Finding Anomalies in Scratch Assignments

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Abstract—In programming education, teachers need to monitor and assess the progress of their students by investigating the code they write. Code quality of programs written in traditional programming languages can be automatically assessed with automated tests, verification tools, or linters. In many cases these approaches rely on some form of manually written formal specification to analyze the given programs. Writing such specifications, however, is hard for teachers, who are often not adequately trained for this task. Furthermore, automated tool support for popular block-based introductory programming languages like Scratch is lacking. Anomaly detection is an approach to automatically identify deviations of common behavior in datasets without any need for writing a specification. In this paper, we use anomaly detection to automatically find deviations of Scratch code in a classroom setting, where anomalies can represent erroneous code, alternative solutions, or distinguished work. Evaluation on solutions of different programming tasks demonstrates that anomaly detection can successfully be applied to tightly specified as well as open-ended programming tasks.

Index Terms—Anomaly Detection, Scratch, Block-Based Programming, Program Analysis, Teaching

I. INTRODUCTION

Teachers frequently have to evaluate students’ implementations of programming assignments to provide feedback and support, assess progress, identify recurring problems, and to derive grades. These tasks are challenging because they require comprehending, analyzing, and debugging different program variants, often containing creative and unique bugs. These tasks can be supported with automated software analysis tools; for example, a common way to assess the correctness of student solutions is to run automated tests. However, programming is increasingly taught at earlier ages, often as early as elementary school, using educational programming languages such as Scratch. This causes several issues: First, automated tools that are common for advanced, text-based programming languages are rarely available for these educational programming languages. Even when they are, teachers at elementary school level often have no training in how to formalize specifications or automated tests; indeed even professional developers often fail to produce adequate tests. Finally, even a thorough test suite may fail to reveal programs that produce the correct result using an incorrect solution path.

To address this problem, we propose the use of anomaly detection for classroom programming scenarios. Anomaly detection is based on the idea that common behavior is more likely correct behavior, and that rare deviations of common behavior (so called anomalies) are likely wrong. In the context of software engineering, anomaly detection has been successfully applied to find bugs in large code bases requiring no specification, no tests, and no manual labor. While code bases in an educational setting tend to be small, they do contain common code constructs which can be exploited to find anomalies that deviate from the common solutions. Fig. 1a shows a common programming example in Scratch: the script continuously checks if the user has pressed the space key, and whenever this happens the sprite is moved by five steps. Fig. 1b shows a script that tries to accomplish the same but uses a wrong block: Instead of the move steps block, the go to position block is used. Generic linters would miss this bug as it is project-specific and does not violate any general programming concepts. Even an automated test only pressing the space key once would incorrectly report this behavior as correct. Given a dataset of students’ solutions for this task, anomaly detection learns common patterns such as to use a move steps block whenever the when green flag. forever and if-then blocks are combined. Consequently, the buggy script in Fig. 1b would be flagged as an anomaly.

In this paper, we introduce the concept of anomaly detection in the classroom. In detail, the contributions of this paper are:

- We formally introduce and implement anomaly detection for Scratch (Section III).
- We empirically evaluate the practical applicability of anomaly detection for Scratch (Section IV).

Evaluated on a dataset of six Scratch programming projects with many different student solutions, our implementation of anomaly detection for Scratch demonstrates that anomaly detection is a reliable way to find generic defects as well as project-specific ones, such as the one in Fig. 1b without any manual labor required from teachers.
II. BACKGROUND

Since programming knowledge, skills and mental models cannot be effectively acquired in the abstract, programming education is heavily based on practical exercises [15]. Students typically implement similar tasks based on textual specifications of what the programs should achieve, practicing concepts they first learned about in theory. In the sense of formative and summative assessment, the results of such tasks can provide educators with clues that they can use to evaluate and improve the students’ learning [13]: Teachers, tutors, and automated tutoring systems need to interact with students during assignments to provide feedback and help during exercise sessions, or to evaluate and grade submissions; this applies equally to textual and visual programming languages. In this section we explore what means for support exist in this setting, and how anomaly detection can help, focusing particularly on the visual programming language SCRATCH.

A. Evaluating Student Programs

In order to teach programming, educators need to have content knowledge (CK) as well as pedagogical content knowledge (PCK) [20]. The latter is required for planning and conducting programming lessons and comprises various aspects that influence the learning process. According to the model of Magnusson et al. [27], PCK includes, amongst others, knowledge about suitable assessment strategies to evaluate students’ understanding. This aspect is particularly important, as studies show that teachers’ insufficient understanding of their students reduces the quality of their teaching [35].

While Grover argues for a range of different assessment types during learning to program [12], the most obvious and common method of assessing programming skills is to evaluate the students’ programs [22]. This can provide important insights to educators—e.g. by exposing misconceptions or gaps in the students’ understanding—but is particularly challenging for novice or inexperienced teachers [37].

