A Supervised Authorship Attribution Framework for Bengali Language

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Abstract

Authorship Attribution is a long-standing problem in Natural Language Processing. Several statistical and computational methods have been used to find a solution to this problem. In this paper, we have proposed methods to deal with the authorship attribution problem in Bengali. More specifically, we proposed a supervised framework consisting of lexical and shallow features, and investigated the possibility of using topic-modeling-inspired features, to classify documents according to their authors. We have created a corpus from nearly all the literary works of three eminent Bengali authors, consisting of 3000 disjoint samples. Our models showed better performance than the state-of-the-art, with more than 98% test accuracy for the shallow features, and 100% test accuracy for the topic-based features.

Keywords: Authorship Attribution, Machine Learning, Naive Bayes, lexical features, topic model.

1. Introduction

Authorship Attribution (AA) is a statistical or computational process which deals with the identification of the author of a particular text. This is a long-standing and well-studied problem in Natural Language Processing. The main application areas of authorship attribution are: author identification, plagiarism detection, author profiling and detection of inconsistencies in the writings of authors. These authorship attribution problems are classified into two categories. The “closed-class” (train and test authors come from the same set), or “open-class” (test authors may be different from train authors). A related variant is authorship verification, where the goal is to verify if a given document/passage has been written by a particular author via, e.g., binary classification.

Authorship Attribution in English, like any other Natural Language Processing problem, has received a lot of attention since the pioneering study of Mosteller and Wallace (Mosteller and Wallace 1963) on the disputed Federalist Papers.
Equivalent works of such kinds are very less in Bengali – one of the most widely spoken South Asian languages. Only three strands of research (Das and Mitra 2011; Chakraborty 2012; Jana 2015) can be found for Bengali, till date. This lack of research progress in Bengali Authorship Attribution could be attributed to shortage of adequate corpora and tools, which has only very recently started to change (Mukhopadhyay et al. 2012).

In this paper we have addressed the problem using two methods – one with lexical features and the other being topic-model features. Our contributions in this paper are as follows:

- Corpus: a new corpus of 3,000 literary passages in Bengali written by three eminent Bengali authors (Section 3).
- Authorship Attribution System: Our AA system incorporates two types of methods to identify authors.
- Shallow Features: Section 4.1 shows an attribution system which incorporates lexical features only. It implements classification system based on character bigrams that achieves 98% accuracy on held-out data (Section 4).
- Feature Selection: Six types of lexical n-gram features and selection of the best-performing combination on an independent development set (Section 4.1.1).
- Learning Curve: how the performance on held-out data changes as the number of training instances varies (Section 4.1.2).
- Feature Ranking: most discriminative lexical features by Information Gain (Section 4.1.3).
- Feature Analysis: frequency analysis of discriminative features, grouped by authors (Section 4.1.3).
- Topic modeling: how the performance of the data is affected by the implementation of topic- models (Section 4.2.2).

2. Related Works

A general overview of the topic of Authorship Attribution has been given in several surveys (Juola 2006), (Stamatatos 2009), (Koppel et al. 2009). As we discussed in Section 1, Authorship Attribution in Bengali is a relatively new problem. Among the three studies we found, (Chakraborty 2012) performed a
ten-fold cross-validation on three classes (Rabindranath, Sarat Chandra, others) with 150 documents in each, and showed that SVM outperforms decision tree and neural network classifiers. The best accuracy was 84%.

An earlier study (Das and Mitra 2011), also worked with three authors – Rabindranath, Bankim Chandra, and Sukanta Bhattacharya. They had 36 documents in total. Unigram and bigram features were rich enough to yield high classification accuracy (90% for unigrams and 100% for bigrams). However, their dataset was not very large to draw reliable conclusions. Further, the authors they experimented with had very different styles, unlike our (more difficult) case where two of the authors often had similar styles in their prose (Rabindranath and Sarat Chandra).

(Jana 2015) looked into Sister Nivedita’s influence on Jagadish Chandra Bose’s writings. He notes that “The results reveal a distinct change in Bose’s writing style after his meeting with Nivedita. This is reflected in his changing pattern of usage of these three stylistic features. Bose slowly moved back towards his original style of writing after Nivedita’s death, but his later works still carried Nivedita’s influence.” This study, while interesting, is not directly comparable to ours, because it did not perform any classification experiments.

