The Text Feature Analyser – a Flexible Tool for Comparing Different Levels of Text Complexity

MARTIN WEISSER

CHEMNITZ UNIVERSITY OF TECHNOLOGY

The following article describes the Text Feature Analyser, an analysis tool that helps the user to conduct automatic analyses on texts, based on features that may serve as indicators to the texts' complexity, genre, specificity/'scientificness', etc. These features can easily be changed, or new ones added, to customise the analysis according to the user's needs and expectations towards the text. A sample analysis of two different texts, dealing with the same subject matter, will be conducted towards the end of the article in order to demonstrate the relevance of some of the pre-defined features.

MOTIVATION FOR THE TOOL

The Text Feature Analyser was written in order to try and provide a solution to a very common problem in dealing with texts written by native and non-native writers of *Academic English*, namely the need to establish an objective basis for the comparison of such texts with regard to their general, objectively observable and measurable features. Although the goals in writing the tool were not originally specifically and exclusively geared towards the study of complexity, ultimately its 'genesis' is due to the aim of identifying means of modelling specific properties that may help us to identify indicators for determining the degree of complexity in any piece of writing.

PREVIOUS ATTEMPTS AT MEASURING TEXTUAL FEATURES

As already hinted at above, complexity is a phenomenon that is multi-facetted and so far, no clear indicators of what makes a text complex have been identified, although there have been different attempts. Ventola (1996) provides an interesting introduction to some of the ideas underlying the controversy writers of academic materials may experience when trying to find advice on which appropriate style(s) to use, as well as to some of the measures that different researchers have employed in order to try and measure complexity and readability in texts. Many of the latter, however, seem to have mainly concentrated on *lexical density* (LD; Ure, 1971) and are frequently based on measures that are difficult to extract automatically from text, such as the number of syllables (Ellis & Hopkins, 1985) or clauses (Halliday, 1985) in a text, paragraph, or sentence, and their relation to the overall number of words in a document or exclusively restricted to *content words*.

The measures/indices Ventola describes in her article include the *Fog Index* (FOG; Ellis & Hopkins, 1985), as well as two different variants of LD, one as defined by Ure (1971), the other a modification of the former, defined by Halliday (1985). Out of the three indices, FOG is the only one which includes a factor for the number of syllables in the unit of analysis (a passage of approximately 100 words), and is calculated based on average sentence length (= number of sentences/word count) plus the number of 3+ syllable words, multiplied by a factor of 0.4. Its index is based on the *raw* number of all *word tokens* in the unit of analysis. The two LD measures, in contrast, are based on ratios that are based not on raw token frequencies, but on the frequencies of *lexical items* (i.e. *content words*). Ure's LD index measures the ratio of content words to the total number of tokens in the text (expressed as a percentage value), whereas Halliday's LD simply gives the ratio of content words to clauses in the passage/document.

A different and more complex approach to identifying important textual features is represented by Biber's *multi-dimensional analysis* of text categories (c.f. Biber, 1988 & 2006). Although his approach is not primarily aimed at identifying features of complexity, some of the features that characterise texts according to his dimensions and situate them on a continuum from spoken to written registers are also relevant to the topic of complexity. Biber's method of analysis, however, is to a large extent based on *tagged corpora*, something that cannot easily be replicated in a relatively small-scale program, such as the Text Feature Analyser. Despite this fact, the Text Feature Analyser already manages to incorporate and measure many of the features that form part of Biber's categories, as well as the ability to easily add further features, as will be discussed in a later section.

DESIGN OF THE TOOL

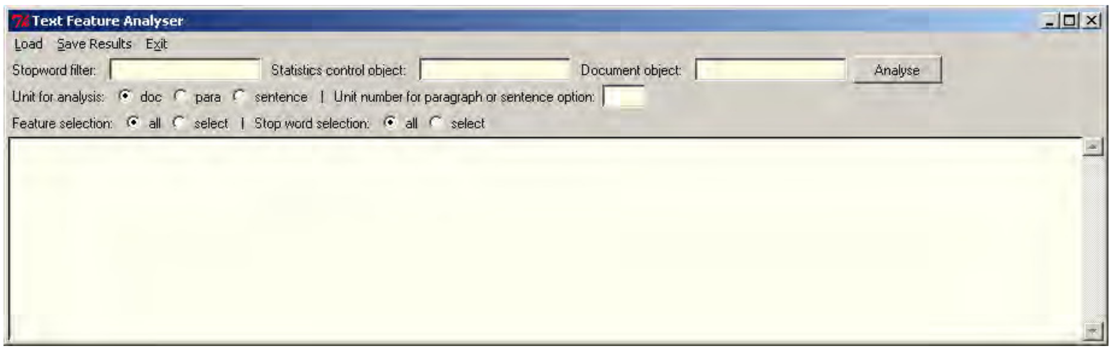
The tool is written in the programming language Perl, a language that is highly suited to the task of conducting linguistic analyses, not least because its designer, Larry Wall, is also a linguist. One of the main design features of Perl is that it enables the programmer to easily specify complex textual patterns that can be matched against any piece of text and counted or manipulated. The Feature Analyser relies heavily on this in order to be able to read in a given text paragraph by paragraph, split up these paragraphs into sentences, and store the latter in a list that can later be manipulated in order to obtain word frequency counts, type/token ratios, etc.

