Binary Code Multi-Author Identification in Multi-Toolchain Scenarios

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Abstract

Knowing the authors of a binary program has significant application to forensic analysis of malicious software (malware), software supply chain risk management, and software plagiarism detection. Since modern software is typically the result of team efforts and there are multiple compilers and optimization levels available to use, it is essential to be able to reliably identify multiple authors across multiple toolchains. However, existing multi-author identification studies were only evaluated with code compiled by a single toolchain, leaving open the question whether existing techniques can work in multi-toolchain scenarios.

In this paper, we explore how toolchains impact programming style at real-world scale and present new techniques for multi-author identification in multi-toolchain scenarios. We show that existing techniques do not work well on real world code in multi-toolchain scenarios. Instead of manually designing code features, we apply deep learning to automatically extract features from the code. Our techniques can achieve 71% accuracy, and 82% top-5 accuracy for classifying 700 authors, which can greatly help analysts prioritize their investigation.

In addition to the new authorship identification results, we provide an in-depth analysis of our learning models and our results. This analysis is essential since authorship identification is not a task easily accomplished by a person. For example, our results show a counter-intuitive phenomena: unoptimized code is more difficult to attribute than optimized code. Our investigation shows strong evidence that compiler optimizations such as function inlining can help learning authorship style.

1 Introduction

The capability to identify authors of binary programs can significantly help analysts perform forensic analysis of malicious software (malware), detect malicious software implants in the software supply chain, and recognize software plagiarism. Malware analysts discover valuable information about malware development through intensive manual authorship analysis: malware developers acquire and share functional components such as command and control, encryption and decryption, beaconing, exfiltration, and domain flux, through online black markets [1, 6, 16] or by forming physically co-located teams [23]. In the software supply chain domain, code that exhibits untrusted styles, such as the ones seen in malware, indicates potential malicious implants. Software plagiarism can be detected by matching programming styles against known code. Because of these use cases, researchers have been developing machine learning based techniques to identify authors.

While machine learning, especially deep learning, has been successful in many domains such as computer vision and natural language processing, applying machine learning to binary code authorship identification presents a significant challenge. Conceptually, a human can identify objects from images in split seconds with very high accuracy. On the other hand, human experts need days or months to analyze the code and infer authorship from software. Due to the difficulty of binary code authorship identification, the realistic goal of applying machine learning is to help human experts, rather than replacing human experts, and to discover new insights on code authorship.

Early authorship identification studies focused on identifying the authors of single author programs [2, 7, 32]. These studies mainly had two steps: (1) design binary code features to reflect low level code properties such as machine instruction details and high level code properties such as program control flow and data flow, and (2) use supervised machine learning techniques, such as Support Vector Machine (SVM) [8] and Random Forests [15], to discover correlations between code features and authorship. When applied to real world software, which typically is written by multiple authors, these single author identification techniques can identify at most one of the multiple authors, or report a merged group identity, which makes single author identification impractical for real world applications.

Recent multi-author identification studies [24, 26] attempted to identify multiple authors by determining a unit of code that can be well attributed to a single author. These multi-author studies showed that attributing at the function level caused too much imprecision, as many functions are cooperated by multiple authors. Therefore, current multi-author identification operates at the basic block level. Attributing at the basic block level requires designing fine-grained code features, as the features used for single author identification may not be applicable at this finer granularity.

While multi-author identification is a significant step towards practical authorship analysis, many research challenges remain. The challenge we will focus on in this paper is how compilation toolchains such as the compiler family, version, and optimization level, impact authorship styles. Existing studies have two major limitations for this challenge. First, existing studies have not thoroughly investigated this issue. Hendrikse [13] investigated the impact of compilation toolchain on single author identification at a small scale; the experiments contained only 20 authors, 280 binaries, and 9 toolchains. However, single author identification is an intrinsically simpler problem than multi-author identification, as it unrealistically assumes that a binary consists of consistent coding style from one author. Other single author identification and multi-author identification techniques were evaluated only in single toolchain scenarios, meaning that they performed training and testing based on binaries generated by the same toolchain [2, 7, 26, 32]. In particular, multi-author identification techniques were evaluated only with code generated by GCC at optimization level -O2 (GCC -O2) [24, 26].

Second, existing studies only reported their accuracy results, without analyzing their machine learning models. Besides improving accuracy, it is important to understand how the models work and extract insights on the impact of compilation toolchains. Is a programmer's programming style reflected on binary code similar across different toolchains? Do we need different machine learning models or different code features for different toolchains? Answering these questions is vital for analysts to make better use of machine learning based techniques.

In this paper, we present the first thorough multi-toolchain, multi-author identification study. We explore how compilation toolchains impact multi-author identification techniques at real-world scale and present new techniques to identify multiple authors in multi-toolchain scenarios. As a baseline, we first conduct a study to evaluate how well our previous multi-author identification techniques [26] will function in a multi-toolchain scenario. We created a multi-toolchain dataset by compiling three large, long-lived open source projects (Apache HTTPD Server [4], Dyninst binary analysis and instrumentation tool suite [29], and Git [11]), with three compilers (GCC, ICC, and LLVM), and five optimization levels (O0, O1, O2, O3, and Os). This yielded a data set consisting of 1,965 binaries generated by 15 toolchains, containing 50 million basic blocks and 700 authors.

We enumerate all toolchain pairs to generate training sets and testing sets, which yields $15 \times 15 = 225$ total evaluation combinations. Among these 225 combinations, 15 represent single toolchain scenarios and the other 210 represent multi-toolchain scenarios. Our results reveal two limitations of existing multi-author identification techniques. First, the accuracy for multi-toolchain scenarios (min: 5%, median: 13%, max: 64%) is significantly lower than the accuracy for single toolchain scenarios (min: 44%, median: 59%, max: 70%). In practice, as we typically do not know which compilation toolchain generated the target binary for authorship identification, applying a mismatched authorship model to perform prediction can lead to extremely low accuracy. Second, there is a significant difference between the accuracy for single toolchain scenarios; the optimization levels influence the accuracy. For example, GCC -O0 has the lowest accuracy (44%) and ICC -O3 has the highest accuracy (70%). This accuracy difference suggests that programmers can have a higher chance of evading current multi-author identification by carefully choosing a toolchain such as GCC -O0 to generate the binary programs. These two limitations confirm the need of new techniques for identifying multiple authors in multi-toolchain scenarios.

We then present two approaches for multi-toolchain, multi-author identification. The first one is a two layer approach. Since previous techniques work better in single toolchain scenarios, it is reasonable to first use toolchain identification techniques [30, 31] to determine which toolchain generated the binary and then apply the corresponding single-toolchain authorship model. Note that while previous authorship identification studies [7, 26] have discussed this approach, none of them have implemented or evaluated it. The second one is a unified training approach, where we construct a training set containing binaries from all known toolchains. With a multi-toolchain training set, we may be able to train an authorship model that can work in multi-toolchain scenarios, albeit at a higher training cost.