Among other recent studies in Authorship Attribution in Indian languages, (Nagaprasad et al. 2015) worked on 300 Telugu news articles written by 12 authors. Support Vector Machine was used on word and character n-grams. It was observed that F-score and accuracy decrease as size of training data decreases, and/or the number of authors increases. Unsurprisingly, there are many recent studies in English Authorship Attribution. For the sake of completeness, we discuss a sample of them in the following.
(Seroussi et al. 2012) showed that author-topic model outperforms LDA for Authorship Attribution tasks with many authors. They came up with a combination of LDA and author-topic model (DADT – disjoint author-document-topic model) that outperforms the vanilla author-topic model and an SVM baseline. (Seroussi et al. 2014) further showed state-of-the-art performance on PAN 11, blog, IMDB, and court judgment datasets.

(Bogdanova and Lazaridou 2014) experimented with cross-language Authorship Attribution. They designed cross-language features (sentiment, emotional, POS frequency, perceptual, average sentence length), and posited that Machine Translation could be used as a starting point to cross-language Authorship Attribution. Using six authors’ English books and their Spanish translations, they obtained 79% accuracy with KNN. The best pairwise accuracy was 95%.

(Nasir et al. 2014) framed Authorship Attribution as semi-supervised anomaly detection via multiple kernel learning. They learned author regions from the feature space by representing the optimal solution as a linear mixture of multiple kernel functions.

(Luyckx and Daelemans 2008) introduced the important problem of Authorship Verification. To model realistic situations, they experimented with 145 authors and limited training data (student essays on Artificial Life). They showed that Authorship Verification is much harder than Authorship Attribution, and that more authors and less training data led to decreased performance. Memory-based learning (e.g., KNN) was shown to be robust in this scenario.

Apart from these authorship attribution is used in various other fields (Bobicev et al. 2013) looked into Authorship Attribution in health forums. In their 30-class classification problem, orthographic features performed well, and Naive Bayes was
shown to perform better than KNN. The best accuracy was close to 90%. An interesting study was presented by (van Cranenburgh 2012), where he focused on content words rather than function words, and showed that tree kernels on fragments of constituency parse trees provide information complementary to a baseline trigram model for Authorship Attribution. Literary texts from five authors were used, and the best (combined) accuracy reached almost 98%.

(Sarawgi et al. 2011) attempted to remove topic bias for identifying gender-specific stylistic markers. They used deep syntactic patterns with PCFG, shallow patterns with token-level language models, morphological patterns with character-level language models, and bag of words (BoW) with MaxEnt classifier. Per-gender accuracy reached 100% using morphological features on blog data. On paper data, BoW features also reached 100% per-author accuracy for both male and female authors.

(Savoy 2013) described, evaluated, and compared the use of Latent Dirichlet allocation (LDA) as an approach to authorship attribution. They proposed a method of modeling each document as a mixture of topic distributions with each topic specifying a distribution over words.

(Rosen-Zovi et al. 2004) introduced the author-topic model, which extends LDA to include authorship information. They showed topics recovered by the author-topic model, follow authorial fingerprints, and demonstrated applications for computing similarity between authors and entropy of author output.

3. CORPUS

In this work we have concentrated on Authorship Attribution (AA) only and not authorship verification, which is a harder problem. Since Bangla is an under resourced language, the amount of digitized text itself is quite less, and also the
available corpus. Though for authorship attribution we could have easily acquired our data set from the available online resources such as Twitter, Blogs, Facebook, etc. But for such data there will be less clear text, leading to more surface variations and also the number of authors will be unbounded, thereby making the problem more difficult and lowering the accuracy values (Layton et al. 2010; Schwartz et al. 2013). That is why we have extracted our corpus from literary texts.

