

# Stylometry-based Approach for Detecting Writing Style Changes in Literary Texts

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**Abstract.** In this paper, we present an approach to identify changes in the writing style of 7 authors of novels written in English. We defined 3 stages of writing for each author, each stage contains 3 novels with a maximum of 3 years between each publication. We propose several stylometric features to represent the novels in a vector space model. We use supervised learning algorithms to determine if by means of this stylometric-based representation is possible to identify to which stage of writing each novel belongs.

**Keywords.** Stylometry, writing style, authorship analysis.

## 1 Introduction

Currently, there is an exponential growth of digital information produced every day in the form of texts written in natural language, such as magazines, books, websites, newspapers, reports, etc. Nowadays, it is possible to process huge amounts of data from sources such as audio, video, images and text with machine learning algorithms. The authorship analysis studies [5], is one of the multiple application that can take

advantage of this situation in order to turn the vast amount of data into practical and useful knowledge.

In authorship analysis, typical features used for text representation in the Vector Space Model (VSM) are words, Bag of Words (BoW) model [11], word  $n$ -grams [16, 22], character  $n$ -grams [7, 22], and syntactic  $n$ -grams [19]. The values of these features can be Boolean [15], tf-idf (term frequency-inverse document frequency), weights [12], or values based on probabilistic models [3]. Another popular statistical-based text representation are the stylometric features [23, 9], such as length of sentences, complexity of sentences, frequent words, spelling errors, etc.

In this paper, we aim to identify changes in the writing style of 7 authors of novels written in English using only stylometric features. Other text representations were evaluated for this corpus such as bag-of-words and  $n$ -grams (words, characters, POS tags, syntactic), in previous work [21]. From the machine learning perspective, this task can be viewed as a multi-class, single-label classification problem,

when the automatic methods have to assign class labels (stages of writing for each author), to objects (text samples). This process requires a training and test set to generate a function that maps the input data with an output label. We examine various stylometric-based features, including lexical usage, punctuation and phraseology analysis; the evaluated machine-learning algorithms are liblinear and libSVM implementations of Support Vector Machines (SVM) and Logistic Regression (LG).

The identification of writing style changes have many applications, for example, it can be used to study early detection of diseases related memory loss and other cognitive abilities [6]. It is also important for the authorship attribution task when it is assumed that the writing style of the author is unique and stable, and can be detected in all his or her writing [1].

The paper is organized as follows. In Section 2, we discuss the related work. In Section 3, we provide some characteristics of the corpus we used for the experiments. In Section 4, we describe the methodological framework. In Section 5, we present the obtained results. Finally, in Section 6, we draw some conclusions and point to possible directions of future work.

## 2 Related Work

In [8], the authors analyzed 14 Agatha Christie novels creating blocks of 10,000 words but they used the first 5 blocks of each novel. They used the wealth of vocabulary, n-grams of words and undefined words. They found that the wealth of vocabulary decreased as the author's age increased. The repeated phrases and the use of undefined words showed the opposite behavior.

The work [17], analyzed novels of different literary genres using LIWC characteristics. The results were correlated with the author's age at the time of writing the work. They concluded that the way people use language changes throughout their lives and that people show consistent changes in their language styles based on their age.

A study to measure the fidelity of an author in his writing style was carried out in [18], specifically the inter-tutorial variation at lexical, syntactic

and semantic levels. A corpus of 20 opinion articles from 6 authors were compiled and the characteristics used were frequent words, slogans, the wealth of vocabulary, POS tags, content words, function words, sentence length, paragraph length, first level syntactic structures (chunks), word length, hapax legomena, distribution of signs of punctuation, adverbs (which end in mind), among others. The study was carried out using the analysis of variance (ANOVA). When evaluating the similarity of the texts through the 5 and 10 most frequent words, the results showed that the authors tend to use this type of words recurrently. The work concluded that the authors tend to maintain the same patterns of language instead of changing them with other options.

An analysis about the change of writing style of the Turkish authors Cetin Altan and Yasar Kemal was performed in [2]. A corpus compiled of 2 novels written in 1971 and 1998 by Kemal and 201 documents written between 1945 and 1991 by Yasar. The characteristics used were word length, length of word types and most frequent words. The principal component analysis (PCA), technique together with discriminant analysis and logistic regression were used to distinguish between old and new jobs. The results showed that the frequency and length of words in the most recent works was significantly higher than in the first works for both authors. To identify the membership of a block either to the old or the new period, the texts were divided into groups of 16 blocks. The works of Altan were identified with higher precision (suppose that this is due to the greater gap of time existing between the works of this author with respect to Kemal). In their conclusions, they indicate that when using discriminant analysis the success rate was of 98.96% and 84.38% for Altan and Kemal respectively.

