Global Journals Inc.

Global Journal of Human-Social Science: A
Arts & Humanities - Psychology
Volume 16 Issue 2 Version 1.0 Year 2016
Type: Double Blind Peer Reviewed International Research Journal
Publisher: Global Journals Inc. (USA)
Online ISSN: 2249-460X & Print ISSN: 0975-587X

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By Refat Aljumily

Newcastle University, United Kingdom

Abstract- In my previous article entitled, "Hierarchical and Non-Hierarchical Linear and Non-Linear Clustering Methods to "Shakespeare Authorship Question" I used Mean Proximity, as a linear hierarchical clustering method and Principal Components Analysis, as a non-hierarchical linear clustering method, Self-Organizing Map U-matrix and Voronoi Map, as non-linear clustering methods to examine various works and plays assumed to have been written by Shakespeare and Sir Francis Bacon, Christopher Marlowe, John Fletcher, and Thomas Kyd to determine which of them wrote some of Shakespeare's disputed plays based on similarities in the use of function words, word-bi grams, and character-tri grams. The article showed that Shakespeare is not the author of all the disputed plays traditionally attributed to him according to the validated cluster analytic results and the stylistic criteria used.

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GJHSS-A Classification : FOR Code: 410199

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Abstract- In my previous article entitled, "Hierarchical and Non-Hierarchical Linear and Non-Linear Clustering Methods to "Shakespeare Authorship Question" I used Mean Proximity, as a linear hierarchical clustering method and Principal Components Analysis, as a non-hierarchical linear clustering method, Self-Organizing Map U-matrix and Voronoi Map, as non-linear clustering methods to examine various works and plays assumed to have been written by Shakespeare and Sir Francis Bacon, Christopher Marlowe, John Fletcher, and Thomas Kyd to determine which of them wrote some of Shakespeare's disputed plays based on similarities in the use of function words, word-bi grams, and character-tri grams. The article showed that Shakespeare is not the author of all the disputed plays traditionally attributed to him according to the validated cluster analytic results and the stylistic criteria used. The article also indicated that the author did not consider it fair to include Edward de Vere(the strongest candidate in the Shakespeare authorship debate) and compare his poemsto Shakespeare's disputed plays because poetry tends to have a particular style and a different structure than plays, and additional test was promised. The present article provides that test.

In this article, I examined the 154 sonnets traditionally attributed to Shakespeare and 38 surviving poems attributed to Edward de Vere. The purpose is to give a hypothesis whether de Vere has an identifiable self-similarity and a measure of how far from/similar to Shakespeare based on the use of function words, word bi-grams, character bi-grams, and character tri-grams applying four different clustering methods: four hierarchical linear methods using Euclidean distance (Single, Average, Complete, and Ward), non-hierarchical linear multidimensional Scaling (MDS), and Kernel K-means clustering and Voronoi mapas non-linear methods. The cophenetic correlation coefficient is used to select the best result obtained from a set of hierarchical analyses applied on the data matrices. The best hierarchical result is then compared to the other three clustering methods applied on the same data matrices. The aim of which is to further validate the results and to draw firm conclusions from the data about the Shakespeare and Edward de Vere authorship debate. Term Frequency. Inverse Document Frequency (TF.IDF)is used to select the most important variables responsible for the clustering results. Oxfordians, supporters of De Vere's case, believe that Edward de Vere, Seventeenth Earl of Oxford, wrote the plays and poems traditionally attributed to Shakespeare. This, however, is not the case. The study results show that Shakespeare and De Vere are not similar in using function words, word bi-grams, character bi-grams, and character tri-grams, that is, Shakespeare is with entirely different stylistic idiosyncrasies from de Vere. The Oxfordian theory of Shakespeare authorship is incorrect and de Vere candidacy is therefore rejected.

Keywords: *stylometry, authorship, term frequency. inverse document frequency, kernel k-means, voronoi, mds, visual clustering assessment tendency.*

I. Introduction

The Oxfordian theory of Shakespeare authorship holds that Edward De Vere, the 17th Earl of Oxford, wrote the plays and verses *claimed to have been authored by Shakespeare.* Many Oxfordians believe that de Vere wrote Shakespeare's plays and sonnets under the pseudonym of Shakespeare. Edward de Vere was born in 1550 to the Earl of Oxford. John de Vere. Edward de Vere was learned at Queen's College and Saint John's College Cambridge and also studied law at Gray's Inn. At a young age, de Vere travelled around Europe, visiting France, Germany, and Italy. Oxfordians take these travels as evidence of de Vere's possibility for writing Shakespeare's plays and poems since the works traditionally attributed to Shakespeare contain a knowledge of geography, foreign language, politics, and immense vocabulary that many find inconsistent with what is known about Shakespeare's education. The Oxfordian theory is based on two types of argument: (i) circumstantial historical evidence and (ii) qualitative stylistic criteria. The circumstantial historical evidence for de Vere's authorship of the Shakespeare works rests largely on biographical information and correspondences between incidents and circumstances in Oxford's life and events in Shakespeare's plays, sonnets, and verses, and these are based on at least four major reasons. One is essentially that de Vere was highly educated to write plays and poems, was trained as a lawyer, was known to have traveled to many of the exact places featured in Shakespeare's plays, was known to have a similar life to many of the major events and to the actions of the characters in Shakespeare's plays, and was given a great amount of literary praise, though only a few number of his poems survive. This makes him a strong candidate for authorship of the Shakespeare works, but logically does no more than that. As for the qualitative stylistic criteria, most Oxfordians believe that Edward De Vere's poetry has

Author: *Newcastle University, Ashfield close Newcastle Upon Tyne, United Kingdom. e-mail: refat.aljumily@newcastle.ac.uk*

many stylistic similarities to the plays and poems traditionally attributed to Shakespeare. These stylistic criteria include verbal parallels, phrases, images, associations and similarities of word and phrase expressing similar thoughts, which are not repeated by other poets of Shakespeare's time. But there is some evidence against the Oxfordian authorship theory. For one thing, some of Shakespeare major works were written after de Vere died in 1604. For another, Tudor Aristocrats had no need to write under nom de plumes. A standard line for why de Vere used the nom de plume of Shakespeare was to avoid breaking an aristocratic convention not to write. Unfortunately we now know that aristocrats such as de Vere did publish and without fear of breaking convention. It appears that this convention was weakly enforced and that aristocratic publishing was frowned upon rather than punished, this convention weakening entirely in Elizabethan times to which Edward De Vere belonged. However, recent studies, advanced by The Shakespeare Clinic-Claremont-McKenna College), found little match between Edward De Vere's poetry and William Shakespeare's. There are many detailed and brief overviews of the Oxfordian case and these are available in, e.g., Anderson (2005) and Farina (2006).

a) *Authorship attribution and Stylometry*

Stylometry—measurement of aspects of style--is a small but a growing field of research that integrates literary stylistics, linguistic stylistics, statistics and computer science in the study of writing styles. The purpose of such a field is genre classification, historical study of language change, literary analysis, forensic linguistics, and authorship attribution. The fast growing areas of stylometry assist in processing the amount of data in various forms, where traditional methods fail due to sparse and noisy data. The focus here is on authorship attribution, authorship attribution is the problem of identifying the authorship of given texts (anonymous, disputed, written under a pseudonym) based on authorial characteristics that are not known to the authors themselves. The style of a text is typically based on a lot of features from different areas: content or theme, genre, structure, authors, to name a few. In the context of authorship attribution, stylometry assumes that the essence of an author style can be identified based on a number of quantitative stylistic criteria, called style discriminators. Obviously, one part of an author's writing style is conscious, deliberate, and open to imitation or borrowing by others. These features are unable to distinguish authors writing in the same genre, similar topics and periods.The other is sub-conscious, that is, independent of an author's direct control, and far less open to imitation or borrowing. Stylometry focuses on the unconscious part of an author's writing style and assumes that these are able to distinguish authors writing in the same genre, similar topics and periods so that the quantitative analytical methods are not influenced by differences in genre or style which changes with time (Holmes, 1998).

b) *Stylometric features*

Generally, there are three types of linguistic features that can be used for attributional stylometry: syntactical, lexical, and structural features. Syntactical features, for example, include frequency of re-write rules, parts of speech, distribution of phrase structures, frequency of syntactic parallelism, etc. Lexical features, for example, include word or sentence length, frequencies of letter pairs, distribution of words of a given length in letters or syllables, frequency of words (function and content words), vocabulary richness (type-token ratio, Simpson's index, Yule's K, etc. Structural features, for example, include, number of words, sentences, or paragraph per text. Since lexical features are easy to compute, extract, and interpret, they play the most important role in attributional stylometry. Many different types of lexical features have been considered as possible style markers for different authorship problems. However, based on the evaluation studies that experimentally examined the usefulness of different stylometric features for attributing authorship, e.g. (Eder, 2011; Grieve, 2007 and Argamon & Levitan, 2005), the preponderance of evidence suggests that the most consistently effective features over a wide variety of authorship attribution problems are function words, word-n grams, and character n-grams, and for this reason, these are used here.

