Misleading Authorship Attribution of Source Code using Adversarial Learning

Erwin Quiring, Alwin Maier and Konrad Rieck

Technische Universität Braunschweig, Germany

Abstract

In this paper, we present a novel attack against authorship attribution of source code. We exploit that recent attribution methods rest on machine learning and thus can be deceived by adversarial examples of source code. Our attack performs a series of semantics-preserving code transformations that mislead learning-based attribution but appear plausible to a developer. The attack is guided by Monte-Carlo tree search that enables us to operate in the discrete domain of source code. In an empirical evaluation with source code from 204 programmers, we demonstrate that our attack has a substantial effect on two recent attribution methods, whose accuracy drops from over 88% to 1% under attack. Furthermore, we show that our attack can imitate the coding style of developers with high accuracy and thereby induce false attributions. We conclude that current approaches for authorship attribution are inappropriate for practical application and there is a need for resilient analysis techniques.

1 Introduction

The source code of a program often contains peculiarities that reflect individual coding style and can be used for identifying the programmer. These peculiarities—or *stylistic patterns*—range from simple artifacts in comments and code layout to subtle habits in the use of syntax and control flow. A programmer might, for example, favor while-loops even though the use of for-loops would be more appropriate. The task of identifying a programmer based on these stylistic patterns is denoted as *authorship attribution*, and several methods have been proposed to recognize the authors of source code [1, 4, 9, 13] and compiled programs [3, 10, 17, 22].

While techniques for authorship attribution have made great progress in the last years, their robustness against attacks has received only little attention so far, and the majority of work has focused on achieving high accuracy. The recent study by Simko et al. [25], however, shows that developers can manually tamper with the attribution of source code and thus it becomes necessary to reason about attacks that can forge stylistic patterns and mislead attribution methods.

In this paper, we present the first black-box attack against authorship attribution of source code. Our attack exploits that recent attribution methods employ machine learning and thus can be vulnerable to adversarial examples [see 20]. We combine concepts from adversarial learning and compiler engineering, and create adversarial examples in the space of semantically-equivalent programs.

Our attack proceeds by iteratively transforming the source code of a program, such that stylistic patterns are changed while the underlying semantics are preserved. To determine these transformations, we interpret the attack as a game against the attribution method and develop a variant of Monte-Carlo tree search [24] for constructing a sequence of adversarial but plausible transformations. This black-box strategy enables us to construct *untargeted attacks* that thwart a correct attribution as well as *targeted attacks* that imitate the stylistic patterns of a developer.

As an example, Figure 1 shows two transformations performed by our attack on a code snippet from the Google Code Jam competition. The first transformation changes the for-loop to a while-loop, while the second replaces the C++ operator << with the C-style function `printf`. Note that the format string is automatically inferred from the variable type. Both transformations change the stylistic patterns of author A and, in combination, mislead the attribution to author B.

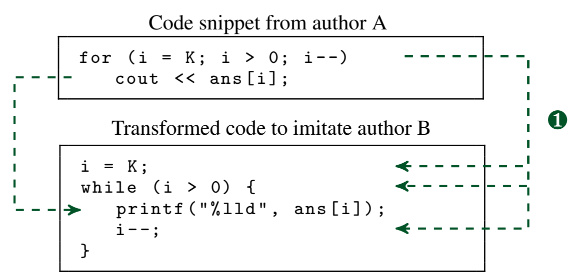


Figure 1: Two iterations of our attack: Transformation ❶ changes the control statement `for` → `while` and transformation ❷ manipulates the API usage `ostream` → `printf` to imitate the stylistic patterns of author B.

We conduct a series of experiments to evaluate the efficacy of our attack using the source code of 204 programmers from the Google Code Jam competition. As targets we consider the recent attribution methods by Caliskan et al. [9] and Abuhamad et al. [1], which provide superior performance compared to related approaches. In our first experiment, we demonstrate that our attack considerably affects both attribution methods [1, 9], whose accuracy drops from over 88% to 1% under attack, indicating that authorship attribution can be automatically thwarted at large scale. In our second experiment, we investigate the effect of targeted attacks. We show that in a group of programmers, each individual can be impersonated by 77% to 81% of the other developers on average. Finally, we demonstrate in a study with 15 participants that code transformed by our attack is plausible and hard to discriminate from unmodified source code.

Our work has implications on the applicability of authorship attribution in practice: We find that both, untargeted and targeted attacks, are effective, rendering the reliable identification of programmers questionable. Although our approach builds on a fixed set of code transformations, we conclude that features regularly manipulated by compilers, such as specific syntax and control flow, are not reliable for constructing attribution methods. As a consequence, we suggest to move away from these features and seek for more reliable means for identifying authors in source code.

Contributions. In summary, we make the following major contributions in this paper:

- *Adversarial learning on source code.* We present the first automatic attack against authorship attribution of source code. We consider targeted as well as untargeted attacks of the attribution method.
- *Monte-Carlo tree search.* We introduce Monte-Carlo tree search as a novel approach to guide the creation of adversarial examples, such that feasibility constraints in the domain of source code are satisfied.
- *Black-box attack strategy.* The devised attack does not require internal knowledge of the attribution method, so that it is applicable to any learning algorithm and suitable for evading a wide range of attribution methods.
- *Large-scale evaluation.* We empirically evaluate our attack on a dataset of 204 programmers and demonstrate that manipulating the attribution of source code is possible in the majority of the considered cases.

The remainder of this paper is organized as follows: We review the basics of program authorship attribution in Section 2. The design of our attack is lay out in Section 3, while Section 4 and 5 discuss technical details on code transformation and adversarial learning, respectively. An empirical evaluation of our attack is presented in Section 6 along with a discussion of limitations in Section 7. Section 8 discusses related work and Section 9 concludes the paper.

2 Authorship Attribution of Source Code

Before introducing our attack, we briefly review the design of methods for authorship attribution. To this end, we denote the source code of a program as x and refer to the set of all possible source codes by $\mathcal{X}$. Moreover, we define a finite set of authors $\mathcal{Y}$. Authorship attribution is then the task of identifying the author $y \in \mathcal{Y}$ of a given source code $x \in \mathcal{X}$ using a classification function f such that $f(x) = y$. In line with the majority of previous work, we assume that the programs in $\mathcal{X}$ can be attributed to a single author, as the identification of multiple authors is an ongoing research effort [see 12, 17].

Equipped with this basic notation, we proceed to discuss the two main building blocks of current methods for authorship attribution: (a) the extraction of features from source code and (b) the application of machine learning for constructing the classification function.

2.1 Feature Extraction

The coding habits of a programmer can manifest in a variety of stylistic patterns. Consequently, methods for authorship attribution need to extract an expressive set of features from source code that serve as basis for inferring these patterns. In the following, we discuss the major types of these features and use the code sample in Figure 2 as a running example throughout the paper.

```
int foo(int a){
  int b;
  if (a < 2)       // base case
    return 1;
  b = foo(a - 1); // recursion
  return a * b;
}
```

Figure 2: Exemplary code sample (see Figure 3, 5, and 6)

Layout features. Individual preferences of a programmer often manifest in the layout of the code and thus corresponding features are a simple tool for characterizing coding style. Examples for such features are the indentation, the form of comments and the use of brackets. In Figure 2, for instance, the indentation width is 2, comments are provided in C++ style, and curly braces are opened on the same line.

Layout features are trivial to forge, as they can be easily modified using tools for code formatting, such as GNU indent. Moreover, many integrated development editors automatically normalize source code, such that stylistic patterns in the layout are unified.

Lexical features. A more advanced type of features can be derived from the lexical analysis of source code. In this analysis stage, the source code is partitioned into so-called *lexems*, tokens that are matched against the terminal symbols of the language grammar. These lexems give rise to a strong

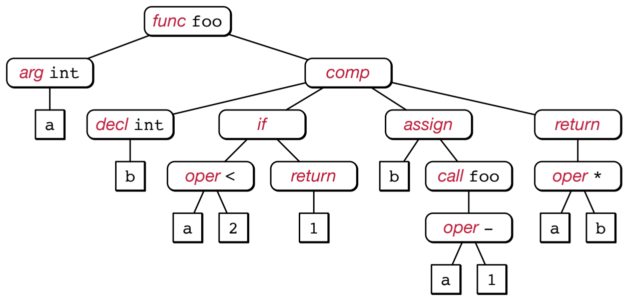


Figure 3: Abstract syntax tree (AST) for code sample in Figure 2.

set of string-based features jointly covering keywords and symbols. For example, in Figure 2, the frequency of the lexem `int` is 3, while it is 2 for the lexem `foo`.

