Universidade Federal da Bahia
Instituto de Matemática e Estatística

Programa de Graduação em Ciência da Computação

A DEEP LEARNING APPROACH TO RECOGNIZE SOURCE CODE AUTHORSHIP

Roberto Sales Caldeira

TRABALHO DE CONCLUSÃO DE CURSO

Salvador
?? de dezembro de 2018

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ROBERTO SALES CALDEIRA

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Este Trabalho de Conclusão de Curso foi julgado adequado à obtenção do título de Bacharel em Ciência da Computação e aprovado em sua forma final pelo Programa de Graduação em Ciência da Computação da Universidade Federal da Bahia.

Salvador, ?? de dezembro de 2018

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DIGITE OS AGRADECIMENTOS AQUI

DIGITE AQUI A CITACAO

—AUTOR (NOTA)

RESUMO

COLOQUE O RESUMO. Se preferir, crie um arquivo separado e o inclua via comando include.

Para evitar problemas de formato neste template (de uso geral), usamos acentuação mostrada abaixo.

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\c{c} \~{a} \'{a} \^{e} \'{\i}
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Não precisa fazer dessa forma, caso use pacotes adequados (latin1, etc.).

Palavras-chave: PALAVRAS-CHAVE.

ABSTRACT

Source code authorship identification is the task of deciding who is the author of a program given its source code. This is usually based on the analysis of previously collected samples from a set of candidate authors. There are several use cases for such a method, including attribution and detection of malicious codes, copyright infringement incident resolution, plagiarism detection, etc. As with texts in natural language, there are many distinguishing features in a piece code, like variable names, indentation style, etc. Some of these features are part of the coding style of a programmer. In this work, we investigate authorship attribution of C++ source codes based on the coding style of the authors. We also propose an end-to-end deep learning method for deciding if two source codes are from the same author, even if the involved authors are unknown to the system.

Keywords: perícia de software, identificação de autoria, aprendizagem profunda

CONTENTS

LIST OF FIGURES

Chapter 1

INTRODUCTION

Programmers often have to choose between tabs and spaces, between `while` and `for` loops, between positioning the open bracket in the current or in the next line, etc. These are some of the choices that can be regarded as coding style. Are these choices distinguishing features? In this chapter we will discuss what is style-based source code authorship identification, what challenges it poses, what has been done and what it is useful for. We will also introduce our contributions on the subject.

1.1 BIOMETRICS AND CODING STYLE

Biometrics is the field of computer vision that studies how certain human characteristics can be used to distinguish individuals. Even though physiological characteristics such as fingerprint, iris and face are probably the first ones that come to mind, the study of behavioral characteristics such as typing rhythm, voice, signature and writing style have brought new less intrusive means of distinguishing people. Even though using behavioral characteristics effectively has been made possible throughout the years, the fact that behavior is way more susceptible to change than physiological characteristics poses a big challenge.

Identifying authors of texts based on their writing styles is not a new topic (MENDENHALL, 1887). Throughout the years, computing has evolved and machine learning has reached its peek, making its way through writing style recognition. Narayanan et al. (2012) made it possible to identify the author of a text among tens of thousands of writers. It was not long until other works managed to distinguish programmers by their coding styles (CALISKAN-ISLAM et al., 2015).

1.2 MOTIVATION

In this work, we mainly consider the task of an investigator interested in deciding whether two anonymous pieces of code were authored by the same programmer or not. The actual authors of these pieces of code may be unknown to the investigator. Also, these codes

may aim to solve different problems, therefore the investigator intends to distinguish them solely based on stylistic features of such pieces. We also consider an easier scenario in which the set of possible authors are known to the investigator and labeled samples for each author are available.

We approach these problems from a deep learning perspective, training a deep neural model that can be subsequently used to solve authorship of source codes and applying it to the different scenarios an investigator can face.

1.3 APPLICATIONS

Resolving source code authorship has a few real-world applications both in industry and academy. Although we have not directly studied those, in this section we briefly describe a few of them.

1.3.1 Plagiarism Detection

Plagiarism can be generally defined as the unauthorized re-use of the work of another individual. Source code plagiarism is a widespread problem in academic institutions. Checking for plagiarism manually is time-consuming and not extremely effective, becoming impractical as the size of the code base increases.

Although automatic source code plagiarism detection is a recurring and well-studied problem (MARTINS et al., 2014), the approaches consolidated by widely used tools such as MOSS (SCHLEIMER et al., 2003), Sherlock (...) (tem uma TODO) and JPlag (PRECHELT et al., 2000) are mainly based on code similarity metrics. Such metrics, however, are highly correlated to the task the code was written to solve.

For example, consider the specific case of *ghostwriting*, in which a student claims the authorship of a code that was neither written by him nor copied from a classmate, but was actually written by another person (a former student, for example). It may not be possible to compare the suspicious code with another code made by the actual author, since the ghostwriter may not be known. On the other hand, if pieces of code of the accused party are available, it is possible to determine if his coding style matches the coding style present in the suspicious code.

