Styler: Learning Formatting Conventions to Repair Checkstyle Errors

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Abstract—Formatting coding conventions play an important role on code readability. In this paper, we present Styler, an automatic repair tool dedicated to fix formatting-related errors raised by Checkstyle, a highly configurable format checker for Java. To fix formatting errors in a given project, Styler learns fixes based on the Checkstyle ruleset defined in the project and predicts repairs for the current errors using machine learning. In an empirical evaluation, we found that Styler repaired 24% of 497 real Checkstyle errors mined from five GitHub projects. Moreover, in a comparison of Styler with the state-of-the-art machine learning code formatters Naturalize and CodeBuff, we found that Styler is the tool that fixes more real Checkstyle errors and also generates smaller repairs. Finally, we conclude that Styler is promising to be used in IDEs and in a Continuous Integration environment to repair Checkstyle errors.

I. INTRODUCTION

Code readability is the first requirement for program comprehension: one cannot comprehend what one cannot easily read. To improve code readability, most developers agree on using coding conventions, so the code is clear and uniformly consistent across a given code base or organization [1], [2].

A major challenge of using coding conventions is to keep all source code files consistent according to the conventions. For that, two main activities must be performed: the detection and the repair of coding convention violations (or errors). The detection of violations can be automatically performed using linters, which are largely used across major programming languages [3]. There are several classes of coding convention that a linter covers, such as formatting-related ones, which are the focus of this work. Therefore, in this paper, we refer to the part of a linter related to formatting as format checker.

To repair a formatting-related convention violation detected by a format checker, developers can either perform the fix manually or use a code formatter. Both alternatives are not satisfactory. Manually fixing coding convention violations is a waste of valuable developer time. With code formatters, the key problem is that they do not take into account the convention rules already configured by the developers for the used format checker.

Inspired by the problem statement of program repair [4], we state in this paper the problem of automatically repairing formatting convention errors: given a program and its format checker rules with at least one rule violation, the goal is to modify the source code formatting, so that no violation is raised anymore by the format checker. In our work, we explore this problem in the context of Checkstyle, a format checker for the Java language. Interestingly, there may be several repairs that all fix the same format checker error, including ones that change other lines in the program rather than the location of the error. This means that the problem statement has an interesting refinement: it is also pertinent to produce the smallest possible formatting repair, which ideally only touches the ill-formatted line.

In this paper, we present Styler, a repair tool dedicated to fix Checkstyle formatting errors in Java source code. The uniqueness of Styler is to be applicable to any formatting coding convention. The key idea of Styler is the usage of machine learning to learn the coding conventions that are specified in a software project. Once trained, Styler predicts where to add or remove formatting characters (e.g. whitespaces, new lines, indentation) in order to fix a formatting convention violation. Technically, Styler uses a sequence-to-sequence machine learning model based on a long short-term memory neural network (LSTM).

We conducted a large scale experiment to evaluate Styler using 497 real Checkstyle errors. Based on four research questions, we found that 1) Styler is able to repair Checkstyle errors based on its novel learning procedure; 2) Styler repairs more real errors than the state-of-the-art of code formatters [5], [6]; 3) Styler produces small and focused repairs; and 4) its prediction time is low (one second on average). To our knowledge, Styler is the first system that repairs Checkstyle errors without a single hard coded strategy for fixing formatting errors.

To sum up, our contributions are:

• A novel approach to fix violations of formatting conventions, capable of learning conventions from any project configured with any arbitrary formatting configuration;
• A tool, called Styler, which implements our approach in the context of Java and Checkstyle [7], which is made publicly available for future research [8];
• A dataset of reproducible formatting-related Checkstyle errors, which contains 497 real errors mined from five GitHub repositories;
• A comparative experiment to evaluate the performance of Styler against two recent code formatters from the state-of-the-art [5], [6].
The remainder of this paper is organized as follows. Section II presents the background of this work, followed by a study we performed on Checkstyle usage in the wild presented in Section III. Section IV presents STYLER, including its workflow and steps. Section V presents the design of our experiment for evaluating STYLER and comparing it with two code formatters: the experimental results are presented in Section VI. Finally, Section VII presents the related works, and Section VIII presents the final remarks.

II. BACKGROUND

A. Coding Conventions

Coding conventions are rules that developers agree on for writing code. They are also referred to as coding style or coding standards. The usage of coding conventions improves code readability and maintainability but it does not change the program behavior.

There are several coding convention classes: naming, control flow style and formatting. In this paper, we focus on the latter: formatting coding conventions. Formatting here refers to the appearance or the presentation of the source code. One can change the formatting by using non-printable characters such as spaces, tabulations and line breaks. In free-format languages such as Java and C++, the formatting does not change the abstract syntax tree, while there are languages such as Haskell or Python where formatting is related to behavior.

For instance, a well-known formatting coding convention is about the placement of braces in code blocks. Figure 1 shows two ways that developers may follow when writing conditional blocks: one developer might place the left brace in a new line, while another one might place it in the end of the conditional line. Agreeing on coding conventions avoids edit wars and endless debates: all developers in a team decide on how to format code once and for all.

```java
if (condition) {
    // do something
    if (condition) {
        // do something
    }
}
```

(a) Left curly in a new line. (b) Left curly in the end of line.

