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Segmenting documents by stylistic character†

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Abstract

As part of a larger project to develop an aid for writers that would help to eliminate stylistic inconsistencies within a document, we experimented with neural networks to find the points in a text at which its stylistic character changes. Our best results, well above baseline, were achieved with time-delay networks that used features related to the author's syntactic preferences, whereas low-level and vocabulary-based features were not found to be useful. An alternative approach with character bigrams was not successful.

1 Introduction

There are many different ways that authors can collaborate in the writing of a text (Posner and Baecker 1992). Variables include whether the granularity of the individual authors' unit of contribution is sentences, paragraphs, or sections; whether or not one of the authors acts as 'editor', revising the writing of all the others; and, if not, whether each author revises only their own work or also that of some or all of the others. Thus a collaboratively written text might be nothing more than a concatenation of segments by each of the participating authors, or it could be essentially the work of a single person 'heavily influenced' by the other participants, or it could be something between these extremes.[1] Regardless of the method by which the authors produce the text, if the result is a sequence of stylistically disparate segments, then it is deprecated and quite possibly hard to read – though

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[1] This paper is an example of its own subject matter. Graham, Hirst and Marthi have very different writing styles. Graham and Marthi wrote text describing their portions of the research; Hirst then wrote the remaining material and incorporated Graham's and Marthi's text into it with extensive editing to try to harmonize the style. Hirst and Graham then argued over such stylistic matters as the inclusion of contractions, which Hirst likes and Graham does not, and sesquipedalians, which Graham likes and Hirst doesn't. The paper has *not* been used as data in the research that it reports.

the reader need not be conscious of the reason for the difficulty, merely finding the text to be 'difficult' or 'badly written'. Baljko and Hirst (1999) showed that although stylistic judgments are subjective, readers who were asked to classify writing samples by style generally agreed with one another in their judgments of stylistic similarity and difference.

By contrast, an ideal collaboratively written text is one in which the authors have 'harmonized' with one another to the point that the text is so stylistically homogeneous that it is no longer possible to find stylistically distinct segments; the authors 'speak with one voice'. Thus a software aid for collaborative writers that would help them achieve this unity of style would not be a 'style checker' in the popular sense, looking for 'good' or 'bad' style (though it could work in conjunction with such a tool); rather, it would look for stylistic inconsistencies in a document and suggest to the authors how they could be ameliorated. Nor need such a tool be limited to collaborative writing; a single writer might inadvertently fail to 'harmonize with herself', especially in a document that is written in several bursts over an extended period of time.

Within this idea lie several research problems, not least of which is the difficulty of presenting linguistically naive users with advice on stylistic nuances and subtleties. However, in this paper we concentrate on the initial problem of detecting the inconsistencies – searching the text for any paragraphs or regions that are stylistically distinct from others. More generally, we can think of this as segmentation of the text by stylistic character. Even by itself, this could be a helpful diagnostic tool for collaborating writers, showing them where they had failed to unify their styles. And the segmentation of text by style (and thus, implicitly, by authorship) has other uses as well in literary studies and in forensic applications such as the detection of plagiarized sections in students' essays.

2 Stylistic segmentation is not authorship identification

Our task, then, is to take a text that might be a sequence of stylistically distinct segments and identify the boundaries between the segments (if any) – the points where the style changes.

Clearly, our problem is related to that of authorship identification, but it is not at all the same problem. Certainly, if we could stylistically identify one segment of a text as John's and another as Mary's, then we would have ipso facto detected a stylistic difference or inconsistency; and conversely, if we could say that the style of an entire text, or one segment of it, is ambiguous or half-way between that of John and that of Mary, then we could say that the authors have harmonized their style.[2] But that's not really what we are trying to do. All we care about is whether or not the text is internally consistent, and it doesn't matter whether that is achieved by revising John's text to match Mary's style or by revising both so that they 'meet

[2] Collins, Kaufer, Vlachos, Butler and Suguru (2004) present a statistical method for detecting whether a complete text falls 'between' the characteristic choices of two authors and might therefore have been written by the two of them collaboratively.

in the middle'. (Nor will we necessarily have a single-author corpus for each of the collaborating writers.)

Nonetheless, the two problems are similar insofar as they involve comparing texts for stylistic similarity or difference. In the case of authorship identification, this involves comparing the target text with an attested corpus of a candidate author; in our case, it involves comparing one region of a text with another. Research in authorship identification has concentrated on determining the textual attributes that are most likely to reflect an author's individual style and on which statistical methods are best employed in the task. (For a review of research in authorship identification, see Holmes (1994) or Love (2002).) The main difference between the two cases lies in the size of the texts being compared. In authorship identification, it is assumed that both the target text and the attested corpus are reasonably large. Because most stylistic attributes are based on the frequency of occurrence of some linguistic or textual feature, the larger the target text and the attested corpus are, the more reliable the result will be; if either is too small, statistical significance cannot be achieved. In our case, however, we could be comparing paragraphs or segments as small as 100 words or less. (Attribution of authorship when the text or the attested corpora are small, which has particular utility in forensic applications, has generally involved non-automated qualitative judgments.)

