Stylistic Fingerprints, POS-tags, and Inflected Languages: A Case Study in Polish

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ABSTRACT

In stylometric investigations, frequencies of the most frequent words (MFWs) and character n-grams outperform other style-markers, even if their performance varies significantly across languages. In inflected languages, word endings play a prominent role, and hence different word forms cannot be recognized using generic text tokenization. Countless inflected word forms make frequencies sparse, making most statistical procedures complicated. Presumably, applying one of the NLP techniques, such as lemmatization and/or parsing, might increase the performance of classification. The aim of this paper is to examine the usefulness of grammatical features (as assessed via POS-tag n-grams) and lemmatized forms in recognizing authorial profiles, in order to address the underlying issue of the degree of freedom of choice within lexis and grammar. Using a corpus of Polish novels, we performed a series of supervised authorship attribution benchmarks, in order to compare the classification accuracy for different types of lexical and syntactic style-markers. Even if the performance of POS-tags as well as lemmatized forms was notoriously worse than that of lexical markers, the difference was not substantial and never exceeded ca. 15%.

Introduction

In classical approaches to authorship attribution, frequencies of the most frequent words (MFWs) and other style-markers such as character n-grams are claimed to outperform other types of style-markers (Koppel et al., 2009; Stamatatos, 2009), even if their performance varies significantly across different languages (Eder, 2011; Evert et al., 2017; Rybicki & Eder, 2011). Also, it has been proven that attribution based on single words and, even more so, on letter n-grams reveal a very high resistance to errors in corpora such as those derived from imperfect OCR (Eder, 2013). A previous study in authorship attribution performed on a large corpus of Polish novels (Rybicki, 2015a) confirmed the usefulness of most frequent words. Defined, for any text analysis software, as simple strings of letter- and non-letter characters, all
these plain features are easily extracted from input texts. One should not underestimate the implications of such an efficient combination of simplicity and performance. Namely, a stylometric test – be it authorship attribution or a distant-reading analysis of literature using quantitative methods – can be applied to any web-scraped plain text file with a high probability of achieving acceptable results.

Very attractive as they are, these shallow text features also have their limitations. Firstly, there is little theory that would explain the phenomenon of the visibility of authorial stylometric signal of the very frequent features – apart from the general and intuitive assumptions that authors might be possessed of their own ‘stylistic fingerprint’ (Kenny, 1982, p. 12) or that the very frequent words, for instance, might define authorial style by establishing the context for the less frequent yet more ‘meaningful’ words (McKenna et al., 1999). Certainly, there exist studies that aim to provide a convincing theoretical background for stylometry (Kestemont, 2014); nevertheless, one can say that we are still at the beginning of the journey. This lack of theory might be the reason why many scholars look askance at frequency-based quantitative analyses and, consequently, that there is little dialogue between quantitative and qualitative approaches to textual analysis.

Second, the above-cited findings (Eder, 2011; Evert et al., 2017; Rybicki & Eder, 2011) cast doubt whether the appropriateness of a quantitative frequency-based method developed for one language easily translates into similar success in another, as has been suggested in earlier studies (Juola, 2009). In fact, the high discrepancy in authorial attribution success observed in the 2013 experiment has been suspected by the researchers to stem from the differences in the inflection of the languages compared. The observation that highly inflected Polish fared worst among less inflected languages such as English or German will be quite relevant in the context of the present study.

To explore further the hypothesis of inflection’s role in attribution: it is obvious that, in inflected languages, different forms of the same word cannot be recognized using generic text tokenization (e.g. via regular expressions). This is a possible source of error, since, in languages such as Polish, word endings play a prominent role; as a result, much of the grammatical information that is easily available in, say, English function words, remains ‘hidden’, or ‘dissolved’, in inflected nouns or verbs, and has no way of making it to the top ranks in frequency lists: these countless inflected word forms make word frequencies sparse, and this complicates most statistical procedures.

Meanwhile, morphologically rich languages with relatively free word-order, such as Polish, are significantly different from the grammatical point of view, and it should not come as a surprise that they make the task substantially different. With its 7 cases multiplied by 2 numbers, singular
and plural (and, to make things even more complicated, vestiges of the dual coexisting with the plural, as in oczyna: oczami ‘eyes’ instrumental), a Polish noun might have up to 14 different inflected forms. As if this were not enough, nouns with two alternative endings for some cases are not infrequent (e.g. reżyserzy: reżyserowie ‘film directors’ nominative plural). This figure is multiplied when adjectives are concerned, since they inflect by case, by number, and by gender: there are three genders in the singular and two in the plural (+human masculine vs. – human masculine). And while regular homonymy within the inflection paradigm of the Polish languages keeps those inflected forms considerably lower than the above-presented worst-case-scenario, this comes at the cost of a greater degree of ambiguity. The same general rule holds for verbs, pronouns and numerals.

