

STYLOMETRIC NETWORKS AND FAKE AUTHORSHIPS

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Submitted: 9 November 2015

Abstract

This paper addresses two problems: (a) whether and how tools developed to analyze network structures can be applied to the stylistic analysis of texts or text corpora and specifically to authorship attribution problems; and (b) whether it is possible to sample text fragments of an author A so as to imitate the style of an author B. The sample corpora in this study comprise 10–500 English novels from the 19th and 20th centuries.

The simple question “Who wrote this text?” does not always have a simple answer: There may be multiple coauthors contributing to varying degrees [1], editors and publishers, and, not least, translators [2]. Even more broadly, authorship attribution can be seen in terms of quantifying authorial style. Besides his or her own idiosyncrasies, however, the author interweaves such threads as the topic and setting of the writings, narration type and genre [3], the influence of literary school, movement or period and finally, his or her tongue(s).

The questions we pose are: How can we disentangle these threads? Can complex networks tools be of use?

Stylometric Networks

Various machine-learning techniques have been used for attributing authorship to texts [4]. The accuracy of such methods in English reaches 95%. Given that networks can represent stylistic likeness between authors or books, community detection [5] can be used as an unsupervised clustering method.

Figure 1 shows that based on nonlemmatized words (over 1/3 synsematic) shared by all texts, supervised techniques perform better (even after accounting for a learning set comprising 4/5 of the corpus). Note that Normalized Mutual Information (NMI) depends not only on the percentage of errors but also on the corpus size; hence comparing supervised and unsupervised methods is nontrivial. Despite the above result, community detection appears feasible in exploratory analysis, since, e.g. it reasonably assigns Fielding’s parodic *Shamela* to Richardson’s novels (including *Pamela*) or clusters together in 5 groups about 30 authors from the Chawton House corpus of women writers. For detailed information on corpora, see Ochab [8].

Fig. 1. Comparison of Louvain [6] modularity optimization (horizontal axis corresponds to resolution) and supervised clustering based on Eder’s delta distance [7]. Different ways a text can be misclassified result in a range of NMI values (horizontal stripes). (© J.K. Ochab)

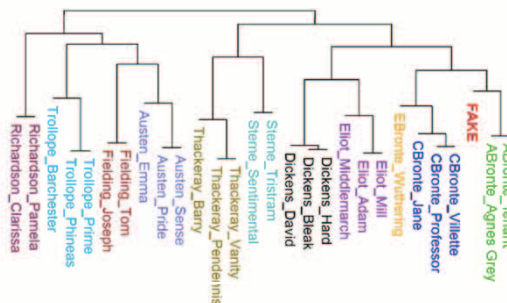
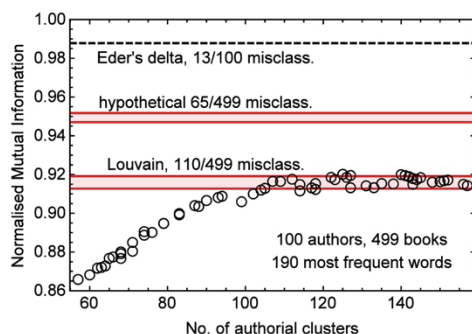


Fig. 2. Clustering of 27 classic English novels together with a computer-generated hybrid text using Thackeray’s vocabulary and distribution of parts of speech from A. Brontë’s *Anne Grey*. The algorithm is fooled when text similarity is measured with 100 most frequent words. (© J.K. Ochab)

Fake Authorships

In order to disentangle—at least partly—what comprises authorial style from the viewpoint of a classic authorship attribution technique, we take a simple approach: We tailor computer-generated texts in a humanly interpretable way to see at what point the technique fails.

Since the Burrows’s Delta method clusters texts based on distances obtained from vectors of word-occurrence frequencies, we tune these frequencies indirectly, using grammar. Namely, we (i) collect words of author A into part-of-speech (PoS) categories [9]; (ii) measure a distribution of PoS in a book by author B to be imitated; and (iii) randomly sample PoS from (ii) but words from (i). This retains A’s word (stylistic) preferences within PoS categories, while statistically conforming to B’s real sentence structures. Figure 2 shows a successful example of fooling the clustering algorithm with such a hybrid. Still, the attribution is highly dependent on the corpus and the range of most frequent words chosen for distance measurement.

References and Notes

- This paper was presented as a contributed talk at Arts, Humanities, and Complex Networks—6th Leonardo satellite symposium at NetSci2015. See <http://artshumanities.netsci2015.net>. JKO acknowledges funding by Grant No. DEC-2013/09/N/ST6/01419 of the National Science Centre of Poland.
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