A primary means to support the analysis of learners’ code is by running automated tests against the solutions. The most common application for this is automated grading: By implementing individual tests for the various requirements that a program should satisfy, the resulting grade can be determined as the ratio of tests that a submission passes. This general principle is implemented in numerous grading tools, which are summarized in various surveys [2], [7], [21]. Automated tests can also serve as feedback to students, or as the basis for producing hints and corrections [14], [33].

In practice, a primary challenge for the application of automated tests lies in their creation. First, it requires the existence of appropriate automation frameworks in which to specify and execute these tests, which are not always available. Second, creating suitable tests is challenging, even for professional developers [3]. [4], [32], [34].

Static analysis tools are sometimes applied for checking style, code smells, and bugs in student code. For example, the industrial strength FINDBUGS [19] tool has been investigated in an educational domain [8], and can be integrated into the build tool chain of modern autograders [24]. Such static analysis tools require no specification effort from the teacher, but the scope of the feedback they can produce is limited: They can only report generic, assignment-independent issues.

B. The SCRATCH Programming Language

SCRATCH [28] is a block-based programming language. Programmers can choose from over one hundred blocks [4] which resemble puzzle pieces. The blocks can be composed visually with each other in the SCRATCH editor [6] to define the behavior of SCRATCH programs. A collection of blocks that are connected to one unit is called a script. Usually, a script begins with a hat block which is an event listener. The hat block is followed by an arbitrary number of blocks that define the actions to execute after the event of the hat block was triggered. Scripts belong to actors [38], that is, either the stage or one of the sprites. The stage is the background of the program; sprites are the objects acting on the stage. Fig. 1 illustrates two SCRATCH scripts, both are triggered by the green-flag event—that is, start executing when the program starts—by clicking the green flag symbol in the SCRATCH editor. More details on SCRATCH and formalizations thereof can be found in the literature [28], [38], [39].

Blocks have different shapes and colors to distinguish between different categories of statements and expressions, for example, event listeners, or control structures. Generally, we distinguish between command blocks and reporter blocks. When executed, a command block performs different actions under specified conditions. Hat blocks, control blocks, stack blocks, and cap blocks are types of command blocks. A reporter block describes an expression to evaluate and produces a scalar value, for example, an integer, Boolean, or a string.

C. Program Analysis for SCRATCH

The increasing popularity of SCRATCH as an introductory programming environment has triggered research on analyzing the resulting programs. In particular, the observation that SCRATCH programmers tend to develop certain negative habits while coding [30] has led to investigations into the general quality problems in SCRATCH programs using static analysis tools. It has been shown that various types of code smells are prevalent [1], [17], [36], [40] and have a negative impact on code understanding [16]. There are tools for finding code smells in SCRATCH programs such as HAIRBALL [5], QUALITY HOUND [40] or SAT [6], and LITTERBOX [10] detects predefined bug patterns automatically.

Testing frameworks have also been proposed for SCRATCH. In particular, ITCH [23] translates a small subset of SCRATCH programs (say/ask blocks) to Python programs and then runs tests on these programs. The WHISKER tool [39] executes automated tests directly in the SCRATCH IDE, and supports property-based testing. BASTET [38] provides a general program analysis framework that can be used for any configurable program analysis, such as software model checking.

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1 https://en.scratch-wiki.info/wiki/Blocks last accessed February 12, 2021
2 https://scratch.mit.edu/projects/editor/ last accessed February 12, 2021
D. Anomaly Detection

An alternative to the common types of program analysis described above is offered by the concept of anomaly detection. The general principle is that likely rules about software projects, programming practices, or API usage are inferred automatically from source code, version histories, or execution traces. Violations of these rules (anomalies), are then reported as likely bugs. The quality of the reported violations depends on how rules are encoded, the algorithms used for mining the rules and determining outliers, as well as the data source.

There is a variety of technical approaches: Techniques based on frequent itemset mining techniques capture co-occurrences of methods and variables [25], [29]. These techniques can be extended to capture control flow information using graph models [9], [31], [43], [44]. For example, the JADET tool [44] extracts temporal properties that capture common sequences of method calls on instances of JAVA classes. An alternative lies in the use of n-gram language models to capture the regularities of software source code, and then to report aspects of code with low probabilities as suspicious [41].

A common assumption of these approaches is that anomaly detection is applied on large software projects, or on large collections of software projects that share some properties (e.g., common dependencies), such that the data mining algorithms succeed in extracting relevant patterns. In contrast, programs in an educational context tend to be small and on their own do not provide sufficient opportunity for mining properties. However, in contrast to a regular software engineering scenario there is redundancy in terms of multiple student solutions for the same problem, which we aim to exploit in this paper.