While previous studies focused on designing new code features, we instead use deep learning to automatically extract low level features from raw bytes. We apply feed-forward neural networks to multi-author identification.

To the best our knowledge, we are the first project to apply deep learning to this problem and show that it can reliably identify low level code features. We focus on two areas when applying deep learning. First, we investigate what should be used as inputs to Deep Neural Networks (DNNs) and find that while using only raw bytes as inputs can achieve reasonable accuracy, complementing raw bytes with higher-level structural features can further improve accuracy. Second, deep learning requires tuning several important learning hyper-parameters to achieve good results, such as the learning rate, the number of layers, and the number of hidden units per layer. We follow the general practices recommended by deep learning researchers [5, 12], and report our experiences of applying these practices so that future research on applying deep learning to authorship identification can benefit from our experiences.

We evaluated our techniques with our multi-author, multi-toolchain data set. We focused on three aspects of our techniques: whether the two layer approach and the unified training approach can address the issue of mismatched models, whether DNN can improve accuracy over traditional machine learning techniques such as SVM, and understanding and improving the accuracy differences between optimization levels. Our results showed that with toolchain identification, we achieved 59% accuracy for identifying 700 authors. Replacing SVM with DNN, we improved this accuracy to 71%. In addition, DNN achieved 82% top-5 accuracy and 86% top-10 accuracy, showing that our techniques can effectively prioritize investigation. For the unified training approach, SVM training did not scale to this data set, while DNN achieved 68% accuracy. Our results also showed that DNN reduced the accuracy difference between optimization levels and improved accuracy for all 15 individual toolchains (min: 62%, median 69%, max: 79%).

To gain more insights on how compilation toolchain impacts multi-author identification and on how the machine learning models work, we investigated the structure of the learning models, including the feature weights of SVM and the activations of neurons in DNN. We learned three lessons: (1) different toolchains mainly have disjoint sets of features that are indicative of authorship; (2) DNNs can internally determine which toolchain generated the binary without explicitly training for toolchain identification; and (3) unoptimized code is more difficult to attribute at the basic block level. Previous studies have reported accuracy results, but have not analyzed their models.

2 Background

We discuss four areas of existing authorship identification studies as background: the binary code features used to capture programming styles, commonly used workflow, relationship between accuracy and the complexity of the programs used in evaluation, and relationship between accuracy and the compilation toolchains.

2.1 Binary Code Features

Binary code features are extracted at block level or function level, and are then accumulated to the corresponding operation level. For example, single author identification accumulates features to the program level and multi-author identification accumulates features to the basic blocks level. As multi-author identification requires identifying authors at the basic block level, we discuss only basic block level features.

Existing block level features describe a wide variety of code properties, such as instruction details, control flow, data flow, and external dependencies. Low level code features include byte n-grams [18, 32], instruction idioms [7, 18, 19, 31, 32, 33], and individual instruction components such as instruction prefixes, instruction operands, and constant values [26].

Higher-level structural features describe program control flow, data flow, function and loop context of a basic block, and external dependencies. Control flow features [26] describe the types of incoming and outgoing CFG edges (such as conditional taken, conditional not taken, direct jump, and fall through), and exception handling (such as whether a basic block throws exceptions and whether a basic block catches exceptions). Data flow features [26, 9] have three main types: (1) the number of input variables, output variables, and internal variables, (2) features that describe how a basic block uses a stack frame, and (3) features that describe data flow dependencies of variables. Context features [26] include the loop nesting level of a basic block and loop size of the enclosing loop. External dependency features included function names of external library call targets [32].

2.2 Workflow

A common workflow used in single author identification studies has four major steps: (1) design a large number of simple candidate features; (2) extract the defined features using binary code analysis tools such as IDA Pro [14] or Dyninst [29]; (3) select a small set of features that are indicative of authorship by using feature selection techniques such as ranking features based on mutual information between features and authors [32]; and (4) apply a supervised machine learning technique, such as Support Vector Machine (SVM) [8] or Random Forests [15], to learn the correlations between code features and authorship. Rosenblum et al. [32] used instruction, control flow, and library call target features, and used SVM for classification. Caliskan et al. [7] added data flow features, constant data strings, and function names derived from symbol information, and used Random Forests for classification.

Multi-author identification studies [26, 24] adapted this workflow with three modifications. First, they performed attribution at the basic block level. Second, they found that library code such as Standard Template Library (STL) and Boost C++ Library (Boost) is often inlined and needs to be distinguished from users's code. Third, as a programmer typically writes more than one basic block at a time, they used a Conditional Random Field (CRF) model to capture potential author correlations between adjacent basic blocks.

2.3 Complexities of Programs

Single author identification studies performed evaluations of their techniques on single author programs such as Google Code Jam (GCJ), and multi-author programs that have a clear major author such as university course projects and certain programs extracted from Github. Rosenblum et al. reported 51% accuracy for classifying 191 authors on -O0 binaries from GCJ and 38.4% accuracy for classifying 20 authors on -O0 binaries from university course projects. Caliskan et al. improved GCJ accuracy to 92% for classifying 191 authors on -O0 binaries, and 89% accuracy for classifying 100 authors on -O2 binaries. They also extracted some programs from Github that have a major author who contributed more than 90% of the code, and got 65% accuracy for classifying 50 authors.

These studies reported significantly lower accuracy on multi-author programs than on GCJ. There are at least two reasons for this accuracy difference. First, university course projects and programs extracted from Github contained code that was not written by the major author. This code can confuse machine learning algorithms. For example, course projects contained skeleton code from the professor and the extracted Github programs still had code from other authors and third party libraries. Second, these multi-author programs are typically more complex than the programs from GCJ. Programs from GCJ are typically written quickly, and not written with common software engineering practices, making them less appropriate for evaluation compared to real world software.

Multi-author identification studies instead used large, long-lived, real world open source software that follows common software engineering practices such as Apache HTTP Server. They achieved 59% accuracy for identifying 284 authors using SVM and 65% accuracy with CRF. We will follow this practice and evaluate our techniques with real world software.

2.4 Impacts of Compilation Toolchains

Caliskan et al. repeated single toolchain evaluations with four toolchains (GCC -O0, -O1, -O2, -O3), with the programs from GCJ. In other words, they trained and tested at the same optimization level. They reported that -O0 code has the highest accuracy (96%), and -O3 code has lowest accuracy (89%), but did not investigate why there is such an accuracy difference between optimization levels. They assumed that they could use previous toolchain identification techniques [30, 31] to identify the toolchain. Hendrikse [13] performed the only multi-toolchain study, though still based on single author identification, using the programs from GCJ. He repeated single toolchain evaluations with 9 toolchains (GCC, MSVS, and ICC with -O0, -O2, and -Os) and reported no significant accuracy difference between optimization levels (-O0: 92%, -O2: 93%, and -Os: 94%). He created a multi-toolchain data set by randomly sampling a program from one of the 9 toolchains, and reported 92% accuracy. However, this study was at a small scale, as the experiments contained only 20 authors.