This brings us back to the question of authorial attribution, this time in the distinct context of rich inflection. Presumably, the problem of the morphological abundance can be overcome – at least to some extent – by lemmatization, or transforming the original sequence of words into their base forms, as in the following example: w jednym z pomniejszych miast perskich mieszkali dwaj bracia (original words), w jeden z pomniejszy miasto perskie mieszkać dwa brat (lemmatized words). From a theoretical point of view, the difference between a sequence of original forms and lemmatized words is not as big as it might seem. After all, any stylometric inference based on word frequencies means in fact reducing a very complex phenomenon – the natural language – into its simple representation, while filtering out a vast amount of original information. Lemmatization is no different in this respect, except that it reduces the language even more, by cutting off grammatical information held by the original word forms.

Being an obvious remedy for data sparseness, lemmatization should increase the visibility of the authorial signal. However, an opposite hypothesis is also plausible, namely one can assume that the (grammatically richer) original word forms preserve a cleaner authorial signature than the grammar-less lemmas. Finally, a hypothesis that the signal is hidden between the original forms and the lemmas – i.e. in the grammatical structure itself – cannot be ruled out. From a linguistic point of view, this third scenario is rooted in fundamental questions of the authorial freedom of choice vs. constrains of the language.

In principle, grammar will always constrain the authorial freedom of choice to a significantly greater degree than it constrains the (usually very individual) lexical repertoire. If an author wishes to describe a given entity with an adjective, there exist numerous words to choose from: e.g. the entity’s size may be big, large, great, considerable. However, if we take into account grammatical categories, the entity will inevitably be represented by a sequence [Adjective] + [Noun]. Moreover, despite some limitations in combining words (such as the impossible Chomskyan green dreams), these
limitations are much more rigid on the syntactic level than on the lexical level: once a transitive verb is introduced, it has to be followed by an object. Additionally, the case of the object cannot be freely chosen – it is assigned by the verb. Therefore, we can easily formulate a pre-empirical assumption that authors enjoy much larger freedom of choice on the level of lexis compared to syntax. Certainly, novelists usually try to be creative and do not adhere to most typical collocations, but even a highly experimental artistic novel cannot ignore language constraints.

It is quite clear, then, that grammar should not be excluded from the experimental setup of the present study. Yet, the problem of extracting the grammatical structure from texts (referred to as parsing) is far more complex than lemmatization. It is true that, despite new developments in this area, automatic parsing is still somewhat unreliable and obtaining a tailor-made tree bank is beyond our capabilities; however, straightforward insight into grammar can be obtained using Part-of-Speech (POS) tags combined into n-grams (Wiersma et al., 2011). Attempts to solve this problem have already yielded promising results (Baayen et al., 1996; Hirst & Feiguina, 2007) – yet, once again, mostly in English.

The downside of such an approach is that the POS n-grams can provide us with a rather rough model of syntax or, in the words of Wiersma et al. (2011), ‘a good aggregate representation of syntax’. However, since these features were compared in the context of repetitive authorial decisions – conscious or unconscious – that make texts by the same author more similar to each other than to texts by other authors, there was some hope that such an experiment might provide an insight to the various degrees of linguistic choice at the lexical and/or syntactic level.

Because of the complexity of individual word forms’ grammatical information, morphologically rich languages are usually annotated with so-called positional tags, i.e. sequences of codes for all the values of grammatical categories that pertain to a word, where only one segment of a tag stands for the part of speech itself. To illustrate, while the English word impossible is tagged AJ0 (Adjective, general or positive), the Polish niemożliwemu, the Dative Singular of the same adjective impossible, must be described by a fairly verbose tag: adj:sg:dat:m1:pos, where ‘adj’ stands for Adjective, ‘sg’ for singular, ‘dat’ for Dative, ‘m1’ for Masculine-Virile, ‘pos’ for Positive Grade. Consequently, this complex tag is a bundle of inflectional features of the word; its code for case, number, and gender sg:dat:m1 can also form a part of a substantive or participle, whereas the first segment of the sequence, ‘adj’, is the only part of the tag that is directly comparable to its English counterpart.