We have therefore drawn on ideas from research on authorship identification, especially research on determining the textual attributes that are most likely to reflect a distinguishable style. However, we have adapted this work to our own particular needs.

3 Related work

In one of the few studies into the application of stylistic statistics to small samples, Glover and Hirst (1996) asked a number of subjects to watch an episode of a television series and write a description of it. They then randomly combined one subject's description of the first half of the episode with another's description of the second, thus creating artificial collaboratively written texts. Glover and Hirst found that stylometric statistics could distinguish the pairs written by different subjects from pairs written by a single subject with reasonable probability, even though the texts involved were almost all less than 500 words in length. Juola (1997) demonstrated a technique that, using samples as small as 500 characters, can correctly classify all the disputed *Federalist Papers*. By combining particular sentence- and chunk-boundary detectors with a particular multi-pass parser, Stamatatos, Fakotakis and Kokkinakis (1999, 2000) developed a complex but effective method for ascribing the authorship of fairly small samples of modern Greek text. Despite these positive indications, there has been no study with a large corpus of small texts using a broad range of statistics; most researchers therefore remained skeptical that stylistic statistics could provide much information for very small samples.

Most of these studies used fairly conventional statistical techniques; however, the use of neural nets in conjunction with stylometric statistics is becoming increasingly popular. The pioneering work in this regard was undertaken by Matthews and

Merriam (1997). They used a very small set of function-word frequencies as input to a multilayer perceptron to examine sections of four plays that have been attributed both to Shakespeare and to Fletcher, producing results that accord reasonably well with accepted scholarship. Tweedie, Singh and Holmes (1996a) present an extensive review of the uses of neural nets in stylometry. In their own work (Tweedie, Singh and Holmes 1996b) in this connection, involving the *Federalist Papers*, they trained a single network with a small hidden layer on a subset of the function words originally used by Mosteller and Wallace (1964) and reproduced Mosteller and Wallace's results. Neural nets have also found popularity in genre detection (e.g. Kessler, Nunberg and Schütze 1997), where stylometric statistics have been used as indicators of genre for some time.

4 Models of 'bad' collaboratively written text

For our experiments, we need a corpus of examples of 'bad' collaborative writing in which the stylistic disparities are marked. Clearly, it is infeasible, or even impossible, to gather large amounts of naturally occurring data of this kind; so, following the idea underlying the work of Glover and Hirst (see section 3 above), we instead created synthetic data that models it by concatenating a corpus of Usenet postings and removing all textual indications of boundaries (such as headers and signatures). Our assumption was that in the resulting text, the concatenation points would be just those points at which the style of the text changes. Of course, this is an idealization: it is possible that two consecutive postings could be stylistically indistinguishable, even if by different authors; and a single posting could be stylistically disparate, for a variety of reasons including embedded quotations (see below) and multiple authors (although this is very rare in the data that we used).

The Usenet postings that we used were the articles in all issues of *Risks Digest*[3] from 5 April 1996 to 1 April 1999. This corpus serves our purposes well because it reflects the level of writing that is typical of business and technical documents: it is generally well-written – that is, it is generally grammatically well-formed and free of flames, advertisements, and spam – and it is fairly well-controlled for genre and topic. Also, it is comparatively large: slightly over 750,000 words; there are 15,556 paragraphs with a mean length of 49.9 words and a standard deviation of 40.9 words. The articles average just over 4 paragraphs in length; specifically, 24% of the paragraph breaks are article boundaries.

To prepare this corpus for our experiments, it was necessary to remove and record structural indications of article boundaries, which were standard e-mail headers and, frequently, authors' e-mail signatures. To make the data comply with our assumption that article boundaries correspond to auctorial changes, we also had to weed out embedded quotations from articles, as they were usually not written by the author of the enclosing article. (To conserve material, and to see how our experiments would fare on non-articles, we 'recycled' the larger quotations by replacing them

[3] *Forum on Risks to the Public in Computers and Related Systems* (comp.risks), ACM Committee on Computers and Public Policy, Peter G. Neumann, moderator.

in the corpus outside of any article, thereby treating them as complete articles in their own right.) The corpus was rather too large to do all this manually; we discuss elsewhere (Graham 2000) the details of the automatic processing (mostly by means of Perl scripts), and here just briefly mention some of the problems that the corpus presented. While it was easy to find standard e-mail headers, signatures were harder: we managed to remove 89% of signatures with about 18% false positives. Those that we were not able to remove were either highly idiosyncratic or were obviously difficult to distinguish from text. Embedded quotations turned out to be a surprisingly challenging problem, necessitating the development of several heuristics; in the end, we were able to correctly identify 95% of quotations, with only about a 20% rate of false positives.

