Abstract—Block-based programming languages like Scratch have become increasingly popular as introductory languages for novices. These languages are intended to be used with a “tinkering” approach which allows learners and teachers to quickly assemble working programs and games, but this often leads to low code quality. Such code can be hard to comprehend, changing it is error-prone, and learners may struggle and lose interest. The general solution to improve code quality is to refactor the code. However, Scratch lacks many of the common abstraction mechanisms used when refactoring programs written in higher programming languages. In order to improve Scratch code, we therefore propose a set of atomic code transformations to optimise readability by (1) rewriting control structures and (2) simplifying scripts using the inherently concurrent nature of Scratch programs. By automating these transformations it is possible to explore the space of possible variations of Scratch programs. In this paper, we describe a multi-objective search-based approach that determines sequences of code transformations which improve the readability of a given Scratch program and therefore form refactoring. Evaluation on a random sample of 1000 Scratch programs demonstrates that the generated refactorings reduce complexity and entropy in 70.4% of the cases, and 354 projects are improved in at least one metric without making any other metric worse. The refactored programs can help both novices and their teachers to improve their code.

Index Terms—Search-Based Refactoring, Scratch, Readability

I. INTRODUCTION

Scratch [1] is a block-based programming language created to introduce novices to the world of programming in a fun way. The shapes of the blocks ensure that only syntactically valid code can be assembled, and high-level programming statements make it easy and quick to create working programs and games. Programming with Scratch is usually learned in a self-directed way [1] or taught by instructors who often are not skilled programmers themselves. As a result, Scratch programs tend to have low code quality [2], which in turn has been found to negatively impact the pedagogical effectiveness [2], [3]. For example, Fig. 1a contains a Scratch script in which a sprite is controlled in a loop. While functionally correct, the use of a loop-condition nested in an if-block makes the code unnecessarily complicated.

In software engineering, code with low quality is typically refactored [4], which means that the design is improved without changing the implemented behaviour, for example by extracting or moving methods. Such common refactorings tend to rely on abstraction mechanisms that are only available in higher programming languages [5], but not in Scratch. Even when they are available, their use might not be desirable in the context of young programming learners who are already busy trying to understand the most basic programming concepts. However, it is still possible to improve Scratch code using refactorings tailored for the specifics of the Scratch programming language. In particular, in this paper we focus on refactorings intended to improve the readability of the code, which is directly linked to its understandability [6]. For example, Fig. 1b shows a refactored and more readable version of Fig. 1a which has the same functionality, yet uses fewer blocks, less complex control flow, and overall just looks tidier.

At this level of granularity, even small learners’ programs may offer overwhelmingly many opportunities to apply such refactorings. In order to support programming learners and their teachers, we propose an automated approach to identify sequences of changes to programs that lead to an overall improvement in readability and therefore form refactorings. We define a set of atomic Scratch code transformations based on rewriting control structures as well as the event-driven distribution of code to concurrent scripts. All implemented refactorings are designed to preserve program semantics by respecting important dependencies such as data, time and control [7]. Given a candidate program, we then use a meta-heuristic search algorithm to navigate the search space of possible transformation sequences in order to find versions of the program that reduce its complexity, entropy and size, which are three important factors that have been established to influence code readability [6].
In detail, the contributions of this paper are as follows:

- We propose a set of 26 atomic code transformations for 
  Scratch programs (Section III-A).
- We introduce a search-based approach to generate se-
  quences of transformations that improve the readability
  of Scratch programs (Sections III-B to III-E).
- We evaluate an implementation of this approach on a
  random sample of 1000 learners’ programs (Section IV).

Our experiments demonstrate that search-based refactoring
improves Scratch programs: Out of 1000 projects, 704 are
improved with respect to complexity and entropy, and 354 pro-
jects result in dominating solutions, i.e., programs that are better
in at least one metric, and not worse in any. Our approach is
implemented as part of the LITTERBOX [8] analysis framework
for Scratch programs, and is freely available to support
learners, teachers, and researchers.

II. BACKGROUND

A. Search-based Refactoring

Refactoring describes the process of improving code quality
without changing functionality. Concrete refactorings, i.e.,
generic and re-usable steps to alter code with the intent to
improve its quality, are often defined in order to remove code
smells [4]. For example, duplicated code can be refactored by
replacing repeated segments of code with calls to an extracted
function capturing the common functionality. Many common
refactorings can be automated, and software developers have a
wealth of different automated refactorings at their disposal
in modern integrated development environments [9], [10].

However, developers still face the challenge of having to decide
when and where to apply which refactoring. Search-based
refactoring [11] aims to address this challenge by exploring the
search space of possible program refactorings for a given
program, guided by fitness functions that measure aspects of
code or design quality. Since it is difficult to capture code
quality with a single metric, it is common to use multiple
different metrics and multi-objective search algorithms when
applying search-based refactoring [12]. It has been shown that
this approach can successfully lead to improvements [13]–[15],
and the field is an active area of research [16]–[18].

B. Code Quality Analysis for Scratch

In Scratch, programs are created by dragging and dropping
puzzle-like blocks in the Scratch editor [1]. In total, there are
over one hundred blocks to choose from. Blocks connected
to each other form scripts. Every script belongs to either the
background of the game, the so called stage, or to a sprite, i.e.,
an object acting on the stage. The first block of a script usually
is a hat block, i.e., an event listener that triggers execution of
the script. Blocks have different visual shapes, allowing only
grammatically valid combinations of blocks. In the case of hat
blocks, for example, blocks can only be added at the bottom,
but not at the top. Control blocks like if-statements or loops

https://scratch.wiki.info/wiki/Blocks, last accessed 2021–06–02.
https://scratch.mit.edu/projects/editor/, last accessed 2021–06–02.