i. *Function words*

Ideally, any stylometric analysis would include varieties of syntactic usage as criteria. Where parsed corpora are unavailable, however, function words often mark syntactic usage indirectly. There are distinct categories of function words for grammatical use and their presence indicates particular constructions. Examples, i.e. use of relativizers as indicator of dependent clauses and thus of degree of syntactic complexity, prepositional phrases as opposed to possessives ('the road's end' / 'the end of the road') etc. Function words (prepositions, pronouns, conjunctions, particles, etc) appear in most if not all texts written by a given author, regardless of topic. Since usage is independent of topic, function words are likely to indicate authorship as opposed to other characteristics.

ii. *Word n-grams*

A word n-gram is defined as a sequence of words, where each n-gram is composed of *n* words: for example, the sentence "it is a new nice car", which consists of 6 words, consists of 5 bi-grams "it-is" "is-a" "a-new" "new-nice" "nice-car" and 4 word tri-grams "it-is-a" "is-a-new" "a-new-nice" "new-nice-car"), and so on; in general, a text that contains *x* words will contain *x* - (*n* - 1) word n-gram tokens The relative frequency of word n-gram tokens are calculated by dividing the frequency of a given word n-gram token, e.g. 4-gram, in a text by the total number of 4-gram word tokens. Wordn-grams help to capture all possible n-word combinations used to complete sentences in a given text. Segmentation of a text into a bag of n-word combinations give new hints or clues to identify the style of an individual author.

iii. *Character n-grams*

A character n-gram is defined as a string of contiguous alphanumeric symbols, perhaps including also punctuation symbols. For example, the clause 'the child laughed', which consists of 15 letters, consists of 15 1-gram tokens (T, H, E, C, H, I, L, D, L, A, U, G, H, E, D), 14 2-gram tokens (TH, HE, EC, CH, HI, IL, LD, DL, LA, AU, UG, GH, HE, ED), 13 3-gram tokens (THE, HEC, ECH, CHI, HIL, ILD, LDL, DLA, LAU, AUG, UGH, GHE, HED) and so on; in general, a text that contains *x* characters will contain *x* - (*n* - 1) n-gram tokens. The relative frequency of n-gram tokens are calculated by dividing the frequency of a given n-gram token, e.g. 3-gram, in a text by the total number of 3-gram tokens. Naturally, some will argue that character n-grams are letters. Of course, they function as letters in a given word. Yet they are quite basic elements to distinguish between authors since they capture all possible 2-3 character combinations occurring in words in a given text. This approach represents an author's stylistic choice of vocabularieswhich can capture n-character combinations used by author.

c) *Stylometric Methods*

Historically, attribution methods used in authorship attribution were statistical univariate methods measuring a single textual feature, for example word length, sentence length, frequencies of letter *n*-grams, and distribution of words of a given length in syllables. Common univariate methods are T-test, which compares the averages of two samples and Z-score, which calculates the mean occurrence and the standard deviation of a particular feature and compares it within the normal distribution table. These univariate methods were used to analyze texts in terms of a single stylometric criterion or two and the results derived from them are therefore described as a simple form of statistical analysis. Other examples of the univariate approach are those based in Bayesian probability and cumulative sums. (Holmes, 1998)

Today, univariate methods are far less popular in the domain of authorship attribution than they once were. Their limitation is self-evident and has been noted by numerous authors (e.g. Grieve, 2005, Holmes, 1994) except perhaps in very special cases, authorial style is a combination or more or less numerous characteristics, but univariate analysis permits investigation of only one characteristic as a time, and results for different characteristics are not always or even usually compatible, and the consequence is unclear overall results.

More recently, therefore, multivariate methods have increasingly been used, e.g. (Aljumily, 2015A, 2015B; Khandelwal et al, 2015; Forsyth, 2007; Juola, 2006).These are essentially variations on a theme: cluster analysis. Cluster analysis aims to detect and graphically to reveal structures or patterns in the distribution of data items, variables or texts, in *n*-dimensional space, where *n* is the number of variables used to describe an author's style. Cluster analysis methods are proven to be the best performing methods in authorship attribution: works by the same author can be grouped according to their genre or writing styles and authors can be distinguished from one another: the work x of author A can be different from or similar to his/her work y or work z, and the work of author A can be distinguished from the work of author B or author C or disputed work(s) (D, E, F, etc).(Moisl, 2015; Everitt et al., 2001)

After selecting the stylistic feature, we represent a text as a numerical vector $X = (x_1, \ldots, x_i, \ldots x_n)$, where *n* is the number of stylistic features and x_i is the relative frequency of feature *i* in the text. Once labeled texts have been represented mathematically in this way, we applied four different clustering methods to group the texts into similar or dissimilar clusters.

a. *Hierarchical clustering*

Hierarchical clustering is characterized by a tree-like structure called a cluster hierarchy or dendrogram. Most hierarchical methods fall into a category called agglomerative clustering. In this category, clusters are consecutively formed from vectors on the basis of the smallest distance measure of all the pairwise distance between the vectors. Let $X=\{x_1, x_2, x_3, \ldots, x_n\}$ be the set of vectors. We begin with each vector representing an individual cluster. We then sequentially merge these clusters according to their similarity. First, we search for the two most similar clusters, that is, those with the nearest distance between them and merge them to form a new cluster in the dendrogram or hierarchy. In the next step, we merge another pair of clusters and link it to a higher level of the hierarchy, and so on until all the vectors are in one cluster. This allows a hierarchy of clusters to be constructed from the left to right or the bottom to top. The proximity between two vector profiles is calculated as the Euclidean distance between the two profiles taken on by the two vectors. Euclidean distance is the actual geometric distance between vectors in the space and Euclidean distance is the square root of the sum of the squared differences in the variables' values. This is expressed by the function:

$$d_{Euclid\ (BC)} = \sqrt{\left(X_{B-X_C}\right)^2 + \left(Y_{B-Y_C}\right)^2}$$

b. MDS

Multidimensional Scaling (MDS) is a dimensionality reduction method which can be used for clustering if the data dimensionality is reduced to three or less. MDS preserves the proximities among pairs of objects on the basis that the proximity is an indicator of the relative similarities or dissimilarities among the physical objects which the data represents, and therefore of information contained in: if a low-dimensional representation of the proximities can be built, then the representation preserves the information contained in the original data. Given an *m*×*m* proximity matrix *P* derived from an *m*×*n* data matrix *D* using one of the linear distance metrics, MDS finds an *m*×*k* reduced-dimensionality representation of *D*, where *k* is a user-specified parameter. MDS is not a single method but family variants. (Moisl, 2015; Lee & Verleysen, 2007; Borg & Groenen, 2005). Given an *m*×*n* data matrix *D*, therefore, the first step is to measure the *m*×*m* Euclidean distance matrix *E* for *D*. A simplified view of how the method works is as follows:

- We find mean-centre *E* by calculating the mean value for each row *Ei* (*for i = 1. . .n*) and subtracting the mean from each value in *Ei*.
- We calculate an *m*×*m* matrix *S* each of whose values *Si, j* is the inner product of rows *Ei* and *Ej*, where the inner product is the sum of the product of the corresponding elements as described earlier in the discussion of vector space basis and the *T* superscript denotes transposition:

$$S_{i,j} = \sum_{k=1\ldots m}(E_{i,k}, \times E^{T}_{j,k})$$

- We calculate the eigenvectors and eigenvalues *E1 E2* of *S*, as discussed above.
- We use the eigenvalues to find the number of eigenvectors *K* (k_1, k_2, k_3……k_n) worth keeping.
- We project the original data matrix *D* into the reduced *k*-dimensional space:

$$D^{T}_{reduced} = E^{T}_{reduced} \text{x } D\ matrix^{T}$$

c. Kernel K-means

This method works well when the function that generates data is nonlinear. Kernel K-means projects vectors in input space to a higher dimensional feature space by using a nonlinear transformation Ø. This gives a linear separator in the dimensional feature space that will act as a nonlinear separator in input space. Let X={x_1, x_2, x_3, …,x_n} be the set of vectors and 'C' be the number of clusters.

- We randomly initialize 'C' cluster center. We then calculate the distance of each vector and the cluster centre in the transformed feature space using the following objective function:

$$D(\{\Pi_c\}_{c=1}^{k}) = \sum_{c=1}^{k} \sum_{xi\ \epsilon\ \Pi c} \|\text{Ø}(X_i) - \mu_c\|^2$$

Where:

$$\boldsymbol{\mu}_{\boldsymbol{c}} = \frac{\sum \boldsymbol{X_i}\, \boldsymbol{\epsilon \Pi_c} \quad \text{Ø}(\boldsymbol{X_i})}{\boldsymbol{\Pi_c}}$$

Where

C^{th} cluster is denoted $\Pi_{C.}$

μc denotes the mean of the cluster ΠC.

Ø (x_i) denotes the vector (x_i) in transformed feature space.

- We assign vector to that cluster centre whose distance is minimized.
- We repeat from step (2) until all vectors are reassigned.

