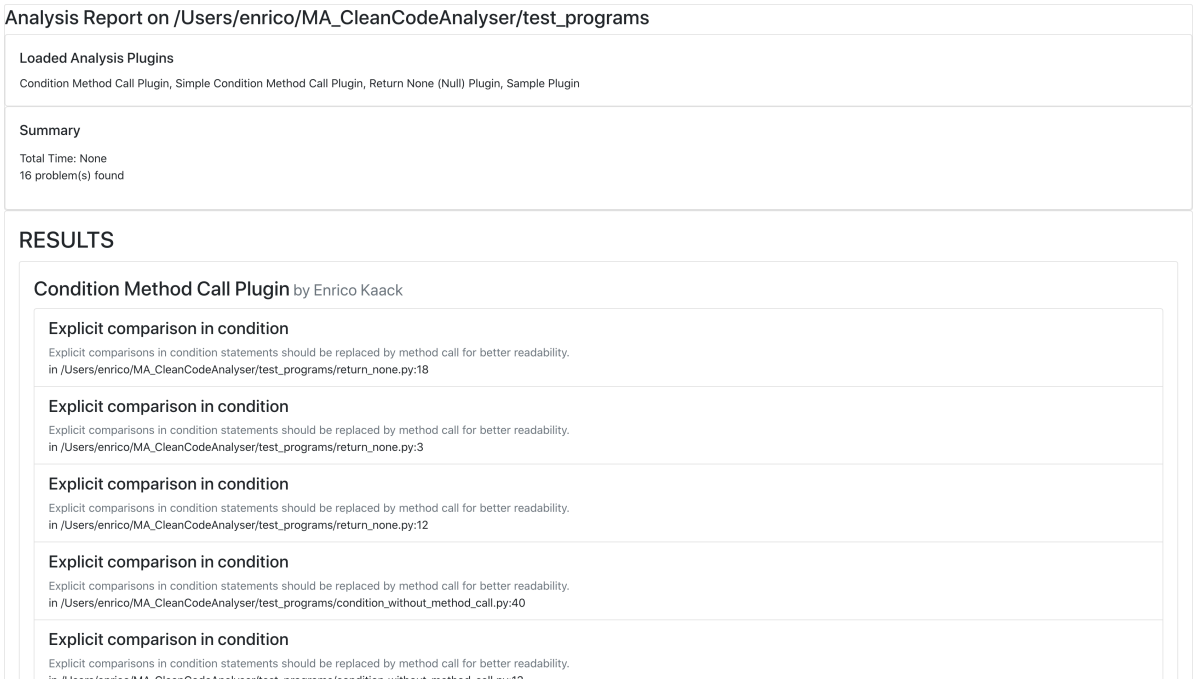


Figure 3.1: Output of the HTML Output Plugin, displayed in a browser.

Another feature would be a configuration to disable specific analysis plugins, that one does not want to run on the project. With the current architecture, this would be possible by moving the analysis plugin file outside the plugin directory. A configuration with command-line parameters or with a per-project, hidden config file would have a better user experience. The latter could also be committed to the version control system, so every team member has the same configuration. Continuing on configuration possibilities, having configuration possibilities for plugins would increase flexibility for a plugin developer. Introducing configurable warn levels like ‘warning’ or ‘error’ could help in continuous integration pipelines to decide if a build succeeds but the warnings are reported or if a build should fail because of error-level problems. Some rules could be seen as recommendations (warning level), whereas other rules would be unacceptable (error level).

Lastly, a feature to disable problem reporting for a specific code location could bring a boost in user acceptance. While some clean code rules are objective and can be measured precisely, some rules are more general recommendations that may not apply to every occurrence of this situation. For instance, the clean code guidelines generally suggest not to have more than three function arguments; it may be necessary or even inevitable to have four arguments. The CCAP should report this as a problem, but

the user should be able to decide if it is acceptable. In this case, the problem type on this specific location should not be reported in the future. In the current version, the user has no way to ignore a specific problem. Consequently, over time the number of problems the user has to ignore will accumulate until the user abandons the tool since it does not provide an added value over the frustration of manually ignoring problems.

3.2 Clean Code Classification

In the previous chapter, we have presented a platform to check for clean code rules. This platform requires analysis plugins to detect certain problems. These handwritten rules work well on certain rules, but certain rules may require a complicated analysis of the AST, the data-flow or the inter-module dependencies. Some rules on the other hand are subjective and we do not see a way of detection those rule violations with an algorithm. Therefore, this chapter introduces an approach to evaluate different supervised machine learning models to classify code into clean code or problematic code. Furthermore, we describe how we modify the code to test the generalisation capabilities of the models. The mentioned machine learning models include random forest classifier, support-vector-Machines, gradient boosting classifier and a recurrent neural network based on Long short-term memory units.

The objectives are to train, evaluate and compare Source Code Snippet Classification models and to modify the input data to represent a problematic code in an unseen way.

In the following we describe the approach in detail. The strucutre follows a machine-learning typical pipeline of data collection, preprocessing, encoding, splitting and training.

3.2.1 Challenges

Lack of datasets The most crucial components of every machine learning experiment are labeled datasets. For clean code detection, our research has shown no datasets with labeled clean code violations that could be used. As a result, we evaluated differnent different appraoches:

Solution 1: Related research fields like code completion often use the py150 dataset to train models [16]. This dataset contains 150.000 python files, sourced from GitHub. For supervised classification tasks, this dataset is inadequate due to its missing labels.

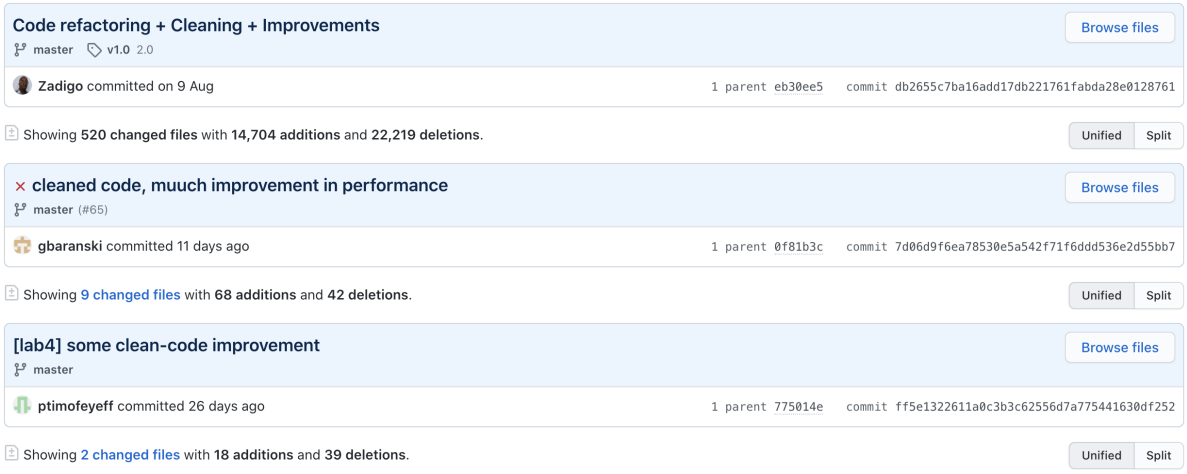


Figure 3.2: Example commit messages from different repositories. Those examples highlight (1) the missing naming convention, (2) inclusion of additional performance improvements and (3) several edits in multiple files. Those commits are found by searching GitHub for "clean code improvements" and filtering for Python language and commits. Sources: [1], [2], [3]

Solution 2: Another possible data source would be git commit histories. We could scan the history for commits that fixed unclean code. The previous code could than be labeled "unclean" and the commited code would be "clean". Same applies to issues and referenced pull requests on GitHub. We dismissed this approach for several reasons (see figure 3.2 for an illustrative example):

1. There is no annotation in neither issues descriptions nor git commit messages that would reliably tell, if the change is changing a violation of the clean code rules.

2. Even if we would be able to find commits that improve chaotic code, we could not ensure automatically, that the commit message is correct and only the improvement is included in the commit.

3. Searching for commits, we found several clean code improvements and refactorings of large portions of the code base in one commit. Additionally, it is often not explicitly mentioned, which rule applied for the improvement. Consequently, a training with such data could only lead to binary classification into clean code or unclean code. From a practical standpoint, it is advantagous to name the explicit rule violation and to explain how to improve.

[1] `https://github.com/Zadigo/ecommerce_template/commit/db2655c7ba16add17db221761fabda28e0128761`
[2] `https://github.com/gbaranski/homeflow/commit/7d06d9f6ea78530e5a542f71f6ddd536e2d55bb7`
[3] `https://github.com/ptimofeyeff/distributed-computing/commit/`

Label	RETURN NONE	CONDITION SIMPLE	CONDITION COMPARISON
0	99.79%	97.36%	95.14%
1	0.21%	2.64%	4.86%

Table 3.1: Class distribution for the train/test dataset before the split. Label [0] represents clean code and label [1] marks problematic code of the corresponding category.

Solution 3: Although Python code is available in abundance in form of open-source projects, it is possible to manually label source code that violates clean code guidelines. For the following reasons, we dismissed this approach:

1. Curating a hand-labeled dataset is a lot of work that takes time.
2. Manual labeling does not ensure correct labeling. A human can make mistakes or can subjectivly misinterpret chaotic code as clean code. The quality of the dataset could suffer and limit the machine learning models performance.

Solution 4: Given any amount of Python files, we could use the analysis plugins from section TODO analysis plugin to reliably detect violations of the corresponding rule. Based on this labeled data, we can train the classifier to detect these rules. If there would be a labeled dataset for more complex clean code rules, we could transfer the findings to these more complex rules. We choose this solution as to solve the dataset problem and train classifier, with more details given in chapter TODO. As a second step, we manipulated the input data, so the original analysis plugin could not detect the still existing problems anymore. With the second step, we show that the classifier generalise well enough to may work on complex clean code rules.

Inbalanced Dataset ?? A second challenge is a major inbalance between the classes labeled as problematic code and clean code. For the three different problem types, RETURN NONE, CONDITION COMPARISON SIMPLE and CONDITION COMPARISON, the class distribution is shown in table 3.1.

Solution 1: Due to the inbalance, we do not choose accuracy as a suitable evaluation metric, since classifiying all samples as clean code would result in a accuracy of 99.79% for the RETURN NONE problem type. Instead, we use precision and recall as metric,

`ff5e1322611a0c3b3c62556d7a775441630df252`

with a f1 score as single, weighted metric. More details about the metrics are in chapter TODO.

Solution 2: We will apply undersampling and oversampling techniques on the data and evalaute the difference in model performance. Undersampling removes random samples from the majority class and thus balance class labels. Oversampling replicates random samples from the minority class to balance class labels while also increasing the overall amount of data. This technique is only used on the trainings data. Since it changes the data distribution, an additional train-dev dataset is used as an additional test set to evaluate the impact of the resampling on the model performance.

Solution 3: Our approach of training different classifier is a solution to the data inbalance, since different classifier have a different sensitivity to data balance.

SVM quadratic complexity in training Support-Vector Machines have a quadratic time complexity on the number of trainings data. Consequently, the training takes a lot of time and the oversampling strategy worsen the trainingstime additionally.