1.3.2 Copyright Infringement

Software forensics is the science of examining source code and binary code in order to identify, preserve, analyze and present facts and opinions about pieces of software. Although it can also be used in civil proceedings, it is most often associated with the investigation of a wide variety of computer crimes, one of which is copyright infringement.

Code correlation analysis plays an important role at copyright disputes. In this case, an analyst has labeled codes from the involved parties and the task of determining if there was infringement or not.

1.3.3 Cyber Attack Identification

Cyber attack identification is a powerful application of software forensics in cyber security. Files left behind by an intruder during a cyber attack may have just enough information for an analyst to identify who the intruder is or to relate such an attack to a previous incident. Therefore, comparing the coding style of the attacker to those from authors of previous attacks or authors of public code repositories is of great interest to the analyst.

1.3.4 Exposing Anonymous Programmers

Although there are many helpful applications of source code authorship identification, systems capable of de-anonymizing programmers pose a threat to those who want to remain anonymous, in special for anonymous open source contributors (DAUBER et al., 2017). There may be good reasons for a programmer to be anonymous, like working in a software a hostile government does not like.

An example of a famous open source anonymous programmer is Bitcoin's creator, Satoshi Nakamoto. If we had a set of labeled codes from programmers that are likely to be Nakamoto, we could try to match their coding style to the early versions of Bitcoin, of course, assuming that Nakamoto didn't try to obfuscate his own coding style.

1.4 CHALLENGES

Although comparison metrics have been shown to work well for source codes, extracting features that encode the author's style and, therefore, are independent of the task being solved have shown to be challenging. For example, features such as methods and variables names can often be misleading. This task gets even more challenging as we need to select features that are steady across different programs and capable of distinguishing between programmers. In this work, we propose an end-to-end model that solves this problem.

Also, the environment the programmer is inserted can heavily affect the difficulty of the task. For example, in projects that have a rigid style guide to be followed, much less of the programmer's own coding style might prevail. We don't study the impact of such environments in this work. Moreover, in multi-contributor projects, usually powered by VCS (version control systems), certain pieces of code can contain contributions of many authors, turning the task of relating a single author to the style present on such piece very hard. Although we believe our contributions can be applied to multi-contributor environments, we leave this for future work.

In each of the mentioned applications, the claimed author may act adversarially and try to actively modify the coding style of the program. In the ghostwriting scenario, the involved parties may act together to make the style of the code written by one to match the other's. During a cyber attack development, an attacker may explicitly try to hide his own coding style. In a copyright infringement, the suspect may modify the code to match his own style. In this work, adversary interference is not considered.

1.5 RELATED WORK

Spafford and Weeber (1993) were among the first that suggested attributing source code based on style. Even though they suggested a lot of features, they did not propose an automated method nor a thorough analysis on how those features were useful. Hayes and Offutt (2010) examined the conjecture that programmers are unique and that this uniqueness can be observed in the code they write. They conducted an experiment with programmers and graduate students, and found that programmers do have distinguishable style features that are consistently used.

Ranking approaches to source code authorship attribution were proposed by Burrows and Tahaghoghi (2007), Burrows et al. (2007, 2009) and Frantzeskou et al. (2007). Burrows and Tahaghoghi used an information retrieval technique to solve the task, obtaining token-level n-gram representations of the source codes, building an index from these representations and querying that index for programs with unknown authors. The authors of the top-ranked programs were considered the authors of the queried program. Frantzeskou et al. used byte-level n-gram features to tackle the problem. An author profile is composed of the most frequent n-grams in training data of that author. Then, the author of an unclaimed program is considered the one with the most common n-grams to this code. Both works achieved high accuracy on very small suspect sets but did not scale well.

Use of abstract syntax trees (ASTs) for authorship attribution was first introduced by Pellin (2000). Caliskan-Islam et al. (2015) have proposed using fuzzy ASTs and random forests to classify authorship of source code. Moreover, they proposed a coding style feature set for C/C++ source codes and a dataset for authorship attribution, based on Google Code Jam, which is a programming competition that resembles laboratory conditions. Dauber et al. (2017) showed that Caliskan-Islam et al. results could be extended to previously unexplored conditions, by adapting their techniques to work for small blocks of code of GitHub repositories.

Macdonell et al. (1999) introduced neural networks to the subject by using feed-forward neural networks and multiple discriminant analysis to attribute source codes. Bandara and Wijayarathna (2013) studied how deep neural networks could be competitive to previous methods given enough training data. Alsulami et al. (2017) applied LSTMs to the AST structure of a code.

1.6 CONTRIBUTION

In this work, we introduce the concept of *coding style descriptors*, which are compact representations that capture distinguishing stylistic features of a source code. We propose an end-to-end deep model that produces coding style descriptors from source code. Then, we study how the generated descriptors encode meaningful properties to the source code attribution problem by solving many of its variations.