Fig. 1: Two ways of placing left curly brace in code blocks.

B. Coding Convention Checkers

A challenge faced by developers is to keep their code compliant with the agreed coding conventions. Basically, every new change, every new commit must satisfy the convention rules. Manually checking whether new code changes do not violate the coding conventions is not an option because it would be too time-consuming and error-prone.

To overcome this problem, a mechanism to automatically check whether code follows the coding convention rules is required. Such a tool is known as a linter. A linter is a static analysis tool that warns software developers about possible code errors or violations of coding conventions [3]. Note that linters may go beyond coding conventions and also perform some basis static analysis on the program behavior.

Linters, or coding convention enforcers [9], usually can be integrated in IDEs and/or in build tools. When integrated in IDEs, the developer manually runs the linter before she commits her changes. If she does not do it, she might face a lot of errors raised by the linter after the end of the building step for a release or for shipping the program. On the other hand, when a linter is integrated in build tools, it is automatically executed in continuous integration (CI) environments. The important coding conventions might be configured to make CI builds break when they are violated. This way, developers are forced to repair coding convention violations early in the software development process.

Several linters have been developed depending on the programming language: e.g. ESLint [10] for JavaScript, PyLint [11] for Python, StyleCop [12] for C#, RuboCop [13] for Ruby. For Java, which is our target language in this paper, the most commonly used coding convention enforcer is Checkstyle [7]. Checkstyle supports predefined well-known coding conventions, such as the Google Java Style Guide [2] and the Sun Code Conventions [14]. Checkstyle also allows developers to configure a specific ruleset to match their own preferences. Checkstyle is a flexible linter that can be integrated in both an IDE (e.g. IntelliJ, Eclipse, and NetBeans) and in a build tool (e.g. Maven and Gradle). In the Java ecosystem, Checkstyle is often executed in Continuous Integration environments, such as Travis and Circle CI.

III. STUDY OF CHECKSTYLE USAGE IN THE WILD

To date, there is little empirical knowledge of how coding convention enforcers are used in the wild, despite their wide usage by practitioners. To fill this gap and to found our work on a solid empirical basis, we investigate the usage of Checkstyle in open source projects. In this section, we report on our study to measure the popularity of Checkstyle and to understand which Checkstyle rules are used.

A. Checkstyle Usage

Method. To obtain projects using Checkstyle, we queried GitHub for open source projects having the ‘maven-checkstyle-plugin’ specified in their build configuration (the pom.xml file). We retrieved ~106K results. For a given repository, we can have several hits, since the repository can have several pom.xml files all with the keyword ‘maven-checkstyle-plugin’. We analyzed all of these entries to generate a list of unique repositories, resulting in 16,252 open source projects (on November 2, 2018). Once we obtained these projects, we searched them for the presence of Checkstyle configurations (a checkstyle.xml file), and for the presence of continuous integration configuration file (.travis.yml file). By doing so, we obtained a short list of projects that use both Checkstyle and Travis CI.

Results. We found 5,177 (31.85%) projects containing the checkstyle.xml file, and 3,065 (18.86%) having a .travis.yml file. There are 1,519 projects (9.35%) that
belong to both sets of projects. Checkstyle is a heavily used development tool over the sampled Java/Maven projects.

B. Checkstyle Rules’ Usage

Method. To check the Checkstyle rules usage in the wild, we extracted the rules from the checkstyle.xml file contained in the 5,177 projects that use Checkstyle.

Results. We found 296 different rules being used in the considered projects: 155 of these rules are predefined Checkstyle rules, and we observe 141 rules manually created by developers to specify a coding convention that is not present out-of-the-box in Checkstyle. Note that Checkstyle has currently 156 rules, which means that all but one rules are actually used in practice (AnnotationOnSameLine is never used in our sample).

The rule prevalence is high: almost half of the rules (47.44%) are used in more than 1K projects. Figure 2 shows the usage of the top-10 rules related to formatting, which is the target of this paper. The most used rule is RightCurly, used in 3,814 projects. The usage of each rule is very varied, ranging from 3,814 to 287 projects per rule. Twenty-one formatting rules are used in more than 1K projects.

Fig. 2: The top-10 Checkstyle rules related to formatting.

IV. STYLER

STYLER is a repair tool dedicated to fix Checkstyle formatting-related errors in Java source code according to a given Checkstyle ruleset. In this section, we present the technical principles and architecture of STYLER.

A. Checkstyle Error Class

STYLER is about learning and repairing errors related to formatting coding conventions (see Section II-A). For instance, consider that a developer specified that her preference is that the left curly token “{” in a conditional block must always be placed in a new line (as shown in Figure 1a). If this rule is not satisfied, Checkstyle triggers a formatting-related error (see Figure 4a). In order to fix this violation, a new line break should be inserted in the program before the token “{”.

In Checkstyle, there are different classes of checks: some are about formatting, some are about naming, some are lightweight linting checks. In STYLER, we exclusively focus on formatting checks: indentation, whitespace before and after punctuation, line length etc. We ignore Checkstyle errors that are not related to formatting, e.g. UnusedImports and MethodName, etc.