We are the first project to investigate the impact of compilation toolchains on multi-author identification, develop new techniques for multi-toolchain, multi-author identification, and evaluate our techniques with real world software. Our results do not align with the results of these existing studies, as we achieved highest accuracy with -O3 code and lowest accuracy with -O0 code. In Section 7.3, we will present our analysis as to why we see such an accuracy difference.

3 Multi-toolchain Study

We evaluate the effectiveness of our previous techniques for multi-author identification [26] in a multi-toolchain scenario.

3.1 Data Set Generation

To evaluate their techniques, we created a multi-toolchain dataset by compiling three large, long-lived open source projects (Apache HTTPD Server [4], Dyninst binary analysis and instrumentation tool suite [29], and Git [11]), with three compilers (GCC 4.8.5, ICC 15.0.1, and LLVM 3.5.0), and five optimization levels (O0, O1, O2, O3, and Os) on a 64-bit Red Hat Linux 7 platform. For each of the 15 toolchains, we used the following steps to generate the author label as ground truth for each basic block.

1. Use git-author [27] to get a weight vector of author contribution percentages for all source lines in these projects. The source lines of STL and Boost

code were attributed to author identity "STL" and "Boost", respectively.

2. Compile these projects with debugging information using the given compiler and optimization level, and obtain a mapping between source lines and machine instructions. The compiler may generate binary code that does not correspond to any source line, such as the default constructor for a class when the programmer does not provide it. We exclude this code from our data set.
3. Derive weight vectors of author contribution percentages for all machine instructions and basic blocks in the compiled code. We first derived the weight vector for each instruction by averaging the contribution percentages of the corresponding source lines. We then derived the weight vector of a basic block by averaging the vectors of the instructions within the basic block.
4. Take the major author as the author label, based on the weight vector of contribution percentages of a basic block.

We generated a data set consisting of 1,965 binaries generated by 15 toolchains, containing 50 million basic blocks and 700 authors. The 1,965 binaries consisted of 131 programs, with each program having 15 different versions.

3.2 Evaluation Methodology

We enumerate all toolchain pairs to generate training sets and testing sets. For each evaluation pair, we used the following evaluate strategy.

We used Dynisnt [29] to extract code features, Liblinear [10] for linear SVM , and CRFSuite [28] for linear CRF. We performed the traditional leave-one-out cross validation, where each program was in turn used as the testing set and all other programs were used as the training set. So, the testing set contained the binary of the testing program generated by the testing toolchain, and the training set contained the binaries of the training programs generated by the training toolchain.

Each round of the cross validation had two steps. First, we selected the top 45,000 features that had the most mutual information with the major authors, as done in our previous work [26]. Second, we trained a linear SVM and a linear CRF and predicted the author of each basic block in the testing set. We calculated accuracy as the percentage of correctly attributed basic blocks. We parallelized this cross validation with HTCondor [17], where each round of the cross validation is executed on a separate machine.

3.3 Results

Table 1 shows the accuracy for all the evaluation pairs using SVM. We make three observations from the result table. First, our previous techniques did not work well in multi-toolchain scenarios, as shown in the non-diagonal cells. The red-shaded cells show the minimum (5%), median (13%), and maximum (64%) accuracy achieved in multi-toolchain scenarios. Second, these techniques achieved much higher accuracy in single toolchain scenarios, as shown in the diagonal cells. The green-shaded cells show the minimum (44%), median (59%), and maximum (70%) accuracy achieved. However, there is a 26% accuracy difference between the minimum and maximum. Third, by comparing the accuracy numbers in each column, we find that we always get the highest accuracy for a testing toolchain when we use the model trained on binaries generated by the same toolchain. This observation supports the idea that as long as we can identify the toolchain that generated the testing binary, we know which authorship model is the most appropriate to use.

We were not able to get any accuracy results with CRF because CRF training took too long to finish. We commented in our previous work that we spent 7 days to train a CRF model. The previous data set had 900,583 basic blocks and 284 authors, whereas in this study, the data used in each evaluation pair had average 1.5 million basic blocks and 700 authors. As the training of a linear CRF has a time complexity quadratic in the number of labels and linear in the total number of data instances [36], it is not surprising that we cannot finish CRF training in any reasonable amount of time.

The results of our study confirm that we need new approaches for authorship identification in multi-toolchain scenarios and investigate the accuracy differences between optimization levels.

4 Approaches

We compare two approaches for multi-toolchain, multi-author identification. First, we attempt to identify the toolchain that generated the target binary and then apply the corresponding single toolchain authorship model. We call this the *two layer approach*. Second, we construct a training set that contains binaries from all known toolchains and then train a multi-toolchain model. We call this the *unified training approach*.

4.1 Two Layer Approach

Besides training multiple single-toolchain authorship models, the other key component of the two layer approach is to perform toolchain identification. Toolchain identification is typically performed at the function level

Table 1: Evaluation results of our previous techniques [26]. The diagonal cells (in bold font) represent the single toolchain results and the green-shaded cells represent the minimum, median, maximum accuracy. The non-diagonal cells represent the multi-toolchain results and the red-shaded cells represent the minimum, median, maximum accuracy.

Train \ Predict		GCC					ICC					LLVM				
		-O0	-O1	-O2	-O3	-Os	-O0	-O1	-O2	-O3	-Os	-O0	-O1	-O2	-O3	-Os
GCC	-O0	**45%**	8%	7%	7%	8%	9%	7%	7%	7%	7%	8%	8%	7%	7%	7%
	-O1	8%	**59%**	25%	22%	16%	8%	14%	16%	16%	14%	7%	10%	24%	23%	16%
	-O2	7%	27%	**63%**	38%	18%	6%	14%	17%	17%	14%	6%	10%	28%	29%	18%
	-O3	7%	25%	41%	**66%**	16%	6%	14%	19%	18%	14%	6%	9%	25%	25%	16%
	-Os	8%	19%	20%	17%	**55%**	7%	13%	13%	13%	13%	7%	11%	19%	19%	14%
ICC	-O0	9%	6%	6%	6%	6%	**47%**	6%	7%	7%	6%	6%	6%	8%	7%	6%
	-O1	7%	13%	13%	12%	11%	7%	**58%**	19%	19%	45%	7%	9%	16%	16%	12%
	-O2	6%	14%	15%	15%	10%	7%	20%	**66%**	64%	21%	6%	8%	19%	19%	12%
	-O3	6%	13%	15%	15%	10%	8%	20%	64%	**66%**	21%	5%	8%	19%	19%	12%
	-Os	7%	13%	13%	12%	11%	7%	45%	20%	20%	**58%**	6%	9%	16%	16%	12%
LLVM	-O0	9%	9%	9%	8%	9%	9%	9%	8%	8%	9%	**44%**	9%	8%	8%	8%
	-O1	9%	10%	9%	8%	10%	7%	9%	8%	8%	9%	7%	**52%**	16%	15%	21%
	-O2	8%	19%	19%	18%	13%	8%	14%	17%	17%	14%	7%	18%	**69%**	63%	40%
	-O3	8%	19%	19%	18%	13%	7%	14%	17%	17%	14%	6%	17%	63%	**70%**	37%
	-Os	8%	19%	18%	16%	14%	7%	13%	14%	14%	13%	6%	21%	40%	38%	**61%**

[31]. The program level is not suitable for toolchain identification as a binary may contain code generated by different toolchains. For example, a programmer may compile their code with one toolchain and then statically link a library that was generated by a different toolchain. On the other hand, a function is typically generated by one toolchain, as the source code of a function is in a single source file and the source file is typically the compilation unit.

