Automatically Categorizing Written Texts by Author Gender

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Abstract

The problem of automatically determining the gender of a document's author would appear to be a more subtle problem than those of categorization by topic or authorship attribution. Nevertheless, it is shown that automated text categorization techniques can exploit combinations of simple lexical and syntactic features to infer the gender of the author of an unseen formal written document with approximately 80 per cent accuracy. The same techniques can be used to determine if a document is fiction or non-fiction with approximately 98 per cent accuracy.

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1 Introduction

1.1 Text categorization

The last 10 years has seen an explosion of research in automated text categorization (Sebastiani, 2002). In the text categorization problem, we are given a set of two or more categories and examples of texts in each category and are asked to correctly categorize unseen texts. The components of a text categorization system are now well understood:

(1) Document representation—choose a large set of text features that might potentially be useful for categorizing a given text (typically words that are neither too common nor too rare) and represent each text as a vector in which entries represent (some non-decreasing function of) the frequency of each feature in the text.
(2) Dimension reduction—optionally, use various criteria for reducing the dimension of the vectors, typically by eliminating features that do not seem to be correlated with any category (Yang and Pedersen, 1997), by using latent semantic indexing (Deerwester *et al.*, 1990), or by stepwise iteration of a learning algorithm (see below).

(3) Learning method—use some machine learning method to construct one or more models of each category. Yang (1999) compares and assesses some of the most promising algorithms, which include k-nearest-neighbour, neural nets, Winnow, SVM, etc. (If multiple models are learned, methods such as bagging and boosting (Bauer and Kohavi, 1999) can be used to combine the models.)

(4) Testing protocol—finally, use some testing protocol, such as bootstrapping or *k*-fold cross-validation to estimate the reliability of the system.

1.2 Stylometry

Driven by the problem of Internet search, the text categorization literature—outside of the stylometric research community—has, with a few exceptions (Argamon-Engelson *et al.*, 1998; Wolters and Kirsten, 1999), concerned categorization by topic rather than categorization by writing style. The problem considered in this paper concerns categorization by style and thus is more similar to the stylometric work that has been vigorously pursued for decades, mostly in the context of authorship attribution (Holmes, 1998; McEnery and Oakes, 2000). Although some important crossover work between stylometrics and text categorization has been done (Forsyth, 1999), the bulk of stylometric research has differed from the more recent work in text categorization in a few important ways. Whereas categorization by topic is typically based on keywords that reflect a document's content, categorization by author style uses precisely those features that are independent of content. Thus, stylometric models for categorization have typically been based on hand-selected sets of content-independent, lexical (Mosteller and Wallace, 1964), syntactic (Baayen *et al.*, 1996; Stamatatos *et al.*, 2001), or complexity-based (Yule, 1938) features. Researchers in text categorization by topic typically use much larger feature sets, often in conjunction with automated feature selection methods (Yang and Pedersen, 1997); some work in the stylometric community has also considered automated methods for selecting features (Forsyth and Holmes, 1996). Moreover, stylometric research has tended to use statistical methods such as multivariate analysis (Burrows, 1992; Holmes and Forsyth, 1995), rather than machine-learning algorithms for categorization, although a number of researchers have applied machine learning methods to stylometric problems (Matthews and Merriam, 1993; 1997; Merriam and Matthews, 1994, Forsyth, 1999).

1.3 Gender

The object of this paper is to explore the possibility of automatically classifying formal written texts according to author gender. This problem differs from the typical text categorization problem, which focuses on categorization according to topic. It also differs from the typical stylometric problem, which focuses on authorship attribution—individual authors are more likely to exhibit consistent habits of style than are large classes of authors. We will see, however, that using ideas from both the

stylometric community and the text categorization community, we are able to achieve surprising results.

Whereas a substantial literature has been devoted to isolating distinguishing characteristics of male or female linguistic styles (Lakoff, 1975; Holmes, 1993), this paper goes beyond earlier work in two ways.