In contrast to code layout, lexical features cannot be easily manipulated, as they implicitly describe the syntax and semantics of the source code. While the lexem `foo` in the running example could be easily replaced by another string, adapting the lexem `int` requires a more involved code transformation that introduces a semantically equivalent data type. We introduce such a transformation in Section 4.

Syntactic features. The use of syntax and control flow also reveals individual stylistic patterns of programmers. These patterns are typically accessed using the *abstract syntax tree* (AST), a basic data structure of compiler design [2]. As an example, Figure 3 shows a simplified AST of the code snippet from Figure 2. The AST provides the basis for constructing an extensive set of syntactic features. These features can range from the specific use of syntactic constructs, such as unary and ternary operators, to generic features characterizing the tree structure, such as the frequency of adjacent nodes. In Figure 3, there exist 21 pairs of adjacent nodes including, for example, `(func foo)`$\longrightarrow$`(arg int)` and `(return)`$\longrightarrow$`(1)`.

Manipulating features derived from an AST is challenging, as even minor tweaks in the tree structure can fundamentally change the program semantics. As a consequence, transformations to the AST need to be carefully designed to preserve the original semantics and to avoid unintentional side effects. For example, removing the node pair `(decl int)`$\longrightarrow$`(b)` from the AST in Figure 3 requires either replacing the type or the name of the variable without interfering with the remaining code. In practice, such transformations are often non-trivial and we discuss the details of manipulating the AST in Section 4.

2.2 Machine Learning

The three feature types (layout, lexical, syntactic) provide a broad view on the characteristics of source code and are used by many attribution methods as the basis for applying machine-learning techniques [e.g., 1, 4, 9, 21]

From code to vectors. Most learning algorithms are designed to operate on vectorial data and hence the first step for application of machine learning is the mapping of code to a vector space using the extracted features. Formally, this mapping can be expressed as $\phi : \mathcal{X} \longrightarrow \mathcal{F} = \mathbb{R}^d$ where $\mathcal{F}$ is a d dimensional vector space describing properties of the extracted features. Different techniques can be applied for constructing this map, which may include the computation of specific metrics as well as generic embeddings of features and their relations, such as a TF-IDF weighting [1, 9].

Surprisingly, the feature map ϕ introduces a non-trivial hurdle for the construction of attacks. The map ϕ is usually not bijective, that is, we can map a given source code x to a feature space but are unable to automatically construct the source code x' for a given point $\phi(x')$. Similarly, it is difficult to predict how a code transformation $x \mapsto x'$ changes the position in feature space $\phi(x) \mapsto \phi(x')$. We refer to this problem as the *problem-feature space dilemma* and discuss its implications in Section 3.

Multiclass classification. Using a feature map ϕ, we can apply machine learning for identifying the author of a source code. Typically, this is done by training a *multiclass classifier* $g : \mathcal{X} \longrightarrow \mathbb{R}^{|\mathcal{Y}|}$ that returns scores for all authors $\mathcal{Y}$. An attribution is obtained by simply computing

$$f(x) = \arg\max_{y \in \mathcal{Y}} g_y(x).$$

This setting has different advantages: First, one can investigate all top-ranked authors. Second, one can interpret the returned scores for determining the confidence of an attribution. We make use of the latter property for guiding our attack strategy and generating adversarial examples of source code (see Section 5)

Different learning algorithms have been used for constructing the multiclass classifier g, as for example, support vector machines [21], random forests [9], and recurrent neural networks [1, 4]. Attacking each of these learning algorithms individually is a tedious task and thus we resort to a *black-box attack* for misleading authorship attribution. This attack does not require any knowledge of the employed learning algorithm and operates with the output $g(x)$ only. Consequently, our approach is agnostic to the learning algorithm as we demonstrate in the evaluation in Section 6.

3 Misleading Authorship Attribution

With a basic understanding of authorship attribution, we are ready to investigate the robustness of attribution methods and to develop a corresponding black-box attack. To this end, we first define our threat model and attack scenario before discussing technical details in the following sections.

3.1 Threat Model

For our attack, we assume an adversary who has black-box access to an attribution method. That is, she can send an arbitrary source code x to the method and retrieve the corresponding prediction $f(x)$ along with prediction scores $g(x)$. The training data, the extracted features, and the employed learning algorithm, however, are unknown to the adversary, and hence the attack can only be guided by iteratively probing the attribution method and analyzing the returned prediction scores. This setting resembles a classic *black-box attack* as studied by Tramèr et al. [26] and Papernot et al. [19]. As part of our threat model, we consider two types of attacks—*untargeted* and *targeted attacks*—that require different capabilities of the adversary and have distinct implications for the involved programmers.

Untargeted attacks. In this setting, the adversary tries to mislead the attribution of source code by changing the classification into *any* other programmer. This attack is also denoted as *dodging* [23] and impacts the correctness of the attribution. As an example, a benign programmer might use this attack strategy for concealing her identity before publishing the source code of a program.

Targeted attacks. The adversary tries to change the classification into a chosen *target* programmer. This attack resembles an *impersonation* and is technically more advanced, as we need to transfer the stylistic patterns from one developer to another. A targeted attack has more severe implications: A malware developer, for instance, could systematically change her source code to blame a benign developer.

Furthermore, we consider two scenarios for targeted attacks: In the first scenario, the adversary has no access to source code from the target programmer and thus certain features, such as variable names and custom types, can only be guessed. In the second scenario, we assume that the adversary has access to two files of source code from the target developer. Both files are not part of the training- or test set and act as external source for extracting template information, such as recurring custom variable names.

In addition, we test a scenario where the targeted attack solely rests on a separate training set, without access to the output of the original classifier. This might be the case, for instance, if the attribution method is secretly deployed, but code samples are available from public code repositories. In this scenario, the adversary can learn a substitute model with the aim that her adversarial example—calculated on the substitute—also transfers to the original classifier.

3.2 Attack Constraints

Misleading the attribution of an author can be achieved with different levels of sophistication. For example, an adversary may simply copy code snippets from one developer for impersonation or heavily obfuscate source code for dodging. These trivial attacks, however, generate implausible code and are easy to detect. As a consequence, we define a set of constraints for our attack that should make it hard to identify manipulated source code.

Preserved semantics. We require that source code generated by our attack is semantically equivalent to the original code. That is, the two codes produce identical outputs given the same input. As it is undecidable whether two programs are semantically equivalent, we take care of this constraint during the design of our code transformations and ensure that each transformation is as semantics-preserving as possible.

Plausible code. We require that all transformations change the source code, such that the result is syntactically correct, readable and plausible. The latter constraint corresponds to the aspect of imperceptibility when adversarial examples are generated in the image domain [11]. In our context, plausibility is important whenever the adversary wants to hide the modification of a source file, for instance, when blaming another developer. For this reason, we do not include junk code or unusual syntax that normal developers would not use.

No layout changes. Layout features such as the tendency to start lines with spaces or tabs are trivial to change with tools for code formatting (see Section 6.4). Therefore, we restrict our attack to the forgery of lexical and syntactic features of source code. In this way, we examine our approach under a more difficult scenario for the attacker where no layout features are exploitable to mislead the attribution.

3.3 Problem-Feature Space Dilemma

The described threat model and attack constraints pose unique challenges to the design of our attack. Our attack jointly operates in two domains: On the one hand, we aim at attacking a classifier in the feature space $\mathcal{F}$. On the other hand, we require the source code to be semantically equivalent and plausible in the problem space $\mathcal{X}$. For most feature maps ϕ, a one-to-one correspondence, however, does not exist between the two spaces and thus we encounter a dilemma.

Problem space $\rightsquigarrow$ feature space. Each change in the source code x may impact a set of features in $\phi(x)$. The exact amount of change is generally not controllable. The correlation of features and post-processing steps in ϕ, such as a TF-IDF weighting, may alter several features, even if only a single statement is changed in the source code. This renders target-oriented modification of the source code difficult.

For example, if the declaration of the variable `b` in line 2 of Figure 2 is moved to line 5, a series of lexical and syntactic features change, such as the frequency of the lexem `b` or the subtree under the node `assign` in Figure 3.

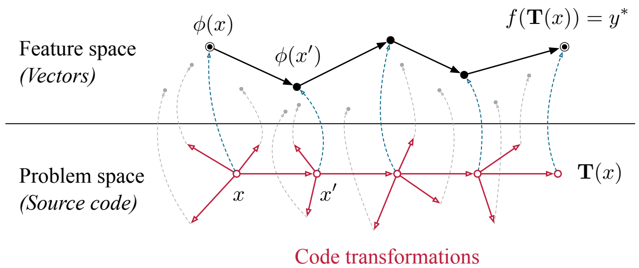


Figure 4: Schematic depiction of our approach. The attack is realized by moving in the problem space using code transformations while being guided by Monte-Carlo tree search in the feature space.