Toolchain identification can be summarized in three steps. First, we define and extract candidate binary code features. Rosenblum et al. [31] used instruction idioms, which represented consecutive machine instructions, and graphlets, which represented subgraphs extracted from the Control Flow Graph (CFG) of a function. Second, we perform feature selection by ranking features based on the mutual information with toolchain labels. Third, as a compilation unit typically contain more than one function, we perform joint classification by training a Conditional Random Field model to capture the correlations between code features and toolchain labels. Note that training a CRF model for toolchain identification is significantly faster compared to multi-author identification, as there are only 1.4 million functions and 15 toolchain labels in our data set.

The two layer approach needs to maintain multiple classifiers: one toolchain identification classifier, and one authorship identification classifier for each toolchain. On the other hand, maintaining multiple classifiers brings two advantages. First, each single-toolchain authorship model can capture the distinct characteristics of each toolchain. Second, the training effort of each model is modest.

4.2 Unified Training Approach

The unified training approach constructs a multi-toolchain training set. This idea is based on a general machine learning practice called data set augmentation [12]. Data set augmentation aims to improve the accuracy of a classifier by adding training examples that have been modified with transformations that do not change the label of the example. For example, in object recognition in computer vision, a cat image remains a cat image if it is shifted one pixel to the right. Similarly, the code written by an author remains code written by this author if it is compiled by a different toolchain.

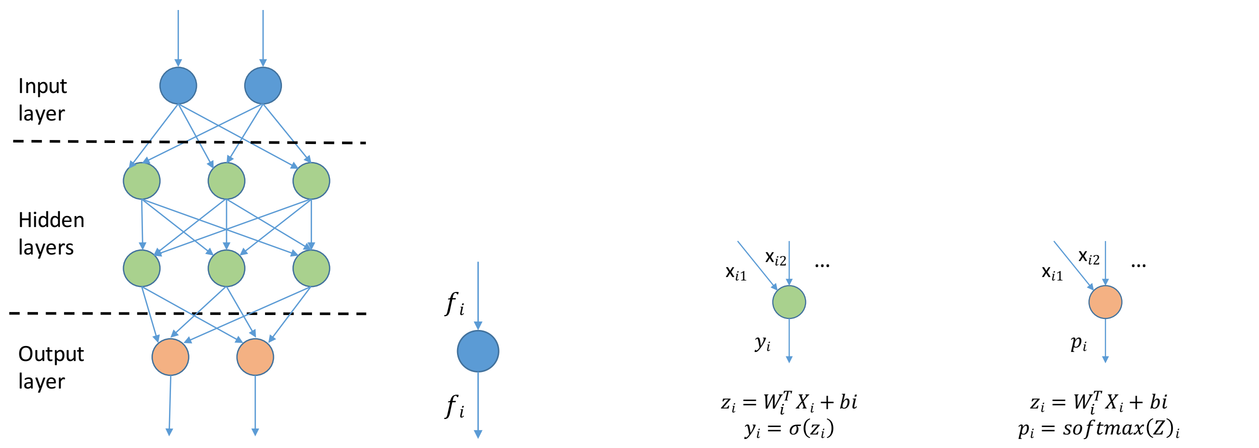
Compared to the two layer approach, the unified training approach needs to maintain only one classifier. However, training this classifier requires significantly more computing power, as the size of the training set is multiplied by the total number of available toolchains.

5 Applying Deep Learning

We apply deep learning to automatically learn features from raw bytes of basic blocks. We first introduce the basics of feed-forward neural networks and then focus on how to construct inputs to the network.

5.1 Basics of Feed-forward Nerual Networks

Figure 1 illustrates an example of a feed-forward neural network and breaks down its individual components. As shown in Figure 1a, nodes in the network are arranged into layers: one input layer, multiple hidden layers (two in this example), and one output layer. Typically, nodes between adjacent layers are fully connected, and there are no backward edges or cross layer edges.



(a) A network example (b) An input layer node (c) A hidden layer node (d) An output layer node

Figure 1: Overview of a feed-forward neural network. Nodes are arranged into an input layer, hidden layers, and an output layer. Nodes in adjacent layers are fully connected. An input layer node outputs the input value f_i without modification. A hidden layer node defines learning parameters weights W_i and bias b_i, and performs a linear transformation with the input X_i. The result of the linear transformation z_i then goes through a non-linear activation function σ to generate the output to the next layer. An output layer node also defines W_i and b_i and generates the prediction probability for a class.

As shown in Figure 1b, a node in the input layer takes an input value f_i and outputs the same value f_i. The information used for constructing inputs is application specific. Two common choices are using manually designed features and using raw data as inputs. Examples of raw data include individual pixels in computer vision tasks and raw bytes in our case.

The internal computation of a hidden layer node is shown in Figure 1c. The number of hidden layers and the number of nodes in a hidden layer are two hyper-parameters that need tuning. A node in a hidden layer takes multiple inputs from the previous layer and generates new output value to the next layer. Denote $X_i = [x_{i1}, x_{i2}, \ldots, x_{in}]^T$ as the input vector, where n represents the total number of nodes in the previous layer. The inputs first go through a linear transformation, defined as $z_i = W_i^T X_i + b_i$, where weights $W_i = [w_{i1}, w_{i2}, \ldots, w_{in}]^T$ and bias b_i are two learning parameters, whose values are determined in the training process. Note that each node has separate weights and bias. The output is then defined as $y_i = \sigma(z_i)$, where σ is called the activation function. σ is a non-linear function so that the whole network can represent a non-linear prediction space. While the Rectified Linear Unit (ReLU) is a commonly used activation function, we found that the Scaled Exponential Linear Unit (SELU) [21] achieved better results.

The goal of the output layer is to generate a probability vector $P = [p_1, p_2, \ldots, p_m]^T$, where p_i represents the probability that the input data instance belongs to class i and m is the total number of classes. As shown in Figure 1d, similar to a node in a hidden layer, the inputs first go through a linear transformation $z_i = W_i^T X_i + b_i$, where $Z = [z_1, z_2, \ldots, z_m]^T$. The output is defined as $p_i = softmax(Z)_i$, where $softmax(Z)$ is a function that normalizes a vector of arbitrary values to a probability vector; $softmax(Z)_i$ is the ith element in the probability vector, defined as $softmax(Z)_i = (e^{z_i})/(\sum_{k=1}^{m} e^{z_k})$. We can then report the class with the highest probability as the prediction result, or report the top-k classes by choosing the k highest probabilities.