First, most of the previous work considered spoken language (Key, 1972; Trudgill, 1972; Labov, 1990; Eckert, 1997), which, unlike the formal written texts (i.e. books and articles) we consider, includes intonational, phonological, and conversational cues. The relatively few studies on gender differences in writing have focused on more informal contexts—such as student essays (Mulac *et al.*, 1990, Mulac and Lundell, 1994), electronic communications (Herring, 1996) and correspondence (Biber *et al.*, 1998; Palander-Collin, 1999)—and some researchers (Berryman-Fink and Wilcox, 1983; Simkins-Bullock and Wildman, 1991) have asserted that no difference between male and female writing styles in more formal contexts should be expected.

Second, there has been scant evidence thus far that differences between male and female writing are pronounced enough that they could be parlayed into an algorithm for categorizing an unseen text as being authored by a male or by a female. In this paper, we employ machine learning algorithms on a genre-controlled corpus of 566 documents taken from the British National Corpus (BNC) to construct models for performing just such a task. We show that these models classify unseen texts according to author gender with accuracy of approximately 80 per cent.

2 The Corpus

The BNC includes 920 documents in British English that are labelled both for author gender and for genre: fiction and several non-fiction genres and sub-genres as will be shown below. All the experiments reported in this paper were performed on a genre-controlled subset of the BNC constructed as follows: in each sub-genre, we use all the documents in the smaller (male or female) class and randomly select an equal number of documents from the other class, discarding the excess documents. The resulting corpus contains 566 documents (a full listing of which can be found at http://www.ir.iit.edu/~argamon/gender.html).

No single author wrote more than three documents in this corpus. All of the non-fiction documents and 75 per cent of the fiction documents are from the years 1975–1993; the remaining fiction documents are from the years 1960–1974. The documents contain between 554 and 61,199 words with an average of about 34,320 words each (female 34,795; male 33,845).

3 Document Representation

Unlike some earlier studies on authorship attribution (see Holmes, 1998; McEnery and Oakes, 2000), we do not begin with a small hand-selected

set of features deemed most likely to distinguish between categories. Rather, we begin with a very large set of lexical and quasi-syntactic features that were chosen solely on the basis of their being more-or-less topic-independent. The features include a list of 405 function words (which appear at least once in the corpus) and a list of *n*-grams of parts-of-speech using the BNC's tag set of seventy-six parts of speech (POS; such as PRP = preposition, NN1 = singular noun, and AT0 = article) and punctuation marks. (A full listing of all these features can be found at http://shekel.jct.ac.il/~argamon/gender-style.) We use the 500 most common ordered triples, 100 most common ordered pairs and all the single tags as features. For example, a common triple is PRP_AT0_NN1 as in the phrase 'above the table'. The use of parts-of-speech n-grams is a relatively efficient way to capture the heavier syntactic information shown by Baayen *et al.* (1996) and Stamatatos *et al.* (2001) to be useful for distinguishing writing styles.

Each document is thus represented as a vector of length 1,081 (the total number of features), in which each entry represents the number of appearances of the feature in the document divided by document length. So that different feature types all have values in roughly the same range, the values associated with function words and POS doubles were multiplied by two and those associated with POS triples were multiplied by four.

We will use automated methods to significantly reduce the number of features actually used for classification. However, these methods make use of iterated runs of our learning algorithm, so we turn first to the details of this learning algorithm.

4 The Learning Method

Our objective is to use a set of training documents to find a linear separator between male-authored and female-authored documents. That is, we seek a weight vector w such that for each training document, x, the vector dot-product $w.x$ exceeds a threshold T if and only if x was authored by a female. Our method for finding the weight vector w is a variant of the Exponential Gradient (EG) algorithm of Kivinen and Warmuth (1997), which itself is a generalization of the Balanced Winnow algorithm of Littlestone (1987). These algorithms have useful theoretical mistake-bound properties and have previously been shown to be effective for text-categorization by topic (Lewis *et al.*, 1996; Dagan *et al.*, 1997).

Briefly, our method works as follows. We initially define two component weight vectors $w^+ = \{1, 1, \ldots, 1\}$ and $w- = \{-1, -1, \ldots, -1\}$, defining $w = w^+ + w^-$. We then calibrate the vectors w^+ and w^- using the following iterative procedure. The training examples are randomly ordered. For each training example x, we define $c(x) = 1$ if x is female-authored and $c(x) = 0$ otherwise. Let $s(w,x) = 1$ if $w \cdot x > 0$ and $s(w,x) = 0$ otherwise, where w is the weight vector at the time that example x is encountered, and let w_i and x_i be the ith element in w and x, respectively.