B. STYLER Workflow

Figure 3 shows the STYLER workflow. It is composed of two main components: ‘STYLER training’ for learning how to fix formatting errors and ‘STYLER prediction’ for actually repairing a concrete Checkstyle error. STYLER receives as input a software project, including its source code and its Checkstyle ruleset.

The component STYLER training is responsible for learning how to repair Checkstyle errors on the project according to its project-specific Checkstyle ruleset. It creates the training data based on source code files in the project (step A). Then, it translates the training data into abstracted token sequences (step B) in order to train a LSTM neural network (step C). The learned LSTM model is eventually used to predict repairs.

The component STYLER prediction is responsible for predicting fixes for Checkstyle errors. It first localizes Checkstyle errors by running Checkstyle on the project (step D). Then, STYLER encodes the error line(s) into an abstracted token sequence (step E). Then, the token sequence is given as input to the LSTM model (step F). The model predicts fixes for the given Checkstyle error based on the learned model (learned in the STYLER training). These fixes are in the format of abstracted token sequences, so they are translated back to Java code (step G). Finally, STYLER runs Checkstyle on the new file containing the predicted fix (step H). If no Checkstyle error is raised, it means that STYLER has successfully repaired the error. As STYLER only impacts the formatting of the code, its repairs never change the abstract-syntax tree of the code and its behavior.

C. STYLER in Action

Consider the error presented in Figure 4a. This error was raised by a violation of the Checkstyle LeftCurly rule: the left curly should be on a new line. Checkstyle provides, for a given error, the location (line and column) where the Checkstyle rule is violated. The Java source code that caused such an error is shown in Figure 4a.

STYLER encodes the incorrectly formatted lines (Figure 4b) into the abstracted token sequence shown in Figure 4c. Then,
In order to have enough data for learning, our key insight is to generate the training data. The idea is to modify Java source files in the project in order to trigger Checkstyle-formatting rule violations. Then, one obtains a pair of files: $\alpha$ is the one without the formatting error, and $\beta$ is the one with the formatting error. $\alpha$ is a repaired version of $\beta$, and we can use supervised machine learning to predict $\alpha$ given $\beta$.

The protocol for injecting Checkstyle errors in a project consists of automated insertion or deletion of formatting characters (spaces, tabulations, and new lines) in Java source files. These modifications require a careful procedure in order 1) for the project to still compile 2) not to change the behaviour. For this, we specify the locations in the source code files that are suitable to perform the modifications. For insertions, the suitable locations are before or after any token. For deletions, the suitable locations are 1) before or after any punctuation (`,` `;` `(` `)` `[` `]` `{` `}` `;`); 2) before or after any operator (`+` `-` `*` `=` `+=` ...); and 3) in any token sequence longer than one indentation character.

\begin{algorithm}
\caption{Injection of a Checkstyle error in a file.}
\label{algorithm:checkstyle-injection}
\begin{algorithmic}
\Input program source code
\Input ruleset Checkstyle configuration
\Input files from program that are allowed to be selected
\Output file' with Checkstyle error(s)
\State var modification_types: a set of pre-defined modification types
\State file ← select_random_file(f{	extprime}iles)
\State errorInjected ← FALSE
\While errorInjected \texttt{not true} do
\State modificationType ← random(modificationTypes)
\State file' ← applyModification(modificationType, file)
\If length(file').length <> length(file) \texttt{then}
\State go to line 4
\EndIf
\State checkstyleErrors ← run_checkstyle(ruleset, file')
\If length(checkstyleErrors) <> 1 \texttt{then}
\State go to line 4
\EndIf
\State save_file(file')
\State errorInjected ← TRUE
\EndWhile
\State return file'
\end{algorithmic}
\end{algorithm}

Algorithm 1 is executed $X$ times on the project in order to artificially create $X$ Checkstyle errors. The input for the algorithm is the project, and a set of source code files without any prior Checkstyle error. Then, the algorithm selects a random file from the set of files to be used for the injection (line 2). A loop (in line 4) makes sure that the algorithm only stops when a single Checkstyle error was successfully injected in the selected file. Inside that loop, a random modification type – insertion or deletion and the character used – is selected (line 5). Next the modification type is applied to the file, generating a new version of the format (line 6). If the number of Java tokens in the modified file is different than the number of tokens in the original file (line 7) it means the injected modifications accidentally went beyond formatting. In this case, the modification is simply discarded and the algorithm proceeds with a new injection (line 8). Otherwise, Checkstyle is executed on the modified file (line 10). If there exists zero or more than one Checkstyle error (line 11), the algorithm tries...
again an injection (line 12). Otherwise, a single Checkstyle error was successfully injected in a file of the program, which is the output of the algorithm (line 17). This is a sample that can be used for training.

E. Token Abstraction

STYLER encodes the Java source code into an abstract token sequence that is required to predict formatting changes.

Mapping Java source code to abstract tokens. We first parse the Java file containing a Checkstyle error. Then, we translate each Java token to an abstract token by keeping the value of the Java keywords, separators, and operators (e.g. + → +) and by replacing the other token types such as literals, comments, and identifiers by their types (e.g. x → Identifier).

