# Author Identification using Stylometric Features

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**Abstract**

In this work we present a strategy for author identification for documents written in Portuguese. It takes into account a writer-independent model which reduces the pattern recognition problem to a single model and two classes, hence, makes it possible to build robust system even when few genuine samples per writer are available. We also introduce a stylometric feature set, which is based on the conjunctions of the Portuguese language. Experiments on a database composed of short articles from 10 different authors and Support Vector Machine (SVM) as classifier demonstrate that the proposed strategy can produced results comparable to the literature.

**Keywords**: Pattern Recognition, Author Identification, Stylometry.

## 1 Introduction

There exists a long history of linguistic and stylistic investigation into author identification which goes back to the late nineteenth century, with the pioneering studies of Mendenhall [11] and Mascol [10] on distributions of sentence and word lengths in works of literature and the gospels of the New Testament. Modern work in author identification was preceded by Mosteller and Wallace in the 1960s, in their seminal study The Federalist Papers [13]. All these have been motivated by the fact that we usually leave indicative of authorship in our writings due to the fact that we have distinctive ways of writing [12].

In recent years, practical applications for author identification have grown in several different areas such as, criminal law (identifying writers of ransom notes and harassing letters), civil law (copyright and estate disputes), and computer security (mining email content). Chaski [5] points out that in the investigation of certain crimes involving digital evidence, when a specific machine is identified as the source of documents, a legitimate issue is to identify the author that produced the documents, in other words, “Who was at the keyboard when the relevant documents were produced?”.

In order to identify the author, one must extract the most appropriate features to represent the style of an author. In this context, the stylometry (application of the study of linguistic style) offers a strong support to define a discriminative feature set. The literature shows that several stylometric features that have been applied include various measures of vocabulary richness and lexical repetition based on word frequency distributions. As observed by Madigan et al [9], most of these measures, however, are strongly dependent on the length of the text being studied, hence, are difficult to apply reliably. Many other types of features have been tried out, including word class frequencies [7, 1], syntactic analysis [3], word collocations [16], grammatical errors [8], word, sentence, clause, and paragraph lengths [2].

To deal with the problem of author identification usually a writer-specific model (also known as personal model) is considered. It is based on two different classes, $\omega_1$ and $\omega_2$, where $\omega_1$ represents authorship while $\omega_2$ represents forgery. The main drawbacks of the writer-specific approach are the need of learning the model each time a new author should be included in the system and the great number of genuine samples of texts necessary to build a reliable model. To surpass this problem, we propose an strategy based on a forensic document examination approach. It uses the dissimilarity representation [14] and can be defined as writer-independent approach as the number of models does not depend on the number of writers. In this light, it is a global model by nature, which reduces the pattern recognition problem to a global model with two classes, consequently, makes it possible to build robust author identification systems even when few genuine samples per author are available.

In this work we present a method for author identification based on a writer-independent approach. A stylometric feature set for the Portuguese language, which is based on counting the conjunctions, is also introduced. We also compare different fusion strategies using a ROC (Receiver Operating Characteristics) and show that majority voting is an efficient strategy for the problem of author identification. Comprehensive experiments on a database composed of short articles and Support Vector Machine (SVM) as classifier demonstrate that the proposed strategy can produced results comparable to the literature.

The remaining of this paper is divided as follows: Section 2 introduces the basic concepts of forensic stylistics and describes the linguistic features used in this work. Section 2.2 describes the basic concepts of the SVM. Section 3 describes how the writer-independent approach works. Section 3.1 presents the database used in this work. Section 4 describes the proposed method for author identification while Section 5 reports the experimental results. Finally, Section 6 concludes this work.

# 2 Forensic Stylistics

Forensic stylistics is a sub-field of forensic linguistics and it aims at applying stylistics to the context of author identification. The stylistic is based on two premisses:

- Two writers (same mother-tongue) do not write in the same way.
- The writer does not write in the same way all the time.

The stylistic can be classified into two different approaches: qualitative and quantitative.