(More detailed information, together with mathematical equations and codes can be found in, e,g., Blondel, 2016; Chitta, 2013; Rogers and Girolam, 2011)

d. Voronoi Map

Voronoi map is a nonlinear clustering method used to partition a manifold into regions or cells based on distance to vectors in a specific subset of the manifold surface. These regions are called cells which surround each vector. The partition of a manifold surface into areas surrounding vectors is a tessellation. Each cell contains all vectors that are closer to its defining vector than to any other vector in the set. Subsequently, the boundaries between the cells are equidistant between the defining vectors of adjacent cells. That is, the neighborhood of a given vector in a Voronoi tessellation is defined as the set of vectors closer to its defining vector than to any other vector in the set. The set of neighborhoods defined by the Voronoi tessellation is known as the manifold's topology (Moisl, 2015).Let *X* be a metric space with distance *d*. Let *K* be a set of indices (whose members label members of another set) and let (P_k) *k* ϵ *k* be a cell in the space *X*. The Voronoi cell R_k related to the cell P_k is the set of all vectors in *X* whose distance to P_k is not bigger than their distance to the other cells P_j, where *j* is any index different from *k*. That is, if d(x, Z)= inf {d(x,z)│zϵZ} denotes the distance between the point x and the subset Z, then:

$$\text{Rk}=\{\text{x } \epsilon \text{X} \mid \text{d(x,Yk)} \leq \text{d(x,Pj)for all j} \neq \text{k}\}$$

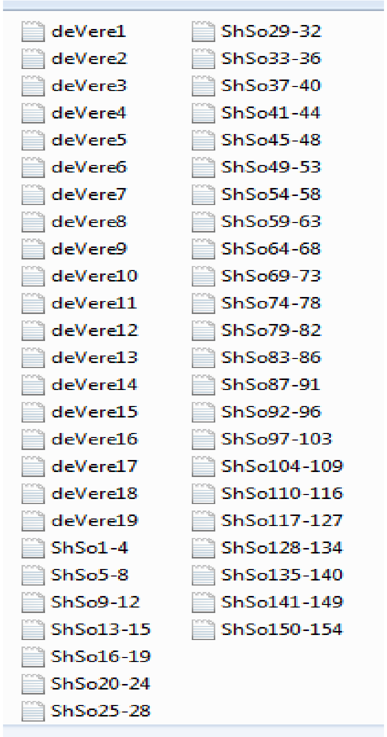
The Voronoi map is simply the tuple of cells (Rk) k ϵ k.

The application of Voronoi map on a given data matrix is a three-stage process. The first step is the construction of a 2-dimensional Voronoi plot for a set of vectors in a data matrix. The second is the construction of Delaunay Triangulation (Voronoi map) on the same 2 dimensional plot. The third step is the computation of the Voronoi map to obtain a 2-dimensional topology of the Voronoi map for the set of vectors in a data.

e. Data and preprocessing

We collected 193 electronic raw texts representing all the (154) known sonnets of Shakespeare, taken from The Project Gutenberg EBook of Shakespeare's Sonnets, by William Shakespeare, and some (38) surviving poems available in the public domain that are widely agreed to be written by Edward de Vere, taken from Literature online http://literature.proquest.com/searchFulltext.do?id=Z200338111&childSectionId=Z200338111&divLevel=2&queryId=2911490928155&trailId=15256B22E85&area=poetry&forward=textsFT&queryType=findWork). We converted the texts into ASCII.txt.doc format, and removed anything that isn't body text (e.g. headings, numbers, section headings, titles, etc). Some texts were really short, containing less than 20 lines. Such texts were impossible to cluster. Thus, we decided to adjust test text sizes and make them of comparable length. For each author, we aggregated every 3 or 4 works into one independent text file which should be analyzed. We had 49 text files as a test set, 30 text files for Shakespeare named ShSo1-4 to ShSo49-154, and 19 text files for de Vere, named deVere1 to deVere19. These texts are shown in Table/1.

Table 1 : 49 text files representing Shakespeare 154 sonnets and de Vere's 38 poems



deVere1
deVere2
deVere3
deVere4
deVere5
deVere6
deVere7
deVere8
deVere9
deVere10
deVere11
deVere12
deVere13
deVere14
deVere15
deVere16
deVere17
deVere18
deVere19
ShSo1-4
ShSo5-8
ShSo9-12
ShSo13-15
ShSo16-19
ShSo20-24
ShSo25-28
ShSo29-32
ShSo33-36
ShSo37-40
ShSo41-44
ShSo45-48
ShSo49-53
ShSo54-58
ShSo59-63
ShSo64-68
ShSo69-73
ShSo74-78
ShSo79-82
ShSo83-86
ShSo87-91
ShSo92-96
ShSo97-103
ShSo104-109
ShSo110-116
ShSo117-127
ShSo128-134
ShSo135-140
ShSo141-149
ShSo150-154

Finally, we tokenized (segmented) each input text.doc into a bag of words and then removed content words. Content words are the words which appear less frequently in text files but provide less information in identifying the important style features of each text file. After this preprocessing, each text file is represented by a variable vector of style features. These style features are variables that attempt to represent the data used for this authorship test. We generated a lexical frequency data matrix (D1) with 5081 lexical types, a lexical frequency data matrix(D2) with 4893 lexical types, and a lexical frequency data matrix(D3) with 4889 lexical types. We reduced the dimensionality of (D1, D2, and D3) to 100, 80, 80 respectively. In each of these data matrices, each text file is represented by text lexical type score. Then all text lexical type scores are ranked in descending order according to their scores. A set of the highest FW/W.bi-gram/Char.bi-tri-gram score text files are selected as text FW/W.bi-gram/Char.bi-tri-gram summary based on Variance Term Frequency. Inverse Document Frequency (VTF.IDF), in which:

- The variance for each column was calculated and saved as vector $v_{variance}$.
- The TF/IDF for each column was calculated and saved as vector $v_{tf/idf}$.
- The 49 vectors were then sorted in descending order of magnitude and plotted:

The first set consists of 100 function words and is shown in Figure/1.

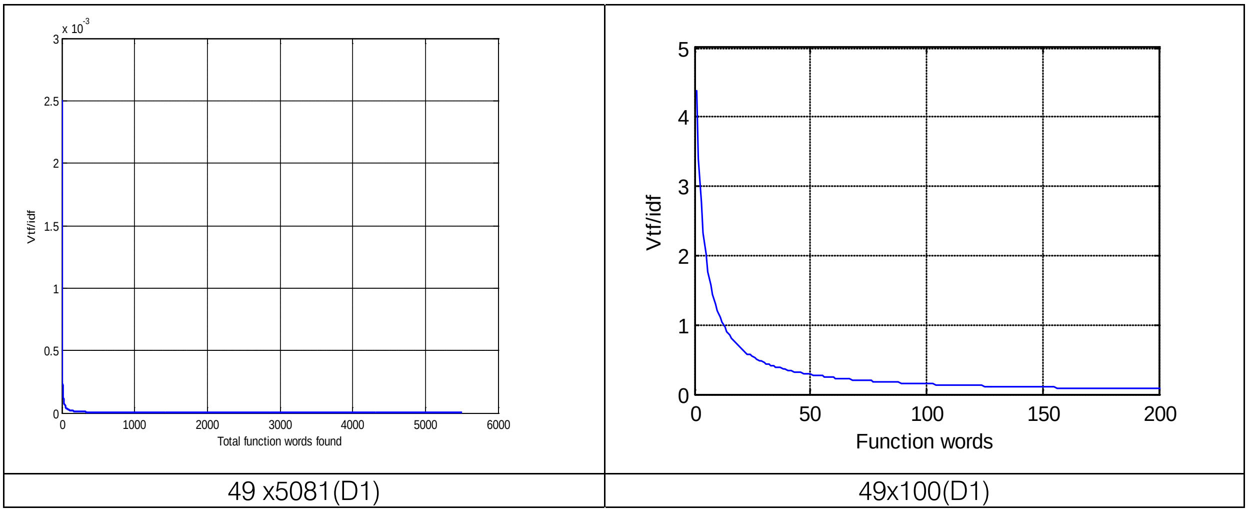


Figure 1 : The selection of FWs from D1

The second set consists of 80 word bi-grams and is shown in Figure/2.

