Hypothesis Generation

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1.0 INTRODUCTION

The aim of science is to understand reality. An academic discipline, philosophy of science, is devoted to explicating the nature of science and its relationship to reality, and, perhaps predictably, both are controversial; for an excellent introduction to the issues see (Chalmers 1999). In practice, however, most scientists explicitly or implicitly assume a view of scientific methodology based on the philosophy of Karl Popper (Popper 1959; Popper 1963), in which one or more non-contradictory hypotheses about some domain of interest are stated, the validity of the hypotheses is tested by observation of the domain, and the hypotheses are either confirmed (but not proven) if they are compatible with observation, or rejected if they are not. Where do such hypotheses come from? In principle it doesn't matter, because the validity of the claims they make can always be assessed with reference to the observable state of the world. Any one of us, whatever our background, could wake up in the middle of the night with an utterly novel and brilliant hypothesis that, say, unifies quantum mechanics and Einsteinian relativity, but this kind of inspiration is highly unlikely and must be exceedingly rare. In practice, scientists develop hypotheses in something like the following sequence of steps: the researcher (i) selects some aspect of reality that s/he wants to understand, (ii) becomes familiar with the selected research domain by observation of it, reads the associated research literature, and formulates a research question which, if convincingly answered, will enhance scientific understanding of the domain, (iii) abstracts data from the domain and draws inferences from it in the light of the research literature, and (iv) on the basis of these inferences states a hypothesis to answer the research question. The hypothesis is subsequently tested for validity with reference to the domain and emended as required.

Linguistics is a science, and as such uses or should use scientific methodology. The research domain is human language, and, in the process of hypothesis generation, the data comes from observation of language use. Such observation can be based on introspection, since every native speaker is an expert on the usage of his or her language. It can also be based on observation of the linguistic usage of others in either spoken or written form. In some subdisciplines like historical linguistics, sociolinguistics, and dialectology, the latter is in fact the only possible alternative, and this is why D'Arcy (this volume) stresses the importance of linguistic corpora in language variation research: corpora are 'the foundation of everything we do'.

Traditionally, hypothesis generation based on linguistic corpora has involved the researcher listening to or reading through a corpus, often repeatedly, noting features of interest, and then formulating a hypothesis. The advent of information technology in general and of digital representation of text in particular in the past few decades has made this often-onerous process much easier via a range of computational tools, but, as the amount of digitally-represented language available to linguists has grown, a new problem has emerged: data overload. Actual and potential language corpora are growing ever-larger, and even now they can be on the limit of what the individual researcher can work through efficiently in the traditional way. Moreover, as we shall see, data abstracted from such large corpora can be impenetrable to understanding. One approach to the problem is to deal only with corpora of tractable size, or, equivalently, with tractable subsets of large corpora, but ignoring potential data in so unprincipled a way is not scientifically respectable. The alternative is to use mathematically-based computational tools for data exploration developed in the physical and social sciences, where data overload has long been a problem. This latter alternative is the one explored here. Specifically, the discussion shows how a particular type of computational tool, cluster analysis, can be used in the formulation of hypotheses in corpus-based linguistic research.

The discussion is in three main parts. The first describes data abstraction from corpora, the second outlines the principles of cluster analysis, and the third shows how the results of cluster analysis can be used in the formulation of hypotheses. Examples are based on the *Newcastle Electronic Corpus of Tyneside English* (NECTE), a corpus of dialect speech (Allen *et al*. 2007). The overall approach is introductory, and as such the aim has been to make the material accessible to as broad a readership as possible.

2. DATA CREATION

'Data' comes from the Latin verb 'to give' and means 'things that are given'. Data are therefore things to be accepted at face value, true statements about the world. What is a true statement about the world? That question has been debated in philosophical metaphysics since Antiquity and probably before (Bunnin and Yu 2009; Flew and Priest 2002; Zalta 2009), and, in our own time, has been intensively studied by the disciplines that comprise cognitive science (for example Thagard 2005). The issues are complex, controversy abounds, and the associated academic literatures are vast -- saying what a true statement about the world might be is anything but straightforward. We can't go into all this, and so will adopt the attitude prevalent in most areas of science: data are abstractions of what we observe using our senses, often with the aid of instruments (Chalmers 1999).

Data are ontologically different from the world. The world is as it is; data are an interpretation of it for the purpose of scientific study. The weather is not the meteorologist's data –measurements of such things as air temperature are. A text corpus is not the linguist's data –measurements of such things as average sentence length are. Data are constructed from observation of things in the world, and the process of construction raises a range of issues that determine the amenability of the data to analysis and the interpretability of the analytical results. The importance of understanding such data issues in cluster analysis can hardly be overstated. On the one hand, nothing can be discovered that is beyond the limits of the data itself. On the other, failure to understand relevant characteristics of data can lead to results and interpretations that are distorted or even worthless. For these reasons, a detailed account of data issues is given before moving on to discussion of analytical methods.