Arguably, a Polish unlemmatized text has a much lower type/token ratio than a lemmatized one. Equally obviously, a comparable English text (for instance, an English translation of a Polish text) produces a lower TTR.
Finally, the difference of TTR in a lemmatized and unlemmatized English text is much less prominent. In the context of automatic POS tagging, the difference accounts for a substantial increase in the difficulty of this task as the rich morphology in Polish requires a vast number of tag-types. The tagset of the National Corpus of Polish (Przepiórkowski et al., 2012) amounts to over 1,000 tags, a full degree of magnitude more than the mere 140 tags in the CLAWS-8 tagset for English. This means, among other things, that a Polish POS-tagged text would produce much lower frequencies for every POS type. And if this were not enough, the relatively free word order in Polish makes one expect a higher number of different POS-tag combinations (n-grams), since a sequence of two or more parts of speech can occur in different order. It is true that several restrictions on Polish word order might slightly attenuate this phenomenon, e.g. the preposition can never be placed in postposition, and the negation of the verb must immediately precede the latter, nevertheless the increase in the number of possible POS-tag n-grams is still remarkable.

**Hypothesis**

With all the above remarks taken into the consideration, we can now formulate the research questions to be addressed in this study: firstly, we aim to empirically examine the amount of authorial signal that resides in grammar as assessed through POS-tags; secondly, we aim at comparing the performance of original word forms against lemmatized forms (a scenario in which some of the grammatical information is stripped out). Additionally, we aim to test the extent to which particular segments of positional tags (analysed separately and combined into n-grams) might be useful in this respect. Therefore, apart from the entire tags, their segments have also been assessed, namely n-grams of single categories, as well as combinations of two tag segments. In this approach the Polish word sequence jedną czerwoną ranę (one red wound in the Accusative form) was analysed as word forms, as lemmas (e.g. jeden czerwony rana), and as different chains of POS-tag parts:

1. entire tags, e.g. [adj:sg:acc:f:pos] + [adj:sg:inst:f:pos] + [subst:sg:acc:f];
2. POS tags in the strict sense, or the first segments only, e.g. [adj] + [adj] + [subst];
3. tags cut off after their second segment, e.g. [adj:sg] + [adj:sg] + [subst:sg].

The above word forms, lemmas and different variants of grammatical tags were further combined into n-grams (ranging from 1 g to 3 g), resulting in 15 distinct types of style-markers assessed individually in controlled authorship attribution tests.
Our working hypothesis is that the grammatical layer will exhibit some traces of authorial signal, yet they will not overshadow the primary signal produced by the lexical layer. As for the lemmatized vs. unlemmatized words as efficient style-markers, we hypothesize that an input text partially stripped out of grammar, i.e. lemmatized, will exhibit a slightly stronger authorial voice compared to original word forms.

**Data and Method**

In order to corroborate the above hypotheses, we compiled a tailored corpus of 189 novels in Polish. It is true that restricting the choice to exclusively one genre (literary novels) will not allow us to generalize the results to the Polish language in its entirety. However, we wanted to control for genre in our experiments, as it is usually a crucial factor in authorship attribution. Similarly, we choose novels because of their naturally large size, which will prevent the authorial signal from being blurred by the short sample effect.

The corpus consists of Polish novels from the 20th century, all of them drawn from the National Corpus of Polish. They were processed using the Pantera tagger (Acedański, 2010) fully automatically. No stop lists were used, punctuation marks were treated on a par with words, certainly the same holds for POS-tags. The full dataset consisted of 189 Polish novels written by 46 authors; each author was represented by 3 to 6 texts (4.1 on average). The chronological range was maintained to be possibly narrow, in order to minimize the potential impact of diachronic linguistic change; it has been reported that chronology is a strong signal in most-frequent-word-based stylometry (Burrows, 1996; Rybicki, 2015b). Smaller subsets of the main corpus were also analysed in two additional cross-check experiments, one involving 99 novels by 33 authors, and the other 30 novels by 10 authors (in both setups, the even number of 3 books per author was secured). Due to copyright restrictions, the novels used in this study could not be made publicly available. However, we post all frequency tables used in this study, as well as the full set of the results, followed by the code needed to replicate the tests, on our GitHub repository: https://github.com/computationalstylistics/PL_lemmatization_in_attribution.