The purpose of training is to determine the values for W and b, which can be summarized in four steps [12].

1. Initialize the weights and biases. Typically, weights are randomly sampled from a Gaussian or uniform distribution; biases are set to heuristically chosen constants. The specific choice of the distributions depends on the used activation function.
2. Calculate the loss for a training example. Suppose the training example belongs to the Lth class. We calculate the output of each node along the layers in the network, and get the prediction probability vector P. A common loss function is cross-entropy. In this context, it is defined as $-log(p_L)$. Intuitively, the larger p_L is, the more likely we make the correct prediction and the smaller the loss.
3. Update weights and biases by gradient descent. This step aims to reduce the loss by updating the weights and biases. The direction of the update is specified by the negative of the gradient, as it represents the fastest direction along which the loss decreases. The magnitude of the update is specified by a user-defined hyper-parameter called the learn-

ing rate.

4. Repeat the second and third steps over the training set until converging. Since the training set for deep learning is typically too large to fit in memory, a common practice is to split the training set into multiple mini-batches, where one mini-batch contains dozens or hundreds of data instances. Only one mini-batch is loaded into memory at a time.

As a user of feed-forward neural networks, we need to construct appropriate inputs to the network and tune key hyper-parameters such as the learning rate, the number of layers, and the number of unit in each hidden layers.

5.2 Extract Low Level Features

A key advantage of deep learning is that it can automatically learn features from data. So, we use raw bytes of a basic block as inputs, as opposed to designing the features ourselves. As manual feature design is unlikely to cover all relevant code properties, using raw bytes can also potentially capture information that is not represented by existing features. To provide raw bytes as input, we have two issues to address. First, the length of a basic block is variable, but a feed-forward network takes a fixed number of inputs. For this issue, we empirically decided to use the first 70 bytes of the basic block as we found over 99% of the basic blocks are short than 70 bytes. For basic blocks shorter than 70 bytes, we add padding after the code bytes.

Second, how do we represent the value of a byte as the inputs to the network? Ideally, we would like a representation that will allow the network to capture instruction fields such as instruction prefixes, opcodes, and operands, and the encoding of machine instructions, For the x86-64 architecture, instruction fields do not necessarily align with byte boundaries. For example, the lower four bits of a REX prefix byte represents four different fields. Therefore, we use bit values as inputs. Specifically, we translate bit value 0 to input value -1, bit value 1 to input value 1, and padding bit to value 0. This representation allows the network to distinguish padding from real code bits.

However, using only raw bytes of a basic block as input cannot capture higher-level structural features such as control flow, data flow, and the context. This is because structural properties are the results of interactions between multiple basic blocks and extracting structural code features is the result of extensive, semantic analysis of the binary code [3, 25, 34]. We reuse existing basic block level structural features [24, 26, 32] as additional inputs.

6 Evaluation

We evaluated our techniques with the same multi-toolchain data set discussed in Section 3. Recall that this data consists of 1,965 binaries generated by 15 toolchains, containing 50 million basic blocks and 700 authors.

We focus on two aspects of our techniques: how well the two layer approach and the unified training approach can perform multi-toolchain, multi-author identification, and whether DNN can improve accuracy over traditional machine learning techniques such as SVM. As either the two layer approach or the unified training approach can be paired with either SVM or DNN, we evaluated the following four techniques: `two-layer-svm`, `two-layer-dnn`, `unified-svm`, and `unified-dnn`.

6.1 Evaluation Methodology

Our evaluations are based on leave-one-out cross validation, where all 15 versions of a program are considered as a fold. So, in each round of cross validation, the training set contains all 15 versions of 130 programs, and the testing set contains all 15 versions of the other program.

For `two-layer-dnn`, we train a toolchain identification classifier with linear CRF using all binaries in the training set. We then train 15 single-toolchain authorship classifiers with feed-forward neural networks, where each classifier is trained with the corresponding version of the 130 programs. For testing, we first use the toolchain identification classifier to determine the which toolchain generated the functions in the testing binaries, and then we apply the corresponding single-toolchain authorship model to predict the authors of all basic blocks. The steps for `two-layer-svm` is similar to the steps for `two-layer-dnn`, but we replace feed-forward neural networks with linear SVM. For both `unified-svm` and `unified-dnn`, we train a multi-toolchain authorship model with all binaries in the training set and then predict the authors of binaries in the testing set. Accuracy is calculated as the number of correctly attributed basic blocks over the total number of basic blocks.

We used Dynisnt [29] to extract code features, Liblinear [10] for linear SVM, CRFSuite [28] for linear CRF, and TensorFlow [37] for deep learning. It is straightforward to parallelize the training and testing of neural networks in TensorFlow. In our experiments, we used four CPUs for training and testing each feed-forward neural networks. We parallelized our evaluations with HTCondor [17]. Note that the two layer approach has more parallelism than the unified training approach. For the unified training approach, we can parallelize different rounds of cross validation. For the two layer approach, we can parallelize different rounds of cross validation, as well as the training of toolchain identification and all single-toolchain authorship models within a round of cross validation.

6.2 Evaluation Results

A key question to answer in our evaluations is how well we can perform multi-toolchain, multi-author identification. Our results show that `two-layer-svm`, `two-layer-dnn`, and `unified-dnn` achieved 59%, 71%, and 68% accuracy for classifying 700 authors on code generated by 15 toolchains, as opposed to as low as 5% accuracy when a mismatched authorship model is used. Our techniques can help prioritize investigation: `two-layer-dnn` achieved 82% top-5 accuracy and 86% top-10 accuracy. Our results show that `unified-svm` did not scale to the merged training set containing all 15 toolchains.

To better understand the accuracy achieved the two layer approach, we investigated how the accuracy of toolchain identification impact multi-author identification. Our toolchain identification classifiers achieved 93% accuracy for identifying 15 toolchains, where accuracy is calculated as the number of functions that we identified the correct toolchain over the total number of functions. To investigate the impact of 7% error rate on toolchain identification, we repeated experiments with `two-layer-svm` and `two-layer-dnn` using an oracle for toolchain identification. We observed less than 1% accuracy improvement by using an oracle for toolchain identification. Therefore, we believe current toolchain identification techniques are good enough for multi-toolchain, multi-author identification.

We then compared `two-layer-dnn` and `two-layer-svm` on two aspects to understand how `two-layer-dnn` improved accuracy. First, we broke down the accuracy achieved by DNN and SVM in single toolchain scenarios. Table 2 shows that DNN improved not only the overall accuracy, but also the accuracy for all 15 toolchains. In addition, `two-layer-dnn` had a slightly reduced accuracy difference between optimization levels, as ICC -O0 had the lowest accuracy (62%) and ICC -O3 had the highest accuracy (79%), compared to `two-layer-svm`, where LLVM -O0 had the lowest accuracy (44%) and LLVM -O3 had the highest accuracy (70%).