We then automatically determined sentence boundaries and tagged the corpus with parts of speech. Following van Halteren, Zavrel and Daeemans (1998), we used three different part-of-speech taggers (Ratnaparkhi 1996; Schmid 1995; Brill 1995) in order to improve the accuracy of our tagging.

5 Experimental method

We took two distinct approaches to the problem. The first was to use neural networks to decide whether or not two segments of text are stylistically distinct. This will be described in this and the next two sections. Our second approach was to use the distance between letter bigram frequencies to make this decision. This will be described in section 8.

The main strengths of a neural network–based approach are that neural nets are often more tolerant of noise in the data and more apt to generalize than conventional statistical classification methods. These two properties are important to us, as our methodology is fundamentally statistical and not based on heuristics, and our data is quite noisy. The existence of a large body of excellent neural network simulation software was also a great benefit: we used the SNNS (Stuttgart Neural Network Simulator) system from the Universities of Stuttgart and Tübingen (SNNS 1990–1998).

Our use of neural nets differs from their use in other studies related to authorship attribution. First, we train our neural nets not on corpora produced by a small number of known authors, but on a corpus written by a large number of unknown authors. Second, we compute a broad range of stylometric statistics on a large number of very small samples of work, including many thought not to be reliable on such samples. Third, our neural net architectures need to be different from those used by previous workers in this area, as we require our nets to tell us whether or not two samples are different, rather than to fit a single sample into one of a set of pre-defined classes. Finally, we use some stylometric statistics, such as distribution of punctuation, that have been widely ignored in the literature because researchers have felt they are prone to contamination (Holmes 1994).

Thus we cast the problem of text segmentation by stylistic character as a binary classification problem for neural networks. The network is presented with statistical data (as described in section 6 below) from two segments of the text, where a

segment, for us, is always exactly one paragraph. The network's job is to classify the pair of segments as either stylistically distinct or not: 1 or 0 respectively. In production use, the segments presented would be consecutive paragraphs of a text; classifying them as stylistically distinct would imply that there is a change of style, possibly due to an authorship boundary, between them. Although we could in principle have chosen differently, in our experiments we also presented only consecutive paragraphs as data, because articles on similar topics will often be found consecutively, making our networks' task more realistic; to have randomly pulled paragraphs from anywhere in the corpus to assemble a test set would have destroyed this structure and compromised this element of realism.

6 Features used

There was little *a priori* indication as to which statistics would be best suited to small sample sizes, so we chose several categories of statistics that have been used previously in authorship attribution, stylistic analysis, genre detection, and information retrieval, in order to compare the efficacy of each. Here, we will briefly define each of these statistics and discuss our motivation for including it.

6.1 Surface features

For each sample we computed the average word-length and the frequency of each word-length, in terms of both characters and syllables. (Holmes (1994) reports that word character-length distributions, far from characterizing the work of any particular author, depend more on the genre in which an author is writing, but we included them anyway because of the simplicity of the computation.) It is true that syllable-length and character-length correlate very strongly, but we felt that the cognitive processes alleged to underlie the usefulness of each category were sufficiently distinct to justify our studying both. The syllable-count for each word was taken from the MRC2 electronic dictionary (Wilson 1987). (Character counts greater than 15 were treated as 15; syllable counts greater than six were treated as six.) We also computed the frequencies in the text of each part-of-speech category (as defined in the Penn Treebank (Marcus, Santorini and Marcinkiewicz 1993)), a measure that has been used in many studies. And we computed sentence length in terms of words, although most scholars believe this information is too genre- and topic-specific to characterize authorship. While there does seem to be a consensus that sentence-length distributions provide more information than average sentence length alone, the small size of our samples makes it extremely unlikely that sentences of any one length will occur more than once in any sample.

The use of function-word frequencies also has a long history in stylistic research, including the well-known work of Mosteller and Wallace (1964). To decide which words to use, we simply examined all words in the Brown corpus (Kučera and Francis 1967) with frequencies above 0.2%, and manually removed from this list all words commonly used either as content words (i.e. verbs or nouns, excluding pronouns). The 40 words that emerged from this process are listed in Table 1. In

Table 1. *Function words and punctuation marks for which we computed per-sample frequencies*

the	of	and	to	a	in	that	he	for	it
with	as	his	on	at	by	i	this	not	but
from	or	an	they	which	you	one	her	all	she
there	their	we	him	when	who	more	no	if	out
.	?	!	:	;	,	—	(	)	[
]	{	}	<	>	"	“	”	‘	/

addition, we decided to record the frequency distribution of common punctuation marks (Table 1). Some researchers have been very reluctant to consider punctuation in their studies, since this is often beyond the control of the text's original author; however, since our corpus is not copyedited, we decided to include it.