We create formatting tokens as follows. For each pair of subsequent Java tokens, we create an abstract formatting token that depends on the presence of a new line. If there is no new line, we count the number of whitespaces, and we represent it like n_SP, where n is the number of whitespaces (i.e. → 1_SP). If there is no whitespace between two Java tokens (e.g. x=), we add 0_SP between the tokens. The same process is applied for tabulations.

If there are new lines between two Java tokens, we first count the number of new lines: we represent it as n_NL, where n is the number of new lines. Then, we calculate the indentation delta (Δ) between the line containing the previous token and the line containing the next token: the delta is the difference of the indentation between the two lines (the indentation is composed of whitespace or tabulation characters, exclusively, depending of the project). Positive indentation deltas are represented by Δ_ID (indent), negative ones are represented by Δ_DD (dedent), and deltas equal to zero (there is no indentation change between two lines) are ignored, they are not represented by an abstract token. The complete representation after the calculation of the number of new lines and the indentation delta is n_NL_Δ(ID/DD); for instance, in Figure 4b, the new line between lines 812 and 813 is represented by 1_NL_4_ID, i.e. one new line and indentation delta +4.

Gliding Window. In order to repair formatting errors, the abstraction must capture both the error in the code and the context surrounding the error. Therefore, STYLER considers a token window of k lines before and after the error. The exact value of k is made big enough to contain important information, and at the same time, to not include information that may add some noise during learning and prediction.

Once the context surrounding the error is tokenized, we place two tags around the error for further identification of the location of the error and the Checkstyle error type. The tag consists of the name of the Checkstyle-rule that was broken and raised the error. For instance, the error presented in Figure 4a is about the Checkstyle-rule LeftCurly, so the tags around the error are <LeftCurly> and </LeftCurly> as shown in Figure 4c.

To insert the tags concerning the error type in the token sequence, we need to find a place so that they surround the tokens related to the origin of the error, and at the same time to minimize the number of tokens between the two tags to have precise information about the location. We place the tags according to the location information given by Checkstyle (line and column). When Checkstyle provides the line and the column, we put the <ErrorType> n tokens before the error and </ErrorType> n tokens after. When Checkstyle provides the line but not the column (i.e. when the error is a violation on the LineLength rule), we include all the tokens of the line and we place the <ErrorType> i tokens before and </ErrorType> j tokens after. In the experiment presented in this paper, we set k = 5, n = 10, i = 2, and j = 13 based on meta-optimization (see Section V).

In the end of the tokenization, the token sequence includes abstract tokens for all Java tokens plus formatting tokens, as shown in Figure 4c. By construction, each abstract token for a Java token is followed by a formatting token. For this reason, the token sequence always has twice as much as the number of real tokens in the considered Java source code snippet.

F. Machine Learning Model

Learning (Figure 3–step C). STYLER aims to translate a buggy token sequence (input sequence) to a new token sequence with no Checkstyle errors (output sequence). STYLER uses a sequence-to-sequence translation based on a recurrent neural network LSTM (Long Short-Term Memory), similar to what is used for natural language translation. Thanks to the token abstraction employed by STYLER (Section IV-E), the input and output vocabularies are small enough (resp. ~150 and ~50), and well handled by the state-of-the-art of LSTM models. We use LSTM with bidirectional encoding, which means that the embedding is able to catch information on the surrounding context in the two directions, which is especially good in our case: for instance, an error triggered by the Checkstyle rule WhitespaceAround, which checks that a token is surrounded by whitespaces, requires both contexts before and after the token.

Predicting/Repairing (Figure 3–step F). Once the LSTM model is trained, STYLER can be used for predicting fixes for an erroneous sequence I as in Figure 4c. For an input sequence I, the LSTM model predicts n alternative formatting token sequences. These alternatives are all potential repairs for the formatting error (Figure 4d). In LTMs, the standard to generate multiple predictions is a technique called beam search, that we use off-the-shelf.

Note that the LSTM model predicts formatting token sequences, but the goal is to have token sequences containing Java and formatting tokens, so they can further be translated back to Java code. Then, STYLER generates a new abstracted token sequence (O_i) for each formatting token sequence (F_i), based on the original input I, such as in Figure 5a.

Recall that I is composed of pairs of Java tokens and formatting tokens (see Section IV-E), therefore its number of formatting tokens is \( L_I = \text{length}(I)/2 \). However, an
LSTM model does not enforce the output size, thus we cannot guarantee that the length of a predicted formatting token sequence \(L_F = \text{length}(F_i)\) is equal to \(L_I\).

If \(L_F > L_I\), STYLER uses the first \(L_I\) formatting tokens from \(F_i\) and ignores the remaining ones to generate \(O_i\), such as in Figure 5b.

If \(L_F < L_I\), STYLER uses all formatting tokens from \(F_i\), and copies the \(L_F + 1, L_F + 2, \ldots, L_I\) original formatting tokens from \(I\), such as in Figure 5c.

