Exploring the Impact of Code Style in Identifying Good Programmers

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Abstract

Code style is an aesthetic choice exhibited in source code that reflects programmers’ individual coding habits. This study is the first to investigate whether code style can be used as an indicator to identify good programmers. Data from Google Code Jam was chosen for conducting the study. A cluster analysis was performed to find whether a particular coding style could be associated with good programmers. Furthermore, supervised machine learning models were trained using stylistic features and evaluated using recall, macro-F1, AUC-ROC and balanced accuracy to predict good programmers. The results demonstrate that good programmers may be identified using supervised machine learning models, despite that no particular style groups could be attributed as a good style.

Keywords

code style, identify good programmer, stylistic features

1. Introduction

Code style represents the physical layout of code (e.g., indentation, bracket placement), which reflects an individual’s personal programming habits that do not affect its functionality [1]. Figure 1 shows two code snippets that are functionally similar but written in two different styles. Code style has an impact on various aspects of software engineering, including software maintenance [2] and speed of software development [3]. However, no prior studies have been conducted to see whether good programmers can be detected by looking at their coding style. This paper investigates the potential for using code style to identify good programmers.

\begin{verbatim}
  int sum(int a, int b)
  { return a+b; }

  int sum(int a, int b)
  { 2
     return a+b;
  }
\end{verbatim}

(a) Style 1 (b) Style 2

Figure 1: Two functionally same code snippets written in different styles

Establishing a link between code style and good programmers can have several implications. Many software repositories contain style guidelines that are used to enforce a specific code style in order to maintain software quality [4]. However, these style guides are often opinionated and arbitrary [5, 6]. If a specific code style exhibited by programmers can be identified as a good style, it can be used to create non-arbitrary style guidelines for better software maintenance.

In the software industry, the developers hired by a company directly affect the quality of the codebase that they maintain. During recruitment, the candidates who apply for jobs often have to solve a set of programming problems. However, existing hiring practices do not account for the possibility that a skilled programmer could have a bad day and fail to answer a question correctly. Thus, in some circumstances a judgment may be unfair. If positive stylistic features can be identified in a programmer’s code, they can be used as an additional criterion to enhance recruitment processes. This study is an initial attempt to determine whether such relationships between competent programmers and their code style can be established.

To conduct the study, the solutions collected from Google Code Jam (GCJ) [7] were used as the dataset. 30 stylistic metrics were extracted from the codes and used as features for analysis. Two methods of analysis were used. At first, clustering algorithms were applied to the data to discover style groups and check whether good programmers belonged to a particular style group. Secondly, supervised machine learning models were trained using stylistic features to predict good programmers. The models were evaluated using recall, macro-F1, area under curve of ROC (AUC-ROC), and balanced accuracy.

Results show that, although style groupings were found, there were no specific groups with which good programmers could be associated. However, supervised machine learning models showed that good programmers can be predicted to some extent. Based on the evaluated metrics, a Balanced Random Forest achieved the best re-
2. Related Work

To the best of our knowledge, this is the first time code style has been used to identify good programmers. Early research conducted by Oman and Cook proposed a taxonomy for code styles to help people grasp a coherent view on the basis and application of code styles [5]. The four major categories of their taxonomy are general practices, typographic style, control structure style and information structure style. They also concluded in further research that code style is more than cosmetic and that it can affect areas such as code comprehension [9].

Caliskan et al. proposed a Code Stylometry Feature Set (CSFS) with which they performed source code authorship attribution [10]. Their feature set is language agnostic and can be used for other programming languages as well. With their method, they achieved 94% accuracy in classifying 1600 authors and 98% accuracy in classifying 250 authors. They concluded that this method can help in the identification of authors of malicious programs, ghostwriting detection, software forensics and copyright investigation.

Mirza and Cosma explored the suitability of using code style in detecting plagiarism in the BlackBox dataset [11]. BlackBox is a project that collects data from users of the BlueJ which is a Java IDE [11]. Their study showed that code style is suitable for detecting plagiarism.

For evaluating software projects, Zou et al. explored how code style inconsistency can affect pull request integration in projects on Github [3]. By analyzing 117 public repositories, they concluded that code styles with specific criteria can influence both the acceptance of pull requests and the time required to merge a pull request.

Mi and Yu conducted a study on stylistic inconsistency in software projects [2]. They proposed a collection of stylistic metrics for C++ projects and used these metrics to analyze small-scale Github projects. By using hierarchical agglomerative clustering they showed that stylistic differences exist between source files in a project. They concluded that, using the degree of stylistic inconsistency as a basis, code comprehensibility and software maintainability could be improved in the future.