Feature space $\rightsquigarrow$ problem space. Any change to a feature vector $\phi(x)$ must ensure that there exists a plausible source code x in the problem space. Unfortunately, determining x from $\phi(x)$ is not tractable for non-bijective feature maps, and it is impossible to directly apply techniques from adversarial learning that operate in the feature space.

For example, if we calculate the difference of two vectors $\phi(z) = \phi(x) - \phi(x')$, we have no means for determining the resulting source code z. Even worse, it might be impossible to construct z, as the features in $\phi(z)$ can violate the underlying programming language specification, for example, due to feature combinations inducing impossible AST edges.

This dilemma has received little attention in the literature on adversarial learning so far, and it is often assumed that an adversary can change features almost arbitrarily [e.g. 6, 11, 18]. Consequently, our attack does not only pinpoint weaknesses in authorship attribution but also illustrates how adversarial learning can be conducted when the problem and feature space are disconnected.

3.4 Our Attack Strategy

To tackle this challenge, we adopt a mixed attack strategy that combines concepts from compiler engineering and adversarial learning. For the problem space, we develop code transformations (source-to-source compilations) that enable us to maneuver in the problem space and alter stylistic patterns without changing the semantics. For the feature space, we devise a variant of Monte-Carlo tree search that guides the transformations towards a target. This variant considers the attack as a game against the attribution method and aims at reaching a desired output with few transformations.

An overview of our attack strategy is illustrated in Figure 4. As the building blocks of our approach originate from different areas of computer science, we discuss their technical details in separate sections. First, we introduce the concept of semantics-preserving code transformations and present five families of source-to-source transformations (Section 4). Then, we introduce Monte-Carlo tree search as a generic black-box attack for chaining transformations together such that a target in the feature space is reached (Section 5).

4 Code Transformations

The automatic modification of code is a well-studied problem in compiler engineering and source-to-source compilation [2]. Consequently, we build our code transformations on top of the compiler frontend *Clang* [28], which provides all necessary primitives for parsing, transforming and synthesizing C/C++ source code. Note that we do *not* use code obfuscation methods, since their changes are (a) clearly visible, and (b) cannot mislead a classifier to a targeted author. Before presenting five families of transformations, we formally define the task of *code transformation* and introduce additional program representations.

Definition 1. A code transformation $T : \mathcal{X} \longrightarrow \mathcal{X},\ x \mapsto x'$ takes a source code x and generates a transformed version x', such that x and x' are semantically equivalent.

While code transformations can serve various purposes in general [2], we focus on *targeted* transformations that modify only minimal aspects of source code. If multiple source locations are applicable for a transformation, we use a pseudo-random seed to select one location. To chain together targeted transformations, we define *transformation sequences* as follows:

Definition 2. A transformation sequence $\mathbf{T} = T_1 \circ T_2 \circ \cdots \circ T_n$ is the subsequent application of multiple code transformations to a source code x.

To efficiently perform transformations, we make use of different program representations, where the AST is the most important one. To ease the realization of involved transformations, however, we employ two additional program representations that augment our view on the source code.

Control-flow graph with use-define chains. The control flow of a program is typically represented by a *control-flow graph* (CFG) where nodes represent statements and edges the flow of control. Using the CFG, it is convenient to analyze the execution order of statements. We further extend the CFG provided by Clang with *use-define chains* (UDCs). These chains unveil dependencies between usages and the definitions of a variable. With the aid of UDCs, we can trace the flow of data through the program and identify data dependencies between local variables and function arguments. Figure 5 shows a CFG with use-define chains.

Declaration-reference mapping. We additionally introduce a declaration-reference mapping (DRM) that extends the AST and links each declaration to all usages of the declared variable. As an example, Figure 6 shows a part of the AST together with the respective DRM for the code sample from Figure 2. This code representation enables navigation between declarations and variables, which allows us to efficiently rename variables or check for the sound transformation of data types. Note the difference between use-define

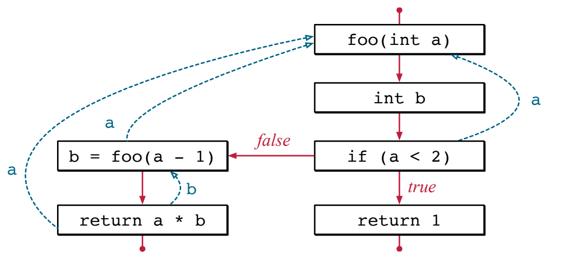


Figure 5: Control-flow graph with use-define chains for the code snippet from Figure 2. The control flow is shown in red (solid), use-define chains in blue (dashed).

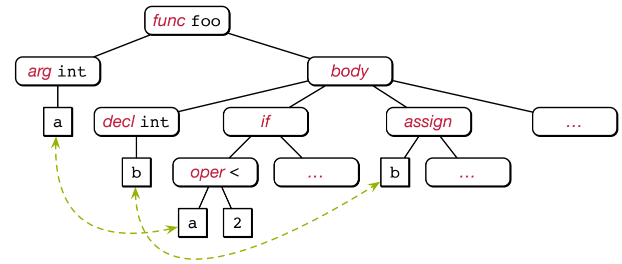


Figure 6: Abstract syntax tree with declaration-reference mapping for the code snippet from Figure 2. Declaration references are shown in green (dashed).

Table 1: Implemented families of transformations.

Transformation family	#	AST	CFG	UDC	DRM
Control transformations	5	•	•	•	
Declaration transformations	14	•			•
API transformations	9	•	•		•
Template transformations	4	•			•
Miscellaneous transformations	4	•			

chains and declaration-reference mappings. The former connects variable usages to variable definitions, while the latter links variable usages to variable declarations.

Based on these program representations, we develop a set of generic code transformations that are suitable for changing different stylistic patterns. In particular, we implement 36 transformers that are organized into five families. Table 1 provides an overview of each family together with the program representation used by the contained transformers.

In the following, we briefly introduce each of the five families. For a detailed listing of all 36 transformations, we refer the reader to Table 8 in Appendix C.

Control transformations. The first family of source-to-source transformations rewrites control-flow statements or modifies the control flow between functions. In total, the family contains 5 transformations. For example, the control-flow statements `while` and `for` can be mutually interchanged by two transformers. These transformations address a developer's preference to use a particular iteration type. As another example, Figure 7 shows the automatic creation of a function. The transformer moves the inner block of the for-statement to a newly created function. This transformation involves passing variables as function arguments, updating their values and changing the control flow of the caller and callee.

Declaration transformations. This family consists of 14 transformers that modify, add or remove declarations in source code. For example, in a widening conversion, the type of a variable is changed to a larger type, for example, `int` to `long`. This rewriting mimics a programmer's preference for particular data types. Declaration transformations make it necessary to update all usages of variables which

```
for (int j = i; j < i + k; j++) {
  if (s[j] == '-')
    s[j] = '+';
  else
    s[j] = '-';
}
```

```
inline void setarray(string& s, int& j) {
  if (s[j] == '-')
    s[j] = '+';
  else
    s[j] = '-';
}
[...]
for (int j = i; j < i + k; j++)
  setarray(s, j);
```

Figure 7: Example of a control transformation. ❶ moves the compound statement into an own function and passes all variables defined outside the block as parameters. ❷ calls the new function at the previous location.

can be elegantly carried out using the DRM representation. Replacing an entire data type is a more challenging transformation, as we need to adapt all usages to the type, including variables, functions and return values. Figure 8 shows the replacement of the C++ `string` object with a conventional `char` array, where the declaration and also API functions, such as `size`, are modified. Note that in our current implementation of the transformer the `char` array has a fixed size and thus is not strictly equivalent to the C++ `string` object.

API transformations. The third family contains 9 transformations and exploits the fact that various APIs can be used

```
string s;
cin >> s;
for (int i = 0; i < s.size(); i++) {
    if (s[i] == '+')
```

```
char s[1000];
cin >> s;
for (int i = 0; i < strlen(s); i++) {
  if (s[i] == '+')
```

Figure 8: Example of a declaration transformation. ❶ replaces the declaration of the C++ `string` object with a `char` array, ❷ adapts all uses of the object.

```
cout << fixed << setprecision(10);
[...]
for (long long t = 0;
  t < (long long)(T); t++) {
  [...]
  cout << "Case #" << t + 1 << ": "
    << d / l << '\n';
}
```

```
for (long long t = 0;
  t < (long long)(T); t++) {
  [...]
  printf("Case #%lld: %.10f\n",
    t + 1, d / l);
}
```

Figure 9: Example of an API transformation. ❶ determines the current precision for output; ❷ replaces the C++ API with a C-style printf. The format specifier respects the precision and the data type of the variable.

to solve the same problem. Programmers are known to favor different APIs and thus tampering with API usage is an effective strategy for changing stylistic patterns. For instance, we can choose between various ways to output information in C++, such as `printf`, `cout`, or `ofstream`.

