MP-CodeCheck: Evolving Logical Expression Code Anomaly Learning with Iterative Self-Supervision

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Abstract
Machine programming (MP) is concerned with automating software development. According to studies, software engineers spend upwards of 50% of their development time debugging software. To help accelerate debugging, we present MP-CodeCheck (MPCC). MPCC is an MP system that attempts to identify anomalous code patterns within logical program expressions. In designing MPCC, we developed two novel programming language representations, the formations of which are critical in its ability to exhaustively and efficiently process the billions of lines of code that are used in its self-supervised training.

To quantify MPCC’s performance, we compare it against ControlFlag, a state-of-the-art self-supervised code anomaly detection system; we find that MPCC is more spatially and temporally efficient. We demonstrate MPCC’s anomalous code detection capabilities by exercising it on a variety of open-source GitHub repositories and one proprietary code base. We also provide a brief qualitative study on some of the different classes of code anomalies that MPCC can detect to provide an abbreviated insight into its capabilities.

CCS Concepts: • Computing methodologies → Learning settings; • Software and its engineering → General programming languages; Semantics.

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1 Introduction
Software debugging has been found to consume upwards of 50% of all software development time [14]. Machine programming (MP), the field concerned with the automation of all aspects of software development [21], has seen advances in software development related tasks such as code auto-completion [12, 24, 54], code generation and program synthesis [6, 7, 18, 22, 23, 26, 28, 31, 34, 37, 39, 41, 43, 45, 52, 55, 59, 60], program transformation [20, 36] and repair [4, 8, 16, 32, 57], code similarity and recommendation [35, 58], learned optimizations [10, 38, 44], and performance regression testing [3, 5, 30, 42, 53], amongst others. The latter few tasks support the MP goal of software adaptation, which focuses on evaluating or transforming higher-order program representations or legacy software programs to achieve certain characteristics (e.g., performance, security, etc.). An open challenge in software adaptation is reasoning about legacy software. In such code bases, software defects may arise from a number of issues. These include, but are not limited to, logical errors, poorly organized code, and technical debt. Even defects that do not have a clearly negative impact on a system may leave it susceptible to future vulnerabilities. Some of these defects manifest in weaknesses (or brittleness) in logical expressions. In an attempt to help remedy this, we present MP-CodeCheck (MPCC), a self-supervised, inventive, and adaptive MP system which detects anomalous logical expressions at the source code level.

For the purposes of this paper, we trained MPCC on over two billion lines of semi-trusted source code for common logical expression programming patterns, which we refer to as expression blocks. Using the intuition that deviation from trusted programming techniques and paradigms can lead to potential erroneous programming, MPCC uses mined expression blocks to identify anomalous code that make the program incorrect, prone to future bugs, or contain technical debt. For example, consider the following C/C++ example that (incorrectly) checks if a variable x is NULL:

```c
// malformed, but legal double NULL equality check
if (NULL == x == NULL)
{
  throw std::runtime_error("x is NULL.");
}
```

While this code snippet may look suspicious, it compiles without warning in the default configuration of Visual Studio 2022 and produces only a warning using GCC with compiler flag -Wpointer-arith. However, the code’s logical expression – when considered holistically – is erroneous. With x set to NULL, the execution of the if statement will first check whether NULL == x, which will evaluate to true. Then the
if statement will continue its evaluation from left to right and compare true == NULL, which will evaluate to false. This will (incorrectly) cause the exception code that was meant to throw an exception when $x = NULL$ to be skipped. Given this, the system will likely dereference $x$ at a later time causing an illegal memory access. MP-CodeCheck was designed to identify these issues. In fact, MP-CodeCheck found this anomaly, and others like it, in a large-scale production-quality software repository.

In this paper, we make the following contributions:

1. We present MP-CodeCheck (MPCC), a system that aims to identify anomalous logical expressions in code by incorporating several novel code representations and an iteratively-refined heuristic framework that guides MPCC’s self-supervised engine.