6.2 Entropy features

It has been suggested that the amount of structure in an author's writing can be measured by using lexical entropy (see Holmes 1994). The lexical entropy H of a passage of text is defined as follows:

$$H \stackrel{\text{def}}{=} -\sum_i \left(\frac{iV_i}{N}\right) \log \left(\frac{iV_i}{N}\right)$$

where N is the total number of tokens in the sample and V_i is the number of types that appear exactly i times. Although we calculated lexical entropy for each of our samples, a seemingly more promising measure, at the character level rather than the lexical level, is given by Juola (1997). For a sample of text C characters long, Juola selects a 'window-size' parameter c such that $0 < c < C$. A 'window' contains c consecutive characters. Suppose such a window begins at index i (i.e. at the ith character), $1 \leq i \leq C - c + 1$. Juola then calculates the length of the longest sequence of characters beginning after the window (i.e. at index $c + i + 1$) that is identical to some sequence of characters within the window. Letting this quantity equal L_i, Juola's statistic is then defined as:

$$\hat{L} \stackrel{\text{def}}{=} \frac{\sum_{i=1}^{C-c} L_i}{C - c}.$$

The method can be shown to converge to the information-theoretic entropy as $c \to \infty$. Juola's work on authorship attribution used windows of as little as 500 characters, and so is of clear relevance here. However, our very short samples required even smaller windows: we used 250 characters if the sample was more than 1000 characters long and a quarter of its length if it was between 200 and 1000 characters. For samples of fewer than 200 characters, we simply used $L = 1.75$ (which is the estimate by Brown, Della Pietra, Della Pietra, Lai and Mercer (1992) of the entropy of English), and so extremely short samples are indistinguishable with respect to this feature.

Table 2. *The statistics that we computed and their grouping into ten categories for our experiments*

1.	Average word length, frequency of i-letter words $1 \leq i \leq 15$ (words with length >15 counted as 15-letter words)
2.	Average syllables/word, frequency of i-syllable words $1 \leq i \leq 6$ (words with >6 syllables counted as 6-syllable words)
3.	Average words/sentence
4.	Relative frequencies of various parts of speech
5.	Relative frequencies of function words (see table 1)
6.	Relative frequencies of punctuation (see table 1)
7.	Lexical entropy H, Juola's measure $\hat{L}$
8.	Normalized type/token ratio R, Simpson's index, modified Yule's characteristic, modified Honoré's measure
9.	Ratio of hapax legomena $\left(\frac{V_1}{V}\right)$ and hapax dislegomena $\left(\frac{V_2}{V}\right)$
10.	First five terms of corrected Waring–Herdan distribution

6.3 Vocabulary features

Many statistics that have appeared in the literature attempt to measure the richness of an author's vocabulary. We computed the standard type/token ratio R, as well as Simpson's index, Yule's characteristic, and Honoré's measure; all these are defined and discussed extensively by Holmes (1994). In other work (Graham 2000), we present methods to normalize the output of the latter two statistics so that they don't bias neural networks. We also present a complex method for normalizing the type/token ratio so that it is less sensitive to sample size. For samples too small even for this method we used the average of the type/token ratios calculated across our entire corpus.

As some researchers have postulated that an author's style is reflected in hapax legomena and hapax dislegomena, we computed both measures for all of our samples, i.e. the ratios of V_1 and V_2 to V, the total number of types. Most researchers seem to believe that even in large samples, these measures are untrustworthy; thus much work has been spent in attempting to develop statistical models – relations between i and V_i – to characterize authors' vocabularies. According to Holmes (1994), the best results have been achieved by the Waring–Herdan distribution. So, following Holmes, we used a corrected version of this distribution in our study, and computed only the first five terms of the distribution for each sample.

6.4 Summary

Table 2 lists a summary of the statistics that we computed for each of our samples. The table also shows how the statistics were grouped into ten categories for our experiments below.

7 Experiments and results

Except in a few instances, all of our networks were randomly initialized with weights between -1 and 1, which proved to be a smooth-enough surface. The networks

Table 3. *The lowest test MSEs and corresponding training MSEs that were obtained with multilayer perceptrons trained on various categories of statistics (as defined in table 2). Boldface indicates the best result. Backprop WD = backpropagation with weight decay; Backprop M = backpropagation with momentum. Asterisks denote networks built along the lines of mixtures of experts; two asterisks imply all weights were changed during learning, one implies only the weights of the gating network were changed*

Categories used	Size of hidden layer	Size of input layer	Learning algorithm	Best MSE during training	Best MSE during test
All	25	266	Backprop WD	0.1814	0.1953
1	12	32	Backprop M	0.1836	0.1770
2	8	16	Backprop M	0.1831	0.1763
3	4	2	Backprop M	0.1892	0.1814
4	30	72	Backprop M	0.1612	0.1638
5	25	80	Backprop M	0.1720	0.1725
6	16	40	Backprop M	0.1659	0.1664
7	4	8	Backprop M	0.1883	0.1779
8	20	8	Simulated Annealing	0.1929	0.1803
9	7	4	Backprop M	0.1878	0.1781
10	16	10	Simulated Annealing	0.1912	0.1798
* All	40	266	Backprop M	0.1861	0.1781
* 4,5,6	50	192	Backprop M	0.1715	0.1680
** **4,5,6**	**50**	**192**	**Backprop M**	**0.1380**	**0.1584**