As an example, Figure 9 depicts the replacement of the object `cout` by a call to `printf`. To this end, the transformer first checks for the decimal precision of floating-point values that `cout` employs, that is, we use the CFG to find the last executed `fixed` and `setprecision` statement. Next, the transformer uses the AST to resolve the final data type of each `cout` entry and creates a respective format string for `printf`.

Template transformations. The fourth family contains 4 transformations that insert or change code patterns based on a give template. For example, authors tend to reuse specific variable names, constants, and type definitions. If a template file is given for a target developer, these information are extracted and used for transformations. Otherwise, default values that represent general style patterns are employed. For instance, variable names can be iteratively renamed into default names like `i`, `j`, or `k` until a developer's tendency to declare control statement variables is lost (dodging attack) or gets matched (impersonation attack).

Miscellaneous transformations. The last family covers 4 transformations that conduct generic changes of code statements. For example, the use of curly braces around compound statements is a naive but effective stylistic pattern for identifying programmers. The compound statement transformer thus checks if the body of a control statement can be enclosed by curly braces or the other way round. In this way, we can add or remove a compound statement in the AST.

Another rather simple stylistic pattern is the use of return statements, where some programmers omit these statements in the `main` function and others differ in whether they return a constant, integer or variable. Consequently, we design a transformer that manipulates return statements.

5 Monte-Carlo Tree Search

Equipped with different code transformations for changing stylistic patterns, we are ready to determine a sequence of these transformations for untargeted and targeted attacks. We aim at a short sequence, which makes the attack less likely to be detected. Formally, our objective is to find a short transformation sequence $\mathbf{T}$ that manipulates a source file x, such that the classifier f predicts the target label y^*:

$$f\big(\mathbf{T}(x)\big) = y^* \,. \tag{1}$$

In the case of an untargeted attack, y^* represents any other developer than the original author y^s, that is, $y^* \neq y^s$. In the case of a targeted attack, y^* is defined as a particular target author y^t.

As we are unable to control how a transformation $T(x)$ moves the feature vector $\phi(x)$, several standard techniques for solving the problem in (1) are not applicable, such as gradient-based methods [e.g. 11]. Therefore, we require an algorithm that works over a search space of discrete objects such as the different transformations of the source code. As a single transformation does not necessarily change the score of the classifier, simple approximation techniques like Hill Climbing that only evaluate the neighborhood of a sample fail to provide appropriate solutions.

As a remedy, we construct our attack algorithm around the concept of *Monte-Carlo tree search* (MCTS)—a strong search algorithm that has proven effective in AI gaming with AlphaGo [24]. Similar to a game tree, our variant of MCTS creates a search tree for the attack, where each node represents a state of the source code and the edges correspond to transformations. By moving in this tree, we can evaluate the impact of different transformation sequences before deciding on the next move. Figure 10 depicts the four basic steps of our algorithm: selection, simulation, expansion and backpropagation.

Selection. As the number of possible paths in the search tree grows exponentially, we require a *selection policy* to identify the next node for expansion. This policy balances the tree's exploration and exploitation by alternately selecting nodes that have not been evaluated much (exploration) and nodes that seem promising to obtain a better result (exploitation). Following this policy, we start at the root node and recursively select a child node until we find a node u which was not evaluated before. Appendix A gives more information about the used selection policy.

Simulation & Expansion. We continue by generating a set of unique transformation sequences with varying length that start at u. We bound the length of each sequence by a predefined value. In our experiments, we create sequences with up to 5 transformations. For each sequence, we determine the classifier score by providing the modified source code to the attribution method. The right plot in Figure 10 exemplifies

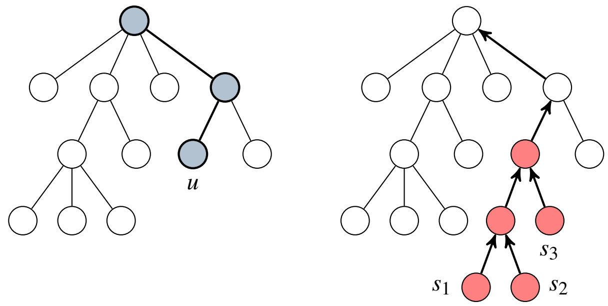


Figure 10: Basic steps of Monte-Carlo tree search. The left plot shows the selection step, the right plot the simulation, expansion and backpropagation.

the step: we create three sequences where two have the same first transformation. Next, we create the respective tree nodes. As two sequences start with the same transformation, they also share a node in the search tree.

Backpropagation. As the last step, we propagate the obtained classifier scores from the leaf node of each sequence back to the root. During this propagation, we update two statistics in each node on the path: First, we increment a counter that keeps track of how often a node has been part of a transformation sequence. In Figure 10, we increase the visit count of node u and the nodes above by 3. Second, we store the classifier scores in each node that have been observed in its subtree. For example, node u in Figure 10 stores the scores from s_1, s_2 and s_3. Both statistics are used by the selection policy and enable us to balance the exploration and exploitation of the tree in the next iterations.

Iteration. We repeat these four basic steps until a predefined iteration constraint is reached. After obtaining the resulting search tree, we identify the root's child node with the highest average classifier score and make it the novel root node of the tree. We then repeat the entire process again. The attack is stopped if we succeed, we reach a previously fixed number of iterations, or we do not obtain any improvement over multiple iterations.

Appendix A provides more implementation details on our variant of MCTS. We finally note that the algorithm resembles a black-box attack, as the inner working of the classifier f is not considered.

6 Evaluation

We proceed with an empirical evaluation of our attacks and investigate the robustness of source-code authorship attribution in a series of experiments. In particular, we investigate the impact of untargeted and targeted attacks on two recent attribution methods (Section 6.2 & 6.3). Finally, we verify in Section 6.4 that our initially imposed attack constraints are fulfilled.

6.1 Experimental Setup

Our empirical evaluation builds on the methods developed by Caliskan et al. [9] and Abuhamad et al. [1], two recent approaches that operate on a diverse set of features and provide superior performance in comparison to other attribution methods. For our evaluation, we follow the same experimental setup as the authors, re-implement their methods and make use of a similar dataset.

Dataset & Setup. We collect C++ files from the 2017 *Google Code Jam* (GCJ) programming competition [29]. This contest consists of various rounds where several participants solve the same programming challenges. This setting enables us to learn a classifier for attribution that separates stylistic patterns rather than artifacts of the different challenges. Moreover, for each challenge, a test input is available that we can use for checking the program semantics. Similar to previous work, we select eight challenges from the competition and collect the corresponding source codes from all authors who solved these challenges.

In contrast to prior work [1, 9], however, we set more stringent restrictions on the source code. We filter out files that contain incomplete or broken solutions. Furthermore, we format each source code using `clang-format` and expand macros, which removes artifacts that some authors introduce to write code more quickly during the contest. Our final dataset consists of 1,632 files of C++ code from 204 authors solving the same 8 programming challenges of the competition.

For the evaluation, we use a *stratified* and *grouped* k-fold cross-validation where we split the dataset into $k-1$ challenges for training and 1 challenge for testing. In this way, we ensure that training is conducted on different challenges than testing. For each of the k folds, we perform feature selection on the extracted features and then train the respective classifier as described in the original publications. We report results averaged over all 8 folds.

Implementation. We implement the attribution methods and our attack on top of Clang [28], an open-source C/C++ frontend for the LLVM compiler framework. For the method of Caliskan et al. [9], we re-implement the AST extraction and use the proposed random forest classifier for attributing programmers. The approach by Abuhamad et al. [1] uses lexical features that are passed to a long short-term memory (LSTM) neural network for attribution. Table 2 provides an overview of both methods. For further details on the fea-

Method	Lex	Syn	Classifier	Accuracy
Caliskan et al. [9]	•	•	RF	90.4% $\pm$ 1.7%
Abuhamad et al. [1]	•		LSTM	88.4% $\pm$ 3.7%

Table 2: Implemented attribution methods and their reproduced accuracy. (Lex = Lexical features, Syn = Syntactic features)

Method	Untargeted	Targeted T+	Targeted T-
	Success rate of our attack		
Caliskan et al. [9]	99.2%	77.3%	71.2%
Abuhamad et al. [1]	99.1%	81.3%	69.1%

Table 3: Performance of our attack as average success rate. The targeted attack is conducted with template (T+) and without template (T-).

ture extraction and learning process, we refer the reader to the respective publications [1, 9].