Finally, after creating \(n\) abstracted token sequences \(O_i\), STYLER continues its workflow (Figure 3–step G).

\[
\begin{align*}
F_1 & = \text{Error} (\text{0_SP \ Identifier 0_SP}, \text{1_SP \ Identifier 1_SP}) \\
O_1 & = \text{Error} (\text{0_SP \ Identifier 1_SP}, \text{1_SP \ Identifier 1_SP}) \\
I & = \text{Error} (\text{0_SP \ Identifier 0_SP}, \text{1_SP \ Identifier 1_SP})
\end{align*}
\]

(a) \(\text{length}(F_i) = \text{length}(I)/2\).

\[
\begin{align*}
F_1 & = \text{Error} (\text{0_SP \ Identifier 0_SP}, \text{1_SP \ Identifier 1_SP}) \\
O_1 & = \text{Error} (\text{0_SP \ Identifier 1_SP}, \text{1_SP \ Identifier 1_SP}) \\
I & = \text{Error} (\text{0_SP \ Identifier 0_SP}, \text{1_SP \ Identifier 1_SP})
\end{align*}
\]

(b) \(\text{length}(F_i) > \text{length}(I)/2\).

\[
\begin{align*}
F_1 & = \text{Error} (\text{0_SP \ Identifier 0_SP}, \text{1_SP \ Identifier 1_SP}) \\
O_1 & = \text{Error} (\text{0_SP \ Identifier 1_SP}, \text{1_SP \ Identifier 2_SP}) \\
I & = \text{Error} (\text{0_SP \ Identifier 0_SP}, \text{1_SP \ Identifier 1_SP})
\end{align*}
\]

(c) \(\text{length}(F_i) < \text{length}(I)/2\).

Fig. 5: Generation of the sequence \(O_i\) based on the predicted formatting tokens \(F_i\) and the input \(I\).

G. Implementation

STYLER is implemented in Python. We use javalang [15] package for parsing and OpenNMT-py [16] for the machine learning part. The code is publicly available [8].

The main model configuration is as follows: the token embedding is of size 64, we train the LSTM model over 50,000 iterations with a batch size of 8, with the data produced as described in Section IV-D. The beam search creates \(n = 5\) potential repairs.

V. Evaluation Design

A. Research Questions

RQ #1 [Feasibility]: To what extent does STYLER properly work on a synthetic setup that is completely controlled?

To answer this research question, we conducted an experiment on a large dataset of synthetic Checkstyle errors (see Section V-B1) that we created using STYLER’s approach for generating training data. Then, we calculated to what extent STYLER repairs these synthetic errors. This allows us to verify if STYLER is able to create enough training data so that the learning can be effective for repairing formatting errors.

RQ #2 [Accuracy]: To what extent does STYLER repair Checkstyle errors mined in the wild, compared to other systems? STYLER might work properly from a technical viewpoint (RQ #1), but, to measure its real value, we conducted an experiment on real Checkstyle errors mined from GitHub repositories (see Section V-B2). This allows us to understand to what extent STYLER repairs formatting errors that have occurred in practice. Moreover, we compare STYLER to state-of-the-art code formatters (see Section V-C) to investigate if, and to what extent, STYLER outperforms the competing methods.

RQ #3 [Quality]: What is the size of repairs generated by STYLER, compared to other systems?

There may be several repairs that fix a given Checkstyle error, including ones that change other lines in the program rather than only the ill-formatted line. In this research question, we compare the size of the repairs produced by STYLER against the repairs from other systems.

RQ #4 [Performance]: How fast is STYLER for learning and for predicting formatting repairs?

Finally, we investigate the performance of STYLER for fixing Checkstyle errors: this is a valuable information for who is interested in using STYLER as a pre-commit hook in IDEs or in a Continuous Integration environment.

B. Datasets

In this section, we describe the approaches we used for creating the datasets, including one dataset of synthetic errors and one containing real formatting errors collected on GitHub/Travis.

1) Synthetic-error dataset: To create the synthetic-error dataset, we first selected projects and then we injected formatting errors in them. For selecting projects, we first selected the ones that were active in November, 2018 from the 1,519 projects that use Checkstyle presented in Section III: this resulted in 147 projects. Second, for each project, we ran Checkstyle, and we discarded the ones in which Checkstyle errors were raised: to inject errors, we need a version of a given project without errors. Third, we discarded small projects in order to have enough different files to inject errors (in our case less than 20 files). Finally, when we had ten projects that passed through those three filters, we stopped looking for projects.

For injecting errors in the projects, we used the same injection protocol presented in Section IV-D for creating training data. The usage of the same protocol for creating synthetic errors is meaningful to validate the feasibility of STYLER (RQ #1), i.e. if the data generated during the learning process is effective for repairing errors created in the same way. We executed the Algorithm 1, 1,000 times per project in order to create 1,000 seeded formatting errors of it, each one containing a single Checkstyle formatting error.

2) Real-error dataset: To create the dataset of real Checkstyle errors, we first selected projects from GitHub that use both Checkstyle and Travis CI, out of two datasets: 1) Blue–dataset: from the 147 active projects that we used in the synthetic-error dataset creation, we found 30 projects also containing actual Checkstyle errors in Travis CI logs; and 2) TaleCI-dataset: from 349 projects used in [17], we found 18 projects with Checkstyle errors in Travis CI logs.
From the 47 projects (30 + 18, where one project overlaps, “square/okhttp”), we try to reproduce Checkstyle errors with the following procedure. For each project, we first clone the remote repository from GitHub. Then, we search in the history of the project for the last commit \(c_n\) that contains modifications in the `checkstyle.xml` file: this commit is used as a starting point for the reproduction of real errors.