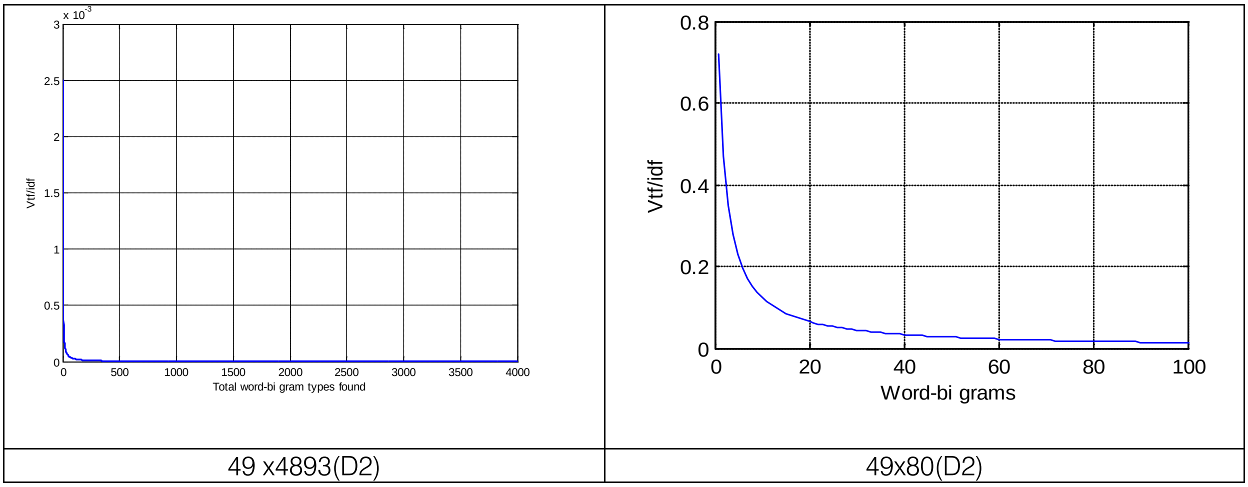
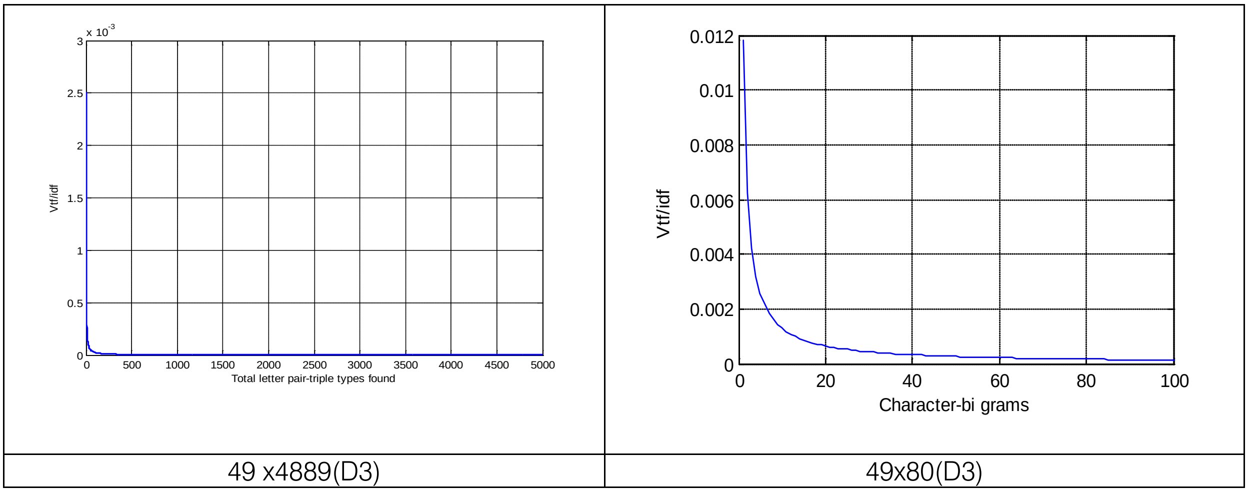


Figure 2 : The selection of word bi-grams from D2



The third set consists of 80 word bi-grams and is shown in Figure/3.

Figure 3 : The selection of character bi/tri-grams from D3

Here, the intention was to determine which author uses a given 3-character combination based on his usage of all words in a data matrix, and, for this reason, content words were kept and not removed from this data matrix.

d) Analysis of D1, D2, D3

As described above, a variety of clustering methods are used to examine the three data matrices (D1, D2, D3) generated in Figures/1,2,3. For each data matrix, we run an assessment of clustering tendency test to examine the proximity matrix to determine whether or not a non-random structure actually exists in (D1, D2, D3) prior to applying four hierarchical clustering methods (average, Single, Ward, Complete). The cophentic is used to validate and select the most best hierarchical method. Then we applied MDS, Kernel K-means, and Voronoi, to examine (D1, D2, D3) and also to validate the clustering results. Specifically:

- Hierarchical clustering methods are all linear methods based on preservation of distance relations in data space, though they differ in how distance among clusters is defined.
- MDS is a linear method based on preservation of distance relations among objects in data space.
- Kernel K-means identifies nonlinearly separable clusters based on defining k centers, one for each cluster.
- Voronoi map is a nonlinear method based on dividing the space into cells, each of which consists of points closer to one particular object than to any others.

i. *FW analysis (D1)*

The hierarchical clustering analysis generated by Average linkage analysis seems to fit the data matrix (D1) more well than the clusterings produced by Single analysis, Complete analysis, Weighted average analysis, Ward analysis, and Median analysis, as shown in Table/2.

Table 2 : Cophenetic correlation coefficient for (D1) and for four hierarchical clustering analyses

Hierarchical clustering method	Cophenetic correlation coefficient
Single	0.7135
Complete	0.4893
Average	0.7794
Ward	0.684

Average linkage analysis is therefore selected: it defines the degree of closeness between any pair of subtrees (X, Y) as the mean of the distances between all ordered pairs of objects in X and Y: If X contains *x* objects and Y contains y objects, the distance is the mean of the sum of (X_i , Y_j), for *i* = 1..*x*, *j* = 1..*y*, as shown in Figure/4.

$$D_{avg}(A,B) = \frac{\sum_{1=1..m,\, j=1..n} d(a_i \in A, b_j \in B)}{m \times n}$$

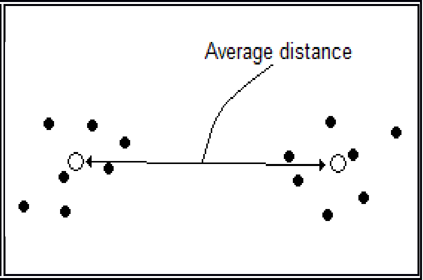
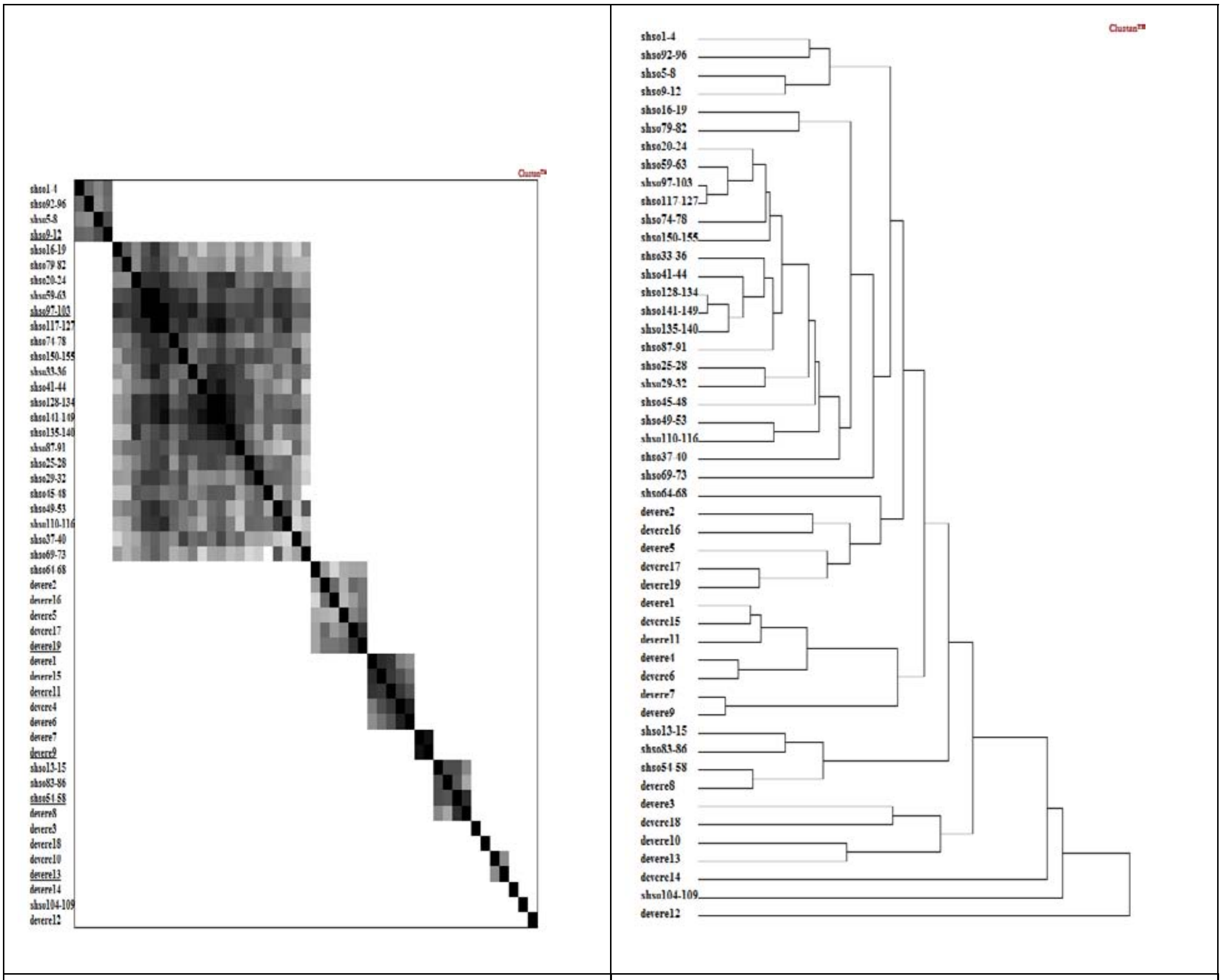


Figure 4 : Average linkage clustering

The result of the assessment of clustering tendency test indicates the presence of 12 well separated clusters in (D1), as shown in Figure/6 (left).