Then we take the examples one at a time and iteratively update the weights after each example using the formulae

$$w_i^+ \leftarrow w_i^+ (1 + \beta x_i)^{(c(x) - s(w,x))}$$

$$w_i^- \leftarrow w_i^- (1 + \beta x_i)^{(s(w,x) - c(x))}$$

β is a learning constant greater than zero; in all our experiments we used $\beta = 3$. Thus weights that improperly reduce the dot product are increased, and vice versa. It should be noted that, as in EG, but unlike Balanced Winnow, we allow x_i to take on non-binary values. However, as in Balanced Winnow, but unlike EG, we restrict $s(w,x)$ to binary values.

Once all the examples have been used for training, they are randomly reordered and another cycle of updates is run. This continues until all training examples are correctly classified or until 100 consecutive cycles fail to produce improvement in the number of training examples correctly classified. Along the way, any element of w^+ or w^- that drops below some threshold (0.000001 of the sum of all the weights) is set to zero.

The intuition behind the update rule is that weights of features that appear most prominently in misclassified documents are changed most dramatically. A well-known advantage of multiplicative update rules such as we use is that the weights of irrelevant features tend to zero. As a result of this property, the learning algorithm itself can be used for feature reduction: by iteratively running the learner, eliminating low-weighted features and rerunning, we can produce models with fewer and fewer features. Experimental results using this method will be discussed below.

5 Results

Table 1 (top row) shows accuracies obtained from ten separate runs of fifty-six-fold cross-validation (that is, ten examples in each fold) using feature sets consisting of function words only (FW), parts-of-speech only (POS), and both function words and parts-of-speech (FWPOS). For function words, 73.7 per cent (± 0.86 per cent stderr) of the documents are correctly classified, for parts-of-speech, 70.5 per cent (± 0.90 per cent), and for the full feature set, 77.3 per cent (± 0.79 per cent). Clearly, the combined feature set is the best choice, despite the fact that using more features than documents (that is, more free parameters than constraints) might easily have led to over-fitting to the training set at the expense of testing accuracy.

Table 1 Accuracies with standard errors for ten cross-validation runs each (see text for details) for different train/test domains and different feature sets

Domain	FW	POS	FWPOS
All	73.7 ± 0.86	70.5 ± 0.90	77.3 ± 0.79
Fiction	78.8 ± 1.1	77.1 ± 0.85	79.5 ± 1.1
Nonfiction	68.5 ± 1.3	67.2 ± 1.2	82.6 ± 0.99

One of the difficulties in obtaining greater accuracy overall is the difference between fiction and non-fiction. These differences are generally greater than the difference between male and female writing styles and thus training on fiction and non-fiction documents together actually harms results. When we train together, accuracy on fiction test documents is 74.5 per cent and on non-fiction is 79.7 per cent. When we train only on fiction documents (thus using a substantially smaller training set), results of thirty-six-fold cross-validation (maintaining ten examples per fold) actually increase to 79.5 per cent. Likewise, when training on non-fiction only, accuracy on non-fiction test documents increased to 82.6 per cent. This is because, as we shall see in detail below, the frequencies of the critical distinguishing features are different in fiction and non-fiction. In fact, when training is performed on fiction (non-fiction) only, non-fiction (fiction) documents are categorized with barely more than 50 per cent accuracy—no better than random!

Table 1 (rows 2 and 3) shows the results of training and testing separately on fiction and non-fiction using different feature sets. What is most remarkable is the extent to which results for non-fiction improve when both feature sets are used in tandem. The reasons for this will be discussed below. The full breakdown of results for different sub-genres—respectively, training (using all features) on all documents together and training (likewise using all features) separately on fiction and non-fiction—is shown in Table 2.