were trained typically for thousands of epochs, and stopped manually when they plateaued. (Details of training and network sizes are given by Graham (2000).) Largely to conserve our data and time, we used the simplest possible strategy for testing our networks; we trained them on 90% of our data and tested them on the other 10%. We didn't perform any cross-validation, but we are confident that the results that we have obtained are not aberrations because, though our best networks exhibited the usual pattern of overfitting to the training data upon intensive training, many of our networks actually found the test data easier than the training data, even after many thousands of learning steps. Thus, we are confident that no trivial patterns existed in our training or test sets that might invalidate our results.

Because all of our networks use logistic sigmoid activation functions (as most of our data points have magnitudes between 0 and 1), their outputs are always in the range 0 to 1. Thus, we have used the Mean Squared Error (MSE) of our networks, taken over the entire training or test set, to obtain a general idea of the network's performance. For our best-performing network, described below, we also computed performance in terms of recall, precision, and accuracy.

7.1 Experiments with multilayer perceptrons

Table 3 shows the best results that we obtained with standard multilayer perceptron networks using various categories of our data as inputs. These results are selected

from tests run with many different hidden-layer sizes and many different learning algorithms, including simulated annealing and various forms of backpropagation (Rumelhart, Hinton and Williams 1986; Bishop 1995). The networks that are marked with asterisks in the table were generated as follows. The best networks that we had developed for the component categories were used as the bottom layer of the network, and a 'gating' network (a network with as many inputs as categories of statistics, containing a hidden layer of size noted in the table) was then used to join these component networks. In the network marked with two asterisks, all the weights in the resultant large network were then allowed to change during learning; in the networks with only one asterisk, only those in the gating network were allowed to change. While this model is based on mixtures of experts as described by, for instance, Bishop (1995), it is noteworthy that the performance of our network with two asterisks is better than that of the corresponding network with one asterisk.

The data presented in Table 3 suggest many interesting conclusions. Most significantly, it is categories 4, 5 and 6 of statistics – those that characterize an author's syntactic preferences (part-of-speech and punctuation frequencies as well as function-word frequencies) – that are best at identifying authorship boundaries, both individually and together. Features at a lower level (categories 1 to 3: syllable- or character-length distributions and sentence lengths) do not do nearly as well, nor do statistics intended to measure vocabulary richness or structure (categories 7 to 10: entropy statistics, Waring–Herdan frequencies, and so on).

It is also clear that combining too many unrelated statistical categories in the same network yields poor results. If the network is organized into a mixture of experts, the results are somewhat better, but do not reach the levels of the better component networks unless the categories are related. The fact that each of the three categories comprising the final network in Table 3 were individually fairly good and measured a related aspect of writing goes some way to explaining the surprising result that this network was so much better than the others. It is also worth noting that, though we tried various learning algorithms, sometimes one succeeding better than another, the organization of the network and the statistical category being tested had far more effect on the test MSE than any choice of algorithm. In the next section we expand on this point by demonstrating how an entirely different architecture further improved our results.

7.2 Results with time-delay neural networks

Time-delay neural networks (Lang, Waibel and Hinton 1990) have traditionally been used in situations where data are generated over time, and where each datum in a set is produced by the same process in all time intervals. By grouping corresponding data items from consecutive sets into 'features', with each item in a feature joined by coupled weights to a unit of the input layer, this homogeneity and dependence is incorporated into the architecture of the network. Other than having coupled weights, these networks may have arbitrary topologies, and may even have coupled units in their hidden layers that act in much the same way as in the input layer.

Table 4. *Some of the results obtained with various time-delay neural networks. Boldface indicates the best result*

Categories used	Number of hidden units	Training MSE	Test MSE
4,5,6	48	0.1412	0.1497
4,5,6	32	0.1420	0.1500
4,5,6	**20**	**0.1380**	**0.1495**
4,5,6	12	0.1427	0.1501
4,5,6	8	0.1394	0.1499
4,5,6	4	0.1415	0.1501
4,5,6	2	0.1473	0.1504
4,5,6	0	0.1600	0.1619
All	30	0.1874	0.1804
8	4	0.1888	0.1806
2	7	0.1832	0.1739
4	8	0.1544	0.1592

Intuitively, it is easy to cast our experiment to fit this model; the later paragraphs of a contribution must depend on earlier paragraphs. Since our data sets are consistently ordered, we automatically have that each datum from one set measures the same underlying feature as the corresponding datum from any preceding set.

Given that time-delay networks take longer to train than multilayer perceptrons of similar size, we constructed only networks that used two consecutive data sets. Further, at most one layer of hidden units was used, and no coupled weights were used there.

