Separating the articles of authors with the same name

José M. Soler*
Departamento de Física de la Materia Condensada, C-III, Universidad Autónoma de Madrid, E-28049 Madrid, Spain
(Dated: February 1, 2008)

I describe a method to separate the articles of different authors with the same name. It is based on a distance between any two publications, defined in terms of the probability that they would have as many coincidences if they were drawn at random from all published documents. Articles with a given author name are then clustered according to their distance, so that all articles in a cluster belong very likely to the same author. The method has proven very useful in generating groups of papers that are then selected manually. This simplifies considerably citation analysis when the author publication lists are not available.

Citation analysis has become an essential tool for research evaluation. Generally, the evaluation referees are provided with a list of publications of the individuals or groups to be evaluated, although frequently these are in a format (say, on paper) that is not easy to use for searches in citation databases. Furthermore, the widespread accessibility of these databases to the full research community has stimulated less formal evaluations, in which publication lists are not available. In such cases, the publication lists themselves must be generated from the databases, complementing the author names with their affiliations and research fields. When even these are not well known (say, because only the last affiliation and research field are known) the search must be based on the author name only. This poses the problem of extracting the articles of the desired author, among those of other authors with the same name.

In this work I address this problem by defining a distance between any two given articles, based on the coincidences between them. This allows to cluster related articles, so that all the articles of a cluster are likely to belong to the same author. This reduces the problem to that of selecting the appropriate clusters, rather than each individual article.

Distances between documents have been proposed on the basis of coincidences of words and phrases as well as n-grams (sequences of n consecutive characters) and these distances have been used for a wide range of tasks, like language classification, or collecting documents on a given subject. In the present case, we are interested in relating documents whose full text is usually not available, while their abstract is generally available but relatively expensive to handle in terms of database access and storage. Instead, documents are characterized by a record with a variety of fields, like author names and addresses, title, research field, keywords, journal and year of publication, etc. Since coincidences in all these fields are significant for identifying their authors, the problem arises of how to combine them in a consistent way. Thus, one needs to answer questions like: are two papers ‘closer’ if they were published in the same journal or if they have n common words in their titles? Or if they have a common coauthor?

To solve this problem, I will propose the following general idea: imagine that you draw two documents at random from the entire database of $N_D$ documents. The probability that they coincide in everything (that is, that the same document is drawn twice) is obviously $1/N_D$. The probability that they coincide in any given feature is also well defined in principle. For example, if $n_j$ of the documents in the database were published in a given journal $j$, the probability that the two random articles were published in that journal is $(n_j/N_D)^2$. The probability that the two random articles had a journal-of-publication coincidence less or equal likely than that is $\sum_{j=i}^{N_j} (n_i/N_D)^2$, with the $N_j$ journals ordered by decreasing order of their number of articles in the database.

Then I will define the distance $D_{ij}$ between two documents $i$ and $j$ by

$$D_{ij} = \log_{10}(P_{ij}) - \log_{10}(1/N_D)$$ (1)

where $P_{ij}$ is the probability that two random documents would have overall coincidences less or equal likely than those between $i$ and $j$. Clearly, $i = j \Rightarrow P_{ij} = 1/N_D$ and $D_{ij} = 0$. On the other extreme, if $i$ and $j$ do not coincide in anything, then $P_{ij} = 1$ and $D_{ij} = \log_{10}(N_D)$ will be maximum.

Obviously, $P_{ij}$ is highly nontrivial to calculate, especially for multiple, correlated coincidences. However, it turns out that very crude approximations still lead to meaningful distances that are useful for our purposes. Therefore, as a first approach, I will make two extremely crude approximations: 1) assume that all possible values of a given field (say author names, like R. Smith and J. M. S. Torroja) are equally probable; and 2) ignore any correlations between different coincidences (like address words Harvard and Massachusetts). I will divide each field in ‘words’, and allow only one instance of each word within the field (that is, if the word Spain appears twice in the list of author addresses, I will take it only once). Some words, like articles and prepositions of the title, will be excluded. Thus, each field will be characterized by an estimated number of possible word values occurring in it.