Winnow is able to overcome differences between genres by exploiting subtle dependencies between features. Less subtle learning methods are

Table 2 Accuracy averaged over ten cross-validation runs, broken down by genre of the test documents, with training either on all documents or on fiction or non-fiction documents only

Testing on genre	Number of documents	Train on all	Train on fiction
Fiction	264	74.5	79.5
Fiction/female	132	74.8	81.7
Fiction/male	132	74.2	77.3
			Train on non-fiction
Non-fiction	302	79.7	82.6
Non-fiction/female	151	79.2	83.3
Non-fiction/male	151	80.2	81.9
Arts (non-academic)	16	76.0	76.3
Arts (academic)	24	75.6	77.5
Belief and thought	24	84.9	85.0
Biography	54	87.0	90.0
Commerce	10	60.0	84.0
Leisure	16	85.7	81.3
Science	26	74.2	78.5
Social science (non-academic)	52	77.5	83.0
Social science (academic)	38	82.9	78.4
World affairs	42	79.21	82.9

The number of documents indicated on each line of column 2 reflects an equal number of male and female documents. (See text for further details of the experimental technique.)

unable to deal successfully with this problem. Thus, Naive Bayes, which ignores feature dependences, correctly classifies fiction documents with only 64.4 per cent accuracy and non-fiction documents with 60.9 per cent accuracy. Ripper, which is a decision-tree learner that greedily selects feature thresholds for optimal category separation, correctly classifies fiction documents with 64.9 per cent accuracy and non-fiction documents with 73.7 per cent accuracy. (Results are for the full feature set; results for FW and POS vary only slightly.)

6 Feature Reduction

How many features actually contribute to categorization and which ones contribute most? To test this we ran the following experiment. For each model obtained in a cross-validation trial, we chose the 128 most important features (where the importance of a feature in a given model is defined as the absolute value of its weight in the model multiplied by its average frequency in the training set) in each direction and ran the cross-validation trial again using only those 256 features. We then repeated the process using only the 128 most important features (sixty-four from each side) in the obtained model. This process was iterated down to just eight features from each side. The results are shown in Fig. 1. Optimal performance seems to lie between sixty-four and 128 features per side. For the full feature set, non-fiction reaches accuracy of 83.7 per cent at 128 features per side and fiction reaches 79.9 per cent at sixty-four features per side. Most significantly, however, the drop-off in performance is extremely slow. Even using as few as eight features (from the full feature set) on a side, we obtain accuracy of 79.1 per cent for non-fiction and 76.8 per cent for fiction.

In fact, when training and testing on fiction using only function words, optimal performance (79.4 per cent) is achieved when using only eight words from each side. Not surprisingly, certain features tended to survive down to the final iteration in different trials. For example, the function words that consistently appear in the final iteration training on fiction are: male features—*a*, *the*, *as*; female features—*she*, *for*, *with*, *not*.

Fig. 1 Averaged cross-validation accuracies for training/testing on fiction and on non-fiction, plotted over different numbers of features, ranging from the full feature sets of 1,081 (FWPOS), 676 (POS), and 405 (FW) features, down to eight features in each case. (See text for detail on experimental technique.)

Feature reduction for Fiction

Feature reduction for Non-fiction
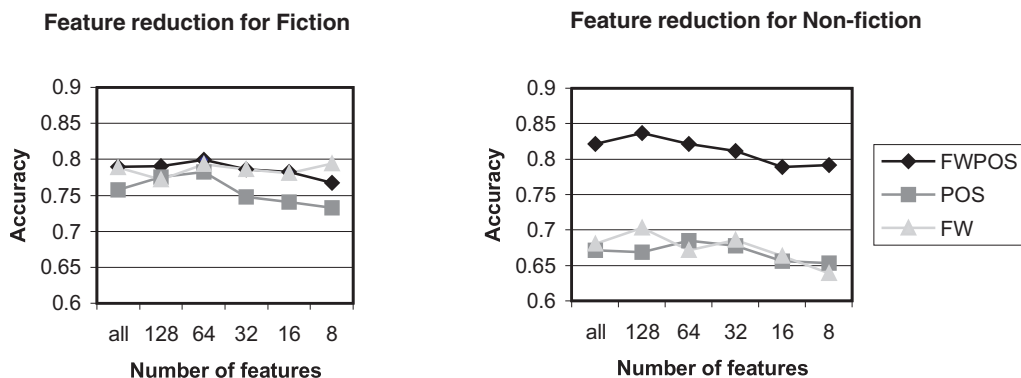
When training on non-fiction we find: male features—*that*, *one*; female features—*for*, *with*, *not*, *and*, *in*. Similar phenomena appear when using parts-of-speech. In another paper, not yet published, we have analysed differences in usage between males and females for certain classes of words. The picture that emerges is that the male indicators are largely noun specifiers (determiners, numbers, modifiers) whereas the female indicators are mostly negation, pronouns, and certain prepositions. Although a given feature's Winnow weight does not necessarily reflect the feature's mean frequency difference between males and females, a comparison of male and female usage of determiners, pronouns, prepositions, negation, and the conjunction *and* (Table 3) reveals significant differences in usage between males and females both in fiction and in non-fiction. These results bear out and significantly extend results of earlier research on gender differences (Holmes, 1993; Biber *et al.*, 1998).