III. ANOMALY DETECTION FOR SCRATCH

In this section, we describe how anomaly detection can be implemented for SCRATCH programs. We build on an existing approach that was presented for object-oriented programs [42], [44] and adjust it for SCRATCH programs.

A. Modeling Control Flow with Script Models

We aim to find violations of temporal activations of blocks, and therefore model the control flow of SCRATCH programs. The control flow between blocks in a script is represented by its script model, which describes how the control of the program execution flow is passed between the blocks of a SCRATCH program. Formally, we define a script model as follows:

Definition 1 (Script Model). A script model is a tuple \( m = (L, B, G, l_0, L_x) \), with a finite set \( L \) of control locations, a finite set \( B \) of command blocks, a control transition relation \( G \subseteq L \times (B \cup \{\epsilon\}) \times L \), an initial control location \( l_0 \in L \), and a set of control exit locations \( L_x \subseteq L \). A control location can be reached by executing the blocks on the transitions in the control transition relation, starting from the initial location \( l_0 \).

Epsilon (\( \epsilon \)) moves are used (1) for abstracting away command blocks that are irrelevant for anomaly detection, and (2) as a convenience feature to create the script models. Epsilon elimination as known from \( \epsilon \)-NFAs [18] is applicable. All definitions that follow assume that script models are \( \epsilon \)-free, that is, that all \( \epsilon \)-moves have been eliminated upfront.

Example 1. Fig. 2 illustrates a script model and (1) how particular blocks can be abstracted away by (2) replacing them by \( \epsilon \)-moves and (3) eliminating the \( \epsilon \)-moves in the end. In this example, the reporter block (\( \text{key pressed} \)) is removed to discover more generic patterns.

Note that we generally abstract away reporter blocks in this work to discover more generic patterns.

In contrast to a control flow graph or automaton, a script model contains transitions that are labeled with control blocks despite the fact that the semantics of these blocks is encoded into the graph structure. Fig. 1 provides an example where the control block (\( \text{forever} \)) must precede the control block (\( \text{if-then} \)).

Example 2. Fig. 3 shows the script models of the SCRATCH scripts from Fig. 1. The nodes of this graph refer to control locations in a script, and the edges in between them denote blocks that can be executed from these locations.

B. Extracting Block Patterns from Script Models

Every single script (represented by a script model) implements a set of temporal properties that define how the script behaves over time. In a later step, behavioral patterns are mined by analyzing the temporal properties of a large set of script models—in contrast to related work [44], we do not use object usage models. Before we define the notion of temporal properties, we define the transitive closure of a script model:

Definition 2 (Transitive Closure). Given an \( \epsilon \)-free script model \( m = (L, B, G, l_0, L_x) \), we define the transitive closure \( G^+ \subseteq L \times B \times L \) of its control transition relation \( G \) recursively as \( G^+ = G \cup \{(l_1, b, l_3) | (l_1, b, l_2), (l_2, b, l_3) \in G^+ \} \).
**Definition 3 (Temporal Properties [44]).** The temporal property relation \( \preceq \subseteq B \times B \) of a script \( m \in M \) defines the pairs of blocks that occur one after the other in its control flow, possibly interleaved with the execution of other blocks. That is, \( \preceq = \{(b_1, b_2) \mid \langle b_1, l_1 \rangle \in G^+ \land \langle l_1, b_2, \cdot \rangle \in G^+ \} \). We write \( b_1 \preceq b_2 \) if and only if \( (b_1, b_2) \in \preceq \). We use the alternative notation \( \text{props}(m) \subseteq B \times B \) to denote the temporal properties of a given script \( m \).

In other words, the temporal property relation is defined by the blocks that we can reach eventually in the script model starting from a block at hand.

**Example 3.** Using the temporal property relation we can now analyze pairs \( (b_1, b_2) \in \preceq \) of blocks, where one block \( b_1 \) may precede the other block \( b_2 \). Fig. 4 shows the temporal property relation for the script model illustrated in Fig. 3a.

We use the notion of patterns to learn about common temporal behavior of scripts (and their models), which is central for detecting anomalies (deviations from common patterns).

**Definition 4 (Pattern [44]).** A pattern \( p \subseteq B \times B \) is a set of temporal properties, where one temporal property is a pair of blocks. A pattern \( p \) is supported by a script \( m \) if \( p \) defines a subset of its temporal properties, that is, if \( p \subseteq \text{props}(m) \). The set of all possible patterns is denoted by the symbol \( P \).

**Definition 5 (Pattern Support [44]).** Given a list of scripts \( \mathcal{M} = \langle m_1, \ldots, m_n \rangle \), the support \( \text{supp}(p, \mathcal{M}) \rightarrow \mathbb{N}_0 \) of a pattern \( p \) is the number of scripts that support the pattern, that is, \( \text{supp}(p, \mathcal{M}) = | \{ m \mid p \subseteq \text{props}(m) \land m \in \mathcal{M} \} | \).