We also introduce the Codeforces dataset for source code attribution, a C++ dataset with more than 30,000 samples extracted from Codeforces, a website specialized in holding online programming competitions. We briefly describe how the dataset was constructed

and how it differs from previously published datasets.

Chapter 2

METHODOLOGY

In this chapter, we present a formulation for the source code attribution problem (Section 2.1), we describe how the Codeforces dataset was assembled (Section 2.2) and present an end-to-end model to solve the problem (Section 2.3.3).

2.1 PROBLEM FORMULATION

Although there are many variations of the source code attribution problem, in this chapter we will focus on one of them. In Chapter 3, we analyze a variation of the problem.

Given two source codes A, B, we want to determine if A and B were written by the same programmer. For that end, we have a dataset of source codes labeled with their authors, which can be used to train a classifier. However, the authors of A and B are not necessarily represented in this set.

2.2 DATASETS

The first step to develop an effective deep learning model is to gather enough training data. In this work, we decided to work with C++ source codes written in a laboratory environment – we assume the whole code is written by the author under no external style enforcement such as a style guide.

2.2.1 Google Code Jam

Although there are many public C++ laboratory datasets, the Google Code Jam[1] dataset (CALISKAN-ISLAM et al., 2015) is probably the biggest of them all. Samples from this dataset are collected from previous editions of Google Code Jam, an annual programming competition held by Google. In this competition, participants are given algorithmic tasks to be solved in a limited amount of time. Thus, it's very likely that code written by a participant manifests his own coding style.

[1] ⟨https://codingcompetitions.withgoogle.com/codejam⟩

Google Code Jam holds nearly 10 rounds every year. Most of these rounds are eliminatory. Thus, the availability of samples from less experienced participants is expected to be low. If we want to build a balanced training set not biased by the way experienced participants code, we are limited by the small amount of code less experienced participants wrote.

Although this dataset was not extensively used throughout the development phase, it was a reference for the Codeforces dataset introduced in Section 2.2.2.

2.2.2 Codeforces

Codeforces[2] is a website specialized in holding online programming contests. Contest format is similar to Google Code Jam's, but they are not eliminatory. Thus, we are able to find a lot of samples from both non-experienced and experienced users.

We wrote a Python script that receives target constraints for the dataset and scrapes Codeforces for samples. Using this script, we assembled a balanced dataset with more than 30,000 C++ samples from nearly 2,000 authors, meaning that we have around 15 samples per author. This dataset was packaged and made public[3].

2.3 SOURCE CODE EMBEDDING MODEL

In this section, we propose a deep learning model that embeds source codes, from their string representations, into a denser latent space (Fig. 2.1). In Section 2.3.1, we describe what is a style descriptor. In Section 2.3.3, we describe the network architecture used in our work. In Section 2.3.4, we describe how our embedding network was trained to generate meaningful descriptors.

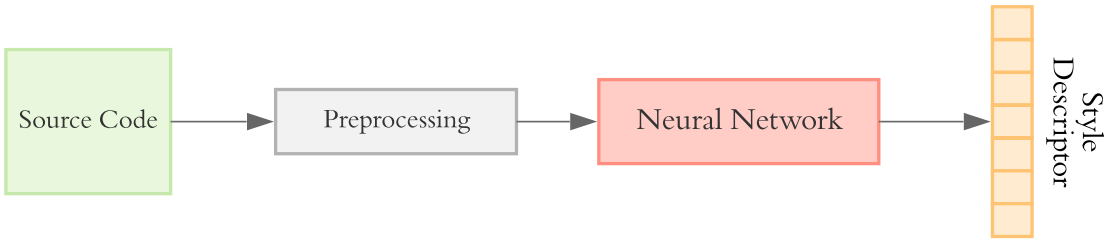


Figure 2.1: Overview of style descriptor generation pipeline.

2.3.1 Coding Style Descriptor

The performance of machine learning methods is heavily affected by the choice of data representation. Thus, much of the effort of the machine learning community has been

[2] ⟨http://codeforces.com⟩
[3] link-pro-dataset

put into developing algorithms that transform otherwise unmanageable data into representations that can be effectively used by learning methods (BENGIO et al., 2013).

A Coding Style Descriptor (hereon referred simply as *style descriptor*) is a d-dimensional representation of a source code in a latent space. A latent space is a space where representations of similar objects lie close to each other. Therefore, the latent space of style descriptors should capture stylistic similarities of source codes. Ideally, style descriptors should encode everything a machine learning model needs to solve the problem posed in Section 2.1 and its variations. Thus, we can build simpler classifiers for these problems if we can provide a good embedding function $f(x) \in \mathbb{R}^d$, which maps source codes to d-dimensional descriptors.

Deep feed-forward networks are a natural approach to representation learning. In the remainder of this chapter, we will mainly study deep learning embedding techniques and apply them to our problem.

