Are Machine Programming Systems using Right Source-Code Measures to Select Code Repositories?

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ABSTRACT

Machine programming (MP) is an emerging field at the intersection of deterministic and probabilistic computing, and it aims to assist software and hardware engineers, among other applications. Along with powerful compute resources, MP systems often rely on vast amount of open-source code to learn interesting properties about code and programming and solve problems in the areas of debugging, code recommendation, auto-completion, etc. Unfortunately, several of the existing MP systems either do not consider quality of code repositories or use atypical quality measures than those typically used in software engineering community to select them. As such, impact of quality of code repositories on the performance of these systems needs to be studied.

In this preliminary paper, we evaluate impact of different quality repositories on the performance of a candidate MP system. Towards that objective, we develop a framework, named GitRank, to rank open-source repositories on quality, maintainability, and popularity by leveraging existing research on this topic. We then apply GitRank to evaluate correlation between the quality measures used by the candidate MP system and the quality measures used by our framework. Our preliminary results reveal some correlation between the quality measures used in GitRank and ControlFlag’s performance, suggesting that some of the measures used in GitRank are applicable to ControlFlag. But it also raises questions around right quality measures for code repositories used in MP systems. We believe that our findings also generate interesting insights towards code quality measures that affect performance of MP systems.

CCS CONCEPTS

• Computing methodologies → Learning paradigms; • Software and its engineering → Software notations and tools; • Extra-functional properties.

KEYWORDS

machine programming, AI, machine learning, code repositories, code quality, software engineering

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1 INTRODUCTION

Last several years in the field of software engineering have seen emergence of new types of software systems that employ techniques from combination of artificial intelligence (AI), deep learning (DL), machine learning (ML), and formal methods to assist software developers. Gottschlich et al. [9] have coined the term Machine Programming (MP) to describe these systems. In general, MP systems aim to improve programmer productivity by assisting them in various tasks such as automatic code generation [12, 13, 16], code recommendation and search [18, 36], automated bug detection and program repair [5, 11, 35], automatic completion of program constructs for integrated development environments (IDES) [4, 6, 33], and language-to-language translation [29]. Several commercial tools, such as GitHub CoPilot [7] and OpenAI Codex [4, 27], can also be classified as MP systems. GitHub CoPilot is an AI-based pair programming system that suggests completions of source code. OpenAI Codex is an AI system that learns to generate Python programs that solve problems specified in natural language descriptions.

Majority of the existing MP systems rely on data mined from open-source code repositories to train their AI models. This is either because these systems use self-supervised or unsupervised learning techniques to mitigate the shortage of labeled code datasets1 required for supervised learning techniques or for cost purpose (as labeling is an effort-intensive task). For instance, Codex is trained on the dataset containing functions written in Python and their doctstrings (documentation), and the dataset is obtained by mining 54 million open-source repositories on GitHub.

Unfortunately, the reliance of MP systems on open-source code repositories can be problematic, if quality of the open-source code repositories used for mining is left unchecked. And this is primarily the case with most of the MP systems. For instance, ControlFlag [11] considers open-source GitHub repositories having at least 100 stars as good quality and mines programming patterns from those repositories to generate a dataset of known, good patterns for training. However, it is unclear if the number of stars of a GitHub repository indeed reflects its actual quality, when commonly-used quality models, such as ISO/IEC 25000:5000 [14], consider other quality measures such as accuracy, functionality, etc.

1IBM’s project CodeNet [28] aims to alleviate the problem of shortage of labeled code datasets by providing curated code examples.
and also when the number of GitHub stars is typically considered a popularity metric than a quality metric [1, 2]. As such, it may be plausible to launch an attack on ControlFlag and degrade its performance by intentionally increasing the number of stars of a bad-quality repository! Quality of the training dataset is one of the important factors in determining quality of the learned AI model. As such, impact of quality of code repositories on the performance of MP systems needs to be studied.

