Advancing Code Readability: Mined & Modified Code for Dataset Generation

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Abstract

Deep learning-based models are achieving increasingly superior accuracy in classifying the readability of code. Recent research focuses mostly on different model architectures to further improve code readability classification. The models mostly use (parts of) the same labeled dataset, consisting of 421 code snippets. However, it is known that deep learning-based approaches improve with a large amount of data. Consequently, a larger labeled dataset could greatly advance the research field of code readability classification. In this work, we investigate the use of a new dataset consisting of 69k code snippets together with its novel generation approach. The generation approach involves the extraction and modification of code snippets from public GitHub repositories. The generated dataset is evaluated using a survey with 200 participants and by training a state of the art code readability classification model both with and without the new dataset. In the future, our dataset might increase the accuracy of all readability classification models.

Contents

1. INTRODUCTION

Code readability is of utmost significance in the domain of software development. In the domain of software development, the significance of code readability cannot be overstated. Together with understandability, it serves as the foundation for efficient collaboration, comprehension, and maintenance of software systems [28, 1]. Maintenance alone will consume over 70 % of the total lifecycle cost of a software product and for maintenance, the most time-consuming act is reading code [7, 10, 30, 5]. Therefore, it is important to ensure a high readability of code. In order to archive this, we need to measure readability. In the last years, researchers have proposed several metrics and models for assessing code readability with an accuracy of up to 81.8 % [7, 28, 11, 31]. In recent years, deep learning-based models are able to achieve an accuracy of up to 88.0 % [20, 21, 34, 23, 17, 18].

However, a major limitation of these models is not their architecture, but the amount of available data for Java code readability classification, which comprises 421 code snippets [7, 11, 31]. The current training data originates from questionnaires, where humans have manually labeled the code snippets. This has two drawbacks: Firstly, manual labeling requires a lot of effort. Secondly, the dataset is too small for deep learning, as those require To address those drawbacks, we aim to automatically generate more training data.

Deep learning-based models perform better the more training data they get [13]. Therefore, one approach to further improve existing models is to gather more training data. This requires, as it was done previously, a lot of effort and persons willing to rate code based on their readability.

The main idea of this work is to investigate whether it is possible to achieve higher accuracy in code readability classification using automatically generated data.

In a first step, following the approach of Allamanis et al. [2], we download GitHub[1] repositories with high code quality. Our criteria for high code quality are an elevated number of stars, forks, method comments the use of and compliance with a checkstyle[2] specification. For example, developers prefer high code quality and therefore star or fork repositories with high code quality more likely. We select Java files from the repositories that meet our criteria and extract methods from the Java classes in these files and label them as well readable (Assumption 1).

[1] `https://github.com/`, accessed: 2024-02-29
[2] `https://checkstyle.sourceforge.io/`, accessed: 2024-02-09

In a second step, all selected Java files are manipulated so that its code is subsequently less readable. You can find an exemplary result of this in TODO. We extract methods from the Java classes in these files and label them as poorly readable (Assumption 2).

After both steps, we have a new, automatically generated dataset for code readability classification.

How can we manipulate code so that it is less readable afterwards? We introduce a tool called Readability Decreasing Heuristics. This is a collection of heuristics that, when applied to Java files, lower the readability of it. Such heuristics are replacing spaces with newlines or increasing the indentation of a code block by a tab or multiple spaces. Most changes also decrease readability when applied in reverse (replacing newlines with spaces, decreasing indentation).

Methods in Java are syntactically the same, before and after applying Readability Decreasing Heuristics. Functionality does not change either. However, if various modifications are applied many times, those changes are capable of lowering the readability of source code, as TODO suggests.

To verify whether the well-readable-assumption (Assumption 1) and the poorly-readable-assumption (Assumption 2) hold we conducted a survey on prolific. We ask Java programmers to rate methods that were mined and modified. Therefore, human annotators rated each code snippet with a readability score. The annotators are selected by prolific[3]. The readability rating is based on a five-point Likert scale [14] ranging from one (i.e., very unreadable) to five (i.e., very readable). We apply the same rating as done previously [7, 11, 31], but, other than before, we will not use the rating for labeling the training data. Instead, we only use the ratings to validate some randomly selected methods to confirm our assumptions (Assumption 1 and 2). All snippets are automatically labeled.

Besides the user study we will evaluate our approach by comparing performance of the towards model of Mi et al. [23] when trained with the new and the old dataset. The comparisons are based on common metrics such as accuracy, F1-score and MCC [8].

Our contributions are as follows:

- We combine and unify existing datasets [7, 11, 31]
- We propose a approach to mine well readable methods
- We create a tool to decrease the readability of Java class files

[3] `https://www.prolific.scom/`, accessed: 2023-09-30

- We propose a novel dataset generation approach and introduce a new readability classification dataset
- We evaluate our generation approach with a user study
- We evaluate our generation approach by comparing the model performance of the towards model of Mi et al. [23] trained with and without the new dataset

The survey confirms both, the well-readable-assumption (Assumption 1) and the poorly-readable-assumption (Assumption 2). Although our approach for creating a dataset works in principle, we are not able to address enough aspects of code readability with the proposed heuristics. Thus, our dataset probably only addresses a partial problem of code readability.

2. BACKGROUND AND RELATED WORK

In the following subsections you find an overview of the background and related work on code readability and our approach to dataset creation.

2.1. CODE READABILITY

We start with an overview over definitions of code readability.

Buse and Weimer provides one of the first definitions: "We define readability as a human judgment of how easy a text is to understand."

Tashtoush et al. combines numerous other aspects from various definitions. According to them code readability can be measured by looking at the following aspects [35]:

- Ratio between lines of code and number of commented lines
- Writing to people not to computers
- Making a code locally understandable without searching for declarations and definitions
- Average number of right answers to a series of questions about a program in a given length of time

Recent definitions of code readability are shorter, trying to focus on the key aspects. Oliveira et al. defines readability as "what makes a program easier or harder to read and apprehend by developers" [26].

Also Mi et al. summarizes code readability as "a human judgment of how easy a piece of source code is to understand" [22]. This comes close to the definition of Buse and Weimer [7].

There are various related terms to readability: Understandability, usability, reusability, complexity, and maintainability [35]. Among those especially complexity and understandability are closely related to readability.

Readability is not the same as complexity. Complexity is an “essential” property of software that arises from system requirements, while readability is an “accidental” property that is not determined by the problem statement [7, 6].

Readability is neither the same as understandability, as the key aspects of understandability are [31, 16, 38, 4]:

- Complexity
- Usage of design concepts
- Formatting
- Source code lexicon
- Visual aspects (e.g., syntax highlighting)

Posnett et al. states that readability is the syntactic aspect of processing code, while understandability is the semantic aspect [28].

Based on Posnett et al., Scalabrino et al. writes about readability: "Readability measures the effort of the developer to access the information contained in the code, while understandability measures the complexity of such information" [31, 28].

For example, a developer can find a piece of code readable but still difficult to understand. Recent research gives evidence that there is no correlation between understandability and readability [32].

Comparing the definitions of code readability in literature we can see, that there are some common aspects in most definitions. These are:

- Ease/complexity of understanding/comprehension/apprehension
- Human judgment/assessment
- Effort of the process of reading (differentiation to understandability)

Based on this, we come up with the following definition:

Code readability is the human assessment of the effort required to read and understand code.

```java
/**
* Logs the output of the specified process.
*
* @param p the process
* @throws IOException if an I/O problem occurs
*/
private static void logProcessOutput(Process p) throws IOException
{
        try (BufferedReader input = new BufferedReader(new
        ↪  InputStreamReader(p.getInputStream())))
        {
                StrBuilder builder = new StrBuilder();
                String line;
                while ((line = input.readLine()) != null)
                {
                        builder.appendln(line);
                }
                logger.info(builder.toString());
        }
}
```

Listing 1.: An example for well readable code of the highly rated Cassandra GitHub repository.

In the last years, researchers have proposed several metrics and models for assessing code readability with an accuracy of up to 81.8 % [7, 28, 11, 31]. In recent years, deep learning-based models are able to achieve an accuracy of to 88.0 % [20, 21, 34, 23, 17, 18]on available datasets. Examining these works more closely in the following, we delve into their intricacies.

2.2. CONVENTIONAL CALCULATION APPROACHES

A first estimation for source code readability was the percentage of comment lines over total code lines [1]. Then researchers proposed several more complex metrics and models for assessing code readability [7, 28, 11, 31]. Those approaches used handcrafted features to calculate how readable a piece of code is. They were able to achieve up to 81.8 % accuracy in classification [31].