The qualitative approach assesses errors and personal behavior of the authors, also known as idiosyncrasies, based on the examiner's experience. According to Chaski [5], this approach could be quantified through databasing, but until now the databases which would be required have not been fully developed. Without such databases to ground the significance of stylistic features, the examiner's intuition about the significance of a stylistic feature can lead to methodological subjectivity and bias. In this vein, Koppel and Schler [8] proposed the use of 99 error features to feed different classifiers such as SVM and decision trees. The best result reported was about 72% of recognition rate.

The second approach, which is very often refereed as stylometry, is quantitative and computational, focusing on readily computable and countable language features, e.g. word length, phrase length, sentence length, vocabulary frequency, distribution of words of different lengths. It uses standard syntactic analysis from the dominant paradigm in theoretical linguistics over the past forty years. Examples of this approach can be found in Tambouratzis et al [18] and Chaski [5]. Experimental results show that usually this approach provides better results than the qualitative one. For this reason we have chosen this paradigm to support our work.

## 2.1 Linguistic Features

The literature suggests many linguistic features to be used for author identification. In [4], Chaski discusses about the differences between scientific and replicable methods for author identification. Scientific methods are based on empirical, testable hypotheses, and the use of these methods can be done by anyone, i.e., it is not dependent on a special talent. In the same work, nine empirical hypotheses that have been used to identify authors in the past are reported: Vocabulary Richness, Hapax Legomena, Readability Measures, Content Analysis, Spelling Errors, Grammatical Errors, Syntactically Classified Punctuation, Sentential Complexity, Abstract Syntactic Structures.

Vocabulary Richness is given by the ratio of the number of distinct words (type) to the number of total words (token). Hapax Legomena is the ratio of the numbers of words occurring once (Hapax Legomena) to the total number of words. Readability Measures compute the supposed complexity of a document, and are calculations based on sentence length and word length. Content Analysis classifies each word in the document by semantic category, and statistically analyze the distance between documents. Spelling Errors quantifies the misspelled words. Prescriptive Grammatical Errors test errors such as sentence fragment, run-on sentence, subject-verb mismatch, tense shift, wrong verb form, and missing verb. Syntactically Classified Punctuation takes into account end-of-sentence period, comma separating main and dependent clauses, comma in list, etc. Finally, Abstract Syntactic Structures computationally analyzes syntactic patterns. It uses verb phrase structure as a differentiating feature.

In this work we propose the use of conjunctions of the Portuguese language. Just like other language, Portuguese has a large set of conjunctions that can be used to link words, phrases, and clauses. Table 1 describes all the Portuguese conjunctions we have used in this work.

Such conjunctions can be used in different ways without modifying the meaning of the text. For example, the sentence "Ele é *tal qual* seu pai" (He is like his father), could be written is several different ways using other conjunctions, for example, "Ele é *tal e qual* seu pai", "Ele é *tal como* seu pai", "Ele é *que nem* seu pai", "Ele é *assim como* seu pai". The way of using conjunctions is a characteristic of each author, and for this reason we decided to use them in this work.

**Table 1. Conjunctions of the Portuguese language**

| Group | Conjunctions |
|---|---|
| Coordinating additive | e, nem, mas também, senão também, bem como, como também, mas ainda. |
| Coordinating adversative | porém, todavia, mas, ao passo que, não obstante, entretanto, senão, apesar disso, em todo caso contudo, no entanto |
| Coordinating conclusive | logo, portanto, por isso, por conseguinte. |
| Coordinating explicative | porquanto, que, porque. |
| Subordinating comparative | tal qual, tais quais, assim como, tal e qual, tão como, tais como, mais do que, tanto como, menos do que, menos que, que nem, tanto quanto, o mesmo que, tal como, mais que. |
| Subordinating conformative | consoante, segundo, conforme. |
| Subordinating concessive | embora, ainda que, ainda quando, posto que, por muito que, se bem que, por menos que, nem que, dado que mesmo que, por mais que. |
| Subordinating conditional | se, caso, contanto que, salvo que, a não ser que, a menos que |
| Subordinating consecutive | de sorte que, de forma que, de maneira que, de modo que, sem que |
| Subordinating final | para que, fim de que |
| Subordinating proportional | à proporção que, quanto menos, quanto mais à medida que. |