In all, 5 different variants of features were tested for attribution success: (1) unlemmatized words (original word forms); (2) lemmatized words; (3) full tags; (4) POS-tags in the strict sense, i.e. the labels of the Part of Speech alone; (5) two initial tag parts. All these were analysed in n-grams, at n from 1 to 3; which resulted in 15 independent classification experiments. The analyses were performed for 35 features, and then for 100, 150, 200 and onward up to 2,000 most frequent items, by increments of 50. Finally, four supervised machine-learning classifiers were compared: Burrows’s Delta, Cosine Delta, Support Vector Machines (SVM), and Nearest Shrunken
Centroids (NSC). The entire experimental setup was repeated for the three variants of the corpus, comprising 189, 99 and 30 novels, respectively.

The choice of the four classification methods was based on their time-proven applicability to solving authorship attribution tasks. Delta, a simple distance-based method introduced by Burrows (2002), enjoys a reasonable share of attention in stylometry due to its simplicity and efficiency. Next comes its variant known as the Cosine Delta, which has been proven to outperform most of distance-based classifiers (Evert et al., 2017). The Nearest Shrunken Centroids, another distance-based learner, has also been successfully applied to text classification (Jockers & Witten, 2010). Support Vector Machines is a widely-known multidimensional classifier, commonly believed to be one of the best machine-learning techniques for data analysis. It has been shown that the performance of this method is very high indeed (Jockers & Witten, 2010; Koppel et al., 2009). In our approach we use a simple SVM setup: linear kernel (rather than polynomial) with the cost parameter set to 1 (rather than optimized in cross-validation). While parameter tuning usually improves the performance of SVM, we aimed at keeping the experimental conditions identical for all analysed scenarios.

One has to emphasize, however, that the classification setup we deal with here is substantially different from typical attribution problems, since it involves multiple classes, instead of the usual two or three. Such a situation is referred to as the ‘needle in a haystack’ attribution scenario (Koppel et al., 2009), i.e. a type of attribution in which the real author is hidden among a very high number of false candidates. An obvious question arises whether a multi-class setup – significantly more demanding than a standard attribution experiment – is a good choice to assess the performance of different style-markers in a given corpus. An answer to this question is twofold. Firstly, it must be remembered that, since there are not so many prolific authors, the number of available texts is also limited; moreover, the access to electronic versions of those texts is also restricted. Our corpus is no exception – the main criterion of including particular texts was their availability. Secondly and more importantly, a corpus of diverse authors, authors’ genders, genres, topics, audience targets etc. eliminates possible biases that we can easily overlook. Above all, however, we should emphasize that we did not aim to improve the overall accuracy in absolute terms. Rather, we aimed at comparing the efficiency of several style-markers under identical conditions of the experiment.

The analyses were done using a custom script for R, based on the crossv() function of the stylo package (Eder et al., 2016). Particular combinations of style-markers, n-grams, and classifiers, were assessed independently. The scores for subsequent ranges of the most frequent items were recorded in a leave-one-out cross-validation scenario. In such a case, all the texts but one were put into the training set, and the remaining single sample was classified
against the training set. The same procedure was performed iteratively over the corpus, in each iteration a subsequent text (one at a time) being excluded for classification. The resulting row of predicted classes was then compared against the expected classes, and the number of correct ‘guesses’ was recorded as the model’s general accuracy.

Being conceptually very simple and compact, however, accuracy is considered to overestimate the actual classification performance. For this reason, a routinely applied toolbox of measures not only includes accuracy, but also recall, precision, and particularly the F1 score. The reason why these somewhat less intuitive measures are often neglected in stylometric studies, is that they are not designed for assessing multi-class scenarios. Since in our experiment 46 authorial classes were involved, we relied on macro-averaged versions of precision, recall and the F1 score (Sokolova & Lapalme, 2009). Keeping in mind that the F1 score in a way combines the information provided by both recall and precision, this will be our primary diagnostic measure hereafter.

Results

The high number of particular attribution tests for different classification methods, features, n-grams, and datasets, calls for a structured way of presenting the results. For this reason, we will start with a manual inspection of a somewhat random subset of outcomes. We will then summarize the differences between the three datasets, the four classifiers, and finally, we will discuss the performance of particular style-markers: original words, lemmas and POS-tags.