Several tools have been developed that can check stylistic inconsistencies and help programmers improve code style. Ala-Mutka et al. developed style++ that helps students learn good C++ programming conventions [12]. Mäkelä et al. developed Japproach that checks whether Java programs have a particular style and if style related issues exist in them [13]. Ogura et al. developed style-coordinate to decrease inconsistency and improve code readability [1].

### Table 1

| Round          | 2015 | 2016 | 2017 |
|----------------|------|------|------|
| Qualification  | 10744| 11401| 11342|
| Round 2        | 1650 | 1641 | 1824 |
| Round 3        | 266  | 296  | 286  |
| World Finals   | 22   | 20   | 21   |
not within the control of a programmer. Furthermore, term frequency based features were also excluded as they largely depend on the corpus being used. Following these criteria, 30 stylistic features were extracted. The features are listed in Table 2.

### 3.2. Approach

This section discusses the setups for exploring the effects of code style on classifying good programmers. Two methods were used for this purpose: (1) clustering techniques and (2) supervised machine learning algorithms.

#### 3.2.1. Analyzing Using Clustering Techniques

Clustering is a method of partitioning objects into homogeneous groups on the basis of similarity among those objects [14]. t-SNE is one such algorithm that can discover the potential number of clusters in a dataset with high dimensions [15]. For each problem in the contests, t-SNE graphs were plotted with the intent of finding groups that conform to a particular style. Each data point in the plots represents a solution submitted by a programmer. The data points are labeled as:

- Red: reached World Finals
- Green: reached Round 3
- Light blue: other programmers

To further validate the clustering provided by t-SNE, Hierarchical Agglomerative Clustering (HAC) with Ward linkage was performed and dendrograms were plotted. HAC is a clustering algorithm that treats every data point as a cluster and they are gradually merged to form a single cluster [16]. The number of clusters indicated by the dendrograms was matched with the number of clusters indicated by t-SNE before further analysis was performed.

To analyze the properties of the t-SNE clusters, solutions to each problem in the dataset were clustered using K-Means With K=number of clusters estimated by t-SNE. The solutions in the data were then labeled based on the cluster they belonged to. This labeled data was fitted to a Random Forest Classifier to obtain the feature importance of the tree. Based on the tree’s feature importance, it was determined what style groups exist and whether good programmers belong to a specific style group.

#### 3.2.2. Analyzing using Supervised Machine Learning Algorithms

Supervised learning is a method of training a model that can make predictions based on labeled data [17]. For predicting good programmers, the following models were
trained: Logistic Regression (LR), Support Vector Classifier (SVC), K-Nearest Neighbors (KNN), Decision Tree (DT) and Random Forest (RF). A Dummy classifier was also trained to act as a performance baseline for comparison [18]. The models were trained for each problem in the dataset. Table 1 shows that the number of participants in Round 3 is far less than the participants in the previous rounds. That is, the proportion of "good" programmers in the dataset is much lower in comparison to the other programmers. This makes the classification an imbalanced classification problem [19]. To balance the training data, the up-sampling technique SMOTE [20] was used prior to training the above mentioned models. Furthermore, Balanced Random Forest (BRF) and RUS Adaboost classifier (RUSAda) were also trained which performs under-sampling to balance training data [21]. For bias-free results, all trained models were K-fold cross-validated.

4. Experimental Analysis

4.1. Performance Evaluation

The clusters created for analysis were evaluated empirically. Although the analyzed dataset had labels and the results could be evaluated using a metric, this was not done, as evaluating clustering algorithms using labels is not recommended [22]. For the supervised algorithms recall, macro-F1 and Area Under Curve of ROC (AUC-ROC) were used to evaluate the models. Recall is the measure of the fraction of good programmers correctly identified as good programmers [23]. Recall is calculated as equation (1). F1 is an evaluation metric measured by combining precision and recall, and it is calculated as (3) [23]. Macro-F1 is the arithmetic mean of the per class F1 scores. It has been selected as an evaluation criterion because the training data was imbalanced, and macro-F1 is a good metric for imbalanced data [24]. AUC-ROC is the area under a ROC curve that allows comparison between models [23]. Apart from these evaluation metrics, balanced accuracy was also reported. Balanced accuracy is defined as the average of recall obtained on each class [25].

\[
\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \tag{1}
\]

\[
\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \tag{2}
\]

\[
F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}
\]

| Features                | Importance |
|-------------------------|------------|
| newLineBeforeOpenBrace  | 0.282      |
| tabsLeadLines           | 0.163      |
| numTabs/length          | 0.151      |
| numSpaces/length        | 0.103      |

4.2. Results and Discussion

After analyzing the contest results from 2015, 2016, and 2017, it was discovered that they were similar. Therefore, only the results of one year (2016) are shown in this section.