2. We present a spatial and temporal learning and inference performance comparison between MPCC and ControlFlag [25] across 6,000 C/C++ repositories.

3. We provide an analysis of MPCC’s anomaly detection capabilities across ten GitHub repositories that are intentionally varied in size and lifetime.

2 Related Work

There have been many recent works in the field of machine programming. In this section, we discuss some of the works that we have found are most relevant to MPCC.

2.1 Self-supervised Systems

The emergence of self-supervised MP systems may be promising for large-scale machine learning, due to their ability to function on the enormous corpora of unlabeled open-sourced code training data. In the domain of natural language processing, large pre-trained language models [9, 15, 51] have already shown to be powerful tools for few-shot learning in language processing tasks [48, 50] where task-specific or domain-specific labeled datasets may be unavailable. For code processing tasks, GitHub alone hosts over 46 million public software repositories, presenting one source of abundant but unlabeled code data. Recent self-supervised code processing systems such as OpenAI’s Codex [12], Intel’s ControlFlag [25], Microsoft Research’s BugLab [4], and the basis for DeepMind’s AlphaCode [31], among others, have taken advantage of the vast amount of available code data to achieve impressive results for their respective tasks of code generation, idiosyncratic code pattern detection, bug detection and repair, and competitive programming.

Codex [12] and the underlying model for AlphaCode [31] are both large transformer language models pre-trained on large amounts of unlabeled GitHub code. This model setup allows for Codex variants and AlphaCode to then be fine-tuned on some small dataset of domain-specific examples to perform a particular task; AlphaCode, for example, is fine-tuned on a competitive programming dataset to generate
solutions to complex programming tasks. ControlFlag [25] mined over one billion lines of unlabeled open-source C/C++ code for common and uncommon code patterns to detect idiosyncratic programming patterns. Once trained, it performs inference on user-supplied code and suggest corrections on anomalies it has found. BugLab [4] takes an adversarial approach to learning software bug detection and repair by co-training a bug detection and repair model alongside a bug injection model such that the bug injection model learns to generate data from which the bug detection and repair model is trained. This boot-strapped technique does not require any external labeled training data.

Other systems such as Snorkel [49] combine weak supervision techniques to enable users to train state-of-the-art models without hand-labeling (much) training data.

### 2.2 Program Repair / Program Synthesis

Anomaly detection is closely related to other types of automated program reasoning such as program repair and program synthesis. These systems can be broken down into human-in-the-loop systems and closed loop systems.

**Human-in-the-loop Systems.** A primary challenge in automated program reasoning is code semantic understanding; an incorrect implementation with even minor syntactic differences (e.g., in C/C++ == (equality), = (assignment)) can produce drastically different software results. One way that previous systems have attempted to address this issue is to incorporate humans into the overall system. That is, humans can guide the MP system’s choice and potentially reinforce its learning algorithm.

Code recommendation systems are one such family of program reasoning systems. A code recommendation system is an automated system that ingests data (in some form) and then recommends some code fragment that is meant to satisfy the supplied input. Microsoft IntelliSense [40], Tabnine [1] and GitHub Copilot [2] are examples of commercially-deployed code completion suggestion tools. They can be integrated into interactive development environments (IDEs) and provide real-time suggestions for the programmer in the IDE. IntelliSense [40] uses knowledge of programming language semantics to suggest possible variables, methods, fields, type parameters, constants and classes, among other completions, as the programmer edits code in the IDE. Tabnine [1] and Copilot [2] train deep neural networks to learn from large corpora of source code to autocomplete whole lines or whole functions of code. Tabnine offers the option to fine-tune learned models on the user’s (or user’s team’s) code to provide guidance aligned with the user’s own code practices. Copilot adapts to edits made to its suggestions to match the user’s coding style. Chaurasia and Mooney incorporate humans into a natural language-to-code generation system [11] by using dialog to clarify user intent until it has enough information to produce correct code.