Visual Clustering Tendency for (D1)

Hierarchical average clustering(D1)

Figure 6 : Assessment of clustering tendency test (left) and average linkage clustering (right) D1

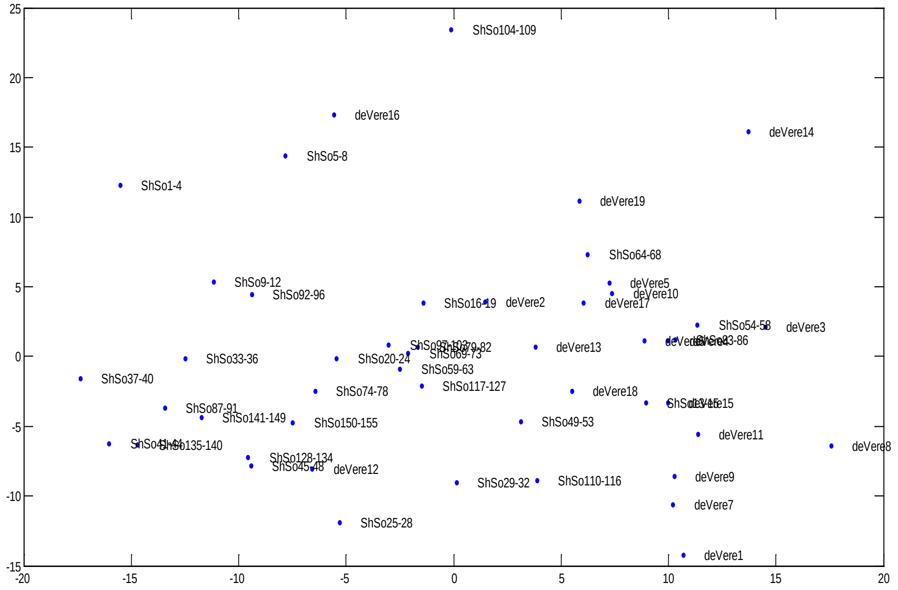
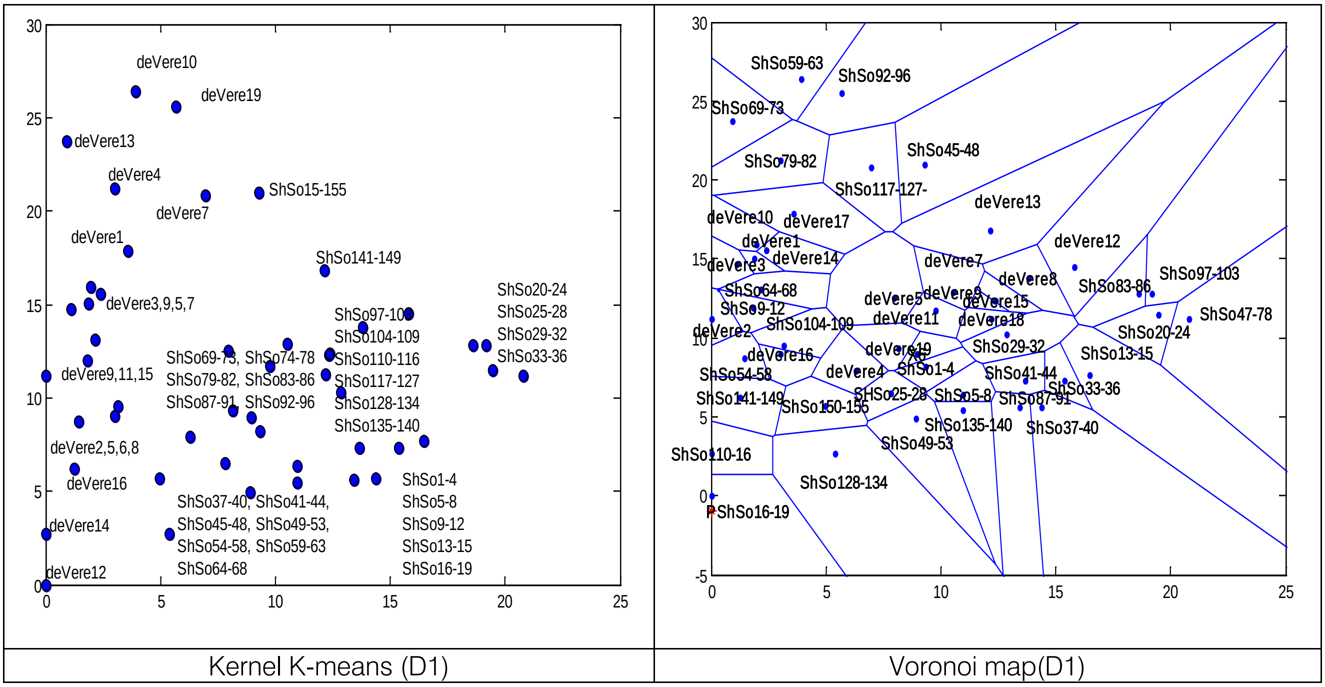


Figure 7 : MDS non-hierarchical linear clustering for D1



Kernel K-means (D1)

Voronoi map(D1)

Figure 8 : Kernel K-means and Voronoi map non-linear clustering for D1

Examination of all the clustering methods applied to the function words matrix (D1) rows as shown in Figures/6, 7, 8 reveals a strong consistency in the way that the 49 text files are clustered in terms of their relative distance from one another. The analyses show that Shakespeare's texts are much more similar to each other than they are to de Vere's. Only few de Vere's works clump together with Shakespeare, e.g. de Vere19 and ShSo29-32 and deVere 19 and ShSo25-28 in MDS analysis in MDS, but this does not mean or indicate that de Vere wrote these works; it is just a similarity between the genre conventions or in the use ofthe same function words. To identify the function words in which they most differ, we compared the variable centroids of each column data matrix: for a given data matrix, we calculated each one of the columns by taking the centroid of variable values for the row vectors in each data matrix, and plotted the results. A variable with a larger amount of variability in its centroid than the other variables in (D1) is taken to be the most important discriminator between Shakespeare and de Vere because there is much change in the values of that variable throughout text file row vectors. Ten of the function words (in, to, by, with, shall, and, not, from, yet, for) are looked at and selected for the current purpose. They showed the most variation among them, the other 90 function words showed the least variation among them. The centroids for Shakespeare and de Vere tested in D1 are first calculated and the results are plotted on the same 2-Ds, so it is immediately apparent which function words are relatively rare or frequent in which authors as shown in Figure/9.

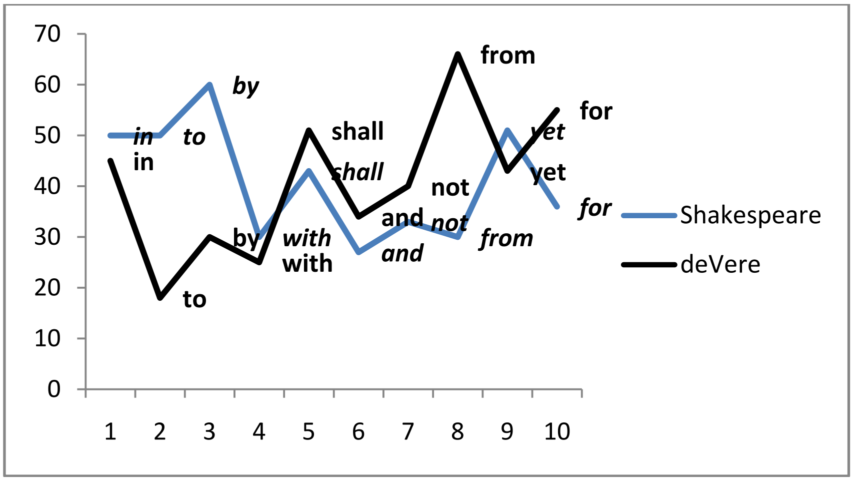


Figure 9 : Shakespeare's usage of a set 10 function words vs de Vere's

As can been seenin Figure/9, the variation between Shakespeare and de Vere, in the use of function words for the selected set of function words, is appreciably greater than the variation within them. These function words distinguished the works of the two authors very well and on the basis of function words comparison, we assume mathematically-based characteristics of the writing style of Shakespeare and de Vere. Shakespeare tends to use 'to', 'by', 'shall', 'and', 'not', 'from', 'yet', and 'for' more than does de Vere, who seems to use a lot more 'from' and 'for'. The other 2 function words 'in' and 'with' seem almost frequent for the two authors. In summary, the use of function words is significantly different between Shakespeare and de Vere.

The hierarchical clustering analysis generated by Average linkage analysis seems to fit the data matrix (D2) more well than the clusterings produced by Single analysis, Complete analysis, Weighted average analysis, Ward analysis, and Median analysis, as shown in Table/3.