A small subset of the results is presented in Table 1. Here we report the performance for the full corpus of 189 novels, original word forms (MFWs), n-gram size set to 1 (i.e. single words), the Cosine Delta classifier, and 8 different vectors of the most frequent features. At a glance, one can identify a sweet spot of performance at 200 MFWs, but a broader picture shows that similar local areas of better (or worse) performance are not infrequent. In

| MFWs | accuracy | precision | recall | F1 score |
|------|----------|-----------|--------|----------|
| 35   | 0.687    | 0.640     | 0.662  | 0.637    |
| 100  | 0.825    | 0.821     | 0.816  | 0.805    |
| 150  | 0.867    | 0.878     | 0.857  | 0.855    |
| 200  | 0.888    | 0.911     | 0.890  | 0.885    |
| 250  | 0.857    | 0.883     | 0.860  | 0.848    |
| 300  | 0.862    | 0.884     | 0.866  | 0.858    |
| 350  | 0.873    | 0.889     | 0.879  | 0.872    |
| 400  | 0.878    | 0.899     | 0.885  | 0.882    |
| …    | …        | …         | …      | …        |
fact, the classifier reaches its plateau of optimal performance at around 700 MFWs, to slightly decrease for the vectors of more than 1,200 MFWs.

Due to the obvious limitations of presenting the results in a tabular format, below we present the outcomes in a form of compact plots, so that reasonable amounts of information can be shown concurrently. To further increase the clarity of the plots, we will report the F1 scores only, while delegating all the remaining measures to the GitHub repository.

Conveniently, the comparison starts with an overview of the three datasets we used in our study, i.e. the corpora of 189, 99, and 30 novels, respectively. As it turns out, the general outcome of the experiment depend, in good accord with intuition, on the size of the corpus. The best average scores were obtained for the 30-novel subset; the subcorpus of 99 novels fared somewhat less well; the performance of the entire set of 189 novels, however, turned out to be very similar to that of 99 novels (Figure 1). As a whole, the results were poorer than expected, even taking into account the fact that the big number of 46 authorial classes – the needle-in-a-haystack scenario – was responsible for this effect. For the subset of 99 texts by 33 authors, the highest F1 score achieved was as high as 0.91 for the most effective set of input parameters. For the entire set of 189 novels, the highest observed score was 0.92. For 30 novels by 10 authors, the score of 1 was reached for some style-markers combined with Cosine Delta and, to a lesser extent, with NSC.

![Figure 1](image_url)

**Figure 1.** Overall performance (F1 scores) for three datasets of 189, 99, 30 novels. Particular curves represent all the style-marker types and all the classifiers.
Despite being compact, the resulting plot (Figure 1) is rather difficult to read. For this reason, the information to be plotted will be further reduced in the following figures. The undeniable collinearity between the three corpora of 189, 99, and 30 novels – despite a few notable exceptions that will be discussed below – allow us to focus exclusively on a single dataset. Therefore, in the following sections we will show the behaviour of the 189-novel corpus alone, delegating the all the remaining results to the GitHub repository.

The next comparison was that among our four classifiers. As shown in Figure 2, the curves representing performance for each of the classifiers tend to differ significantly. The top (blue) lines are those for Cosine Delta, outperforming all the other techniques, as evidenced in recent scholarship as well (Evert et al., 2017). Next go the performance curves for Classic Delta that, up to ca. 150-word vectors, run together with those for SVM; but then more and more Classic Delta curves come to the fore while those for SVM (grey) show a decrease in performance. NSC exhibits its full potential when long vectors of features are concerned, which stands in contrast with the behaviour of SVM – while NSC seems to struggle when the feature space is limited, SVM feels overwhelmed by the abundance of features. Delta’s overall good performance (in both Classic and Cosine variants) can be partially explained by the fact that in multi-class setups, distance-based methods usually outperform SVM (Luyckx & Daelemans, 2011).

![Cosine, Delta, NSC and SVM](image)

**Figure 2.** Overall performance (F1 scores) for the dataset of 189 novels and four different classifiers: Classic Delta, Cosine Delta, SVM and NSC.
Next comes the comparison of particular style-markers’ types. The main research question here is whether lemmatization improves the accuracy of classification. In Figure 3, for Cosine Delta, the classical frequent word approach (MFWs) is highlighted, while all the other curves are kept in the background. Most frequent word 1-grams (on top) are followed by 2-grams, and then 3-grams (at the bottom). As can be observed, this simple and time-proven type of features turns out to be the clear winner of the experiment, at least when Cosine Delta and 189-novel dataset is concerned. At the same time, however, the same features combined into 3-grams turn out to be unsatisfactory as style-markers, reaching the F1 rate of ca. 0.77. There is an explanation of this phenomenon: being highly inflected, Polish has also a free word-order, which exponentially increases the number of available word 3-grams (let alone wider n-grams) and leads to substantial data sparseness.

