Rank Distance as a Stylistic Similarity

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Abstract

In this paper we propose a new distance function (rank distance) designed to reflect stylistic similarity between texts. To assess the ability of this distance measure to capture stylistic similarity between texts, we tested it in two different machine learning settings: clustering and binary classification.

1 Introduction

Computational stylistics investigates texts from the standpoint of individual style (author identification) or functional style (genres, registers). Because in all computational stylistic studies/approaches, a process of comparison of two or more texts is involved, in a way or another, there was always a need for a distance function to measure similarity (more precisely dissimilarity) of texts from the stylistic point of view. Such distance measures were proposed and used for example in authorship identification (Labbé and Labbè, 2001; Burrows, 2002) or clustering texts by genre (Luyckx et al., 2006).

In this paper we propose a new distance measure designed to reflect stylistic similarity between texts. As style markers we used the function word frequencies. Function words are generally considered good indicators of style because their use is very unlikely to be under the conscious control of the author and because of their psychological and cognitive role (Chung and Pennebaker, 2007). Also function words prove to be very effective in many author attribution studies. The novelty of our approach resides in the way we use information given by the function word frequencies. Given a fixed set of function words (usually the most frequent ones), a ranking of these function words according to their frequencies is built for each text; the obtained ranked lists are subsequently used to compute the distance between two texts. To calculate the distance between two rankings we used Rank distance (Dinu, 2003), an ordinal distance tightly related to the so-called Spearman’s footrule (Diaconis and Graham, 1977).

Usage of the ranking of function words in the calculation of the distance instead of the actual values of the frequencies may seem as a loss of information, but we consider that the process of ranking makes the distance measure more robust acting as a filter, eliminating the noise contained in the values of the frequencies. The fact that a specific function word has the rank 2 (is the second most frequent word) in one text and has the rank 4 (is the fourth most frequent word) in another text can be more relevant than the fact that the respective word appears 349 times in the first text and only 299 times in the second.

To assess the ability of this distance function to capture stylistic similarity between texts, we tested it in two different machine learning settings: clustering and binary classification.

Compared with other machine learning and statistical approaches, clustering was relatively rarely used in stylistic investigations. However, few researchers (Labbé and Labbè, 2001; Luyckx et al., 2006) have recently proved that clustering can be a useful tool in computational stylistic studies. Apart of this, clustering is a very good test bed for a distance measure behavior. We plugged our distance function into a standard hierarchical clustering algorithm and test it on a collection of 21 nine-
teenth century English books (Koppel et al., 2007). The results are very encouraging. The family trees produced grouped together texts according to their author, genre, even gender.

Also a distance measure can be used to solve classification problems if it is coupled with proper learning algorithm. One of the simplest such algorithms is nearest neighbor classification algorithm. We chose nearest neighbor algorithm because its performance is entirely based on the appropriateness to the data of the distance function on which it relies. In this way the accuracy of the classification will reflect the adequacy of the distance measure to data and domain on which the method was applied. We used the new distance function in conjunction with nearest neighbor classification algorithm and tested it on the well known case of authorship of disputed Federalist papers. The method attributed all disputed papers to Madison, the result being consistent with that of Mosteller and Wallace.

To check if the usage of ranks of function words is better suited for capturing stylistic differences than the usage of actual frequencies of the function words, we repeated the above experiments on clustering and binary classification with the standard euclidean distance between the vectors of frequencies of the same function words that were used in computing the rank distance. The comparison is in favor of rank distance.

2 Rank Distance and Its Use as a Stylistic Distance Between Texts

Rank distance (DINU, 2003) is an ordinal metric able to compare different rankings of a set of objects. It is tightly related to the Spearman’s footrule (Diaconis and Graham, 1977), and it had already been successfully used in computational linguistics, in such problems as the similarity of Romance languages (DINU and DINU, 2005).

A ranking of a set of \( n \) objects can be represented as a permutation of the integers \( 1, 2, \ldots, n \), \( \sigma \in S_n \). \( \sigma(i) \) will represent the place (rank) of the object \( i \) in the ranking. The Rank distance in this case is simply the distance induced by \( L_1 \) norm:

\[
D(\sigma_1, \sigma_2) = \sum_{i=1}^{n} |\sigma_1(i) - \sigma_2(i)|
\] (1)

This is a distance between what is called full rankings. However, in real situations, the problem of tying arises, when two or more objects claim the same rank (are ranked equally). For example, two or more function words can have the same frequency in a text and any ordering of them would be arbitrary.

The Rank distance allocates to tied objects a number which is the average of the ranks the tied objects share. For instance, if two objects claim the rank 2, then they will share the ranks 2 and 3 and both will receive the rank number \( (2+3)/2 = 2.5 \). In general, if \( k \) objects will claim the same rank and the first \( x \) ranks are already used by other objects, then they will share the ranks \( x+1, x+2, \ldots, x+k \) and all of them will receive as rank the number:

\[
\frac{(x+1)+(x+2)+\ldots+(x+k)}{k} = x + \frac{k+1}{2}.
\]

In this case, a ranking will be no longer a permutation \( (\sigma(i) \) can be a non integer value), but the formula (1) will remain a distance (DINU, 2003).