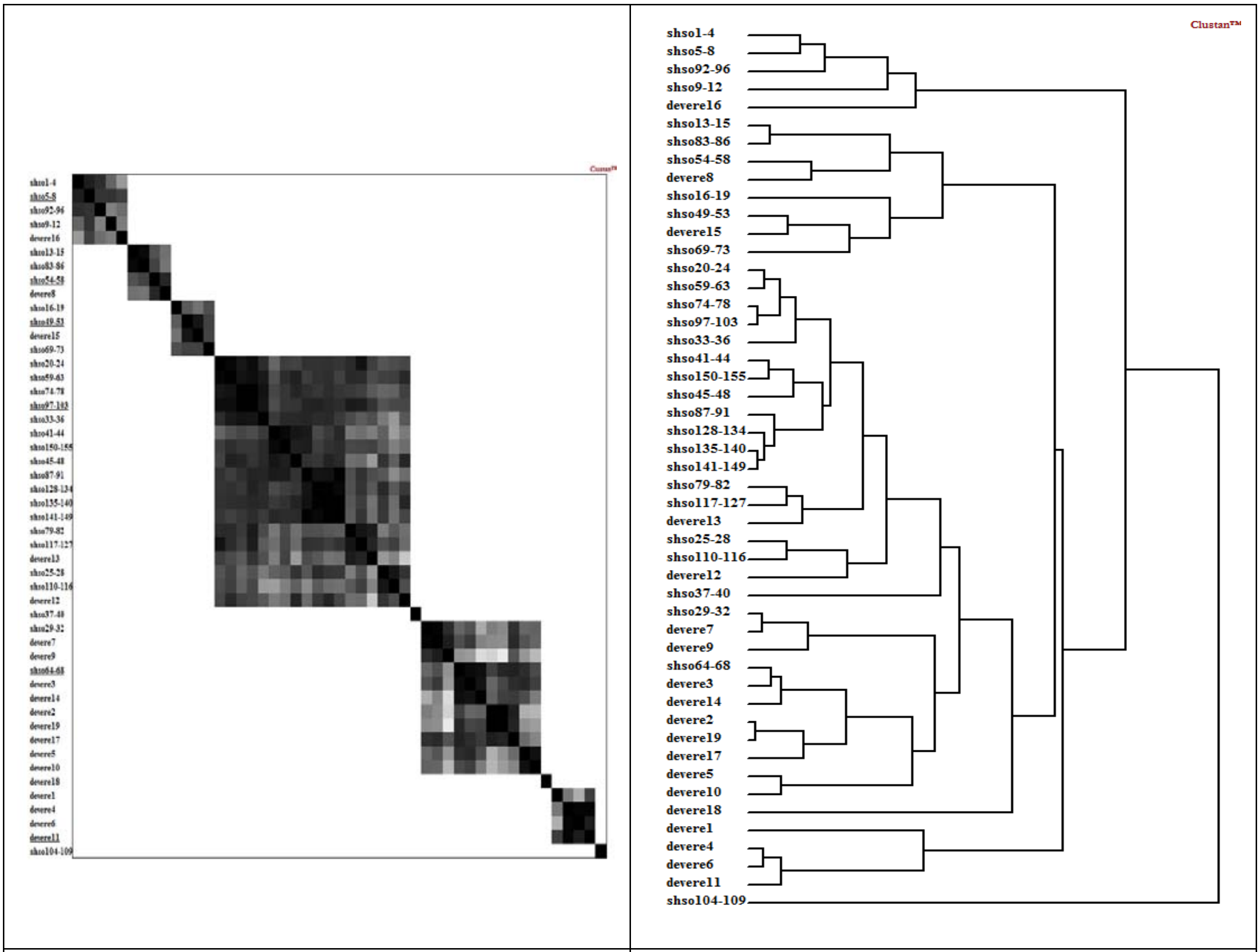
Table 3 : Cophenetic correlation coefficient for (D2) and for four hierarchical clustering analyses

Hierarchical clustering method	Cophenetic correlation coefficient
Single	0.7105
Complete	0.7893
Average	0.8724
Ward	0.633

ii. *Word bi-grams analysis (D2)*

Average linkage analysis is selected and the analysis is shown in Figure/10.

The result of the assessment of clustering tendency test indicates the presence of 9 well separated clusters in (D2), as shown in Figure/10 (left).



Visual Clustering Tendency for (D2) | Hierarchical average clustering(D2)

Figure 10 : Assessment of clustering tendency test (left) and average linkage clustering (right) D1

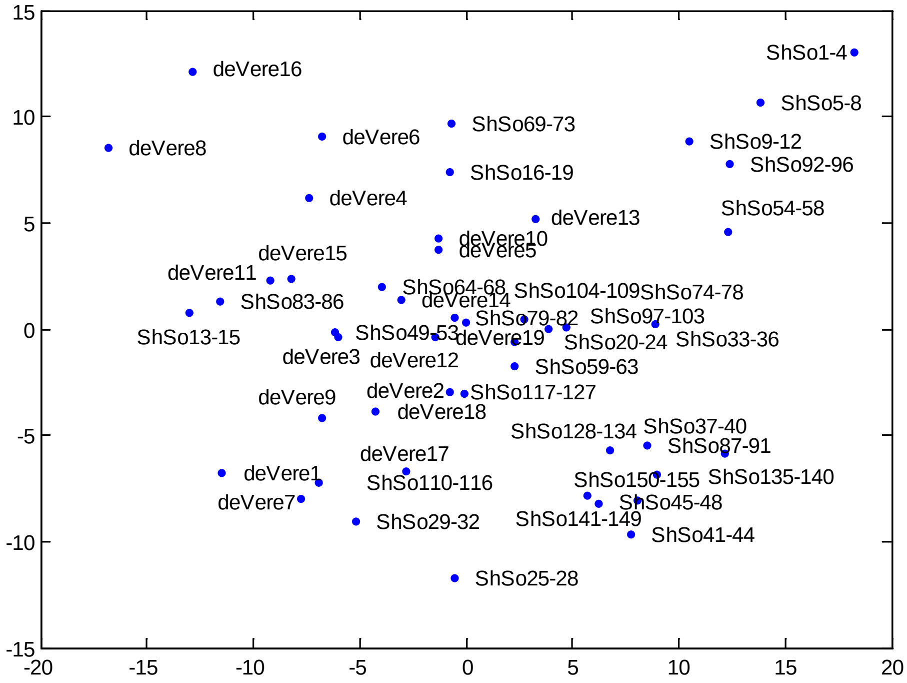
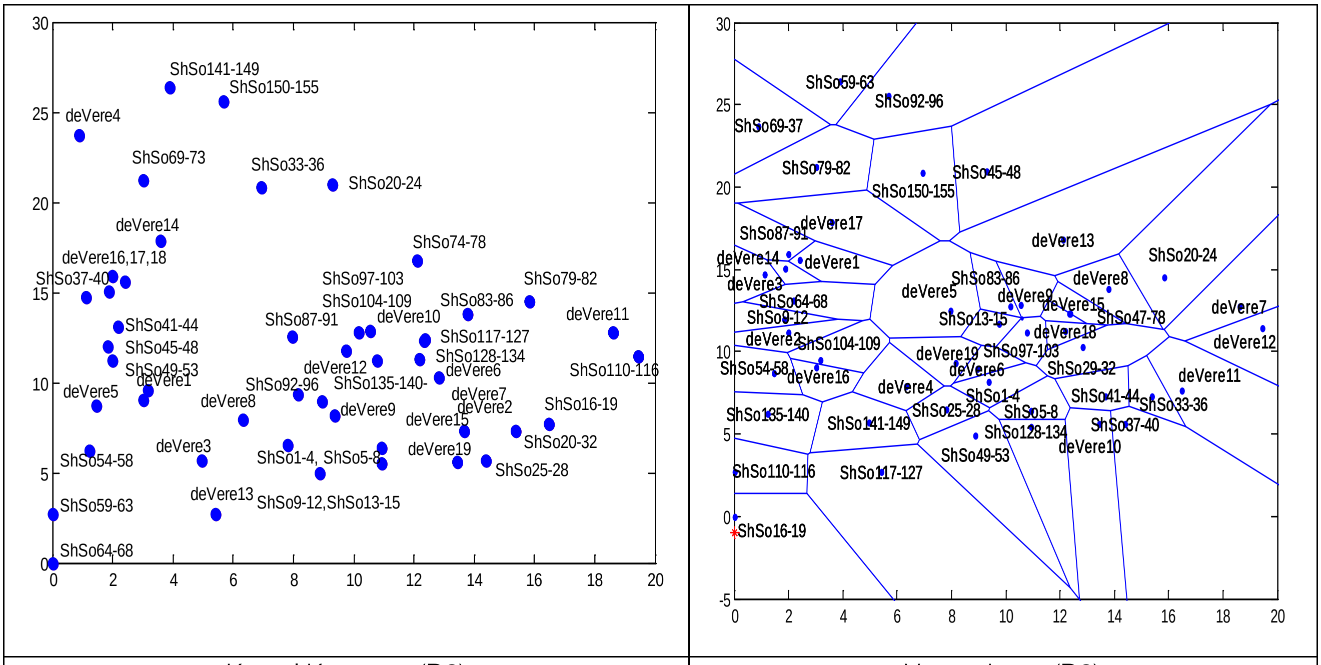


Figure 11 : MDS of D2



Kernel K-means (D2)

Voronoi map(D2)

Figure 12 : Kernel K-means and Voronoi map non-linear clustering for D2

As can be seen in Figures/ 10, 11, 12, the four clustering analyses distinguish Shakespeare's from de Vere's texts, except that few texts (e.g. de Vere 16, de Vere8, de Vere 15, and de Vere7) are clustered with the Shakespeare texts or Shakespeare's text ShSo64-68 is clustered closer to de Vere's texts in the hierarchical analysis. As previously said, this does not mean that de Vere wrote these works, but as a similarity between the genre conventions and in using the same set of bi-gram words. The 10 most distinctive word bi-grams 'that I', 'in my', 'to be', 'of my', 'not to', 'and shall', 'on me', 'me no', 'for to', 'of his' that determine the clustering results are selected from D2 on basis of the Centroid analysis and the amount variation among them. They are plotted using centroid line graph as before. The graph for our comparison is shown Figure/13.

