Author Identification for Marathi Language

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ABSTRACT

This is era of new technology; most of information is collected from internet, web sites. Some people uses data from research papers, thesis, and website as it is and publish as their own research without giving proper acknowledgement. This term is known as plagiarism. There are two types of plagiarism detection methods, i) Extrinsic plagiarism detection ii) Intrinsic plagiarism detection. Through extrinsic plagiarism utilizing reference corpus plagiarism is observed, while in intrinsic plagiarism identification, using author's writing style, plagiarism can be identified. If the anonymous text is written by unknown author. By using authorship analysis we can find original author of text. Authorship analysis is having three types i) Author identification ii) Author characterization and iii) Similarity detection. This paper mainly focuses on author identification for Marathi language. To calculate projection in two different files, we used feature vectors of main author file and summary file of other authors. The result of average projection shows, there is similarity in main author file and summary file of different authors, it also shows summary file of each author is having impact of main author file.

Keywords:
Plagiarism detection
Author identification
Marathi language.

1. Introduction

Plagiarism includes copying material, every word from phrase or as a paraphrase, from any book to websites, course notes, oral or visual displays, lab reports, pc assignments, or artistic works. Plagiarism includes reproducing any individual else’s work, whether or not it be posted article, chapter of a book, a paper from a buddy or some file, or whatever. In addition, plagiarism involves the exercise of employing another person to alter or revise the work that a student submits as his or her own, whoever that other man or woman may be. Authorship identification is the ability to identify unidentified authors based on their previous work and statements. The main method in authorship identification is to look at and identify features by an author using stylometric features. We can find the writing style of author by identifying textual features that they used while writing document [1].

1.1. Authorship Analysis

Authorship analysis is a method of analyzing the features of the writing part in order to draw conclusions from its authorship [1]. Authorship analysis having three types: i) Authorship Identification, ii) Authorship characterization, iii) Similarity detection.

A. Authorship identification: It defines the likelihood of a part of the writing being produced by a specific author by examining the author's other writings.

B. Authorship characterization: Authorship characterization reviews the characteristics of an author and produces the author profile based on his or her writing.

C. Similarity detection: Similarity detection examines several pieces of writing and judges whether they have been published by a single author without actually identifying the author [1].