Being the best performer, however, frequent word 1 g are followed very closely by their immediate competitor, i.e. frequent lemmatized word 1 g (Figure 4). The general picture of the lemmatized words is very similar to that of the unlemmatized ones, in terms of both the dispersion between particular n-grams, and the sequence of the curves: 1 g are on top, then go 2 g, while 3 g are below any acceptance level. Another noteworthy observation is the fact that both lemmatized and unlemmatized 1 g (and 2 g, to a lesser extent), rise well above the 0.8 line, which serves as the (mostly unattainable) ceiling for other style-markers.
However, the rather small divergence between the lemmatized and unlemmatized words calls for further exploration. Even if manual inspection of the respective curves (Figures 3–4) shows that one of the style-markers outperforms the other, rigorous statistical testing might suggest otherwise. A standard way to compare two independent variables, is to scrutinize them using the t-test. In our case, however, the variables in question don’t meet the formal requirements for t-testing, since neither of them follows the normal distribution, and their variances differ significantly. In such a case, Wilcoxon test should be used instead. According to Wilcoxon test, the difference between lemmatized and unlemmatized words (for Cosine Delta and the dataset of 189 novels), is indeed significant with a marginally low $p$-value <0.00001. The results of a systematic series of tests for each

Table 2. Difference between the F1 scores for grammatical word 1 g (i.e. MFWs) and lemmatized word 1 g (i.e. lemmas), assessed by means of Wilcoxon tests for each combination of classifiers and datasets. The numbers represent the $p$-values obtained in each individual test. The asterisks indicate conventional levels of significance.

| corpus     | Delta    | Cosine   | SVM      | NSC      |
|------------|----------|----------|----------|----------|
| 189 novels | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| 99 novels  | 0.000*** | 0.000*** | 0.004**  | 0.002**  |
| 30 novels  | 0.051    | 0.248    | 0.003**  | 0.698    |

Figure 4. Performance of lemmatized words in the corpus of 189 novels, assessed by Cosine Delta.
combination of the classification method and the dataset are provided in Table 2. In most cases, the unlemmatized words (MFWs) outperform the lemmatized words to a significant degree, the exception being the dataset of 30 novels. Here, a clear winner of the competition cannot be pointed out, at least for Cosine Delta and NSC.

Finally, the behaviour of syntactic style-markers – as assessed via POS-tag n-grams in their various flavours – should be commented on. First and foremost, they turned out to be substantially different in comparison to lexical markers. As shown in Figure 5, the overall performance of full POS-tags is worse than both lemmatized and unlemmatized words. Also, the spread of the POS-tag curves for different n-grams is smaller (the curves are rather flat) than that of words, which suggests that the POS-tags are more robust (but also more resistant to hyperparameter fine-tuning) than lexical markers. Last but definitely not least, worth noticing is the performance of particular n-grams as a function of the number of features tested. Unlike the lexical markers, full POS-tag 1 g don’t outperform longer n-grams. It is true that 1 g initially win, but they are immediately overtaken by 2 g, and then even by 3 g. More interestingly, the 1 g reveal a further (and constant) decrease of performance, as if longer feature vectors contained more and more stylometric noise.

![full POS-tags](image)

**Figure 5.** Performance of full POS-tags in the corpus of 189 novels, assessed by Cosine Delta.
The above picture of syntax-based attribution is corroborated by the other variants of POS markers, particularly POS-tags in the strict sense (or, the first tag-parts alone), as shown in Figure 6. Here, 2 g proved optimal, but they reveal a constant decrease of performance for longer vectors of features, until they are overtaken by 3 g (the success rate of 1 g could be assessed only for the vector of 35 features, reaching the F1 score of 0.643, whereas the number of available 2 g was exhausted at the 1,000 features mark). The behaviour of POS-tags reduced to their first and second segment (Figure 7) confirms the general picture of syntactic features, except that the 3 g turned out to be the least successful style-markers examined in this study. Worth mentioning is the fact that even the the worst choice of features would still lead to the impressive attributive score of ca. 0.75.