2.1 Formulation of a research question

In general, any aspect of the world can be described in an arbitrary number of ways and to arbitrary degrees of precision. The implications of this go straight to the heart of the debate on the nature of science and scientific theories, but to avoid being drawn into that debate, this discussion adopts the position that is pretty much standard in scientific practice: the view, based on Karl Popper's philosophy of science (Popper 1959; Popper 1963; Chalmers 1999), that there is no theory-free observation of the world. In essence, this means that there is no such thing as objective observation in science. Entities in a domain of inquiry only become relevant to observation in terms of a hypothesis framed using the ontology and axioms of a theory about the domain. For example, in linguistic analysis, variables are selected in terms of the discipline of linguistics broadly defined, which includes the division into subdisciplines such as sociolinguistics and dialectology, the subcategorization within subdisciplines such as phonetics through syntax to semantics and pragmatics in formal grammar, and theoretical entities within each subcategory such as phonemes in phonology and constituency structures in syntax. Claims, occasionally seen, that the variables used to describe a corpus are 'theoretically neutral' are naive: even word categories like 'noun' and 'verb' are interpretative constructs that imply a certain view of how language works, and they only appear to be theory-neutral because of familiarity with long-established tradition.

Data can, therefore, only be created in relation to a research question that is defined on the domain of interest, and that thereby provides an interpretative orientation. Without such an orientation, how does one know what to observe, what is important, and what is not?

The domain of interest in the present case is the *Newcastle Electronic Corpus of Tyneside English* (NECTE), a corpus of dialect speech interviews from Tyneside in North-East England[1] (Allen *et al*. 2007).

Figure 1

Moisl *et al*. (2006) and Moisl and Maguire (2008) have begun the study of the NECTE corpus with the aim of generating hypotheses about phonetic variation among speakers in the Tyneside dialect area using cluster analysis. The research question asked in that work, and which serves as the basis for what follows here, is:

> *Is there systematic phonetic variation in the Tyneside speech community, and , if so, what are the main phonetic determinants of that variation?*

These studies went on to correlate the findings with social data about the speakers, but the present discussion does not engage with that.

2.2 Variable selection

Given that data are an interpretation of some domain of interest, what does such an interpretation look like? It is a description of entities in the domain in terms of variables. A variable is a symbol, and as such is a physical entity with a conventional semantics, where a conventional semantics is understood as one in which the designation of a physical thing as a symbol together with the connection between the symbol and what it represents are

[1] http://www.ncl.ac.uk/necte/

determined by agreement within a community. The symbol ‘A’, for example, represents the phoneme /a/ by common assent, not because there is any necessary connection between it and what it represents. Since each variable has a conventional semantics, the set of variables chosen to describe entities constitutes the template in terms of which the domain is interpreted. Selection of appropriate variables is, therefore, crucial to the success of any data analysis.

Which variables are appropriate in any given case? That depends on the nature of the research question. The fundamental principle in variable selection is that the variables must describe all and only those aspects of the domain that are relevant to the research question. In general, this is an unattainable ideal. Any domain can be described by an essentially arbitrary number of finite sets of variables; selection of one particular set can only be done on the basis of personal knowledge of the domain and of the body of scientific theory associated with it, tempered by personal discretion. In other words, there is no algorithm for choosing an optimally relevant set of variables for a research question.

Which variables are suitable to describe the NECTE speakers? In principle, when setting out to perform a classification of a speech corpus, the first step is to partition each speaker's analog speech signal into a sequence of discrete phonetic segments and to represent those segments symbolically, or, in other words, to transcribe the audio interviews. To do this, one has to decide which features of the audio signal are of interest, and then to define a set of variables to represent those features. These decisions were made long ago with respect to the NECTE interviews.

NECTE is based on two pre-existing corpora, one of them collected in the late 1960s by the *Tyneside Linguistic Survey* (TLS) project (Strang 1968; Pellowe *et al*. 1972), and the other in 1994 by the *Phonological Variation and Change in Contemporary Spoken English* (PVC) project (Milroy *et al*. 1997). For present purposes we are interested in the 63 interviews that comprise the TLS component of NECTE, and it happens that the TLS researchers had already created phonetic transcriptions of at least part of each interview. This saved the NECTE project the arduous labour of transcription, but at the same time bound us to their decisions about which phonetic features are of interest, and how they should be symbolically represented as variables. Details of the TLS transcription scheme are available in (Allen *et al*. 2007) as well as at the NECTE website[2]; a short excerpt from the TLS transcription scheme is given in figure 2 below:

Figure 2

Two levels of transcription were produced, a highly detailed narrow one designated 'States' in figure 2, and a superordinate ‘Putative Diasystemic Variables’ (PDV) level which collapsed some of the finer distinctions transcribed at the ‘States’ level. We shall be dealing with the less detailed PDV level.

2.3 Variable value assignment

The semantics of each variable determines a particular interpretation of the domain of interest, and the domain is 'measured' in terms of the

[2] http://www.ncl.ac.uk/necte/appendix1.htm

semantics. That measurement constitutes the values of the variables: height in metres = 1.71, weight in kilograms = 70, and so on. Measurement is fundamental in the creation of data because it makes the link between data and the world, and thus allows the results of data analysis to be applied to the understanding of the world.

Measurement is only possible in terms of some scale. There are various types of measurement scale, and these are discussed at length in, for example, any statistics textbook, but for present purposes the main dichotomy is between numeric and non-numeric. Cluster analysis methods assume numeric measurement as the default case, and for that reason the same is assumed in what follows. Specifically, we shall be interested in the number of times each speaker uses each of the NECTE phonetic variables. The speakers are therefore 'measured' in terms of the frequency with which they use these segments

2.4 Data representation

If they are to be analyzed using mathematically-based computational methods, the descriptions of the entities in the domain of interest in terms of the selected variables must be mathematically represented. A widely used way of doing this, and the one adopted here, is to use structures from a branch of mathematics known as linear algebra. There are numerous textbooks and websites devoted to linear algebra; a small selection of introductory textbooks is (Anton 2005; Poole 2005; Blyth and Robertson 2002).