2. Literature Survey

The PAN workshop brought together experts and researchers around the exciting and future-oriented topics of plagiarism detection, authorship identification, and the detection of social software misuse. It started in 2009. But relevant to Plagiarism the track started in 2011. The table1 shows that PAN Features used, and technique applied from the year 2011 to 2018.
| Reference Number | Features | Technique used |
|------------------|----------|----------------|
| [2]              | Bag of words features are used | In this paper author used Approach over known authors documents, using support vector machines. author treat each paragraph as a separate document and apply the n-cut clustering algorithm. |
| [3]              | 1. Lexical features 2. Character level 3. various length-related features 4. syntax related features | In this paper author was used Support vector machine classifier for classification. |
| [4]              | Language-dependent Content and Stylometric Features | Author used SVM and random forests as classifiers and regressors. |
| [5]              | Word ngrams, Character ngrams, POS, tag ngrams, Word lengths, Sentence lengths, Sentence length ngrams, Word richness, Punctuation ngrams, Text shape ngrams. | Author explored three different regressor algorithms: trees, random forests, and support vector machines. |
| [6]              | n-gram | PPM (Prediction by Partial Matching) compression algorithm based on an n-gram statistical model. |
| [7]              | phrase-level and lexical-syntactic features 1. Word prefixes 2. Word suffixes 3. Stopwords 4. Punctuation marks 5. N-grams (one gram to Fivegram features calculated) 6. Skip-grams (one gram to Fivegram features calculated) 7. Vowel combination 8. Vowel permutation | A similarity vector using the LSA algorithm for each word in the test documents Different distance/similarity measures were tested, including the Jaccard similarity for the vocabulary feature vector, the cosine similarity for the Frequency vector of all the combined Lexical syntactic features and Chebyshev Distance, Euclidean distance and cosine similarity for the LSA vectors. |
| [8]              | 1. Character 2. Words 3. Lemma and Part of Speech | Our method is based on the analysis of the average similarity (ASUnk) of an unknown authorship text with the closeness to each of the samples of an author, comparing it to the Average Group Similarity (AGS) between samples of an author. |
| [9]              | Bag of words using character n-grams | Author used Ensemble Particle Swarm Model Selection (EPSMS) for the selection of classification models for each data set. For classification we used the neural network classifier implemented in the CLOP toolbox. |
| [10]             | stylometric features 1. Basic features 2. Lexical features 3. Character features 4. Syntactic features 5. Coherence features | Author follows the unmasking approach. |
| [11]             | 1. length of the sentences, 2. variety of vocabulary, 3. Words, n-characters grams, n-4. Words gram, punctuation marks. | Author compares all documents inside a corpus using the cosine similarity, euclidean distance or the correlation coefficient. For the task of Author Verification, we used the Classification and Regression Trees (CART) algorithm which constructs binary trees using the features and thresholds that |
|   |   |   |
|---|---|---|
| [12] | profiles of character 3-grams for representing information about the Different categories of authors. | yield the largest information gain at each node |
| [13] | word bag, stop word bag, punctuation bag, part of speech (POS) bag | KNN Algorithm is used |
| [14] | 1. counting text elements 2. constructing syntactic n-grams | Integrated syntactic graph is used. |
| [15] | 1. Char Sequences 2. Word Uni-grams 3. POS-tags Features | PCA Linear SVC |
| [16] | phoneme-based features, character-based features, token-based features, syntax-based features, semantic-based features | k-NN classifier |
| [17] | signatures, chat slang, context, emotionality, semantic similarity, Jaccard similarity and BOW | NB classifier |
| [18] | Stylistic Features 1. Stylometry based approaches 2. Content based approaches 3. Topic based approaches | Navies Bayes, Support Vector Machine, Random Forest, J48 and Logistics. These algorithms was used. |
| [19] | lexical, syntactic and graph-based features | Support Vector Machines (SVM). |
| [20] | character n-grams | Vector Space Model, Similarity Overlap Metric |
| [21] | Basic Statistics, Token Statistics, Grammar Statistics, Stop-Word Terms, Pronoun Terms, Slang Terms, Intro-Outro Terms, Bigram Terms, Unigram Terms, and Terms. | Supervised vote/veto meta-classifier approach |
| [22] | Stylistometric features or word n-grams. | k-NN classifier |
| [23] | n-grams | Distance measure technique used. |
| [24] | n-Grams | Support Vector Machine classifier |
| [25] | n-grams | Local n-gram Technique is used. |
| [26] | Bag of words, Bigram, Trigram, Comma Dots, Numbers, Capitals, Words per paragraph, Sentences per paragraph, Square brackets. | Support Vector Regression and Neuronal Networks models |
| [27] | n-grams of POS tag sequences | vector space model |
| [28] | stylistic and statistical features | SVM, Bayes, KNN |
| [29] | stylistic features ranging from characters to syntactic and semantic units | SVM |
| [30] | n-grams | SVM |
| [31] | First words of sentences or lines, nouns, verbs, punctuation. | principal component analysis |
| [32] | stylometric properties, grammatical characteristics and pure statistical features | SVM classifier |
| [33] | Linguistic Features | SVM |
| [34] | n-grams | LSA |
| [35] | Unigram-Tf-idf, Unigram Character, Character4-gram | GenIM method |
| [36] | Stylistic Total number of words Average number of words per sentence | SVM, K-means clustering Algorithm implemented in CLUTO |
3. Text Corpus

Similar to other language work, work in the Marathi language is also appreciable. But the work is not accessible as an online resource, so far it's offline. Actually, there is no generic Marathi text corpus accessible. For the development of text corpus, we have considered 10 paragraphs for taking summary from 50 users in their own writing. We have used 500 summary files from 50 users as a database for author identification.