In this paper, we evaluate if quality of open-source repositories indeed impacts the performance of the MP systems by choosing ControlFlag as a candidate for evaluation. Towards that goal, we develop a framework, named GitRank, to rank open-source repositories on quality, maintainability, and popularity. We derive quality measures from existing literature [15, 20, 30–32] and known quality models such as ISO/IEC 25000:5000 [14], SQO-OSS [30]. We also consider commonly-used popularity and maintainability measures [3, 25] as existing research suggests that the number of GitHub stars — the measure used by ControlFlag to determine quality of a repository — is a popularity measure [1, 2]. We then apply GitRank to rank randomly-selected 500 GitHub repositories, having C++ as their primary language and at least 100 GitHub stars — the same criteria used by ControlFlag. We then use the ranked repositories to analyze their impact on the performance of ControlFlag. Our findings so far suggest that ControlFlag’s performance shows some correlation with the code quality measures used in GitRank. The performance, on the other hand, shows negative correlation with the code quality measures used in ControlFlag. We believe that our findings provide first set of insights into the types of MP systems that could be robust to quality of repositories.

**Contributions.** This paper makes following contributions:

- We believe to the best of our knowledge that this is the first attempt at evaluating the impact of quality of the code repositories on an MP system, specifically ControlFlag.
- We gather insights from existing research in the field of software engineering to measure quality, maintainability, and popularity of code repositories and build GitRank that combines several of the commonly-used metrics together. We, nonetheless, do not claim the novelty of the framework. All the measures that we use to rank repositories are known.

### 2 FRAMEWORK FOR RANKING OPEN-SOURCE REPOSITORIES

We now describe our framework, named GitRank, to rank open-source repositories based on quality, maintainability, and popularity. (We discuss GitRank here briefly to provide enough context for this work — reference [10] describes the framework in full details.) GitRank can be broken down into two phases. Given a set of open-source repositories to be ranked, in the first phase, we obtain values of quality, maintainability, and popularity measures of every repository individually. In the second phase, we then compare values of measures across repositories to calculate quality, popularity, and maintainability scores that are then used to calculate overall score for every repository.

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**Phase 1: Obtaining values of measures for every repository.**

Let us denote the set of open-source repositories to be ranked as $R$, and the set of quality, maintainability, and popularity measures that we use as $M$. The outcome of the first phase is a 2-dimensional table of $R \times M$, where every row in the table corresponds to a repository from $R$, while every column corresponds to one of $M$ measures. Table 1 contains the set of measures that we use. Out of a typical set of source code measures used in software engineering, we consider a subset that is applicable to open-source repositories and is common across set of languages. For instance, we do not consider depth of inheritance, a common measure used in object-oriented languages to determine complexity of maintaining code, as it is not applicable to other languages that are not object-oriented. Note, however, that the selection of code measures currently is ad-hoc — we selected a set of commonly used measures to study their applicability to MP systems. We explain some of the non-obvious measures below.

- Cyclomatic complexity of a source code is a well-known measure of the structural code complexity [21]. We determine the cyclomatic complexity of a repository by averaging over cyclomatic complexity of individual functions.
- We consider code formatting as a code quality measure. We divide the total number of formatting errors by the lines of source code (SLoC) [24] to obtain the density of style errors.
- Security issues are an important class of errors that need no explanation. An example of a security error would be using a potentially dangerous function such as `strcpy` in C language (CWE-676 [22]). Security issues could be of varying severity levels. In GitRank, we consider three severity levels: low, medium, and high. We divide the total number of security errors reported for every level by the lines of source code (SLoC) to obtain the level-specific error density.
- Maintainability index is a well-known, composite metric that incorporates a number of traditional source code metrics into a single number that indicates relative ease of maintaining source code [26]. We use the modified formula of MI [34] to obtain MI for individual modules from a repository:

$$MI = 171 - 5.22\ln(V) - 0.23C - 16.21\ln(L)$$

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*We could not find existing open-source framework that combines metrics of our interest and ranks repositories.

*This is predominantly given the preliminary nature of the study. We have nonetheless surveyed several software engineering topics to select the code measures.
As discussed in the introduction section, the objective of this work is to evaluate if quality of open-source repositories indeed impacts performance of MP systems. Towards that objective, we choose ControlFlag as a candidate MP system.

Where \( V \) is the Halstead volume, \( C \) is the cyclomatic complexity, and \( L \) is the lines of code. MI for a repository is then obtained by averaging over MI for individual modules.

- We also consider the number of closed issues over a period of time (last 2 years, last 1 year, last 6 months, and last 1 month, with increasing importance in that order) from the date of evaluation to determine maintenance activity of a repository. This is because we want to value current maintenance activity of a repository more.

### Phase 2: Obtaining quality, popularity, and maintainability score of repositories.

Once the values of the measures for all the repositories are obtained, in the second phase, we calculate scores of all the repositories for all three categories and then combine them to determine overall score.