Vectors are fundamental in data representation. A vector is just a sequence of numbered slots containing numerical values. Figure 3 shows a four-element vector each element of which contains a real-valued number: 1.6 is the value of the first element v_1, 2.4 the value of the second element v_2, and so on.

Figure 3

A single NECTE speaker's frequency of usage of the 158 phonetic segments in the transcription scheme can be represented by a 158-element vector in which each element is associated with a different segment, as in Figure 4.

Figure 4

This speaker uses the segment at Speaker_1 twenty three times, the segment at Speaker_2 four times, and so on.

The 63 speaker vectors can be assembled into a matrix M, shown in figure 5, in which the 63 rows represent the speakers, the 158 columns represent the phonetic segments, and the value at M_{ij} is the number of times speaker *i* uses segment *j* (for i = 1..63 and j = 1..158):

Figure 5

This matrix M is the basis of subsequent analysis.

3. DATA ANALYSIS

Once the data matrix has been created, a variety of computational methods can be used to classify its row vectors, and thereby the objects in the domain that the row vectors represent. In the present case, those objects are the NECTE speakers. The discussion is in 4 main parts:

- Part 1 motivates the use of computational methods for clustering.
- Part 2 introduces a fundamental concept: vector space.
- Part 3 describes how clusters can be found in vector space.
- Part 4 deals with some issues that arise in clustering.

All four parts of the discussion are based on the NECTE data matrix M developed in the preceding section.

3.1 Motivation

We have seen that creation of data for study of a domain requires description of the objects in the domain in terms of variables. One might choose to observe only one aspect -the height of individuals in a population, say- in which case the data consists of more or less numerous values assigned to one variable; such data is univariate. If two values are observed -say height and weight- then the data is bivariate, if three trivariate, and so on up to some arbitrary number *n*; any data where *n* is greater than 1 is multivariate.

As the number of variables grows, so does the difficulty of classifying the objects that the data matrix rows represent by direct inspection. Consider, for example, figure 6, which shows a matrix describing nine people in terms of a single variable *Age*.

Figure 6

It's easy enough to classify these people into three groups: young (1-3), middle-aged (4-6), and old (7-9) just by looking at the matrix. If one adds a second variable *weight*, as in figure 7, classification based on direct examination of the matrix is a little more difficult.

Figure 7

The groups are the same as before, and there is a correlation between age and weight: the young group weighs least, the middle aged group weighs most, and the old group weighs a little less than the middle-aged one. Now increase the number of variables to, say, six, as in figure 8.

Figure 8

One can spend a long time looking at these numbers without coming up with a coherent grouping. And what if the number of variables is increased even more to, say, the 158 variables of the NECTE data matrix M? That matrix is too large to be shown here in its entirety, so only a dozen variables are given for nine of the speakers in figure 9, but even this is sufficient to make the required point.

Figure 9

Group these speakers on the basis of this phonetic segment frequency data. Difficult? Impossible? Try all 158 variables, and classify not just 9 but 63 speakers.

In general, as the number of variables grows, so does the difficulty of understanding the data, that is, of conceptualizing the interrelationships of variables within a single data item on the one hand, and the interrelationships of complete data items on the other. The moral is straightforward: human cognitive makeup is unsuited to seeing regularities in anything but the smallest collections of numerical data. To see the regularities we need graphical aids, and that is what clustering methods provide.

3.2 Vector space

Though it is just a sequence of numbers, a vector can be geometrically interpreted (Anton 2005; Poole 2005; Blyth and Robertson 2002). To see how, take a vector consisting of two elements, say $v = (30,70)$. Under a geometrical interpretation, the two elements of v define a two-dimensional space, the numbers at $v_1 = 30$ and $v_2 = 70$ are coordinates in that space, and the vector v itself is a point at the coordinates (30,70), as shown in figure 10.

Figure 10

A vector consisting of three elements, say $v = (40, 20, 60)$ defines a three-dimensional space in which the coordinates of the point v are 40 along the horizontal axis, 20 along the vertical axis, and 60 along the third axis shown in perspective, as in figure 11.

Figure 11

A vector $v = (22, 38, 52, 12)$ defines a four-dimensional space with a point at the stated coordinates, and so on to any dimensionality n. Vector spaces of dimensionality greater than 3 are impossible to visualize directly and are therefore counterintuitive, but mathematically there is no problem with them;

two and three dimensional spaces are useful as a metaphor for conceptualizing higher-dimensional ones.

When numerous vectors exist in a space, it may or may not be possible to see interesting structure in the way they are arranged in it. Figure 12 shows vectors in two and three dimensional spaces. In (a) they were randomly generated and there is no structure to be observed, in (b) there are two clearly defined concentrations in two dimensional space, and in (c) there are two clearly defined concentrations in three-dimensional space.