We have created the corpus from the available digitized works of three Bengali literary geniuses:

1. Rabindranath Tagore (1861-1941)
2. Sarat Chandra Chattopadhyay (1876-1938)
3. Bankim Chandra Chattopadhyay (1838-1894)

Table 1: Corpus statistics. Values in parentheses are standard deviations. Mean and standard deviation are taken across passages.

| Author                        | Overall          | Train           | Test            | Development     |
|-------------------------------|------------------|-----------------|-----------------|-----------------|
| Rabindranath Tagore           | Mean #words      | 221.18 (26.08)  | 215.28 (27.21)  | 228.60 (23.73)  |
|                               | Mean #characters | 3232.61 (385.44)| 3139.87 (405.12)| 3352.16 (339.98)|
| Sarat Chandra Chattopadhyay   | Mean #words      | 188.99 (29.57)  | 186.18 (30.29)  | 192.49 (30.05)  |
|                               | Mean #characters | 2661.23 (421.84)| 2628.64 (432.10)| 2695.18 (423.85)|
| Bankim Chandra Chattopadhyay  | Mean #words      | 841.05 (256.86) | 832.38 (250.32) | 846.44 (261.31) |
|                               | Mean #characters | 13259.56        | 13153.46        | 13325.55 (4284.03)|
|                               |                  | (4188.04)       | (4083.46)       | 13405.75 (4290.50)|

Note that each of these male authors lived in the golden era of Bengali Renaissance. Thus, each of their writing styles could be thought as quite similar in tune with Mosteller and Wallace study (1963). Each of these authors has an extensive repertoire of works ranging from novels, short stories, poetry, drama, and songs. The works of all three authors are now available in digitized form, because of the
efforts by Society for Natural Language Technology Research (SNLTR). For the three authors first we removed the poetry and songs. From these large texts belonging to three classes, we sampled 3000 sample texts, 1000 from each class. Each of these sample texts contained 25 random passages, thus producing a balanced corpus. Our corpus statistics is shown in Table 1. It can be noted that our corpus has been divided into balanced training, development and test sets with 1500 texts in training, and 750 texts in development and test sets each. We have done stratified sampling as it provides greater precision than a simple random sample and it can very well work with smaller size samples (Stattrek). We also took care that the sets were disjoint.

Note from Table 1 that the passages of Bankim Chandra Chattopadhyay were lengthier than the other two authors. The reason could be the usage of more compound and complex sentences by the author, in his writings, than the other two authors.

4. AUTHORSHIP ATTRIBUTION SYSTEM

Our authorship attribution system consists of three classes. Here we have considered two types of features. The first one constitutes shallow features, which were used by many previous researchers and topic-model features.

4.1. Shallow Features

Among the shallow features we found that the most frequent n-grams gave the best results. The feature representations we have considered for our experiments are:

- **Stop Words**: There are 355 Bengali stop-words.
- **Most Frequent unigrams, bi-grams and tri-grams**: We have considered 500 for each.

1 The complete works of these three authors are available from http://www.nltr.org/.
• Most frequent character bi-grams and tri-grams: We have considered top 500
for each

In each of the feature categories we have experimented with three feature
representations:
  • tf: term frequency
  • tfidf: term frequency inverse document frequency
  • binary: presence or absence of the term, 1 for presence and 0 for absence

Section 4.1.1 shows that such lexical features give great performance and also
show that these are good enough to identify the class of a particular text.

We have used classification for identification of the author. We have used three
classifiers from Weka: Naive Bayes (NB), Support Vector Machine (SMO) and
Decision Tree (J48), to test the development set. Among the classifiers J48 gave
the worst accuracy. As NB produced the least Root relative squared error, we have
only considered NB as our final classifier. Moreover, NB is faster than SMO and
easy to conceptualize.

It can be seen from Table 2 that word unigrams give the best performance. Section
4.1.1 shows that our best values are obtained from character bigrams (tf). So we
build our final model consisting of 300 most frequent character bigrams (tf) as
features on Naive Bayes classifier.
Table 2: Percentage accuracy of three classifiers when trained on the training set and tested on the development set. For each category of feature, 500 most frequent were used. For stop words, there were 355. The Best number in each column is boldfaced.

