Author Verification using PPM with Parts of Speech Tagging

Notebook for PAN at CLEF 2014

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Abstract In this paper we describe a compression-based authorship verification model used in conjunction with a parts of speech tagger. We use standard language-specific parts of speech taggers on the texts in question to generate a stream of symbols representing each word, run the PPM (Prediction by Partial Matching) algorithm on the resulting stream, and use Bobicev's method of calculating and comparing cross-entropies to determine text authorship.

1 Introduction

Authorship attribution is generally described as determining the author of a particular disputed work. This is framed as a problem of authorship identification, where, given a sample of documents of known authorship, identify which author wrote the unknown text. This may also be framed as a problem of authorship verification, where we simply want to get a binary answer of whether the author in question wrote a particular text. This is one of the tasks set for PAN2014, an evaluation lab for methods relating to various aspects of stylometry[2][3].

PPM is a popular off-the-shelf compression method that has been explored for attribution purposes[7][1][4], but it has primarily only been explored for raw texts, and primarily only for the English language. We extract the statistical model powering PPM and use its predictive capabilities on a per-word basis as opposed to a per-character basis in previous experiments. We pre-process the texts in question to convert into POS-symbol streams, use PPM to calculate entropies, then calculate the probability of authorship based on these entropies.

2 Methodology

The basis of our method is extremely simple: run the texts in question through a parts of speech tagger and label each corresponding part with a symbol, then run the PPM algorithm on the resulting symbols, and calculate the cross-entropy between the known and unknown texts. This method is an extension of [1], in that we use the same method of calculating cross-entropies and running a pairwise t-test on the results. We change things slightly by simply preprocessing the text by running the parts of speech tagger.

2.1 Parts of speech tagging

The effectiveness of PPM on texts is purely dependent on whether or not the context size of the model can accurately capture word usage patterns. While PPM usage has been studied on English texts[8][9], it appears that its effectiveness is relatively unknown on other forms of texts. We posit that this is due to the fact that the effectiveness of PPM per-language requires context-sizing tweaks to accurately capture patterns in symbols for other languages. We decide to reduce the texts in question to symbols representing the parts of speech of the original words, and assess the effectiveness of the PPM statistical model on per-word instead of per character instances.

We used TreeTagger[6][5] for converting texts to their parts of speech equivalents, due to the fact that it had support for English, Dutch, and Spanish language tagging. Unfortunately due to time constraints we were not able to test other English speech of taggers (of which there are numerous), nor were we able to test this method for the Greek corpus.

2.2 Prediction by Partial Matching (PPM)

PPM is a compression technique that makes use of a combination of a previously seen context along with Markov chains to generate a statistical model that represents the originally seen text. Symbols on an input stream simultaneously update the model, in addition to being arithmetically coded in the resulting output stream. For the purposes of authorship attribution it is simpler to discard the arithmetic coder and any 'state' optimizations in place for compression; we are mostly only concerned with the statistical model for which we use to calculate the next character probabilties, and thus the resulting entropies, of the text in question.

The basic methdology for PPM is as follows:

1. Assume: a context structure already containing previously seen symbols in the stream
2. Read a symbol s from the stream
3. Query the context structure as to whether an n-order chain exists containing $n-1$ previously seen symbols along with s
4. If an n-order chain does not exist...
   (a) Query the $n-1$-order chain with $n-2$ previously seen symbols along with s
   (b) Repeat for progressively smaller chains until an order -1 chain is reached
5. Increment the symbol counter in the context structure for n, $n-1$, ... -1 order chains. If the symbol does not exist, initialize it in all context-matching chains that do not yet contain the symbol s.
6. Repeat for each successive symbol s

We wrote our own version of PPM in C using a hard-coded symbol context-size of 5. Code for this is available on Github[1].