2.3.2 Preprocessing

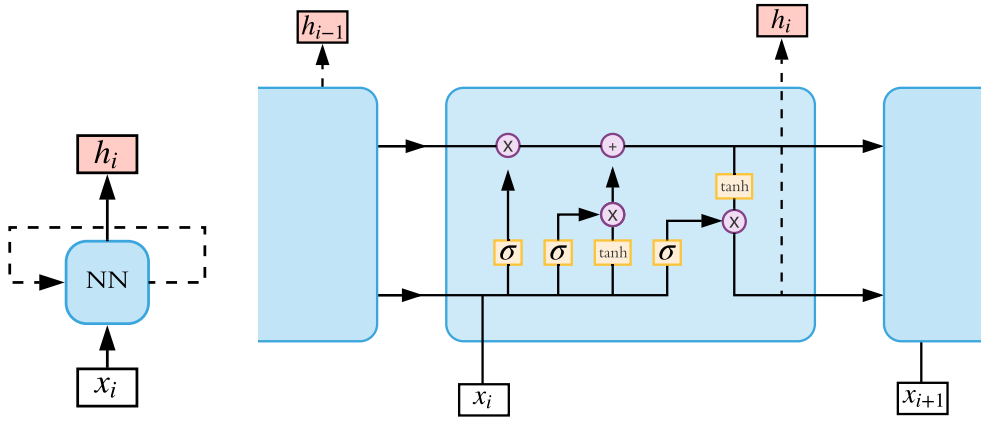
The model we propose is end-to-end. Thus, the code is minimally preprocessed. Using Tensorflow static graph, it is not possible to support arbitrary input sizes in a batch. Therefore, we must crop our source code to a maximum line length M and a maximum number of lines L, converting it to a $L \times M$ char matrix. We chose to pick the last L lines of the code and the first M characters of each line. The positions that do not correspond to a char in the source code are masked out both during inference and during optimization. For the models we propose, we chose values of M and L that incurred the best improvement while keeping the training time and memory consumptions affordable.

2.3.3 Neural Network

2.3.3.1 Background Recurrent neural networks (RNNs) were introduced to solve the lack of persistence of feed-forward networks. They are networks with loops in them. They are fed from an external input – a sequence x – and from their own output h (Fig 2.2a). Although generic RNNs are powerful and in theory are capable of learning any kind of sequence dependency, in practice they struggle to handle those that are long-term. The problems of training RNNs with gradient descent were studied by Bengio et al. (1994).

LSTM Long Short-Term Memory (LSTM) network was a special kind of RNN introduced by Hochreiter and Schmidhuber (1997). LSTMs were specifically developed to avoid the long-term dependency problem. It accomplishes that with its special cell design (Fig. 2.2b). During sequence unrolling, it learns what to remember and what to forget through carefully regulated gates – depicted as sigmoid layers. Moreover, besides being fed with its own output, it maintains an internal cell state which helps it to remember such dependencies. Although LSTMs usually produce sequences, it is a common procedure to take only the last produced element as its output.

Given the efficiency of LSTMs, many researchers have focused on studying other



(a) A generic RNN (b) An LSTM cell

Figure 2.2: A quick view on the internals of an LSTM.

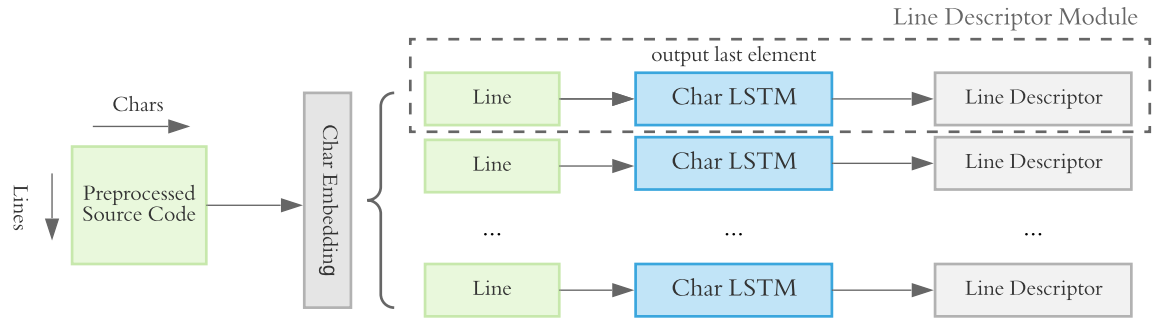
variations of it (GREFF et al., 2015).

Bidirectional LSTM Long Short-Term Memory cells are very good at remembering. However, they can only infer based on previous elements of the input sequence. A bidirectional LSTM (IRSOY; CARDIE, 2013) is an extension of the usual LSTM that supports inferring based on both previous elements and subsequent elements of a sequence. It maintains two hidden layers: one for the left-to-right propagation and other for the right-to-left propagation. The results of these two passes are combined into a single result, usually through concatenation or averaging.

