A Deep Context Grammatical Model For Authorship Attribution

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Abstract
We define a variable-order Markov model, representing a Probabilistic Context Free Grammar, built from the sentence-level, delexicalized parse of source texts generated by a standard lexicalized parser, which we apply to the authorship attribution task. First, we motivate this model in the context of previous research on syntactic features in the area, outlining some of the general strengths and limitations of the overall approach. Next we describe the procedure for building syntactic models for each author based on training cases. We then outline the attribution process—assigning authorship to the model which yields the highest probability for the given test case. We demonstrate the efficacy for authorship attribution over different Markov orders and compare it against syntactic features trained by a linear kernel SVM. We find that the model performs somewhat less successfully than the SVM over similar features. In the conclusion, we outline how we plan to employ the model for syntactic evaluation of literary texts.

Keywords: Authorship Attribution; Syntactic Features; Markov Models

1. Introduction
Syntactic features for authorship attribution have received considerable attention recently. Parts of speech tags have been studied extensively, (see Stamatatos (2009) and Luyckx (2010) for comprehensive overviews), Gamon (2004) trained an SVM over a transition rule feature set, Luyckx and Daelemans (2008) have used shallow parsing, Kaster et al. (2005) have examined the role of parse depth in classification, Feng et al. (2012) have established the efficacy of employing a number of different deep grammatical features in an SVM classifier, and van Cranenburgh (2012) successfully employs a tree-kernel SVM. Raghavan et al. (2010) train a Probabilistic Context Free Grammar (PCFG) for each author, and then parse test cases using these models, choosing the model which parses with highest probability. Purely syntactic approaches have generally been found inferior to traditional lexical approaches in terms of pure attribution accuracy. However, there is some evidence (Feng et al., 2012; Raghavan et al., 2010) that combining syntactic features with traditional lexical features is superior to either approach when used alone. Stamatatos (2009) describes a number of other shortcomings with the syntactic approach, including the language dependence of the parsing/tagging tools required in order to prepare the source text, and the introduction of error/noise by the parsing process. The latter is of particular concern for applications to social media contexts where loose grammar, slang, abbreviations and acronyms are common (and hence where character ngrams are perhaps most resilient). Regarding Raghavan’s particular approach, Feng et al. (2012) observe that since lexical leaf production rules are constituents of the PCFG model employed, it is difficult to assess the relative discriminative powers of the lexical and syntactic feature components. As such, it is not clear from their study the extent to which syntactic features per se contribute to classification. Also, if off-the-shelf PCFGs are used, then each text needs to be reparsed for each author model, which is computationally expensive.

One particular motivation for removing lexical information is that syntactic features are among those most relevant to traditional literary analysis. Therefore it is potentially beneficial, in the context of computational studies of literary texts, to employ models which discriminate via features similar to those employed in general comparative literature studies. Hence syntactic features have been of particular interest to researchers who have focused on literature (Feng et al., 2012; Jautze et al., 2013).

2. Deep Context Grammatical Modeling
We take an approach which is closest to Raghavan et al. (2010). We retain the core premise of creating author-specific PCFGs and assigning texts to whichever model parses with the highest probability. We abstract from lexical information simply by building our own model and discarding the lexical level.

We develop this approach by exploiting conditional probabilities through vertical Markovization, i.e. increasing the Markov order to consider ancestors preceding the production rule, effectively counting at increasing depths the context wherein a rewrite rule occurs. This technique has been employed extensively in PCFG parsers, for instance by Johnson (1998), Collins (2003), Charniak (2000), and Klein and Manning (2003), and 2-order Markov feature sets have been used for authorship attribution by Feng et al. (2012). Intuitively, these techniques are relevant to authorship attribution of literary texts, since sentence structure features prominently in traditional literary analysis, and previous studies (Feng et al., 2012; Jautze et al., 2013) have demonstrated that sentence structural forms differ significantly between cases in author and genre studies. We build a sentence-deep variable-order Markov model similar to a generalized suffix tree, which we call a generalized parse-suffix tree, and compare different probability estimators at varying Markov orders.

Our purpose in this article is to define the model and demonstrate its efficacy as a representation of an individual author’s style. To do so, we compare the attribution
accuracy to that of a linear kernel SVM over broadly equivalent syntactic features, which is the basic model employed by Feng et al. (2012). While our model performs slightly below the latter, the proximity of the accuracy of the model to this benchmark suggests that a uniform-weighted high-order Markov model captures most of the syntactic variance between authors, and is thus a strong and intuitive formal model for further stylistic literary modeling and analysis.

3. Model And Algorithms

The data set’s training and test cases are consecutive sequences of sentence-level parse trees with the lexical levels removed.1 We train a model for each author with grammars drawn from a set of their respective works. The total number of tags per text is set to a fixed number, by curtailing the depth of the final input tree. We then estimate the probability of a test case given each model, and return the author whose model maximizes the probability.