**Example 4.** Consider the list \( \mathcal{M} = \langle m_1, m_2 \rangle \) of script models, which correspond to the scripts illustrated in Fig. 4. When considering the set of the temporal properties in Fig. 4 as one pattern, this pattern has support 1 based on the scripts \( \mathcal{M} \). The script in Fig. 4a adheres to every temporal property of this pattern, whereas the script in Fig. 4b does not exhibit several of the temporal properties of the pattern. Fig. 5 shows the missing temporal properties of the script—indicated with the color red and dotted lines. As the script does not have a \([\text{move steps}]\) block, all the temporal properties containing the block \([\text{move steps}]\) are missing. Therefore, the buggy script does not support the pattern and it has a support of 1.

Even though script models and block patterns are closely related and their graphical representation is similar, there are some key differences: The level of abstraction of patterns is higher than the level of abstraction of script models. While a script model only abstracts away reporter blocks, and therefore represents a limited set of scripts, there is an unlimited variety of scripts that may support a pattern. For example, a temporal property like \( [\text{if-then}] \prec [\text{if-then}] \) is supported by both a script in which a single \([\text{if-then}]\) block occurs in a loop and a script in which there are two directly consecutive \([\text{if-then}]\) blocks.

The set of actual patterns found in a set of script models (with corresponding temporal property relations) is computed using frequent itemset mining:

**Definition 6 (Frequent Itemsets [44]).** Frequent itemset mining \( \text{freq} : 2^{B \times B} \times \mathbb{N} \rightarrow 2^{B \times B} \) takes a set of sets of temporal properties and a minimum support threshold \( k \in \mathbb{N} \) as argument and produces a set of patterns that occur in at least \( k \) sets.

**C. Violations of Block Patterns**

Based on the concepts that we have described in previous sections, we now discuss how we identify anomalies in SCRATCH programs. Anomaly detection can help to show the absence of functionality. Note that anomaly detection is performed on closed patterns only, which are defined as follows:

**Definition 7 (Closed Pattern [44]).** A pattern is called closed if each pattern that is a superset has less support.

**Definition 8 (Violation [44]).** A script \( m \) violates a pattern \( p \) if the pattern is not a subset of the temporal properties of the script, that is, if and only if \( p \nsubseteq \text{props}(m) \).

Violations hint at scripts that do not support every temporal property of a common pattern. Therefore, the violation of a block pattern always consists of two sets of temporal properties: A set of sequential constraints which are adhered to, and a set of missing temporal properties—the deviation.

**Definition 9 (Deviation [44]).** Given a script \( m \) and a pattern \( p \), the deviation is the set of temporal properties \( \text{devi}(m, p) = p \setminus \text{props}(m) \) that are missing in the script.

**Example 5.** Fig. 5 which compares the temporal properties of the scripts in Fig. 4 shows the violation of the buggy script. The deviation consists of all five temporal properties related to the \([\text{move steps}]\) block.
Not all violations hint at defects or contribute new knowledge. The *confidence value of a block pattern violation* is defined by the confidence of its deviation and measures how many scripts exhibit the exact same deviation from the same pattern the violation violates.

**Definition 10 (Violation Confidence [44])**. Given a list of scripts $m = (m_1, \ldots, m_n)$, a script $m$ and a pattern $p$, the confidence of a violation of pattern $p$ of script $m$ is the ratio $c = s/(s + v)$, with the support $s = \text{supp}(p, m)$ and the number of violations that violate $p$ the same way $m$ does: $v = \{|m_i | \text{devi}(m_i, p) = \text{devi}(m, p) \land m_i \in m|\}$. 

**Definition 11 (Anomaly [44])**. An anomaly is a violation of a block pattern by a script that the violation confidence is above a particular threshold (minimum confidence).

The actual identification of anomalies is implemented based on Formal Concept Analysis. A lattice of closed patterns is traversed from the top element (the pattern with the highest support) down to elements with lower support (until a min-support limit is reached) [44]. The anomalies found are ranked and filtered using methods from Association Rule Mining to report anomalies likely pointing at erroneous behaviour [42].

D. Implementation

Our tool chain for anomaly detection for Scratch uses an extended version of LITTERBOX [10] to generate a collection $\langle m_1, \ldots, m_n \rangle$ of script models for a collection of Scratch projects. These script models are handed over to JADET [44] to mine patterns and check for violations. JADET’s algorithms for pattern and violation mining are not Java-specific: This allowed us to adapt JADET to check Scratch code without algorithmic adaptations. Note that while JADET was designed to operate on object usage models to check for correct API usage, we use script models that are not restricted to code that interacts with particular variables or objects.