2.3. DEEP LEARNING BASED APPROACHES

In recent years code readability classification is dominated by machine learning, especially deep learning approaches. As the quality of the models increased, so did their accuracy (see Table 1).

```
private
        static
void
debug( Process
v1
)       throws IOException
{
        // Doo debug
        try (BufferedReader   b
        = new
        BufferedReader(
        new InputStreamReader(
        v1.getInputStream()
        )
        )
        )
        {
                StrBuilder b2=new StrBuilder();String v2;while
                ↪  (null!=(v2=input.readLine())){b2.appendln(v2);}
                ↪  // Doo stuff
                m.info(  builder.toString()
                );
        }
}
```

Listing 2.: The same example as in Listing 1 but modified to be poorly readable.

IncepCRM was the first introduced deep learning model called for code readability classification. It automatically learns multi-scale features from source code with minimal manual intervention [20].

In a follow up paper Convolutional Neural Networks (ConvNets) were introduced to code readability classification in a model called DeepCRM. Other than previously, DeepCRM employs three ConvNets with identical architectures and was trained on differently preprocessed data [21].

Another study proposes an approach using Generative Adversarial Networks (GANs). The proposed method involves encoding source codes into integer matrices with multiple granularities and utilizing an EGAN (Enhanced GAN) [34]. It was able to surpass the accuracy of previous readability classification models as shown in Table 1.

The limitation of previous deep learning-based code readability models was to focus primarily on structural features. This was addressed by proposing a method that extracts features from visual, semantic, and structural aspects of source code. Using a hybrid neural network composed of BERT, CNN, and

Table 1.: Accuracy scores of two-class readability classification models.

Model	Type	Accuracy
Buse [7]	Conventional	76.5 %
Possnet [28]	Conventional	71.7 %
Dorn [11]	Conventional	78.6 %
Scallabrino [31]	Conventional	81.8 %
Mi_IncepCRM [20]	Deep Learning	84.2 %
Mi_DeepCRM [21]	Deep Learning	83.8 %
Sharma [34]	Deep Learning	84.8 %
Mi_Towards [23]	**Deep Learning**	**85.3 %**
Mi_Ranking [17]	Deep Learning	83.5 %
Mi_Graph [18]	Deep Learning	88.0 %

BiLSTM, the model processes RGB matrices, token sequences, and character matrices to capture various features [23].

Up to this point, code readability classification was considered mainly as a task that is applied to a single code snippet at once. A new approach was introduced that frames the problem as a ranking task. The proposed model employs siamese neural networks to rank code pairs based on their readability [17].

All previous accuracy scores in two class classification were surpassed by the introduction of a graph-based representation method for code readability classification. The proposed method involves parsing source code into a graph with abstract syntax tree (AST), combining control and data flow edges, and converting node information into vectors. The model, comprising Graph Convolutional Network (GCN), DMoNPooling, and K-dimensional Graph Neural Networks (k-GNNs) layers, extracts syntactic and semantic features [18].

You can find an overview over the accuracy scores for the models mentioned in Table 1.

Until now many deep learn architectures and components were introduced with the goal to surpass previous classification accuracy scores. Their common limitation is a dataset consisting of 36077 code snippets for training and evaluation. The main contribution of this work is not a model that outperforms a state of the art model but rather a new dataset (generation approach). For evaluation we opted for the *Mi_Towards* model (hereinafter referred to as towards model) from Mi et al. [23]. We did not choose the best performing one, *Mi_Graph*, as its main contribution is to use the AST representation of the code, while our

dataset generation approach includes features that are not represented in the AST [18].

2.4. DATA AUGMENTATION

All the mentioned models were trained with (a part of) the data from Buse, Dorn and Scalabrino consisting of a total of 421 Java code snippets. The data was generated with surveys. They therefore asked developers several questions, including how well readable the proposed source code is [7, 11, 31]. We will refer to this dataset as *merged* dataset.

The problem that there is little data in the area of code readability classification for machine learning models has been recognized.

A recent paper addressed the challenge of acquiring a larger amount of labeled data using augmentation. The researchers proposed this to artificially expand the training set instead of the time-consuming and expensive process of obtaining labels manually. They employ domain-specific transformations, such as manipulating comments, indentations, and names of classes/methods/variables, and explore the use of Auxiliary Classifier GANs to generate synthetic data. They advance to a classification accuracy of 87.3 % [22]. Lately researchers successfully enhanced the data augmentation approach by incorporating domain-specific data transformation and Generative Adversarial Networks (GANs) [19]. The results of both show, that more data has a significant impact on the reached classification accuracy. However, they artificially augment data based on the 36077 code snippets of the merged data set. Therewith their augmented data is based on the small dataset. Our new dataset is not.

Recently researchers developed a methodology to identify readability-improving commits, creating a dataset of 122k commits from GitHub's revision history. This dataset was used to automatically identify and suggest readability-improving actions for code snippets. They trained a T5 model to emulate developers' actions in improving code readability, achieving a prediction accuracy between 21 % and 28 %. The empirical evaluation shows that 82-91 % of the dataset commits aim to improve readability, and the model successfully mimics developers in 21 % of cases [37]. This shows the potential of a large dataset. However, the approach dataset and model results are hardly comparable with previous studies due to the usage of commits instead of code snippets. We, on the other hand, keep to use code snippets.

2.5. DIVERSE PERSPECTIVES

There is also other important research in the field of readability classification that does not directly affect this work, but could have implications for future work.

Fakhoury et al. showed based on readability improving commit analysis that previous models do not capture what developers think of readability improvements. They therefore analyzed 548 GitHub[1] commits manually. They suggest considering other metrics such as incoming method calls or method name fitting [12].

Oliveira et al. conducted a systematic literature review of 54 relevant studies on code readability and legibility, examining how different factors impact comprehension. The authors analyze tasks and response variables used in studies comparing programming constructs, coding idioms, naming conventions, and formatting guidelines [26].

In a recent study participants demonstrated a consistent perception that Python code with more lines was deemed more comprehensible, irrespective of their level of experience. However, when it came to readability, variations were observed based on code size, with less experienced participants expressing a preference for longer code, while those with more experience favored shorter code. Both novices and experts agreed that long and complete-word identifiers enhanced readability and comprehensibility. Additionally, the inclusion of comments was found to positively impact comprehension, and a consensus emerged in favor of four indentation spaces [29].

Choi, Park et al. introduced an enhanced source code readability metric aimed at quantitatively measuring code readability in the software maintenance phase. The proposed metric achieves a substantial explanatory power of 75.7 %. Additionally, the authors developed a tool named Instant R. Gauge, integrated with Eclipse IDE, to provide real-time readability feedback and track readability history, allowing developers to gradually improve their coding habits [9].

Mi et al. aim to understand the causal relationship between code features and readability. To overcome potential spurious correlations, the authors propose a causal theory-based approach, utilizing the PC algorithm and additive noise models to construct a causal graph. Experimental results using human-annotated readability data reveal that the average number of comments positively impacts code readability, while the average number of assignments, identifiers, and periods has a negative impact [24].

Segedinac et al. introduces a novel approach for code readability classification using eye-tracking data from 90 undergraduate students assessing Python code snippets [33].

2.6. DATA GENERATION

In addition to related work on models and datasets, there is also related work that uses some of the ideas that we employ in our proposed approach for data generation.

Loriot et al. created a model that is able to fix Checkstyle[4] violations using Deep Learning. They inserted formatting violations based on a project specific format checker ruleset into code in a first step. They then used a LSTM neural network that learned how to undo those injections. Their approach is working on abstract token sequences. Their data is generated in a self-supervised manner [15]. A similar idea has been explored by Yasunaga and Liang [39]. We will use the idea of intentional degradation of code for data generation.

Another concept we will employ is from Allamanis et al. They cloned the top open source Java projects on GitHub[1] for training a Deep Learning model. Those top projects were selected by taking the sum of the z-scores of the number of watchers and forks of each project. The projects have thousands of forks and stars and are widely used among software developers and thus the authors assumed the code within to be of good quality [2]. We will also use fork and star counts as criteria for well readable code (Assumption 1).

3. MINED AND MODIFIED CODE FOR DATASET GENERATION

In the following subsections we will describe our approach.

3.1. WORK ON EXISTING DATASETS

Most of the related work (see Section 2) uses a combination of the data of Buse and Weimer, Dorn and Scalabrino et al. The raw data from their surveys can be downloaded [5], but their data is not uniformly formatted, including ratings that are not Java code snippets, as well as the individual ratings rather than the mean of the ratings used for training machine learning models. Other than our

[4] `https://checkstyle.org/`, accessed: 2023-07-25
[5] `https://dibt.unimol.it/report/readability/`, accessed: 2024-02-18

mined and modified code snippets theirs do not all have the scope of a method, but instead consist of a few lines of code.