3.1. Model

Each input tree starts at a root node with reserved label R, from which descends the estimated grammatical parse of the sentence with the lexical leaves removed. We record the counts of every production rule under all Markov orders to sentence depth. Upon insertion of each input tree, we increment the model by these counts, recording the occurrence of rules in contexts of all available depths. Table 1 provides the table and Figure 2 the tree structure, after insertion of $T_1$ and $T_2$.

For efficient insertion and retrieval, we distribute these counts across a suffix-tree augmented with production rules to sentence depth. We record its depth; ii) in the dictionary attached to that model node, increment by one the value associated with the key representing that node’s children, i.e. the production rule activated at that node in the input tree.

The final detail is the use of suffix pointers to traverse upwards to equivalent nodes at lower Markov orders. These are used to perform the recursive insertions quickly, and later to switch efficiently during probability estimation. Figure 2 illustrates the model after $T_1$ and $T_2$ are inserted. For clarity, only suffix pointers for tag DT are shown.

3.2. Probability Estimation

The task is to assign a given text $S$ to an author-model $M_i$. Let $M_i$, $1 \leq i \leq k$ be $k$ author models. $S$ contains $n$ sentences, $s_j$ which are calculated sequentially, $P(S|M_i)$ being the product of the probability of its sentences under $M_i$, i.e. $P(S|M_i) = \prod_j P(s_j|M_i)$. Using this, we apply Bayes’ rule, i.e.:

$$P(M_i|S) = P(S|M_i) \cdot P(M_i)/P(S).$$

We drop the denominator and attribute the text to the highest scoring model $M_i$, where:

$$t = \arg\max_i P(S|M_i) \cdot P(M_i).$$

Since in the test cases we here consider, every author has an equal number of cases in the training and test sets, we drop the prior and this simplifies here to:

$$t = \arg\max_i P(S|M_i).$$

Generally, priors representing a known disproportion, or adaptive priors such as Dirichlet, can be employed without altering $P(S|M_i)$. We now describe $P(S|M_i)$. The probability of a sequence is the product of its sentences, and the probability of a parsed sentence is the product of the probability of its rules. The probability of a given rule is estimated at the position in the model-tree that corresponds to its position in the input tree, when this depth is less than or equal to the Markov assumption. When the rule’s occurrence in the input tree is deeper than the Markov assumption, we traverse the suffix-pointers (Figure 2) until we reach the desired depth. Now we return the count for the

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1We employ a standard parser – Stanford PCFG Lexicalized, English model(Klein and Manning, 2003).
rule at the node over the total count at that node (see Table 1). We here employ 5 probability estimations $Q_1, Q_2, Q_3, Q_4$ and $Q_5$, which assume Markov orders of 1 to 5 successively (or the highest possible lower order given the node’s depth in the input tree), where a production rule is order 1. As a final point, since a node may occur in a test sentence which is not represented in the model, we use a zero-frequency estimator to give a small probability for an unseen occurrence. Preliminary investigations explored back-off estimators (Katz, 1987) and PPM escape estimators (Cleary and Witten, 1984; Moffat, 1990). However it proved more effective to penalize cases of non-occurrences of a context more heavily than these estimators permit. Hence we opt for the heuristic that a non-occurring tag’s probability is its model-wide frequency over the total number of parsed tags, and we keep positive occurrences as described above.

4. Tests: Authorship Attribution

Following standard practice, we examine performance on two separate sample sets: the first consists of 10 works by 10 19th Century/early 20th Century novelists drawn from Project Gutenberg (www.gutenberg.org); the second consists of 10 works by contemporary suspense/mystery writers.

We parsed the texts using the Stanford NLP English model and discarded lexical levels. We randomly separated them into 5 groups, of 2 works per author, and performed 4 vs 1 cross-validation across these 5 groups, of which we report the mean accuracy. Employing the 5 $Q_i$ probability models described above, we sampled text from the start of each document, rising in increments of 1000 tags to 5000.

As we state in the introduction, lexical approaches have been consistently found to outperform syntactic ones, and we do not re-evaluate these against our own model, since the general trend has been well demonstrated in the previous.