E. Application

We envision that a primary application for anomaly detection is to support teachers during formative assessment: A major advantage of anomaly detection is that it highlights noteworthy or problematic behavior without requiring a detailed and laborious inspection of all student programs. It therefore seems particularly suitable also for real-time feedback during programming classes. Anomaly detection could similarly support summative assessment, although teachers would in this case need to be particularly aware that common erroneous behavior does not represent anomalies. Besides a general understanding of what an anomaly is, however, no further training should be required in order to use anomaly detection in the classroom. It is also conceivable that anomaly detection could be integrated into hint generation techniques, such that students receive feedback automatically, without the need for teacher interaction. In this context, richer data, for example using a history of previous solutions to the task at hand, could help to improve the quality of reported anomalies.

IV. Empirical Evaluation

To investigate the practical applicability of anomaly detection in Scratch, we aim to empirically answer the following research questions:

**RQ1** Can anomalies be found in assignment solutions?
**RQ2** Do erroneous solutions lead to more anomalies?
**RQ3** Which categories of anomalies can be identified?

We implemented our approach as an extension of LITTER-BOX [10] and JADET [42, 44] and it is available at: https://github.com/se2p/scratch-anomalies

A. Datasets

We use a dataset consisting of student solutions for six different programs:

- Monkey: The aim of this program is to make the sprite of a circus director continuously move towards a monkey [11].
- Elephant: The aim of this program is to simulate a dancing elephant by continuously switching its costumes (i.e., images representing different poses) [11].
- Cat: A cat sprite should indicate with a speech bubble whenever it catches the ball [11].
- Horse: A horse sprite should continuously change color, but when it touches the mouse pointer it should rotate [11].
- Fruit: The player controls a fruit bowl with the cursor keys, and has to catch fruit dropping down from the top [39].
- Open: For this dataset, the students first implemented three tightly specified tasks for training, before they were asked to implement something similar to the previous tasks, but were not given any further specification of what program specifically to create. Thus, unlike the other projects, this is an open task and there is no specification.

For each of these tasks we collected student solutions during programming sessions conducted by qualified teachers. For the Monkey, Elephant, Cat, and Horse tasks solutions were produced by primary school children aged 8–10, the Open task was solved by children aged 9–12, and the Fruit task was solved by children aged 12–13. The numbers of solutions as well as size and complexity metrics are stated in Table I. Note that we use the full datasets including empty projects of students who did not engage at all, since this also represents the actual use case of a teacher applying our approach.

| Project | Solutions | Blocks | Statements | Scripts | Sprites | WMC |
|---------|-----------|--------|------------|---------|---------|-----|
| Monkey  | 130       | 5.48   | 4.56       | 2.03    | 2.06    | 2.83|
| Elephant| 130       | 9.45   | 9.40       | 1.18    | 1.16    | 1.87|
| Cat     | 129       | 7.57   | 5.82       | 3.06    | 1.99    | 5.51|
| Horse   | 73        | 3.70   | 2.89       | 1.10    | 1.10    | 1.86|
| Fruit   | 42        | 54.26  | 38.50      | 6.86    | 3.05    | 16.57|
| Open    | 295       | 34.45  | 28.61      | 7.38    | 4.37    | 13.92|

B. Anomaly Mining

To mine violations, we extract the script models for each of the six datasets, and then use JADET to mine violations.
Extracted Script Models: Table [11] shows the number of projects and the resulting script models mined for every task. The creation process finished in less than two seconds for every dataset. All experiments on our datasets were conducted on an off-the-shelf laptop computer as would be available to teachers.

Mining Parameters: JADET offers four parameters to configure violation mining: The minimum support and minimum size of a violated pattern, the maximum deviation level of violations, and the minimum confidence. For minimum size and maximum deviation level, we fixed the values at the defaults used by JADET: The minimum size of a violated pattern was set to 2 as we are interested in violations independently of their size, and 10,000 for the maximum deviation level as we are interested in all violations, no matter how many temporal properties are missing.

C. Experiments

We conducted several experiments to answer the questions:

RQ1: To answer RQ1, we computed statistics on the script models extracted, as well as patterns and violations reported by JADET. Since the chosen approach to anomaly mining has not been used in this context before, it is unclear what parameter values are best for the minimum support and minimum confidence. We therefore conducted a sensitivity analysis on these two parameters with minimum size (= 2) and maximum deviation level (= 10,000) as fixed variables, changing only minimum support and minimum confidence. For the minimum support we tested the values {1, 5, 10, 15, 20}, where 20 is the default JADET value. For confidence we tested the values {0.1, 0.2, ..., 0.9}. Intuitively, larger values for both parameters are expected to produce higher quality anomalies; however, if the values are too large then there is a risk of missing relevant anomalies. Assuming a teaching scenario, we thus choose the configuration with the highest possible values that reports at least 10 anomalies for each dataset.