Before we calculate the scores of all the repositories, we first normalize values of all the measures to the range of 0% to 100%, with 0% being the lowest normalized value and 100% being the highest. This is performed by obtaining the lowest and the highest value of every measure and computing the position of a value within the range of the lowest and the highest value. If we use \( m \) to represent a measure and \( V_m \) to represent the set of values for that measure before normalization (a column in the \( R \times M \) table), then the formula for normalization is:

\[
\frac{(v - v_{\text{min}}) \times 100}{v_{\text{max}} - v_{\text{min}}} \forall v \in V_m \forall m \in M
\]

Normalized values of the measures are then used to compute the quality score \( q_r \), the maintainability score \( x_r \), and the popularity score \( p_r \) of every repository \( r \) as follows. For maintainability score, \( x_r \), we use different weights for the measures based on their importance towards the score. Otherwise, we assign equal weight to all the measures for \( q_r \) and \( p_r \). We compute overall score \( s_r \) of a repository \( r \) as a mean of \( q_r \), \( x_r \), and \( p_r \). All of these scores are also normalized to the range of 0% to 100%, with 0% being the lowest and 100% being the highest.

\[
q_r = 100 - \frac{n_{cc} + n_{stg} + n_{sm} + n_{sh}}{5}
\]

\[
x_r = \frac{51 \times n_{mi} + 9 \times n_{c2y} + 9 \times n_{c1y} + 9 \times n_{c0m} + 12 \times n_{cm} + 12 \times n_{cm}}{100}
\]

\[
p_r = \frac{n_{ss} + n_{str} + n_{fr}}{3}, \quad s_r = \frac{q_r + x_r + p_r}{3}
\]

### 3 EVALUATION

As discussed in the introduction section, the objective of this work is to evaluate if quality of open-source repositories indeed impacts performance of MP systems. Towards that objective, we choose ControlFlag as a candidate MP system.

A brief background on ControlFlag. We provide background on ControlFlag for the purpose of explaining our results. ControlFlag is an MP system that aims to find typographical errors in code automatically. Towards that goal, it uses a self-supervised learning approach that relies on the dataset of commonly-used programming patterns that is generated by mining open-source repositories. It formulates the problem of finding erroneous programming patterns as an anomaly detection problem, where erroneous patterns are anomalies. ControlFlag clusters mined patterns using abstract representations, and every pattern along with its statistical frequency are stored in the dataset. It uses two levels of abstractions (L1 and L2), with L2 being more abstract than L1.

ControlFlag considers GitHub repositories having at least 100 stars as high quality and minas patterns from them for training purpose. We conducted experiments to answer two research questions:

- **RQ1:** Does ControlFlag perform poorly on repositories that are ranked low by GitRank than high?
- **RQ2:** Does ControlFlag perform poorly on low-starred (less than 100 stars) repositories than high-starred (more than 100 stars) repositories?

In a sense, both the questions use ControlFlag as a common test to determine if the source code measures used by GitRank (in RQ1) and the measures used by ControlFlag (in RQ2) capture the relative quality of the repositories. The question that has an affirmative answer would suggest that the code measures used in that test impact ControlFlag’s output. For instance, if answer to RQ1 is affirmative, then it suggests that the code measures used by GitRank impact ControlFlag’s output. And in the case of RQ2, an affirmative answer would mean the number of GitHub stars impacts ControlFlag’s output.

We answer these research questions by comparing the datasets obtained from mining the repositories used in those questions. Specifically, we design two sets of experiments for our evaluation:

**Experiment 1.** We designed experiment 1 to answer RQ1. In particular, we randomly select 500 repositories out of the list of C++ repositories provided in ControlFlag’s code repository. (In order to ensure that ControlFlag’s code quality measure does not impact this experiment, we select 500 repositories from a list of repositories having more than 100 stars.) We then rank those repositories using GitRank and divide them into two halves — the top half containing 250 repositories having higher rank than the bottom 250 repositories. GitRank considers the top half as the set of higher-quality repositories than the bottom half (that is considered as a set of lower-quality repositories). We then generate training datasets using both the sets and evaluate quality of those datasets using three tests described below. We denote the dataset obtained from the top 250 repositories by \( D_{t1} \) and the one obtained from the bottom 250 repositories by \( D_{b1} \).