Table 2: Mean % accuracies of 4 vs 1 cross-validation on sample set of 10 classic novelists for PCFG model and Linear SVM.

| Sample Size | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ |
|-------------|-------|-------|-------|-------|-------|
| 1000        | 49    | 47    | 51    | 48    | 45    |
| 2000        | 53    | 49    | 59    | 59    | 47    |
| 3000        | 71    | 70    | 76    | 76    | 71    |
| 4000        | 78    | 82    | 86    | 84    | 77    |
| 5000        | 80    | 84    | 86    | 87    | 85    |

Table 3: Mean % accuracies of 4 vs 1 cross-validation on sample set of 10 contemporary suspense novelists for PCFG model and Linear SVM.

| Sample Size | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ |
|-------------|-------|-------|-------|-------|-------|
| 1000        | 46    | 44    | 50    | 49    | 52    |
| 2000        | 58    | 63    | 63    | 59    | 58    |
| 3000        | 67    | 67    | 66    | 68    | 70    |
| 4000        | 71    | 71    | 69    | 75    | 79    |
| 5000        | 78    | 73    | 76    | 84    | 87    |

Table 2A: Classics - PCFG

| Sample Size | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ |
|-------------|-------|-------|-------|-------|-------|
| 1000        | 39    | 39    | 44    | 36    | 37    |
| 2000        | 50    | 53    | 50    | 58    | 48    |
| 3000        | 65    | 59    | 70    | 74    | 67    |
| 4000        | 76    | 78    | 85    | 84    | 74    |
| 5000        | 84    | 85    | 89    | 86    | 78    |

Table 2B: Classics - SVM

| Sample Size | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ |
|-------------|-------|-------|-------|-------|-------|
| 1000        | 58    | 55    | 46    | 44    | 37    |
| 2000        | 72    | 72    | 64    | 55    | 50    |
| 3000        | 74    | 78    | 80    | 71    | 60    |
| 4000        | 83    | 82    | 80    | 77    | 68    |
| 5000        | 89    | 88    | 85    | 85    | 69    |

Table 3A: Suspense Writers - PCFG

| Sample Size | $Q_1$ | $Q_2$ | $Q_3$ | $Q_4$ | $Q_5$ |
|-------------|-------|-------|-------|-------|-------|
| 1000        | 58    | 55    | 46    | 44    | 37    |
| 2000        | 72    | 72    | 64    | 55    | 50    |
| 3000        | 74    | 78    | 80    | 71    | 60    |
| 4000        | 83    | 82    | 80    | 77    | 68    |
| 5000        | 89    | 88    | 85    | 85    | 69    |

Table 3B: Suspense Writers - SVM
ous literature. Rather, we compare our model against an SVM over similar feature sets, in order to evaluate the relative performance of the algorithms themselves, rather than the relative performance of different classes of features, i.e., lexical and syntactic. Stamatatos (2009) cites SVMs as among the best machine learning algorithms for authorship attribution, and a linear SVM has been previously been employed by Feng et al. (2012) over syntactic features, so we chose this as our benchmark for evaluating the algorithm. Specifically, we used LIBLINEAR through R (Fan et al., 2008; Helleputte, 2010) with the Crammer and Singer (2001) form, re-selecting the 3000 most common features across all training sets for each cross-validation. We normalized to document frequency over chosen features, then scaled according to the training set. We selected features from the model according to Markov orders 1 to 5, where an order 1 feature is a production rule, and higher orders include ancestors. Table 2 presents the respective results for the Classics set and Table 3 for the contemporary fiction.

5. Results

Our model performs slightly below the SVM at highest sample sizes, and significantly below at some smaller sizes. This is somewhat expected since the SVM weights different features in order to differentiate the candidate training sets. The SVM responds to higher orders inconsistently, and performance deteriorates for the highest, probably due to the small sample sizes for these more complex features. The PCFG model generally improves with Markov order at the larger sample sizes, i.e. given enough sample data. For instance in Table 3 the PCFG reaches 87% at order 5 from 78% at order 1, while the SVM peaks at 89% at order 1. Hence, given a more advanced learning algorithm such as an SVM, deeper syntactic features have comparatively limited effect. Our model tacitly imposes uniform weighting across the tree structure, implicitly claiming that a simple and consistent grammatical relation can differentiate authors. For this simpler model, with stronger constraints, the increased Markov order generally improves performance, indicating that the deep sentence structure of authors is a determinable characteristic, and that authors become more distinguishable when their models are compared at greater depths.

We have only carried out a perfunctory process of feature selection for the SVM, and a more rigorous and comprehensive process of selection and pruning would most likely produce better results. Nonetheless our relatively simple model produces competitive results, whilst making stronger theoretical claims regarding author differentiation, e.g. in its uniform weight attribution as described above.

6. Conclusion

We have described a variable-order PCFG model and demonstrated its general efficacy as a syntactic classifier by comparing its performance to a linear SVM. This high-order Markov model over the deep syntactic structure of a collection of classes of texts successfully models most of the syntactic difference between the classes. For future work we will make use of this model for stylometric analysis of authors and genres, for instance to return characteristic sentence and phrase structures for different classes, drawn from the suffix-tree models, which will be compared to traditional stylistic comparisons of the authors under examination. We also plan to create a variable weighted version of the PCFG to increase attribution accuracy.

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