Second, we compared the accuracy of SVM and DNN for different sizes of basic blocks. As shown in Figure 2a, we can see that SVM suffers when there are small basic blocks. This observation aligns with the results presented in our previous study [26] and can be explained simply as small basic blocks provide fewer code features for prediction. On the other hand, DNN achieved much higher accuracy on small basic blocks. We attribute this improvement to the advantage of deep learning: our DNN models extract features at bit level, which can capture information that is not represented by existing low level features. For larger basic blocks (byte size larger than 20), both DNN and SVM have varying accuracy, and DNN does not seem to outperform SVM. Note that we only use the first 70 bytes of a basic block, but this decision does not hurt accuracy for blocks larger than 70 bytes. Figure 2b shows the cumulative distribution of basic blocks in different sizes. Since about 80% of the total basic blocks are smaller than 20 bytes, the accuracy improvement on small basic blocks explains the overall improvement of DNN.

Since `unified-svm` did not scale to the merged training set, it shows that `unified-dnn` has better training scalability. We observed similar accuracy results from `unified-dnn` compared to `two-layer-dnn`: (1) `unified-dnn` has similar accuracy differences between optimization levels, where O0 code has lowest accuracy, and O2 and O3 code have highest accuracy; (2) `unified-dnn` has a similar accuracy trend in terms of block sizes.

Last, we discuss the needed training time. For `two-layer-dnn`, it took about 30 hours to train a DNN model and about 10 hours to train a linear CRF model for toolchain identification. For `two-layer-svm`, it took about 20 hours to train a linear SVM, and we use the same linear CRF models for toolchain identification. For `unified-dnn`, it took about 240 hours to train a DNN model. Note that we can significantly speed up the training of DNN models by deploying them on GPUs and more CPUs. We believe the training cost of `unified-dnn` is practical.

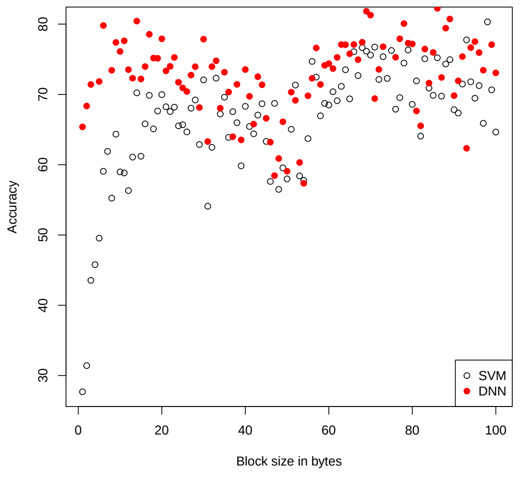
6.3 Experiences of Deep Learning

As we are the first project to apply deep learning to multi-author identification, we report our experiences of deep learning tuning. We used the Adam optimizer in our experiments, as it has been shown empirically to be more effective than other optimization methods [20]. We first discuss several factors that are fundamental for us to achieve any success on training DNN models:

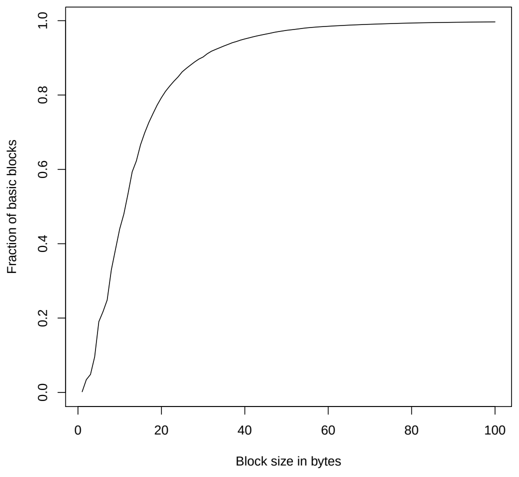
1. Use a small initial learning rate. Typical values for the initial learning rate are between 10^{-5} and 1, with a default value 0.01 [5]. We followed this recommendation and found that we needed a small initial learning rate, around 10^{-4}. Too large values such as 0.01 and 0.001 caused the training loss to increase with training and eventually diverge to infinity.
2. Using SELU as the activation function allows training deeper networks compared to using ReLU, and we achieved better results when using SELU. The best SELU network had 10 hidden layers, while the

Table 2: Comparison of single toolchain results between SVM and DNN. For convenience of comparison, we copy the results for SVM from the diagonal cells in Table 1. DNN improved accuracy for all 15 toolchains.

	O0		O1		O2		O3		Os		Avg	
	SVM	DNN	SVM	DNN	SVM	DNN	SVM	DNN	SVM	DNN	SVM	DNN
GCC	45%	64%	59%	69%	63%	70%	66%	75%	55%	66%	58%	69%
ICC	47%	62%	58%	68%	66%	79%	66%	79%	58%	68%	60%	73%
LLVM	44%	63%	52%	64%	69%	77%	70%	77%	60%	69%	60%	71%
Avg	45%	63%	57%	67%	66%	76%	67%	77%	58%	68%	59%	71%



(a) Model Comparison



(b) Cumulative Distribution

Figure 2: Comparison between accuracy of SVM and DNN on basic blocks in different sizes. DNN significantly outperforms SVM for small basic blocks. As there are more small basic blocks, DNN achieved better overall accuracy.

best ReLU network had 5 hidden layers.

3. Shuffle the training data before training. We started with dividing data into mini-batches by iterating every binary in the training set and putting consecutive basic blocks into one mini-batch. As adjacent basic blocks are likely written by the same author, this caused each mini-batch to have code from only a few authors and different mini-bathes to have disjoint sets of authors, which in turned caused the training to repeatedly optimize the weights and biases for different authors and led to fluctuating training accuracy. Shuffling the training data so that each mini-batch contains code from more authors makes the training converge to a high training accuracy.

We did not observe significant improvement by tuning the number of hidden units per layer. Our networks are set to have 800 hidden units per layer. We let all hidden layers have the same number of units as Larochelle et al. [22] empirically showed that an even-sized network architecture performs no worse than a decreasing-sized or an increasing-sized architecture. Our results align with this recommendation. The decision of 800 hidden units per layer is based on two considerations. First, a hidden layer wider than the input layer typically performs better than a hidden layer narrower than the input layer [5]. Our input layer has 704 units (560 units for 70 bytes and 144 units for structural features), so our hidden layer should be wider than 704 units. Second, on the other hand, too wide hidden layers will significantly increase training time as the number of learning parameters is quadratic in the number of units per layer. We tried more units and fewer units per layer and observed about the same or lower accuracy.