| Feature Representation | Feature Category          | J48  | NB   | SMO  |
|------------------------|--------------------------|------|------|------|
| Binary (Presence/Absence) | Stop words               | 89.73| 96.40| 96.00|
|                        | Word unigrams            | 92.80| 97.60| 98.40|
|                        | Word bigrams             | 67.87| 73.47| 73.87|
|                        | Word trigrams            | 36.80| 40.00| 40.00|
|                        | Character bigrams        | 84.53| 96.40| 96.40|
|                        | Character trigrams       | 79.60| 93.07| 92.27|
| Tf (Term Frequency)    | Stop words               | 92.93| 95.73| 97.60|
|                        | Word unigrams            | 94.93| 97.47| 98.80|
|                        | Word bigrams             | 69.20| 74.13| 74.40|
|                        | Word trigrams            | 36.80| 39.07| 40.67|
|                        | Character bigrams        | 90.93| 97.33| 98.67|
|                        | Character trigrams       | 85.07| 94.27| 96.93|
| Tfidf (Term Frequency  | Stop words               | 92.53| 95.87| 97.73|
| Inverse Document Frequency) | Word unigrams         | 95.20| 97.60| 98.93|
|                        | Word bigrams             | 65.87| 74.13| 74.00|
|                        | Word trigrams            | 36.80| 40.00| 40.67|
|                        | Character bigrams        | 91.47| 97.33| 98.40|
|                        | Character trigrams       | 85.07| 94.93| 97.93|

4.1.1. Feature Selection

We can find from Table 2 that among the different lexical features we considered; stop words, word unigrams, character bigrams and character trigrams give the best results. Hence we look into the performance of these features only in terms of their feature representations (tf/tfidf/binary) on the development set. The results are as shown in Table 1. We find that the highest development accuracy of 97.87% was obtained for 300 character bigrams.

Figure 1 shows that in almost all cases, increasing the number of features led to improved performance on the development set. However, we find over-fitting for character bigrams and trigrams beyond a certain number of features (around 300). This observation offers a completely organic feature selection strategy – cut off where the development accuracy dips for the first time. We have used Information Gain for feature selection, so e.g. the top k n-grams are the most discriminative k n-grams within the most frequent.
Fig. 1: Impact of number of features on accuracy. X-axis is Number of Features, and Y-axis is Percentage Accuracy on the development set (can be viewed in grayscale).

4.1.2. Learning Curve
With the feature set and classifier now optimized on the development data, we re-trained the model on train set (1,500 instances) and train + development set (2,250 instances), and measured accuracy on the test set that was untouched so far. In both cases, we obtained 97.73% test accuracy – thereby showing the viability of our approach on completely untouched held-out data. To be noted is the fact that this high test accuracy is similar to the high development accuracy we obtained in Section 4.1.1. This is because our samples were drawn from the same universe of authors. Furthermore, our test accuracy is superior to the state-of-the-art (84% reported by (Chakraborty 2012)), and more reliable because we worked with a
much larger sample of passages than (Chakraborty 2012) and (Das and Mitra 2011), and because we followed a more rigorous experimental paradigm by splitting our data into three parts and selecting the model on the development set.

In order to check the effect of size of training data on the performance, we plotted two learning curves, shown in Figure 2. Figure 2a shows the case when we train on the training data only, and test on the test data. Figure 2b shows the case when we train on a set consisting of both training and development data and test on test data. In both cases, we varied the number of training samples from 100 to 1,500 in steps of 100².

We empirically observed that the best test accuracy of 98.4% was obtained for 300 training instances + the development set (the first spike in Figure 2b). In general, the performance almost always stayed within a tight band between 95% and 99%, thus indicating the validity of our approach, and (relative) insensitivity to the number of training examples. We would like to recommend that 500 training examples should be good enough for practical applications.

Fig. 2: Learning curves. X-axis is Number of Training Samples, and Y-axis is Percentage Accuracy on the test set (can be viewed in grayscale).

² For Fig. 2b, the development set part was fixed, only the training samples were varied.
4.1.3. Feature Ranking

We next investigated the most discriminative features among Bengali stop words. The top 20 stop words are shown in Table 3, ordered by Information Gain (IG) on the training set. Note that apart from pronouns such as তার, এ, and চোর we also obtained do-verbs such as কর, কিরো কিরেত in the top ranks. This is an interesting finding.