Figure 12

The existence of concentrations like those in (b) and (c) indicate relationships among the entities that the vectors represent. In (b), for example, if the horizontal axis measures weight and the vertical one height for a sample human population, then members of the sample fall into two groups: tall, light people on the one hand, and short heavy ones on the other.

This idea of identifying clusters of vectors in vector space and interpreting them in terms of what the vectors represent is the basis of cluster analysis. In what follows, we shall be attempting to group the NECTE speakers on the basis of their phonetic usage by looking for clusters in the arrangement of the row vectors of M in 158-dimensional space.

3.3 *Cluster analysis*

Where the vectors are two or three-dimensional they can simply be plotted and any clusters will be visually identifiable, as we have just seen. But what about when the vector dimensionality is greater than 3 -say 4, or 10, or 100? In such a case direct plotting is not an option. How exactly would one draw a 6-dimensional space, for example? Many data matrix row vectors have dimensionalities greater than 3 -the NECTE matrix M has dimensionality 158- and, to identify clusters in such high-dimensional spaces some procedure more general than direct plotting is required. A variety of such procedures is available, and they are generically known as cluster analysis methods. This section looks at these methods.

The literature on cluster analysis is extensive. A few recent books are (Everitt 2001; Kaufman and Rousseeuw 2005), but many textbooks in fields like multivariate statistical analysis, information retrieval, and data mining also contain useful and accessible discussions, and there are numerous relevant and often excellent websites.

The discussion of cluster analysis is in four parts. The first introduces distance in vector space, the second describes one particular class of clustering methods, the third applies that type of method to the NECTE data matrix M, and the fourth interprets the result of the NECTE analysis.

3.3.1 Distance in vector space

Where there are two or more vectors in a space, it is possible to measure the distance between any two of them and to rank them in terms of their proximity to one another. Figure 13 shows a simple case of a 2-dimensional space in which the distance from vector A to vector B is greater than the distance from A to C.

Figure 13

There are various ways of measuring such distances, but the most often used is the familiar Euclidean one:

$$dist(AB) = \sqrt{(5-1)^2 + (4-2)^2}$$

Figure 14

3.3.2 Cluster analysis methods

Cluster analysis methods use relative distance among vectors in a space to group the vectors into clusters. Specifically, for a given set of vectors in a space, they first calculate the distances between all pairs of vectors, and then group into clusters all the vectors that are relatively close to one another in the space and relatively far from those in other clusters. 'Relatively close' and 'relatively far' are, of course, vague expressions, but they are precisely defined by the various clustering methods, and for present purposes we can avoid the technicalities and rely on intuitions about relative distance.

For concreteness, we will concentrate on one particular class of methods: hierarchical cluster analysis, which represents the relativities of distance among vectors as a tree. Figure 15 exemplifies this.

Figure 15

Column (a) shows a 30 x 2 data matrix that is to be cluster analyzed. Because the data space is 2-dimensional the vectors can be directly plotted to show the cluster structure, as in the upper part of column (b). The corresponding hierarchical cluster tree is shown in the lower part of column (b). Linguists use such trees as representations of sentence phrase structure, but cluster trees differ from linguistic ones in the following respects:

- The leaves are not lexical tokens but labels for the data items -the numbers at the leaves correspond to the numerical labels of the row vectors in the data matrix.
- They represent not grammatical constituency but relativities of distance between clusters. The lengths of the branches linking the clusters represent degrees of closeness: the shorter the branch, the more similar the clusters. In cluster A vectors 4 and 19 are very close and thus linked with very short lines; 2 and 3 are almost but not quite as close as 4 and 19, and are therefore linked with slightly longer lines, and so on.

Knowing this, the tree can be interpreted as follows. There are three clusters labelled A, B, and C in each of which the distances among vectors are quite small. These three clusters are relatively far from one another, though A and B are closer to one another than either of them is to C. Comparison with the vector plot shows that the hierarchical analysis accurately represents the distance relations among the 30 vectors in 2-dimensional space.

Given that the tree tells us nothing more than what the plot tells us, what is gained? In the present case, nothing. The real power of hierarchical analysis lies in its independence of vector space dimensionality. We have seen that direct plotting is limited to three or fewer dimensions, but there is no dimensionality limit on hierarchical analysis -it can determine relative distances in vector spaces of any dimensionality and represent those distance relativities as a tree like the one above. To exemplify this, the 158-

dimensional NECTE data matrix M was hierarchically cluster analyzed, and the results of the analysis are shown in the next section.

3.3.3 Hierarchical cluster analysis of the NECTE data

Recall that the NECTE data is a 63 x 158 matrix M in which each of the 63 rows represents a speaker, each of the columns represents a phonetic segment, and the value at M_{ij} is the number of times speaker *i* uses phonetic segment *j*. Each row vector is therefore a phonetic profile of a different NECTE speaker; the aim is to classify the speakers in terms of the similarity of their phonetic profiles or, put another way, in terms of the relative distances among the row vectors in the 158-dimensional space. The resulting tree is shown in figure 16.

Figure 16

Plotting M in 158-dimensional space would have been impossible, and, without cluster analysis, one would have been left pondering a very large and incomprehensible matrix of numbers. With the aid of cluster analysis, however, structure in the data is clearly visible: there are two main clusters, NG1 and NG2; NG1 consists of large subclusters NG1a and NG1b; NG1a itself has two main subclusters NG1a(i) and NG1a(ii).