Figure 2 shows the t-SNE clusters of all the problems in the dataset of the year 2016. The caption of each image shows the round and the problem number. From the graphs, it can be said that 4 stylistic clusters exist for each solution. The most important features of the clusters determined by a Random Forest Classifier are shown in Table 3. The importance of all other features was less than 0.05. It is seen that newLineBeforeOpenBrace and tabsLeadLines are the most prominent features in separating the clusters. A manual inspection of the codes also proved the findings to be true. The discovered clusters are formed around the following feature combinations:

- new line before opening braces, tabs lead lines
- no new line before opening braces, tabs lead lines
- new line before opening braces, whitespace lead lines
- no new line before opening braces, whitespace lead lines

Although style clusters were found, the good programmers were almost equally distributed among them. As a result, we cannot conclude that good programmers belong to a specific cluster.

The results of the supervised machine learning models are shown in Table 4. BRF, LR, SVC and RUSAda performed better than the dummy model, which indicates that some patterns can be identified by the models that can be used to predict good programmers. Also, BRF outperformed all models in terms of Recall, macro-F1 and AUC-ROC. While different studies have used code style for various aspects such as author identification and plagiarism detection, none of the studies have dealt with good programmer identification. Therefore, we cannot compare our results with those of existing studies. However, our results can inspire further research on the relationship between code style and the coding ability of programmers.
Table 4
Prediction Results of Supervised Learning Models

| Model   | Recall | macro-F1 | AUC-ROC | Balanced Accuracy |
|---------|--------|----------|---------|------------------|
| BRF     | 0.650  | 0.511    | 0.695   | 0.645            |
| LR      | 0.641  | 0.523    | 0.692   | 0.651            |
| SVC     | 0.601  | 0.523    | 0.689   | 0.639            |
| RUSAda  | 0.510  | 0.50     | 0.626   | 0.590            |
| Dummy   | 0.485  | 0.412    | 0.499   | 0.489            |
| KNN     | 0.469  | 0.494    | 0.593   | 0.565            |
| DT      | 0.287  | 0.525    | 0.542   | 0.542            |
| RF      | 0.185  | 0.339    | 0.664   | 0.537            |

5. Threats to Validity

This section presents aspects that may threaten the validity of the study:

- **Internal validity**: The result of our analysis largely depends on the stylistic features that were used. Using other stylistic features may affect the results. However, many existing studies [10, 26] have used these features for their analysis, so they can be relied upon.

- **External validity**: The analysis was done on the source files of the GCJ dataset. Therefore, the findings of this study may not be generally applicable to contests in other formats. Furthermore, as only C++ codes were selected for analysis, it cannot be said whether stylistic features of other programming languages will show similar results. Additionally, the criteria for defining a good programmer are subjective and could be defined in other ways depending on the context. In such contexts, our results can not be generalized.

To ensure the reliability of the study, the analysis results are made publicly available in Jupyter notebooks at github.com/rafed/GcjStyleAnalysis.
6. Conclusion

This paper explores whether code style can be used to identify good programmers. The study was conducted on C++ solutions from the Google Code Jam contest. Clustering techniques such as t-SNE and hierarchical agglomerative clustering were used to discover whether style clusters exist and if good programmers could be attributed to any of them. Although four style clusters were found, good programmers could not be associated with a particular cluster. However, supervised machine learning showed that stylistic attributes can be used to predict good programmers. Seven machine learning models were trained and evaluated using recall, macro-F1 and AUC-ROC. A Balanced Random Forest yielded the best results with 0.650 recall, 0.511 macro-F1 and 0.695 AUC-ROC. The results indicate that code style can be used as a measure to identify good programmers.

Future research will examine if defining style guidelines based on the coding style of skilled programmers enhances the quality of software. Additionally, it is possible to investigate how the current recruitment procedures might be efficiently linked with the prediction of good programmers utilizing code style. There is also potential for improving our results using other techniques.

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