We converted and combined the three datasets into one: code-readability-merged. In recent years, Huggingface[6] established as the pioneer in making models and datasets available. Therefore we decided to publish the merged dataset on Huggingface[7].

We refer to this dataset as the *merged* one.

3.2. CLASSIFICATION CONSIDERATIONS

When classifying the readability of code, the state of the art is to perform a binary classification into well readable and poorly readable code [20, 21, 34, 23, 17].

However, code readability classification is not a binary classification task per se. Mi et al. introduced a third, neutral class to address this problem [18]. When rating code snippets, a Likert scale [14] from 1 (very unreadable) to 5 (very readable) was used [7, 11, 31]. While the amount of classes varies, one can encode the data internally as a single-value representation between 0 and 1 where a higher value means higher readability. The output of the model is well readable if the value after the last layer is above 0.5 and poorly readable otherwise.

Our evaluation model is the towards model of Mi et al. [23] and uses the single-value representation. We want to show how they transformed the rating scores into a binary classification problem. First, the mean values of all scores are calculated. In a second step, the snippets are ranked according to their mean score. Then, the top 25 % of the data is labeled as well readable (1.0) and the bottom 25 % is labeled as poorly readable (0.0). The 50 % of the data in between is not used at all [23].

While this transformation is fine in principle, especially with the argument that the data in the middle is neither well readable nor poorly readable, it has drawbacks that only 50 % of the available data is used for model training and evaluation:

First, the available data is further reduced from 421 to 210 Java code snippets. Note that a bottleneck in readability classification is the small amount of available data. So this is a significant loss.

[6] `https://huggingface.co/`, accessed: 2024-02-18
[7] `https://huggingface.co/datasets/se2p/code-readability-merged`, accessed: 2024-02-18

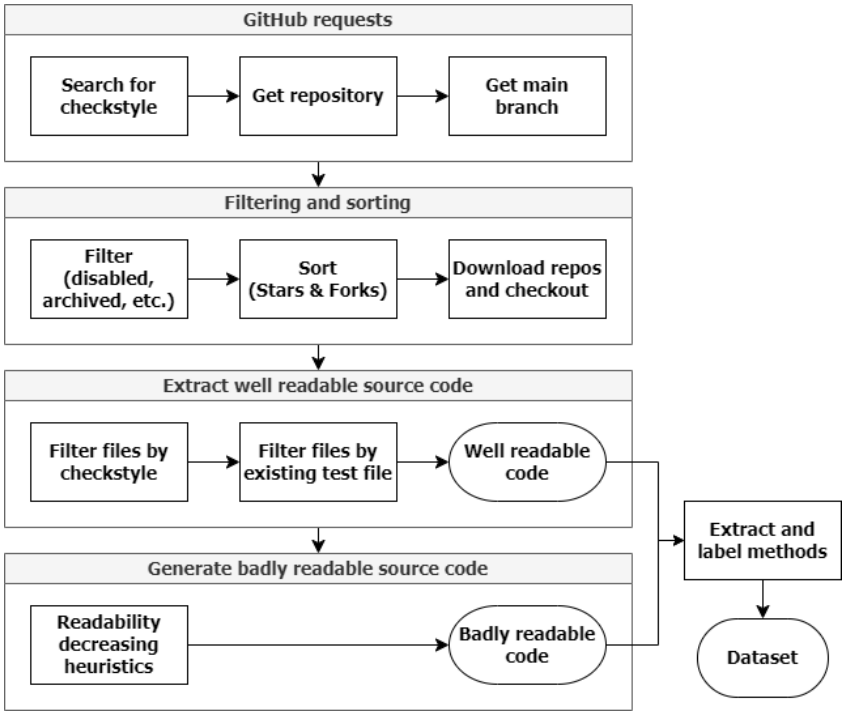


Figure 1.: The used dataset generation approach.

Secondly, evaluation is performed with only those 210 snippets as well. Thus, the model was only evaluated on 50 % of the available data. We suspect that this might be a thread to validity. It could be that the performance of the model is remarkably lower when the evaluation is performed with random, unseen data that also contains moderately readable code snippets.

However, we will both continue to use the binary classification approach as well as to the towards model [23] to make our results comparable to theirs.

3.3. DATASET GENERATION APPROACH

In contrast to previous datasets for readability classification, our dataset is generated using an automated approach. The aim is to mine and modify code from GitHub to obtain both well readable and poorly readable methods. This approach is novel to the best of our knowledge. You can find a visualization in Figure 1.

While we refer to the merged data set (Section 3.1) as the merged data set, the data set generated by our approach is referred to as the new data set.

Since we ultimately extract methods from code, code snippets and methods are synonyms for our mine-and-modify approach. This is not the case with the merged data set, as there a code snippet is not necessarily an entire method.

The approach is divided into four parts. The first three steps are used to mine well readable Java code. In a final step, we will modify the well readable code to achieve our second goal, namely poorly readable source code.

We start by querying the GitHub REST API[8] for repositories that use checkstyle (query string: "checkstyle filename:pom.xml"). The repository informations (including the URL) are stored together with the main branches. We remove all repositories that do not fulfill these criteria:

- The repository is not a fork of another repository
- The repository is not archived
- The repository is not disabled
- The repository language is Java
- The repository has at least 20 stars
- The repository has at least 20 forks

The remaining ones are sorted by their star and fork count (equally weighted). The 100 best are cloned and their main branch is checked out.

In a third step we run checkstyle[2] against the projects own checkstyle configuration to get all Java class files, that pass the own checkstyle test. A tool from Maximilian Jungwirth[9] was used for this purpose. From the Java classes that passed this filter we extract all methods that have a comment of any kind at the beginning of the method. This results in 36077 methods which we assume to be well readable.

The fourth and final step is to generate poorly readable code from the well readable one. Therefore we use the proposed Readability Decreasing Heuristics (see Section 3.4). Afterwards we again extract all methods with a comment at the beginning of the method. Initially we planned to not require comments for the poorly readable dataset part. However, it turns out that in this case all well readable methods have a comment while most of the poorly readable do not have one. This lead to shortcut learning, whether a method has a comment or not instead of learning to distinguishing the methods by all other criteria as well. After removing code snippets that are identical for the original and the

[8] `https://docs.github.com/en/rest`, accessed: 2024-02-15
[9] `https://github.com/sphrilix`, accessed: TODO

variant with reduced readability (see Section 3.4) and balancing the data set using random sampling, the result is a data set consisting of 69k code snippets.

3.4. READABILITY DECREASING HEURISTICS

In this section we explain how we achieved to decrease the readability of code using Readability Decreasing Heuristics (RDH). The RDH are a set of code manipulation heuristics that are applied to Java files. One part is performed on the abstract syntax tree (AST) representation of the Java files using the spoon library[10] [27]. Another part is executed when pretty-printing the AST back into Java files. This part cannot be displayed in the AST and is therefore executed at source code level immediately after the reverse transformation. From now on, we will use the abbreviation *RDH* or *RDH tool* when referring to the entire program. If a specific manipulation or a configuration of the RDH tool is meant, we will use *[name] rdh* or *[name]* instead.

The RDH tool initially converts the Java code of any well readable Java class file into an AST. In the end the AST is parsed back to Java code using an pretty printer. If nothing else is done, this results in the `none` rdh. Note that the code produced by the tool in this way will be slightly different from the original input code, as the styling and formatting of the original code will be overwritten by the default formatting of the Java Pretty Printer of the spoon library[10] [27].

Various code changes can be made between the two steps and during printing. The renaming is done while the code is in its AST representation to ensure that the declarations and usages of variables, fields and methods are all renamed to the same new identifier. The other transformations are performed when the AST is converted back to source code. This includes adding additional spaces, adding or removing newlines and changing the indentation of code in term of tabs.

The individual methods are then extracted from the class files. As mentioned (see Section 3.3), we require a method comment for all methods. We therefore use the removeComment rdh after completing the method extraction.

The RDH tool works with a configuration file in which one can specify a probability for each heuristic that can be applied. We have chosen the probabilities so that the generated code snippets are still realistic in the sense that they could also be written by humans. You can find the configurations in Table 3 and an exemplary file for the none rdh in appendix II

[10] `https://spoon.gforge.inria.fr/`, accessed: 2024-15-02

Table 2.: Readability Decreasing Heuristics that are not included in the final version of the new dataset and why.