**Closed Loop Systems.** Some systems operate in an end-to-end manner to generate and modify code, without any human user feedback. Many program synthesis systems using sketching [52], inductive program synthesis [6, 18, 19, 22, 23, 33, 37, 39, 45, 46], and natural language descriptions [27, 43, 47, 56] operate in this closed loop manner to generate code satisfying some input specification.

One explored application of program transformation is transpilation, which is a technique in translating code from one programming language to another. Kamil et al. [26] demonstrate a technique to lift low-level Fortran code to a high-level predicate language summary and lowering it back down into Halide code to achieve performance speedups. Chen et al. [13] also develop a tree-to-tree model to translate programs from one programming language to another.

**Automated program repair (APR) [29]** is the task of automatically repairing software to reduce the work of human engineers while maintaining program usability and avoiding software regression. BugLab [4] is one example APR system that co-trains a bug detection and repair model alongside a bug injection model such that the bug injection model learns to generate harder-to-find bugs, the bug detection and repair model learns to find and repair harder to find bugs. Li et al. [32] present a technique that uses prior bug fixes and surrounding code context to modify a buggy program’s abstract syntax tree. Some APR works have also leveraged natural language to model reasoning about automated repair, such as Yasunaga and Liang [57] who use a buggy program’s diagnostic feedback error message to localize then generate a repaired version of the erroneous line in the software source code. TFix [8] is another end-to-end text-to-text system that fixes buggy code without labels by pre-training a model on natural language then fine-tuning it on generating code fixes. Hoppity [17] approaches automatic program debugging by learning a sequence of graph transformations over a buggy program represented as a graph structure.

**Code similarity systems** analyze code fragments and determine if they are semantically (i) similar, (ii) dissimilar, or (iii) equivalent. Such systems can be used for a variety of purposes. For example, they can help to identify existing code intent and suggest alternatives that may be less brittle and easier to understand. The MISIM neural code similarity system uses a context-aware semantics structure to lift semantics from code syntax. It then scores the semantic similarity of any two semantics structures via an extensible learned scoring algorithm (usually in the form of a deep neural network) [58]. Such a system could be used for many things, one being language-to-language transpilation. The Aroma code recommendation system performs code search using a novel simplified parse tree (SPT), which elides away many syntactical details of the original code [35]. Using the SPT, the Aroma system aims to take incomplete code snippets and return (more) complete code snippets.
These systems, however, focus on syntactic bugs that cause incorrect or failed program execution. **Semantic program repair** is the task of fixing non-syntactic bugs that cause program behavior divergent from what the programmer intended. Devlin et al. [16] propose an approach for automatic semantic program repair without access to the code’s intended correct behavior at either training or test time: the system first proposes many potential bug repairs then scores them using a learned neuro-symbolic network, outputting the highest-scoring candidate as the solution.

### 3 MP-CodeCheck System Design

MPCC’s system overview is shown in Figure 1. At the highest level, MPCC can be thought of as a code anomaly detection system, similar to ControlFlag [25]. However, MPCC has at least two fundamental design departures from such prior works. First, it uses novel code representations that help its anomalous code detection engine. Second, it uses an iterative, programmatic heuristic to guide its self-supervised engine. As described in Section 4, we have found that these design elements can reduce computational overhead (see Section 4) as well as reducing false positives (see Section 5). Moreover, by using these design elements together, MPCC can manually or automatically be augmented to fit different programming languages, development environments, or stylistic constraints. Without these capabilities, it can be challenging or impossible to achieve similar customization (and debugging augmentation) when using a machine learning-only approach. This is especially true for systems that do not provide insight into their underlying mechanics (e.g., ControlFlag’s string pattern matching algorithm). We describe both of these design elements in this section.