We perform a sanity check in `checkstyle.xml` file from the commit \(c_n\), to be sure that we can properly run Checkstyle on the project: we check if the `checkstyle.xml` file does not contain any unresolved variable from Maven or any other build tool; second, we check if additional configuration files referred in the `checkstyle.xml` file can be found.

If the project passes through these sanity checks, we gather all commits since \(c_n\), inclusive: this process ensures that all commits are based on the same version of the Checkstyle ruleset. For each selected commit, we check it out, and we check if the `pom.xml` file overrides any Checkstyle configuration option: if it does, we discard that commit because we cannot untangle the Maven+Checkstyle configuration with high accuracy. Otherwise, we run Checkstyle on the commit source tree. If at least one Checkstyle error is raised, we save the Java files where the errors happened and also the metadata information about the errors (the Checkstyle error types and their location).

We note that there are projects where the same Checkstyle errors happen over and over again in sequential commits, i.e. the developers do not fix them just when they happen for the first time. This is a potential bias for our results. To overcome this problem, we search for duplicate Java files (according to the file content) among all files that we saved after reproducing Checkstyle errors, and we keep only one file when duplicates are found.

After the removal of duplicates, we select files containing a single Checkstyle error related to formatting. We perform this selection to accurately evaluate repairs predicted by `STYLER`. Finally, we keep projects where all criteria yield at least 20 errors related to formatting. By applying this systematic reproduction and selection process, the final dataset contains 497 real Checkstyle errors spread over 5 projects.

C. Systems Under Comparison

We selected two state-of-the-art formatting systems to be compared with `STYLER`. They are both based on machine learning and aim to assist developers to fix code formatting-related issues without any prior or ad-hoc formatting rules. We do not use IDE-based tools because they require manual configuration.

1) `NATURALIZE`: `NATURALIZE` [5] is a tool dedicated to assist developers on fixing coding conventions related to naming and formatting in Java programs. It learns coding conventions from a codebase and suggests fixes to developers such as variable renames and formatting modifications, based on the n-gram model.

2) `CODEBUFF`: `CODEBUFF` [6] is a generic code formatter applicable to any programming language with an ANTLR grammar. Instead of formatting the code according to ad-hoc rules for a language, `CODEBUFF` aims to infer the formatting rules given a grammar for the language and a set of files following the same formatting rules. For each token, a KNN model makes the decision to indent it or to align it with another token based on the AST of the source file.

D. Setting-up the Tools

1) `NATURALIZE` and `CODEBUFF` adaptation: To use `NATURALIZE`, we slightly modified it: i) `NATURALIZE` recommends multiple fixes, so we take the first recommendation for a given error as being the repair; and ii) we changed `NATURALIZE` to only work for indentation, excluding fixes regarding naming conventions (which are out of the scope of this paper). To run `CODEBUFF`, we give it the required configuration, incl. the number of spaces for indentation. This number is based on the most common indentation used in the considered projects (usually two or four spaces).

2) Training tools: We trained `STYLER` for each project in our two datasets (see Section V-B). The training process includes a step for creating the training data (see Figure 3—step A), where we set for the creation of 9,000 errors per project.

To conduct a fair evaluation, we ensure that i) `STYLER` learns repairs based on the same Checkstyle ruleset that was used to trigger the errors to be repaired in the evaluation, and ii) `STYLER` does not capture potential repairs that occurred after the errors themselves. Therefore, we selected files for training `STYLER` as follows. For each project from the synthetic dataset, we selected a set of error-free files based on the same commit that we used to generate the synthetic errors (Section V-B1) so that the files for training and the files for testing (evaluation) are different. For each project from the real-error dataset, we selected all files without errors from the last commit that modified the `checkstyle.xml` file used to collect the real errors (Section V-B2).

We take special care of reducing randomness in the observed results: all three systems, `STYLER`, `NATURALIZE` and `CODEBUFF` were trained using the same Java files.

3) Testing tools: Finally, having trained `STYLER`, `NATURALIZE`, and `CODEBUFF`, and setting up `NATURALIZE` and `CODEBUFF` to work for our purpose, we run `STYLER` to try to repair the 10,000 errors (10 projects × 1,000) from the synthetic dataset (for RQ #1), and we run all the three tools to try to repair the 497 errors from the real-error dataset (for RQ #2, RQ #3, and RQ #4).

4) Summary of the training and testing data: Table I shows the number of projects, Checkstyle errors, and violated Checkstyle rules on the training data created by `STYLER` and on the testing synthetic and real-error datasets. In total, we obtained 10,497 errors from 15 projects for testing `STYLER`. The two datasets are complementary: the strength of the synthetic dataset is its size, both in terms of the number of errors and the number of violated rules, while the strength of the real-error dataset is its representativeness of problems happening in the field.
TABLE I: Statistics on the training and testing data.

|        | Dataset | # projects | # errors | # rules |
|--------|---------|------------|----------|---------|
| Training | Synthetic | 15 | 135,000 | 31 |
|         | Synthetic | 10 | 10,000 | 31 |
| Testing | Real     | 5  | 497     | 9      |
|         | Total    | 15 | 10,497 | 31 |

VI. EVALUATION RESULTS

A. Experiment on the Feasibility of STYLER using Synthetic Checkstyle Errors (RQ #1)

To evaluate the feasibility of STYLER, we run it on synthetic errors in a controlled setup, and we calculate the proportion of successfully repaired errors over the total number of synthetic errors. We found that STYLER has an overall accuracy of 97.5% across all projects. It means that the considered LSTM is able to fix the formatting errors for all projects (recall that each project has a specific Checkstyle configuration). Moreover, STYLER shows a stable effectiveness: its accuracy ranges in the interval [96%, 99.3%] for the errors from 10 projects.