4. HYPOTHESIS GENERATION

Given that there is structure in the relative distances of the row vectors of M, what does that structure mean in terms of the research question?

'*Is there systematic phonetic variation in the Tyneside speech community, and, if so, what are the main phonetic determinants of that variation?*'.

Because the row vectors of M are phonetic profiles of the NECTE speakers, the cluster structure means that the speakers fall into clearly defined groups with specific interrelationships rather than, say, being randomly distributed around the phonetic space. A reasonable hypothesis to answer the first part of the research question, therefore, is that there is systematic variation in the Tyneside speech community. This hypothesis can be refined by examining the social data relating to the NECTE speakers, which shows, for example, that all those in the NG1 cluster come from the Gateshead area on the south side of the river Tyne and all those in NG2 come from Newcastle on the north side, and that the subclusters in NG1 group the Gateshead speakers by gender and occupation.

The cluster tree can also be used to generate a hypothesis in answer to the second part of the research question. So far we know *that* the NECTE speakers fall into clearly-demarcated groups on the basis of variation in their phonetic usage. We do not, however, know *why,* that is, which segments out of the 158 in the TLS transcription scheme are the main determinants of this regularity. To identify these segments (Moisl & Maguire 2008), we begin by looking at the two main clusters NG1 and NG2 to see which segments are most important in distinguishing them.

The first step is to create for the NG1 cluster a vector that captures the general phonetic characteristics of the speakers it contains, and to do the same for the NG2. Such vectors can be created by averaging all the row vectors in a cluster using the formula

$$v_j = \frac{\sum_{i=1..m} M_{ij}}{m}$$

where v_j is the jth element of the average or 'centroid' vector v (for j = 1..the number of columns in M), M is the data matrix, Σ designates summation, and m is the number of row vectors in the cluster in question (56 for NG1, 7 for NG2). This yields two centroid vectors.

Next, compare the two centroid vectors by co-plotting them to show graphically how, on average, the two speaker groups differ on each of the 158 phonetic segments; a plot of all 158 segments is too dense to be readily deciphered, so the six on which the NG1 and NG2 centroids differ most are shown in Figure 17.

Figure 17

The six phonetic segments most important in distinguishing cluster NG1 from NG2 are three varieties of [ə], [ɔː], [ɪ], and [eɪ]: the Newcastle speakers characteristically use $ə_1$ and $ə_2$ whereas the Gateshead speakers use them hardly at all, the Gateshead speakers use $ə_3$ much more than the Newcastle speakers, and so on. A hypothesis that answers the second part of the research question is therefore that the main determinants of phonetic variation in the Tyneside speech community are three kinds of [ə], [ɔː], [ɪ], and [eɪ]. The subclusters of NG1 can be examined in the same way and the hypothesis thereby further refined.

Having formulated two hypotheses about Tyneside speech, they need to be tested against additional evidence from a source or sources other than NECTE and emended or even discarded if that is what the evidence requires.

5. SUMMARY

This discussion set out to show how one type of computational analytical tool, cluster analysis, can be used to generate hypotheses about large digital linguistic corpora when the data abstracted from them is too complex to be interpreted by direct inspection. This approach to hypothesis generation is useful primarily when dealing with corpora in languages that have been relatively little studied, such as endangered languages, but even for intensively-studied ones like English, where hypotheses can usually be generated from the existing research literature, cluster analysis can produce surprises, as Moisl and Maguire (2008) showed for Tyneside English.

6. WHERE TO GO NEXT

The foregoing discussion was introductory, and anyone wishing to use cluster analysis in actual research applications has some additional reading to do. There is no shortage of such reading: the literature on cluster analysis, both in traditional printed form and on the Web, is extensive. Much of it is, however, quite technical, and this can be an obstacle to those new to the subject. It's important to have a secure intuitive grasp of the underlying concepts before trying to assimilate the technicalities, so a good way into the literature is to start with the Web, using 'cluster analysis' as the search string. There are numerous good and even excellent introductory-level cluster analysis websites, and working through these lays the groundwork for more advanced reading. Romesburg (1984) is an accessible first textbook, followed by Everitt *et al*. (2001); the latter contains an extensive bibliography for further reading.

Knowing the theory of cluster analysis is a necessary but not sufficient condition for using it in research. Software is required to do the actual work. The standard statistics packages available in university and other research environments include a few types of clustering method, but more specialized ones provide a greater range of methods and, generally, better output graphics; a Web search using the string 'cluster analysis software' gives a good overview of what is available. Also very useful are Web directories of cluster analysis and related resources such as Fionn Murtagh's *Multivariate Data Analysis Software and Resources Page* (http://astro.u-strasbg.fr/~fmurtagh/mda-sw/).

The data to be cluster analyzed may contain characteristics that can distort the result or even render it invalid as a basis for hypothesis generation. These characteristics, which include variation in the lengths of documents in multi-document corpora, data sparsity, and nonlinearity, must be recognized and where necessary eliminated or at least mitigated prior to undertaking the analysis. Given its importance, the research literature contains surprisingly little on such matters; see Pyle (1999) and Moisl (2007, 2008b, 2010)

Finally, anyone proposing to use cluster analysis has to face the reality that, to do so respectably, knowledge of the basics of linear algebra and of statistics is a prerequisite. Some introductory textbooks on linear algebra are Anton (2005), Blyth (2002), and Poole (2005); introductory statistics textbooks are too numerous to require individual mention, and are available in any research library as well as on the Web.