Heuristic	Reason
`inlineMethod`	Makes methods too long
`add0`	Limited survey capacity
`insertBraces`	Limited survey capacity
`starImport`	No effect after comment extraction
`inlineField`	Limited survey capacity
`partiallyEvaluate`	Might increase readability

Some of the heuristics were not included in the final version of the new dataset. You can find them in Table 2 together with the reason why they were not included.

We also added Code2Vec [3] to the tool. This makes it possible to rename methods not only to iterating or arbitrary strings or numbers, but also to other realistic method names. The idea was to use worse method names predicted by Code2Vec and rename the methods to these. However, due to time and resource limitations regarding the survey, we did not pursue this approach. However, there is a corresponding mode supported by the tool which can be used for further research.

3.5. CONSTRUCTION OF QUESTIONNAIRES

We evaluated the generated data set and the new approach with a survey. To do this, we had to carefully select suitable code snippets from the dataset. An overview of the approach can be found in Figure 2.

The first step was to find realistic configurations for the RDH tool. After an initial data set with the heuristics was created, a pilot study was conducted. Subsequently, the heuristics that proved to be too strong were checked and, if necessary, adjusted to be weaker according to the results of the pilot survey. The result consisted of 9 different rdhs, which can be found in Table 3. Together with the original methods this resulted in 10 different configurations.

The configurations are based on probabilities for different heuristics. A heuristic is applied with the specified probability to each occurrence of the object to which it refers. For example, when removeComment is applied with a probability of 10 % to each comment that occurs within the code snippet. The exact scope of changes is therefore uncertain. It can happen (especially with short methods

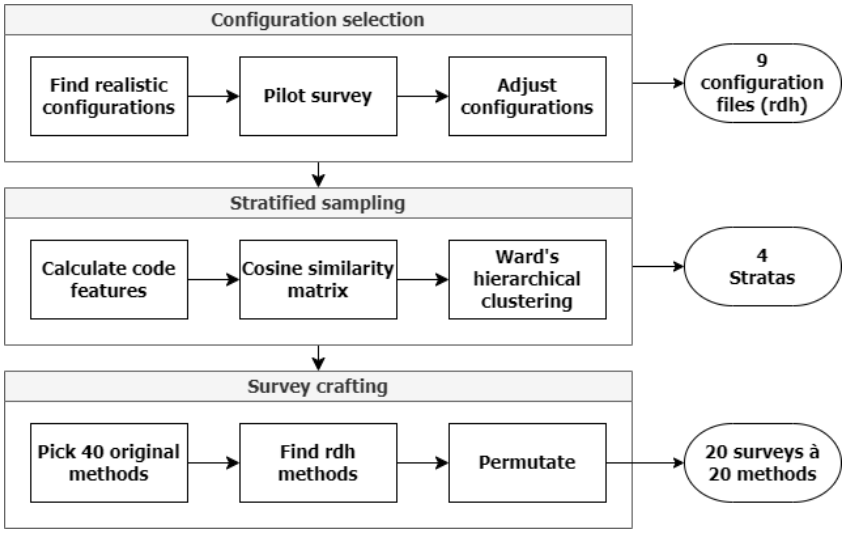


Figure 2.: Steps performed to craft questionnaires from the new dataset.

such as getters and setters) that a method is not changed at all. For example, if a method only has a single comment and we use removeComment, the probability that the method will not be changed is 90 %.

In a second step, we applied stratified sampling [36] to distinguish between very simple methods such as getter and setter and more complex methods. In order to be able to compare the original methods with their modified variants, we only carried out the random sampling for the original methods and compared the rdh methods with these in a later step.

Thus, we first calculated features for the original code snippets. This was done using the tool of Scalabrino et al. [31]. A 110-dimensional feature vector was calculated for each original code snippet. Next we computed the cosine similarity metrix between all feature vectors using scikit[11]. Finally, using the fastcluster implementation [25] of Ward's hierarchical clustering we were able to cluster the methods into an arbitrary amount of clusters.

By comparing the merge distances in each step (see Figure 3), we found that a cluster size of 4 makes the most sense: the merge distance of 5 to 4 is small, so we should still perform this merge, but the merge distance of 4 to 3 is large, so it is better not to perform this merge. Also, 4 is the size with the last possibility for a small merge distance. Each of the clusters is one stratum of our stratified sampling. We manually assigned a name to each of the 4 strata (see Table 4).

[11] `https://scikit-learn.org/stable/modules/generated/sklearn.metrics.pairwise.cosine_similarity.html`, accessed: 2024-02-20

Table 3.: Chosen configurations and their probabilities for the Readability Decreasing Heuristics.

Configuration	**Probabilities**
none	-
comments_remove	removeComment: 10 %
newline_instead_of_space	newLineInsteadOfSpace: 15 %
newlines_few	removeNewline: 30 % spaceInsteadOfNewline: 5 %
newlines_many	add1Newline: 15 % add2Newlines: 5 %
rename	renameVariable: 30 % renameField: 30 % renameMethod: 30 %
spaces_many	Add1Space: 20 % Add2Spaces: 10 % spaceInsteadOfNewline: 5 %
tabs	remove1IncTab: 20 % add1IncTab: 10 % remove1DecTab: 10 % add1DecTab: 10 % incTabInsteadOfDecTab: 5 % decTabInsteadOfIncTab: 5 %
all7	all probabilites/7

In a third step, we crafted the questionnaires from the strata. We decided to provide all 10 previously mentioned configurations for each original method, as we want to compare the original methods with their rdh variants. Since we have a survey capacity of 400 code snippets, we need to select 40 original code snippets (and then add all their rdh).

We opted for a random sample within the strata. However, we distributed the 40 snippets across the strata as shown in Table 4.

This decision was made due to the relatively high frequency of methods that do not differ from their original methods (see Figure 4). Another reason for this decision is that particularly simple methods are rather uninteresting for the classification of readability, as they are often generated (e.g. by IDEs) and usually follow a straightforward pattern.

After selecting the 40 original methods, we next selected all $9 * 40$ rdh variants that belong to the original methods. This was mostly done automatically based

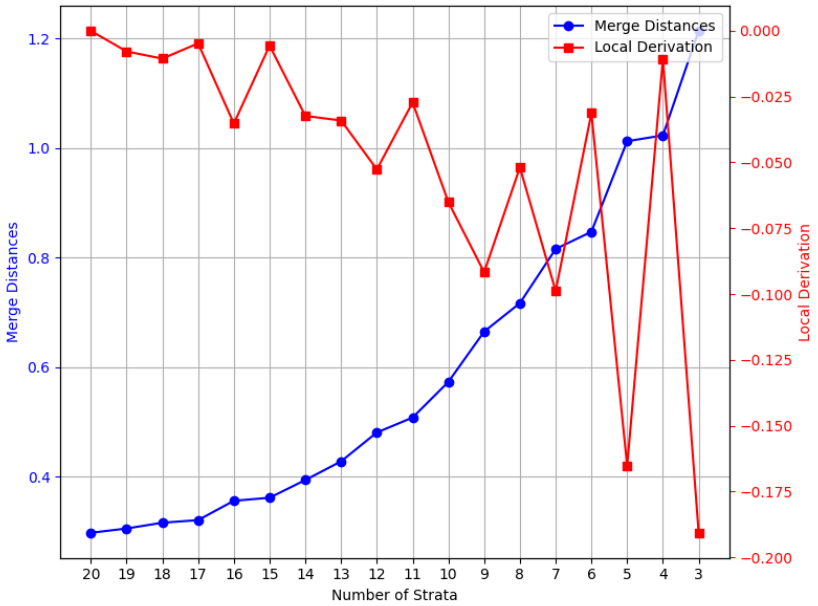


Figure 3.: Merge distances and local derivation for number of strata.

on the names of the original methods and the names of the rdh variant methods. However, if the method was renamed at an earlier stage due to the method renaming heuristic, the new method did no longer match the original method, in which case we had to match them manually.

Once we collected all 400 methods, we distributed them across the 20 questionnaires, each with 20 methods. In order not to manipulate the raters, we decided that a variant of each method could only appear once in each questionnaire. For example, if the original method is in questionnaire 1, the removeComment variant (or another variant of the same method) must not be included in the same questionnaire.

For this purpose, we created four permutation matrices with 10 snippets each. The number 10 was chosen because it is possible to distribute 10 snippets, each with 10 variants, across at least 10 survey questionnaires without violating our condition. By combining two 10-permutation matrices, we were able to create 10 survey questionnaires with 20 code snippets each. An implication of this approach is that each questionnaire contains each variant kind exactly twice. By doing this twice, we obtain the desired distribution of 20 questionnaires with 20 methods each. Our condition applies: There is only one variant of the same method in each questionnaire.