RQ #1: To what extent does STYLER properly work on a synthetic setup that is completely controlled? STYLER has an overall accuracy of 97.5% over 10,000 synthetic Checkstyle errors from ten projects. STYLER’s machine learning model is able to capture the Checkstyle configuration for each project, with stable high effectiveness. Our approach to generate training data is novel and promising for future research on machine learning on code beyond format repair.

B. Experiment on the Accuracy of STYLER using Real Checkstyle Errors (RQ #2)

To evaluate the effectiveness of STYLER, we run it on real errors mined from GitHub repositories. We also compare STYLER against NATURALIZE and CODEBUFF, and the main metric is still the number of successfully repaired errors. Table II shows the results: STYLER, NATURALIZE, and CODEBUFF are presented as columns, and the five projects from the real-error dataset are presented one per row.

TABLE II: Correct repairs on real errors (RQ #2).

|         | STYLER | NATURALIZE | CODEBUFF | # errors |
|--------|--------|------------|----------|----------|
| okhttp  | 16 (18.6%) | 11 (12.8%) | 2 (2.3%) | 86 |
| dagger | 11 (47.8%) | 19 (82.6%) | 7 (30.4%) | 23 |
| nino   | 71 (24.8%) | 2 (0.7%)  | 2 (0.7%) | 286 |
| picasso| 3 (6.1%)  | 3 (6.1%)  | 3 (6.1%) | 49  |
| be5    | 17 (32.1%) | 49 (92.5%) | 52 (98.1%) | 53 |
| Total  | 119 (23.9%) | 84 (16.9%) | 66 (13.3%) | 497 |

STYLER repairs 23.9% of all the real errors. This is the greatest overall accuracy among the three considered tools (NATURALIZE 16.9%, and CODEBUFF 13.3%). Remarkably, NATURALIZE and CODEBUFF repair 92.5% and 98.1% of the errors from the project be5, respectively. Yet, NATURALIZE and CODEBUFF are unstable, e.g. NATURALIZE repairs from 0.7% to 92.5% across the projects.

It is notable that STYLER’s performance over the real-error dataset is significantly lower than over the synthetic dataset. The reason is that the distribution of the real errors is different from the distribution of the synthetic errors. In RQ #1, by construction, the training data is drawn from the exact same distribution as the testing data, which makes the ideal setup for learning. In this second experiment, we use the same training data but we test the system against the real error distribution, which mismatches. To overcome this problem, an interesting area of future work is to devise a data creation protocol that results a distribution close to the real one. An alternative solution would be to train directly from real repaired errors, but, as stated previously, it is hard to collect 10000 repaired Checkstyle errors for the same Checkstyle configuration.

RQ #2: To what extent does STYLER repair Checkstyle errors mined in the wild, compared to other systems? STYLER repaired 23.9% (119/497) of real Checkstyle errors, which is better than the state-of-the-art code formaters NATURALIZE and CODEBUFF. 82 real errors were exclusively repaired by STYLER. To our knowledge, this is the first ever experimental result on automatic repair of formatting errors.

C. Size of the Repairs (RQ #3)

One dimension of repair quality is the size of the diff (added + deleted lines) between the source code with a Checkstyle error and the repaired source code. Among all repairs that pass all Checkstyle rules, the diff should be as small as possible for being the least disrupting for the developers.

We calculated the size of the diff from the errors that STYLER, NATURALIZE and CODEBUFF repaired. Figure 6 shows the results on the real-error dataset: the x axis presents the size distribution of the diffs, and each boxplot represents one tool. All boxplots have boxes from the first to the third quartile, and whiskers from the 5th to the 95th percentile.

Both STYLER (represented by green boxplots) and NATURALIZE (represented by yellow boxplots) have median diff sizes equal to six changed lines. CODEBUFF (represented by blue boxplots) produces significantly larger diff sizes and has a median equals to 14. In the worst cases, NATURALIZE produces the worst diffs, the third quartile is larger, and considering the 95th percentile, NATURALIZE reaches 23 changed lines, while STYLER has no more than seven lines.

Fig. 6: Size of the repairs generated by STYLER, NATURALIZE, and CODEBUFF on the real-error dataset. The two whisker boundaries of the boxplots represent the 5th and the 95th percentiles (RQ #3).
RQ #3: What is the size of repairs generated by STYLER, compared to other systems?

STYLER has a median repair size of six changed lines. CODEBUFF clearly produces bigger formatting repairs. NATURALIZE produces small formatting repairs, yet with less reliable predictability, compared to those generated by STYLER. The ability to produce small diffs is an essential property of automatic source code manipulation, and our results show that STYLER can be realistically given to developers.