Solution: We reduced the number of experiments with SVM and just evaluate some simple cases for baseline performance.
source: Time Complexity Analysis of Support Vector Machines (SVM) in LibSVM

3.2.2 Dataset

The source of our dataset are open-source python projects on GitHub. We queried the top starred python repositories and handselected 18 repositories. Although most top stared repositories are data science frameworks, we additional choose projects from domains such as web server, automation and containerisation. See table TODO for a list of all 18 repositories A script downlaoded all projects in their main branch with the current head. See table TODO attachment for the corresponding git hashs. Afterwads, we removed all non-python files. Next, we uniformly sampled 20% of all files and seperated those into a holdout set for final testing. Additionally, we perform our train/test split on the file level and not on the sample level. As described later in chapter 3.2.3, we use a sliding window approach to convert source files with dynamic length into fixed length samples. Due to the sliding window approach, we may have one problematic code line in multple samples. If we would do a train/test split on sample level, we may

Parameter								RN			CCS			CC		
over-samp.	under-samp.	emb-size	epochs	batch-size	#lstm-cells	dropout		Train	Train/Test	Test	Train	Train/Test	Test	Train	Train/Test	Test
-	-	32	3	256	10.0	0.2|0.2										
							F1	0.9937	0.9931	0.9927	0.9935	0.9817	0.9825	0.9916	0.9799	0.9812
							Recl	0.9906	0.9948	0.9912	0.9957	0.9864	0.9875	0.9925	0.9811	0.9832
							Prec	0.9968	0.9913	0.9941	0.9912	0.9769	0.9776	0.9908	0.9787	0.9791
-	0.5	32	3	64	10.0	0.2|0.2										
							F1	0.9995	0.8107	0.8072	0.9987	0.9699	0.9713	0.9978	0.9688	0.9699
							Recl	1.0	1.0	1.0	0.9985	0.9968	0.9971	0.9988	0.9968	0.9978
							Prec	0.999	0.6817	0.6768	0.9989	0.9445	0.9469	0.9968	0.9424	0.9436

Table 3.2: TODO lstm

indroduce samples covering one problematic line at different positions in both datasets (see figure TODO for visualisation). This would diminish the validity of metrics calculated from the test dataset. Table 3.2 shows an example for a train and test metrics of an neural network with LSTM cells. Without over- or undersampling, we achieve near perfect results for all problem types. If we apply undersampling to the train data, we basically remove some samples labeled as negative (in this case containing clean code). We observe a drop in precision but a near perfect recall. A decrease in precision and a constant recall means an increase in false positives. Since we removed some negative samples with undersampling, the overfitted model has not seen those samples that exist in the test set. Consequently, we decided to perform a train/test split on file level as described earlier.

We ensured to have a similiar data and label distribution on all data sets. Table 3.3 shows general and problem specific metrics on file level for the train, test and holdout set. The problem specific metrics are collected after processing the code files as described in chapter 3.2.3. We define the metrics as follows:

We calculate the *average lines of code per file* for n files with l_i as the lines of code for file i with the following equation:

$$\textit{average LOC per File} = \frac{\sum_{i=0}^{n} l_i}{n}$$

For the *proportion of lines of code containing a problem*, we assume one line contains the problem. Therefore, we define this metric for n files with l_i lines of code per for the ith file and p_i problems in the ith file as follows:

$$\textit{LOCs containing problem} = \frac{\sum_{i=0}^{n} p_i}{\sum_{i=0}^{n} l_i}$$

Last, we calculate the number of problems per file for n file and p_i problems in the ith

	Metric	Train	Test	Holdout
	Lines of Code	2,530,455	246,813	671,554
	Number of Files	13,330	1,481	3,702
	average LOC per File	189.83	166.65	181.40
Return None	LOCs containing problem	0.07%	0.09%	0.08%
	Problems per File	0.14	0.15	0.14
Condition Comparison Simple	LOCs containing problem	1.29%	1.21%	1.32%
	Problems per File	2.44	2.02	2.4
Condition Comparison	LOCs containing problem	2.34%	2.31%	2.44%
	Problems per File	4.44	3.85	4.42

Table 3.3: General and problem specific metrics for the train, test and holdout set. The lines of code containing a problem and the problems per file are similiar.

Problem Type	Label	Train	Test	Holdout
Return None	[0]	99.79%	99.73%	99.78%
	[1]	0.21%	0.27%	0.22%
Condition Comparison Simple	[0]	97.34%	97.49%	97.23%
	[1]	2.66%	2.51%	2.77%
Condition Comparison	[0]	95.13%	95.21%	94.9%
	[1]	4.87%	4.79%	5.1%

Table 3.4: Label frequency for all problem types on the train, test and holdout set.

file as:

$$\textit{Problems per File} = \frac{\sum_{i=0}^{n} p_i}{n}$$

The most important metrics for the data distribution is the proportion of lines of code containing the problem type and the average number of problems per file. For the first, we ovserve a maximal difference of 0.02 percentage points for the RN problem type, 0.11 pecentage points for CCS and 0.13 percentage points for the CC problem type. This directly translates into the label distribution on sample level shown in table 3.4 with a maximal difference 0.06, 0.26 and 0.31 percentage points for the three problem types. The number of problems per file is lower in test set for the CCS and CC problem type. Nevertheless, since the first metric and the label frequency are compareable, we assume our datasets having a similiar data distribution.

TODO per project analysis table in attachments.

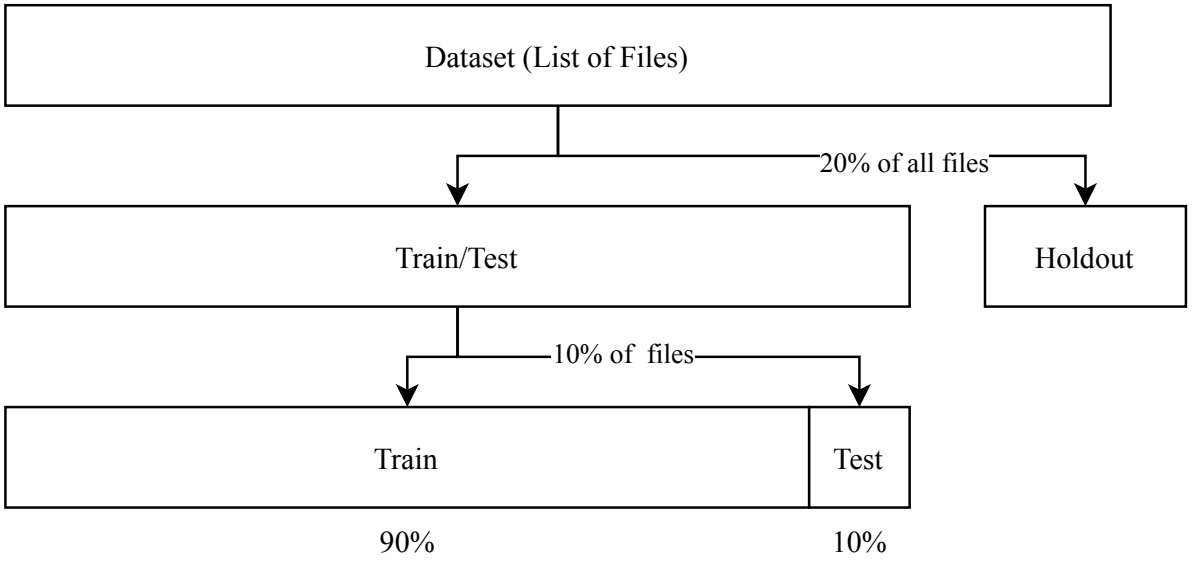


Figure 3.3: Split of the dataset. First, 20% of all files are seperated into a holdout set for later testing. The remainding 80% of the files are split into 90% training and 10% test data.

3.2.3 Processing

For the processing steps, we create a pipeline with the d6tflow framework[3]. Each processing step is a task, that stores its results depending on the parameter configuration in a pickle file. This allows to define a pipeline once and run it with different parameter combinations. The scheduler automatically determines what tasks to run and what task outputs are already stored in pickle files. Consequently, running the pipeline is more efficient and repeatable.

The processing pipeline consists of tasks to read the files into a datastructure, to processes source code and find the problems, to create a vocab dictionary, to convert the data into labeled samples and to split the data into a train, traintest and test set. See overview TODO for a schematic representation of the pipeline.

Files into internal Data Structure

First, a scanner walks recursively in all subdirectories of the input folder to find all files. If the file has a *.py* extension, its file path and the file content will be stored in a dictionary. The dictionaries for all file are collected into a list. Reading all files into main memory increases the performance for downstream tasks, since main memory

[3] `https://github.com/d6t/d6tflow`

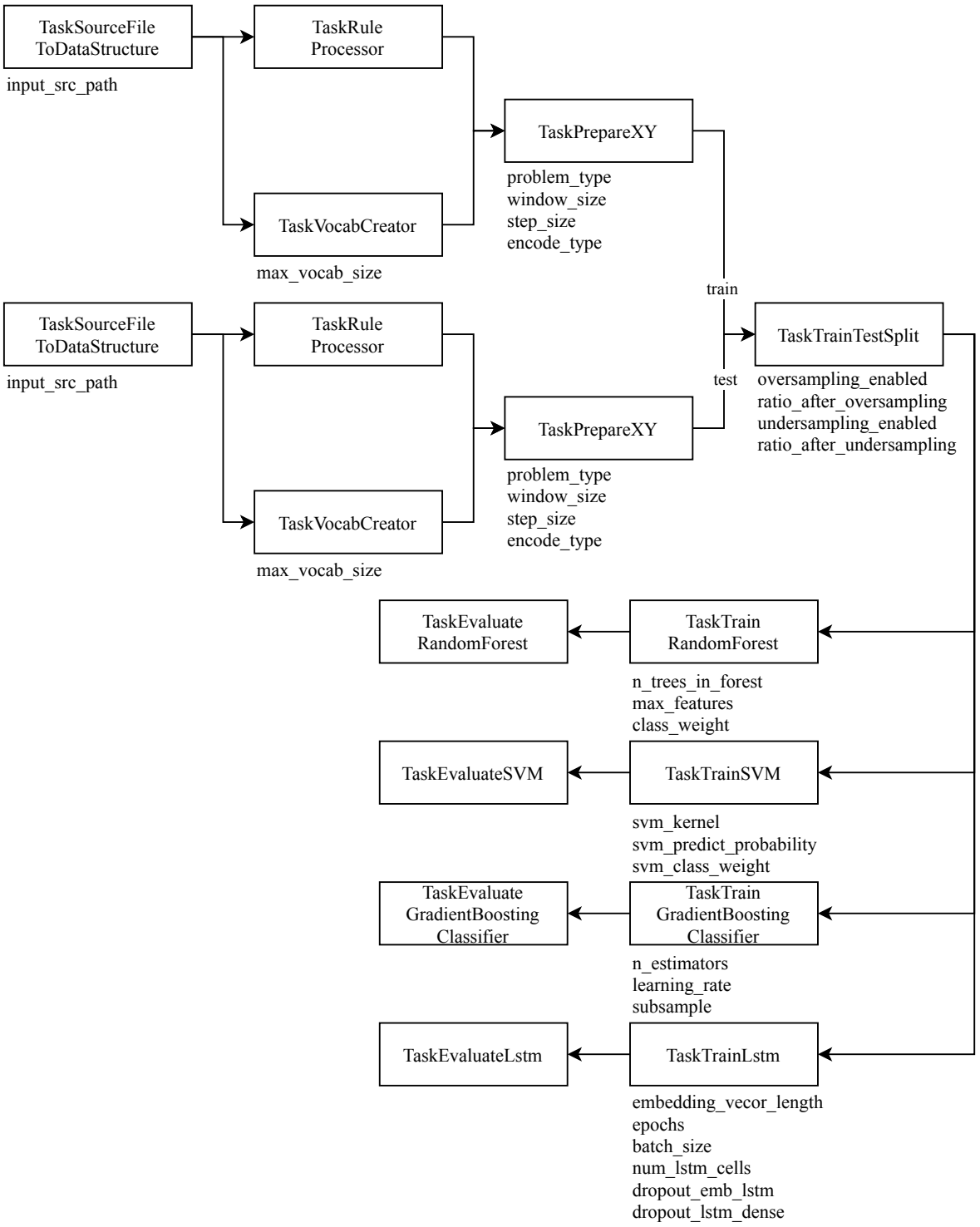


Figure 3.4: Schematic representation of the pipeline for RQ2 with configurable parameters. TODO describe

access is faster than disk access. Although the size of the systems main memory limits the dataset size, a file contains text and is therefore several kilobytes in size. The train dataset with 13,330 files is 86.47MB in accumulated file size.