Another interesting fact that is explained by analysis of the data is that for non-fiction, using function words and parts-of-speech together yields considerably greater accuracy than either feature type by itself. This is because the combination of features is able to exploit anomalies such as that women use the prepositions *for* and *with* significantly more frequently than do men, but men use the set of all other prepositions (PRP) with about the same frequency as do women and the preposition *of* (which in the BNC gets its own tag, PRF) with greater frequency than women. Similarly, men use the pronoun *he* with about the same frequency as do women but women use the set of all other pronouns much more than men do. In particular, what distinguishes non-fiction is that, as in fiction, men use significantly more determiners (AT0, DT0) than do women, but, unlike fiction, women use the most frequent determiner, *the*, with about the same frequency as men.

The extent to which frequencies of a small number of features can be parlayed into effective categorization is illustrated by the following fact:

Table 3 Frequency means (per 10,000 words) and standard errors for a variety of features in male/female fiction/non-fiction documents

	Fiction		Non-fiction	
Feature	**Male μ ± stderr**	**Female μ ± stderr**	**Male μ ± stderr**	**Female μ ± stderr**
PNP	732 ± 14	809 ± 15	291 ± 12	331 ± 17
he	145 ± 4.7	135 ± 4.7	47.5 ± 3.5	48.1 ± 4.3
she	67 ± 4.3	139 ± 6.9	8.73 ± 1.7	21.5 ± 2.3
AT0	735 ± 9.5	626 ± 8.7	884 ± 9.1	822 ± 12
DT0	160 ± 2.9	153 ± 2.0	220 ± 4.0	204 ± 4.6
the	520 ± 8.6	418 ± 7.5	611 ± 8.4	614 ± 12
XX0	84 ± 2.4	98 ± 2.2	54 ± 1.5	55 ± 2.3
PRP	623 ± 6.0	615 ± 5.7	767 ± 5.9	763 ± 7.0
PRF	170 ± 4.2	158 ± 3.7	355 ± 7.2	324 ± 7.9
for	55.7 ± 1.1	61.3 ± 1.0	77.9 ± 1.6	90.7 ± 1.4
with	58.6 ± 1.1	66.5 ± 1.0	56.9 ± 1.1	67.8 ± 1.4
and	234 ± 4.9	249 ± 5.5	242 ± 3.9	287 ± 5.2

Parts of speech are indicated using the BNC tag set (PNP = pronouns; AT0 = determiners *a*, *an*, *the*, *no*; DT0 = other determiners; XX0 = *not*, **n't*; RF = preposition *of*; PRP = other prepositions).

of the fifty-eight documents in which *the* appears with frequency <408 and *herself* appears with frequency >5, all but two are by females.

7 Categorization by Genre

An interesting phenomenon that is evident in Table 3 is that the differences between male and female usages of various features parallel more extreme differences between fiction and non-fiction: determiners, which are used more by men, are used more by all authors in non-fiction; pronouns and negation, which are used more by women, are used more by all authors in fiction. The extreme differences between fiction and non-fiction suggest that distinguishing between the two genres ought to be an easier task than distinguishing between male and female authors. And indeed it is. Using the same corpus and same learning technique as above on the fiction/non-fiction problem, ten runs of fifty-six-fold cross-validation yields accuracy of 98 per cent. Table 4 shows results for each of the three feature sets.

The misclassified documents are the following:

Fiction:
- *Possession,* A. S. Byatt;
- *The Remains of the Day*, Kazuo Ishiguro;
- *Now We Are Thirty-Somethings*, Charles Jennings;
- *Now Then Davos*, Martin Wiley, David Harmer, and Ian McMillan;
- *The Siege of Krishnapur*, J. G. Farrell;
- *A Landing on the Sun*, Michael Frayn.