In [6], were conducted experiments in order to identify writing style changes over the time in authors with Alzheimer's disease. They compiled a corpus gathering novels from 3 authors: Agatha Christie (15 novels), and Iris Murdoch (20 novels), affected by the Alzheimer disease and P.D James (15 novels), who was unaffected by the disease. The experiments were conducted using a set of well-known features in authorship attribution and

**Table 1.** Corpus description

| Author                 | Initial Stage |                   | Middle Stage |                    | Final Stage |                     |
|------------------------|---------------|-------------------|--------------|--------------------|-------------|---------------------|
|                        | Year          | Novel             | Year         | Novel              | Year        | Novel               |
| Booth Tarkington (BT)  | 1899          | Gentleman         | 1914         | Penrod             | 1919        | Ramsey              |
|                        | 1902          | Vanrevels         | 1915         | Turmoil            | 1921        | Alice Adams         |
|                        | 1905          | Canaan            | 1916         | Seventeen          | 1922        | Gentle Julia        |
| Charles Dickens (CD)   | 1838          | Nicholas Nickleby | 1848         | Dombey and Son     | 1859        | Two Cities          |
|                        | 1838          | Oliver Twist      | 1850         | Copperfield        | 1861        | Expectations        |
|                        | 1841          | Barnaby           | 1853         | Bleak house        | 1865        | Our mutual friend   |
| Frederick Marryat (FM) | 1830          | The King's Own    | 1839         | The panthom ship   | 1845        | The Mission         |
|                        | 1831          | Jacob Faithful    | 1839         | A diary in America | 1847        | New Forrest         |
|                        | 1831          | Newton Forster    | 1840         | Olla Podrida       | 1848        | The Little Savage   |
| George MacDonald (GM)  | 1863          | David Elginbrod   | 1873         | Gutta Percha       | 1888        | Electrical Lady.txt |
|                        | 1864          | Adela             | 1875         | A double story     | 1891        | Flight of Shadow    |
|                        | 1865          | Alec Forbes       | 1876         | Thomas Wingfold    | 1892        | Hope of góspel      |
| George Vaizey (GV)     | 1901          | School Story      | 1908         | Flaming June       | 1914        | Cassandra           |
|                        | 1902          | Pixie             | 1908         | Big Game           | 1914        | College Girl        |
|                        | 1902          | Houseful of Girls | 1910         | Marriage           | 1915        | Claire              |
| Louis Tracy (LT)       | 1903          | Wings of morning  | 1907         | The captain        | 1912        | Romance of NY       |
|                        | 1904          | The revelers      | 1909         | Inmortals          | 1916        | The day of wrath    |
|                        | 1905          | Disapperance      | 1909         | The stoneway girl  | 1919        | Mortimer fenley     |
| Mark Twain (MT)        | 1869          | Innocents Abroad  | 1883         | Mississippi        | 1897        | The Equator         |
|                        | 1872          | Roughing It       | 1884         | Huckleberry Finn   | 1905        | What is man?        |
|                        | 1876          | Tom Sawyer        | 1889         | King Arthur        | 1906        | Dollar              |

authorship verification, including frequent words, function words, characters, character n-grams, POS tags big-maps, POS tags entropy, most frequent words, among others. Both strategies unmasking technique and an SVM classifier were used to detect changes in authors' style. Experiments concluded that the proposed method was unable to detect the changes in the writing style caused by the disease and could not find any set of characteristics that would reliably discriminate the age of the authors.

### 3 Corpus

The corpus used in our study includes texts downloaded from the Project Gutenberg [20]. We selected books of native English speaking authors that had their literary production in a similar period. In this paper, all experiments were conducted for the corpus of sixty-three documents

by seven authors. Table 1, shows the final corpus description.

In order to label the corpus with the writing time period, we first performed a chronological ranking of the novels by each of the seven authors based on the date of publication. Then we defined three writing stages (initial, middle and final), each stage contains three novels and there are at least two years of separation between the novels in each stage.

### 4 Methodology

In order to evaluate the performance of the classification models, we conformed testing sets with 3 novels (1 per stage), and training sets with 6 novels (the remaining 2 stage). There are in total nine novels for each author, thus twenty-seven different pairs of training-testing sets were obtained for each author. With this