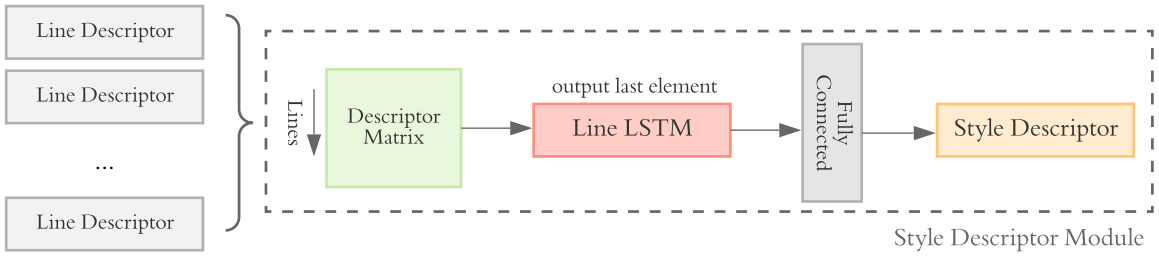
LSTM Stacking The sequence produced by a LSTM network can be re-used as input for another LSTM network. This is called LSTM stacking. As it is the case with other types of networks, deepening a LSTM network usually improves its performance (GRAVES et al., 2013). Intuitively, it allows each layer to independently learn different levels of abstraction.

2.3.3.2 LSTM Network Our proposed architecture is heavily based on bidirectional LSTM stacks and can be split in three parts: the char embedding layer, the line descriptor module (Fig. 2.3a) and the style descriptor module (Fig. 2.3b).

Char Embedding Layer Neural networks can't handle discrete types – like chars – naturally. Hence, we need to map the alphabet Σ of characters of source codes to real-valued vectors. We could simply convert each char to a $|\Sigma|$-dimensional one-hot vector. As opposed to arbitrarily defining a mapping, we can also let the network learn it (GAL; GHAHRAMANI, 2016).



(a) Char embedding layer and line descriptor module



(b) Style descriptor module

Figure 2.3: The architecture of the LSTM-based model.

The char embedding layer is responsible for learning an embedding $f_c(x) \in \mathbb{R}^{d_c}$ that maps chars to d_c-dimensional vectors. Thus, each char in the source code is converted to a real-valued vector. Hereon, we will simply refer to char embeddings as chars.

Line Descriptor Module This module is responsible for learning an embedding $f_l(x) \in \mathbb{R}^{d_l}$ that maps lines of code to d_l-dimensional descriptors. Each line of the source code is fed – char by char – to the same char-level bidirectional LSTM stack. The last element of the sequence produced by this LSTM is taken as the line descriptor.

Style Descriptor Module The line descriptors generated by the line descriptor module are stacked back into a descriptor matrix. This module is responsible for learning an embedding $f_s(x) \in \mathbb{R}^d$ that maps descriptor matrices to d-dimensional style descriptors. Thus, the whole descriptor matrix is fed – line by line – to a line-level bidirectional LSTM stack. The last element produced by this LSTM is passed through a fully-connected layer and normalized to lie on the boundary of the d-sphere. The result is taken as the desired style descriptor.

We believe this architecture encourages the network to learn in a divide-and-conquer manner, by learning the individual features of each line and how to combine them into a single descriptor. Moreover, it mitigates the backpropagation issue RNNs have when dealing with large sequences, since the whole source code is broken into smaller pieces that are fed to LSTMs separately. Our selection of hyperparameter values for this architecture

are given in Table 2.1. They were chosen through careful tuning, as described in Chapter 3.

Parameters	Value
α, triplet loss margin	0.2
maximum line length	80
maximum number of lines	120
d_c, char embedding size	72
d_l, line descriptor size	64
d, style descriptor size	128
char-level LSTM hidden units (stacked)	128/64
line-level LSTM hidden units	128
fully-connected layer units	256

Table 2.1: Hyperparameters selected for the LSTM-base model during validation.

2.3.4 Optimization

Although we decided the architecture of our model, we still have to make it learn. For that end, we review two optimization methods widely used in multi-class identification problems.

2.3.4.1 Softmax Cross-Entropy Loss The softmax function is commonly used in multi-class classification problems. In a d-class scenario, let $f(x) \in \mathbb{R}^d$ be the output of our neural network for a sample x. The softmax activation for this sample is given as

$$q(i) = \frac{e^{f(x)_i}}{\sum_j e^{f(x)_j}} \,. \tag{2.1}$$

$q(i)$ assume values ranging from 0 to 1, and $\sum_i a_i = 1$. Therefore, we can reinterpret $q(i)$ as the estimation of probability the sample x belongs to class i. The softmax cross-entropy loss is given as

$$\mathcal{L} = -\sum_{i=1}^{d} p(x,i) \log q(i) \,, \tag{2.2}$$

where $p(x,i)$ is the actual probability the sample x is from class i (usually a one-hot vector). Thus, by minimizing $\mathcal{L}$, we minimize the cross-entropy between the probability distribution p and an estimated distribution q.