Problem Detection

As a next step, the analysis plugins from the CCAP (see chapter 3.1.1) process every file and store the line number along with the problem type. As a result, for every file list of problematic line numbers and the corresponding type is available for further processing. The CCAP only covers the two analysis plugins for the problem types CONDITION COMPARISON and RETURN NONE. For model training, we introduce the simple alogrithm to detect comparisons in conditions as problem type CONDITION COMPARISON SIMPLE (described in chapter 3.1.1)

Data Encoding

The data encoding step transform the internal data representation into input vectors x and output vectors y. The transformation is descirbed in the following, multi-stage process.

Fixed Length Sequence The length of source code is dynamic, wheras the input size of our models is fixed. Therefore, the character stream of varaible length has to be transformed into a token stream of fixed size. To extract meaningful tokens from the character stream, we use the python tokenizer from its standard library. The tokenizer seperates the character stream based on the python syntax definition into tokens. All tokens contain a token type (like a name or operator token), the corresponding characters in the source code and a start and end position (line and column number). Next, the token stream is divided into a fixed size token sequence using a sliding window aproach (size: 20, step size: 3).

Vocabulary Creation To represent a token value with a number, every token value needs a numeric representation. Therefore, the occurence of each token value is counted and the index in an descending ordered list for each token value represents the token as an integer. To ignore potential capitalization missmatches, all token values are lower-case. The overall size of the vocabulary is configurable. If the size is smaller than the size of the distinct token value set, the least common token values will be replaced by an unknown token. The unknown token has a numeric representation one bigger than

the vocabulary size. We found that using a vocabulary size of 100,000 results in an acceptable 3.9% unknown token frequency.

Index-Based Encoding The textual token values are encoded with an Index-Based encoding. The most common token values have a numerical representation based on their index in a vocabulary (created with all token values of the train data). Optional, the type of each token is encoded by its numerical representation in the standard library. The type and value encoding are then combined alternating in a final encoding vector that represents an input sample.

Label Extraction With the internal representation, the ground truth is encoded as a line number. A transformation is necessary to label each sample corresponding to a given problem type. Label 1 is assigned, if the sample contains the given problem type. A sample contains a problem type, if it contains all tokens from the problematic line. If the sample is missing a token of the problematic line at the beginning or end, the label is 0 for non-problematic code.

Train/Test Split

TODO train test split before, or is it better here?

Code Manipulation

In research question TODO, we evaluate the models generalisation to detect similar pattern the model was not trained on. Therefore, we manipulate the code that it is still a rule violation, but the original analysis plugins would not spot them. The pipeline for code manipulation differ from the pipeline for RQ2 by an additional code manipulation task and a removal of the training step (see figure)

Return None For the problem type RETURN NONE, we manipulate the code to have an inline if statement that only returns None in one branch. Therefore, a function may still return None, but the analysis plugin would not detect this. Listing 3.4 shows an example for this case. Although a modification of the analysis plugin could cover the variations as well, we want to see how well machine learning models could perform on this task.

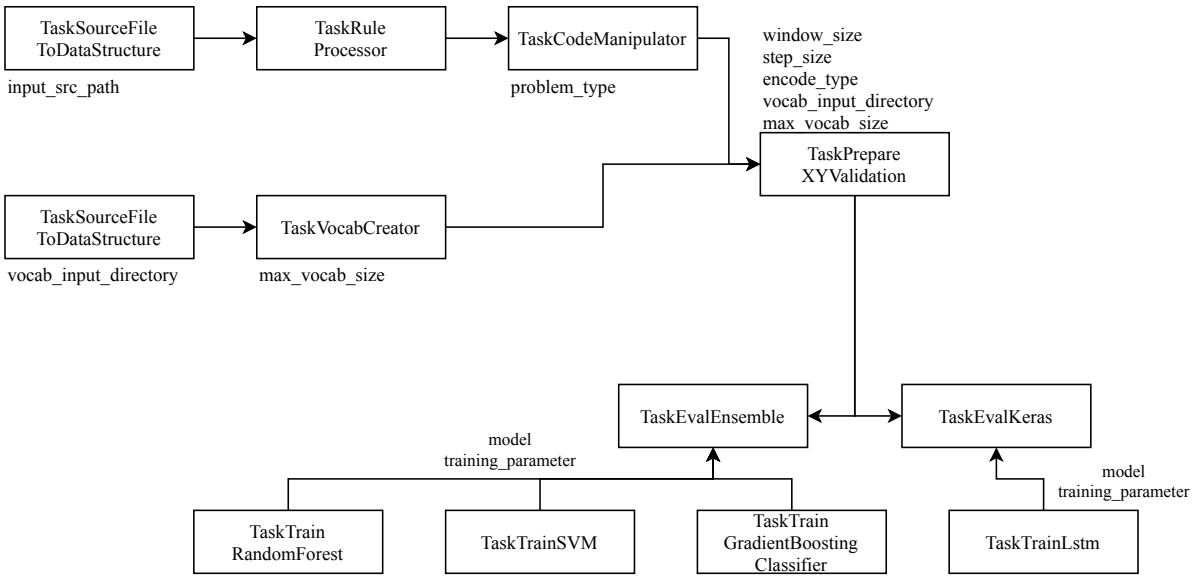


Figure 3.5: Pipeline for code manipulation and evaluation. TODO detailed description

To modify the original code, we use the preprocessed code with problems detected as in chapter 3.2.3. For every source code line containing the RETURN NONE problem, we use regular expressions to replace the *return None* with a variation as seen in 3.4.

The following data encoding step is similiar to the one for model training, although this modified samples will only be used during evaluation.

```
def f(a,b):
    #detected by the analysis plugin
    return None

    #not detected by the analysis plugin
    return None if a < b else b

    #not detected by the analysis plugin
    return a  if  a < b else None
```

Listing 3.4: Samples for returning None. The first return would be flagged by the analysis plugin, the second and third return are modified variations that would be ignored by the analysis plugin. The performance of the machine learning models on detecting the latter will be evaluated.

Condition Comparison The analysis for the CONDITION COMPARISON problem type is an advancement of the analysis of the CONDITION COMPARISON SIMPLE

problem type. See listing 3.5 for examples of the different analysis results. Since the results of CONDITION COMPARISON are the modification of the CONDITION COMPARISON SIMPLE, we use the first as ground truth for evaluating the generalisation. Since the CONDITION COMPARISON SIMPLE problems are a subset of the CONDITION COMPARISON problems, we use a similar approach as before (see 3.2.3) to transform all problem occurances to be undectable by the CONDITION COMPARISON SIMPLE analysis plugin.

```
def f(a,b):
#detected by CONDITION COMPARISON SIMPLE
#detected by CONDITION COMPARISON
if a < b:
    pass

#not detected by CONDITION COMPARISON SIMPLE
#detected by CONDITION COMPARISON
if not a < b:
    pass

#not detected by CONDITION COMPARISON SIMPLE
#detected by CONDITION COMPARISON
if isSmaller(a,b) or a < b:
    pass
```

Listing 3.5: Sample statements for the differnce between the two analysis plugins CONDITION COMPARISON and CONDITION COMPARISON SIMPLE.

3.2.4 Models

Classifying code samples is a binary classification problem since we consider each problem type as a seperate classification task. We train and evaluate a random forest classifier, a support-vector machine based classifier, a gradient boosting classifier and a neural network with LSTM cells.

Random Forest We use a random forest classifier with 100 decision trees to perform the binary classification. Additional to over- and undersampling, we experiment with an automatic class weighting inverse proportional to class frequency. The other hyperparamter follow the default implementation of the scikit-learn library: The quality measure of a split follows the gini function, the tree depth is unlimited and the number

of features to consider for each split is the square-root of the number of features overall.

Support Vector Machine We use the support vector classification from the scikit-learn library. As a kernel function, we choose the radial basis function for a performance baseline. Additionally, we try the class weighting inverse proportional to the class frequency to combat the inbalanced dataset.

Gradient Boosting Classifier For gradient boosting classifier, we mainly vary the number of boosting steps and the learning rate. Furthermore, we experiment with stochastic gradient boosting by setting the subsample parameter to 0.4 and 0.7. Other hyperparameter settings follow the default value of the scikit-learn library.

Neural Networks with LSTM Cells Our neural network consists of five layer (see listing 3.6). First, we use an embedding layer with an embedding size of 32. The input is the Index-Based encoded samples without type encoding. This layer is trained end-to-end with the complete network on the trainings-data. Furthermore, this layer covers most trainable parameters of the model. As a hidden layer, we use 10 LSTM cells with a prior and posterior dropout layer with a default 0.2 dropout. To perform binary classification, our model ends with a dense mapping onto a single neuron. The binary result is determined based on a 0.5 threshold for the output of the last neuron.

We vary the hyperparameters for batch size, number of epochs, embedding size and number of LSTM cells.

```
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, 20, 32)            3200064
_________________________________________________________________
dropout (Dropout)            (None, 20, 32)            0
_________________________________________________________________
lstm (LSTM)                  (None, 10)                1720
_________________________________________________________________
dropout_1 (Dropout)          (None, 10)                0
_________________________________________________________________
dense (Dense)                (None, 1)                 11
=================================================================
Total params: 3,201,795
Trainable params: 3,201,795
Non-trainable params: 0
```

Listing 3.6: Summary of our LSTM network. We use an embedding layer of size 32, 10 LSTM cells, a dropout layer before and after the LSTM layer with a defaut dropout ratio of 0.2 and a dense mapping to a single output neuron for binary classifcation with a threshold of 0.5.

4 Quantitative Evaluation

Research questions Description of the evaluation environment/setup Results/answers per research question Optional comparison to prior work Discussion and analysis of strengths/problems Note: see

4.1 Research Questions

RQ1 Can the Clean Code Analysis Platform be a useful addition to developers workflow besides existing tools?

RQ2 What models perform well on detecting non-clean code?

RQ3 Can the models detect modified non-clean code that can not be detected by the original rule checker?

4.1.1 RQ1: Can the Clean Code Analysis Platform be a useful addition to developers workflow besides existing tools?

Motivation Several tools are established that aim to improve code quality and detect unclean code. Every new tool with similar claims has to prove its usefulness beside the preexisting tools. We compare the CCAP with existing tools based on the design goals expandability, useability and integration. Additionally, we will mention and compare useful features unique to existing tools.

Approach To evaluate, if the CCAP is a useful addition, we compare different features to see, if it can supplement or replace existing tools. As described in section 2.6, the compared tools are Sonarcube, PMD Source Code Analyser Project, Codacy and PyLint.