4. Proposed System

We would like to propose a system for Author Identification in Marathi Language. The system workflow is given below:

### 4.1. Input Text

First the system reads two files. Main file and summary of written by Authors file. The file format is .txt

### 4.2. Punctuation removal

This step removes the punctuations present in the file, e.g. punctuations = "!()-[]{};"|'<>./?@#$%^&*_~"
4.3. Stopword Removal

Stop words are simply a set of words widely used in any language. Here are the Stopwords:

Table 2. List of Stopwords

| Stopwords | }

4. Avg sentence length

5.2. Vocabulary richness features

1. Hapax legomenon
2. Hapax dislegemena

Hapax Legomena and Hapax DisLegemena

Hapax Legomena is a term that appears only once in a sense, either in the written record of the whole language, a single text. Hapax legomenon is a Greek phrase which is means something that told onetime only.

Similarly, Hapax DisLegemena is the word that is used twice. Following table3 shows that features of original sample files from database.

Table 3: Features of Original Sample files

| Files   | Avg_SentLengthByChar | Avg_SentLengthByWord | hapaxLegomenon | hapaxDisLegemena | AvgWordFrequencyClass | AvgSentenceLength |
|---------|----------------------|----------------------|----------------|------------------|-----------------------|------------------|
| OG_File1 | 1198                 | 57                   | 423.41         | 0.11             | 1.79                  | 7                |
| OG_File2 | 1441                 | 74                   | 441.88         | 0.19             | 1.55                  | 9                |
| OG_File3 | 1612                 | 79                   | 443.08         | 0.1              | 1.77                  | 9                |
| OG_File4 | 2797                 | 128                  | 492.72         | 0.07             | 1.84                  | 7                |
| OG_File5 | 2896                 | 154                  | 508.75         | 0.09             | 1.95                  | 7                |
| OG_File6 | 2757                 | 141                  | 499.04         | 0.06             | 1.89                  | 7                |
| OG_File7 | 2841                 | 141                  | 503.69         | 0.04             | 1.82                  | 7                |
| OG_File8 | 991                  | 63                   | 417.43         | 0.12             | 1.69                  | 13               |
| OG_File9 | 740                  | 30                   | 358.35         | 0                | 1                     | 4                |
| OG_File10 | 1173                | 44                   | 417.43         | 0.1              | 1.76                  | 11               |

5. Feature Extraction

Feature extraction can be defined as the process of extracting a set of new features from the set of features generated in the selection stage feature. Feature extraction is a basic and fundamental step to pattern Recognition and machine learning problem. There is no text corpus available for Marathi language.

We concentrated on two major features: Lexical features and Vocabulary richness features. These include features like Average sentence length by word, Average sentence length by character, AvgWordFrequencyClass, Avg sentence length, Hapax legomenon, Hapax dislegemena.

We have extracted the following features:

5.1. Lexical features

1. Average length of sentence by word
2. Average length of sentence by character
3. AvgWordFrequencyClass

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| Files | Avg_SentLengthByCh | Avg_SentLengthByWord | hapaxLegemena | hapaxDisLegemena | AvgWordFrequencyClass | Avg sentence length |
|-------|-------------------|----------------------|---------------|------------------|-----------------------|-------------------|
| File1 | 777.0             | 47.0                 | 395.12        | 0.1063           | 1.80                  | 23                |
| File2 | 880               | 67.0                 | 412.11        | 0.13             | 1.82                  | 20                |
| File3 | 1390.0            | 86.0                 | 449.98        | 0.154            | 1.87                  | 29                |
| File4 | 1230              | 82.0                 | 468.25        | 0.123            | 1.85                  | 22                |
| File5 | 1178              | 86                   | 434.0         | 0.14             | 1.78                  | 24                |
| File6 | 879               | 81.0                 | 398.0         | 0.13             | 1.87                  | 22                |
| File7 | 758               | 58.0                 | 369.0         | 0.15             | 1.83                  | 20                |
| File8 | 627.0             | 41.0                 | 376.12        | 0.176            | 1.62                  | 14                |
| File9 | 598.0             | 34.0                 | 361.09        | 0.23             | 1.62                  | 11                |
| File10| 686.0             | 36.0                 | 371.35        | 0.051            | 1.90                  | 36                |