C. Code Readability

Considering the context of programming education, an
alternative perspective on code quality is how the code affects
program comprehension. While difficult to quantify, readability
of source code intuitively describes how easy it is to understand
it. Buse and Weimer [27] created a model of code readability
based on subjective human judgements of given code snippets,
and demonstrated that this metric strongly correlates with
different aspects of code quality. The model is based on a
collection of syntactic features such as line length or types of
tokens used. Posnett et al. [6] demonstrated that this readability
model can be explained in terms of only three essential features:
size, complexity, and entropy. They used the common metric
of lines of code to measure size, the Halstead metric suite to
measure complexity, and demonstrated that this metric strongly correlates with
readability therefore lies in considering and optimising some metrics representative of
size, complexity, and entropy.

III. APPROACH

A. Code Transformations for Scratch

In order to refactor Scratch programs to more readable
versions, we aim to find sequences of code transformations

https://scratch.mit.edu/projects/editor/ last accessed 2021–06–02.
which, when applied together, improve the program. To this end, we define atomic transformations on the abstract syntax tree (AST) of SCRATCH programs. Each transformation can be applied to individual nodes, subtrees, or the edges between these. A transformation takes the AST of a program \( S_n \) as input, transforms it accordingly, and returns the modified AST representing the new program version \( S_{n+1} \) as output. For every transformation we also maintain information about where it is applied to. An atomic transformation can potentially be applied at different locations of the AST depending on its structure, but transformations may require certain preconditions to hold in order to be applicable. In order to determine for a given program \( S_n \) which concrete transformations are possible, we define the function \( \text{findPossibleTransformations}(S_n) \) for each type of transformation, which operationalises the matching of suitable locations in the AST as well as the preconditions of the transformation and returns a list of all possible instantiated transformations, applicable to the AST \( S_n \).

For most code transformations we also define their inverse transformations (\( \Leftrightarrow \)) to enable the search to reach relevant intermediate states of program transformations. In particular, we expect that these transformations enable the search to escape local optima and potentially enable more powerful transformations in the subsequent search. In total, we define 26 atomic transformations which are categorised as either (1) control flow transformations or (2) concurrency transformations:

**Control flow transformations** transform an individual script by reordering its blocks or replacing control blocks by equivalent combinations of blocks. Control blocks can be nested and hard to read, but can often be simplified as the abstraction level of the SCRATCH blocks varies, e.g., a \( \text{forever} \) loop which contains a conditional termination can be simplified to a \( \text{repeat until} \) loop. Furthermore, for conditionals, we apply transformations based on logical equivalences of their conditions. We define the following control flow transformations:

- **Swap Statements** Swap two statements that are independent of each other, if swapping does not create new dependencies.
- **Loop Unrolling** (\( \Leftrightarrow \) Sequence to Loop) Unroll a \( \text{repeat times} \) loop by repeating its body.
- **Forever If to Forever Wait** (\( \Leftrightarrow \) Forever Wait to Forever If) Replace an \( \text{if} \) block inside a \( \text{forever} \) loop with a \( \text{wait until} \) block with the same condition.
- **Extract Loop Condition** (\( \Leftrightarrow \) Inline Loop Condition) Transform a \( \text{forever} \) loop that conditionally terminates the script or the program to a \( \text{repeat until} \) loop.
- **Split If Body** (\( \Leftrightarrow \) Merge Double If) Split the body of an \( \text{if} \) block. Replace the \( \text{if} \) block by one containing the first part of the body, add another \( \text{if} \) for the remaining statements.
- **If Else to If If Not** (\( \Leftrightarrow \) If If Not to If Else) Split an \( \text{if else} \) block into two \( \text{if} \) blocks. The second \( \text{if} \) block checks on the negated initial condition.
- **Ifs to Conjunction** (\( \Leftrightarrow \) Conjunction to Ifs) Transform two nested \( \text{if} \) blocks into an \( \text{if} \) block which checks for the conjunction of the initial conditions.
- **If If Else to Conjunction** (\( \Leftrightarrow \) Conjunction to If If Else) Replace an \( \text{if} \) containing an \( \text{if else} \) by two \( \text{if} \) blocks. The condition of the first \( \text{if} \) is the conjunction of the two initial conditions; the second condition is the one of the first if.
- **If Else to Disjunction** (\( \Leftrightarrow \) Disjunction to If Else) Replace an \( \text{if} \) block in the else case of an \( \text{if else} \) block by an \( \text{if} \) with the disjunction of the two conditions if the then cases of the initial conditionals have the same statements.