7. THE FUTURE FOR CLUSTER ANALYSIS IN LINGUISTIC VARIATION STUDIES

Cluster analysis has long been and continues to be a standard data processing tool across a broad range of physical and social sciences. The advent of digital electronic text in the second half of the twentieth century has driven the emergence of research disciplines devoted to search and interpretation of large digital natural language document collections, among them Information Retrieval (Manning *et al*. 2008), Data Mining (Hand *et al*. 2001), Computational Linguistics (Mitkov 2005), and Natural Language Processing (Manning and Schütze 1999), and here too cluster analysis is a standard tool. As increasingly large digital collections become available for research into linguistic variation, traditional analytical methods will become intractable, and use of the computational tools developed by these text processing disciplines, including cluster analysis, will become the only realistic option.

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WORD COUNT: 6690 (including References)

Figure 1: The NECTE dialect area

	OU	PDV	(code)	states	lexical examples
1	$\boxed{\text{i:}}$ NL	i:	0002	i i i i i i	week, treat, see
		I	0004	i i i i i	week, relief
		ɛ	0006	e ɛ e ɛ	beat
		eI	0008	ɛi əi e ɛi	see
		Iə	0010	iɛ iɛ iə	feed
		Ii	0012	ii(back) ii(low) i	we, see

Figure 2: Extract from the TLS transcription scheme

$$V = \begin{array}{|c|c|c|c|} \hline 1.6 & 2.4 & 7.5 & 0.6 \\ \hline \multicolumn{1}{c}{1} & \multicolumn{1}{c}{2} & \multicolumn{1}{c}{3} & \multicolumn{1}{c}{4} \end{array}$$

Figure 3: A numerical vector

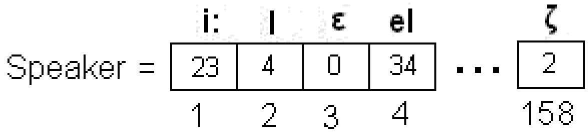


Figure 4: A NECTE data vector

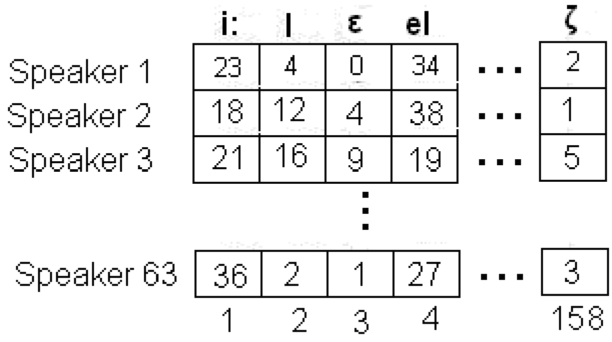


Figure 5: A fragment of the NECTE data matrix M

	Age
Person 1	14
Person 2	12
Person 3	15
Person 4	41
Person 5	47
Person 6	43
Person 7	83
Person 8	76
Person 9	81

Figure 6: Univariate data

	Age	**Weight (kg)**
Person 1	14	25
Person 2	12	21
Person 3	15	26
Person 4	41	83
Person 5	47	82
Person 6	43	80
Person 7	83	71
Person 8	76	73
Person 9	81	72

Figure 7: Bivariate data

	Age	Weight (kg)	Height (m)	Size of family	Years worked	Trips abroad
Person 1	14	25	1.4	5	2	2
Person 2	12	21	1.36	5	0	0
Person 3	15	26	1.5	4	1	1
Person 4	41	83	1.74	7	15	46
Person 5	47	82	1.72	3	17	23
Person 6	43	80	1.66	6	21	0
Person 7	83	71	1.65	2	36	12
Person 8	76	73	1.68	5	34	29
Person 9	81	72	1.81	4	42	0

Figure 8: Multivariate data

	$d_{initial}$	εμ	n	$b_{initial}$	aI	$k_{initial}$	ɭ	a	k_{final}	tʃ	æ	p_{medial}
Speaker 1	22	19	177	39	6	44	13	11	47	10	37	8
Speaker 2	27	6	210	32	9	45	18	8	40	17	46	6
Speaker 3	32	16	188	57	8	27	23	6	29	6	42	6
Speaker 4	33	20	191	45	6	47	21	16	40	3	42	7
Speaker 5	43	27	304	58	13	53	28	12	74	14	76	10
Speaker 6	34	9	202	54	14	26	14	14	45	5	53	6
Speaker 7	33	0	222	27	54	47	27	11	40	16	51	18
Speaker 8	22	16	186	41	3	56	19	10	29	8	53	8
Speaker 9	30	27	214	54	12	29	20	6	45	7	54	8