| Files | Avg_SentLengthByCh | Avg_SentLengthByWord | hapaxLegemena | hapaxDisLegemena | AvgWordFrequencyClass | Avg sentence length |
|-------|-------------------|----------------------|---------------|------------------|-----------------------|-------------------|
| File1 | 758.0             | 47.0                 | 389.18        | 0.050            | 1.71                  | 23                |
| File2 | 796               | 49.0                 | 387.10        | 0.02             | 1.74                  | 22                |
| File3 | 947.0             | 51.0                 | 397.02        | 0.02             | 1.88                  | 25                |
| File4 | 864.0             | 53.0                 | 434.0         | 0.03             | 1.85                  | 23                |
| File5 | 1164              | 52.0                 | 489           | 0.086            | 1.83                  | 20                |
| File6 | 1516.0            | 84.0                 | 0.051         | 445.43           | 1.82                  | 10                |
| File7 | 1526.0            | 94.0                 | 456.43        | 0.1392           | 1.67                  | 19                |
| File8 | 496.0             | 29.0                 | 343.39        | 0.074            | 1.77                  | 14                |
| File9 | 565.0             | 27.0                 | 343.39        | 0.0              | 1.0                   | 13                |
| File10| 1071.0            | 53.0                 | 404.30        | 0.058            | 1.82                  | 18                |

| Files | Avg_SentLengthByCh | Avg_SentLengthByWord | hapaxLegemena | hapaxDisLegemena | AvgWordFrequencyClass | Avg sentence length |
|-------|-------------------|----------------------|---------------|------------------|-----------------------|-------------------|
| File1 | 794.0             | 45.0                 | 391.20        | 0.090            | 1.78                  | 11                |
| File2 | 1056.0            | 64.0                 | 418.96        | 0.157            | 1.72                  | 16                |
| File3 | 1020.0            | 56.0                 | 398.21        | 0.18             | 1.85                  | 14                |
| File4 | 2093.0            | 104.0                | 468.21        | 0.061            | 1.83                  | 9                 |
| File5 | 1524.0            | 102.0                | 485.11        | 0.071            | 1.84                  | 10                |
| File6 | 1754.0            | 107.0                | 480.12        | 0.078            | 1.86                  | 12                |
| File7 | 1825.0            | 111.0                | 475.35        | 0.11             | 1.74                  | 16                |
| File8 | 715.0             | 46.0                 | 387.12        | 0.12             | 1.72                  | 23                |
| File9 | 631.0             | 31.0                 | 358.35        | 0.0              | 1.0                   | 10                |
| File10| 812.0             | 31.0                 | 378.41        | 0.07             | 1.86                  | 10                |
6. Result

\[
\text{projection} = \frac{\mathbf{A}_S \cdot \mathbf{O}_S}{|\mathbf{A}_S \cdot \mathbf{O}_S|}
\]  

(1)

\(\mathbf{A}_S\) Feature vector of summary file written by author  
\(\mathbf{O}_S\) Feature vector of main author file from database