Non-fiction:
- *Thank you for having me*, Maureen Lipman;
- *A Crowd is not Company*, Robert Kee;
- *T. S. Eliot: A Friendship*, Frederick Tomlin;
- *Walking on Water*, Andy Martin;
- Unpublished letters and manuscripts, Unlisted female author;
- *Falling for Love: Teenage Mothers Talk*, Sue Sharpe.

Examination of the six misclassified non-fiction documents reveals that all are biographical or diary-like works. Significantly, of the six misclassified fiction documents, five are by male authors (the sole exception is *Possession* by A. S. Byatt).

Table 4 Accuracies and standard errors for ten runs of fifty-six-fold cross-validation for the fiction/non-fiction problem for all three feature sets

Feature set	Accuracy
FWPOS	98.2 ± 0.003
POS	97.5 ± 0.003
FW	97.9 ± 0.003

8 Conclusions

This paper has presented convincing evidence of a difference in male and female writing styles in modern English books and articles. Such a difference is sufficiently pronounced that it can be exploited for automated text classification with accuracy of approximately 80 per cent (and higher in some cases). We have shown some of the features selected as being useful for classification, and have seen for some of them how their frequency distributions in the BNC differ for male and female authors.

The overall approach is essentially that of recent research in text categorization. The main difference between this work and text categorization by topic is in the choice of features: we use the kinds of content-independent features used by researchers in authorship attribution. Best performance is achieved when both function words and parts-of-speech n-grams are used in tandem. We have seen that whereas reasonable categorization is possible even using a relatively small number of such features, these features should be judiciously selected from a large initial set using principled feature reduction techniques. We have also found that the Winnow-like algorithm we used is superior for this type of problem to less subtle techniques such as decision trees and Naive Bayes.

The methods we have used in this work should work well for other style-based categorization problems. We have already seen that these methods distinguish fiction from non-fiction with about 98 per cent accuracy. Other problems that might be tackled using this approach could include text categorization according to various demographic groupings of authors or intended audience, sub-genres, chronology, publication forum, and so forth.

References

Argamon-Engelson, S., Koppel, M., and Avneri, G. (1998). Style-based text categorization: what newspaper am I reading? In *Proceedings of AAAI Workshop on Learning for Text Categorization*, pp. 1–4.

Baayen, H., van Halteren, H., and Tweedie, F. (1996). Outside the cave of shadows: using syntactic annotation to enhance authorship attribution. *Literary and Linguistic Computing*, **11:** 121–32.

Bauer, E. and Kohavi, R. (1999). An empirical comparison of voting classification algorithms: bagging, boosting, and variants. *Machine Learning*, **36:** 105–39.

Berryman-Fink, C. L. and Wilcox, T. R. (1983). A multivariate investigation of perceptual attributions concerning gender appropriateness in language. *Sex Roles*, **9:** 663–81.

Biber, D., Conrad, S., and Reppen, R. (1998). *Corpus Linguistics: Investigating Language Structure and Use*. Cambridge: Cambridge University Press.

Burrows, J. F. (1992). Not unless you ask nicely: the interpretative nexus between analysis and information. *Literary and Linguistic Computing*, **7:** 91–109.

Dagan, I., Karov, Y., and Roth, D. (1997), Mistake-driven learning in text categorization. In *EMNLP-97: 2nd Conference on Empirical Methods in Natural Language Processing*, pp. 55–63.

Deerwester, S., Dumais, S. T., Landauer, T. K., Furnas, G. W., and Harshman, R. A. (1990). Indexing by latent semantic analysis. *Journal of the Society for Information Science*, **41**(6): 391–407.

Eckert, P. (1997). Gender and sociolinguistic variation. In Coates, J. (ed.), *Readings in Language and Gender*. Oxford: Blackwell, pp. 64–75.

Forsyth, R. S. (1999). New directions in text categorization. In Gammerman, A. (ed.), *Causal Models and Intelligent Data Management.* Heidelberg, Germany: Springer, 151–85.

Forsyth, R. S. and Holmes, D. I. (1996). Feature finding for text classification. *Literary and Linguistic Computing*, **11:** 163–74.

Herring, S. (1996). Two variants of an electronic message schema. In Herring, S. (ed.), *Computer-Mediated Communication: Linguistic, Social and Cross-Cultural Perspectives*. Amsterdam: John Benjamins, pp. 81–106.