Further, we show the term frequency of the features in the last three columns of Table 3, grouped by authors. Note that in all cases, Bankim Chandra’s passages contain many more of the stop words, indicating that the passages are longer and more complex (as mentioned in Section 3). Among Rabindranath and Sarat Chandra, the variations are less systematic. Sometimes Sarat Chandra has more occurrences of a particular word, sometimes Rabindranath.

Table 3: Feature ranking of most discriminative Bengali stop words (by information gain). PhTr = phonetic transcription (approximate); IG = information gain (on training set); FR, FS, and FB denote term frequency of the feature in the training set for Rabindranath, Sarat Chandra and Bankim Chandra, respectively.

| Rank | Word       | PhTr | Meaning | IG  | FR  | FS  | FB  |
|------|------------|------|---------|-----|-----|-----|-----|
| 1    | তার       | /tər/ | I do    | 0.898 | 9249 | 8572 | 42637 |
| 2    | এ         | /ə/  | this/these | 0.864 | 2288 | 2398 | 14174 |
| 3    | তা       | /tə/ | that    | 0.852 | 4899 | 3815 | 17559 |
| 4    | যে         | /jə/ | who     | 0.851 | 5595 | 4537 | 18624 |
| 5    | যে         | /jə/ | that/which | 0.843 | 4640 | 3186 | 14045 |
| 6    | যে         | /jə/ | no      | 0.828 | 4442 | 4321 | 19162 |
| 7    | যে         | /jə/ | that/which | 0.792 | 2035 | 1778 | 10172 |
| 8    | যে         | /jə/ | what    | 0.776 | 2152 | 3085 | 9912 |
| 9    | যে         | /jə/ | that/which | 0.762 | 2779 | 1946 | 10074 |
| 10   | যে         | /jə/ | or      | 0.748 | 4446 | 4361 | 16436 |
| 11   | যে         | /jə/ | after/other | 0.677 | 1332 | 1232 | 6738 |
| 12   | যে         | /jə/ | that    | 0.672 | 1364 | 1402 | 6634 |
| 13   | যে         | /jə/ | person/people | 0.660 | 958  | 646  | 4657 |
| 14   | যে         | /jə/ | having done | 0.657 | 1031 | 1245 | 5306 |
| 15   | যে         | /jə/ | and/also | 0.639 | 2294 | 2408 | 8669 |
| 16   | এই       | /əi/ | this    | 0.629 | 1055 | 752  | 4441 |
| 17   | যে         | /jə/ | not    | 0.601 | 413  | 425  | 3137 |
| 18   | যে         | /jə/ | to do   | 0.600 | 461  | 380  | 3215 |
| 19   | যে         | /jə/ | to be   | 0.578 | 502  | 343  | 2989 |
| 20   | যে         | /jə/ | he/she  | 0.578 | 2812 | 2128 | 7028 |
4.2. Author Topic Modeling

Author-Topic models have been used for authorship-attribution by some researchers ((Steyvers et al. 2004), (Rosen-Zvi et al. 2004)), for English. In each of these works, topic-modeling for authorship attribution gave better results, than the usual methods. In line with these findings we have tried topic-modeling for authorship attribution, which is done for the first time. We have used Mallet for topic modeling. Mallet is an open-source toolkit which implements the three topic modeling algorithms – Latent Dirichlet Allocation (LDA) (Blei et al. 2003), Pachinko Allocation (Li and McCallum 2006), and Hierarchical LDA (Blei and Jordan 2004), among others.

4.2.1. Data

We have considered the same stratified random sample of 3000 texts for our experiments. Among these, 1500 are in the training set, 750 are in the development and test sets each. Like all other topic-modeling tools which work for English only, Mallet also cannot handle Unicode data. For this, we first created a dictionary of unigrams and corresponding alphabetical indexes. We had to convert the Unicode unigrams to corresponding alphabetical indexes for all the 3000 sample texts.

4.2.2 Topics as Features

We first converted the Unicode words in 3000 sample files into corresponding alphabetic indexes. These files were then input to Mallet. We did the topic modeling for a maximum of 100 topics. Topic modeling assigns unique topic ids to the topics. The output consisted of the topic ids along with the probability of occurrence of that particular topic in a particular file. The output is sorted with respect to the probabilities.