**Experiment 2.** The objective of the second experiment is to answer RQ2. The second set of experiments to obtain two sets of GitHub repositories having C++ as their primary language: the first set of 250 repositories having more than 100 stars and the second set of 250 repositories having less than 100 stars. The first set of repositories would be considered high-quality by ControlFlag (because they have more than 100 stars), while the second
of connectivity in the graph and denoted by \( c_{\text{degree}} \). Intuitively, \( c_{\text{degree}} \) ensures that the patterns are "peer-reviewed" by many repositories (or peers).

- When every pattern receives similar, if not exactly same, contribution from every repository (measured as \( c_{\text{stddev}} \)). Intuitively, \( c_{\text{stddev}} \) measures the deviation in the training dataset in terms of contributions of various repositories to different patterns and ensures that no one repository skews the confidence in a pattern by contributing heavily to it.

Both of the above criteria ensure that a single repository does not skew training dataset in ControlFlag by contributing heavily than other repositories. Such an adversarial case would degrade the quality of the dataset. Note however that a collusion attack is still possible wherein multiple repositories collectively contribute patterns in malicious manner to degrade quality of the dataset.

### Result analysis.

The results answer RQ1 in affirmative and RQ2 in negative. Specifically, in experiment 1, dataset \( D_{b1} \) wins test \( T_1 \) for both L1 and L2 abstraction levels. It, however, loses to \( D_{b2} \) on test \( T_2 \). We consider test \( T_1 \) as more authoritative as it is administered by ControlFlag itself — \( T_2 \) uses our graph based formulation, which is independent of ControlFlag. Test \( T_1 \) reports the number of patterns from the evaluation repository that are not found in the given dataset. In other words, it compares the coverage of the patterns in the given dataset — less number of missing patterns indicates better coverage. Finally, recall that \( D_{b1} \) is marked as higher-quality than \( D_{b2} \) by GitRank.

Experiment 2, on the other hand, does not have a clear winner. Dataset \( D_{b1} \), marked as high-quality based on ControlFlag measures, wins test \( T_1 \) for L2 abstraction level, while it loses test \( T_1 \) for L1 abstraction level. Similarly, dataset \( D_{b2} \), which is marked as low-quality based on ControlFlag measures, wins test \( T_2 \) for L1 abstraction level, while it loses test \( T_2 \) for L2 abstraction level. Recall that in this experiment, dataset \( D_{b1} \) is marked as high-quality while dataset \( D_{b2} \) is marked as low-quality by ControlFlag.

The anomalies for test \( T_1 \) indicate possible programming errors in code. As such, \( D_{b1} \) finds 4 anomalies in the evaluation repository and performs better than others. In summary, when we compare the datasets directly — a standalone statistical test without the evaluation repository — using the number of total and unique patterns, we find test \( T_1 \) to be more authoritative.

Across both the experiments, the test \( T_2 \) marks \( D_{b2} \) as an overall winner on \( c \), but different datasets win on the basis of \( c_{\text{degree}} \) and \( c_{\text{stddev}} \). This indicates that some datasets have high degree of

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\( a \) randomly-selected candidate repository having C++ as its primary language and more than 100 GitHub stars.
Table 2: Table showing results of the tests T1 and T2 for experiment 1 and 2. Dataset statistics are numbers per LoC, summed up for all the repositories in the dataset. Bold values in columns show the best result for that test across both the experiments. (Results of test T3 are not presented in the table for the purpose of space. They are rather discussed in text.)

| Experiment | Dataset | Style errors | Security warnings | Security errors | Patterns missing | Anomalies | Patterns missing | Anomalies |
|------------|---------|--------------|-----------------|----------------|-----------------|-----------|-----------------|-----------|
| Experiment 1 | D1s | 5.42 | 0.03 | 0.06 | 640 | 0 | 0.00/0.17 | 0 | 0 | 0.17 | 7.28 | 6.11 |
| | D2s | 11.94 | 0.08 | 0.27 | 834 | 0 | 0.00/0.17 | 0 | 0 | 0.16 | 6.34 | 5.19 |
| Experiment 2 | D1t | 5.42 | 0.03 | 0.06 | 394 | 0 | 0.00/0.17 | 0 | 0 | 0.17 | 7.28 | 6.11 |
| | D2t | 7.99 | 0.06 | 0.17 | 494 | 0 | 0.00/0.17 | 0 | 0 | 0.15 | 6.27 | 5.42 |

Peer-review activity (e.g., 0.17 value of $c_{degree}$ for D1t) and high confidence, while some datasets have skewed contributions of patterns (e.g., 7.28 value of $c_{stddev}$ for D1t) and low confidence.