Table 4.: Computed strata, manually assigned names based on the methods within and distribution for survey creation.

Stratum	Method Type	Percentage	Count
Stratum 0	Simple methods	10 %	4
Stratum 1	Complex methods	40 %	16
Stratum 2	Magic number methods	10 %	4
Stratum 3	Medium complex methods	40 %	16
Total		**100 %**	**40**

Finally, the methods of each questionnaire were randomly shuffled within itself. This was done to minimize the impact of the position of a snippet or variant within a survey on the rating.

Once the survey was completed, we aggregated the ratings across all strats and all methods. We grouped the results into the 10 rdhs. In this way, we assess whether the rdhs work, which rdhs work best and how strong the impact of each rdh on readability is. In addition, we use the results of the survey to label our new dataset, which consists of the original and all7 rdh methods.

Each snippet of the well readable code (original) is labeled with the mean value of all ratings of the original variant across all survey results. Similarly, we label the all7 code snippets with their mean value. Note that in the binary classification with the underlying towards model, this results in the original methods being labeled well readable and the all7 rdh poorly readable.

3.6. READABILITY CLASSIFICATION MODEL

Next we investigate whether it is possible to score a higher accuracy as the towards model in classifying code readability with our new dataset.

Therefore we created our own implementation of the towards model using Keras[12]. In contrast to the publicly available code of Mi et al.[13], our model includes (batch) encoders required for the model to be trained on new data and to perform the prediction task for new code snippets. In addition, our model supports fine-tuning by freezing certain layers as well as storing intermediate results, such as the encoded dataset. During evaluation, the model returns the evaluation statistics in form of a JSON file.

[12] `https://keras.io/about/`, accessed: 2024-02-20
[13] `https://github.com/swy0601/Readability-Features`, accessed: 2024-02-20

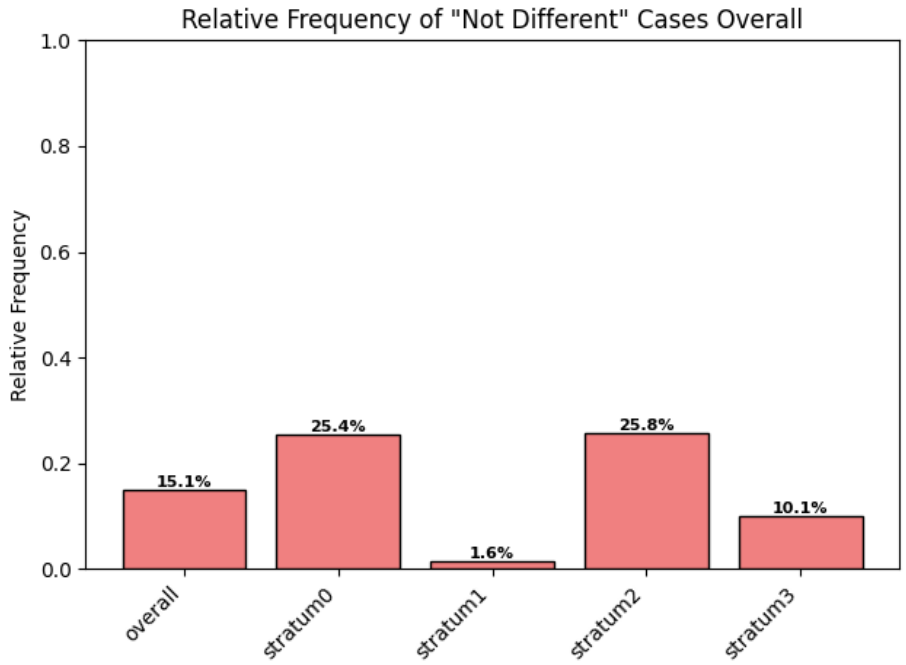


Figure 4.: Frequency of the case that a rdh-method is not different from its original method.

During implementation, we encountered the following potential problem with the model: The token length for the bert encoding (bert-base-cased[14]) used in the model is 100. What is a token in a piece of code? In addition to special tokens that mark the beginning *[CLS]* and the end *[SEP]* of the input, each word is represented by a token. However, each special character (such as */(),;=* and many more) is also represented by its own token. Java identifiers are split according to the convention of upper and lower case. Long words are in turn divided into several tokens.

Consider the method from Listing 1. With a token limit of 100, the last encoded token is the last closing parenthesis in line 9. Everything from line 10 onwards is not encoded, which means that the information is lost for the semantic part of the model. To put it in other words: The model of Mi et al. only considers the first few lines of code snippets in its semantic component.

The visual and structural encoders have similar limitations, but to a much smaller extent. The structural encoder encodes the first 50 lines of each code snippet

[14] `https://huggingface.co/google-bert/bert-base-cased`, accessed: 2024-02-20

Figure 5.: Overview over the used scripts and their output.

and the visual encoder encodes the first 43 lines. While the constraints for these two encoders seem to be long enough to fully capture most code snippets, the semantic encoder seems to be too limited to do so.

Although we want to note these limitations, we will keep them to allow a fair comparison of the datasets.

Our code is publicly available on GitHub[15].

You can find an overview over all programs used to create the merged dataset, the new dataset, the model and all our evaluation results in Figure 5.

4. EVALUATION

Note that we assume two things for the data generation approach:

Assumption 1 **(well-readable-assumption)** The selected repositories contain mostly well readable code.

[15] `https://github.com/LuKr02011`, accessed: TODO

Assumption 2 **(poorly-readable-assumption)** After applying Readability Decreasing Heuristics, the code is poorly readable.

We are conducting a user study to determine the quality of the new data set. In detail the aim of the user study is to answer the following key questions:

1. Does the well-readable-assumption (Assumption 1) hold?
2. Does the poorly-readable-assumption (Assumption 2) hold?

Therefore, we come up with the following research questions:

Research Question 1: ***(select-well)*** *Can automatically selected code be assumed to be well readable?*

In our new approach for generating training data, we assume that the code from repositories is well readable under certain conditions (Assumption 1). We want to check whether that holds. To answer this question we will use the results of the user study.

Research Question 2: ***(generate-poor)*** *Can poorly readable code be generated from well readable code?*

It is not sufficient to have only well readable code for training a classifier. We also need poorly readable code. Therefore, we will try to generate such code from the well readable code. We will investigate whether this is possible in principle, and we will propose an automated approach for archiving this: Readability Decreasing Heuristics.

As the name already suggests, the applied transformations on the source code are only heuristics. To answer, whether the generated code is poorly readable (Assumption 2) we will utilize the results of the user study.

Research Question 3: ***(new-data)*** *To what extent can the new data improve existing code readability classification models?*

It was shown that Deep Learning models get better the more training data is available [13]. This holds under the assumption that the quality of the data is the same or at least similar. We want to check if the quality of our new data is sufficient for improving the deep learning-based readability classifier of Mi et al. [23]. Therefore we will train their proposed model with combinations of the merged and the new dataset and compare the evaluation statistics.

4.1. SURVEY

The results of our survey are divided into two parts: The results of the pilot survey (see Section 4.1), which were used to improve the main survey pre-launch, and the results of the main survey (see Section 4.1), which were used to answer our research questions (RQ1 and RQ2) and to craft our dataset.

PILOT SURVEY

1. Experimental setup: We manually sampled 20 code snippets across all strata but mainly from statum 1, due to reasons mentioned in subsection 3.5. From 6 to 14 January 2024 10 participants, mostly students, participated in the survey. They survey participants were not paid. Additionally to rating 20 code snippets the participants were also asked to answer additional questions to provide feedback about the survey:

1. *Short answer*: How long did it take you to complete the survey?
2. *Single choice (1 (very unclear) to 5 (very clear)):* How clear was your task?
3. *Long answer:* What problems were with the task? If there were none, leave blank.
4. *Long answer:* What problems were there with the survey tool? If there were none, leave blank.
5. *Long answer:* What improvements would you make to the survey? If none, leave blank.
6. *Long answer:* you have any other feedback? If none, leave blank.

The participants answers can be found in appendix I.