RQ2: To answer RQ2, we investigated how correctness of programs relates to whether anomalies are reported. We used a manual classification [38] of the Monkey, Cat, Elephant, and Horse datasets for which the programs are small enough to allow a binary correct/incorrect classification; only non-empty projects were classified. For the Fruit dataset, we used the number of failed tests of the grading test suite used in prior work [39] as a measurement of the degree of correctness, and correlated this to the number of anomalies reported. For the Open dataset a classification in correct/incorrect is not possible, since there was no specification.

RQ3: To answer RQ3 we manually classified the top-10 violations reported for each of the datasets. Two authors of the paper independently classified each of the violations as either:

- **Defective**: The violation hints at a defect in a script that stops it from working in the intended way.
- **Smelly**: The violation hints at a script that has quality issues but does not break the functionality of the program.
- **Non-defective**: Adherence to the violated pattern would not contribute to the functionality or quality of the program.

To support objective classification, we agreed on subcategories for every category above, by following the principles of Qualitative Content Analysis [29]. One author inspected all violations to classify and inductively developed subcategories on different levels: Specific subcategories of the above and more abstract subcategories, moving away from script and violation details. We discussed the resulting abstract subcategories with all the authors and agreed on the following subcategories:

- **Bug pattern (defective)**: The violation hints at a defect that a generic SCRATCH linter such as LITTERBOX [10] could find equally well.
- **Missing block (defective)**: The violation hints at a missing project-specific block.
- **Wrong order of blocks (defective)**: The violation hints at a script with the right blocks assembled in the wrong order.
- **Unnecessary block(s) (smelly)**: The violation hints at blocks which are unnecessary, but do not change the functionality of the program.
- **Distinguished work (non-defective)**: The violation does not hint at defects or smells in a script.

During independent classification by two of the authors, we inspected the full SCRATCH program only if the script itself would not provide sufficient information. We classified every violation into one of the subcategories. Examples for the subcategories are shown in Section IV-G.

D. Threats to Validity

As JADET was left unchanged in all areas that affect the correctness of the results, the main threat to internal validity is our own process that extracts the script models. To mitigate this threat, we wrote automated tests to validate the correctness of the script models it creates, and manually inspected a large number of script models in the development and classification process. To avoid bias in the manual classification process, we agreed on subcategories for every main category, for example, **bug pattern** is a subcategory of **defective**. In the classification process, we assigned both the main categories and the—less subjective—subcategories to every violation. In addition, every violation was classified by two authors and divergent assignments were discussed and resolved. Threats to external validity arise from our choice of parameters as well as the datasets used. We evaluated the effects of the parameters on quantity and quality, but further studies will be necessary to identify parameters that are acceptable for users. Besides the parameters, the quality of violations depends on various properties of the dataset it is applied to, such as the quality of submissions or sizes, and our findings may not generalize to other datasets. However, our dataset covers different scenarios in terms of class sizes as well as programming tasks, and we explicitly included closed as well as open tasks.

E. RQ1: Can anomalies be found in solutions?

Whether or not anomalies can be detected heavily depends on the parameters of the mining procedure. To find an appropriate parameterization to analyze script models extracted from SCRATCH programs, we conducted a sensitivity analysis; the
Table II: Summarized characteristics of the solutions, by task

| Project | #Solutions | #Models | #Patterns | #Violations | #Anomalies |
|---------|------------|---------|-----------|-------------|------------|
| Monkey  | 130        | 264     | 13        | 65          | 22         |
| Elephant| 130        | 154     | 9         | 34          | 10         |
| Cat     | 129        | 446     | 18        | 91          | 30         |
| Horse   | 73         | 80      | 8         | 39          | 10         |
| Fruit   | 42         | 295     | 749       | 1414        | 460        |
| Open    | 295        | 2207    | 289       | 684         | 169        |

results are shown in Fig. 6. Based on this analysis, we chose a minimum support of 20 and a minimum confidence of 0.9 for all datasets except the Horse example, where there are fewer solutions and we therefore used minimum support 10 and minimum confidence 0.7.

Table III summarizes the results of the model extraction and anomaly detection for the chosen parameterization. The number of models derived for each of the programs depends on the number of scripts in the solutions, and is thus roughly proportional to the number of scripts in the solutions as described in Table I with Cat, Fruit, and Open resulting in the most models. The number of patterns extracted is lower than the number of models in all but the Fruit example. For the Open example, the lower number of patterns is expected since there is more variety in the solutions, as students were free to implement their own ideas. In the Fruit game, on the other hand, all students implemented the identical game. In contrast to the other four closed examples, there is some redundancy within the scripts in each project, as the behavior of the apple and the banana sprites share several aspects—both drop from random locations at the top of the stage to the bottom and check whether they touch the bowl or the bottom. This shared behavior contributes to the number of patterns found.