Rank distance can be used as a stylistic distance between texts in the following way:

First a set of function word must be fixed. The most frequent function words may be selected or other criteria may be used for selection. In all our experiments we used the set of 70 function words identified by Mosteller and Wallace (Mosteller and Wallace, 1964) as good candidates for author-attribution studies. The set is given in Table 1.

Once the set of function words is established, for each text a ranking of these function words is computed. The ranking is done according to the function word frequencies in the text. Rank 1 will be assigned to the most frequent function word, rank 2 will be assigned to the second most frequent function word, and so on. The ties are resolved as we discussed above. If some function words from the set don’t appear in the text, they will share the last places (ranks) of the ranking.

The distance between two texts will be the Rank distance between the two rankings of the function words corresponding to the respective texts.

3 Clustering Experiments

One good way to test the virtues of a distance measure is to use it as a base for a hierarchical cluster-

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| for | not | not | so | some | to | with | with |
| from | not | not | so | some | to | with | with |

Table 1: Function words used in computing the distance
In our experiments we used an agglomerative hierarchical clustering algorithm (Duda et al., 2001) with average linkage.

In the first experiment we cluster a collection of 21 nineteenth century English books written by 10 different authors and spanning a variety of genres (Table 2). The books were used by Koppel et al. (Koppel et al., 2007) in their authorship verification experiments.

The resulted dendogram is shown in Figure 1. As can be seen, the family tree produced is a very good one, accurately reflecting the stylistic relations between books. The books were grouped in three big clusters (the first three branches of the tree) corresponding to the three genre: dramas (lower branch), essays (middle branch) and novels (upper branch). Inside each branch the works were first clustered according to their author. The only exceptions are the two essays of Emerson which instead of being first cluster together and after that merged in the cluster of essays, they were added one by one to this cluster. Apart of this, the family tree is perfect. Even more, in the cluster of novels one may distinguished two branches clearly separated that can correspond to the gender or nationality of the authors: female English (lower part) and male American (upper part).

For comparison, the dendogram in Figure 2 show the same books clustered with the same algorithm, but using the standard euclidean distance instead of the rank distance as measure of stylistic similarity. The same set of function words as in the case of rank distance was used. This time though, each text was represented as a vector of

| Group               | Author | Book                          |
|---------------------|--------|-------------------------------|
| American Novelists  | Hawthorne | Dr. Grimshawe's Secret        |
|                     | Melville | Redburn, Moby Dick            |
|                     | Cooper   | The Last of the Mohicans, The Spy, Water Witch |
| American Essayists  | Thoreau  | Walden, A Week on the Concord |
|                     | Emerson  | Conduct of Life, English Traits |
| British Playwrights | Shaw     | Pygmalion, The Man of Property |
|                     | Wilde    | The Picture of Dorian, Woman of No Importance |
| Bronte Sisters      | Anne    | Agnes Grey, Tenant of Wildfell Hall |
|                     | Charlotte | The Professor, Jane Eyre |
|                     | Emily   | Wuthering Heights |

Table 2: The list of books used in the experiment
relative frequencies of these function words in the text. The relative frequency of a particular function word in a text is calculated as the number of appearances of the respective function word in the text divided by the length (in tokens) of the text. The distance between two texts is given by the euclidean distance between the corresponding vectors of relative frequencies of function words. In the family tree obtained using euclidean distance, most of the books are still grouped according to their author, but the distinct clusters corresponding to genre and gender disappeared and the novels of Melville were separated: one being clustered with the essays of Thoreau (Moby Dick) and the other with the novels of Hawthorne.

4 Binary Classification Experiments

When a distance measure is available, the most natural choice of a classification algorithm is the nearest neighbor algorithm (Duda et al., 2001). We tested the nearest neighbor classification algorithm combined with both rank distance and euclidean distance on the case of the 12 disputed federalist papers (Mosteller and Wallace, 1964). In our experiments we followed the Mosteller and Wallace setting, treating the problem as a binary classification problem. Each one of the 12 disputed papers has to be classified as being written by Hamilton or Madison. For training are used the 51 papers written by Hamilton and the 14 papers written by Madison.

Tested on disputed papers, the nearest neighbor classification algorithm combined with rank distance attributed all the 12 papers to Madison. This matches the results obtained by Mosteller and Wallace and is in agreement with today accepted thesis that the disputed papers belong to Madison. When the nearest neighbor classification algorithm was combined with euclidean distance only 11 papers were attributed to Madison, the paper 56 was attributed to Hamilton.

5 Discussion

In this paper we have proposed a new distance measure based on the ranking of function words, designed to capture stylistic similarity between texts. We have tested it in two different machine learning settings: clustering and binary classification; we have compared its performance with that of standard euclidean distance on vectors of frequencies of the function words. Though testing on more data is needed, the initial experiments shown that the new distance measure is indeed a good indicator of stylistic similarity and better suited for capturing stylistic differences between texts than the standard euclidean distance.

In future work it would be useful to test this distance measure on other data sets and especially in other machine learning paradigms like one-class classification to solve authorship verification problems (Koppel et al., 2007).

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