---

*E-mail: jose.soler@uam.es
For example, if the estimated number of journals is $N_J$, the approximated probability that they are equal for two random articles is $1/N_J$. More generally, if the estimated number of possible word values in a field is $N$, and there are $n_i$ and $n_j$ different words in that field of articles $i$ and $j$, the probability that exactly $n_{ij}$ of them coincide (in any order) is

$$p(n_{ij}|n_i, n_j, N) = \frac{n_i! n_j! (N-n_i)! (N-n_j)!}{N! n_i! (n_i-n_{ij})! (n_j-n_{ij})! (N-n_i-n_j+n_{ij})!}$$

which is the probability of getting $n_{ij}$ common balls from two independent random extractions of $n_i$ and $n_j$ balls out of a set of $N$ different balls. The probability of getting at least $n_{ij}$ coincidences is simply $P(n_{ij}|n_i, n_j, N) = 1 - \sum_{n=1}^{n_{ij}} p(n_i, n_j, N)$. Then, ignoring also correlations between different fields, I will approximate the distance between $i$ and $j$ by

$$D_{ij} \simeq \log_{10}(N_D) + \sum_{f=1}^{N_F} \log_{10} \left( \frac{P(n_{ij}^f|n_i^f, n_j^f, N^f)}{P(n_{ij}^f|n_i^f, n_j^f, N^f)} \right)$$

where $f$ indexes the $N_F$ different record fields.

Table I shows the estimated number of possible values for the fields provided by the standard records of the ISI-Thomson Web of Knowledge database. Notice that most of the assumed values are much lower than the true number of possible options. Rather, they are set so that $1/N$ is roughly the probability of the most frequent word in that field (i.e. $\sim 10^{-3}$ is the estimated probability of an author name like R. Smith). Even thus, when two articles are ‘close’ (i.e. when they belong to the same author), the neglect of correlations implies a large underestimation of the probability of the combined coincidences, making $D_{ij}$ negative. The important point, however, is that, when the two articles do not belong to the same author, the coincidences are rarely sufficient to make $D_{ij} < 2$, which is what one would expect for the probability $P_{ij} \simeq 10^2/N_D$ that two random articles belong to the same author (assuming that the average author has published $\sim 10^2$ articles).

It is not frequent that an author changes the affiliation and, simultaneously, the field of research (for example after finishing the PhD). Still, it is common that she/he publishes a pending work in the former field (and perhaps with some of the former coauthors) but using already the new affiliation. In this case, it is possible to trace the common author identity in the two groups of apparently unrelated papers. To allow this, I define a new set of distances as

$$d_{ij} = \min_k (D'_{ik} + D'_{kj}), \quad \text{where } D'_{ij} = \max(D_{ij}, 0)$$

where $k$ runs over all the papers with the given author name. A similar redefinition of distances has been proposed for nonlinear dimensionality reduction, where $k$ was restricted to a small neighborhood of $i$ and $j$. In the present case, however, distances are strongly non Euclidian and multidimensional scaling has not proven particularly useful.

The problem of classifying or clustering a set of elements according to their distances is highly nontrivial. In our case, however, this task is facilitated by the neglect of correlations and the subsequent underestimation of distances between articles of the same author, since this creates a large gap between these distances and those among different authors. In practice, I simply make clusters of papers that have zero distance (notice that the definition of $d_{ij}$ implies that all the distances among the cluster members must be zero). The resulting clusters of papers, generated with the values of Table I tend to give some ‘false negatives’ (i.e. different clusters that belong to the same author) but rarely ‘false positives’ (papers of different authors within the same cluster), except perhaps for the most common author names (for these, it may be necessary to increase $N_D$, or to decrease the other values of Table I in order to increase the distances).

The clusters are then presented interactively (by showing one or more representative papers of the cluster), in different possible orders, for their selection or rejection. Other clues, like the period of publication of the cluster papers, or the distance to previously selected clusters, are also provided to help in the selection. Thus, in most cases it is very obvious which clusters must be selected, and the selection process is very fast and straightforward. Once the largest clusters have been considered, it is convenient to switch to an order of presentation by increasing distance to the selected papers and, as soon as this distance becomes larger than $\sim 3$, the remaining clusters may be rejected altogether. This is important since, most generally, the main inconvenience is the large number of small clusters (many of them with a single paper) that apparently belong to different authors. The following shows the begining of the selection dialog for a typical case of intermediate complexity (for the name of this author, Soler JM):