**Concurrency transformations** are based on the event-driven nature of SCRATCH programs. For example, it is common practice to place independent functionality in separate concurrent scripts. Consequently, sometimes it is possible to split loops and scripts into several smaller scripts, which are executed concurrently. For instance, the **Extract Independent Subscripts** transformation splits a script into multiple independent scripts. In order to preserve the semantics of the program it is important that dependencies between statements are considered when deciding which transformations can be applied:

- **Control dependencies**: We consider control dependencies using a classical control dependence graph; it is not possible to split statements if one is control dependent on the other.
- **Data dependencies**: We consider data dependencies by building a data dependence graph based on a classic reaching definitions analysis. As an adaptation to SCRATCH, this analysis has to take not only the variables in the program into account, but also the attributes of the sprites and the stage. In particular, for each sprite we consider its position, rotation, costume, size, and visibility as attributes, and define for each of the program statements in SCRATCH whether it defines or uses this attribute.
- **Time dependencies**: SCRATCH programs tend to make heavy use of timing-related statements, for example to control the speed of movement of sprites, to synchronise interactions between sprites, or to encode the steps of sequences of animations or interactions. If a statement is a successor of a timing-related statement, then it is not possible to split the script between these statements as the concurrent execution would not adhere to the same timing. For each block in the SCRATCH language we determined whether it is timing-related, and we use a simple forward-may dataflow analysis to identify which statements are time-dependent on which other statements.

We define the following concurrency transformations:

- **Split Loop** (\( \Leftrightarrow \) Merge Loops) Split the body of a loop if there are no dependencies between the statements of its body and splitting does not create new ones. Replace the initial loop body by the first part of the body, add another loop for the remaining statements of the body.
- **Split Script** (\( \Leftrightarrow \) Merge Scripts) Split a script if there are no dependencies upwards.
- **Extract Independent Subscripts** Split a script with dependencies into new scripts which do not depend on each other but respect the dependencies in the initial script. We define no inverse transformation since it would produce too many options of which scripts to combine and in which order.
Extract Events from Forever (\(\Leftarrow\) Merge Events into Forever) Replace a \(\text{forever}\) loop with \(\text{key pressed}\) conditionals by scripts triggered by \(\text{when key pressed}\) event listeners.

Split Script after Until (\(\Leftarrow\) Merge Scripts after Until) Split a script after a \(\text{repeat until}\) loop. Add a new script with a \(\text{wait until}\) and the same condition.

B. Fitness Functions

The aim of the code transformations is to improve the readability of the code. In order to guide the search to achieve this objective, we require fitness functions that encode relevant aspects of code quality. A common approach in search-based refactoring is to use different metrics in a multi-objective optimisation scenario. Intuitively, we would like to improve the readability of SCRATCH programs by avoiding unnecessary complexity, keeping programs as small as possible, and optimising coherence of the code within individual scripts. These objectives are reminiscent of work on modelling subjective code readability, which has been shown to be influenced by size, complexity, and entropy [6]. Consequently, we define the following fitness functions:

1) Total number of blocks: In order to keep solutions as simple as possible and to avoid that the search unnecessarily inflates programs, one goal of optimisation is to minimise the size of programs. We measure the size of a SCRATCH program in terms of the blocks it consists of. Blocks can represent not only statements but also expressions. For example, the script in Fig. 1a consists of nine blocks: An event block, the forever loop, the say and move statements, the if statement, the stop statement, the sensing block checking if the space key has been pressed, and the two drop-down boxes are also counted as blocks since they can be replaced with other blocks. The refactored script in Fig. 1b only consists of six blocks.

2) Block Category Entropy: The concept of entropy is used in information theory to describe the uncertainty or surprise in a random variable, and can be thought of as the amount of information contained in the variable. A higher entropy describes a higher uncertainty of a variable. It has been shown that the entropy of the tokens in source code is directly related to the readability of the code [6], and we therefore aim to minimise it. We measure entropy at the level of blocks in a script. The blocks in the SCRATCH programming language are organised in different categories depending on which aspects of functionality they address. The main categories are motion, looks, control, sensing, operators, variables, and events. We calculate entropy in terms of the categories of blocks within a script, which intuitively means that a script has low entropy if it is only responsible for one type of functionality. The category entropy for a script \(S\) is calculated as Shannon entropy \(H(S)\) given the number of blocks of category \(c_i\) as \(\text{count}(c_i)\), and total number of blocks as \(\text{numberOfBlocks}(S)\):

\[
H(S) = - \sum_{i=1}^{n} p(c_i) \cdot \log_2 p(c_i), \quad \text{with}
\]

\[
p(c_i) = \frac{\text{count}(c_i)}{\text{numberOfBlocks}(S)}
\]

For example, the script in Fig. 1a contains one event block, one looks block, one motion block, two sensing blocks, two control blocks, and the two menu blocks. As the total number of blocks is 9, the entropy is

\[
H(S) = - \left( \frac{1}{9} \cdot \log_2 \frac{1}{9} + \frac{1}{9} \cdot \log_2 \frac{1}{9} + \frac{1}{9} \cdot \log_2 \frac{1}{9} + \frac{2}{9} \cdot \log_2 \frac{2}{9} + \frac{2}{9} \cdot \log_2 \frac{2}{9} + \frac{2}{9} \cdot \log_2 \frac{2}{9} \right) = 2.50.
\]

In contrast, the refactored script in Fig. 1b contains only one block of each type, such that

\[
H(S) = - \left( \frac{1}{6} \cdot \log_2 \frac{1}{6} + \frac{1}{6} \cdot \log_2 \frac{1}{6} + \frac{1}{6} \cdot \log_2 \frac{1}{6} + \frac{1}{6} \cdot \log_2 \frac{1}{6} + \frac{1}{6} \cdot \log_2 \frac{1}{6} + \frac{1}{6} \cdot \log_2 \frac{1}{6} \right) = 2.58.
\]

Thus, the refactored script has a higher entropy as there is higher uncertainty about the categories of blocks used.

Since we aim to improve the constituent scripts of a program, as fitness function we compute the average category entropy for each script in the program.