As a sanity check, we reproduce the experiments conducted by Caliskan et al. [9] and Abuhamad et al. [1] on our dataset. Table 2 shows the average attribution accuracy and standard deviation over the 8 folds. Our re-implementation enables us to differentiate the 204 developers with an accuracy of 90% and 88% on average, respectively. Both accuracies come close to the reported results with a difference of less than 6%, which we attribute to omitted layout features and the stricter dataset.

6.2 Untargeted Attack

In our first experiment, we investigate whether an adversary can manipulate source code such that the original author is not identified. To this end, we apply our untargeted attack to each correctly classified developer from the 204 authors. We repeat the attack for all 8 challenges and aggregate the results.

Attack performance. Table 3 presents the performance of the attack as the ratio of successful evasion attempts. Our attack has a strong impact on both methods and misleads the attribution in 99% of the cases, irrespective of the considered features and learning algorithm. As a result, the source code of almost all authors can be manipulated such that the attribution fails.

Attack analysis. To investigate the effect of our attack in more detail, we compute the ratio of changed features per adversarial sample. Figure 11 depicts the distribution over all samples. The method by Caliskan et al. [9] exhibits a bimodal distribution. The left peak shows that a few changes, such as the addition of include statements, are often sufficient to mislead attribution. For the majority of samples, however, the attack alters 50% of the features, which indicates the tight correlation between different features (see Section 3.3). A key factor to this correlation is the TF-IDF weighting that distributes minor changes over a large set of features.

In comparison, less features are necessary to evade the approach by Abuhamad et al. [1], possibly due to the higher sparsity of the feature vectors. Each author has 12.11% non-zero features on average, while 53.12% are set for the method by Caliskan et al. [9]. Thus, less features need to be changed and in consequence each changed feature impacts fewer other features that remain zero.

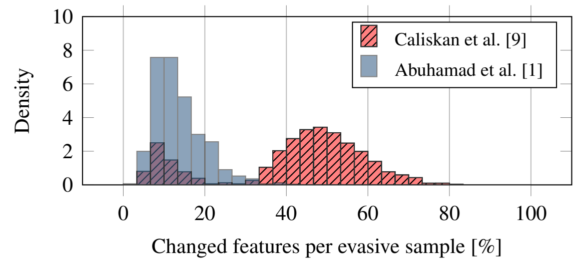


Figure 11: Untargeted attack: Histogram over the number of changed features per successful evasive sample for both attribution methods.

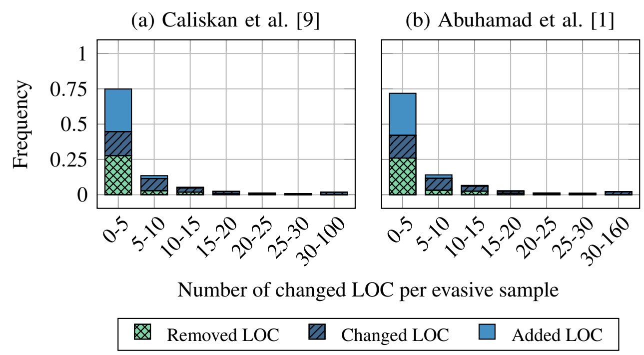


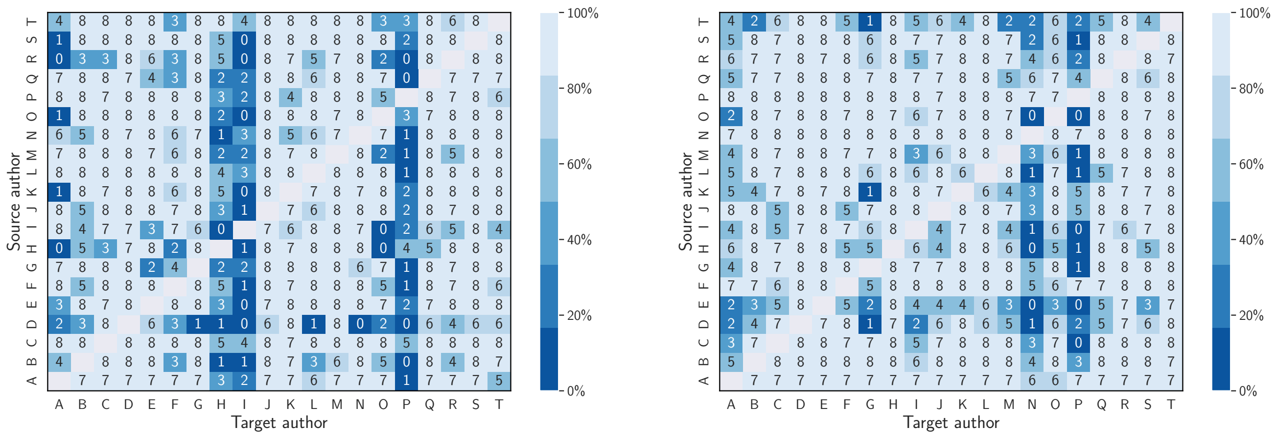
Figure 12: Untargeted attack: Stacked histogram over the number of changed lines of code (LOC) per successful evasive sample for both attribution methods. The original source files have 74 lines on average (std: 38.44).

Although we observe a high number of changed features, the corresponding changes to the source code are minimal. Figure 12 shows the number of added, changed and removed lines of code (LOC) determined by a context-diff with difflib for each source file before and after the attack. For the majority of cases in both attribution methods, less than 5 lines of code are added, removed or changed. This low number exemplifies the targeted design of our code transformations that selectively alter characteristics of stylistic patterns.

Summary. Based on the results from this experiment, we summarize that our untargeted attack severely impacts the performance of the methods by Caliskan et al. [9] and Abuhamad et al. [1]. We conclude that other attribution methods employing similar features and learning algorithms also suffer from this problem and hence cannot provide a reliable attribution in presence of an adversary.

6.3 Targeted Attack

We proceed to study the targeted variant of our attack. We consider pairs of programmers, where the code of the source author is transformed until it is attributed to the target author. Due to the quadratic number of pairs, we perform this experiment on a random sample of 20 programmers. This results in 380 source-target pairs each covering the source code of 8 challenges. Table 7 in Appendix B provides a list of the



(a) Caliskan et al. [9]

(b) Abuhamad et al. [1]

Figure 13: Impersonation matrix for both attribution methods. Each cell indicates the number of successful attack attempts for the 8 challenges.

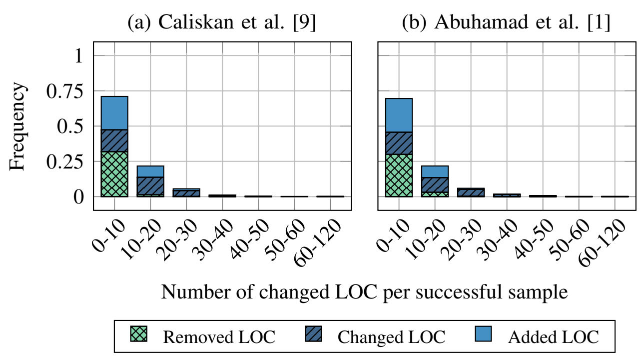


Figure 14: Targeted attack: Stacked histogram over the number of changed lines of code (LOC) per successful impersonation for both attribution methods. The original source files have 74 lines on average (std: 38.44).

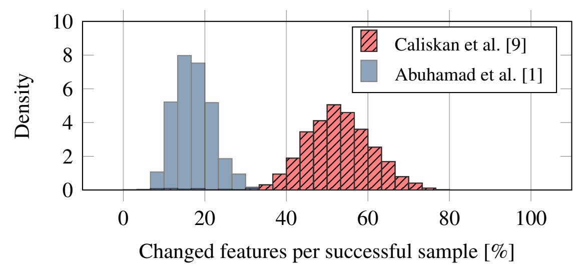


Figure 15: Targeted attack: Histogram over the number of changed features per successful impersonation for both attribution methods.

selected authors. We start with the scenario where we retrieve two samples of source code for each of the 20 programmers from various GCJ challenges—not part of the fixed 8 train-test challenges—to support the template transformations.