Table 4 gives some of the results we obtained with time-delay networks. The most obvious feature of this table is how well the combination of categories 4, 5 and 6 again appears to work with this network architecture. These error levels are more than 5% better on the test data than we previously observed, and, as we discuss below, lead to recalls and precisions far above chance levels. Selected single categories that we tested also led to better results when time-delay architectures were employed, whereas all the categories together produced results somewhat inferior to the mixture-of-experts model used earlier. So, while time-delay networks are usually more effective in contexts such as this, a mixture-of-experts model may sometimes be able to exploit patterns in various individual categories that are obscured when only one hidden layer is available.

7.3 Evaluation of results

We now evaluate these results by comparing them to a baseline. Three baselines suggested themselves. The first, and simplest, is always to say that there is no authorship boundary; this is the most probable case in our test data, as the ratio of non-boundaries to boundaries is 0.76 to 0.24. This method results in a mean squared error of 0.2552 for our entire corpus, 0.2359 on the test set alone. A second baseline is an algorithm that randomly outputs 1 or 0 in the ratio 0.76 to 0.24. This algorithm

Table 5. *Precision, recall, F-measure, and accuracy of our best time-delay network on the test suite. The threshold is the value below which the network outputs are considered to be 0 and above which they are taken to be 1*

Threshold	Precision	Recall	*F*	Accuracy
0.0500	0.2867	0.9191	0.4370	0.4413
0.1500	0.3670	0.7402	0.4907	0.6374
0.2500	0.4598	0.6029	0.5217	0.7392
0.3000	0.5124	0.5564	0.5335	0.7704
0.3200	**0.5314**	**0.5392**	**0.5352**	0.7791
0.3400	0.5394	0.5196	0.5293	0.7820
0.3600	0.5565	0.5074	0.5308	0.7883
0.4000	0.5780	0.4632	0.5143	0.7935
0.4500	0.5850	0.4216	0.4900	0.7929
0.4700	0.6036	0.4069	0.4861	**0.7970**
0.5000	0.6183	0.3652	0.4592	**0.7970**
0.5500	0.6000	0.2941	0.3947	0.7872
0.6500	0.6693	0.2083	0.3177	0.7889
0.7500	0.7258	0.1103	0.1915	0.7802

generally produces MSE's of 0.316 on the entire corpus. A third baseline is to use the ratio of boundaries to non-boundaries to determine the real value between 0 and 1 that minimizes the MSE and then always output this value. This value is 0.2552 in the entire corpus and 0.2359 in the test corpus; it yields an MSE of 0.1901 for the entire corpus and 0.1801 for the test corpus. The fact that many of our poorer networks achieved minimum MSE's worse than these values shows that such results are poor indeed.

We now consider the results of our best network in terms of recall, precision, *F*-measure, and accuracy. Recall is the fraction of pairs representing authorship boundaries that were correctly identified as such; precision is the fraction of pairs identified as authorship boundaries for which the decision was correct; *F* is the harmonic mean of recall and precision ($F = 2PR/(P + R)$); and accuracy is the fraction of all decisions that were correct. However, these measures cannot be meaningfully computed for the first and third baselines. For the first baseline, always say that there is no authorship boundary, precision and recall are zero, and accuracy is simply equal to the fraction of non-boundaries in the data (which is 76.4% in the test data). The same will be true of the third baseline, output the optimal value that minimizes MSE, if the value is below the threshold for output that is deemed to be 1 and its inverse otherwise. The second baseline, random guessing with appropriate probabilities, achieves a precision of just above 25% with a recall of similar magnitude and an overall accuracy of 62.6%.

In contrast to this, Table 5 presents precision, recall, *F*-measure, and accuracy on our test data for our very best network – the 20-hidden unit network cited in Table 4. The table shows the effect of setting different thresholds for output deemed to be 1. These results show that we are able to achieve better than 53% precision and recall simultaneously if we choose the threshold value correctly. Such a result for a random process, even one having knowledge of the relative frequency of contribution

boundaries, is extremely improbable. The accuracy of our most accurate network is 79.7%; it is 77.9% where the values of precision and recall are closest in magnitude. This is an improvement not only over the randomized baseline algorithm, but also slightly overtakes the accuracy of 76.4% of the first baseline on the test set.

8 Character *n*-grams

We now turn to experiments that apply a completely different method of authorship attribution, letter *n*-grams, at the paragraph level. Letter *n*-gram methods have been used successfully on large pieces of text, but not attempted on smaller texts containing only a few paragraphs, or in situations where there are a number of different authors. We examine here whether letter *n*-grams alone can be used to find stylistic boundaries in fairly short texts.