3) Complexity: The Halstead suite of metrics intends to quantify different complexity-related properties of a program such as volume, difficulty, or effort. The metrics are calculated using information about the operators and operands used in the program. As operators we count all blocks representing statements, events, and blocks from the “operators” category, while we define literals, variables, parameters, and drop-down menu options as operands. We use the Halstead difficulty as target metric to optimise, as it intends to quantify how easy it is to understand a program while reading or programming. It is calculated as follows:

\[
D = \frac{\#\text{unique operators}}{2} \cdot \frac{\#\text{total operands}}{\#\text{unique operands}}
\]

For example, the script in Fig. 1a consists of seven operators (the blocks) and four operands (the two literals and the two drop-down menu options), all of which are unique. Consequently, the Halstead difficulty is \(\frac{7}{2} \cdot \frac{4}{7} = 3.5\). The refactored script in Fig. 1b consists of five operators and three operands, and thus has a lower Halstead difficulty of \(\frac{5}{2} \cdot \frac{3}{5} = 2.5\). Similar to Section III-B2 we compute the average Halstead difficulty per script and use this as fitness value for the optimisation.

C. Refactoring Representation

In order to enable the search to find program transformations, a suitable representation is required for these transformations. One possibility would be to apply the search directly on syntax trees in the style of genetic programming, and thus to generate a completely transformed AST as result of the search. However, presenting a modified program that may be very different from its original version to the user without explanation of how this was derived is not acceptable for our use case. Consequently, we need the search to evolve sequences of refactorings that explain the changes. However, storing concrete code transformations as lists would create the following problem: Each transformation in a sequence depends on the state of the program after the previously executed alteration. Standard search operators such as mutation and crossover (Section III-D) may thus break individuals of the...
search if the state of the AST has changed as part of other transformations (for example, a merge transformation in a sequence may no longer be applicable if a prior transformation removes one of the merged scripts).

To overcome this issue, we use an integer representation inspired by grammatical evolution [30]. In grammatical evolution, the genotype is given by a list of integers (codons). The phenotype is obtained by applying a mapping as follows:

Starting at the first production of starting symbol \( n_0 \) for a given grammar, we choose the \( r \)th production rule out of \( n \) available rules for a current non-terminal \( x \). For a single codon \( c \) the chosen production rule \( r \) is calculated as follows:

\[
r = c \mod n
\]

When a production is selected, the next codon is decoded. If no more codons are left, or for one state of program the set of production rules is empty, the mapping stops.

Conceptually, the grammar to produce a sequence of transformations of length \( n \) is given by the following grammar:

\[
\text{solution} ::= \text{transformation}_1 \text{ transformation}_2 \ldots \text{transformation}_n
\]

The terminals of our grammar are individual transformations of the AST applicable to the given state of a program. The following production defines the possible transformations for a given state of a program \( S_n \):

\[
\text{productions} ::= \text{findPossibleTransformations}(S_n)
\]

The resulting program state \( S_{n+1} \) is returned by applying the transformation. With this representation we do not need to store lists of concrete transformations, but the genotype is a simple list of integers that encode the applied production rules. Consequently individuals always represent valid sequences of transformations, and it is straightforward to define search operators. Note, however, that the same integer may represent different AST transformations in different solutions.

Example: Consider the program \( S_0 \) in Fig. 2a and suppose \( \text{findPossibleTransformations}(S_0) \) returns the following possibilities:

1) replace the left \( \text{if} \) blocks with a \( \text{wait until} \) block
2) replace the right \( \text{if} \) blocks with a \( \text{wait until} \) block
3) merge the two loops

Now, let the following list of integers be given as an example encoding of a phenotype for the program \( S_0 \):

\[
T = \langle 5 \ 9 \ 10 \ 42 \ 17 \ 8 \ 13 \ 2 \ 13 \rangle
\]

The decoding would start with the codon 5. Since the described three productions are applicable for the initial program, the decoding to the first transformation thus looks as follows:

\[
5 \mod 3 = 2 \quad \rightarrow \quad S_1 = \text{merge_loops}(S_0)
\]

Since the calculated production rule was 2, the third option of all possible productions for the given state is chosen (0 would have been the first option). Afterwards the newly created program \( S_1 \) (seen in Fig. 2b) is evaluated again by computing \( \text{findPossibleTransformations}(S_1) \). Suppose this results in just one possible production, the \( \text{If If Not to If Else} \) transformation of the two consecutive \( \text{if} \) blocks. So the next decoding of our codon with the number 5 would look as follows:

\[
9 \mod 1 = 0 \quad \rightarrow \quad S_2 = \text{if\ not\ to\ if\ else}(S_1)
\]

This creates the new state \( S_2 \), seen in Fig. 2c. Assuming \( \text{findPossibleTransformations}(S_2) = \emptyset \) the evaluation of our solution \( T \) is finished, with \( S_2 \) being the final state of the refactored program that can be evaluated by its fitness.

D. Search operators

The number of required code transformations is unknown a priori and can be different for each program. We therefore chose a variable length for the encoding and rely on the search to find a suitable length for each solution. For each randomly generated individual of our initial population, we first select a random number \( n \) in the range \([1..\text{max}]\), with \( \text{max} \) being the maximum number of codons in a phenotype. We then generate \( n \) random codons by uniformly sampling integers in the range of 0 to
an upper bound $x$. As constraint, $x$ must be bigger than the maximum number of possible code transformations, otherwise the decoding of a solution might never choose productions with a higher number than $x$ due to the modulo operator.