#### 3.1 Novel Code Representations

MPCC combines existing and novel code representations for its predicate expression classification system. Most of MPCC’s internal code manipulation uses representations that are implemented using various graph structures, generally in the form of a tree (e.g., abstract syntax tree (ASTs), flattened non-binary tree, etc.). We have designed two new representations to enhance MPCC’s ability to reason about the semantic properties of logical expressions: **basic expression blocks** and **complex expression blocks**. We describe them as follows.

##### 3.1.1 Basic and Complex Expression Blocks

A novelty in MPCC code representation is in its utilization of **basic and complex expression blocks**. The purpose of these blocks is to help the system reason about the semantics of logical expressions that may be asymmetrically spread across multiple logical operations in the same control structure. The formation of semantically rich compound expressions – often found in complex expression blocks – has helped MPCC distill semantically complex expressions that are both nominal (i.e., non-anomalies) and anomalous. This distillation helps MPCC identify more true positives as well as assisting in reducing false positives. We formally define basic and complex expression blocks as follows.

A **basic expression block** is a predicate expression that contains no logical conjunction operators (i.e., it contains no logical-ANDs, logical-ORs). Every predicate expression can be divided into its basic expression blocks as shown in Figure 2. A **complex expression block** is a composition of at least two basic expression blocks, normalized across variable (identifier) names. The intuition behind a complex expression block (or **complex block**) is that program semantics are often encapsulated across multiple, disjoint predicates in a control structure. For example, in Figure 2, for each of the complex blocks, multiple predicates with a single, shared identifier must be satisfied for the complete logical expression to be true (e.g., x in the left-most yellow complex block, y in the blue complex block, and p in the right-most yellow complex block). These shared identifiers often embed semantic relationships between the basic expression blocks.

To illustrate this concretely, consider the following common programming idiom to ensure a variable is within a minimum and maximum bounds:

\[
\text{if } (\min < x \&\& x < \max) \{ \ldots \}
\]
The identifier \( x \) is present in both of the basic expression blocks (i.e., \( \min < x \) and \( x < \max \)). As such, if used with MPCC a new complex expression block that conjoins both \( \min < x \) and \( x < \max \) would be constructed. When applied during inference, if MPCC constructed a complex expression block that had such a signature (after being normalized), it would flag the block as non-anomalous as it would have learned this expression is nominal.

Our experience with MPCC is that this use of complex expression blocks to capture compound programmatic semantics helps identify more complex programming anomalies, while simultaneously flagging nominal complex code structures that are common, such as the minimum and maximum expression discussed here.

3.2 Programmatic Evolution of Self-Supervision
A second novelty of MPCC is in its machine-driven guidance on the evolution of its heuristic-based rules. This evolutionary process is a key aspect in the development of the core elements of the system as well as in improving the quality of the results. This step is captured in Step 5 in MPCC’s Training in Figure 1. In this process, the knowledge that the self-supervised system learns, the common and uncommon control structure patterns, is used to inform human programmers in their construction of heuristics, representations, and rules that further improve the self-supervised learning. This iteration was done over a dozen times during the construction of MPCC.

A key reason for why this approach is critical to MPCC is that in our experience, isolated self-supervision is generally insufficient to learn complex and nuanced concepts in programming languages; on its own, self-supervision often produces a large number of false positives. Instead, a heuristic-driven and iterative learning approach, that utilizes subject matter experts for reinforcement learning, helps to properly guide MPCC through nuanced and unknown software design patterns, whether infrequent but correct, or frequent and incorrect.

Moreover, although it is not captured in this paper, in our early experiments, which did not use this human-in-the-loop iterative feedback loop, MPCC’s false positive rate for code anomalies exceeded \( \approx 90\% \). When combining humans and machines in MPCC’s design, it has reached \( \approx 31\% \) false positive rate (see Table 1), a \( 3 \times \) reduction in false positives.