Results Table TODO shows a summary of the features.

Finding 1: Expandability For expandability of analysis plugins, CCAP is comparable to PyLint, that also offer plugins to analyse the raw string, the token stream or the AST. PMD allows plugins to analyse the AST or define XPath rules. Since XPath rules can be used in the CCAP as well (using a third-party library in the plugin), PMD offers fewer expansion possibilities. Sonarqube, on the other hand, provides the most possibilities for extension. Not only can developers analyse the AST, specify XPath rules, but they have access to an additional semantic model of the code that provides direct access to structures such as methods, parameters, return values. This semantic model simplifies analysis in comparison to the AST analysis. Additionally, Sonarqube allows plugins to expose an API for other plugins to use. This different type of plugin further increases the possibilities for rule checking plugins. The least expandability offers Codacy, that allow customising or disabling existing rules, but does not offer to add rules to the existing ruleset.

Regarding output plugins, no compared tool offers the output customisation of CCAP. PMD and PyLint have different predefined output formats like JSON, HTML, CSV or text. Although PyLint allows customising the message format using a formatting string as a command-line argument, they do not offer extensions for the output. Sonarqube displays the analysis reports in its WebUI. The scanner tool, SonarScanner, sends the reports to the server component, that renders the results in the browser. Codacy's local scanner produces text output; the cloud version also has a WebUI.

Finding 2: Integration shortcomings The CCAP has significant shortcomings in its integrations into IDEs, build processes and CI pipelines. All contestant tools provide plugins for build systems like Gradle or Maven. Except for Codacy, all tools have IDE integrations into the most common editors. Sonarqube and Codacy have integrations into source control systems. Same applies to PMD and PyLint since they are included in Codacy and therefore have the same integrations.

Finding 3: Useability For a plugin developer, the useability of the plugin system is simple for CCAP and PyLint. Both tools have the same plugin mechanism and a simple plugin interface. PMD has a similar, straightforward plugin interface, but its Java plugin has to be bundled into a jar file before adding to the classpath. The latter applies to Sonarqube as well; additionally, the powerful and rich plugin API makes it harder to use.

For the user, installing CCAP is like installing every other python package. Running

from the command-line is fast and can be automated, e.g. using git pre-commit hooks. The same workflow would be achieved with PyLint. Sonarqube is more complex to install due to its multiple components, but after the setup, the WebUI and integrations into most developer workflow have the best useability. Codacy as a cloud service only requires permission to access the source code repository to start scanning the code.

Finding 4: Multi-Language scanning Sonarqube, PMD and Codacy offer multi-language scanning. This multi-language ability is advantageous for code repositories with multiple languages and for reusing the same tools and infrastructure for multiple projects with different programming languages. Supporting multi-language scanning is not possible with CCAP and would require a redefinition of the architecture. Although multi-language support was not a design goal, it would be a significant advantage for adoption.

Finding 5: Maturity and Community-Support The maturity and community-support of tools impact the integration of the tools into the developer workflow. Some integrations are community-made and shared, so everybody has an advantage. The community support would also be necessary for CCAP to write and share additional analysis plugins and to integrate into different workflows.

Summary In summary, CCAP offers a good, but not best in class expandability with analysis plugins. It has a high useability for plugin developer and users. The lack of integrations for different workflows reflects the lack of community support and maturity. We see the CCAP as an addition to the powerful Sonarqube. The simple, yet robust expandability of the CCAP could supplement the shortcomings of Sonarqube in its powerful, but complex expandability. For instance, a code reviewer could code problematic code into a simple python plugin, distributes it to the team and would hopefully not reencounter the same problem. Additionally, the CCAP could be used to teach about Clean Code and to enforce specific coding rules to students, since the local setup is straightforward. Clean Code rules could be turned into analysis plugins by students or teachers without having to understand a complicated interface.

4.1.2 RQ2: What models perform well on detecting non-clean code?

Motivation As we have shown with the CCAP and the analysis plugins, it is possible to write an algorithm that can detect certain code patterns like non-clean code patterns. If we are able to write a well-tested detection algorithm, we do not need error-prone machine learning models to detect code patterns. Nonetheless, if we can not design an algorithm that detects the desired code pattern reliably, we may perform better using a machine learning model. Additionally, if we encode a subjective pattern, it may not be possible to design an algorithm to objectively detect such a pattern. As a solution, we could label code parts as our pattern and use machine learning approaches to implicitly extract rules to detect such a pattern.

For this research question, we will evaluate different machine learning models on different code patterns and compare the results.

Approach For answering the research question, we will use the approach detailed in chapter 3.2. The dataset, consisting of 18 projects from GitHub, is prepared as described in chapter 3.2.2. The data is split into 90% train and 10% test data. We use the training dataset to train Random Forest, Gradient Boosting Classifier, Support Vector Machines and an LSTM-based neural network. Due to the class imbalance, we will additionally train with an oversampled dataset (oversampling rate of 0.5) and an undersampled dataset (undersampling rate of 0.5). Since our test set contains real-world code samples, we expect it to represent a real-world label distribution, and we, therefore, accept the potential effects of the data imbalance. Nevertheless, we will try to train with an over- and undersampled dataset to observe the effect on the performance.

Our evaluation metrics are recall, precision and the combined f1 score. Due to the data imbalance, accuracy is not a meaningful metric. A high recall means a high detection rate of non-clean code. The costs of a false negative prediction are potential costs in unclean code (maintainability, understandability). With high precision, a detected non-clean code sample is likely to be a non-clean code sample and the system reports less false positives. The immediate cost of false-positive predictions (resulting in a lower precision) is the extra developer time needed. Additionally, the cry wolf effect comes into play [4]. In our case, a developer who has seen a false alarm will take subsequent alarms less serious. Additionally, a study has shown that a higher false alarm rate in advisory warning system in cars results in a lower, subjective evaluation of the system [14]. A low subjective evaluation of developers would lead to a decrease in adoption rate, which

consequently leads to more unfixed problematic code. Since both recall and precision are important to the success of our models, we decided to use the equally weighted f1 score as a single-value evaluation metric. Additionally, to compensate for the cascading effect of a low precision due to the cry wolf effect, we require a precision of 0.8 as a satisficing metric. This means we accept all models that return two false positive and eight true positive samples. On the other hand, we define the recall as our optimising metric.

We evaluate all models for the three different problem types RETURN_NONE (RN), CONDITION_COMPARISON_SIMPLE (CCS) and CONDITION_COMPARISON (CC). We expect the CC type to be the most difficult to learn since it is the most complex rule. CCS and RN should be easier to learn due to less possible variations in the code structure.

Results We list all hyperparameter configurations and the corresponding training, test and holdout performance for all problem types in the appendix (Table A1-A4). We report the detailed analysis in a seperate finding for each model. Additionally, we describe our findings when comparing the models for the given classification task.

Finding 1: poor SVM performance SVM performed poorly. Based on the f1 score, the best configuration has an f1 of 0.0066, a recall of 0.0134 and a precision of 0.0044. In other words, only 1.34% of positive samples are recognised as positive. The model seems to fail to separate the two classes. A reason may be the class imbalance since only 0.21% of all samples are non-clean code (positive) with the RETURN_NONE type. In this configuration, we used undersampling with a ratio of 0.5, since oversampling was not feasible due to the increase in train time (see section 3.2.1). After undersampling, 1/3 of all samples are therefore positive and 2/3 are negative. Since the time to train is still too long, we only took half of the undersampled dataset.

We additionally used the SVM in a configuration with an automatic class weighting that is inverse-proportional to the class frequency. The recall score increases by 57-fold to 0.7660, whereas the precision decrease by half to 0.0026. We conclude that the SVM is very sensitive to class imbalance, which is an improper characteristic of our imbalanced classification problem. Additionally, a precision of 0.0026 is not useable for any application. We can not boost the precision with more data to help the model to distinguish true positives and false positives, since the train time will increase quadratically. We a baseline that low we do not expect much improvement with further investigation

and therefore conclude that there is no valid reason to further invest in the SVM model.

Finding 2: Random Forest Generally, the random forest classifier performs with an f1 score over 0.8 for all problem types with an oversampling ratio of 0.5, 100 trees, no additional class weighting and type encoding. For RN, this configuration has a 0.8379 f1, 0.7221 recall and 0.9978 precision on the test dataset. For CCS and CC, the f1 with 0.9329 and 0.929 are even better. The recall for those problem types increases to 0.8898 and 0.8888 while the precision remains high with 0.9803 and 0.9731, respectively. The random forest classifier therefore fulfils our satisficing condition of a precision score higher than 0.8.

Generally, we observe a performance increase by applying oversampling, especially for the RN problem type. From an f1 score of 0.7699 for 100 trees, no additional class balance and type encoding to 0.8379 with an oversampling ratio of 0.5. Since only 0.21% of RN train samples are positive, oversampling those to half of the number of majority samples will lead to a bigger increase in training samples than oversampling less imbalanced problem types such as CCS and CC. This explains the better performance of the latter problem types since the oversampled train dataset is larger than for RN. Furthermore, we observe a negligible difference of 0.02 in f1 score for oversampling to a ration of 1.0 (same amount of samples for both labels).

Another common pattern is a worse performance on undersampled train sets. We observe a significant drop in performance for the RN problem type if we use a 0.5 undersampling ratio. Similarly, the performance for CCS and CC drops, although the decrease is smaller. Furthermore, we observe a moderate performance drop with 0.1 undersampling. From this pattern and the aforementioned observations for oversampling, we infer that a random forest classifier can profit from more data, even if they contain duplicated samples for the minority class due to oversampling. This can also explain the larger drop for undersampling for the RN problem type since the non-clean code class contains fewer samples for RN than for CCS and CC (2,078 for RN with 0.5 undersampling, 263,136 for CCS and 481,980 for CC). With fewer samples, the undersampling process reduces the overall amount of samples by deleting samples from the majority class. With an undersampling ratio of 0.1, fewer examples are deleted and the effect is less impactful but still observable. This effect is also visible in the smaller difference in performance between the CCs and CC problem type with undersampling. For CCS, the random forest classifier performs slightly worse than for CC, since only 131,568 samples have a CCS problem type whereas 240,990 samples contain the CC problem type.

The impact of class weighting in comparison to equivalent configurations seems to be negligible. To evaluate the impact of class weighting, we compare the variation in this parameter with otherwise identical configurations. For an oversampling ratio of 0.5 with type encoding, we see 0.8379, 0.9329 and 0.929 in test f1 performance without class weighting and 0.8352(-0.0027), 0.9287(-0.0042) and 0.9267(-0.0023) in test f1 score performance. The difference is not significant. For undersampling with a ratio of 0.5 and type encoding, the f1 score changes from 0.2583, 0.806 and 0.8632 test f1 score without class weighting to 0.2709(+0.0126), 0.8111(+0.0051) and 0.8671(+0.0039) test f1 score with class weighting. Again, the difference is not significant. Without resampling and without type encoding, the f1 test performance decreases from 0.7814, 0.9057 and 0.9116 without class weighting to 0.7475(-0.0339), 0.8894(-0.0163) and 0.8913(-0.0203) with class weighting. Last, without resampling but with type encoding, the f1 test score decreases from 0.7699, 0.9208 and 0.9211 without class weighting to 0.7506(-0.0193), 0.9064(-0.0144) and 0.9071(-0.014) with class weighting. All changes due to class weighting are not significant, so class weighting does not have any positive influence on the performance of the random forest classifier.