When mutating an individual of length $n$, each codon is modified with probability $1/n$, by either (1) replacing it with a random codon, (2) inserting a new codon at the location, or (3) deleting the codon. We use single-point crossover, which would not have been directly applicable on a list of code transformations, but is easy for integer lists.

E. Algorithm

We evaluate the candidate program transformation sequences regarding three fitness values with conflicting objectives (see Section III-B) and therefore use the NSGA-II [31] search algorithm, which has been shown to be effective for many software engineering problems [32]. The algorithm can optimise for conflicting objectives, due to its reliance on Pareto dominance, which is defined as follows: One solution $x_1$ dominates a second solution $x_2$ if $x_1$ is not worse in any objective than $x_2$, and $x_1$ is strictly better than $x_2$ in at least one objective [31]. In other words, $x_1$ dominates $x_2$, written as $x_1 \prec x_2$, when the following holds for objectives $f_1, \ldots, f_M$:

\[
(\forall m \in \{1, \ldots, M\} : f_m(x_2) \leq f_m(x_1)) \land \\
(\exists m \in \{1, \ldots, M\} : f_m(x_2) < f_m(x_1))
\]

All solutions are sorted into lists based on their Pareto dominance, the so-called Pareto fronts. All solutions in the first front are not dominated by another solution, all solutions in the second front are not dominated by any other solution except for the ones in the first front, and so on. The Pareto fronts help to determine which solutions are better than others, even with conflicting objectives. They are specifically built in a way, that one solution of the first front is definitely better than a solution in the second front. This means, with the NSGA-II and its fast-non-dominated-sort of populations, we have an algorithm that can separate lists of better and worse solutions, even for conflicting objectives. When deciding which solutions to include in the next population from within a Pareto front, NSGA-II aims to improve diversity by sorting individuals according to the crowding distance [31].

NSGA-II runs until a stopping criterion is met. In our case, we stop the evolution after a fixed number of generations or after a set threshold of seconds has passed. The fixed value of generations sets a base for the comparison of solutions. The timeout is important to cover for cases where particularly large programs or inefficient refactorings delay experiments.

IV. EVALUATION

In order to achieve a better understanding of the effectiveness of search-based refactoring for SCRATCH, we conducted an empirical analysis. A primary question is how often SCRATCH programs can be improved using our approach in the first place, therefore the first research question is as follows:

Research Question 1 (RQ1): How effective is search-based refactoring for SCRATCH?

The second research question aims to shed light on how the resulting programs look like:

Research Question 2 (RQ2): How do refactored SCRATCH programs differ?

Finally, we would like to understand which transformations are used in order to derive the refactored programs:

Research Question 3 (RQ3): How are the SCRATCH programs transformed?

A. Experimental Setup

An artifact that contains all data and software to reproduce our study is available online: https://github.com/se2p/artifact-scam2021

1) Implementation: We used LITTERBOX [8] to implement the search algorithm and transformations presented in this paper. LITTERBOX provides a parser that reads the JSON-format representation of SCRATCH programs and creates an AST. Each transformation consists of two parts: First, an AST-visitor encodes the matching and preconditions to derive the concrete transformations. Second, a concrete transformation implements the actual transformation for a specified target location. At the end of the search, our prototype produces CSV statistics, and creates one modified version of the SCRATCH input file for each individual of the final Pareto front.

2) Experiment Subjects: We randomly sampled 1000 publicly shared SCRATCH programs from the SCRATCH website between 2021–05–13 and 2021–06–10. The projects were created between 2020–05–28 and 2021–03–13. We restricted our sampling to programs with at least ten code blocks, to exclude projects that are just art or contain no functionality. We furthermore excluded remixes, which are modified and shared versions of already uploaded SCRATCH project[s] to ensure our dataset does not include the same code twice.

3) Experiment Setting: We executed LITTERBOX on each of the constituent programs in sequence to apply the search-based refactorings. For this, we used a fork of LITTERBOX in Git revision 6b193f88. We conducted our experiments on dedicated computing machines, each featuring two Intel Xeon E5-2620v4 CPUs with 2.10 GHz and 256 GB of RAM. The nodes are running Debian GNU/Linux 10.9 and OpenJDK 11.0.11. We limit each execution of LITTERBOX using the SLURM job scheduling system [33] to one CPU core and 8 GB of RAM; we set the available Java heap to 6 GB. We set the population size for NSGA-II to 30 chromosomes, and a maximum generation of 100 generations, and a maximum run time for the search process of 1800 s.

To answer RQ1, we compare the original projects with the Pareto front of refactored versions for each project and each run. We use the Vargha-Delaney $A_{12}$ effect size to quantify the difference with respect to each of the metrics; when comparing improvement of multiple metrics we average the effect sizes of each of the constituent metrics. Since all objective functions are minimised, an effect size $< 0.5$ represents an improvement.

https://en.scratch-wiki.info/wiki/Remix last accessed 2021–06–27.

https://scratch.mit.edu last accessed 2021–06–25.
We use a Wilcoxon rank sum test with $\alpha = 0.05$ to determine when metrics are significantly improved. To answer RQ2 we consider only the best individual within a Pareto front with respect to each metric. We use a Wilcoxon rank sum test to determine if differences are significant. To answer RQ3 we look at the distribution of code transformations contained in the solutions produced across all projects and runs.