4 Quantitative Results
In this section, we present quantitative results on the MP-CodeCheck system. These include (i) performance metrics of MPCC compared to ControlFlag and (ii) MPCC’s inference accuracy metrics with respect to false positive rates across several open-source GitHub repositories (see Table 1).

4.1 Computational Performance Metrics
Figure 3 details the performance results of our experimental study comparing MPCC to ControlFlag. We trained both systems on the open-source code data recommended by the ControlFlag repository’s README\(^4\), which consists of 6,000 repositories containing 1.1 billion lines of C code with some minor C++-specific code (\(< 5\%)\). The training metrics we gathered include training time (in minutes), maximum memory utilized during training (in MB), number of software halts during training, and resulting trained model size (in GB). For inference, we ran both systems on the open-source GitHub Load Balancer\(^5\) repository and collected metrics on model loading and inference time across the entire repository.

4.2 MPCC’s Basic and Complex Expression Blocks for Computational and Spatial Efficiency
MPCC’s basic and complex expression block representations are core components of its efficient training, inference, and

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\(^1\)All experiments run on the same system: OS: 64-bit Windows 11 Home; Processor: 11th Gen Intel(R) Core (TM) i7@ 2.80GHz; Ram: 16.0 GB; Drive: 1TB SSD

\(^2\)We tried to compare MPCC’s inference results to those from ControlFlag, but were unable to due to computational tractability limitations in ControlFlag’s open-source system.

\(^3\)https://github.com/IntelLabs/control-flag/blob/master/README.md

\(^4\)https://github.com/github/glb-director

\(^5\)https://github.com/github/gl-master
| Repository       | Size (MB) | Est. Year | # of Anoms | # of Expr. | Anoms Per Expr. | Top 20 False Positive % |
|------------------|-----------|-----------|------------|------------|------------------|-------------------------|
| git/git          | 40.07     | 2008      | 41         | 31,298     | 0.131%           | 55%                     |
| curl/CURL        | 15.92     | 2010      | 16         | 13,983     | 0.114%           | 56.25%                  |
| iovisor/bcc      | 15.14     | 2015      | 7          | 3,607      | 0.194%           | 42.86%                  |
| netdata/netdata  | 44.26     | 2013      | 48         | 26,092     | 0.184%           | 30%                     |
| php/php-src      | 125.27    | 2011      | 76         | 47,994     | 0.158%           | 10%                     |
| proprietary*     | 196.06    | 1999      | 66         | 12,948     | 0.510%           | 20%                     |
| qemu/qemu        | 116.28    | 2012      | 122        | 79,050     | 0.154%           | 35%                     |
| raspberrypi/pico-sdk | 7.25    | 2021      | 22         | 1,226      | 1.79%            | 27.28%                  |
| shakevsky/keybuster | 2.47   | 2020      | 2          | 393        | 0.509%           | 0%                      |
| ventoy/Ventoy    | 112.2     | 2020      | 22         | 17,316     | 0.127%           | 35.29%                  |

**Table 1.** Results of MPCC’s Inference on 10 Repositories Ranging in Size and Year of Establishment.

4.3 System Accuracy

In Table 1, we show our experimental results for MPCC inference accuracy. We tested MPCC on ten repositories with an intentional variation in repository size and year of establishment. For each repository, MPCC parses all C and C++ source files for control expressions then classifies each as anomalous or non-anomalous according to the scoring system explained in Section 3. In our experiments, we set the anomaly threshold to 1000: if a logical expression is assigned a complexity score greater than 1000, then MPCC flags it as an anomaly. We then manually inspected 20 anomalies with the highest anomaly complexity scores per repository to determine whether the flagged anomaly is not in fact an anomaly (i.e., it is a false positive).