Enabling type encoding improves our f1 performance for all configurations overall problem types except for the RN type without over- or undersampling. We already mentioned the extreme class imbalance for the RN problem type and therefore accept this type as an outlier to the general observation. The improvement in f1 scores is due to the improvement in recall of around 0.02 for all problem types excluding the aforementioned exception. This data implies that the additional type information is useful to more reliably determine our kinds of problematic code. We guess this boils down to the smaller variance in token types. For example, a string token is always threaded as the same token no matter the content. Since the content could change and may not be included in the dictionary, the variance in the type encoding is lower and therefore, easier to learn. TODO print feature importance!!!

Overall, it seems like a random forest classifier can handle class imbalance fairly well, as long as the distribution is not too unbalanced as for RN problem type. The performance deteriorates if the imbalance exceeds a critical threshold (for RN); otherwise, it has a minor impact. We base this conclusion on several observations: First, we see better performance for the CCS and CC problem type overall, both of which have a more balanced distribution than the RN problem type although. It is important to note that the different problem types also have different difficulty levels for the model. But we assume the RN type is easier to detect for a model since the model only has to learn

two subsequent tokens anywhere in the sequence. Therefore, we attribute this effect to the class distribution, but we remark that this may be tested in an additional, isolated experiment. Second, without over- or undersampling, we observe similar performance for CCS and CC, despite their different frequency in the train set (0.21% of samples contain the RN type, 2.66% CCS and 4.87% CC). And finally, we would expect a bigger impact of class balancing, if the random forest classifier would be sensitive to class imbalance. Additionally, encoding the token types results in a better performance than only encoding token values.

overfitting for random forest

Finding 3: Gradient Boosting Classifier The overall best performing gradient boosting works with 300 boosting steps and a learning rate of 0.2. For the RN problem type, it delivers an f1 score of 0.9196, a recall score of 0.8666 and a precision of 0.9796. Comparable performance is measured for the CC type: 0.9008 f1, 0.8673 recall and 0.937 precision. The performance decreases for the CCS type to 0.8419 f1, 0.7902 recall and 0.9009 precision for the same, best-performing configuration. A decrease in performance for the CCS problem type applies to all configuration in comparison to the CC type. Nevertheless, the gradient boosting classifier fulfils our satisficing criteria of a precision score higher than 0.8.

Over- and undersampling does not have a positive effect: The f1 score of the 200 stages, 0.2 learning rate and 1.0 subsampling drops by 0.3459 for a 0.5 oversampling ratio for the RN problem type. With an undersampling ratio of 0.5, the f1 score decreases by 0.3761 to 0.4545 on the test set. The performance deterioration for the CCS and CC type are lower but still significant: For CCS, the f1 score drops by 0.0782 to 0.6948 with oversampling and by 0.0494 to 0.6836 with undersampling. Using over- or undersampling as rebalancing strategies does not improve the performance of the classifier. The best classifier configuration performs better on the RN and CC problem type compared to the CCS problem type (0.9196 and 0.9008 vs 0.84119 f1 on test dataset). This allows two implications: Since the RN type is strongly underrepresented in the train set (class frequency of 0.21%) compared to the CCS class (2.26% class frequency), the gradient boosting classifier does not suffer from strong class imbalances. On the other hand, the CCS problem type seems harder to learn, contradictory to our assumptions about the difficulty levels of the different problem types.

Furthermore, we experimented with giving only a subsample of the train data to the individual base learners for fitting (subsampling ratio of 0.7 and 0.4). Since we see

the exact same performance metrics, this hyperparameter has no effect on the model's performance.

By contrast, increasing the number of boosting stages improves every precision metric for all problem types. From a f1 score of 0.6177, 0.5974 and 0.7314 for RN, CCS and CC at 100 boosting stages, we observe a improvement to 0.8306, 0.774 and 0.8567 at 200 boosting stages and 0.9196, 0.8419 and 0.9008 at 300 boosting stages. Additionally, the train performance for these configurations is similar to the test and holdout performance. Consequently, the classifier does not overfit on the train data and we could further increase the boosting stages to further improve the performance. Since additional boosting stages increase the train time of the model, we did not investigate further into this direction, but we expect by increasing the boosting stages and tuning the learn rate correspondingly, one could maximise the performance.

In conclusion, the gradient boosting classifier is robust to overfitting and rather improves its performance with more boosting steps. We can also observe robustness for class imbalance and we therefore do not profit from our over- and undersampling approach. Subsampling has no effect and we observe an unexpected high difficulty of learning the CCS type for this classifier.

TODO: write in approach what we vary - classify the problems into different difficulties

Finding 4: LSTM The best performing LSTM model is trained with a 32 embedding size, a 256 batch and training with two or three epochs. For the RN problem type, the test f1 score for a two epoch training is insignificantly higher (0.9894 instead of 0.987), whereas for CCS and CC the three epoch training yield a slightly better performance of 0.9808 (instead of 0.9782) and 0.9782 (instead of 0.9774). Since the performance difference is marginal, we see the three epoch training as the best configuration for our LSTM model. Apparently, the LSTM-based neural network fulfils our satisficing condition with a precision higher than 0.8.

Since we have a remarkably high performance, we do not vary all parameters. Instead, we use a 0.5 under- and oversampling as for other models, vary the batch size and number of epochs and try reducing the size of the embedding layer since this layer contains the majority of the trainable parameter (see listing 3.6).

Reducing the size of the embedding layer by half to 16, we do not observe a significant drop in performance compared to a bigger embedding size. With a drop of less than 0.01, using an embedding layer in the size of 32 is unnecessarily large. Even a size of 16 may be still too large and could be reduced further. Since we want to cover multiple

classifiers and the LSTM-based neural network performs well on a reasonable training time of less than one hour without a GPU, we do not investigate the too powerful LSTM further and reduce the number of trainable parameters in the model.

Using oversampling with a ratio of 0.5, we see a perfect recall score of 1.0 (rounded to the fourth decimal) and a near-perfect precision for all problem types. Since we duplicate the samples of the minority class up to the specified ratio, the model can overfit those samples more easily. Although the model overfits the train data, it still generalises well enough for comparable performance to the models trained on the original class distribution.

When we apply undersampling, we observe a drop in precision for all problem types, but a major drop in precision for the RN type (0.9952 to 0.8734). This behaviour is comparable to the performance drop of the random forest classifier with undersampling. We conclude, similar to the random forest classifier that the LSTM-based neural network reacts to less training data, especially for the RN problem type. The train set for the latter is significantly smaller than for the over problem types since its class frequency is only 0.21% and therefore more samples from the majority class have to be deleted. In combination with too many trainable weights of our too powerful model, the model can not adjust its weights correctly. Since we reduce the variety of negative samples, it becomes harder to spot these. Consequently, the false positive rate increases and therefore, the precision decreases. The recall remains high since the model has enough samples to correctly label positive samples and the false negatives do not increase.

To sum up, we achieve near-perfect performance with our neural network model. We acknowledge, that our model is too big with too many trainable parameters we do not need for the same performance as shown with the reduction of the embedding layer size. The model does not benefit from oversampling and undersampling impairs the training of the model's weight since it reduces the overall number of samples.

Summary Table 4.1 shows the performance score of the best performing model of each classifier for all problem types. The SVM performs poorly and does not meet our mandatory satisficing condition of precision higher than 0.8. Therefore, we will not evaluate it further. On the other hand, the LSTM-based neural network model outperforms all other models and we expect it to perform well in the next research question recognising modifications of the code.

Both random forest and gradient boosting classifier fulfil the satisficing condition for all problem types. Interestingly, they supplement each other: For the RN problem type,

		RETURN_NONE	COND_COMP_SIMP	COND_COMP
Random Forest				
	F1	0.8486	0.9352	0.9351
	Recall	0.7404	0.8936	0.8976
	Precision	0.9939	0.9809	0.9759
SVM				
	F1			
	Recall			
	Precision			
Gradient Boosting Classifier				
	F1	0.9328	0.8489	0.9088
	Recall	0.9005	0.7953	0.8766
	Precision	0.9675	0.9102	0.9434
LSTM				
	F1	0.9933	0.9805	0.9783
	Recall	0.9933	0.9779	0.9868
	Precision	0.9933	0.9831	0.97

Table 4.1: Best performing classifier for RQ2 based on f1 score of the holdout set.

the gradient boosting classifier performs better with an f1 score of 0.9328, whereas the random forest classifier surpasses the gradient boosting classifier for the CCS and CC problem type with 0.9352 and 0.9351 f1. As discussed, we explain the former result with the better insensitivity to a class imbalance of the gradient boosting classifier, whereas the latter seems to be harder to learn for the gradient boosting classifier. Especially the seemingly difficulties for the CCS type are unexpected.

Note: in a real setup with hand-labelled examples, we expect more variety in the samples so the classifier may even perform better on the next research question

4.1.3 RQ3: Can the models detect modified non-clean code that can not be detected by the original rule checker?

See tables in attachment.

Motivation For the previous research question, we trained models on a dataset. We created the dataset by downloading open-source repositories and applying our analysis plugins from 3.1.1 to label samples as clean or non-clean code. With this automatic approach, it is simle to generate a dataset und to scale the dataset to any size needed

for training. These algorithm that detect non-clean code are the prerequesite for the dataset and a successfull training of machine learning models. This research question wants to put the machine learning approach into a szenario, in which the prerequesite is not met and there no dataset can be generated. This szenario applies to clean code guidelines that can not be checked by an algorithm that analyse the source code or any other representation in a deterministic way. Alternativeley, a deterministic algorithm may only detect a subset of clean-code vilations. Both szenarios boil down to not having samples for all or many structural variations of the rule violation. Therefore, we evaluate, how our previously trained models perform on slightly modified code that still violates the same clean code rule but could not be detected by the original analysis plugins.

Approach To answer this research question, we use all models for all three problem types from the previous research question: For the RN problem type, we manipulate the holdout dataset as described 3.2.3. The code still contain a logical *return None*, although it is not explicitly written as two consecutive code tokens. This should explore, how well the different classifier extracted the structural information and can detect this noisy data.

With the CCS models, we simulate the scenario of having trained on a subset of all variations and testing on the full set of problem variations. We do so by manipulating all rules found by the algorithm for the CC problem type to only contain samples that are not part of the CCS subset. The CCS algorithm could therefore not detect a clean code violation.

Last, we evaluate the models trained on the CC type with our manipulated code to provide a baseline for the CCS trained models. We expect the best performing CC model from the previous experiments should outperform all CCS models and should show similar performance like in the previous research question. We then investigate the the difference between the baseline and the model trained on CCS.

Results For the results, we evaluate the results of the three models: Random Forest Classifier, Gradient Boosting Classifier and LSTM-based neural network. Per model, we analyse the performance for the RN manipulation, the CCS manipulation, teh comparison baseline and compare the results with the results from the previous research question.

Finding 1: Random Forest Classifier The random forest classifier trained on the RN problem type achieves less than 0.06 f1 score. The classifier can not handle this

kind of manipulation.

The best CCS models achieves 0.7158 f1 with 0.758 recall and 0.678 precision. The basline model trained on the CC data reaches a 0.8186 f1 performance with a 0.9782 recall and 0.7038 precision. Compared to the baseline model, the CCS model has a 0.1 lower f1 score. The CCS model is trained with a 0.5 undersampling rate, 100 trees in the forest, class weighting and type encoding. The general better performance of models trained with undersampling is contradictory to the evaluation of the model in the previous experiment, in which oversampling performed better than undersampling. This reflects the baseline performance, for which the models with oversampled training and type encoding perform better than the undersampled counterparts.