Table 9: Projections of main author file on summary file written by author

| Projection of File1 | Projection of File2 | Projection of File3 |
|---------------------|--------------------|--------------------|
| Feature vector of original file | Feature vector of Author file | Projection | Feature vector of original file | Feature vector of Author file | Projection | Feature vector of original file | Feature vector of Author file | Projection |
| O1 S1 | A1 S1 | 1259.96 | O2 S2 | A1 S2 | 1502.67 | O3 S3 | A1 S3 | 1656.90 |
| O1 S1 | A2 S1 | 1267.24 | O2 S2 | A2 S2 | 1505.64 | O3 S3 | A2 S3 | 1671.39 |
| O1 S1 | A3 S1 | 1260.77 | O2 S2 | A3 S2 | 1493.81 | O3 S3 | A3 S3 | 1671.71 |
| O1 S1 | A4 S1 | 1260.08 | O2 S2 | A4 S2 | 1490.71 | O3 S3 | A4 S3 | 1659.55 |
| O1 S1 | A5 S1 | 1263.03 | O2 S2 | A5 S2 | 1504.15 | O3 S3 | A5 S3 | 1664.60 |

| Projection of File4 | Projection of File5 | Projection of File6 |
|---------------------|--------------------|--------------------|
| Feature vector of original file | Feature vector of Author file | Projection | Feature vector of original file | Feature vector of Author file | Projection | Feature vector of original file | Feature vector of Author file | Projection |
| O4 S4 | A1 S4 | 2797.49 | O5 S5 | A1 S5 | 2904.78 | O6 S6 | A1 S6 | 2783.81 |
| O4 S4 | A2 S4 | 2817.58 | O5 S5 | A2 S5 | 2882.72 | O6 S6 | A2 S6 | 2471.87 |
| O4 S4 | A3 S4 | 2791.57 | O5 S5 | A3 S5 | 2896.68 | O6 S6 | A3 S6 | 2719.10 |
| O4 S4 | A4 S4 | 2722.88 | O5 S5 | A4 S5 | 2870.66 | O6 S6 | A4 S6 | 2789.41 |
| O4 S4 | A5 S4 | 2839.97 | O5 S5 | A5 S5 | 2917.76 | O6 S6 | A5 S6 | 2794.38 |

| Projection of File7 | Projection of File8 | Projection of File9 |
|---------------------|--------------------|--------------------|
| Feature vector of original file | Feature vector of Author file | Projection | Feature vector of original file | Feature vector of Author file | Projection | Feature vector of original file | Feature vector of Author file | Projection |
| O7 S7 | A1 S7 | 2753.51 | O8 S8 | A1 S8 | 1059.29 | O9 S9 | A1 S9 | 816.28 |
| O7 S7 | A2 S7 | 2763.22 | O8 S8 | A2 S8 | 1057.72 | O9 S9 | A2 S9 | 810.570 |
| O7 S7 | A3 S7 | 2777.38 | O8 S8 | A3 S8 | 1066.46 | O9 S9 | A3 S9 | 819.15 |
| O7 S7 | A4 S7 | 2869.40 | O8 S8 | A4 S8 | 1054.22 | O9 S9 | A4 S9 | 818.94 |
| O7 S7 | A5 S7 | 2879.50 | O8 S8 | A5 S8 | 1072.00 | O9 S9 | A5 S9 | 820.94 |

| Projection of File10 |
|---------------------|
| Feature vector of original file | Feature vector of Author file | Projection |
| O10 S10 | A1 S10 | 1228.20 |
| O10 S10 | A2 S10 | 1242.74 |
| O10 S10 | A3 S10 | 1230.19 |
| O10 S10 | A4 S10 | 1245.55 |
| O10 S10 | A5 S10 | 1240.36 |
Authorship identification is the ability to identify unidentified authors based on their previous work and statements. We have created database of 500 summary files from 50 users for unidentified authors based on their previous work and statements. We have calculated feature vector of main author file and summary file of authors, we calculated projection of 10 files. The result of average projection shows, there is similarity in main author file and summary file of different authors. The figure 4 shows summary file of each author is having impact of main author file, Summary file number 4,5,6,7 are having more projection of main author file. Currently, most of Marathi native speakers are contributing their research for various topics in Marathi language, but some of researchers are using information from various sources like research papers, books, thesis without giving acknowledgement. There is need to restrict these type of conditions. There is no Author identification tool available for Marathi language. This tool will be helpful to perform quality research in Marathi language.

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