Fig. 7 summarizes the sizes of these patterns. The majority of patterns are small, with only few temporal properties, although all projects have patterns of up to at least nine properties. The larger Fruit task stands out with substantially larger patterns than all other tasks. This is mainly a result of the overall size and complexity of the projects—see WMC and Statements in Table I. Although the Open task contains fairly complex solutions, too, there is less overlap between these solutions, resulting in generally smaller patterns.

These patterns tend to lead to multiple violations, as shown in Table III. However, only a subset of these violations are reported as mentioned in Section III-C. The number of anomalies generally is roughly proportional to the number of patterns, ranging from the configured minimum of 10 (Elephant) to 460 (Fruit). The number of projects that exhibit anomalies seems to directly depend on the number of patterns extracted: For the Elephant, Horse, Monkey, and Cat tasks, less than 15% of the projects had at least one anomaly. The Fruit task again stands out with more than half of the projects having reported at least one anomaly. For 25% of the Open task solutions, at least one anomaly is reported. Fig. 8 summarizes the distribution of

Fig. 6: Tuning results: Numbers of anomalies reported for each of the datasets with different configurations

Fig. 7: Pattern size distributions of our datasets

Fig. 8: Anomaly distributions of our datasets
F. RQ2: Do erroneous solutions lead to more anomalies?

Fig. 9a shows how many violations were reported on correct/incorrect programs for the Monkey, Cat, Elephant, and Horse tasks. Overwhelmingly, the programs for which anomalies were reported are incorrect solutions. The proportion of correct programs with anomalies is slightly higher for the Monkey program. This program has two sprites (circus director and monkey), whereas only the director is supposed to contain scripts. Manual inspection showed that many anomalies are triggered by additional code in the monkey sprite, which was not part of the specification (see Section IV-C). As correctness is a more fine-grained question for the Fruit example, Fig. 10 shows the correlation between anomalies reported and tests failed. There is a weak correlation (Pearson correlation coefficient of 0.27 with \( p = 0.105 \)), demonstrating that solutions with more errors tend to have more anomalies reported, which supports the results on the other tasks.

Fig. 9b shows how many of the incorrect programs had anomalies reported. While for the Cat example half the incorrect programs had an anomaly reported, for the other tasks the proportion is lower. This is a result of the number of patterns and anomalies mined with our parameter settings, and lowering the confidence or minimum support level would lead to more reported anomalies. However, lowering confidence and support thresholds may come at the price of more irrelevant anomalies: Fig. 11 shows the ratio of incorrect programs with anomalies reported to programs with anomalies reported in total for different parameter values. A higher ratio suggests a likely better quality of the reported anomalies, and Fig. 11 confirms that higher confidence and support increase the ratio.

The number of missed incorrect solutions (Fig. 9b) is particularly notable for the Elephant example, where the overall number of incorrect student solutions is also higher: For Elephant solutions to be considered correct, we required a \( \text{Forever} \) loop with costume changes and \( \text{Wait} \) blocks in between. Only 25 student solutions used \( \text{Forever} \) loops, while 48 student solutions used \( \text{Repeat times} \) loops instead, which we counted as incorrect. However, since this solution attempt is so common, it is unlikely to be reported as anomaly. In contrast, 11 students used no loops at all, and thus their programs more likely result in anomalies. In general, if the dataset contains more diverse solutions, then fewer patterns will be found with high support. This suggests that different use cases may require different parameter settings. For example, formative assessment at intermediate points may require different thresholds for support and confidence than summative assessment at the end of the assignment. Note that a further 46 solutions to the Elephant task are empty, i.e., consist only of the hat-block provided as starting point. Since at least two blocks are required in order to form a temporal property, no anomalies are reported for such empty projects (Fig. 9 only shows non-empty projects).

G. RQ3: Which categories of anomalies can be identified?

Fig. 12 summarizes the results of the manual classification of the top ten anomalies for each of the datasets. In total, 46 of the 60 classified anomalies hint at defective code, with 11 anomalies in the subcategory bug patterns, 32 in the subcategory missing blocks and 3 in the subcategory wrong order, 4 anomalies hinted at smelly scripts with unnecessary code, and 10 hinted at non-defective, distinguished work.

Except for the Open task, the majority of the detected anomalies hint at defective code. Most defects (35 out of 46) are project-specific problems that a generic linter would miss: Missing blocks and the wrong order of blocks. The anomalies in the tasks Cat, Elephant and Monkey predominantly show that a specific block, which is essential for the solution of the task, is missing in the student code.
Fig. 12: Results of the manual anomaly classification

Fig. 13: The anomaly ranked third in the Horse task. It belongs to the missing block subcategory, as the block responsible for the required color change of the horse is missing.