The precision of models trained on undersampled datasets is lower than on the models trained on oversampled or not resampled training data. On the other hand, the recal drops to zero (for oversampled or not resampled training data), which means the false negative rate increases. The model classifies most samples as negative and only a few as positive (TODO get numbers). With undersampled training, the model does not seem to be biased towards the negative classification as found with non-resampled or oversampled training data. Since the undersampling of the majority class (negative class, meaning clean code) reduces the number of unique negative samples in the training corpus, this decrease in bias seems reasonable. On the other hand, it is important to note that we test the model on the manipulated CC dataset that contains 5.1% positive samples in comparison to the 2.51% positive samples in the CCS train set without resampling. This may also influence the bias towards the negative samples.

Finding 2: Gradient Boosting Classifier For the manipulated RN type, a gradient boosting classifier with a 0.5 oversampling ratio achieves a 0.24 f1 score with 0.7676 recall and 0.1422 precision. The second best configuration is the equal configuration with a 0.5 undersampling ratio with similar performance scores. The same configuration trained on non-resampeld training data has a near zero f1 and recall performance and a higher 0.349 precision. Decreasing the number of boosting stages with 0.5 over- or undersampling decreases the precision significantly while increasing the recall. With over- or undersampling, the model seems be biased towards classifying samples positive, indicated by the low precision. Without resampling, the classifier is biased towards the negative class and will wrongly assume positives to be negatives. Since the class distribution is compareable to the class distribution of the training dataset, the classifier is biased towards the negative class.

This behaviour is contrary to the overservation during the train and testing for the previous research question: We received a significant better performance without resampling the training data and we concluded, that the gradient boosting classifier is not so sensitive towards class imbalance. The results for the CCS trained model draw a similiar picture: With an oversampling rate of 0.5, the configuration achieves the best f1 score of 0.83 with 0.978 recall and 0.7209 precision. We observe rather similiar performance with an f1 score of 0.8291, a recall of 0.9773 and a precision of 0.7199. The performance of non-resampled configuration drops below 0.53 f1 score. Especially the best performing classifier for the direct classification now has the lowest performance for this task. To sum up, the bad performing model configurations for direct classification perform better in this classification task. Since this applies to both problem types, we interprete these results as follows: With better fitting of the original classification problem, the gradient boosting classifier learnt to detect the sequence of subsequent token types as seen in the RN and CCS training data. After code manipulation, the structure of the code and therefore the sequence of the tokens is changed. The better the model trained to detect the subsequent tokens with more boosting stages or more unique data, the better the performance for the previous experiment. Consequently, the model did not learn the general structure like a direct comparison following within the next few tokens of the "if" keyword, but it overlearnt the subsequent structure of the tokens. On the other side, this is another indicator the model did not train on the surrounding context but instead on the tokens of the problem.

Finding 3: LSTM-based Neural Network For the manipulated RN type, only the model configuration with a 0.5 undersampling, 3 epochs and 256 batch size is able to have a performance better than zero. With an f1 of 0.3895, a recall of 0.847 and a precision of 0.2529, the performance is too low to be any usefull. With the higher recall and lower precision, the models false positive rate is higher.

The same model configuration performs best for the manipulated CC problem type: With a f1 score of 0.6868, a recall of 0.5009 and a precision of 0.9534, the model has a higher false negative rate whereas the positive classification is correct for the most time. There is a major gap to the baseline performance of 0.9502 f1. The second best performance reaches a configuration without resampling but with an embedding size of only 16. The best performing model configurations from the previous experiment score worst in this experiment.

Finding 4: Manipulated RETURN_NONE Classification All models perform unexpected bad on detecting the manipulated RN type. The best random forest configuration for this experiment achieves a 0.0539 f1 score with 0.3022 recall and 0.0296 precision. The gradient boosting classifier improved the f1 score to 0.24, the recall to 0.7676 and the precision to 0.1422. Another increase in performance is scored by the best performing LSTM-based neural network with a f1 score of 0.3895, a recall of 0.847 and a precision of 0.2529.

All models have in common, that the best configuration for this experiment performs far worse than the best configuration for the previous experiment. Additionally, we observe a low precision for all models on the manipulated RN type, meaning a lot of false positive classifications. Wee see the following as possible reasons for this performance characteristics: The problem type appears in the training set only in one variation: A 'return' keyword is followed by a subsequent 'None' value. Only the subsequent occurance of these two tokens needs to be learnt to perform well on the evaluation from the previous experiment. To perform well on this experiment, the model should have learned a more sophisticated approach of a 'None' value after the 'return' keyword before the end of the line. Since this was not part of the training data, it is obvious the model learnt the simple subsequent detection of this pattern, since it yields the best performance.

Finding 5: The Better the Model Performed on RQ2, the Worse in RQ3 Another common observtion accross all models and problem types: Models with lower performance on the previous experiment performed better than the models with good performance on the previous research question. This effect is obvious with the better performane of the models trained on undersampled data, that performed worst on the previous experiment. For gradient boosting classifier, the models without resampling scored best in the previous experiment and are performing worst in this experiment. Additionally, increases in boosting stages that lead to an improvement in previous experiment now lead to a deteriation in performance. Same applies to the LSTM-based neural network results: The undersampling had a negative impact on performance whereas in this experiment, a 0.5 undersampling achieves the only f1 score over zero for the RN type and the best for the manipulated CC type. All of these observations combined lead to the conclusion, that the models did not learn the rule in a broader way, but instead only learnt to detect this specific sequence of tokens as described in 4.1.3 for the RN type. The same argument applies to the manipulated CCS samples.

Improvements As identified in the findings (4.1.3 and 4.1.3), we see the root cause for the bad performance in this research questions in the learning of the specific code pattern and not the generel structure of a problem type. For the RN type, the general structure would be something like a 'None' value somewhere after a 'return' but before before a line break. A slightly more advanced structure could be extracted from the CCS type: A comparison inside a condition (starting with an 'if' statement and closing with the colon) should be marked. With the choosen approach, the model did not train on the general problem structure of the clean code violation but on explicit code patterns. The fitting on explicit code patterns can be broken down into two parts: First, we did not provide the model with the full variety of problem pattern. In the motivation for this research question, we state that it may not be possible to collect many samples with the full variety of problem patterns for an adequate training corpus. A possible approach would be to generate a dataset similar to ours. Therefore, we need an algorithm that can detect a subset of the code pattern (like in our approach with the CCS type) or a similar enough code pattern (like we tried with the RN type). On top of that, we gather hand-labeled samples for more variety. With the hand-labeled samples we fine-tune the model to increase the variety of code patterns the model can generalize on. By combining a scaleable, automatic generated dataset with hand-labeled sampels, we may be able to improve the models performance on the samples that we could not label automatically.

The second cause for the explicit fitting of our models may be our approach in encoding. We use an indexed-based encoding of the source codes token stream. With this approach, we do not exploit code structure in our encoding. Other machine learning tasks on code profit from other encoding types that exploit more strcutre from the code: TODO list some that exploit more structure of the code. Since we identified the lack of learning the problem structure from the samples, the encoding approaches that explicitly take advantage of the structurness of code may improve the this experiment. It may be even possible to train the model on a subset of possible problem variations like we tried with the manipulated CCS type. Additionally, this may be combined with the finetuning on hand-labeled samples to increase the performance to a practical level. The satisficing condition of a precision higher than 0.8 we defined in the previous experiment would also apply to this experiment. A lower precision would lead to the cry wolf effect and the pracitcal use would therefore be small. The use of a different encoding schema, models and fine tuning can also be adapted to one specific problem type. Depending on the number of training samples, the availability of an algorithm to detect a subsample

of the problematic patterns and the structure of the problematic pattern can result in a specific approach that is not universal to other problem types.

Summary

5 Conclusion

An overall short summary of results What was successful, what not (and hypotheses why) Hints for further future work/extension

Bibliography

[1] Go at Google: Language Design in the Service of Software Engineering.

[2] Null Safety - Kotlin Programming Language.

[3] Robert Baggen, José Pedro Correia, Katrin Schill, and Joost Visser. Standardized code quality benchmarking for improving software maintainability. 20(2):287–307.

[4] Shlomo Breznitz. *Cry Wolf: The Psychology of False Alarms*. Lawrence Erlbaum Associates.

[5] G Ann Campbell. Cognitive Complexity-A new way of measuring understandability.

[6] D. Coleman, D. Ash, B. Lowther, and P. Oman. Using metrics to evaluate software system maintainability. 27(8):44–49.

[7] Aurelien Delaitre, Bertrand Stivalet, Elizabeth Fong, and Vadim Okun. Evaluating Bug Finders – Test and Measurement of Static Code Analyzers. In *2015 IEEE/ACM 1st International Workshop on Complex Faults and Failures in Large Software Systems (COUFLESS)*, pages 14–20. IEEE.

[8] Andrew Gerrand. Error handling and Go.

[9] Maurice Howard Halstead et al. *Elements of Software Science*, volume 7. Elsevier New York.

[10] Tony Hoare. Null References: The Billion Dollar Mistake.

[11] ISO/TC 22/SC 32. ISO 26262:2018 Road vehicles — Functional safety.

[12] Robert C Martin. *Clean Code: A Handbook of Agile Software Craftsmanship*. Pearson Education.

[13] T.J. McCabe. A Complexity Measure. SE-2(4):308–320.

[14] Frederik Naujoks, Andrea Kiesel, and Alexandra Neukum. Cooperative warning systems: The impact of false and unnecessary alarms on drivers' compliance. 97:162–175.

[15] Herbert Prahofer, Florian Angerer, Rudolf Ramler, and Friedrich Grillenberger. Static Code Analysis of IEC 61131-3 Programs: Comprehensive Tool Support and Experiences from Large-Scale Industrial Application. 13(1):37–47.

[16] Veselin Raychev, Pavol Bielik, and Martin Vechev. Probabilistic model for code with decision trees. 51(10):731–747.

[17] Mehwish Riaz, Emilia Mendes, and Ewan Tempero. A systematic review of software maintainability prediction and metrics. In *2009 3rd International Symposium on Empirical Software Engineering and Measurement*, pages 367–377. IEEE.

[18] Dag I K Sjøberg, Dag Sjoberg, Bente Anda, and Audris Mockus. Questioning Software Maintenance Metrics: A Comparative Case Study. page 4.

[19] Dave Wichers and Eitan Worcel. Source Code Analysis Tools | OWASP.