It is perhaps surprising that so rudimentary a measure as the distribution of letter bigrams can be used to distinguish authorship. Nonetheless, Kjell and his colleagues (Kjell and Frieder 1992; Kjell, Woods, and Frieder 1994) achieved very good results with it.[4] In this method, word separation, punctuation, and letter-case are all ignored: a text is viewed just as a stream of alphabetic characters, and the distribution of all $26^2 = 676$ letter bigrams in the stream is computed. Each character in the stream (except the first and last) thus participates in two bigrams. A text or set of texts may thus be represented as a 676-component vector – a rather sparse one, as most letter bigrams never occur in English. To determine the authorship of a disputed text, a vector is derived from the attested texts of each candidate author; the candidate whose vector is closest in cosine distance to that representing the disputed text is judged to be the true author. Kjell and colleagues tried the method on *The Federalist Papers*, and found that it classified the attested texts with an accuracy of about 88% and agreed with the classic results of Mosteller and Wallace (1964), which relied on more-complex features such as sentence length and function-word frequency and which are now generally accepted as correct, on all but one of the papers whose authorship was disputed.[5] Using trigrams instead of bigrams was found to affect the accuracy of the method only marginally.[6]

[4] In fact, Merriam (1994) claims that the frequencies of certain letters (i.e. unigram frequencies) are sufficient to distinguish Shakespeare from Marlowe.

[5] The two papers by Kjell and colleagues differ in minor details in method and results. In the earlier paper (Kjell and Frieder 1992), one of the disputed texts, number 58, was taken as authored by Madison, though not included in the vector of his attested texts. The method then agreed with Mosteller and Wallace on 10 of the 11 remaining disputed texts. In the later paper (Kjell *et al.* 1994), text number 58 was treated as disputed and two additional attested texts were included in the vector for Hamilton. Accuracy on the attested texts increased by 1.3 percentage points, and agreement with Mosteller and Wallace on the disputed texts was 11 out of 12.

[6] In the earlier Kjell paper, the use of trigrams increased accuracy, correctly classifying one more attested text. In the later paper, the use of trigrams *decreased* accuracy, wrongly classifying one more attested text. Nonetheless, the authors argue in the later paper that the use of trigrams increases confidence in the results but at too great a computational expense.

8.1 Validation of letter n-gram methods

Our first step was simply to verify that the letter n-gram methods do in fact work for large samples of text. We used five novels each by Jane Austen and Charles Dickens (downloaded in text format from the Web). For each novel, n-gram frequencies were computed for $n = 1$, 2, and 3. Then, for each n and each pair of documents, the cosine distance measure between their n-gram frequency vectors was determined. We found that the distances between pairs of works by the same author are significantly lower than distances between works by different authors. This is especially pronounced for bigrams and trigrams. These results replicate those of Kjell and Frieder in showing that bigrams or trigrams are extremely discriminative when there are only two authors and the text samples are very large (in this case, a few hundred thousand words each).[7]

8.2 Experiments on the Risks corpus

Next, we tried letter n-grams for our primary task of authorship segmentation of the *Risks* corpus.

The first algorithm that we used was to proceed through the file and find the cosine distance between each pair of consecutive paragraphs using letter bigrams. (Trigrams were not used because a few paragraphs of text seemed insufficient to estimate 26^3 parameters.) If the distance exceeded a certain predetermined threshold T, then an authorship boundary was marked. The threshold T was varied, giving the usual tradeoff between precision and recall. Overall, the results were disappointing, and the precision figures were especially troubling – the maximum precision achieved was 0.264. A trivial baseline algorithm, marking all paragraph breaks as boundaries, achieves a precision of 0.24, which is the proportion of authorship boundaries among paragraph breaks (see section 7.3).

An inspection of the data showed that whenever one of a pair of paragraphs was very short, about 20 words or less, that pair was almost always marked as having an authorship boundary. The probable explanation for this is that as the paragraph size decreases, the bigram estimates of the 'true frequency vector' become very unreliable, and fluctuate wildly. To compensate for this, we introduced a factor to move smaller paragraphs 'closer together' – or, more precisely, to move larger paragraphs 'further apart'; a new paragraph distance D' was defined in terms of the original cosine distance D and the sum l of the two paragraph lengths as follows:

$$D' = \begin{cases} D + wl & \text{if } l < c \\ D + wc & \text{if } l \geq c \end{cases}$$

where c is a cutoff point defining what constitutes a 'short' paragraph (we took $c = 20$ words), and w is a weight. This new algorithm was tried with $w = 0.1$, 0.2,

[7] Subsequent to the completion of these experiments, Peng and colleagues (Peng, Schuurmans, Keselj and Wang 2003a, 2003b), who were seemingly unaware of Kjell and colleagues' original work, also reported good results with n-gram language models for the traditional large-text authorship attribution task.

Table 6. *Authorship proportions (of the majority author) achieved by the bigram algorithm, followed by k-means division into two clusters, on Austen and Dickens texts of various block sizes. A 'perfect' result would be 1.0–1.0: each cluster is wholly one author; the worst result would be 0.5–0.5: each cluster is a completely undiscriminated mixture of both authors*

Block size (words)	Ratios	
100	0.40	0.57
200	0.59	0.62
500	0.71	0.78
1000	0.85	0.92

and 0.3. The original algorithm corresponds to $w = 0$, where paragraph length is not taken into account at all.