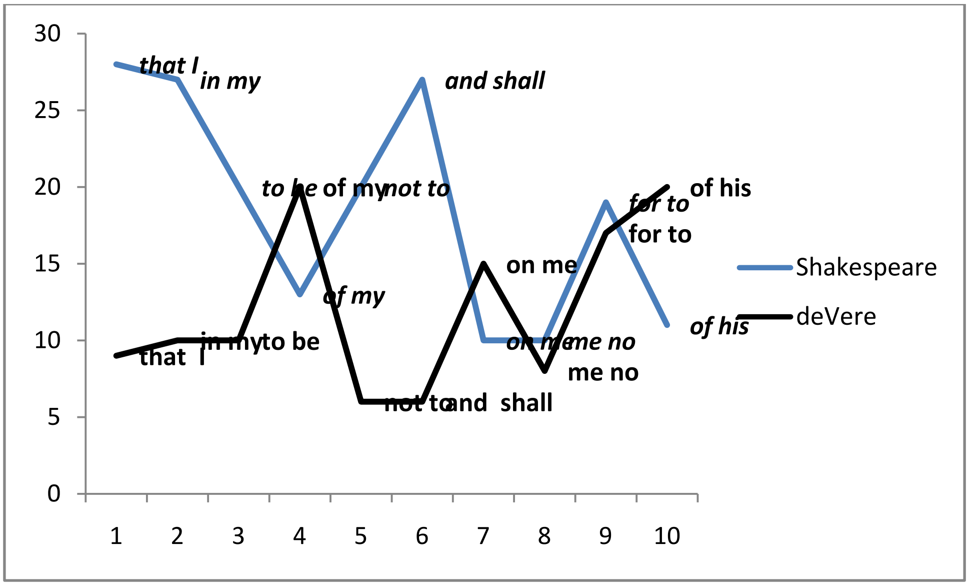


Figure 13 : Shakespeare's usage of a set 10 word bi-grams vs de Vere's

From this plot graph it is clear that the frequencies of the 10 word bi-grams selected from D2 very distinctly separate the writing style of these two authors. Three words 'to be', 'me no', and 'for to' are more frequent in all of the texts by the two authors. 'that I', 'in my', 'of my', 'and shall', and 'on me' are more frequent in the texts by Shakespeare than in those by de Vere. The two word bi-grams 'not to' and 'of his'are more frequent in the texts by de Vere than in those by Shakespeare. In summary, we clearly see that Shakespeare and de Vere have a significantly different writing style when it comes to word bi-grams.

iii. *Character tri-grams analysis (D3)*

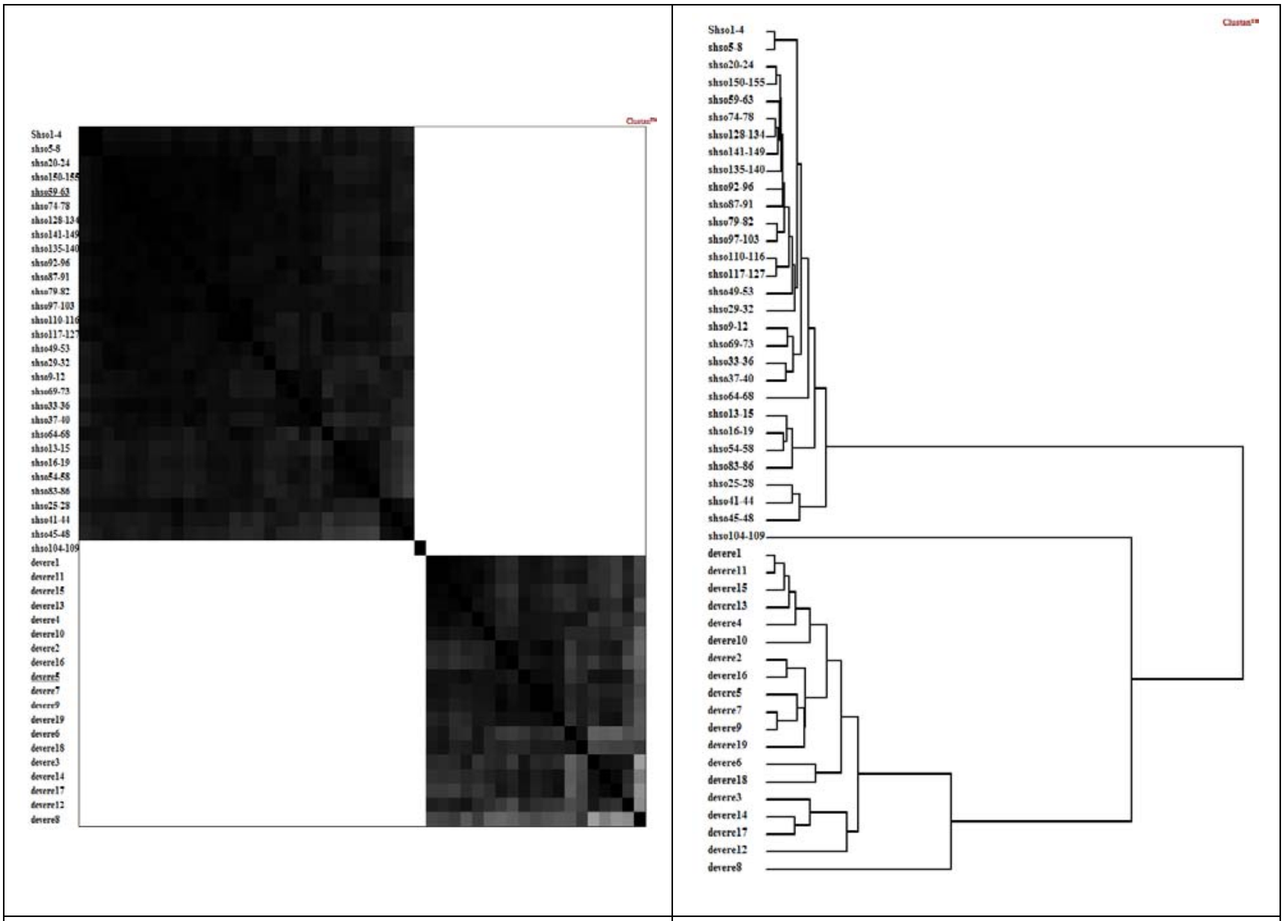
The hierarchical clustering analysis generated by Average linkage analysis seems to fit the data matrix (D3) more well than the clusterings produced by Single analysis, Complete analysis, Weighted average analysis, Ward analysis, and Median analysis, as shown in Table/4.

Table 4 : Cophenetic correlation coefficient for (D3) and for four hierarchical clustering analyses

Hierarchical clustering method	Cophenetic correlation coefficient
Single	0.7100
Complete	0.7992
Average	0.8824
Ward	0.656

Average linkage analysis is selected and the analysis is shown in Figure/10.

The result of the assessment of clustering tendency test indicates the presence of 3 well separated clusters in (D3), as shown in Figure/14 (left).