B. Threats to Validity

1) Internal Validity: Meta-heuristic search is a randomised process, and different seed values for the random-number generator can cause different results. We therefore executed LITTERBOX 30 times on each SCRATCH project to mitigate the influence of randomness. Although we carefully checked our implementation, bugs may always influence results. Our transformations are semantics-preserving by design. To verify this, we used 15 SCRATCH projects from prior work for which we have automated WHISKER tests. To verify that the code transformations preserve the semantics, we executed these tests before and after the search-based refactoring, ensuring that no tests change their outcome.

2) External Validity: We use 1000 SCRATCH projects of different sizes for our experiments. The projects were randomly sampled as described in Section IV-A2. As always with such sampling, our results might not generalise to other projects, and so replication studies will be important for future work.

3) Construct Validity: We use NSGA-II [31] as a search algorithm and the total number of blocks, block category entropy, and complexity (see Section III-B) as search objectives. These three metrics are generally accepted proxies that influence readability. Other metrics may be better suited, and the approach can easily be adapted with other fitness functions. We assume that splitting a script into smaller scripts improves readability, which may not be the case for programming novices. However, an evaluation of subjective readability will require a human study. Although previous work showed NSGA-II to be effective [32], different search algorithms or other parameter settings may influence the achieved results.

C. RQ1: Effectiveness of Search-based Refactoring

Applicable code transformations were found for all but 28 projects in our dataset. The projects which were not transformed are usually either too small, or simply consist of only blocks with data- or time-dependencies to each other in sequential order (e.g., Fig. 5a). In such a case, our transformations are not applicable as they would break the original functionality of the program. We conjecture that these projects are mostly animations or stories which consist of sequences, no repetitions, and no opportunity for concurrency. Indeed the number of scripts per project is noticeably lower for projects that were not transformed (12.4 on average) compared to those that were (14.7 on average). For example, Fig. 5b shows a code snippet of a project that could not be transformed: The project contains six sprites, which in turn consist only of small scripts (cf. Fig. 5b). Even though the scripts are not purely sequential animations, they provide no opportunity for transformation.

![Figure 3: Animations and story projects provide no opportunities for transformations.](image)

(a) Timed sequences of statements (b) Animation with more complex control flow

Table I: Projects improved on combinations of objectives.

| Objectives                     | # projects significantly increased | avg. $A_{12} $ |
|--------------------------------|-----------------------------------|----------------|
| block size                     | 119                               | 0.733          |
| complexity                     | 765                               | 0.216          |
| entropy                        | 779                               | 0.215          |
| block size and complexity       | 88                                | 0.474          |
| block size and entropy          | 86                                | 0.474          |
| complexity and entropy          | 704                               | 0.216          |
| block size, complexity, entropy | 74                                | 0.388          |

Table I summarises the results in terms of the three objectives, considering the entire Pareto front. Out of 972 projects on which transformations were applicable, an average of 74 projects were statistically significantly improved with respect to all objectives, which is over 81.1% of the projects on which code transformations were applicable. Note that Table I checks for strict improvement in all listed dimensions. However, a total of 354 projects result in dominating solutions, i.e., solutions where no objective is worse and at least one is improved.

Overall, 119 projects were significantly improved regarding their block size, 765 regarding their complexity, and 779 regarding their entropy. The lower number of improvements of size is not surprising, as most transformations do not explicitly target size, and may in fact increase size. For example, each split of a script introduces at least one additional block for the additional event handler block. Indeed we included size as one of the optimisation goals mainly to prevent size from growing excessively, rather than trying to reduce it. Note that, even though the effect size of 0.733 suggests that size is more likely to increase than decrease on average, it may still be the case that solutions with smaller size exist on a Pareto front, if the search found no solutions that dominate the original program with respect to all objectives (RQ2 explicitly looks at improvements in each dimension).

The number of projects in which size was improved together with either complexity or entropy is substantially smaller than
the number of cases where it was possible to improve these objectives individually (Table I). However, in those cases where only complexity and entropy were improved, size did not increase by a lot (cf. Section IV-D). Consequently, many improved solutions were found that did not dominate the original program, but still increase our measured objectives. Over 70.4% of all projects and over 77.3% of all refactored programs were improved for both of these objectives together. Consequently, it might be worth exploring explicitly whether our anticipation of size increase would manifest, or whether optimising only for complexity and entropy achieves similar or better results. Alternatively, it might be interesting to define additional transformations that explicitly aim to improve size.

**Summary (RQ1):** 77.3% of the projects were improved in terms of complexity and entropy, and 354 projects resulted in dominating solutions.

**D. RQ2: Changes in Complexity, Entropy and Size**

Figure 4 summarises the differences in terms of the number of blocks for each of the projects, Fig. 4B in terms of the complexity, and Fig. 4C in terms of the entropy.

On average, projects have 86 blocks before the refactoring, and 85 after, considering the smallest projects on each Pareto front ($p < 0.001$). Figure 5 shows an example where the size is reduced successfully: A complex script is split into several smaller event handler scripts. Indeed our refactorings tend to significantly increase the number of scripts ($p < 0.001$). This is an expected result, given that two of the most frequent transformations split scripts into two or more scripts (cf. Section IV-E). As a consequence of scripts being split, we find that the number of long script code smells significantly decreases ($p < 0.001$). In total, 165 long script smells were removed on average per run over the 1000 projects.