Figure 9: Multivariate NECTE data

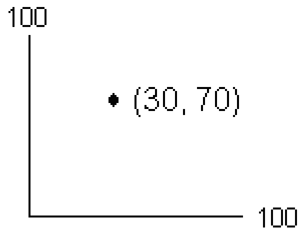


Figure 10: A vector in two-dimensional space

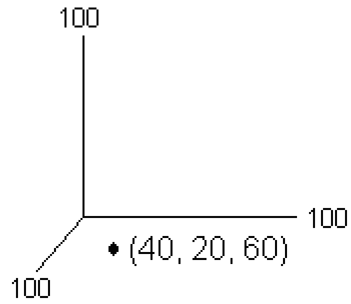


Figure 11: A vector in three-dimensional space

a b c

Figure 12: Multiple vectors in two and three dimensional spaces

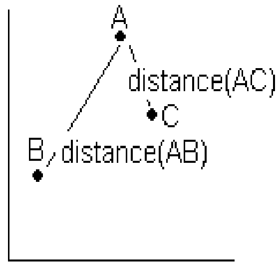


Figure 13: Distance between vectors in two-dimensional space

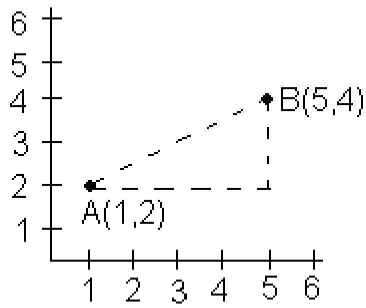
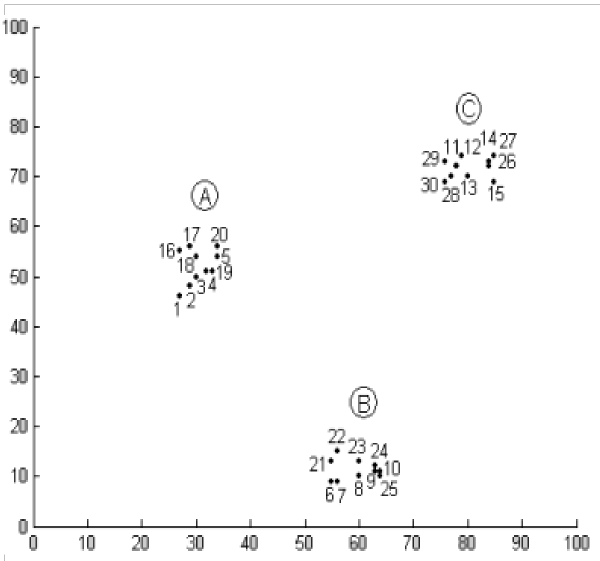
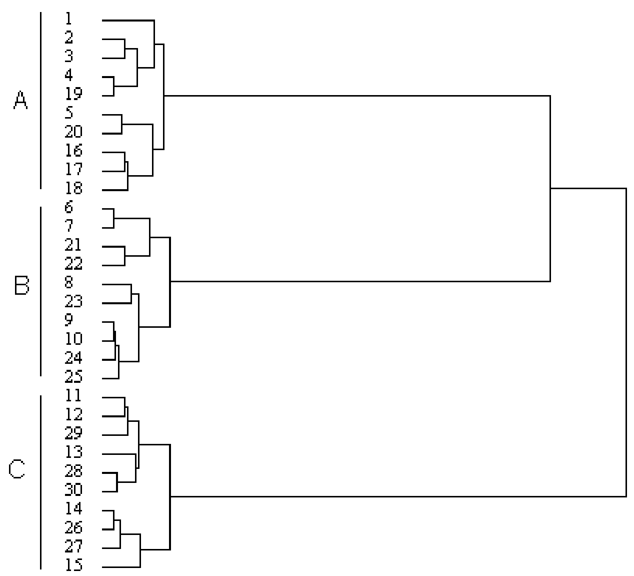


Figure 14: Euclidean distance calculation: 'In a right-angled triangle, the square of the length of the hypotenuse is equal to the sum of the squares of the lengths of the other two sides'.

	v1	v2
1	27	46
2	29	48
3	30	50
4	32	51
5	34	54
6	55	9
7	56	9
8	60	10
9	63	11
10	64	11
11	78	72
12	79	74
13	80	70
14	84	73
15	85	69
16	27	55
17	29	56
18	30	54
19	33	51
20	34	56
21	55	13
22	56	15
23	60	13
24	63	12
25	64	10
26	84	72
27	85	74
28	77	70
29	76	73