**Table 2.** Testing sets for the author Booth Tarkington

|   |                                |    |                                |    |                             |
|---|--------------------------------|----|--------------------------------|----|-----------------------------|
| 1 | Gentleman-Penrod-AliceAdms     | 10 | Vanrevels-Penrod-AliceAdms     | 19 | Canaan-Penrod-AliceAdams    |
| 2 | Gentleman-Penrod-Julia         | 11 | Vanrevels-Penrod-Julia         | 20 | Canaan-Penrod-Julia         |
| 3 | Gentleman-Penrod-Ramsey        | 12 | Vanrevels-Penrod-Ramsey        | 21 | Canaan-Penrod-Ramsey        |
| 4 | Gentleman-Turmoil-AliceAdams   | 13 | Vanrevels-Turmoil-AliceAdams   | 22 | Canaan-Turmoil-AliceAdams   |
| 5 | Gentleman-Turmoil-Julia        | 14 | Vanrevels-Turmoil-Julia        | 23 | Canaan-Turmoil-Julia        |
| 6 | Gentleman-Turmoil-Ramsey       | 15 | Vanrevels-Turmoil-Ramsey       | 24 | Canaan-Turmoil-Ramsey       |
| 7 | Gentleman-Seventeen-AliceAdams | 16 | Vanrevels-Seventeen-AliceAdams | 25 | Canaan-Seventeen-AliceAdams |
| 8 | Gentleman-Seventeen -Julia     | 17 | Vanrevels-Seventeen -Julia     | 26 | Canaan-Seventeen-Julia      |
| 9 | Gentleman-Seventeen -Ramsey    | 18 | Vanrevels-Seventeen- Ramsey    | 27 | Canaan-Seventeen -Ramsey    |

experimental configuration, we ensure that all the novels are part of both sets (training and testing). Table 2 shows the twenty-seven testing sets for the author Booth Tarkington (BT). The training sets are not shown for space reasons.

We examined the performance of different stylometric features and machine learning algorithms. Stylometry is the analysis of style features that can be statistically quantified, such as sentence length, vocabulary diversity, and frequencies (of words, word forms, etc.). The stylometric has many practical applications, being one of the most popular the authorship attribution research, where the stylometric features are used as stylistic fingerprints for finding the author of anonymous or disputed documents.

We used a freely available Python library for obtaining the stylometric features <sup>1</sup> for all text samples. With the obtained features we built vector space models divided into three categories of stylometric analysis: phraseology analysis, punctuation analysis, and lexical usage analysis. The performance of each of the three feature sets was evaluated separately and in combinations. Table 3 shows the stylometric features that belong to each category of analysis. In the case of the lexical usage analysis, we used the list of stop words contained in the NLTK<sup>2</sup> library for Python.

We used the scikit-learn<sup>3</sup> implementation of the following machine learning classifiers: Logistic Regression and SVM (Liblinear and Libsvm implementations). These classification algorithms have proved to be among the best for text classification tasks [10, 13, 14].