The size objective appears to be harder to improve than the other two objectives, which is due to the transformations we defined. Splitting scripts may increase the number of blocks, since each additional script adds a new event handler block. Similarly, splitting loops or conditional statements may increase the block size, even when improving complexity and entropy. However, the number of added blocks tends to be small.

Considering the mean size over all individuals in each Pareto front (which may include the original project if no dominating solution was found), the block size increases from 86 to 89 on average over all projects and runs.

The search succeeds in reducing the Halstead difficulty from an average of 3.4 to 2.1 ($p < 0.001$). Figure 6 is an example where complexity is reduced: On the one hand, the replacement of the repetition with a simple fixed number of iterations reduces the size of the script. On the other hand, the extraction of the unrelated sound block leads to a very small script, which likely skews the fitness calculation which is based on the average per script. It might be worth experimenting with variants of the fitness function (e.g., using the maximum or median) to further improve the guidance for the search.
Figure 7: Entropy of the script decreases from 1.75 to 1.12.

Figure 4(e) shows that entropy is also successfully reduced by the search: On average, the entropy decreases from 1.4 to 1.2 ($p < 0.001$). The category entropy captures how chaotic (uncertain) scripts are with respect to the categories of blocks they use. Intuitively, scripts that proportionally contain more blocks of a category have a lower entropy value. Figure 7 shows an example where two scripts, which have high entropy as they mix together different block categories, are refactored to more coherent scripts. The entropy is improved because the first script is split into two scripts that each have a distinct category of blocks. Furthermore, the useless repeat (1) loops are “unrolled”, thus removing all blocks of the control category.

Some of the transformations (e.g., Split Loop) may increase the number of control and operator blocks in a script, which the entropy fitness interprets as an improvement. It might be worth investigating in the future whether the category entropy should exclude control blocks.

Summary (RQ2): Our approach tends to improve complexity and entropy by splitting scripts into multiple simpler versions, which may add a small number of blocks.

E. RQ3: Program Transformations

Across all solutions the mean number of transformations is 10.1. For each program we produced an average of 21.5 unique solutions. Fig. 8 shows the frequencies of the different transformations relative to the 7218240 transformations aggregated across all runs. The most frequent transformation is Swap Statements with a relative frequency of 26.0%, followed by Merge Scripts with 16.8%, Split Script with 16.5% and Extract Independent Subscripts with 16.4%.

Figure 9 shows a simple example program which shows how the frequent transformations form a refactoring which leads to a dominating solution. The initial script consists of duplicate if blocks which are separated by a say block. The most promising transformation to apply here is the Merge Double If transformation, which merges the duplicate if blocks. However, merging requires two successive if blocks. There are several possibilities to reach the intermediary state in which merging is possible. Either, apply a Swap Statements transformation on one if and the say block. Or, alternatively, split and merge the script in the suitable order, i.e., apply Split Script or Extract Independent Subscripts and merge the split parts back in the suitable order with Merge Scripts to merge the double ifs.

In general, splitting scripts can reduce the entropy of the initial script which may lead to dominating solutions. Merging scripts can be an important intermediate step for further simplifications, and it reduces the number of blocks due to the hat block which is no longer duplicated. However, the final result in Fig. 9 also illustrates an unnecessary application of the Swap Statements transformation: The turn degrees and the move steps blocks have been swapped unnecessarily, and since Swap Statements is the only refactoring which is its own inverse, it may be applied repeatedly. In general, it might be useful to apply minimisation on refactoring sequences before presenting solutions to the user in order to avoid redundant transformations, and it might also be a viable alternative to minimise the size of the refactoring sequence, rather than the program itself, as one of the search objectives.

The least frequent transformations are If If Else to Conjunction, which was only applied 3572 times, and If If Not to If Else with 3572 transformations, followed by Conjunction to If If Else with 3509 occurrences. There are multiple possible reasons for this. First, If If Else to Conjunction worsens all three metrics: Even though the control flow is simplified, the total number of blocks and the complexity are increased since all constituent operator blocks are counted. The same observation also applies to the If If Not to If Else transformation. Second, these transformations have quite strict preconditions on the combination of blocks to be applicable and other transformations may interfere. However, these transformations may be important prerequisites to enable other transformations by resolving nested control flow. Besides these transformations, we note that splitting transformations seem to occur more
We intentionally avoided this type of refactoring since this would introduce programming language aspects that early variants independently of concrete preconditions or code smells. Since we transform code directly, the approach is reminiscent of Genetic Improvement [35]. In principle our search can be seen as a Genetic Algorithm that is applied using an existing program as starting point. In contrast to Genetic Improvement, our modification operators are designed to preserve the program semantics, since our optimisation goal is code quality, rather than orthogonal aspects such as functionality or performance. Our representation of refactoring sequences also differs in terms of the encoding used [36] since explainability of the transformations is an important aspect for our use case.

The number of code transformations that do not change the program semantics found by our search is substantial, which provides further evidence for the concept of neutral program space [37], [38]. It is conceivable that, given the target audience of novice programmers, the code we are attempting to improve is less clean and contains more redundancy, thus providing even more possibilities for semantics-preserving transformations.

**VI. Conclusions**

Although the block-based nature of introductory programming languages makes it easy to assemble code, it has been observed that code quality is often problematic with young learners [2], [12], [21], [26], which may affect understanding and learning [3]. We therefore introduced an automated approach to improve code quality for SCRATCH programs.