D. Performance (RQ #4)

Finally, we evaluate the execution performance of STYLER, to see whether it can be used in practice. We measure the execution time spent when running STYLER on the real-error dataset. Table III shows the results for the five projects, split over the different steps from the STYLER workflow. For training data generation, STYLER took at least three hours and up to four hours, and for training the model, STYLER took about one hour and a half. Therefore, the training of STYLER (data generation + model training) took on average five hours. This can be considered OK, since this training is meant to happen every time the coding conventions change, which means very rarely (a given coding convention usually lasts for years). After STYLER being trained for a given project, it takes in average one second to predict a repair, which is fast enough to be used live.

TABLE III: Statistics on the performance of STYLER per step related to training and predicting (RQ #4).

| Project | Training Data Generation | Training Model | Prediction Average Time |
|---------|--------------------------|----------------|------------------------|
| okhttp  | 4h01                     | 1h31           | 1.67s                  |
| dagger  | 3h46                     | 1h16           | 0.83s                  |
| milo    | 3h00                     | 1h27           | 0.81s                  |
| picasso | 3h33                     | 1h32           | 1.40s                  |
| bc5     | 3h21                     | 1h12           | 0.70s                  |
| Average | 3h32                     | 1h24           | 1.00s                  |

A: Intel® NUC Kit NUC6i5SY
B: On an HPC server with 1 core of GPU

RQ #4: How fast is STYLER for learning and for predicting formatting repairs?

On average, STYLER needs about five hours for training, and one second for predicting a repair. While training time is not an issue since it only happens when the checkstyle.xml file of a given project changes, the prediction time relates to usability. Our result shows that STYLER can be used in IDEs or in a Continuous Integration environment, in a practical industrial setting.

E. Threats to Validity

The real-error dataset contains Checkstyle errors mined from GitHub repositories. It is to be noted that it does not cover all existing formatting rules. Consequently, future research is needed to strengthen external validity.

To compare the quality of repairs produced by STYLER with repairs produced by NATURALIZE and CODEBUFF, we measured the size in lines of the diff between the buggy and repaired program versions. However, the diff size is only one dimension for comparing the tools which only approximates the developer’s perception on formatting repairs. User studies, such as proposing to developers formatting repairs, are interesting future experiments to further investigate the practical value of this research.

VII. RELATED WORK

Research on machine learning on source code is a very active area [18]. Yet, to our knowledge, there is no work on using it for repairing formatting errors.

A. Linter-based Errors Repair

Linters are popular [19]. There are tools to fix errors raised by specific linters. For Python, there exists the autopep8 tool [20], which formats Python code to conform to the PEP 8 Style Guide for Python Code [21]. For Java, there exists the CheckStyle-IDEA [22] plugin for IntelliJ, which is able to highlight the error and in some specific cases suggests fixes. However, it is very limited and, contrary to STYLER, it cannot handle any arbitrary Checkstyle configuration.

B. Code Formatters

A way to enforce formatting conventions lies in code formatters. In Section V-C, we described NATURALIZE [5] and CODEBUFF [6]: NATURALIZE recommends fixes for coding conventions related to naming and formatting in Java programs, and CODEBUFF infers formatting rules to any language given a grammar.

Beyond those academic systems, there are code formatters such as google-java-format [23], which reformats source code according to the Google Java Style Guide [2], and as such fixes violations of the Google Style. However, these formatters are usually not configurable. This is a problem because not all developers are ready to follow a unique convention style. STYLER, on the other hand, is generic and automatically captures the conventions used in a project to fix formatting violations.

C. Learning for Repairing Compiler Errors

There are related works in the area of automatic repair of compiler errors. In this case, the compiler syntax rules are the equivalent of the formatting rules. There, recurrent neural networks and token abstraction have been used to fix syntactic errors [24]. In DeepFix [25], Gupta et al. use a language model for repairing syntactic compilation errors in C programs. Out of 6,971 erroneous C programs, DeepFix was able to completely repair 27% and partially repair 19% of the programs. Later, Ahmed et al. [26] proposed TRACER, which outperformed DeepFix, repairing 44% of the programs. Santos et al. [27] confirmed the efficiency of LSTM over n-grams and of token abstraction for single token compiling errors. These approaches do not target formatting errors, which is the target of STYLER.
VIII. CONCLUSION

In this paper, we presented STYLER, a novel approach to repair formatting errors, implemented for repairing errors raised by Checkstyle in Java programs. STYLER creates a corpus of Checkstyle errors, learns from it, and predicts fixes for new errors, using machine learning.

Our experimental results showed that RQ #1) STYLER’s learning procedure is feasible for repairing Checkstyle errors; RQ #2) STYLER repairs more real errors than the code formatters NATURALIZE and CODEBUFF; RQ #3) STYLER produces smaller repairs than the code formatters; and RQ #4) its prediction time is low so it can be used in IDEs or in a Continuous Integration environment.

STYLER calls for future work. First, improvements on the error injection protocol for creating training data can be done so as to improve the representativeness of generated formatting errors. This might increase the performance of STYLER on real errors. Additionally, STYLER’s novel concept could be extended so as to repair other linter errors, beyond purely formatting ones.

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