Across the ten repositories that we inspected, we found a false positive rate of 31.16%. Anomalies are marked as false positives if they do not introduce excess technical debt. That is, most anomalies that are not false positives (i.e., true positives) possess one or more of the following features:

1. They use improper pointer checking practices.
2. They have unclear arithmetic operations.
3. They have unclear and inconsistent type casting.
4. They have many connected but disjoint predicates (i.e., each predicate performs a check on a different variable) for error checking.
5. They have inefficient usage of logical operators.
6. They have over- or under-utilization of parentheses.
7. They are C++ specific operations.
8. They perform arithmetic and Boolean operations on the same variable.
9. They are potential bugs.

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Note that MPCC’s utilization of ≈ 2× more available memory during training than ControlFlag results in an additional computational efficiency over ControlFlag, as MPCC is able to more fully exercise the available hardware.

6https://stackoverflow.com/questions/39150884/is-there-a-shorter-way-to-write-compound-if-conditions/39151002
7https://stackoverflow.com/questions/16644906/how-to-check-if-a-string-is-a-number/16644949
8https://stackoverflow.com/questions/13214506/shorthand-for-checking-for-equality-to-multiple-possibilities
This example converts the value of the `now_monotonic_sec()` function into a Boolean when the unary `NOT` operator is applied to its return value. Yet, the term is subsequently treated as an integer value for subtraction and greater than comparison. Also, it is not likely performing as the programmer intended. The `!` operator will return 0 or a 1. In this embodiment, the only way for this conditional to evaluate to true would be for `started_t` to be `< -14399` or `< -14400`, depending on the result of the `!`. However, `started_t` is a `time_t` type, which is set to the time of invocation in the line prior to the condition and is unlikely to ever be negative.

This sequence of bitwise logical operations introduces technical debt. The goal of this conditional is to determine whether at least one of the bits where `*m` is active (logical 1), the corresponding bits in `*k` and `*v` is are not equal. While logically correct, this conditional conducts excess logical operations that do not contribute to the readability of the code. We reported this anomaly to the QEMU repository maintainers with a proposal on how to improve the efficiency of the code, and together we agreed upon the following way to write the condition, which both conducts fewer logical operations and more clearly conveys the goal of the conditional:

\[ (*k \& *m) \neq (*v \& *m) \]

This expression incorrectly checks whether a variable, `actor`, is `NULL`. If `actor` is set to `NULL`, the expression, moving left-to-right, would first evaluate `NULL==actor` to `true` then evaluate `true==NULL` to `false`. Likewise, if `actor` is set to anything but `NULL`, the expression will first evaluate `NULL==actor` to `false` then evaluate `false==NULL` to `false`. So, somewhat unintuitively,

\[ \text{null == null == null} \rightarrow false \]
\[ \text{null != null == null} \rightarrow true \]

This behavior is inconsistent with the goal of comparing `actor` to `NULL`. In fact, this logical expression is a potential crash bug.

This expression is flagged as an anomaly by MPCC because of the logical or `||` operators between many predicates. This is a reasonable flag because usually too many predicates in a single conditional can be difficult for a programmer to cognitively reason about; thus, the mental burden can introduce technical debt. However, in this case, upon consultation with four experienced C programmers and the most viewed StackOverflow threads on this topic, this method of checking a character as part of a set of possibilities is common practice in C. Though relatively long and embedded with unnamed constant values, this expression is generally agreed to be easy to understand and thus easy to maintain.

(Q1) Proprietary Repository

```
if ( NULL == actor == NULL )
```

| Anomalous Predicate       | NULL == a == NULL |
|---------------------------|--------------------|
| Expression Block          | complex_1          |
| Classification            | True Positive      |
| Complexity Score          | 1003.25            |

(Q2) netdata/exporting/opentsdb/opentsdb.c

```
if (!now_monotonic_sec() - started_t > 14400)
```

| Anomalous Predicate       | !a()-b             |
|---------------------------|--------------------|
| Expression Block          | complex_2          |
| Classification            | True Positive      |
| Complexity Score          | 1003.1             |