The modified algorithm performed much better than the original. A reasonably good recall of .80 could be achieved with $w = 0.3$, with a precision of 0.292 ($F = 0.427$). But while this is an improvement, the fact remains that less than 0.30 precision is quite poor and still not far above the random-guess baseline. It really does seem impossible to get good performance on this corpus using just letter bigrams. The reason for this is probably the straightforward one, which is that a few paragraphs, which usually contain a few hundred characters, are not enough to estimate 676 parameters well, and that any such estimates are extremely unreliable. Another way of looking at it is that as a feature, letter bigrams are just not rich enough to discriminate between pairs of paragraphs by different authors and pairs of paragraphs by the same author. So no matter what techniques and tricks are used, bigram feature vectors are not sufficiently set apart from each other to be able to draw any conclusions without looking at other features.

8.3 Determining the minimum size needed for n-gram methods

Our experiments showed that *n*-gram methods work well for very large texts, but not for very small ones. Our next task was therefore to find out just how much text was needed to get good performance. We divided the texts in the Austen–Dickens corpus into blocks of various sizes, and tried the methods on each set of blocks. We evaluated performance thus: For each block-size B, bigram feature vectors were computed for the blocks. Then a k-means clustering algorithm was applied to divide the feature vectors into two clusters, and the proportion of blocks by each author in each cluster was computed. So, if the *n*-gram methods were successful, then the feature vectors for blocks by a given author would tend to cluster together, and the proportion would be high. This experiment was run with block sizes ranging from 100 to 1000 words, and the results are given in Table 6. When the block-size B is 100 or 200, the performance is not much better than random. However, when it is 500, a definite jump occurs, and the accuracy jumps to about 75%. So it seems that

the bigram distribution starts to become reliable when the text size is about 500 words, and is very reliable once the text size exceeds a few thousand words.

8.4 Discussion

Our original goal, to use *n*-gram methods to segment the *Risks* corpus by author, was not achieved; the text sizes were just too small to use such a feature, and the results were inferior to those from time-delay neural networks. However, we have demonstrated when such methods do start to become useful: when the individual segments can reasonably be expected to be more than about 500 words long.

A question for future work is whether all *n*-grams need to be used. Most *n*-grams occur very rarely, and so are not particularly useful in discriminating between texts. It would be interesting to find out whether this fact could be used to reduce the number of parameters being estimated, and thereby allow the method to be used on smaller documents.

9 Conclusion

The experiments that we have reported in this paper are intended to support the long-term goal of building a writer's assistant for diagnosing stylistic inconsistency within a document.

The experiments demonstrate that it is possible to design a system that, with significant probability, can infer the presence of authorship contribution boundaries by means of stylistic statistics, despite the very small sizes of the samples of text available. We have also shown that this is best done with statistics that capture high-level elements of style such as preferences in grammatical constructions (part-of-speech, function-word, and punctuation frequencies). Conversely, we have shown that several categories of stylistic statistics perform poorly on short texts. Especially disappointing in this regard was our failure to extend the excellent results of Juola (1997) and those of Kjell and colleagues (Kjell *et al.* 1992, 1994) with *n*-grams.

Our results add force to the contention that neural networks are a useful tool in stylometry. While it certainly does not seem that simple multilayer perceptrons trained on amorphous sets of stylistic data are useful, we have shown that networks trained on individual statistical categories can be joined together to produce a result better than that achievable by any of the component networks alone. Perhaps our most significant contribution is the application of time-delay networks to this field, since we aren't aware of any prior literature in stylometry where this network architecture has been used. The superior performance that these networks usually exhibited compared to more traditional architectures trained on the same data suggests that this learning paradigm deserves considerably more attention than it has been accorded.

Now that we are able to locate stylistic inconsistencies with reasonable probability, an attempt to develop a system to advise users on the creation of stylistically homogeneous documents is potentially feasible. Many hurdles need to be overcome, of course, not least exactly how statistical information about stylistic inconsistencies

could be shaped into a human-comprehensible form. Our use of neural networks as the discriminating mechanism compounds this challenge.

Manual examination of the internals of our most successful networks will be a first step in solving this problem. Conducting further experiments with the three most useful categories of data we have presented here, both to determine what subsets of these categories provide most information and to gain insight into interactions within and amongst the categories, will also be extremely informative and could lead to less computationally intensive methods. It would also be worthwhile to find out whether windows larger than two paragraphs might prove effective, particularly with time-delay networks.

Our success with high-level statistics also raises questions: if part-of-speech tags perform so well, would even higher-level statistics, such as frequencies of noun phrases of various lengths, proportion of prepositional phrases, and so on, be even more useful? Both Stamatatos *et al.* (1999, 2000) and Hatzivassiloglou, Klavans and Eskin (1999) have successfully demonstrated applications for these sorts of statistics, and a study linking these ideas with powerful neural net architectures should prove very interesting.

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