7 Understanding the Models

We investigate the internals of our machine learning models to better understand how the models work. We focused on three toolchains (GCC -O2, ICC -O2 and LLVM -O2). We stress that our observations are anecdotal, meaning that we did not find any conflicting facts, but we cannot prove them either due to the complexity of the data sets and the machine learning models.

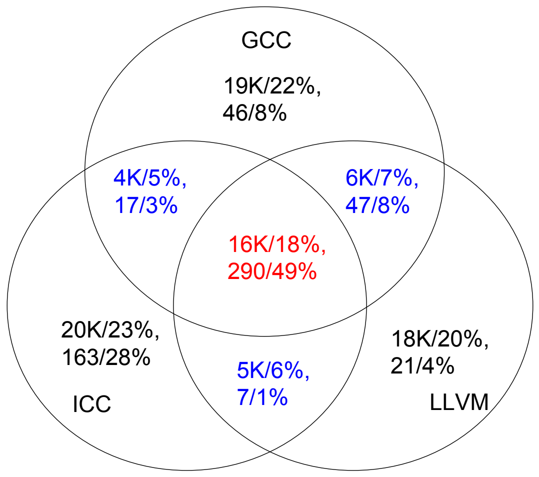


Figure 3: A Venn diagram of selected features in models from `two-layer-svm`. The results are represented in a form "*A*/*B*,*C*/*D*", where *A* represents the total number of features, *B* represents the percentage of total features, *C* represents the number of structural features, and *D* represents the percentage of structural features.

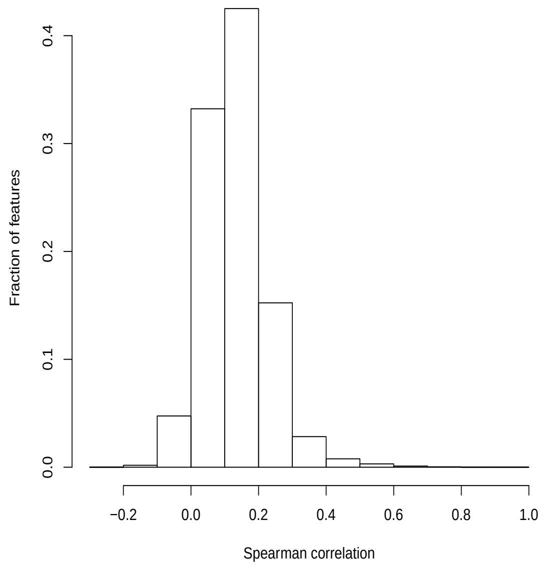


Figure 4: The histogram of Spearman correlations for commonly selected features by all three toolchains in GCC model and ICC model.

7.1 Different Features Are Selected for Different Toolchains

Two key questions for understanding the impact of compilation toolchains on authorship are (1) do we need different features for different toolchains? And (2) if there are features that are indicative of authorship for all toolchains, do these features contribute similarly to the models for the different toolchains? We try to answer these questions by examining the selected features and their weights in `two-layer-svm`. Note that while `two-layer-svm` has lower accuracy than `two-layer-dnn` and `unified-dnn`, we choose to analyze `two-layer-svm` as SVM models are easier to interpret than deep learning models.

For the first question, Figure 3 shows a Venn diagram of the number of uniquely selected features and the number of commonly selected features. We selected 45,000 features each for GCC, ICC, and LLVM. Since some features were selected by more than one toolchain, there are only 88,000 selected features in total. 65% of the selected features are uniquely selected by a single toolchain, with 22%, 23%, and 20% of features uniquely selected by GCC, ICC, LLVM, respectively. On the other hand, only 18% of the selected features are selected by all three toolchains. Among the 88,000 features, there are 591 structural features. 40% of the structural features are uniquely selected by a single toolchain, while 49% of the selected structural features are selected by all three toolchains. Our results show that overall, we need different features for different toolchains, but a much higher percentage of structural features are shared.

For the second question, we analyze the weights of features that are selected by all three toolchains. An SVM model defines a weight for each pair of author a and feature f. When f is observed in a basic block, the larger the weight, the more likely that the basic block is written by a. For a given feature, we can generate a ranking of all authors to summarize its contribution to a model. If a feature has similar rankings for different toolchains, we can conclude that this feature contributes similarly to all models for the different toolchains. Note that we analyze the rankings instead of the actual values of weights because the values of weights of a feature also depend on the other features in the model. As GCC, ICC, and LLVM each have uniquely selected features, the actual values of weights in different models are not directly comparable.

We calculated the Spearman correlation [35] to measure similarities between author rankings. The value of the Spearman correlation of two rankings is between -1 and 1, where -1 means opposite rankings, 0 means that there is no association between two rankings, and 1 means the same ranking. Figure 4 shows the histogram of Spearman correlations for the GCC model and the ICC model. We can see that most features have Spearman correlation values between -0.1 and 0.3, indicating that the rankings for GCC has little or no association with the rankings for ICC. We repeated the same analysis for GCC and LLVM, and ICC and LLVM, with results similar to Figure 4. Therefore, our results suggest that com-

Table 3: Unit distributions in hidden layers. Column "Dom." represents dominant units and "Exc." represents exclusive units.

	GCC		ICC		LLVM	
	Dom.	Exc.	Dom.	Exc.	Dom.	Exc.
Layer 1	0.6%	0.0%	24.0%	1.0%	75.4%	71.4%
Layer 2	10.4%	0.1%	48.6%	6.4%	41.0%	22.6%
Layer 3	7.6%	0.4%	61.4%	10.5%	31.0%	17.5%
Layer 4	8.0%	0.5%	55.6%	7.3%	36.4%	19.5%
Layer 5	9.7%	0.1%	67.4%	3.9%	22.9%	8.4%
Average	7.3%	0.2%	51.4%	5.8%	41.3%	27.9%

monly selected features typically contribute differently to predictions in different toolchains.

7.2 DNNs Can Internally Recognize the Toolchain

In Section 6.2, our evaluation results show that `two-layer-dnn` and `unified-dnn` have similar results. This suggests that `unified-dnn` can internally recognize the toolchain that generated the input data, even without explicitly training for toolchain identification. Note that a similar phenomena was observed in computer vision research, where Zhou et al. [38] found that a deep learning model trained for scene classification (whether an image describes a office or a bedroom) can internally recognize objects (whether an image contains a desk or a bed), even without explicitly training for object classification.

We adapted the techniques presented by Zhou et al. to investigate whether `unified-dnn` can internally identity toolchains. In this investigation, we used DNN with 5 hidden layers and using ReLU as the activation function, as SELU networks are too deep to manually inspect. The basic idea is that the larger the absolute value of the activation of a hidden unit, the more active the unit. By examining the top K activations generated by using a data set as input, we can determine whether a unit is most active for GCC, ICC, or LLVM code.