Although softmax cross-entropy loss is a very powerful tool, it does not naturally account for the fact that the number of classes may be unknown. Although there are techniques to apply softmax in these scenarios (SUN et al., 2014; TAIGMAN et al., 2014), there are other optimization methods designed for such cases. Also, it is not inherently suited for generating descriptors. Hence, we restrict ourselves to use this method only when the number of classes is known.

2.3.4.2 Triplet Loss Schroff et al. (2015) introduced triplet loss for training embedding networks. In their work, the loss function is used in conjunction with a novel triplet mining algorithm to train an embedding network that maps images to descriptors. These descriptors are then used to solve face recognition. Moreover, triplet loss works in scenarios where the number of classes is unknown. Therefore, it is well-suited for deciding if two pieces of code are of the same person, even if they are unknown to the system. In this section, we will study the L_2 triplet loss.

The embedding is represented by $f(x) \in \mathbb{R}^d$. Additionally, we constrain this embedding to the boundary of a unit d-sphere, *i.e.* $\left\|f(x)\right\|_2 = 1$. This makes the Euclidean distance between two embeddings proportional to their cosine similarity.

Let a, p, n (stand for anchor, positive and negative, respectively) be a triplet from the training set such that a and p have the same label (positive pair), but a and n have different labels (negative pair). Also, let $\mathcal{T}$ be the set of all possible said triplets. Then, the L_2 triplet loss is defined as

$$\mathcal{L} = \sum_{(a,p,n)\in\mathcal{T}} \max\Big(\left\|f(a) - f(p)\right\|_2 - \left\|f(a) - f(n)\right\|_2 + \alpha,\ 0\Big), \tag{2.3}$$

where α is a margin that is enforced between positive and negative pairs. If $\mathcal{L} = 0$, then for every triplet $(a, p, n) \in T$, it must be true that

$$\left\|f(a) - f(p)\right\|_2 + \alpha \leq \left\|f(a) - f(n)\right\|_2 . \tag{2.4}$$

When Eq. 2.4 is fulfilled, the negative pair of a triplet will be at least as far as the positive pair plus a margin α. Thus, by minimizing $\mathcal{L}$, we push the distance of positive pairs towards zero as we push the distance of negative pairs to be greater than the correspondent positive's by α. The advantage of this formulation is that, even though all training samples of the same class will form a cluster, they are not required to collapse to a single point. Fig. 2.4 shows a hypothetical scenario of optimization.

Generating all triplets from $\mathcal{T}$ would consider many triplets that easily satistfy Eq. 2.4. This would cause the training to converge slowly, since those triplets would still be fed to the network, but would not contribute to loss minimization. Therefore, it is crucial to select triplets that do not satisfy this condition to keep improving the model. These are called *hard* triplets.

Online Semi-Hard Triplet Mining One way to select hard triplets from the training set is to consider every sample as the anchor a. Then, select such p that minimizes $\left\|f(a) - f(n)\right\|_2$ and such n that maximizes $\left\|f(a) - f(n)\right\|_2$. This does not scale with the size of the training set. Moreover, it can cause outliers to dominate the selection process.

Schroff et al. suggested the online semi-hard triplet mining method to tackle both problems. Instead of picking hard triplets from the whole training set, we pick them from the mini-batch. Also, their work suggests that prioritizing triplets such that negatives lie in the margin area (Fig. 2.4b) helps avoiding local minima early in the training. Such triplets are called *semi-hard*.

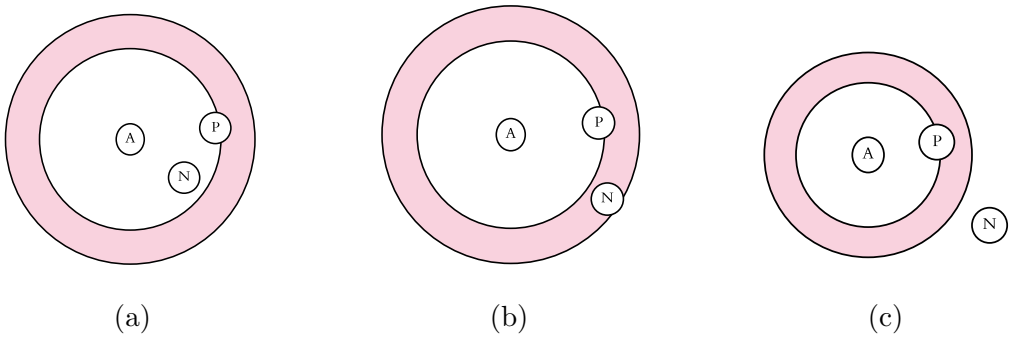


Figure 2.4: The region in red represents the margin area beyond p with diameter α. Before loss optimization (a), the negative pair is closer than the positive. During loss optimization (b), the negative pair is pushed further than the positive, but n is still in the margin area. After loss optimization (c), the positive pair is finally closer and n is beyond the margin.