The tool itself is split into four modular parts, one document object, one statistics control object, one statistics calculation module, and the graphical user interface (GUI) that allows the user to interact conveniently with the other parts of the program, make/edit feature selections, or produce descriptive statistics of the individual features chosen. The results are displayed in a text window, but can also be exported to a format that can be read into a spreadsheet application (such as MS Excel) or a database for further statistical analysis. Two additional text files are used to control the analysis features that are compiled and made available by the program.

USING THE TOOL

Running the Text Feature Analyser

Although the Text Feature Analyser has a graphical user interface (GUI), similar to the one most people are used to from Windows programs, it needs to be run from the *command line/shell* or via a *desktop shortcut* on Windows systems. No installation is necessary, but a Perl interpreter has to be installed on the system, and the program folder copied to a convenient location, such as the user's *home folder*. The program itself is portable and can be run on MS Windows, as well as on Linux or other Unix systems.
Once the program has been copied to the computer, it can be started by either typing 'perl TextAnalyser.pl' or simply 'TextAnalyser.pl', if the system has been appropriately configured, on the command line. If a desktop shortcut has been set up, it may be started by (double-) clicking on the shortcut, which will open the following program window:



Unit for analysis: [✓ doc] para sentence | Unit number for paragraph or sentence option:
Feature selection: [✓ all] select | Stop word selection: [✓ all] select

Fig. 1: Text Feature Analyser startup screen (image reduced)

Loading files

At the top of the program screen, the user finds a menu which controls the files to be loaded/used for analysis (accessible also via Alt + l), saving of analysis results (Alt + s), plus an 'Exit' (Alt +x) entry. Three separate files need to be loaded for an analysis via the 'Stopword filter', 'Stats object' and the 'Document Object' entries. The first provides a user-configurable control file that defines categorised *stop word* filter lists, the second, equally configurable analysis features, whereas the third one imports the document to be analysed, performing a few separate steps when reading the file into memory. Each action for loading a file can also be triggered by double-clicking on the appropriate text box. The user is then provided with a graphical selection dialogue which enables him/her to navigate to an appropriate folder and select the chosen file. If the user cancels such a dialogue, an appropriate default file will automatically selected to prevent the program from producing an error if an analysis without the appropriate control files is inadvertedly started.

The document to be analysed currently has to be in *plain text format*, i.e. may only contain unformatted text, with each paragraph being separated from the next via two hard returns (line breaks). Further import filters, e.g. for web pages or Word documents may be added at a later stage. Upon reading in the file, the program first splits it into paragraphs, then splitting each one of these into individual sentences in turn, using simple end-of-sentence spotting heuristics. Internally, the text is then stored in memory as a list of sentences, where information about the sentences making up each paragraph is stored in a paragraph index in order to conserve memory.

Once the three necessary documents have been chosen, their names appear in text boxes below the menu bar for reference. The 'Analyse' button to their right triggers the analysis routines, based on the options selected from the choices displayed in the following two rows of controls.

Making feature selections

The row labelled: 'Unit for Analysis' allows the user to choose the scope of the analysis, either the whole document ('doc'), or an individual paragraph ('para') or 'sentence'. If one of the two latter options is specified, a corresponding unit number also needs to be provided. If this unit number is not provided in the text box on the very right, or the unit number is too high, an appropriate error message is displayed to the user when attempting an analysis.

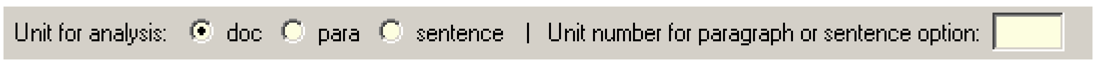
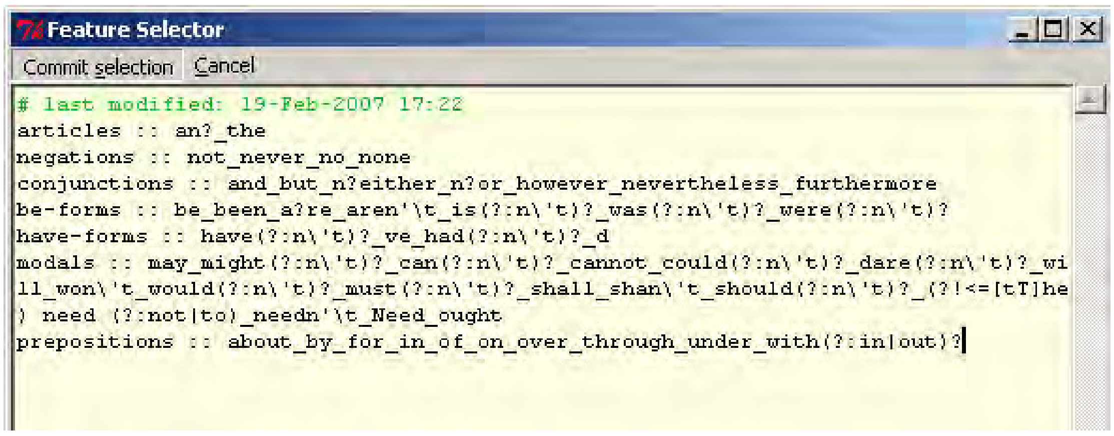