The feedback of the pilot survey was used in the following ways to prepare the prolific study:

- To adjust the survey texts and questions
- To estimate how long completion of one questionnaire will take
- To adjust the RDH settings
- To discover problems with the survey tool
- To discover fundamental problems with the dataset

2. Threats: The results do not generalize. We did not sample the data in a specific, (semi-) automated way, so there is a selection bias. The survey participants were not selected among Java programmers randomly. The final texts for the prolific

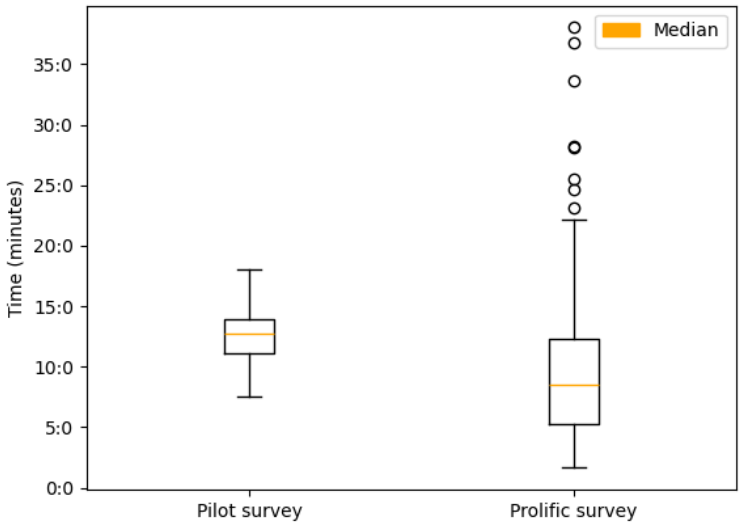


Figure 6.: Time required to complete a questionnaire.

survey were adjusted afterwards. However, we did not use the results from this survey to evaluate our dataset or the generation approach, as the intention of the survey was rather to prepare for the main survey.

3. Results: The pilot survey provided information on how much time it would take to rate 20 code snippets for their readability. An overview of the times required can be found in Figure 6. On this basis, we estimated the time required for a questionnaire at 10 minutes.

Most of the problems that occurred were due to the survey tool (e.g.: "I also felt that I should use the drop-down menu at the top left."). In addition, a manual evaluation of the various rdhs, especially for stratum 1, revealed some clues:

First, the original methods were rated comparably well, which suggests that the well-readable assumption (Assumption 1) is correct.

Secondly, the pretty printer of the RDH tool specified each imported method or class completely with its fully specified classifier. For example, instead of "InputStream", "Java.io.InputStream" was written in the code snippets of the rdhs. This gave the participants the feeling that the code was not written by a human and drastically reduced readability. We then adapted the rdh tool to print the shorter name. However, this has the drawback that it can no longer be assumed that the generated code will compile and behave exactly like the

Table 5.: Mean score ratings for the pilot survey.

Stratum	RDH	Score
Stratum 3	methods	4,6
Stratum 0	tabs_few	4,3
Stratum 2	tabs_few	3,8
Stratum 1	methods	3,7
Stratum 2	methods	3,7
Stratum 3	newlines_many	3,3
Stratum 1	comments_remove	3,1
Stratum 0	spaces_few	3,0
Stratum 1	all_weak_3	3,0
Stratum 1	newlines_many	2,9
Stratum 1	spaces_few	2,6
Stratum 1	misc	2,4
Stratum 2	newlines_few	2,4
Stratum 1	tabs_few	2,2
Stratum 1	tabs_many	2,2
Stratum 1	spaces_many	2,1
Stratum 1	newlines_few	1,7
Stratum 3	tabs_many	1,7
Stratum 1	all_weak	1,3
Stratum 1	all	1,2

original. However, this property was lost anyway when extracting the individual methods from the class files.

Thirdly, some rdhs were configured too strongly, so that for some methods it was no longer assumed that they were written by a human. These rdhs were adjusted and their probabilities reduced accordingly (for example newlines_few). All results can be found in Table 5.

Once the aforementioned adjustments had been made and the feedback on the survey instrument had been implemented, the actual study was carried out.

PROLIFIC SURVEY

In this section we summarize the results of the main study conducted via prolific.

Figure 7.: Tool for rating a code snippet from the perspective of a survey participant.

1. Experimental setup: The survey was conducted using Tien Duc Nguyen's Code Annotation Tool (see Figure 7) along with the platform prolific[16] for the recruitment and payment of participants. The survey was conducted between 31 January and 7 February 2024. A total of 221 participants took part. Each of the 20 questionnaires was answered by 11 participants (similar to the survey of Scalabrino et al. [31]). In one survey, one more participant was assigned by mistake. We end up with a margin of error of 29.55% at a confidence of 95% for an individual snippet. However, we aggregate over strata and multiple snippets later to reduce the error of margin. Each questionnaire consists of 20 code snippets. Consequently, 400 different code snippets are rated in total. The questionnaires were configured in a way that each participant could only take part in one of the questionnaires. You can find the texts for the survey in Appendix III. The questionnaires were crafted as described in Section 3.5.

[16] `https://app.prolific.com/`, accessed: 2024-02-21

Table 6.: Target population for the prolific survey.

Type	Target Population
Target Audience	Java programmers
Unit of Observation	Java programmers
Unit of Analysis	Java programmers
Search Unit	Selected by Prolific (Programming Languages: Java)
Source of Sampling	Prolific

The target population consists of Java programmers selected by prolific. They may be students or work in industry. They can come from any country. Overall, there were no requirements other than familiarity with Java (see also Table 6).

The internal research questions are as follows:

- Does the well-readable-assumption (Assumption 1) hold?
- Does the poorly-readable-assumption (Assumption 2) hold?

The results for these questions are equally important, and thus none of them is prioritized over the other. To answer them, the assumptions are considered as hypotheses along with the following associated null hypotheses:

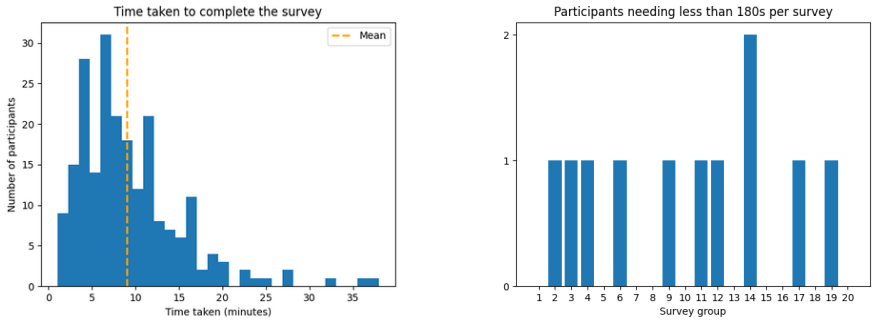
- For Assumption 1: The mined code (original) is better readable than the code from previous studies.
- For Assumption 2: The readability of code does not significantly deteriorate compared to the original code snippet.

The survey neither contained demographic questions nor filter questions. Besides the readability questions, each user was asked the following dependent question: "How would you describe your familiarity with Java?". The user could answer within a five point Likert scale: expert (5), advanced (4), intermediate (3), beginner (2), novice (1).

The expenditure for this survey was about €500.

2. Threats: We identified the following threats:

- **Ill-defined Target Population:** Ensuring a well-defined target population is critical to the survey's quality. To mitigate this threat, we define our target population. Additionally, we conduct a pre-survey evaluation (see Section 4.1) to ensure the adequacy of our target population definition. Thereby, we enhance content and construct validity.



(a) Time required by participants to complete the survey.

(b) Participants per questionnaire requiring less than 3 minutes.

Figure 8.: Time analysis of participants completing the prolific survey.

- **Sampling Method:** Stratified Sampling is well-defined and proven in practice. The approach ensures that our sample represents all parts of the population under investigation. This is improving the survey's external validity.
- **Insufficient Responses for Drawing Conclusions:** To prevent drawing conclusions from an insufficient number of responses, we scale our survey to an appropriate size. This guarantees that we collect a substantial volume of responses, allowing for robust statistical analysis.
- **Piece-work Effect:** Survey participants are paid for taking part and completing a questionnaire. However, they receive the same amount of money regardless of their speed. Therefore, they receive more pay per minute if they hurry. This could have an impact on the accuracy with which they scored the code snippets. A comparison between the time required by a participant for a pilot questionnaire and a prolific questionnaire (see Figure 6) supports this suggestion. Especially the ratings of participants requiring less than 3 minutes (see Figure 8b) to complete a questionnaire could have a negative impact on validity.

3. Results: An overview of the time required by the participants can be found in the Figure 6 and Figure 8a.

The participants' familiarity with Java is shown in Figure 9.

The ratings for each rdh for all strata combined can be found in Figure 10a and Figure 10b. Figure 10a shows that the mean value of our original methods is 3.68, while for all7 it is 3.26. We label each method in both groups with the corresponding mean score.