Attack performance. Table 3 depicts the success rate of our attack for both attribution methods. We can transfer the prediction from one to another developer in 77% and 81% of all cases, respectively, indicating that more than three out of four programmers can be successfully impersonated.

In addition, Figure 13 presents the results as a matrix, where the number of successful impersonations is visually depicted. Note that the value in each cell indicates the absolute number of successful impersonations for the 8 challenges associated with each author pair. We find that a large set of developers can be imitated by almost every other developer. Their stylistic patterns are well reflected by our transformers and thus can be easily forged. By contrast, only the developers I and P have a small impersonation rate for Caliskan et al. [9], yet 68% and 79% of the developers can still imitate the style of I and P in at least one challenge.

Attack analysis. The number of altered lines of code also remains small for the targeted attacks. Figure 14 shows that in most cases only 0 to 10 lines of code are affected. At the same time, the feature space is substantially changed. Figure 15 depicts that both attribution methods exhibit a similar distribution as before in the untargeted attack—except that the left peak vanishes for the method of Caliskan et al. [9]. This means that each source file requires more than a few targeted changes to achieve an impersonation.

Table 4: Usage of transformation families for impersonation

Transformation Family	**Cal. [9]**	**Abu. [1]**
Control Transformers	8.43%	9.72%
Declaration Transformers	14.11%	17.88%
API Transformers	29.90%	19.60%
Miscellaneous Transformers	9.15%	4.76%
Template Transformers	38.42%	48.04%

Table 4 shows the contribution of each transformation family to the impersonation success. All transformations are necessary to achieve the reported attack rates. A closer look reveals that the method by Abuhamad et al. [1] strongly rests on the usage of template transformers, while the families are more balanced for the approach by Caliskan et al. [9]. This

Source Author I

```
1  cout << std::fixed;
2
3
4  for (long long ccr = 1; ccr <= t; ++ccr) {
5    double d, n, ans = INT_MIN;
6    cin >> d >> n;
7    for (double i = 0; i < n; ++i) {
8      double k, s;
9      cin >> k >> s;
10     [...]
11   }
12
13   ans = d / ans;
14   cout << "Case #" << ccr << ": " <<
         setprecision(7) << ans << "\n";
15
16 }
```

Source ⟶ Target

```
typedef double td_d;
[...]
long long ccr = 1;
while (ccr <= t) {
  td_d d, n, ans = INT_MIN;
  cin >> d >> n;
  td_d i;
  for (i = 0; i < n; ++i) {
    td_d k, s;
    cin >> k >> s;
    [...]
  }
  ans = d / ans;
  printf("Case #%lld: %.7f\n",
    ccr, ans);
  ++ccr;
}
```

Target Author P

```
int T, cas = 0;
cin >> T;
while (T--) {
  int d, n;
  cin >> d >> n;
  double t = 0;
  while (n--) {
    int k, s;
    cin >> k >> s;
    t = max((1.0 * d - k) / s, t);
  }
  double ans = d / t;
  printf("Case #%d: %.10f\n", ++cas, ans);
}
```

Iteration	Transformer	Description
❶	Typedef	adds typedef and replaces all locations with previous type by novel typedef.
❷	For statement	converts `for`-statement into an equivalent `while`-statement, as target tends to solve problems via `while`-loops.
❸	Init-Decl	moves a declaration out of the control statement which mimics the declaration behavior of while-statements.
❹	Output API	substitutes C++ API for writing output by C API `printf`. To this end, it determines the precision of output statements by finding `fixed` (line 1) and `setprecision` (line 14) commands.

Figure 16: Impersonation example from our evaluation for the GCJ problem *Steed 2: Cruise Control*. The upper left listing shows the original source file, the upper right its modified version such that it is classified as the target author. For comparison, the lower left listing shows the original source file from the target author (which was not available for the attacker). The table lists the necessary transformations.

difference can be attributed to the feature sets, where the former method relies on simple lexical features only and the latter extracts more involved features from the AST.

Case Study. To provide further intuition for a successful impersonation, Figure 16 shows a case study from our evaluation. The upper two panels present the code from the source author in original and transformed form. The lower left panel depicts the original source text from the target author for the same challenge. Note that the attack has no access to this file. The table lists four conducted transformations. For instance, the target author has the stylistic pattern to use `while` statements, C functions for the output, and particular typedefs. By changing these patterns, our attack succeeds in misleading the attribution method.

Attack without template. We additionally examine the scenario when the adversary has no access to a template file of the target developer. In this case, our template transformers can only try common patterns, such as the iteration variables `i`, `j`, ..., `k` or typedef `ll` for the type `long long`. Table 3 shows the results of this experiment as well. Still, we achieve an impersonation rate of 71% and 69%—solely by relying on the feedback from the classifier. The number of altered lines of code and features correspond to Figures 14 and 15.

Contrary to expectation, without a template, the approach by Abuhamad et al. [1] is harder to fool than the method by Caliskan et al. [9]. As the lexical features rest more on simple declaration names and included libraries, they are harder to guess without a template file. However, if a template file is available, this approach is considerably easier to evade.

Attack with substitute model. We finally demonstrate that an impersonation is even possible without access to the prediction of the original classifier, only relying on a substitute model trained from separate data. We split our training set into disjoint sets with three files per author to train the original and substitute model, respectively. We test the attack on the method by Caliskan et al. [9], which is the more robust attribution under attack. By the nature of this scenario, the adversary can use two files to support the template transformations.

Adversarial examples—generated with the substitute model—transfer in 79% of the cases to the original model, that is, attacks successful against the substitute model are also effective against the original in the majority of the cases. This indicates that our attack successfully changes indicative features for a target developer across models. The success rate of our attack on the original model is 52%. Due to the reduced number of training files in this experiment, the attack is harder, as the coding habits are less precisely covered by the original and substitute models. Still, we are able to impersonate every second developer with no access to the original classifier.

Summary. Our findings show that an adversary can automatically impersonate a large set of developers without and with access to a template file. We conclude that both considered attribution methods can be abused to trigger false allegations—rendering a real-world application dangerous.

6.4 Preserved Semantics and Plausibility

In the last experiment, we verify that our adversarial code samples comply with the attack constraints specified in Section 3.2. That is, we empirically check that (a) the semantics of the transformed source code are preserved, (b) the generated code is plausible to a human analyst, and (c) layout features can be trivially evaded.

Preserved semantics. We begin by verifying the semantics of the transformed source code. In particular, we use the test file from each challenge of the GCJ competition to check that the transformed source code provides the same solution as the original code. In all our experiments, we can verify that the output remains unchanged for each manipulated source code sample before and after our attack.

Plausible code. Next, we check that our transformations lead to plausible code and conduct a discrimination test with 15 human subjects. The group consists of 4 undergraduate students, 6 graduate students and 5 professional computer scientists. The structure of the test follows an *AXY-test*: Every participant obtains 9 files of source code—each from a different author but for the same GCJ challenge. These 9 files consists of 3 unmodified source codes as reference (A) and 6 sources codes (XY) that need to be classified as either *original* or *modified*. The participants are informed that 3 of the samples are modified. We then ask each participant to identify the unknown samples and to provide a short justification.

The results of this empirical study are provided in Table 5. On average, the participants are able to correctly classify 60% of the provided files which is only marginally higher than random guessing. This result highlights that it is hard to decide whether source code has been modified by our attack or not. In several cases, the participants falsely assume that unused `typedef` statements or an inconsistent usage of operators are modifications.

Evasion of layout features. Finally, we demonstrate that layout features can be trivially manipulated, so that it is valid to restrict our approach to the forgery of lexical and syntactic features. To this end, we train a random forest classifier *only* on layout features as extracted by Caliskan et al. [9]. We then compare the attribution accuracy of the classifier on the test set with and without the application of the formatting tool `clang-format`, which normalizes the layout of the code.

Table 5: Study on plausibility of transformed source code.

Participant Group	Accuracy	Std
Undergraduate students	66.7%	23.6%
Graduate students	55.6%	15.7%
Professionals	60.0%	24.9%
Total	60.0%	21.8%
Random guessing	50.0%	—

While the attribution method can identify 27.5% of the programmers based on layout features if the code is not formatted, the performance decreases to 4.5% if we apply the formatting tool to the source code. We thus conclude that it is trivial to mislead an attribution based on layout features.

7 Limitations

Our previous experiments demonstrate the impact of our attack on program authorship attribution. Nonetheless, our approach has limitations which we discuss in the following.