Although in Chapter 3 we use softmax cross-entropy loss for comparison purposes, we mostly worked with triplet loss. Therefore, our main optimization flow is pictured in Fig. 2.5.

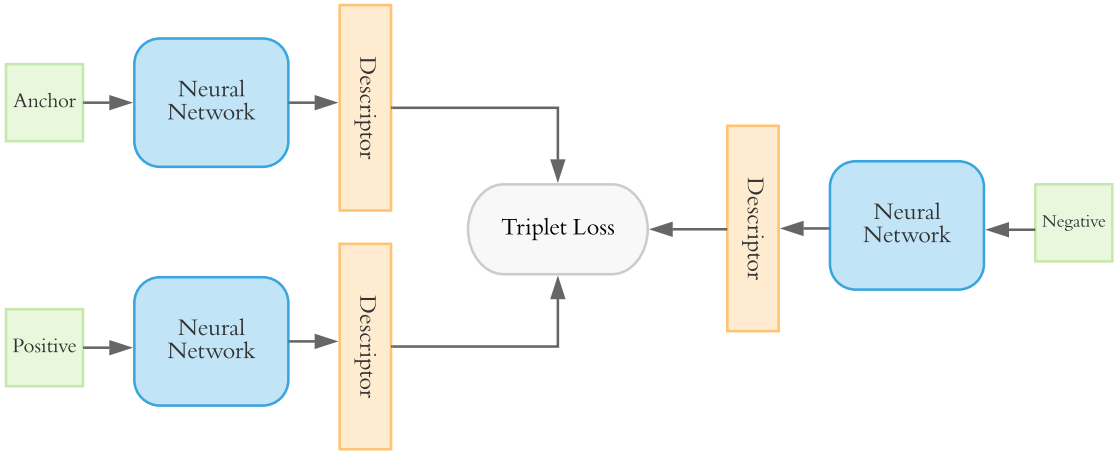


Figure 2.5: Overview of style descriptor generation pipeline.

Chapter 3

EVALUATION

In this chapter, we evaluate our model by solving two variations of the source code attribution problem. In Section 3.1, we describe how we selected the parameters of our model. In Section 3.2, we solve the authorship matching problem suggested in Chapter 2. In Section 3.3, we solve a closed-world identification problem.

3.1 TRAINING AND SELECTION

We trained and validated the proposed model with Tensorflow. We picked the training samples from a balanced dataset with 20,000 C++ examples from 1,000 authors. A validation set was built from another 3,200 samples from 400 authors. No author from the training set was present on the validation set. All the samples were extracted from the Codeforces dataset.

Although programming competitions resemble laboratory conditions, it is common for participants to code on top of a pre-written file, usually called *template*. Although the constructions present on a template file are usually written by the author himself, they are not always used by the piece of code actually written during the competition. Therefore, it is interesting to analyze how classifiers perform when such constructions are stripped out of the code. For that end, we used *clang*[1] to remove unused pieces of code from a C++ program. Moreover, we also removed macros, a construction heavily present in templates of competitive programmers. Therefore, we built two versions of each dataset: one composed of raw source codes and other composed of codes processed by *clang*.

We optimized the model parameters with *RMSprop* (...) for a maximum of 50 epochs, or until the evaluated equal error rate (EER) of the model on the validation set had no improvement for 5 epochs. The version that yielded the highest EER was taken as the final model. During this process, we carefully tuned its hyperparameters.

Finally, we trained two different models with such hyperparameters: one on the raw version of the dataset and other on the *clang* processed version.

[1] link-do-clang

3.2 MATCHING TWO UNKNOWN SOURCE CODES

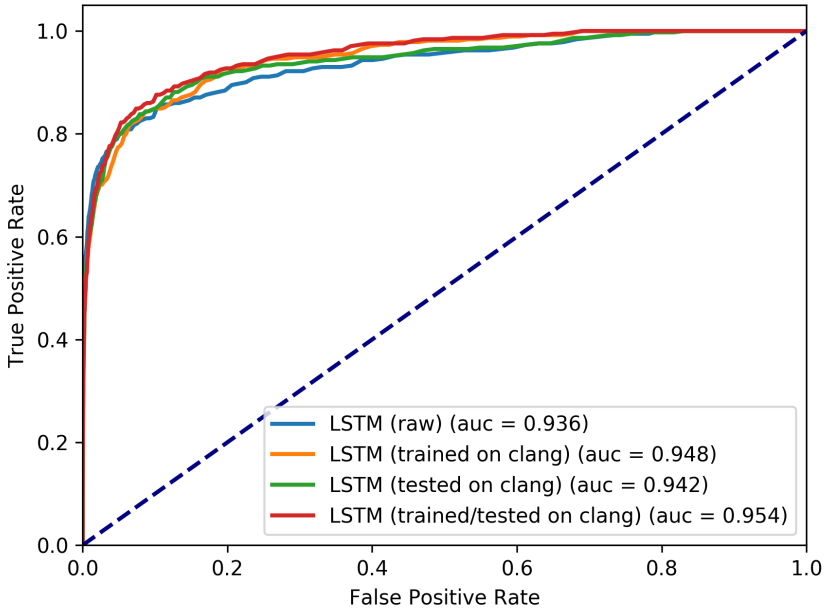


Figure 3.1: ROC curve for each pair of classifier and dataset version.