## 2.2 Author Identification with SVM

As discussed somewhere else, the global approach reduces the problem of author identification to one model with two classes. Therefore, Support Vector Machine (SVM) seems quite suitable since it was originally developed to deal with problems with two classes. Moreover, SVM is tolerant to outliers and perform well in high dimensional data. The concept of SVM was developed by Vapnik [19]. Let us suppose we have a given set of $l$ samples distributed in a $\Re^n$ space, where $n$ is the dimensionality of the sample space, and for each $x_i$ sample there is an associated label $y_i \in \{-1, 1\}$. According to Vapnik, this sample space can be described by an hyperplane separating the samples according to their label ($\{-1, 1\}$). This hyperplane can be modeled using only a few samples from the sample space, namely the support vectors. So training an SVM is simplified to identifying the support vectors within the training samples. After that, a decision function (1) can be used to predict the label for a given unlabeled sample.

$$f(x) = \sum_i \alpha_i y_i K(x, x_i) + b \qquad (1)$$

The function parameters $\alpha_i$ and $b$ are found by quadratic programming, $x$ is the unlabeled sample and $x_i$ is a support vector. The function $K(x, x_i)$ is known as kernel function and maps the sample space to a higher dimension. In this way, samples that are not linearly separable can become linearly separable (in the higher dimensional space). The most common kernel functions are: Linear, Polynomial, Gaussian and Tangent Hyperbolic. These kernels can be seen in Table 2.

**Table 2. Most common kernel functions**

| Kernel Type | Inner Product Kernel |
|---|---|
| Linear | $K(x, y) = (x \cdot y)$ |
| Polynomial | $K(x, y) = (x \cdot y + 1)^p$ |
| Gaussian | $K(x, y) = e^{-\|x-y\|^2/2\gamma^2}$ |
| Tangent Hyperbolic | $K(x, y) = tanh(\kappa x \cdot y - \delta)$ |

One of the limitations with SVMs is that they do not work in a probabilistic framework. There is several situations where would be very useful to have a classifier producing a posterior probability $P(class|input)$. In our case, particulary, we are interested in estimation of probabilities because we want to try different fusion strategies like Max, Min, Average, and Median.

Due to the benefits of having classifiers estimating probabilities, many researchers have been working on the problem of estimating probabilities with SVM classifiers. Sollich in [17] proposes a Bayesian framework to obtain estimation of probabilities and to tune the hyper-parameters as well. His method interprets SVMs as maximum a posteriori solutions to inference problems with Gaussian process priors. Wahba et al [20] use a logistic function of the form

$$P(y = 1|f(x)) = \frac{1}{1 + \exp(-f(x))} \qquad (2)$$

where $f(x)$ is the SVM output and $y = \pm 1$ stands for the target of the data sample $x$. In the same vein, Platt [15] suggests a slightly modified logistic function, defined as:

$$P(y = 1|f(x)) = \frac{1}{1 + \exp(Af(x) + B))} \qquad (3)$$

The difference lies in the fact that it has two parameters trained discriminatively, rather one parameter estimated from a tied variance. The parameters $A$ and $B$ of Equation 3 are found by minimizing the negative log likelihood of the training data, which is a cross-entropy error function.

# 3 The Writer-Independent Approach

The global approach is based on the forensic questioned document examination approach. It classifies the writing, in terms of authenticity, into genuine and forgery, using for that one global model. In the case of author identification, the experts use a set of $n$ genuine articles $Sk_i, (i = 1, 2, 3, \ldots, n)$ as references and then compare each $Sk$ with a questioned sample $Sq$. The idea is to verify the discrepancies among $Sk$ and $Sq$. Let $V_i$ be the stylometric feature vectors extracted from the reference articles and $Q$ the stylometric feature vector extracted from the questioned article. Then, the dissimilarity feature vectors $Z_i = \|V_i - Q\|_2$ are computed to feed $n$ different instances of the classifier $C$, which provide a partial decision. The final decision $D$ depends on the fusion of these partial decisions, which are usually obtained through the majority vote rule. Figure 1 depicts the global approach.