The relatively good performance of higher-order POS-tag n-grams over single items or 2-grams deserves a linguistic interpretation. It clearly shows that syntax (if we believe that it is reflected by sequences of 3 subsequent POS labels) plays a considerable role in the authorial fingerprint, even if it cannot compete with the overwhelming performance of frequent words. Being less noticeable, however, syntactic style-markers are very stable in terms of resistance to the number of analysed n-grams. The F1 attributive score of ca. 0.75 for the worst-case scenario provides us with strong evidence that the syntactic features retain a considerable amount of the authorial fingerprint.
Conclusions

The results obtained in this study allow for a few general observations. Firstly, this study shows that, at least in Polish, lemmatization is not necessarily the way to raise attribution accuracy in that language. Presumably, this claim should be applicable – by extension – to other languages having a rich inflection. This observation is somewhat counter-intuitive, since lemmatization leads to a decrease of the number of types and an increase of the number of tokens per type, which in turn should reduce data sparseness. It turned out otherwise, as if lemmatization, or a crude way of ‘making Polish more like English’, stripped out some relevant information about authorial uniqueness. Since we know what exactly is lost in the process of lemmatization, we can reason that all the suffixes containing inflection play some role in authorship attribution.

A more convincing evidence of the role of grammar in attribution, is provided by our tests involving POS-tag n-grams. Despite significantly worse performance, our syntax-based features exhibited a big potential to distinguish between authors. It is a widely accepted claim that the linguistic originality of an author manifests itself in the lexis, i.e. in predilection to some words and avoidance of other. It is less obvious whether the same can be said of syntactic constructions; intuitively, syntax does not allow as much of freedom of choice as lexis. Our results provide evidence that syntax alone
is responsible for a considerable amount of authorial uniqueness. Even if syntactic features cannot compete with the lexis, they can still be used as efficient style-markers, possibly in combination with traditional features. Interestingly, the loss of accuracy when only grammatical tags were taken into account was not very high (ca. 15%). This is a good hint that writers/authors are only slightly less restricted by syntax than they are by lexis.

Notes

1. Our corpus contains literary sources only. An interesting question – far beyond the scope of this study – is the extent to which the fact that a writer seeks originality makes the fingerprint clearer compared to non-fiction literature.
2. The full set of tables for particular datasets, classifiers, feature types, and their \( n \)-grams, can be found in our GitHub repository.

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References

Acedański, S. (2010). A morphosyntactic Brill tagger for inflectional languages. In Loftsson, H., Rögnvaldsson, E., Helgadóttir, S. (eds) Advances in natural language processing (Vol. 6233), Springer, Berlin, Heidelber. https://doi.org/10.1007/978-3-642-14770-8_3
Baayen, H., Van Halteren, H., & Tweedie, F. (1996). Outside the cave of shadows: Using syntactic annotation to enhance authorship attribution. Literary and Linguistic Computing, 11(3), 121–132. https://doi.org/10.1093/linc/11.3.121
Burrows, J. (1996). Tiptoeing into the infinite: Testing for evidence of national differences in the language of English narrative. In S. Hockey & N. Ide (Eds.), Research in humanities computing (Vol. 4, pp. 1–33). Oxford University Press.
Burrows, J. (2002). “Delta”: A measure of stylistic difference and a guide to likely authorship. Literary and Linguistic Computing, 17(3), 267–287. https://doi.org/10.1093/linc/17.3.267
Eder, M. (2011). Style-markers in authorship attribution: A cross-language study of the authorial fingerprint. *Studies in Polish Linguistics, 6*(1), 99–114. [http://www.ejournals.eu/SPL/2011/SPL-vol-6-2011/art/1171/](http://www.ejournals.eu/SPL/2011/SPL-vol-6-2011/art/1171/)

Eder, M. (2013). Mind your corpus: Systematic errors in authorship attribution. *Literary and Linguistic Computing, 28*(4), 603–614. [https://doi.org/10.1093/llc/fqt039](https://doi.org/10.1093/llc/fqt039)

Eder, M., Rybicki, J., & Kestemont, M. (2016). Stylometry with R: A package for computational text analysis. *R Journal, 8*(1), 107–121. [https://doi.org/10.32614/RJ-2016-007](https://doi.org/10.32614/RJ-2016-007)