We envision different use cases for such an approach: First, teachers of young programming learners very often are not skilled programmers themselves. If the code they use to demonstrate programming to children contains problems, this can be detrimental for the learning outcomes. Second, it is very common for young programming learners to self-study using online tutorials and examples, such that automated hints become important; this is also why we made explainability a central component of our approach. Finally, learning support systems (e.g., [39]–[41]) are often based on syntactically matching aspects of programs, and may fail in the light of alternative solutions. An automated program transformation approach may help to overcome this limitation.

While we demonstrated that search-based refactoring for SCRATCH is feasible, there is ample opportunity and need for further work. Although we applied search techniques common for search-based refactoring, other algorithms and parameters may lead to better solutions, and our set of code transformations can likely be extended. Our implementation currently produces an entire Pareto front of candidate solutions, but users might be overwhelmed, and so the question of how to select one representative individual from the Pareto front is an important one to answer. We used three metrics encoding important aspects of code readability for our initial assessment, but alternative metrics may be better suited to guide the search and to quantify desirable properties of the target code. Furthermore, the explainability of generated refactorings needs to be assessed. Ultimately, answering these questions will require qualitative assessment and evaluation with teachers and children. To support future work, LITTERBOX including our implementation of search-based refactoring is available at https://github.com/se2p/LITTERBOX

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### APPENDIX

The following tables summarize the Scratch code transformations implemented in our approach. Table II showcases transformations enabled by the inherently concurrent nature of Scratch programs, allowing us to split a script into several (smaller) scripts that are executed concurrently. Table III illustrates transformations that are driven solely by changing the way control flow is expressed in the given script, for example, via loop unrolling or merging nested `if` blocks into a single `if` block with multiple conditions. We carefully designed all transformations to maintain program behaviour, taking into account control, data, and time dependencies in the Scratch code. Most transformations can be applied in both directions (↔), while others are uni-directional (→).

Table II: Atomic Scratch code transformations based on the inherently concurrent nature of Scratch programs.

| Transformation | Initial/Transformed Script | Direction(s) | Transformed/Initial Script(s) |
|---------------|-----------------------------|--------------|------------------------------|
| Split the body of a loop if there are no dependencies between the statements of its body and splitting does not create new ones. Replace the initial loop body by the first part of the body, add another loop for the remaining statements of the body. | ![Split Loop](image) | Merge Loops | ![Merge Loops](image) |
| Split a script if there are no dependencies upwards. | ![Split Script](image) | Merge Scripts | ![Merge Scripts](image) |
| Split a script with dependencies into new scripts which do not depend on each other but respect the dependencies in the initial script. | ![Extract Independent Subscripts](image) | → | ![Extract Independent Subscripts](image) |
| Replace a `forever` loop with `key pressed` conditionals by scripts triggered by `when key pressed` event listeners. | ![Extract Events from Forever](image) | Merge Events into Forever | ![Merge Events into Forever](image) |
| Split a script after a `repeat until` loop. Add a new script with a `wait until` and the same condition. | ![Split Script after Until](image) | Merge Scripts after Until | ![Merge Scripts after Until](image) |
| Description                                                                 | Initial/Transformed Script                                                                 | Transformation/Inverse                                                                 | Transformed/Initial Script |
|----------------------------------------------------------------------------|------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------|---------------------------|
| Swap two statements that are independent of each other, if swapping does    | when block up: then move 10 steps                                                          | swap statements                                                                         | Swap Statements           |
| not create new dependencies.                                               | swap statements ← move 10 steps                                                           | swap statements                                                                       |                           |
| Replace a [repeat times] loop by the corresponding number of repetitions    | repeat 3: say Hello!                                                                      | sequence to loop                                                                        |                           |
| of its body.                                                               | forever                                                                                   | forever                                                                                |                           |
| Replace an [if] block inside a [forever] loop with a [wait until] block     | if key space pressed? then say Hello!                                                      | forever wait to forever if                                                                |                           |
| with the same condition.                                                   | else say Hello!                                                                          | forever                                                                                 |                           |
| Transform a [forever] loop that conditionally terminates the script or the   | if mouse down? then disp all                                                          | extract loop condition                                                                  |                           |
| program to a [repeat until] loop.                                          | if mouse down?                                                                            | inline loop condition                                                                    |                           |
| Split the body of an [if] block. Replace the [if] block by one containing   | set my variable to 20                                                                    | split if body                                                                         |                           |
| the first part of the body, add another [if] for the remaining statements   | if not key space pressed? then set my variable to 100                                     | merge double if                                                                        |                           |
| of the body.                                                               | if mouse down?                                                                            | if not key space pressed? then set my variable to 100                                  |                           |
| Split an [if else] block into two [if] blocks. The second [if] block checks | if key space pressed? then move 10 steps                                                  |                                |                           |
| on the negated initial condition.                                          | if key space pressed?                                                                    | if if not to if else                                                                    |                           |
| Transform two nested [if] blocks into an [if] block which checks for the    |                                      |                                |                           |
| conjunction of the initial conditions.                                     | if key space pressed?                                                                    |                                |                           |
| Replace an [if] containing an [if else] by two [if] blocks. The condition   |                                      |                                |                           |
| of the first [if] is the conjunction of the two initial conditions. The    |                                      |                                |                           |
| second condition is the condition of the initial first if block.            |                                      |                                |                           |
| Replace an [if] block in the else case of an [if else] block by an [if]    |                                      |                                |                           |
| with the disjunction of the two conditions if the then cases of the initial |                                      |                                |                           |
| conditionals have the same statements.                                     |                                      |                                |                           |