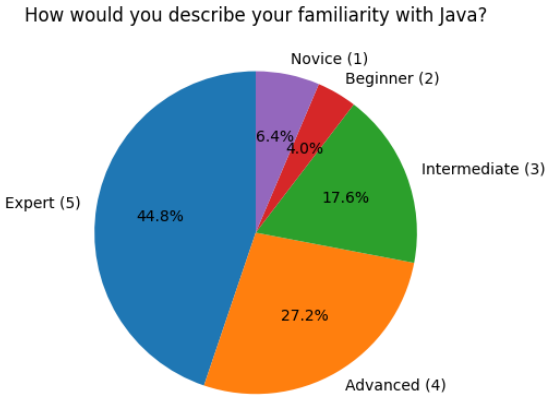


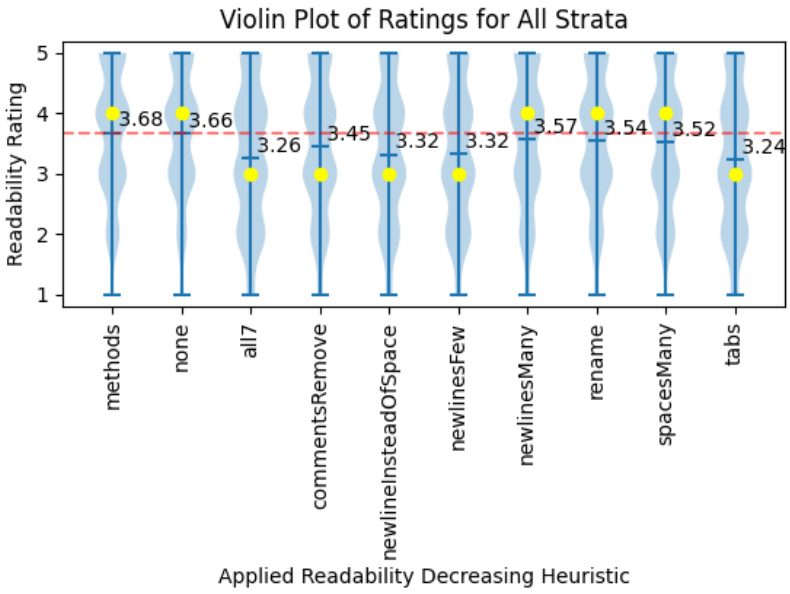
Figure 9.: Familiarity of prolific survey participants with Java.

Summary (RQ1 - select-well):

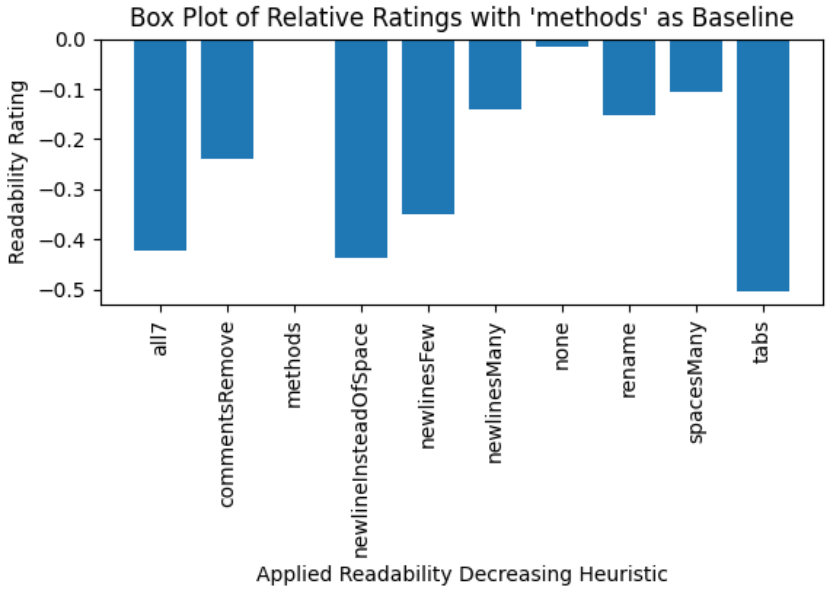
TODO: Add significance test. The readability ratings of code snippets mined from Github are not very accurate as we take the mean of all ratings for all methods and assign it to each snippet. However, the score of 3.68 is 0.23 larger than the mean score for all ratings in the merged dataset (3.45). Therefore we reject the null hypothesis and conclude that well readable assumption (Assumption 1) holds.

We analyzed whether the difference in ratings between the different rdhs is statistically significant. To do this, we used the Mann-Whitney U test to compare the ratings for all snippets for an rdh with the corresponding none rdh snippets. The results can be found in Table 7.

Our results suggest that no modification (none rdh) besides converting to the AST and back makes no difference to the original methods. The difference could just as well be due to random variation with a probability of 92 %. If we compare the rdhs with the none methods, we can be sure that the scores of all methods except newlines many and rename are indeed statistically different from the scores of none. If we consider binary readability classification and split the data for none and newlines many into into two classes (poorly readable: 1,2; well readable: 3-5) we also get significance that the ratings for newlines many are statistically significantly different from none (TODO: Add p Values). This leaves



(a) Absolute survey ratings for each rdh and all strata.



(b) Relative survey ratings for each rdh and all strata compared to original.

Figure 10.: Survey ratings for each rdh and all strata.

Table 7.: Mann-Whitney U test results of each rdh against none.

Comparison	p
None - Methods	9.22×10^{-1}
None - Newlines Few	5.23×10^{-6}
None - Spaces Many	4.07×10^{-2}
None - Newlines Many	3.00×10^{-1}
None - Comments Remove	3.64×10^{-3}
None - Rename	9.90×10^{-2}
None - Newline Instead Of Space	4.57×10^{-6}
None - Tabs	3.06×10^{-8}
None - All7	1.80×10^{-7}

only rename where we can not confirm statistical significance. Overall, this shows that the heuristics actually reduce the readability of the given code.

Summary (RQ2 - generate-poor):

All of the 7 heuristics but rename decrease readability by a significant extend compared to none. We estimate the readability decrease for a certain probability of a certain type as can be seen in Figure 10b. We reject the null hypothesis and conclude that the poorly readable assumption (Assumption 2) holds

4.2. MODEL TRAINING RESULTS

The results of the training, evaluation and fine-tuning can be found in the Table 8.

When we train the model on the new dataset and evaluate it with 10-fold cross-validation, we obtain an average accuracy of 91.8 %. However, if we evaluate the trained model on the merged dataset, we get an accuracy of only 61.9 %. From this we can draw some conclusions:

The towards model works well for our new dataset. However, the readability determined with the all dataset differs from the readability with the new dataset. Otherwise, the values for all-krod and krod-all would be similar to the value for all-all. This indicates that our dataset is not suitable for a general classification of readability, but we may have found a subproblem. However, adding more features to reduce readability and well-designed data augmentation could overcome this limitation.

Table 8.: Performance of different dataset configurations for the same model. New-Merged is training on the new dataset and fine tuning on the merged one.

Train	Eval	Acc	Prec	Rec	AUC	F1	MCC
New	New	91.8 %	92.3 %	91.3 %	91.8 %	91.7 %	83.6 %
New	Merged	61.9 %	63.6 %	63.6 %	63.6 %	63.6 %	23.6 %
Merged	Merged	53.8 %	52.6 %	77.8 %	65.2 %	62.8 %	08.7 %
Merged	Merged	84.7 %	87.7 %	82.3 %	85.0 %	83.7 %	70.4 %
New-Merged	Merged	80.4 %	84.0 %	73.8 %	78.9 %	77.2 %	60.0 %
New210	New210	80.9 %	82.7 %	77.6 %	80.2 %	78.9 %	60.9 %

While the model trained on the new dataset is able to classify readability to a certain degree, the opposite is not the case, as 53.8 % is almost a random classifier. This suggests that fine-tuning a model trained on the new dataset using the entire dataset could lead to better results than the original towards model.

To check whether our implementation of the model works correctly, we also included the merged-merged case in the comparison. Here we achieve a very similar accuracy to Mi et al. (84.7 % vs 85.3 %), which indicates that our implementation of the model works correctly.

We tried to fine-tune with the merged dataset by freezing different layers of the model trained with the new dataset. The best we could achieve was to freeze the input layers as well as the first convolution and pooling layer of all encoders. However, the performance of this fine-tuned model was still worse than the baseline model. This is in direct contrast to our earlier assumption that such fine-tuning could lead to better results. One explanation for this could be that the model is too small to be effective with the larger amount of data. Introducing more or bigger layers so that the model can store more features internally could lead to an improvement. However, this is not part of this work, in which we mainly focus on a new dataset (generation approach).