Evert, S., Proisl, T., Jannidis, F., Reger, I., Pielström, S., Schöch, C., & Vitt, T. (2017). Understanding and explaining Delta measures for authorship attribution. *Digital Scholarship in the Humanities, 32*(Suppl. 2), 4–16. [https://doi.org/10.1093/llc/fqx023](https://doi.org/10.1093/llc/fqx023)

Hirst, G., & Feiguina, O. (2007). Bigrams of syntactic labels for authorship discrimination of short texts. *Literary and Linguistic Computing, 22*(4), 405–417. [https://doi.org/10.1093/llc/fqm023](https://doi.org/10.1093/llc/fqm023)

Jockers, M. L., & Witten, D. M. (2010). A comparative study of machine learning methods for authorship attribution. *Literary and Linguistic Computing, 25*(2), 215–223. [https://doi.org/10.1093/llc/fqq001](https://doi.org/10.1093/llc/fqq001)

Juola, P. (2009). Cross-linguistic transferrence of authorship attribution, or why English-only prototypes are acceptable. *Digital humanities 2009: Conference abstracts* (pp. 162–163). College Park, MD: University of Maryland.

Kenny, A. (1982). *The computation of style: An introduction to statistics for students of literature and humanities*. Pergamon Press.

Kestemont, M. (2014). Function words in authorship attribution: From black magic to theory? In *Proceedings of the 3rd Workshop on Computational Linguistics for Literature (CLFL)* (pp. 59–66). Gothenburg, Sweden: Association for Computational Linguistics.

Koppel, M., Schler, J., & Argamon, S. (2009). Computational methods in authorship attribution. *Journal of the American Society for Information Science and Technology, 60*(1), 9–26. [https://doi.org/10.1002/asi.20961](https://doi.org/10.1002/asi.20961)

Luyckx, K., & Daelemans, W. (2011). The effect of author set size and data size in authorship attribution. *Literary and Linguistic Computing, 26*(1), 35–55. [https://doi.org/10.1093/llc/fqq013](https://doi.org/10.1093/llc/fqq013)

McKenna, W., Burrows, J., & Antonia, A. (1999). Beckett’s trilogy: Computational stylistics and the nature of translation. *Revue Informatique et Statistique dans les Sciences Humaines, 35*(1–4), 151–171. [https://www.rissh.uliege.be/upload/docs/application/pdf/2022-05/wmckennaetc_beckett.pdf](https://www.rissh.uliege.be/upload/docs/application/pdf/2022-05/wmckennaetc_beckett.pdf)

Przepiórkowski, A., Báňko, M., Górska, R. L., & Lewandowska-Tomaszczyk, B. (Eds.). (2012). *Narodowy Korpus Języka Polskiego*. PWN.

Rybicki, J. (2015a). Success rates in most-frequent-word-based authorship attribution: A case study of 1000 polish novels from Ignacy Krasicki to Jerzy Pilch. *Studies in Polish Linguistics, 10*(2), 87–104. [https://doi.org/10.4467/23005920SPL.15.004.3561](https://doi.org/10.4467/23005920SPL.15.004.3561)

Rybicki, J. (2015b). Vive la différence: Tracing the (authorial) gender signal by multivariate analysis of word frequencies. *Digital Scholarship in the Humanities, 31*(4), 746–761. [https://doi.org/10.1093/llc/fqv023](https://doi.org/10.1093/llc/fqv023)

Rybicki, J., & Eder, M. (2011). Deeper Delta across genres and languages: Do we really need the most frequent words? *Literary and Linguistic Computing, 26*(3), 315–321. [https://doi.org/10.1093/llc/fqr031](https://doi.org/10.1093/llc/fqr031)

Sokolova, M., & Lapalme, G. (2009). A systematic analysis of performance measures for classification tasks. *Information Processing and Management, 45*(4), 427–437. [https://doi.org/10.1016/j.ipm.2009.03.002](https://doi.org/10.1016/j.ipm.2009.03.002)
Stamatatos, E. (2009). A survey of modern authorship attribution methods. *Journal of the American Society for Information Science and Technology, 60*(3), 538–556. https://doi.org/10.1002/asi.21001

Wiersma, W., Nerbonne, J., & Lauttamus, T. (2011). Automatically extracting typical syntactic differences from corpora. *Literary and Linguistic Computing, 26*(1), 107–124. https://doi.org/10.1093/llc/fqq017