The authors of the paper performed qualitative inspection of all three datasets (in test T3) and found that all of them contained instances of abnormal patterns that indicate bad programming practices\(^1\). Even dataset D1t contained confusing programming expressions, such as if ($x < \text{string}_\text{literal}$) and redundant expressions such as if (false && x), indicating that not all top-quality repositories are using good programming practices.

**Overall thoughts and future work.** Overall, we find that the results show some correlation between the quality measures used by GitRank and the output of ControlFlag. In other words, selecting lower-quality repositories marked by GitRank would degrade ControlFlag’s performance. We also find that the results show negative correlation between the quality measures used by ControlFlag and its output. Precisely, selecting repositories having less than 100 stars does not necessarily impact ControlFlag’s output. This point corroborates the known observation that the number of GitHub stars is not a quality measure but is a popularity measure.

We nonetheless acknowledge that the results also suggest some future work. To be precise, not all the code measures used in GitRank seems to affect ControlFlag. Specifically, ControlFlag can handle source code having compilation issues, suggesting that the absence of compilation issues is not its quality measure. This observation that quality measures that actually influence the output of ControlFlag could be tuned versions of the typical quality measures considered in software engineering literature raises some interesting questions. It is not clear if similar observations would apply to other MP systems. We plan to answer these questions in the future.

**Reproducibility.** We have published all the data and scripts used in both the experiments publicly under GitRank at https://github.com/nirhasabnis/gitrank/tree/main/case_study/evaluate_MP_systems. GitRank is also available publicly at https://github.com/nirhasabnis/gitrank. ControlFlag used in our evaluation is available at https://github.com/IntelLabs/control-flag.

### 4 RELATED WORK

To the best of our knowledge, we are not aware of any existing work that evaluates impact of quality of open-source repositories on MP systems. Nevertheless, several existing efforts have developed code metrics and models to evaluate open-source projects on quality, maintainability, popularity, among other criteria [15, 19, 20, 23, 30–32]. We briefly summarize some of them below. Stamos et al. [32] compare open-source software development model with the closed-source model by considering structural quality of code and measuring it for code developed using open-source style development. Spinellis et al. [31], on the other hand, apply SSO-OSS platform [30] and combine process and product metrics to evaluate quality aspects of open-source software. Jarzyck et al. [15], on the other hand, evaluate correlation between quality of GitHub projects and characteristics of their team members, thereby analyzing the social aspect of open-source software development. Specifically, they develop metrics reflecting project’s popularity and quality of support offered by its team members and apply statistical regression techniques to analyze their influence on project quality.

### 5 THREATS TO VALIDITY

In this preliminary paper, we selected some of the commonly-used source code measures in software engineering community. As we mentioned previously, our selection is currently ad-hoc. Consequently, it is possible that we could have missed some measures that could lead to better or worse results. Nonetheless, the existing results stand for the given set of selected measures. Another related but different point is about multicollinearity between different measures. Specifically, if multiple measures are correlated with each other by any mean, then they would have higher influence over the results than other measures. We consider the overall question of systematic selection of measures as a future work.

Although, the description and design of our approach is generic and applicable to any MP system, our current evaluation is restricted to ControlFlag. As such, the conclusions would be specific to ControlFlag also (in other words, generalizing them would be incorrect.) Moreover, we used code repositories hosted on GitHub for our study (as ControlFlag only supports GitHub repositories), nonetheless several other hosting platforms exist.

### 6 CONCLUSION

Machine programming (MP) is an emerging field that combines probabilistic approaches (such as artificial intelligence) and deterministic approaches (such as formal methods) to solve problems in software engineering and systems. Several of the existing machine programming systems rely on open-source code without considering its quality, or use atypical quality measures (than the ones typically used in software engineering community).
In this preliminary study, we developed a framework to rank open-source repositories on quality, maintainability, and popularity, and applied it to generate sets of repositories of different quality levels. We then used those repositories to generate training datasets for ControlFlag and analyze their impact on ControlFlag’s performance. Our results so far indicate that ControlFlag’s quality measure—the number of GitHub stars—does not correlate strongly with its performance. On the other hand, the results also indicate that the code quality measures typically used in software engineering have higher correlation with ControlFlag’s performance. We nonetheless observe that certain code quality measures used in GitHubRank do not affect ControlFlag, and we may need to finetune such measures based on an MP system. The results also raise several questions for other MP systems to be addressed in the future.

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