Summary (RQ3 - new-data):

An accuracy within the new dataset of 91.8 % surpasses all previous scores. However, the accuracy of 61.9 % when evaluating on the merged dataset suggests, that the new training data is less valuable than the merged one. We could neither improve this accuracy by applying fine-tuning. While it is possible that we successfully addressed a sub problem of readability, we are not able to improve existing readability models in general.

We also trained the model with a random sample of 210 data points to gain insight into what a change in training size might do. As we can see, the model has similar metrics to the all-all model. If we now compare the accuracy of the new-new compared to the merged-merged model, we see that with a larger dataset an improvement of about 8 % is possible. Similar results are suggested by previous research on data augmentation, where an accuracy of 87.3 % was achieved Mi et al. This emphasizes the importance of finding new ways of generating data for readability classification.

5. DISCUSSION

The main drawback of our approach is that we rely on estimations to create the new dataset. The score labels of our code snippets are rough estimations and not exact values. Accurate ratings would require manual review of 69k code snippets by human annotators and is therefore not feasible. However, for two class classification this does not matter.

A thread related to the study could be the sampling approach used. While we argue that we avoided spending resources on labeling rdh data that is likely not different from the original methods or rather uninteresting, this might also introduce statistical errors to our survey results.

When comparing the model performance trained on the new and merged data set, it should be noted that the merged data set is small. Consequently, comparisons between classifiers trained on the merged dataset may be unreliable [23].

6. CONCLUSIONS

Recent research in the field of code readability classification has mainly focused on various deep learning model architectures to further improve accuracy. Little attention is paid to the fact that only 421 labeled code snippets are available to train these models. We introduced a novel approach to generate data, with which we created a dataset of 69k code snippets. Although our results show that

the dataset does not have the same quality as previous data, it still captures the readability of code and could accordingly help to improve code classification in future research.

The new approach for generating data has an advantage that is not yet used in this work: For the first time, it is possible to generate a dataset with one well readable and a second, less readable and functionally equivalent code snippet. This could be used to train various models, including transformers. Such a transformer could take the code as input and improve its readability. We suspect that such a tool could be of great benefit to programmers.

A current limitation of the new dataset is that it only works for Java code. A suggestion for future work is to overcome this limitation by extending the tool for other programming languages. This is not trivial, as one has to adapt the Readability Decreasing Heuristics to work with another language. Furthermore, a general tool that works for all languages will be difficult if not impossible.

As Mi et al. suggested, another useful representation for code readability studies could be the syntax tree representation of code [18]. One could try to improve the performance of the towards model by adding another representation encoding extractor for Java code that automatically extracts the abstract syntax tree of the code.

An important aspect of the readability of code is the naming. For the scope of methods, the method names are the most important part. Therefore, the towards model could be improved by adding a component that explicitly takes into account how well a method name matches its body. This component might be similar to Code2vec [3].

Further research could also consist of finding and evaluating other encodings that represents the code in a different way.

Another way to improve existing code readability classifiers, such as the towards model, could be to develop a different structure for some layers of the model. We suggest increasing the size and depth of the layers so that the new dataset can be made useful. Alternatively, a completely different model architecture could be developed.

The heuristics described in this work are only part of the possible heuristics that could be developed. Additional heuristics could further improve the diversity of poorly readable code. This could increase the number of internal features that a model can learn, which in turn could increase the accuracy of the model.

In summary, there are many opportunities to further investigate and thus most likely improve the classification of code readability. Our new data set and the generation approach could be useful here.

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I. PILOT SURVEY FEEDBACK

How clear was your task?

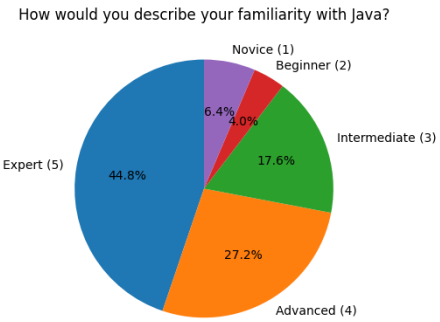

Figure 11.: TODO: Replace

What problems were with the task? If there were none, leave blank.

- Did at first not know where to rate the code.
- I was confused about the textfield for the comments because I only remembered that we should rate the code snippets, not that we have to make comments. Since I was not able to navigate back to the task description, I did not know what to do with them.
- Für einen Anfänger mit sehr wenig Java Erfahrung ist meiner Meinung nach der Code zu kompliziert.
- In the first place, I didn't really understand what readability meant. But after slide 3 or 4, I understood what this was about.
- I found it difficult to categorize the first examples because you don't know what's still to come. For example, what the least readable code is.

What problems were there with the survey tool? If there were none, leave blank.

- Mobile is not easy to use because of the scrolling needed to complete the survey.
- First, I needed to figure out how this tool works and that the rating is done with the stars below. I thought I should write my rating as a comment in

the comment field below. After number 20, I didn't know whether I could close the survey or not.

- I also thought that I should use the drop-down menu on the upper left.
- It is sometimes necessary to swipe horizontally to see all of the code, which is a bit inconvenient.
- Für einen Anfänger ist das Tool meiner Meinung nach nicht geeignet. Der Code ist zu verschachtelt und teilweise unverständlich.
- After finishing the task, at least a message should be shown.
- I didn't understand what the button at the top left meant, where you could select the programming language. There were too many fonts to choose. I also wasn't sure whether to write a comment or not. It wasn't described at the beginning.

What improvements would you make to the survey? If none, leave blank.

- Maybe one sentence that one should use the stars for the rating, then it would be clear. Also, the submit note after the last question could contain that one can close the survey now.
- I suggest making the task description accessible during the rating.
- Maybe the option to leave the survey when clicking to submit.
- Mehr Hilfestellung zum Lesen des Codes. Mehr Beschreibung oder ein zusätzliches Cheat Sheet mit Bedeutungen von Befehlen.
- I think it's a good idea to ask the participant at the beginning to explain what readability means for him.
- I would leave out the buttons described above. I was missing a scrollbar at the bottom of the code-window. A conclusion page with a message like "Thank you for your participation", "You're Done!" or other further information was missing, too.

Do you have any other feedback? If none, leave blank.

- There were drop downs for the programming language, but choosing another language did not change anything. It was a bit confusing that (almost?) all code snippets had very long imports within the code, which made them poorly readable.
- I spent the most time understanding methods with complete Java import names. (org.foo.bar.ClassName).

- GOOD LUCK

II. READABILITY DECREASING HEURISTICS CONFIGURATION FILE

```
newline:
- 0.0  # Probability for no newline
- 1.0  # Probability for one newline
incTab:
- 0.0  # Probability for no tab
- 1.0  # Probability for one tab
decTab:
- 0.0  # Probability for no tab
- 1.0  # Probability for one tab
space:
- 0.0  # Probability for no space
- 1.0  # Probability for one space. Must be 1.0
newLineInsteadOfSpace: 0
spaceInsteadOfNewline: 0
incTabInsteadOfDecTab: 0
decTabInsteadOfIncTab: 0
renameVariable: 0
renameField: 0
renameMethod: 0
inlineMethod: 0
removeComment: 0
add0: 0
insertBraces: 0
starImport: 0
inlineField: 0
partiallyEvaluate: 0
```

III. PROLIFIC SURVEY TEXTS

On Prolific:

Readability of Java Code

We study the readability of Java source code. Therefore, please read Java methods and rate their readability on a scale from 1 (very unreadable) to 5 (very readable).

At the top of the tool:

Readability of Java Code

Read the Java methods and rate their readability on a scale from 1 (very unreadable) to 5 (very readable) using the stars below the code box. To navigate between methods, use the arrows above or below the code box. Make sure to rate each snippet.

Introduction page 1:

This study aims to investigate the readability of Java source code. In this survey, we will show you 20 Java methods. Please read the methods thoroughly and rate how readable you think they are. Before we begin, please answer the following question:

How would you describe your familiarity with Java?

1. Expert
2. Advanced
3. Intermediate
4. Beginner
5. Novice

Introduction Page 2:

Below is an example of the interface for displaying and rating the code. Use the stars below the code box for your rating. Please rate the readability on a scale from 1 (very unreadable) to 5 (very readable). At the top left, you can adjust the syntax highlighting and theme (dark/light) according to your preferences (optional). Comments are not available during this survey.

[EXAMPLE]

Introduction Page 3:

This survey should take about 10 minutes to complete. Now you are ready to go!