Visual Clustering Tendency for (D3)

Hierarchical average clustering(D3)

Figure 14 : Assessment of clustering tendency test (left) and average linkage clustering (right) D3

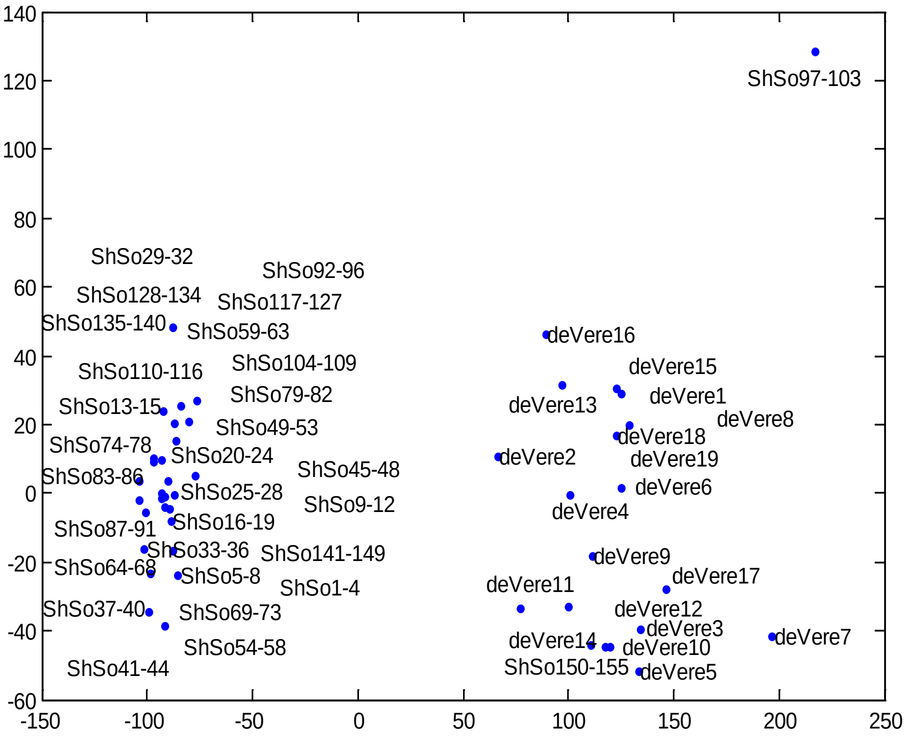
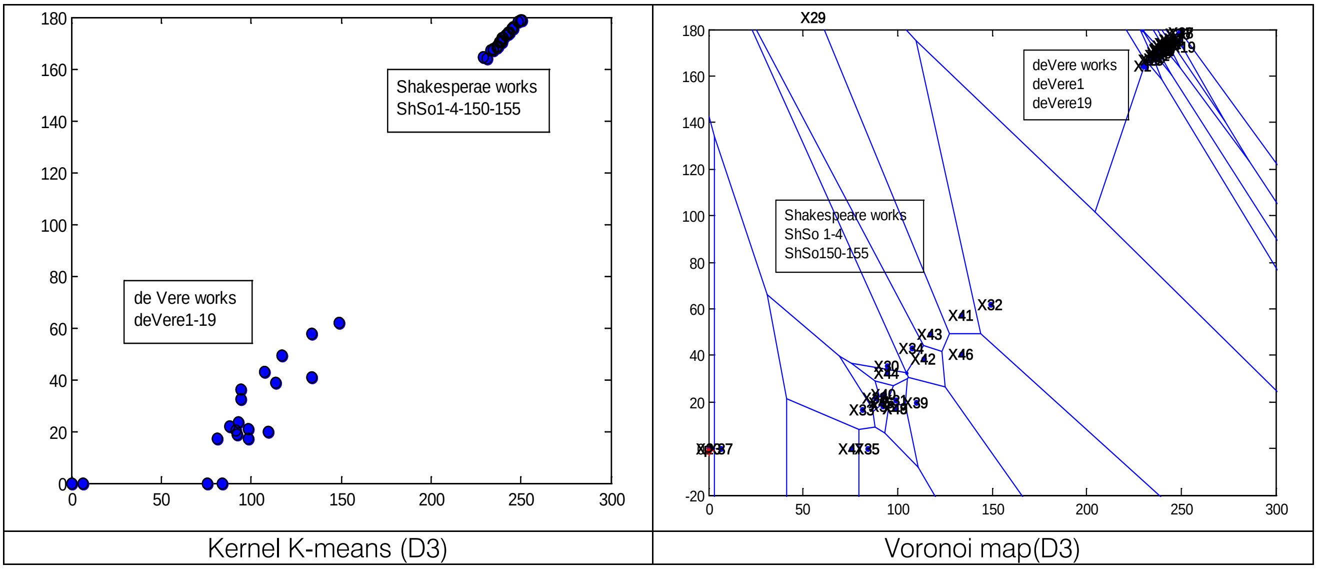


Figure 15 : MDS of D3



Kernel K-means (D3)

Voronoi map(D3)

Figure 16 : Kernel K-means and Voronoi map non-linear clustering for D3

Inspection of Figures/ 14,15,16 shows a close match between the results from different clustering methods. Specifically, there is a strong degree of correspondence between the clusters generated by the analyses based on the frequencies of all 80 character tri-grams. All the clustering methods well separated the 49 text files into two distinct clusters, one for de Vere's works and the other to Shakespeare's works. There is no need to say any more, the whole picture is clear.

As above, we selected the 10 character tri-grams 'oth', 'thy', 'ove', 'sha', 'hou', 'hee', 'fai', 'eet', 'hat', and 'uty' most important in distinguishing the Shakespeare works from de Vere's worksbased on the Centroid analysis and the amount variation among them. They are plotted using centroid line graph as before. The graph for our comparison is shown Figure/17.

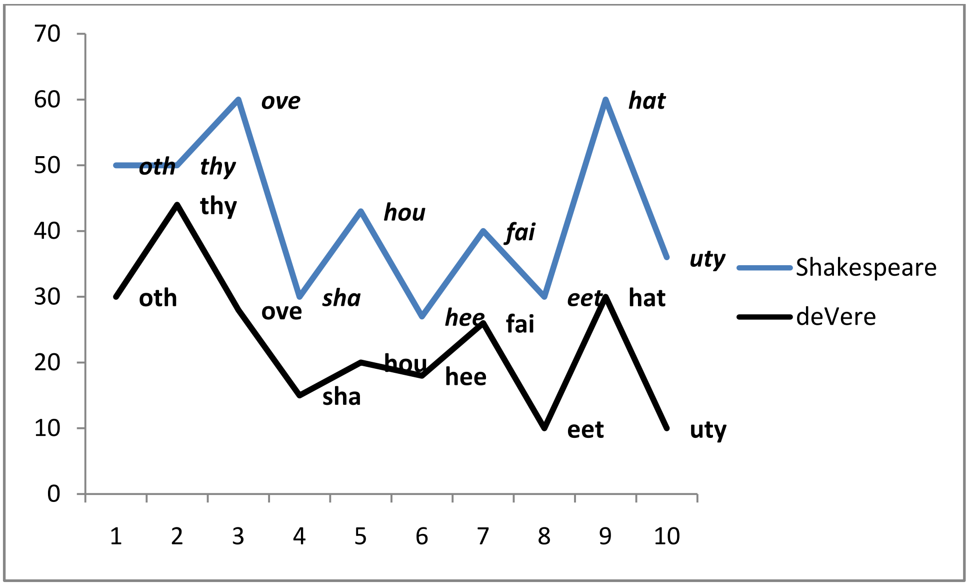


Figure 17 : Shakespeare's usage of a set 10 character tri-grams vs de Vere's

As can be noted, the use of a set of character tri-grams is extremely differentiated Shakespeare's writing style from de Vere. Character tri-grams captured some of the style features used by de Vere and Shakespeare such as suffixes, prepositions, and other frequent features in a natural way without unnecessary complex textual processing.

II. Conclusions

Was Edward de Vere, The Earl of Oxford, the true author of Shakespeare's works?

To answer this question, we conducted a stylometric experiment using hierarchical clustering, MDS, Kernel K-means, and Voronoi mapto cluster analyse a selection of texts in poetry traditionally attributed to Shakespeare and de Vere on the basis of function word, word bi-gram, and character tri-gram frequencies found in them, the aim of which was to find evidence about whether the writing style of Shakespeare's works and de Vere's works are similar to one another, and also to identify the main determinants for that similarity or dissimilarity between different clusters of text files. We constructed three data matrices (D1, D2, D3) and pre-processed them using a range of quantitative tools prior to the actual analysis. We also validated the data through Visual Assessment of Tendency (VAT), and the analyses were validated using Cophenetic Correlation Coefficient Measurement. However, the answer was NO. The function word, word bi-gram, and character n-gram frequency profiles for Shakespeare texts are compared to those of de Vere texts using centroid analysis. Edward de Vere's writing style differs from the Shakespeare profiles on all 4 analyses. Based on this result, it appears strongly improbable that the works traditionally attributed to Shakespeare were written by de Vere. We are very suspect that Edward de Vere did in fact write any of Shakespeare's works. However, because the focus was exclusively on function words, word bi-grams, and character tri-grams and exploratory clustering methods, the study does not claim to have said the last word on this debate, nor to have solved Shakespeare-de Vere authorship question. But, in short, the current research leads the author to believe that de Vere's works will always be different from Shakespeare's works no matter how many text samples we take and what types of methods or stylistic criteria we use to examine this question This is not an easy claim to make, but the writing style of the two authors is clearly and completely very different. Nevertheless, further research on Shakespeare-de Vere authorship debate using different style features and analytic methods should be conducted to expand and support these results further. Finally, given the results, the study concludes that cluster analysis is very effective in attributing authorship and that character n-grams are important feature for author style detection; they can identify authors with a high degree of accuracy.

III. Acknowledgments

The author wishes to thank all those who dedicated their time answering my queries and providing me with valuable comments during the preparation of this study.

Conflicts of Interest

The author declares no conflict of interest.

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