Parameter						RN			CCS			CC		
over-samp.	under-samp.	#trees	class weight	encode type		Train	Test	Holdout	Train	Test	Holdout	Train	Test	Holdout
0.5	-	100.0	None	True										
					F1	1.0	0.8379	0.8486	1.0	0.9329	0.9352	1.0	0.929	0.9351
					Rec	1.0	0.7221	0.7404	1.0	0.8898	0.8936	1.0	0.8888	0.8976
					Prec	1.0	0.9978	0.9939	1.0	0.9803	0.9809	1.0	0.9731	0.9759
1.0	-	100.0	None	True										
					F1	1.0	0.8358	0.8367	1.0	0.9287	0.9322	1.0	0.9273	0.9324
					Rec	1.0	0.719	0.7225	1.0	0.8824	0.8876	1.0	0.8853	0.8925
					Prec	1.0	0.9978	0.9937	1.0	0.9801	0.9815	1.0	0.9736	0.9761
0.5	-	100.0	balanced	True										
					F1	1.0	0.8352	0.8385	1.0	0.9287	0.9321	1.0	0.9267	0.9329
					Rec	1.0	0.7182	0.7249	1.0	0.8826	0.8882	1.0	0.885	0.893
					Prec	1.0	0.9978	0.9942	1.0	0.9799	0.9806	1.0	0.9727	0.9765
0.5	-	100.0	None	False										
					F1	1.0	0.8287	0.8519	1.0	0.9191	0.9217	1.0	0.921	0.9248
					Rec	1.0	0.708	0.7453	1.0	0.869	0.8723	1.0	0.8736	0.8785
					Prec	1.0	0.9989	0.9939	1.0	0.9752	0.977	1.0	0.9739	0.9764
1.0	-	100.0	None	False										
					F1	1.0	0.8162	0.8268	1.0	0.9189	0.9186	1.0	0.9161	0.9214
					Rec	1.0	0.69	0.7084	1.0	0.8692	0.8674	1.0	0.8656	0.872
					Prec	1.0	0.9989	0.9926	1.0	0.9747	0.9763	1.0	0.9729	0.9767
-	-	100.0	None	False										
					F1	0.9999	0.7814	0.7987	0.9998	0.9057	0.9106	0.9998	0.9116	0.9173
					Rec	0.9998	0.6413	0.6658	0.9999	0.8406	0.8489	0.9998	0.8495	0.8571
					Prec	1.0	1.0	0.9979	0.9998	0.9818	0.982	0.9998	0.9835	0.9866
-	-	100.0	None	True										
					F1	0.9999	0.7699	0.7666	0.9998	0.9208	0.9243	0.9998	0.9211	0.9269
					Rec	0.9998	0.6264	0.6226	0.9999	0.8637	0.8694	0.9998	0.8675	0.8759
					Prec	1.0	0.9987	0.9972	0.9998	0.9859	0.9865	0.9998	0.9817	0.9841
-	-	100.0	balanced	True										
					F1	0.9999	0.7506	0.7503	0.9998	0.9064	0.9087	0.9998	0.9071	0.9121
					Rec	1.0	0.6013	0.6018	1.0	0.8385	0.8404	1.0	0.8414	0.8484
					Prec	0.9997	0.9987	0.9959	0.9996	0.9863	0.9891	0.9997	0.9839	0.9863
-	-	100.0	balanced	False										
					F1	0.9999	0.7475	0.7405	0.9998	0.8894	0.8924	0.9998	0.8913	0.898
					Rec	1.0	0.5973	0.5888	1.0	0.8112	0.8149	1.0	0.8136	0.8227
					Prec	0.9997	0.9987	0.9976	0.9996	0.9843	0.9863	0.9997	0.9853	0.9885
-	0.1	100.0	None	True										
					F1	1.0	0.6857	0.654	0.9999	0.9268	0.928	0.9999	0.929	0.9345
					Rec	1.0	0.9027	0.9275	1.0	0.92	0.9243	0.9999	0.8981	0.9064
					Prec	1.0	0.5529	0.5051	0.9999	0.9336	0.9317	0.9999	0.9621	0.9644
-	0.5	100.0	None	False										
					F1	1.0	0.3469	0.3024	1.0	0.8087	0.8157	1.0	0.8581	0.8624
					Rec	1.0	0.9364	0.9712	1.0	0.966	0.9684	1.0	0.9551	0.9566
					Prec	1.0	0.2128	0.1791	1.0	0.6954	0.7046	1.0	0.779	0.785
-	0.5	100.0	balanced	True										
					F1	1.0	0.2709	0.2357	1.0	0.8111	0.8181	1.0	0.8671	0.871
					Rec	1.0	0.9513	0.9775	1.0	0.967	0.9672	1.0	0.9537	0.9562
					Prec	1.0	0.158	0.134	1.0	0.6985	0.7088	0.9999	0.795	0.7998
-	0.5	100.0	None	True										
					F1	1.0	0.2583	0.2227	1.0	0.806	0.8151	1.0	0.8632	0.8693
					Rec	1.0	0.9568	0.9782	1.0	0.9692	0.9709	1.0	0.9562	0.9602
					Prec	1.0	0.1493	0.1257	1.0	0.6899	0.7024	1.0	0.7867	0.7941

Table A1: random forest

Parameter							RN			CCS			CC		
over-samp.	under-samp.	stages	learn-rate	sub-sample	encode type		Train	Test	Holdout	Train	Test	Holdout	Train	Test	Holdout
-	-	300	0.2	1.0	True	*F1*	0.9364	0.9196	0.9328	0.8477	0.8419	0.8489	0.9087	0.9008	0.9088
						Rec	0.9015	0.8666	0.9005	0.7926	0.7902	0.7953	0.8767	0.8673	0.8766
						Prec	0.9742	0.9796	0.9675	0.9111	0.9009	0.9102	0.9431	0.937	0.9434
-	-	200	0.2	1.0	True	*F1*	0.8554	0.8306	0.8499	0.7801	0.773	0.7837	0.8644	0.8567	0.8667
						Rec	0.7695	0.7276	0.765	0.6934	0.6886	0.6992	0.8057	0.7951	0.8081
						Prec	0.9629	0.9676	0.956	0.8916	0.881	0.8915	0.9324	0.9286	0.9344
-	-	200	0.2	0.4	True	*F1*	0.8554	0.8306	0.8499	0.7801	0.773	0.7837	0.8644	0.8567	0.8667
						Rec	0.7695	0.7276	0.765	0.6934	0.6886	0.6992	0.8057	0.7951	0.8081
						Prec	0.9629	0.9676	0.956	0.8916	0.881	0.8915	0.9324	0.9286	0.9344
-	-	200	0.2	0.7	True	*F1*	0.8554	0.8306	0.8499	0.7801	0.773	0.7837	0.8644	0.8567	0.8667
						Rec	0.7695	0.7276	0.765	0.6934	0.6886	0.6992	0.8057	0.7951	0.8081
						Prec	0.9629	0.9676	0.956	0.8916	0.881	0.8915	0.9324	0.9286	0.9344
-	-	100	0.2	1.0	True	*F1*	0.6438	0.6177	0.6441	0.6055	0.5974	0.6021	0.7417	0.7314	0.7437
						Rec	0.4908	0.4584	0.4896	0.4757	0.4699	0.472	0.6241	0.6114	0.6252
						Prec	0.9354	0.9465	0.9412	0.8329	0.8198	0.8314	0.9138	0.9099	0.9175
0.5	-	200	0.2	1.0	True	*F1*	0.9936	0.4847	0.4165	0.9704	0.6948	0.7007	0.9624	0.7933	0.791
						Rec	0.9984	0.9882	0.9989	0.9843	0.9826	0.9842	0.9723	0.9693	0.9711
						Prec	0.9889	0.3211	0.2631	0.9568	0.5374	0.544	0.9528	0.6714	0.6672
-	0.5	200	0.2	1.0	True	*F1*	0.9944	0.4545	0.3817	0.9684	0.6836	0.6917	0.9632	0.7925	0.7905
						Rec	0.9977	0.9874	0.9986	0.9816	0.9793	0.9817	0.9733	0.9714	0.972
						Prec	0.9912	0.2952	0.2359	0.9556	0.525	0.534	0.9533	0.6693	0.6661
0.5	-	100	0.2	1.0	True	*F1*	0.9831	0.2906	0.244	0.945	0.5727	0.5866	0.9363	0.7233	0.7266
						Rec	0.9914	0.9765	0.9954	0.9602	0.9588	0.962	0.938	0.9338	0.9383
						Prec	0.975	0.1707	0.1391	0.9302	0.4083	0.422	0.9347	0.5902	0.5928
-	0.5	100	0.2	1.0	True	*F1*	0.9843	0.2767	0.2278	0.943	0.5641	0.579	0.9381	0.7234	0.727
						Rec	0.9935	0.9827	0.9958	0.957	0.9525	0.9588	0.9416	0.9373	0.9409
						Prec	0.9751	0.161	0.1286	0.9294	0.4007	0.4147	0.9346	0.589	0.5924
0.5	-	100	0.1	1.0	True	*F1*	0.9662	0.2047	0.1716	0.9111	0.4684	0.4863	0.8831	0.6059	0.613
						Rec	0.9714	0.9529	0.9775	0.9217	0.9186	0.9242	0.868	0.8636	0.869
						Prec	0.9611	0.1146	0.0941	0.9007	0.3143	0.33	0.8988	0.4667	0.4735
-	0.5	100	0.1	1.0	True	*F1*	0.9662	0.1901	0.1586	0.9115	0.478	0.4944	0.8853	0.6127	0.6216
						Rec	0.9737	0.9584	0.9814	0.9194	0.9151	0.9215	0.8694	0.8636	0.872
						Prec	0.9587	0.1055	0.0863	0.9038	0.3235	0.3379	0.9019	0.4747	0.4829

Table A2: gradient boosting classifier

Parameter								RN			CCS			CC		
over-samp.	under-samp.	emb-size	epochs	batch-size	#lstm-cells	dropout		Train	Test	Holdout	Train	Test	Holdout	Train	Test	Holdout
-	-	32	2	256	10.0	0.2|0.2	*F1*	0.9936	0.9894	0.9933	0.9905	0.9782	0.981	0.9876	0.9774	0.9778
							Rec	0.9912	0.9851	0.9933	0.9952	0.9864	0.9865	0.9941	0.9857	0.9852
							Prec	0.996	0.9937	0.9933	0.9858	0.97	0.9755	0.9812	0.9692	0.9706
-	-	16	2	256	10.0	0.2|0.2	*F1*	0.9925	0.989	0.9933	0.9864	0.9783	0.9791	0.9841	0.9724	0.9734
							Rec	0.9891	0.9843	0.9933	0.9959	0.9906	0.9886	0.9763	0.9594	0.9599
							Prec	0.9958	0.9937	0.9933	0.9771	0.9664	0.9698	0.992	0.9858	0.9872
-	-	32	3	64	10.0	0.2|0.2	*F1*	0.9919	0.9881	0.991	0.9897	0.9806	0.9808	0.9877	0.9783	0.9781
							Rec	0.985	0.9804	0.987	0.9964	0.9903	0.9889	0.9919	0.9837	0.9834
							Prec	0.9988	0.996	0.995	0.9831	0.9712	0.9728	0.9835	0.9728	0.9728
-	-	32	2	512	10.0	0.2|0.2	*F1*	0.9933	0.9878	0.9916	0.9905	0.9806	0.9797	0.9868	0.976	0.977
							Rec	0.9916	0.9835	0.9919	0.9939	0.9842	0.9818	0.996	0.9894	0.99
							Prec	0.9951	0.9921	0.9912	0.9872	0.977	0.9776	0.9777	0.963	0.9644
-	-	32	3	512	10.0	0.2|0.2	*F1*	0.9935	0.9873	0.9915	0.992	0.9813	0.9809	0.9886	0.9769	0.9774
							Rec	0.9889	0.9796	0.9887	0.9972	0.9886	0.988	0.9967	0.9887	0.9885
							Prec	0.9982	0.9952	0.9943	0.9869	0.9742	0.974	0.9807	0.9655	0.9665
-	-	32	3	256	10.0	0.2|0.2	*F1*	0.9945	0.987	0.9914	0.9928	0.9808	0.9805	0.9906	0.9782	0.9783
							Rec	0.9936	0.9859	0.9947	0.992	0.9795	0.9779	0.9956	0.9868	0.9868
							Prec	0.9953	0.9882	0.9881	0.9936	0.982	0.9831	0.9857	0.9698	0.97
0.5	-	32	3	256	10.0	0.2|0.2	*F1*	1.0	0.9859	0.9864	0.9995	0.9781	0.9795	0.9986	0.9745	0.9746
							Rec	1.0	0.989	0.9951	1.0	0.9814	0.9826	0.9999	0.9853	0.9865
							Prec	0.9999	0.9828	0.9779	0.9991	0.9747	0.9764	0.9973	0.964	0.9631
0.5	-	32	3	256	100.0	0.2|0.2	*F1*	1.0	0.9858	0.9905	0.9997	0.9785	0.9777	0.9993	0.9761	0.9756
							Rec	1.0	0.9796	0.9905	1.0	0.9755	0.9732	1.0	0.9756	0.9766
							Prec	1.0	0.9921	0.9905	0.9995	0.9816	0.9823	0.9986	0.9765	0.9747
-	-	16	3	256	10.0	0.2|0.2	*F1*	0.9899	0.9844	0.9838	0.9908	0.9797	0.9812	0.9876	0.9759	0.976
							Rec	0.998	0.9906	0.9961	0.9923	0.9807	0.9808	0.9879	0.9751	0.975
							Prec	0.982	0.9783	0.9719	0.9893	0.9787	0.9815	0.9874	0.9767	0.9771
-	0.5	32	3	256	100.0	0.2|0.2	*F1*	0.9994	0.8594	0.818	0.9986	0.9555	0.9548	0.998	0.9707	0.9722
							Rec	1.0	1.0	1.0	0.9998	0.9985	0.9981	0.9994	0.9961	0.9965
							Prec	0.9988	0.7534	0.6921	0.9974	0.916	0.9152	0.9966	0.9465	0.9491
-	0.5	32	3	256	10.0	0.2|0.2	*F1*	0.9978	0.6294	0.5796	0.9985	0.9564	0.957	0.9974	0.9561	0.9588
							Rec	1.0	1.0	1.0	0.999	0.9958	0.9965	0.9992	0.9963	0.9957
							Prec	0.9956	0.4593	0.4081	0.9979	0.9201	0.9206	0.9955	0.919	0.9245