[1] `https://github.com/worldwise001/ppm-c/`

2.3 Cross-entropy calculation

We used Bobicev's cross-entropy calculation method for comparing entropies generated by the PPM model[1]. A rundown of the algorithm is as follows:

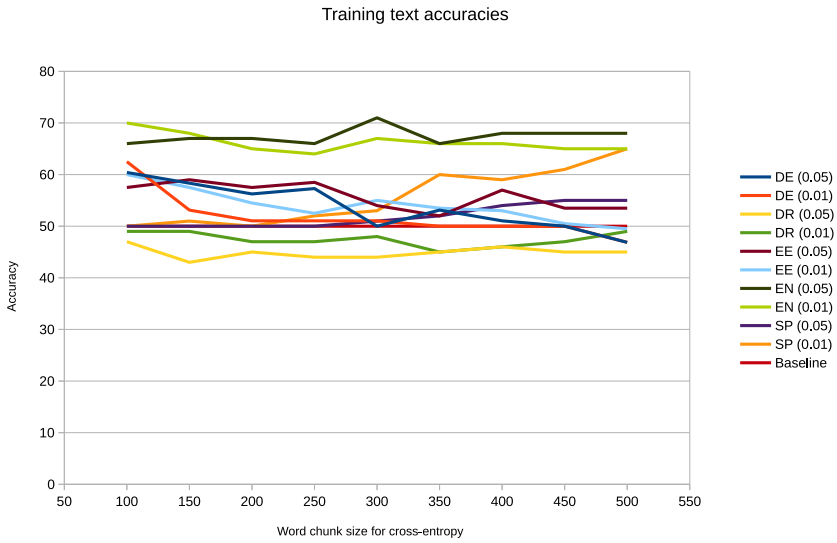
- Concatenate all known-author texts into a text K. Let the unknown-author text be known as text U.
- Split K into k fixed n-size text chunks, and split U into u fixed n-size text chunks.
- Generate same-entropies
  - For each k:
    - Generate a PPM statistical model on $(K - k)$
    - Run the model on k and calculate the resulting entropy.
  - For each u:
    - Generate a PPM statistical model on $(U - u)$
    - Run the model on u and calculate the resulting entropy.
- Generate cross-entropies
  - Generate a PPM statistical model on U
  - For each k:
    - Run the model on k and calculate the resulting entropy.
  - Generate a PPM statistical model on K
  - For each u:
    - Run the model on u and calculate the resulting entropy.
- Compare the same-entropies with the cross-entropies using a pairwise t-test with a null hypothesis that the values are equivalent. If the null hypothesis is accepted, then we can consider that K and U are written by the same author.

Determining the appropriate values for n and the p-value for pairwise t-test required some initial experimentation. We settled on a n value of 300 (i.e. a word chunk size of 300), for most languages, with the exception of Spanish, which had a n value of 100. We also used a standard p-value of 0.05 for most languages, with the exception of Spanish, which used a p-value of 0.01.

3 Results

3.1 Initial testing

We briefly experimented with varying the cross-entropy chunk sizes, in order to determine how the value of 350 words was determined in [1], while simultaneously comparing t-test thresholds across languages. A graph showing the results on the training texts is as follows:



3.2 Training results

Corpus	AUC	C@1	Combined
Dutch Essays	0.64497	0.61046	0.39373
Dutch Reviews	0.4391	0.5	0.2197
English Essays	0.585	0.53	0.31005
English Novels	0.6728	0.71	0.47769
Spanish Articles	0.7858	0.65	0.51077

3.3 Test results

Corpus	AUC	C@1	Combined
Dutch Essays	0.6441	0.61458	0.39585
Dutch Reviews	0.354	0.48	0.16992
English Essays	0.57855	0.54	0.31242
English Novels	0.5398	0.525	0.2834
Spanish Articles	0.79	0.65	0.5135

4 Conclusion and Future Work

We present a variant on the usual compression-based attribution scheme by adding a preprocessing step of converting the texts into their respective parts of speech before analysis. This produced results that were particularly poor for Dutch Reviews, but surprisingly well for Spanish Articles and Dutch Essays. It is likely that more work will be needed to examine the effectiveness of this method, particularly with tweaking the chunk sizes, PPM context sizes, or perhaps experimenting with other parts of speech

taggers. The notable difference in performance between Dutch Reviews and Dutch Essays brings possible questions of determining how the stylistic properties of both texts may be determined and captured effectively for automated analysis.

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