Adversarial examples $\neq$ anonymization. Our attack enables a programmer to hide their identity in source code by misleading an attribution. While such an attack protects the privacy of the programmer, it is not sufficient for achieving anonymity. Note that k-anonymity would require a set of k developers that are equally likely to be attributed to the source code. In our setting, the code of the programmer is transformed to match a different author and an anonymity set of sufficient size is not guaranteed to exist. Still, we consider anonymization as promising direction for further research, which can build on the concepts of code transformations developed in this paper.

Verification of semantics. Finally, we consider two programs to be semantically equivalent if they return the same output for a given input. In particular, we verify that the transformed source code is semantically equivalent by applying the test cases provided by the GCJ competition. Although this approach is reasonable in our setting, it cannot guarantee strict semantic equivalence in all possible cases. Some of the exchanged API functions, for example, provide the same functionality but differ in corner cases, such as when the memory is exhausted. We acknowledge this limitation, yet it does not impact the general validity of our results.

8 Related Work

The automatic attack of source-code authorship attribution touches different areas of security research. In this section, we review related methods and concepts.

Authorship attribution of source code. Identifying the author of a program is a challenging task of computer security that has attracted a large body of work in the last years. Starting from early approaches experimenting with hand-crafted features [14, 16], the techniques for examining source code have constantly advanced, for example, by incorporating expressive features, such as n-grams [e.g., 1, 8, 13] and abstract syntax trees [e.g., 4, 9, 21]. Similarly, techniques for analyzing native code and identifying authors of compiled programs have advanced in the last years [e.g., 3, 10, 17, 22].

Two notable examples for source code are the approach by Caliskan et al. [9] and by Abuhamad et al. [1]. The former inspects features derived from code layout, lexical analysis and syntactic analysis. Regarding comprehensiveness, this work can be considered as the current state of the art. The work by Abuhamad et al. [1] focuses on lexical features as input for recurrent neural networks. Their work covers the largest set of authors so far and makes use of recent advances in deep learning. Table 6 shows the related approaches.

Method	Lay	Lex	Syn	Authors	Results
***Abuhamad et al. [1]**		•		**8903**	**92%**
***Caliskan et al. [9]**	•	•	•	**250**	**95%**
Alsulami et al. [4]			•	70	89%
Frantzeskou et al. [13]	•	•		30	97%
Krsul and Spafford [14]	•	•	•	29	73%
Burrows et al. [8]	•	•		10	77%

Table 6: Comparison of approaches for source code authorship attribution. Lay = Layout features, Lex = Lexical features, Syn = Syntactic features. *Attacked in this paper.

Previous work, however, has mostly ignored the problem of untargeted and targeted attacks. Only the empirical study by Simko et al. [25] examines how programmers can mislead the attribution by Caliskan et al. [9] by mimicking the style of other developers. While this study provides valuable insights into the risk of forgeries, it does not consider automatic attacks and thus is limited to manipulations by humans. In this paper, we demonstrate that such attacks can be fully automated. Our generated forgeries even provide a higher success rate than the handcrafted samples in the study. Moreover, we evaluate the impact of different feature sets and learning algorithms by evaluating two attribution methods.

Adversarial machine learning. The security of machine learning techniques has also attracted a lot of research recently. A significant fraction of work on attacks has focused on scenarios where the problem and feature space are mainly identical [see 6, 11, 18]. In these scenarios, changes in the problem space, such as the modification of an image pixel, have a one-to-one effect on the feature space, such that sophisticated attack strategies can be applied. By contrast, a one-to-one mapping between source code and the extracted features cannot be constructed and thus we are required to introduce a mixed attack strategy (see Section 3).

Creating evasive PDF malware samples [27, 31] and adversarial examples for text classifiers [e.g., 5, 15] represent two similar scenarios, where the practical feasibility needs to be ensured. These works typically operate in the problem space, where search algorithms such as hill climbing or genetic programming are guided by information from the feature space. MCTS represents a novel concept in the portfolio of creating adversarial examples under feasibility constraints, previously examined by Wicker et al. [30] in the image context only.

Also related is the approach by Sharif et al. [23] for misleading face recognition systems using painted eyeglasses. The proposed attack operates in the feature space but ensures practical feasibility by refining the optimization problem. In particular, the calculated adversarial perturbations are required to match the form of eyeglasses, to be printable, and to be invariant to slight head movements. In our attack scenario, such refinements of the optimization problem are not sufficient for obtaining valid source code, and thus we resort to applying code transformations in the problem space.

9 Conclusion

Authorship attribution of source code can be a powerful tool if an accurate and robust identification of programmers is possible. In this paper, however, we show that the current state of the art is insufficient for achieving a robust attribution. We present a black-box attack that seeks adversarial examples in the domain of source code by combining Monte-Carlo tree search with concepts from source-to-source compilation. Our empirical evaluation shows that automatic untargeted and targeted attacks are technically feasible and successfully mislead recent attribution methods.

Our findings indicate a need for alternative techniques for constructing attribution methods. These techniques should be designed with robustness in mind, such that it becomes harder to transfer stylistic patterns from one source code to another. A promising direction are generative approaches of machine learning, such as generative adversarial networks, that learn a decision function while actively searching for its weak spots. Similarly, it would help to systematically seek for stylistic patterns that are inherently hard to manipulate, either due to their complexity or due to their tight coupling with program semantics.

Public dataset and implementation. To encourage further research on program authorship attribution and, in particular, the development of robust methods, we make our dataset and implementation publicly available.[1] The attribution methods, the code transformers as well as our attack algorithm are all implemented as individual modules, such that they can be easily combined and extended.

[1] www.tu-braunschweig.de/sec/research/code/imitator

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A Monte-Carlo Tree Search

In this section, we provide further details about our variant of *Monte-Carlo tree search*. Algorithm 1 gives an overview of the attack. The procedure ATTACK starts with the root node r_0 that represents the original source code x. The algorithm then works in two nested loops:

- The outer loop in lines 3–5 repetitively builds a search tree for the current state of source code r, and takes a single move (i.e. a single transformation). To do so, in each iteration, we choose the child node with the highest average classifier score. This process is repeated until the attack succeeds or a stop criterion is fulfilled (we reach a fixed number of outer iterations or we do not observe any improvement over multiple iterations) (line 3).
- The procedure MCTS represents the inner loop. It iteratively builds and extends the search tree under the current root node r. As this procedure is the main building block of our attack, we discuss the individual steps in more detail in the following.

Algorithm 1 Monte-Carlo Tree Search

```
 1: procedure ATTACK(r_0)
 2:     r ← r_0
 3:     while not SUCCESS(r) and not STOPCRITERION(r) do
 4:         MCTS(r)                      ▷ Extend the search tree under r
 5:         r ← CHILDWITHBESTSCORE(r)    ▷ Perform next move
 6: procedure MCTS(r)
 7:     for i ← 1,N do
 8:         u ← SELECTION(r, i)
 9:         T ← SIMULATIONS(u)
10:         EXPANSION(u, T)
11:         BACKPROPAGATION(T)
```

Selection. Algorithm 2 shows the pseudocode to find the next node which is evaluated. The procedure recursively selects a child node according to a selection policy. We stop if the current node has no child nodes or if we have not marked it before in the current procedure SELECTION. The procedure finally returns the node that will be evaluated next.

As the number of possible paths grows exponentially (we have up to 36 transformations as choice at each node), we cannot evaluate all possible paths. The tree creation thus crucially depends on a selection policy. We use a simple heuristic to approximate the *Upper Confidence Bound for Trees* algorithm that is often used as selection policy (see [7]). Depending on the current iteration index i of SELECTION, the procedure SELECTIONPOLICY alternately returns the decision rule to choose the child with the highest average score, the lowest visit count or the highest score standard deviation. This step balances the *exploration* of less-visited nodes and the *exploitation* of promising nodes with a high average score.

Simulations. Equipped with the node u that needs to be evaluated, the next step generates a set of transformation

Algorithm 2 Selection Procedure of MCTS

procedure SELECTION(r, i)
  $D \leftarrow$ SELECTIONPOLICY(i)
  $u \leftarrow r$
  while u has child nodes **do**
    $v \leftarrow$ SELECTCHILD(u, D) ▷ Child of u w.r.t. to D
    if v not marked as visited **then**
      Mark v as visited
      return v
    else
      $u \leftarrow v$

sequences $\mathcal{T}$ that start at u:

$$\mathcal{T} = \{\mathbf{T}_j \mid j = 1, \ldots, k \text{ and } |\mathbf{T}_j| \leq M\} , \quad (2)$$

where $|\mathbf{T}_j|$ is the number of transformations in $\mathbf{T}_j$. The sequences are created randomly and have a varying length which is, however, limited by M. In our experiments, we set $M = 5$ to reduce the number of possible branches.