Holmes, D. (1998). The evolution of stylometry in humanities scholarship. *Literary and Linguistic Computing*, **13:** 111–17.

Holmes, D. I. and Forsyth, R. S. (1995). The Federalist revisited: new directions in authorship attribution. *Literary and Linguistic Computing*, **10:** 111–26.

Holmes, J. (1993). Women's talk: the question of sociolinguistic universals. *Australian Journal of Communications*, **20**(3): 125–49.

Key, M. R. (1972). Linguistic behavior of male and female. *Linguistics*, **88:** 15–31.

Kivinen, J. and Warmuth, M. (1997). Additive versus exponentiated gradient updates for linear prediction. *Information and Computation*, **132**(1): 1–64.

Labov, W. (1990). The intersection of sex and social class in the course of linguistic change. *Language Variation and Change*, **2:** 205–54.

Lakoff, R. T. (1975). *Language and Women's Place.* New York: Harper Colophon Books.

Lewis, D., Schapire, R., Callan, J., and Papka, R. (1996). Training algorithms for text classifiers. In *Proceedings of 19th ACM/SIGIR Conference on R&D in Information Retrieval*, pp. 298–306.

Littlestone, N. (1987). Learning quickly when irrelevant attributes abound: a new linear-threshold algorithm. *Machine Learning*, **2**(4): 285–318.

Matthews, R. and Merriam, T. (1993). Neural computation in stylometry: an application to the works of Shakespeare and Fletcher. *Literary and Linguistic Computing*, **8:** 203–9.

Matthews, R. A. J. and Merriam, T. V. N. (1997). Distinguishing literary styles using neural networks. In Fiesler, E. and Beale, R. (eds), *Handbook of Neural Computation*. Oxford: IOP and Oxford University Press.

McEnery, A. and Oakes, M. (2000). Authorship studies/textual statistics. In Dale, R., Moisl, H., and Somers, H. (eds), *Handbook of Natural Language Processing*. New York: Marcel Dekker, pp. 234–48.

Merriam, T. and Matthews, R. (1994). Neural computation in stylometry: an application to the works of Shakespeare and Marlowe. *Literary and Linguistic Computing*, **9:** 1–6.

Mosteller, F. and Wallace, D. L. (1964). *Inference and Disputed Authorship: The Federalist*. Reading, MA: Addison Wesley.

Mulac, A. and Lundell, T. L. (1994). Effects of gender-linked language differences in adults' written discourse: multivariate tests of language effects. *Language and Communication*, **14**(3): 299–309.

Mulac, A., Studley, L. B., and Blau, S. (1990). The gender-linked language effect in primary and secondary students' impromptu essays. *Sex Roles*, **23**(9–10): 439–69.

Palander-Collin, M. (1999). Male and female styles in 17th century correspondence. *Language Variation and Change*, **11:** 123–41.

Sebastiani, F. (2002). Machine learning in automated text categorization. *ACM Computing Surveys*, **34**(1), 1–47.

Simkins-Bullock, J. A. and Wildman, B. G. (1991). An investigation into the relationship between gender and language. *Sex Roles*, **24:** 149–60.

Stamatatos, E., Fakotakis, N., and Kokkinakis, G. (2001). Computer-based authorship attribution without lexical measures. *Computers and the Humanities*, **35:** 193–214.

Trudgill, P. (1972). Sex, covert prestige and linguistic change in the urban British English of Norwich. *Language in Society*, **1:** 179–95.

Wolters, M. and Kirsten, M. (1999). Exploring the use of linguistic features in domain and genre classification. In *Proceedings of the Meeting of the European Chapter of the Association for Computational Linguistics*, pp. 142–9.

Yang, Y. (1999). An evaluation of statistical approaches to text categorization. *Journal of Information Retrieval*, **1**(1–2): 67–88.

Yang, Y. and Pedersen, J. O. (1997). A comparative study on feature selection in text categorization. In *Proceedings of ICML-97, 14th International Conference on Machine Learning*, pp. 412–20.

Yule, G. U. (1938). On sentence length as a statistical characteristic of style in prose with application to two cases of disputed authorship. *Biometrika*, **30:** 363–90.