We used 500,000 basic blocks as input and made sure that GCC, ICC and LLVM each accounted for about one third of the total input set. We recorded the top $K = 1000$ activations for each unit and summarized each unit with a tuple (G, I, L), where G is the number of GCC basic blocks in the unit's top K activation list, I is the number for ICC and L is the number for LLVM. We call a unit GCC dominant if GCC basic blocks are the most in the unit's top 1000 activation list and GCC exclusive if GCC basic blocks constitute more than 90%. Similarly, we have ICC and LLVM dominant and exclusive units.

Table 3 breaks down unit distributions in different layers. In the first hidden layer, there are many LLVM exclusive units, but almost no ICC or GCC exclusive units. Layer 2 - 5 have similar unit distributions to each other:

Table 4: Total number of basic blocks (in millions).

	O0	O1	O2	O3	Os
GCC	1.46	1.30	1.29	1.62	1.11
ICC	1.55	1.18	2.36	2.36	1.16
LLVM	1.62	1.21	1.60	1.70	1.14

there are more ICC dominant units than LLVM dominant units, and there is a modest number of GCC dominant units.

We make three observations from our results. First, the large number of LLVM exclusive units suggests that LLVM code has many unique patterns and the network dedicates a significant number of units to represent them. The first hidden layer has a large number of LLVM exclusive units to learn these patterns, indicating that these patterns can be easily derived from the input. Second, the large number of ICC dominant units suggests that ICC code also exhibits distinguishable patterns. Learning these patterns happened mostly in the last four layers. However, the small number of ICC exclusive units suggests that most of these patterns are not unique to ICC code. Third, GCC code has the fewest distinct patterns to learn, where learning the GCC patterns happened mostly in the last four layers. Our observations align with our knowledge about these compilers. Both ICC and LLVM aim to be compatible with and extend GCC, so it is reasonable that GCC code has the fewest unique patterns. On the other hand, as LLVM is developed by a large community of compiler researchers, it is not surprising that LLVM code shows the most unique patterns.

In summary, the distinct activation patterns of our network provide strong evidence that `unified-dnn` can internally determine which toolchain generated the input basic block.

7.3 Unoptimized Code Is More Difficult to Attribute

Traditional wisdom is that compiler optimization can drastically change the structure of binary and distort the styles of the original authors. So, optimized code should be more difficult to attribute than unoptimized code. However, our results in Table 2 show the exact opposite: we achieved higher accuracy on optimized code than unoptimized code. Our investigation suggests that compiler optimizations actually work in our favor for improving accuracy. We find two pieces of supporting evidence.

First, when compiling without optimizations, the compiler tends to generate boilerplate code regardless of the authors; in practice such code provide little useful information for learning author style. In optimized code, the boilerplate code is replaced by optimized code, which reflects the structure and style of the surrounding code,

Table 5: Percentages of basic blocks that contains boilerplate code patterns.

	O0	O1	O2	O3	Os
GCC	14.0%	0.7%	0.7%	0.5%	0.8%
ICC	17.0%	0.2%	0.1%	0.1%	0.2%
LLVM	12.8%	2.1%	1.2%	1.1%	1.7%

Table 6: Percentages of basic blocks caused by function inlining.

	O0	O1	O2	O3	Os
GCC	0.0%	40.6%	41.9%	57.0%	29.1%
ICC	0.0%	0.0%	66.7%	66.7%	0.0%
LLVM	0.0%	0.0%	57.2%	59.8%	37.0%

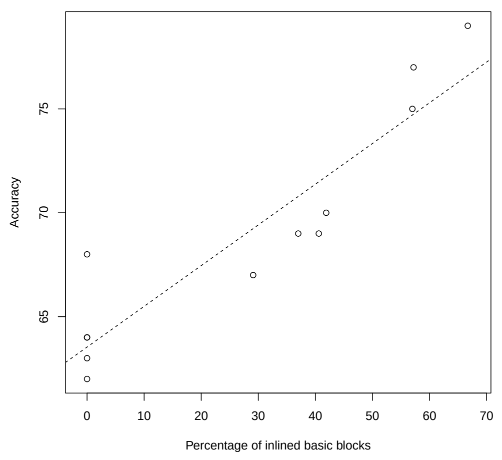


Figure 5: Correlation between inlining and accuracy. Each data point represents a toolchain. The x-axis represents the percentage of inlined basic blocks. The y-axis represents the single-toolchain accuracy achieved by `two-layer-dnn`. The dashed line represents regression line for all points.

so is more useful for learning. In the code that we studied, we identified two prevalent examples of boilerplate code when not using optimizations, function preamble and function epilogue. To estimate the effects of this boilerplate code, we counted the total number of basic blocks and calculated the percentage of basic blocks containing these examples. Table 4 shows the total number of basic blocks for each toolchain and Table 5 shows that -O0 code has a modest number of basic blocks containing boilerplate code (above 12%), while code compiled at other optimization levels have significantly fewer such basic blocks (below 3%). These results suggest that boilerplate code negatively impacts learning.

Second, function inlining can improve learning. When an author's code is inlined at multiple call sites, the compiler creates more data instances in the author's style as compared to no inlining. We used Dyninst to understand the debugging information to determine whether a basic block is from an inlined function. Table 6 shows that -O0 code has no inlined basic blocks and -O3 code has the most inlined basic blocks. We notice that the percentages of inlined basic blocks are positively correlated to the single-toolchain accuracy achieved by `two-layer-dnn`. In Figure 5, we show linear regression analysis between the percentages of inlined basic blocks and the single-toolchain accuracy. This linear regression model has an R-squared coefficient of 0.85 and a p-value of about 10^{-5}, indicating that there is indeed a strong positive correlation between function inlining and accuracy.

In summary, our investigation suggests that compiler optimizations improve learning, making unoptimized code more difficult to attribute.

8 Conclusion

We have presented new techniques to perform multi-toolchain, multi-author identification. We started with an extensive evaluation of existing multi-author identification techniques, showing that existing techniques did not work well in multi-toolchain scenarios. We designed two new techniques to overcome the weaknesses of existing techniques: the two layer approach that combines toolchain identification and single-toolchain authorship identification, and the unified training approach that train multi-toolchain authorship models based on a multi-toolchain data set. We also applied deep learning to multi-author identification, using raw bytes of basic blocks as input to automatically extract low level features. Our techniques achieved 71% accuracy, 82% top-5 accuracy, and 86% top-10 accuracy for classifying 700 authors, showing that analysts can effectively prioritize investigation based on our prediction. Our results also showed that our deep learning models consistently outperformed traditional learning methods such as SVM. We then tried to understand the internals of our machine learning models by investigating the feature weights of SVM and the activations of neurons in DNN. We learned interesting lessons from our investigation, such as that unoptimized code is more difficult to attribute. These lessons learned from investigating our models provide valuable insights on how compilation toolchains impact authorship styles.

In summary, we showed that we can perform practical multi-author identificaiton in multi-toolchain scenarios. Our work lays the foundation for future research topics such as whether we can suppress programming styles to evade identification, whether we can impersonate someone else's coding style to mislead identification, and investigating the impact of code obfuscation techniques on code authorship.

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