<sup>1</sup><https://github.com/jpotts18/stylometry>

<sup>2</sup><http://www.nltk.org/>

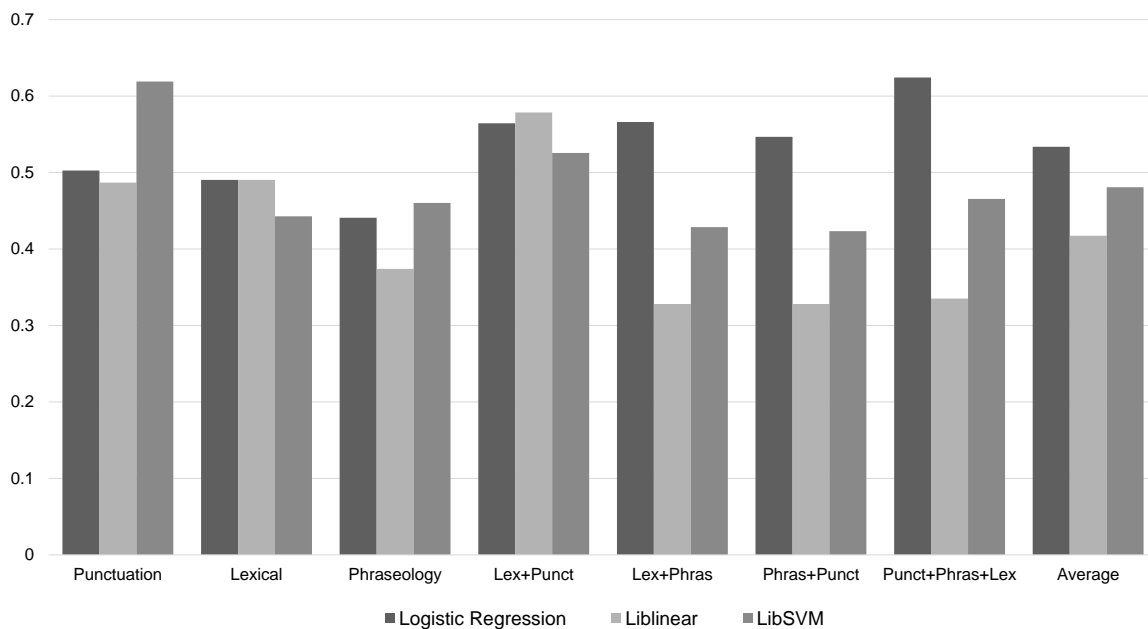
<sup>3</sup><http://scikit-learn.org/>

**Table 3.** Features included in the three types of stylometric analysis

| Analysis Type           | Features   |
|-------------------------|--|
| Phraseology<br>(Phras.) | lexical diversity, mean word length, mean sentence length, stdev sentence length, mean paragraph length, stdev paragraph length, document length |
| Punctuation<br>(Punct)  | commas, semicolons, quotations, exclamations, colons, hyphens, double hyphens  |
| Lexical Usage<br>(Lex)  | stop word list (a, the, of, in, etc.)  |

## 5 Results

We present the results in terms of accuracy achieved by the three stylometric analysis categories. The probability of assigning the correct class (writing stage), to a document at random is 33 %, this value is considered the baseline. First, we evaluated the classification algorithm that is better suited for this type of features. Figure 1, shows that in average the Logistic Regression algorithm obtained better results than the SVM-based algorithms, reaching a 5%, of difference in accuracy. However, the LibSVM algorithm achieved almost 10%, of improvement when using only the punctuation analysis features. For the individual results of each feature set, we only present here the results obtained with the Logistic Regression classifier.



**Fig. 1.** Performance of the classification algorithms with each type of stylometric features

We evaluated the performance of the stylometric analysis individually and in combination for each author separately. Remember that we evaluate the classification performance with twenty-seven (27), testing sets and the final results represent the average obtained with the testing sets.

In Table 4, it can be observed that the highest classification accuracy is obtained in average when using the combination of all stylometric features. However, when the evaluation is performed individually, i.e. using only one type stylometric feature, the features within the punctuation analysis category yielded the best performance.

When analyzing the classification performance of the stylometric features on each author we observed that the classification model built on the punctuation-based features achieved very high performance. These models correctly classified the writing stage of a work above 70% of the times for two authors: Booth Tarkington (BT) and Mark Twain (MT). In the case of Charles Dickens (CD) and George MacDonald (GM), the combination of phraseology-and punctuation-based features

obtained the best performance. The combination of all types of features obtained the best performance for Frederick Marryat (FM), George Vaizey (GV) and Louis Tracy (LT), classifying correctly the writing stage of the works 80% of the times on average.

## 6 Conclusion and Future Work

In this paper, we examined the performance of stylometric-based features for detecting writing style changes of seven authors of English novels. We defined three stages of writing for each author, with three novels each according to the publication date.

The obtained results indicate that the writing stage of a literary work can be identified with high accuracy (more than 70%), for four out of the seven evaluated authors using different the stylometric-based features. Furthermore, the classification models only failed in one of the authors (GM), where they obtained at most 56.8% of accuracy.

**Table 4.** Results in terms of accuracy with the Logistic Regression classifier for each author and type of stylometric analysis

| Analysis Type   | BT           | CD           | FM           | GM           | GV           | LT           | MT           | Average      |
|-----------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| Punctuation     | <b>0.827</b> | 0.346        | 0.531        | 0.531        | 0.235        | 0.346        | <b>0.704</b> | 0.503        |
| Lexical         | 0.667        | 0.407        | 0.457        | 0.272        | 0.481        | 0.630        | 0.519        | 0.490        |
| Phraseology     | 0.185        | 0.481        | 0.543        | 0.333        | 0.580        | 0.667        | 0.296        | 0.441        |
| Lex+Punct       | 0.741        | 0.481        | 0.580        | 0.556        | 0.556        | 0.519        | 0.519        | 0.564        |
| Lex+Phras       | 0.457        | 0.593        | 0.753        | 0.469        | 0.605        | 0.753        | 0.333        | 0.566        |
| Phras+Punct     | 0.235        | <b>0.617</b> | 0.654        | <b>0.568</b> | 0.593        | 0.852        | 0.309        | 0.547        |
| Punct+Phras+Lex | 0.519        | 0.605        | <b>0.877</b> | 0.543        | <b>0.642</b> | <b>0.889</b> | 0.296        | <b>0.624</b> |

We also found that for some authors, such as Louis Tracy, the writing style among the different stages can be identified with very high accuracy (88.9%). Even though the years of separation between each stage is at most three years. This seems to contradict some conclusions of the state-of-the-art where the authors found that the greater the gap of time existing between the novels the change is more evident [2].

This work serves as a baseline for more complex methods. One of the directions for future work will be to examine if is possible to identify the changes in writing style with other types of features such as documents embeddings [11, 4].

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