Table A3: lstm

Parameter							RN			CCS			CC		
over-samp.	under-samp.	kernel	sub-sample	class weight	encode type		Train	Test	Holdout	Train	Test	Holdout	Train	Test	Holdout
-	0.5	rbf	0.5	None	True	*F1*	0.0364	0.0066	nan	nan	nan	nan	nan	nan	nan
						Rec	0.0187	0.0134	nan	nan	nan	nan	nan	nan	nan
						Prec	0.6552	0.0044	nan	nan	nan	nan	nan	nan	nan
-	0.5	rbf	0.5	balanced	True	*F1*	0.5257	0.0052	nan	nan	nan	nan	nan	nan	nan
						Rec	0.8069	0.766	nan	nan	nan	nan	nan	nan	nan
						Prec	0.3898	0.0026	nan	nan	nan	nan	nan	nan	nan
-	0.3	rbf	0.5	balanced	True	*F1*	0.4141	0.0052	nan	nan	nan	nan	nan	nan	nan
						Rec	0.8353	0.7877	nan	nan	nan	nan	nan	nan	nan
						Prec	0.2753	0.0026	nan	nan	nan	nan	nan	nan	nan
-	0.1	rbf	0.5	None	True	*F1*	0.0	0.0	nan	nan	nan	nan	nan	nan	nan
						Rec	0.0	0.0	nan	nan	nan	nan	nan	nan	nan
						Prec	0.0	0.0	nan	nan	nan	nan	nan	nan	nan
-	0.5	rbf	0.3	balanced	True	*F1*	nan	nan	nan	0.4476	0.0622	nan	0.4685	0.1115	nan
						Rec	nan	nan	nan	0.5129	0.5004	nan	0.5647	0.5535	nan
						Prec	nan	nan	nan	0.3971	0.0332	nan	0.4004	0.062	nan
-	0.3	rbf	0.3	balanced	True	*F1*	nan	nan	nan	0.3676	0.0629	nan	0.3807	0.1124	nan
						Rec	nan	nan	nan	0.5151	0.501	nan	0.5622	0.5497	nan
						Prec	nan	nan	nan	0.2857	0.0336	nan	0.2878	0.0626	nan
-	0.5	rbf	0.3	None	True	*F1*	nan	nan	nan	0.0318	0.0208	nan	0.0267	0.0189	nan
						Rec	nan	nan	nan	0.0164	0.0134	nan	0.0137	0.0106	nan
						Prec	nan	nan	nan	0.5553	0.0461	nan	0.5741	0.0829	nan
-	0.1	rbf	0.3	None	True	*F1*	nan	nan	nan	0.0	0.0	nan	nan	nan	nan
						Rec	nan	nan	nan	0.0	0.0	nan	nan	nan	nan
						Prec	nan	nan	nan	1.0	0.0	nan	nan	nan	nan

Table A4: svm. NaN value for configuration that we did not test due to time constrains.

Parameter						RN	CC	Base CC
over-samp.	under-samp.	#trees	class weight	encode type				
-	0.5	100.0	balanced	True	*F1*	0.0539	0.7158	0.8186
					Rec	0.3022	0.758	0.9782
					Prec	0.0296	0.678	0.7038
-	0.5	100.0	None	False	*F1*	0.0509	0.6829	0.8221
					Rec	0.2099	0.6899	0.9783
					Prec	0.0289	0.6761	0.709
-	0.5	100.0	None	True	*F1*	0.0507	0.7148	0.812
					Rec	0.3033	0.7626	0.9796
					Prec	0.0277	0.6726	0.6933
-	0.1	100.0	None	True	*F1*	0.0031	0.3411	0.9419
					Rec	0.0038	0.21	0.9207
					Prec	0.0027	0.9091	0.9641
0.5	-	100.0	balanced	True	*F1*	0.0	0.0295	0.9415
					Rec	0.0	0.015	0.9072
					Prec	0.0	0.9019	0.9784
-	-	100.0	balanced	True	*F1*	0.0	0.0122	0.8954
					Rec	0.0	0.0062	0.8165
					Prec	0.0	0.8855	0.9911
1.0	-	100.0	None	False	*F1*	0.0	0.0157	0.8855
					Rec	0.0	0.0079	0.8059
					Prec	0.0	0.8327	0.9825
-	-	100.0	None	False	*F1*	0.0	0.0036	0.8709
					Rec	0.0	0.0018	0.7754
					Prec	0.0	0.8095	0.9931
1.0	-	100.0	None	True	*F1*	0.0	0.0509	0.9355
					Rec	0.0	0.0261	0.8947
					Prec	0.0	0.9295	0.9802
0.5	-	100.0	None	True	*F1*	0.0	0.0317	0.9453
					Rec	0.0	0.0161	0.9124
					Prec	0.0	0.895	0.9806
-	-	100.0	None	True	*F1*	0.0	0.0103	0.9341
					Rec	0.0	0.0052	0.8858
					Prec	0.0	0.8567	0.9879
-	-	100.0	balanced	False	*F1*	0.0	0.0039	0.7969
					Rec	0.0	0.0019	0.665
					Prec	0.0	0.8527	0.9942
0.5	-	100.0	None	False	*F1*	0.0	0.0141	0.8984
					Rec	0.0	0.0071	0.8266
					Prec	0.0	0.883	0.9838

Table A5: Manipulated code for random forest

Parameter							RN	CC	Base CC
over-samp.	under-samp.	stages	learn-rate	sub-sample	encode type				
0.5	-	200	0.2	1.0	True	*F1*	0.24	0.83	0.7519
						Rec	0.7676	0.978	0.9854
						Prec	0.1422	0.7209	0.6078
-	0.5	200	0.2	1.0	True	*F1*	0.2309	0.8291	0.7466
						Rec	0.8196	0.9773	0.9853
						Prec	0.1344	0.7199	0.601
-	-	100	0.2	1.0	True	*F1*	0.15	0.5254	0.8648
						Rec	0.0891	0.3629	0.8225
						Prec	0.4729	0.9513	0.9117
0.5	-	100	0.2	1.0	True	*F1*	0.1488	0.7314	0.6883
						Rec	0.8706	0.9781	0.9789
						Prec	0.0814	0.5841	0.5307
-	0.5	100	0.2	1.0	True	*F1*	0.1435	0.7303	0.6874
						Rec	0.9055	0.9783	0.9817
						Prec	0.0779	0.5827	0.5288
0.5	-	100	0.1	1.0	True	*F1*	0.1063	0.6377	0.5957
						Rec	0.891	0.9758	0.977
						Prec	0.0565	0.4736	0.4285
-	0.5	100	0.1	1.0	True	*F1*	0.0993	0.6454	0.607
						Rec	0.9077	0.9786	0.9769
						Prec	0.0525	0.4815	0.4402
-	-	200	0.2	0.4	True	*F1*	0.0963	0.3292	0.8948
						Rec	0.0558	0.1995	0.8805
						Prec	0.349	0.9406	0.9096
-	-	200	0.2	1.0	True	*F1*	0.0963	0.3292	0.8948
						Rec	0.0558	0.1995	0.8805
						Prec	0.349	0.9406	0.9096
-	-	200	0.2	0.7	True	*F1*	0.0963	0.3292	0.8948
						Rec	0.0558	0.1995	0.8805
						Prec	0.349	0.9406	0.9096
-	-	300	0.2	1.0	True	*F1*	0.0563	0.2333	0.9174
						Rec	0.0322	0.1331	0.9105
						Prec	0.2222	0.942	0.9243

Table A6: Manipulated code gradient boosting classifier

Parameter								RN	CC	Base CC
over-samp.	under-samp.	emb-size	epochs	batch-size	#lstm-cells	dropout				
-	0.5	32	3	256	10.0	0.2|0.2	*F1*	0.3895	0.6568	0.9502
							Rec	0.847	0.5009	0.996
							Prec	0.2529	0.9534	0.9085
-	-	32	2	512	10.0	0.2|0.2	*F1*	0.0	0.3195	0.9694
							Rec	0.0	0.1902	0.9931
							Prec	0.0	0.9968	0.9467
-	-	16	3	256	10.0	0.2|0.2	*F1*	0.0	0.2831	0.9698
							Rec	0.0	0.165	0.9737
							Prec	0.0	0.9956	0.9659
0.5	-	32	3	256	10.0	0.2|0.2	*F1*	0.0	0.119	0.9692
							Rec	0.0	0.0633	0.9947
							Prec	0.0	0.9851	0.945
-	-	32	2	256	10.0	0.2|0.2	*F1*	0.0	0.1898	0.9728
							Rec	0.0	0.1049	0.988
							Prec	0.0	0.9938	0.958
-	-	32	3	512	10.0	0.2|0.2	*F1*	0.0	0.0037	0.9714
							Rec	0.0	0.0019	0.9929
							Prec	0.0	0.7047	0.9508
-	-	32	3	64	10.0	0.2|0.2	*F1*	0.0	0.0857	0.9721
							Rec	0.0	0.0448	0.9788
							Prec	0.0	0.9742	0.9655
-	-	32	3	256	10.0	0.2|0.2	*F1*	0.0	0.0451	0.9711
							Rec	0.0	0.0231	0.9937
							Prec	0.0	0.9645	0.9494
-	-	16	2	256	10.0	0.2|0.2	*F1*	0.0	0.5738	0.972
							Rec	0.0	0.4036	0.9676
							Prec	0.0	0.9925	0.9765

Table A7: Manipulated code lstm