As an example for the missing block category, Fig. 13 shows a student solution for the Horse task which does not have the block responsible for the required color change. The anomaly shows the absence of this block, and therefore provides important feedback for both the teacher and the student. The student can be made aware of the missing block and the teacher can use the anomaly as an opportunity to discuss in class when a task is considered solved.

Fig. 14 shows a project-specific anomaly of the wrong order subcategory: Although the student’s solution for the Cat task contains most of the blocks necessary for solving the task, they are not in the correct order—the script is defective. To help the student, a teacher can address the script flow in class or trace the script step by step together with the student.

Most of the anomalies in the subcategory bug pattern hinted at the bug patterns Missing Loop Sensing (a condition that should be checked repeatedly in a loop is checked only a single time), Forever Inside Loop (an inner infinite loop prevents code in the outer loop from being reached) and Terminated Loop (a loop is unconditionally stopped after the first iteration) as implemented in LITTERBOX. Fig. 15 shows an anomaly of the Open task that shows a problem for which LITTERBOX does not yet define a bug pattern, but which could be found by a generic checker: Before the script checks if its sprite touches another sprite, the hide block is executed. However, while being invisible a sprite cannot touch other sprites, therefore the actions within the true branch of the if-then are never executed. Based on this anomaly, a teacher can not only help the individual student and explain that the student should have used messages to coordinate the program flow; the anomaly also provides clues about what misunderstandings and misconceptions to touch upon in class.

Besides anomalies that indicate defective code, there are 4 cases of smelly code with extraneous scripts or blocks that do not influence the program behavior, but negatively affect the code quality. In the script in Fig. 16a, the student programmed a countdown using a timer variable and a conditional loop breaking when the timer is equal to zero. Subsequently, the script uses an if-then block to check if the timer equals zero. This block is redundant, since the conditional loop already determines the countdown to stop as soon as the timer is set to zero. Even if the anomaly in Fig. 16b does not explicitly state that the if-then is redundant, it directs the attention to the conditional. Building on such examples of smelly code, broader concepts from software engineering, such as code quality issues, can be incorporated into teaching.

There are 10 cases where there are scripts that trigger anomalies, even though the underlying code is not erroneous.
For the classroom context since the student can be made aware of the actual task and the teacher can (if necessary) adjust teaching activities and pacing, or acknowledge and reward creative extensions of the tasks to encourage student creativity.

RQ3 Summary. Out of 60 classified anomalies, 46 hinted at defective code, 4 hinted at smelly code and 10 hinted at distinguished student work. All of these anomalies provide valuable feedback for teachers.

V. RELATED WORK

Alternative approaches for analyzing Scratch programs introduced in Section II-C include linting, testing, and verification. All of these require some sort of prior, manual work—tests, checks or specifications, whereas anomaly detection requires no manual work. Furthermore, in contrast to generic linters anomaly detection can also find project-specific bugs; on the other hand, anomalies may help to identify new, previously unknown generic checks to implement in linters, such as the hide-show defect (Fig. 15) we discovered in our analysis. The quality and number of reported anomalies, however, depends on the underlying dataset, the number of students, and their overall progress in the programming assignment; these are factors we plan to study in our future work.

Our approach for anomaly detection in Scratch is based on the JADE tool, which is originally designed to analyze object usage models for Java objects [44]. We chose this approach because approaches using the version history [26] are not applicable on Scratch, and our motivation from an educational point of view is to find anomalies in the temporal relation of blocks, rather than relations between variables and method calls [25] or patterns of interactions of multiple objects [41]. However, many different anomaly mining techniques for software have been proposed over the years, and others may also be applicable to our specific domain.

VI. CONCLUSIONS

With programming education becoming more prevalent, even at earlier ages, there is an increasing demand for tools to support educators and learners. To the best of our knowledge, this paper is the first proposal to use anomaly detection on Scratch student code. Anomaly detection requires no manual specification effort, and, as our evaluation demonstrated, is nevertheless effective at finding relevant issues.

Our initial investigation achieved promising results, but also raised many interesting follow-up questions for future investigation: The specific technique of anomaly detection we implemented has several parameters, and other anomaly detection techniques might be able to find other or more interesting anomalies. Understanding what techniques and parameters lead to the results that are most helpful will require further experiments, and a better understanding of when and how teachers and learners would apply anomaly detection. A related question is how to best present anomalies to teachers and students in a way that helps them to understand the problem with their code, and how to fix it. Often, the pattern violated by an anomaly may be able to serve as a hint on a correction.

While programming and code quality are essential aspects of software engineering education, anomaly detection is applicable to any software engineering artifacts for which patterns can be formalized. It may therefore be possible to support education with respect to all phases of the software engineering life cycle.

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