Using the models we trained, we tried to solve the problem of deciding if two source codes are from the same author. For that end, we constructed a test dataset with 3,200 samples from 400 authors. These samples were extracted from the Codeforces dataset, but this set has no intersection of authors with the training and validation sets used to train the models. Therefore, the authors are unknown to the system. Moreover, we ran *clang* on the samples, obtaining a *clang* processed version of the test dataset.

Finally, we ran four evaluations, one for each combination of model and test dataset. The results can be seen in Fig. 3.1 and Table 3.1.

	EER (%)	
	Raw Test Set	***clang* Test Set**
LSTM (trained on raw version)	13.88	12.24
LSTM (trained on *clang* version)	13.25	11.60

Table 3.1: Equal error rate (EER) evaluation of the trained models on each test set.

We can notice that the performance on raw source codes is slightly worse than the others. This can be related to the fact that tested authors are not present in training and validation sets. The model is probably relying more on features present on templates, instead of on stylistic features of the written code. Therefore, the embeddings generalize poorly to unknown authors. The better performance of the *clang* combination supports this claim by showing that learning from features of the written code yields better generalization.

3.3 ONE-TO-MANY AUTHOR IDENTIFICATION

We also evaluated our models on the problem posed by Caliskan-Islam et al.. In their work, 9 C++ source codes from 250 programmers are extracted from the Google Code Jam dataset. From these, 8 are used for training and one for testing. We simply took the models we trained for the previous experiment and replaced triplet loss with softmax cross-entropy loss. Then, we trained on the 250×8 source codes for more epochs.

The rank-n metric evaluations, for $n = 1$ and $n = 3$, can be seen in Table 3.2.

	rank-1 (%)		**rank-3 (%)**	
	Raw Test	**Clang Test**	**Raw Test**	**Clang Test**
LSTM (trained on raw)	74.8%	67.0%	84.4%	79.6%
LSTM (trained on clang)	65.0%	69.0%	78.8%	82.8%
Caliskan-Islam et al.	95.1%	n/a	n/a	n/a

Table 3.2: Rank-n metric for the one-to-many identification problem on 250 programmers of the Google Code Jam dataset.

Although we were not able to match the Random Forest model proposed by Caliskan-Islam et al., we are able to show that the generated descriptors are discriminative. Fig. 3.2 shows the style descriptors of source codes from 12 programmers of Google Code Jam dataset. They were embedded into a two-dimensional space for better visualization.

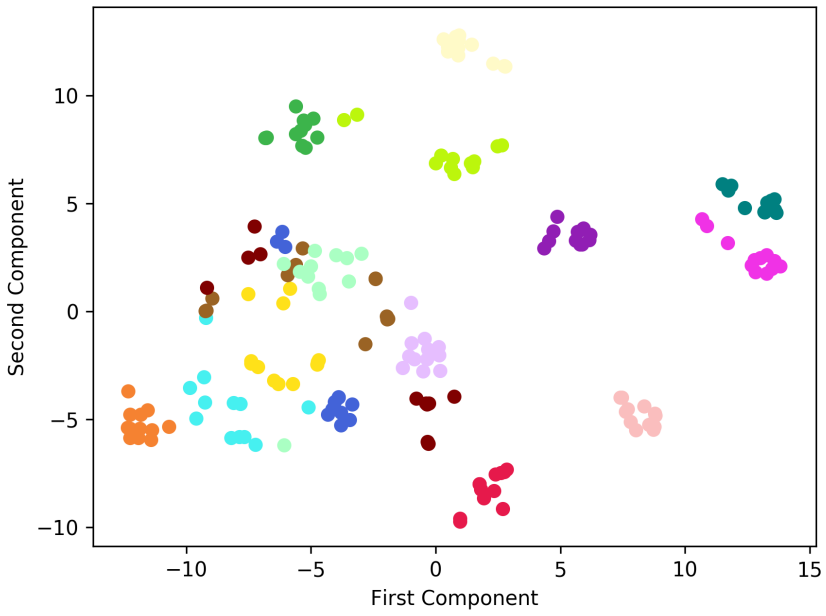


Figure 3.2: 128-dimensional descriptors from 12 authors generated by the LSTM model, trained and test on the *clang* test set. The descriptors were embedded into a two-dimensional space with t-SNE.

Chapter

4

CONCLUSION

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