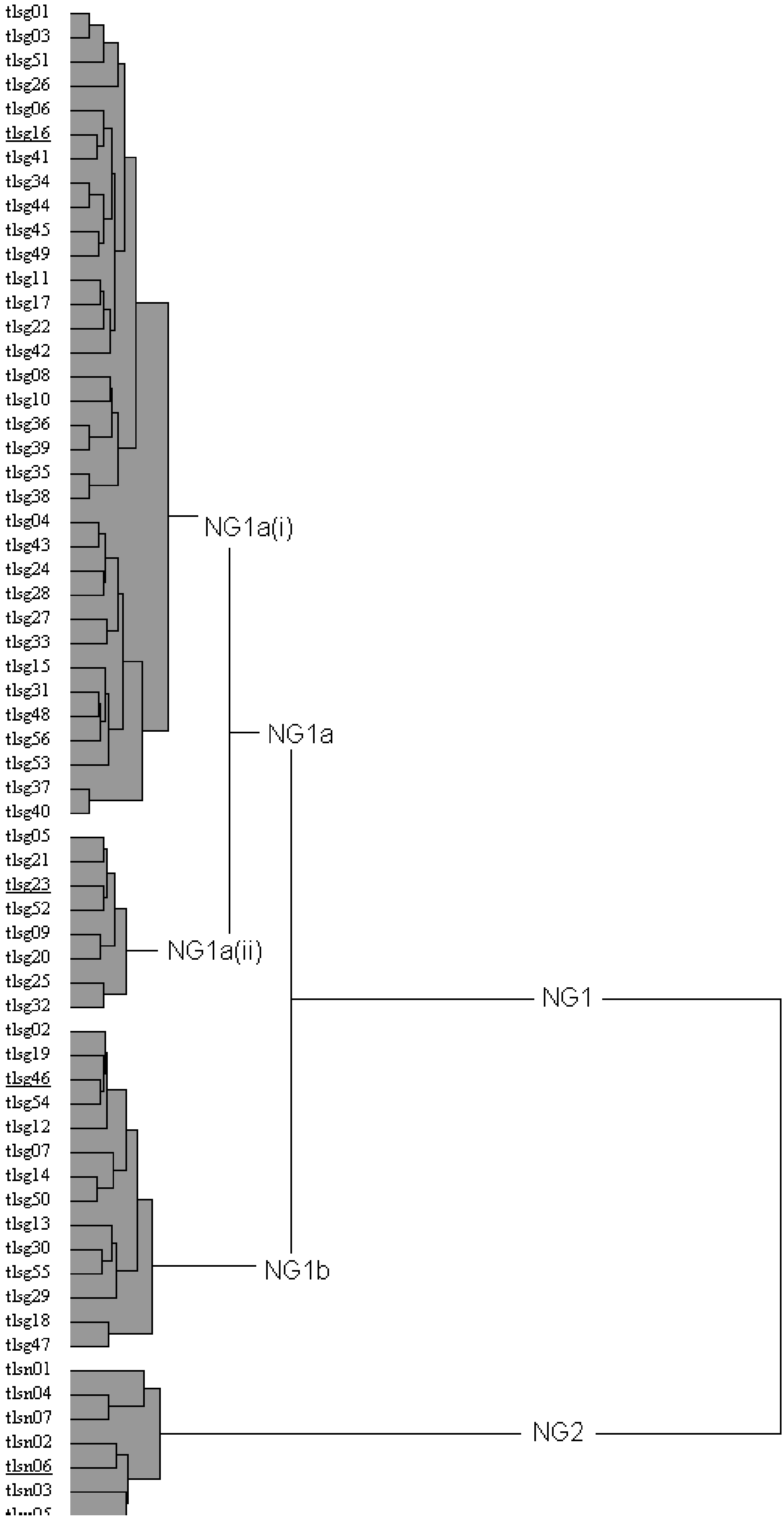




30	76	69

a	b

Figure 15: Hierarchical cluster analysis of two-dimensional data


tlsg01
tlsg03
tlsg51
tlsg26
tlsg06
tlsg16
tlsg41
tlsg34
tlsg44
tlsg45
tlsg49
tlsg11
tlsg17
tlsg22
tlsg42
tlsg08
tlsg10
tlsg36
tlsg39
tlsg35
tlsg38
tlsg04
tlsg43
tlsg24
tlsg28
tlsg27
tlsg33
tlsg15
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tlsg48
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tlsg53
tlsg37
tlsg40
tlsg05
tlsg21
tlsg23
tlsg52
tlsg09
tlsg20
tlsg25
tlsg32
tlsg02
tlsg19
tlsg46
tlsg54
tlsg12
tlsg07
tlsg14
tlsg50
tlsg13
tlsg30
tlsg55
tlsg29
tlsg18
tlsg47
tlsn01
tlsn04
tlsn07
tlsn02
tlsn06
tlsn03
NG1a(i)
NG1a
NG1a(ii)
NG1
NG1b
NG2

Figure 16: Hierarchical cluster analysis of the NECTE data matrix M

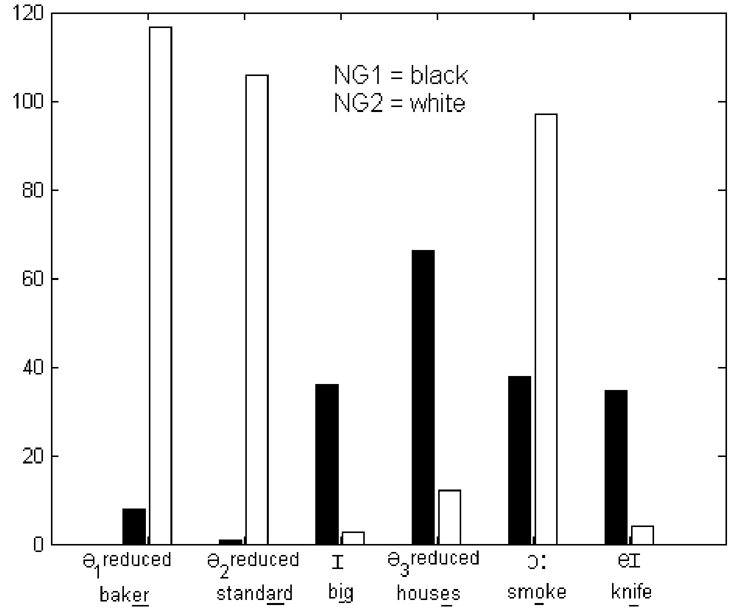

Figure 17: Co-plot of centroids for NG1 and NG2