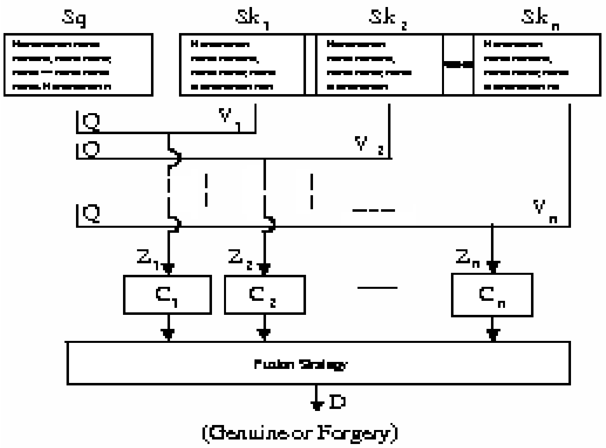


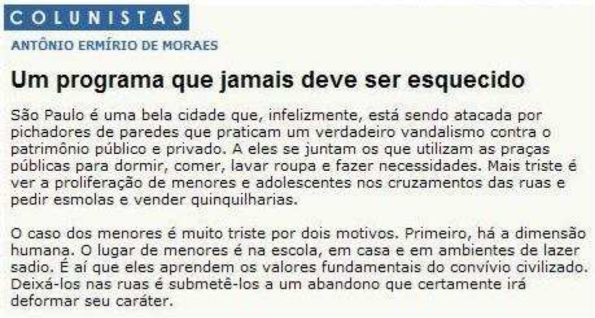
**Figure 1. Architecture of the global approach**

Note that when a dissimilarity measure is used, the components of the feature vector $Z$ tends to be close to 0 when both the reference $Sk$ and the questioned $Q$ comes from the same author. Otherwise, the feature vector $Z$ tend to be far from 0.

### 3.1 Database

To build the database we have collected articles available in the Internet from 10 different people with profiles ranging from sports to economics. Our sources were two different Brazilian newspapers, *Gazeta do Povo* (http://www.gazetadopovo.com.br) and *Tribuna do Paraná* (http://www/parana-online.com.br). We have chosen 15 short articles from each author. The articles usually deal with polemic subjects and express the author's personal opinion. In average, the articles have 600 tokens and 350 Hapax.

One aspect worth of remark is that this kind of articles can go through some revision process, which can remove some personal characteristics of the texts. Figure 2 depicts an example of the article of our database.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Um programa que jamais deve ser esquecido

São Paulo é uma bela cidade que, infelizmente, está sendo atacada por pichadores de paredes que praticam um verdadeiro vandalismo contra o patrimônio público e privado. A eles se juntam os que utilizam as praças públicas para dormir, comer, lavar roupa e fazer necessidades. Mais triste é ver a proliferação de menores e adolescentes nos cruzamentos das ruas e pedir esmolas e vender quinquilharias.

O caso dos menores é muito triste por dois motivos. Primeiro, há a dimensão humana. O lugar de menores é na escola, em casa e em ambientes de lazer sadio. É aí que eles aprendem os valores fundamentais do convívio civilizado. Deixá-los nas ruas é submetê-los a um abandono que certamente irá deformar seu caráter.

**Figure 2. An example of an article used in this work**

## 4 The Author Identification Method

The author identification method works as follows. The first task consist in training the global model which should discriminate between author ($\omega_1$) and not author ($\omega_2$). To generate the samples of $\omega_1$, we have used three articles ($A_i$) for each author. Based on the concept of dissimilarity, we extract features for each article and then compute the dissimilarities among them as shown in Section 3. In this way, for each author we have three feature vectors $((A_1 - A_2),(A_1 - A_3), and(A_2 - A_3))$, summing up 30 samples for training (10 authors). The samples of $\omega_2$ were created by computing the dissimilarities of the articles written by different authors, which were chosen randomly. As stated before, the proposed protocol takes into consideration a set of references ($Sk$). In this case we have used five articles per author as references and seven as questioned ($Sq$ - testing set).