In contrast to the classic game use-case, we can use the returned scores $g(x)$ as early feedback and thus we do not need to play out a full game. In other words, it is not necessary to evaluate the complete path to obtain feedback. For each sequence, we determine the classifier score by passing the modified source code at the end of each sequence to the attribution method. We further pinpoint a difference to the general MCTS algorithm. Instead of evaluating only one path, we create a batch of sequences that can be efficiently executed in parallel. In this way, we reduce the computation time and obtain the scores for various paths.

Expansion. We continue by inserting the respective transformations from the sequences as novel tree nodes under u (see Algorithm 3). For each sequence, we start with u and the first transformation. We check if a child node with the same transformation already exists under u. If not, a new node v is created and added as child under u. Otherwise, we use the already existing node v. We repeat this step with v and the next transformation. Figure 10 from Section 5 exemplifies this expansion step.

Algorithm 3 Expansion Procedure of MCTS

procedure EXPANSION(u, $\mathcal{T}$)
  for T in $\mathcal{T}$ **do** ▷ For each sequence
    $z \leftarrow u$
    for T in **T do** ▷ For each transformer
      if z has no child with T **then**
        $v \leftarrow$ CREATENEWNODE(T)
        z.add_child(v)
      else
        $v \leftarrow z$.GETCHILDWITH(T)
      $z \leftarrow v$

Backpropagation. Algorithm 4 shows the last step that backpropagates the classifier scores to the root. For each sequence, the procedure first determines the last node n of the current sequence and the observed classifier score s at node n. Next, all nodes on the path from n to the root node of the search tree are updated. First, the visit count of each path node is incremented. Second, the final classifier score s is added to the score list of each path node. Both statistics are used by SELECTCHILD to choose the next promising node for evaluation. Furthermore, CHILDWITHBESTSCORE uses the score list to obtain the child node with the highest average score.

Algorithm 4 Backpropagation Procedure of MCTS

procedure BACKPROPAGATION($\mathcal{T}$)
  for T in $\mathcal{T}$ **do**
    $s \leftarrow$ GETSCORE(**T**)
    get n as tree leaf of current sequence
    while n is not None **do** ▷ Backpropagate to root
      n.visitCount $\leftarrow$ n.visitCount + 1 ▷ Increase visit count
      n.scores = n.scores $\cup$ s ▷ Append score
      $n \leftarrow n$.parent ▷ Will be None for root node

We finally note a slight variation for the scenario with a substitute model (see Section 3.1). To improve the transferability rate from the substitute to the original model, we do not terminate at the first successful adversarial example. Instead, we collect all successful samples and stop the outer loop after a predefined number of iterations. We choose the sample with the highest score on the substitute to be tested on the original classifier.

B List of Developers For Impersonation

Table 7 maps the letters to the 20 randomly selected programmers from the 2017 GCJ contest.

Table 7: List of developers for impersonation

Letter	Author	Letter	Author
A	4yn	K	chocimir
B	ACMonster	L	csegura
C	ALOHA.Brcps	M	eugenus
D	Alireza.bh	N	fragusbot
E	DAle	O	iPeter
F	ShayanH	P	jiian
G	SummerDAway	Q	liymouse
H	TungNP	R	sdya
I	aman.chandna	S	thatprogrammer
J	ccsnoopy	T	vudduu

C List of Code Transformations

A list of all 36 developed code transformations is presented in Table 8. The transformers are grouped accordingly to the family of their implemented transformations, i.e, transformations altering the control flow, transformations of declarations, transformations replacing the used API, template transformations, and miscellaneous transformations.

Table 8: List of Code Transformations

Control Transformations

Transformer	**Description of Transformations**
For statement transformer	Replaces a `for`-statement by an equivalent `while`-statement.
While statement transformer	Replaces a `while`-statement by an equivalent `for`-statement.
Function creator	Moves a whole block of code to a standalone function and creates a call to the new function at the respective position. The transformer identifies and passes all parameters required by the new function. It also adapts statements that change the control flow (e.g. the block contains a `return` statement that also needs to be back propagated over the caller).
Deepest block transformer	Moves the deepest block in the AST to a standalone function.
If statement transformer	Split the condition of a single `if`-statement at logical operands (e.g., `&&` or `||`) to create a cascade or a sequence of two `if`-statements depending on the logical operand.

Declaration Transformations

Transformer	**Description of Transformation**
Array transformer	Converts a static or dynamically allocated array into a C++ vector object.
String transformer	*Array option:* Converts a char array (C-style string) into a C++ string object. The transformer adapts all usages in the respective scope, for instance, it replaces all calls to `strlen` by calling the instance methods `size`. *String option:* Converts a C++ string object into a char array (C-style string). The transformer adapts all usages in the respective scope, for instance, it deletes all calls to `c_str()`.
Integral type transformer	Promotes integral types (`char`, `short`, `int`, `long`, `long long`) to the next higher type, e.g., `int` is replaced by `long`.
Floating-point type transformer	Converts `float` to `double` as next higher type.
Boolean transformer	*Bool option:* Converts true or false by an integer representation to exploit the implicit casting. *Int option:* Converts an integer type into a boolean type if the integer is used as boolean value only.
Typedef transformer	*Convert option:* Convert a type from source file to a new type via `typedef`, and adapt all locations where the new type can be used. *Delete option:* Deletes a type definition (`typedef`) and replace all usages by the original data type.
Include-Remove transformer	Removes includes from source file that are not needed.
Unused code transformer	*Function option:* Removes functions that are never called. *Variable option:* Removes global variables that are never used.
Init-Decl transformer	*Move into option:* Moves a declaration for a control statement if defined outside into the control statement. For instance, `int i; ...; for(i = 0; i < N; i++)` becomes `for(int i = 0; i < N; i++)`. *Move out option:* Moves the declaration of a control statement's initialization variable out of the control statement.

API Transformations

Transformer	**Description of Transformations**
Input interface transformer	*Stdin option:* Instead of reading the input from a file (e.g. by using the API `ifstream` or `freopen`), the input to the program is read from stdin directly (e.g. `cin` or `scanf`). *File option:* Instead of reading the input from stdin, the input is retrieved from a file.
Output interface transformer	*Stdout option:* Instead of printing the output to a file (e.g. by `ofstream` or `freopen`), the output is written directly to stdout (e.g. `cout` or `printf`). *File option:* Instead of writing the output directly to stdout, the output is written to a file.
Input API transformer	*C++-Style option:* Substitutes C APIs used for reading input (e.g., `scanf`) by C++ APIs (e.g., usage of `cin`). *C-Style option:* Substitutes C++ APIs used for reading input (e.g., usage of `cin`) by C APIs (e.g., `scanf`).
Output API transformer	*C++-Style option:* Substitutes C APIs used for writing output (e.g., `printf`) by C++ APIs (e.g., usage of `cout`). *C-Style option:* Substitutes C++ APIs used for writing output (e.g., usage `cout`) by C APIs (e.g., `printf`).
Sync-with-stdio transformer	Enable or remove the synchronization of C++ streams and C streams if possible.

Table 8: List of Code Transformations (continued)

Template Transformers

Transformer	Description of Transformations
Identifier transformer	Renames an identifier, i.e., the name of a variable or function. If no template is given, default values are extracted from the 2016 Code Jam Competition set that was used by Caliskan et al. [9] and that is not part of the training- and test set. We test default values such as `T`, `t`, ..., `i`.
Include transformer	Adds includes at the beginning of the source file. If no template is given, the most common includes from the 2016 Code Jam Competition are used as defaults.
Global declaration transformer	Adds global declarations to the source file. Defaults are extracted from the 2016 Code Jam Competition.
Include-typedef transformer	Inserts a type using `typedef`, and updates all locations where the new type can be used. Defaults are extracted from the 2016 Code Jam Competition.

Miscellaneous Transformers

Transformer	Description of Transformations
Compound statement transformer	*Insert option:* Adds a compound statement ({...}). The transformer adds a new compound statement to a control statement (`if`, `while`, etc.) given their body is not already wrapped in a compound statement. *Delete option:* Deletes a compound statement ({...}). The transformer deletes compound statements that have no effect, i.e., compound statements containing only a single statement.
Return statement transformer	Adds a return statement. The transformer adds a return statement to the main function to explicitly return 0 (meaning success). Note that main is a non-void function and is required to return an exit code. If the execution reaches the end of main without encountering a return statement, zero is returned implicitly.
Literal transformer	Substitutes a return statement returning an integer literal, by a statement that returns a variable. The new variable is declared by the transformer and initialized accordingly.