(Q3) QEMU/hw/net/rocker/rocker_of_dpa.c

```
if (!(~*k & *m & *v) | (*k & *m & ~*v))
```

| Anomalous Predicate       | (~*a & *b & *c) | (*a & *b & ~*c) |
|---------------------------|-----------------|-----------------|
| Expression Block          | complex_2       |
| Classification            | True Positive   |
| Complexity Score          | 2046.5           |

(Q4) netdata/exporting/opentsdb/opentsdb.c

```
if (isalpha(*src) || isdigit(*src) || *src=='-' || *src=='_' || *src=='.' || *src=='/' || IS_UTF8_BYTE(*src))
```

| Anomalous Predicate       | a() || b() || *c==123 || *c==123 || *c==123 || *c==123 || d() |
|---------------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| Expression Block          | complex_2           |
| Classification            | True Positive       |
| Complexity Score          | 1032.5              |

Figure 4. Four Qualitatively Analyzed Examples of Anomalous Logical Code Expressions as Detected by MPCC. 7
5 Qualitative Results

Figure 4 presents qualitative results on the MP-CodeCheck system by analyzing four flagged anomalies in detail. Each of the four flagged anomalies, shown in quadrants (Q1)-(Q4) of the figure, were flagged by MPCC because the programming patterns that they exhibit, as represented by MPCC’s novel code representation structure, were uncommon or unseen before in the C code on which MPCC was trained. The first three anecdotal examples (Q1)-(Q3) are true positives, or true anomalies. The first example (Q1) is the same one as introduced in the Introduction (Section 1). The last anecdotal example (Q4) is a false positive: MPCC flagged it as an anomaly, but upon manual inspection, it is actually non-anomalous. We detail our analysis of each anecdotal example in their corresponding quadrants in Figure 4.

6 Conclusion

In this paper, we introduced MP-CodeCheck (MPCC), a self-supervised anomaly detection system for logical expressions. Our early evidence seems to demonstrate that MPCC can assist in one of the more painstaking aspects of software development, debugging, by identifying anomalies in even hardened production-quality code. We also demonstrated that MPCC is more temporally and spatially efficient than ControlFlag, a state-of-the-art self-supervised anomaly detection that also identifies anomalies in logical code expressions. Moreover, our early results across ten high-quality code repositories, rates MPCC with a false positive rate of $\approx 31\%$. In conducting our experimentation with MPCC on these repositories, we identified what we believe are not only anomalies with technical debt, but also more serious ones such as security vulnerabilities and illegal memory accesses (e.g., crash bugs).

7 Broader Impact

MP-CodeCheck uses semi-trust to obtain its training data, which means that MPCC could be susceptible to unintentionally learning from untrustworthy code. For example, if an adversarial attacker were to provide training code data with many instances of malicious programming patterns, the resulting MPCC model would likely exhibit many false negatives and false positives. That is, it may flag non-anomalous code as anomalous and anomalous code as non-anomalous.

Another broader impact to consider is MPCC’s demand for computational resources. MPCC obtains its knowledge by mining billions of lines of code, which demands non-trivial amounts of computation, albeit much less than any deep learning based counterpart. This demand for computation places some amount of strain on both the environment, which can contribute to climate-related issues, and the global supply chain, which can contribute to economic issues.

As a machine programming system, MPCC has the objective of reducing or eliminating some burdens of software development. This may seem to potentially reduce demand for software engineers. However, we believe that the tasks that MPCC alleviates are tasks that, despite being critical to software robustness, are principally only understood deeply enough to be done by a small minority of existing software developers. These tasks also take up a sizable chunk of software development time, whether in hunting down and fixing code anomalies or in fixing bugs manifested by unremedied code anomalies. We believe that by automating anomaly detection, MPCC would increase productivity of software developers and subsequently open up time for more creative tasks such as algorithm design and entrepreneurship, making robust software engineering more accessible to even more software developers.

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