\begin{table}
\centering
\begin{tabular}{|l|c|}
\hline
Field & $\log_{10}$(Size) \\
\hline
Documents ($N_D$) & 8.0 \\
Author names & 4.0 \\
Email & 6.0 \\
Address words & 2.0 \\
Title words & 2.0 \\
Keywords & 3.0 \\
Research field & 2.0 \\
Journal & 2.0 \\
Publication year & 1.0 \\
\hline
\end{tabular}
\caption{Assumed number of possible values taken by the different fields that characterize a document record from the ISI-Thomson Web of Knowledge database.}
\end{table}
Found 142 papers in 18 groups

group, papers, citations = 1 99 4364

group, papers, citations = 2 20 207

group, papers, citations = 3 1 130

group, papers, citations = 4 2 36

group, papers, citations = 5 3 34

group, papers, citations = 6 3 18

group, papers, citations = 7 2 5

group, papers, citations = 8 1 3

group, papers, citations = 9 1 3

group, papers, citations = 10 1 2

group, papers, citations = 11 1 1

group, papers, citations = 12 1 1

group, papers, citations = 13 1 0

group, papers, citations = 14 1 0

group, papers, citations = 15 1 0

group, papers, citations = 16 1 0

group, papers, citations = 17 2 0

group, papers, citations = 18 1 0

Group 1 has 99 papers and 4364 citations in period 1981-2006

Distance to selected groups is ****** A sample paper is

Title: Density-functional method for very large systems with LCAO basis sets
Authors: SanchezPortal, D; Ordejon, P; Artacho, E; Soler, JM;
Source: Int. J. Quantum Chem. (1997) 65, 453:461
Address words: AUTONOMA MADRID FIS MAT CONDENSADA E-28049 SPAIN
NICOLAS CABRERA OVIEDO E-33007

Select this group? (y|n|u|all|none|p|c|d|(number)|help):

The first group of papers is mine, without any false positives. In this case there are neither false negatives (i.e. none of the papers in the other groups are mine), although this is not the most usual case.

In summary, a practical algorithm has been presented for separating the papers of an author from those of other authors with the same name. It semi-automates the separation process by creating clusters of papers that most likely belong to the same author, thus simplifying greatly the generation of an author publication list.

I would like to acknowledge very useful discussions with J. V. Alvarez, R. García, J. Gómez-Herrero, L. Seijo, and F. Yndurain. This work has been founded by Spain’s Ministry of Science through grant BFM2003-03372.

APPENDIX: HOW TO GET AND PROCESS AN ISI-THOMSON SCI FILE

In order to find in practice the merit indicators of an author, one can follow these steps:

1. Download the programs filter and merit from this author’s web page and compile them if necessary.

2. Perform a “General search” in the ISI-Thomson Web of Science database for the author’s name. Appropriate filters may be set already in this step, if desired.

3. Select the records obtained. Usually the easiest way is to check “Records from 1 to last one” and click on “ADD TO MARKED LIST” (if you find too many articles, you may have to mark and save them by parts, say (1-500)—file1, (501-last one)—file2);

4. Click on “MARKED LIST”.

5. Check the boxes “Author(s)”, “Title”, “Source”, “keywords”, “addresses”, “cited reference count”, “times cited”, “source abbrev.”, “page count”, and “subject category”. Do not check “Abstract” nor “cited references”, since this would slow down considerably the next step.

6. Click on “SAVE TO FILE” and save it in your computer.

7. Click on “BACK”, then on “DELETE THIS LIST” and “RETURN”, and go to step 2 to make another search, if desired.

8. Use the filter program to help in selecting the papers of the desired author. Mind for hidden file extensions, possibly added by your navigator, when giving file names in this and next step.

9. Run the merit program to find the merit indicators.
1 Moed, H. F. *Citation Analysis in Research Evaluation*. Springer, Dordrecht, 2005.

2 http://isiknowledge.com.

3 Damashek, M. Gauging similarity with n-grams: Language-independent categorization of text. *Science* 267 (1995), 843–848.

4 Tenenbaum, J. B., de Silva, V., and Langford, J. C. A global geometric framework for nonlinear dimensionality reduction. *Science* 290 (2000), 2319–2323.

5 Roweis, S. T., and Saul, L. K. Nonlinear dimensionality reduction by locally linear embedding. *Science* 290 (2000), 2323–2326.

6 Mardia, K. V., Kent, J. T., and Bibby, J. M. *Multivariate analysis*. Academic Press, London, 1979.

7 http://www.uam.es/jose.soler/tools.