3 Mallet home page http://mallet.cs.umass.edu/
The probability of the occurrence of the topics was generated for each of the 3000 samples distributed in the three sets. We have considered the probabilities as topics and did the classification using Naive Bayes for development set. We have tested the effect of topics on a text sample for the cases - *with stopwords* and *without stopwords*.

*Table 4*: Percentage accuracy of NB classifier when trained on the training set and tested on the development set, for topic models. Highest accuracy values are in bold.

| No. of topics | % Accuracy in NB |
|---------------|------------------|
| 10            | 99.8665          |
| 20            | 100              |
| 30            | 99.3324          |
| 40            | 99.733           |
| 50            | 99.8665          |
| 60            | 99.8665          |
| 70            | 99.466           |
| 80            | 98.7984          |
| 90            | 99.0654          |
| 100           | 98.6649          |

| No. of topics | % Accuracy in NB |
|---------------|------------------|
| 10            | 100              |
| 20            | 99.466           |
| 30            | 98.1308          |
| 40            | 92.6569          |
| 50            | 84.5127          |
| 60            | 83.7116          |
| 70            | 82.51            |
| 80            | 81.3084          |
| 90            | 81.3084          |
| 100           | 81.5754          |

The experiments for both the cases were repeated n times, where n = 10 × i, with i = 1, 2,...,10. It was seen that classification using topic models gave very good accuracy values (upto 100%) with or without stop words as shown in Table 4. Without the stop words, the less the topmost topics were considered the more better the results were. Best result of 100% accuracy is shown when the number of topics is 20. After which we can find overfitting when the number of topics
increases. Next we tried to find out whether the size of training data had an effect on the performance of the model or not. So we ran the classifier for the training set and development set together as training set and tested it against the test set. The experiment was done for both the cases again - with stop words and without stop words. It was seen that for this scenario, the experiment gave best results with stop-words, with the accuracy values ranging within 100% - 98% as shown in Table 5. This showed that the results bettered when the size of the training set increased.

Table 5: Percentage accuracy of NB classifier when trained on the training set + development set and tested on the test set, for topic models. Highest accuracy values are in bold.

| Features            | No. of Topics | % Accuracy in NB |
|---------------------|---------------|------------------|
| With Stop Words     |               |                  |
| 10                  | 100           |                  |
| 20                  | 99.8667       |                  |
| 30                  | 100           |                  |
| 40                  | 100           |                  |
| 50                  | 100           |                  |
| 60                  | 99.7333       |                  |
| 70                  | 99.8667       |                  |
| 80                  | 99.4667       |                  |
| 90                  | 98.8          |                  |
| 100                 | 99.333        |                  |
| Without Stop Words  |               |                  |
| 10                  | 100           |                  |
| 20                  | 99.466        |                  |
| 30                  | 98.1308       |                  |
| 40                  | 92.6569       |                  |
| 50                  | 84.5127       |                  |
| 60                  | 83.7116       |                  |
| 70                  | 82.51         |                  |
| 80                  | 81.3084       |                  |
| 90                  | 81.3084       |                  |
| 100                 | 81.5754       |                  |
5. CONCLUSION

We presented the first large-scale study of authorship in Bengali. Not only we studied the effect of lexical features, we also studied the effect of topic modeling. As part of our study, we constructed a corpus of 3000 literary passages from three eminent Bengali authors. On our balanced dataset, we performed classification experiments, reached state-of-art test accuracy of 98% using character bigrams (tf) character bigrams (tf) as features and Naive Bayes classifier. We further showed how performance varied on held-out data as the number of features and the number of training samples, were altered. In most cases, we obtained a range of accuracy values between 95% and 99%. We analyzed the most discriminating features (stop words) and showed that the passages from one of our authors (Bankim Chandra), were longer and more complex than others. Not only this, we got upto 100% accuracy when we repeated our experiments with topics as features. This showed that topic modeling if used in AA can increase the performance of a system. To the best of our knowledge, our study is the first reliable attempt at authorship attribution in Bengali, especially because prior studies had very limited training and test data. As future work, we would like to extend our approach to other forms of text, such as blogs, news articles, tweets, and online forum threads.
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