In the testing phase, first the text is segmented into tokens. Spaces and end-of-line characters are not considered. All hyphenized words are considered as two words. In the example, the sentence "*eu vou dar-te um pula-pula e também dar-te-ei um beijo, meu amor*!" has 16 tokens and 12 Hapax. Punctuation, special characters, and numbers are not considered as tokens. There is no distinction between upper case and lower case.

Following the protocol introduced previously, a feature vector composed of 77 components (from 77 conjunctions described in Table 1) is extracted from the questioned ($Sq$) and references ($Sk_i$) documents as well. This produces the aforementioned stylometric feature vectors $V_i$ e $Q$. Once those vectors are generated, the next step consists in computing the dissimilarity feature vector $Z_i = \|V_i - Q\|_2$, which will feed the SVM classifiers. Since we have five ($n = 5$) reference images, the questioned image $Sq$ will be compared five times (the SVM classifier is called five times), yielding five votes or scores. When using discrete SVM, it produces discrete outputs $\{-1, +1\}$, which ca be interpreted as votes. To generate scores, we have used the probabilistic framework described in Section 2.2. Finally, the final decision can be taken based on different fusion strategies, but usually majority voting is used.

## 5 Results

In this section we report the experiments we have performed. Different parameters and kernels for the SVM were tried but the better results were yielded using a linear kernel. In such a case, the recognition rate of the system was 75.1%, which compares to several published method in the literature. It is important to notice that the SVM has been trained with just three samples per author. The recognition rate was then computed based on seven articles per author, which did not contribute to the training of the writer independent classifier. Table 3 reports errors Type I and Type II for the proposed method. Statically speaking, Type I error is the false rejection as the system classifies genuine authors as not authors . The Type II error, on the other hand, is known as false acceptance, i.e., a not author classified as author.

**Table 3. Performance of the system**

| Kernel | Type I<br>Error | Type II<br>Error | Average |
|---|---|---|---|
| Linear | 15.7% | 34.2% | 24.9% |

To assess different fusion strategies, we have chosen the well-known ROC (Receiver Operating Characteristics). The area under the ROC (AUC) is convenient way of comparing classifiers. A random classifier has an area of 0.5, while and ideal one has an area of 1. We can observe from Figure 3 that the ROC with greatest AUC is the majority voting rule. This Figure corroborates to the choice of majority voting as fusion strategy.

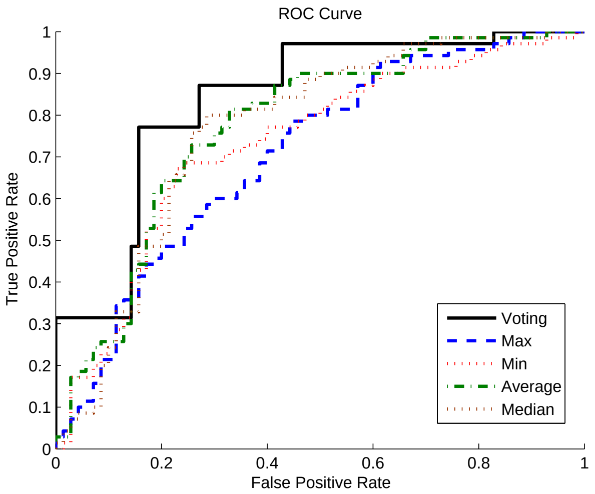

**Figure 3. Comparison of different fusion strategies**

As stated before, few works have been done in the field of author identification for documents written in Portuguese. For this reason is quite difficult to make any kind of direct comparison. To the best of our knowledge, the only work dealing with author identification for documents written in Portuguese was proposed by Coutinho et al [6]. In this work the authors extract features using a compression algorithm and achieve a recognition rate of 78%. However, the size of the texts used for feature extraction is about 10 times bigger.

## 6 Conclusion

In this paper we have presented a method for author identification using a feature set extracted from conjunctions of the Portuguese language. The proposed method is based on a writer-independent approach which reduces the problem of author identification to one model with two classes, which makes it possible to build a robust identification system using few genuine samples per author.

Comprehensive experiments on a database composed of short articles from 10 different authors demonstrate that the proposed strategy produces results comparable to the literature. As future work, we plan to increase the database and define new features so that the overall performance of the system could be improved.

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