Unit for analysis: [✓ doc] para sentence | Unit number for paragraph or sentence option:

Fig. 2: Analysis unit selection

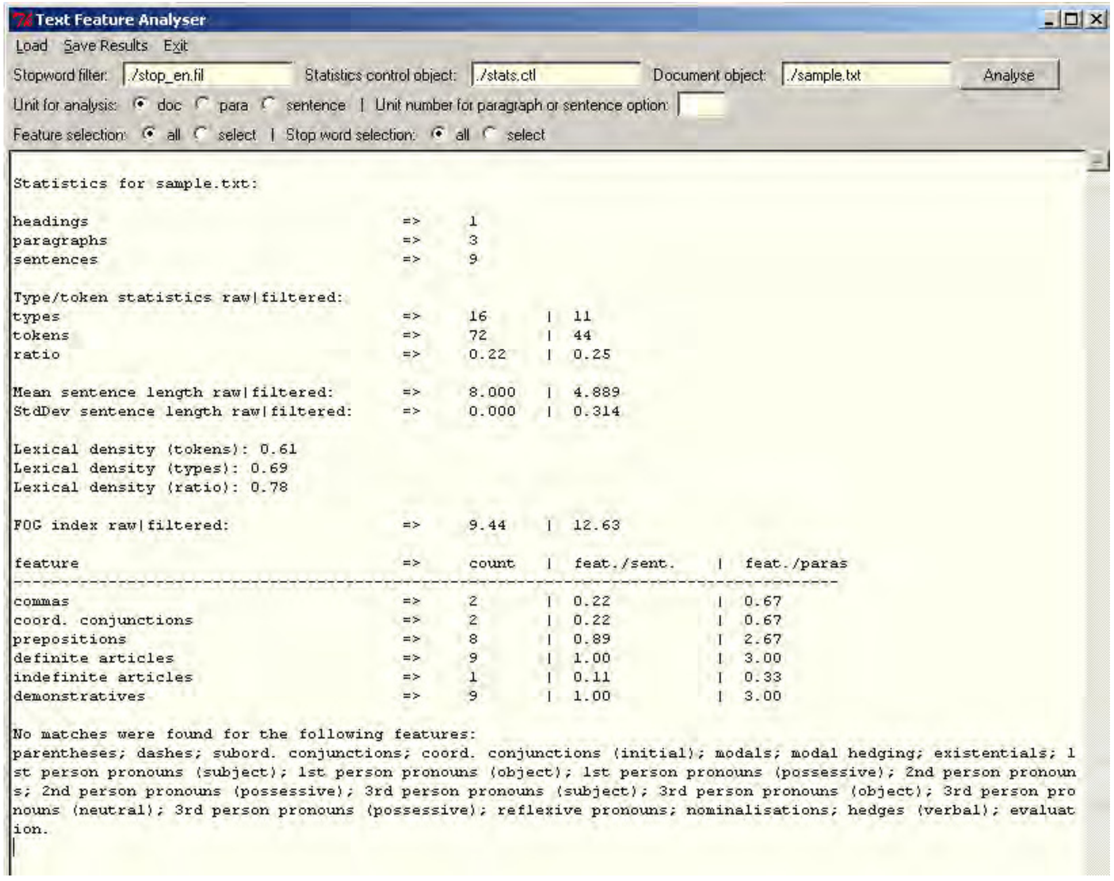
The next row contains the option selectors for feature and stopword selection. Here, the user can either leave the default set to 'all', which means that all features specified in the feature control file will be analysed, or click on the option for 'select', which will open a corresponding editor window that allows the user to modify the defaults by commenting them out or editing them.



```
# last modified: 19-Feb-2007 17:22
articles :: an?_the
negations :: not_never_no_none
conjunctions :: and_but_n?either_n?or_however_nevertheless_furthermore
be-forms :: be_been_a?re_aren'\t_is(?:n\'t)?_was(?:n\'t)?_were(?:n\'t)?
have-forms :: have(?:n\'t)?_ve_had(?:n\'t)?_d
modals :: may_might(?:n\'t)?_can(?:n\'t)?_cannot_could(?:n\'t)?_dare(?:n\'t)?_wi
ll_won\'t_would(?:n\'t)?_must(?:n\'t)?_shall_shan\'t_should(?:n\'t)?_(?!<=[tT]he
) need (?:not|to)_needn'\t_Need_ought
prepositions :: about_by_for_in_of_on_over_through_under_with(?:in|out)?
```

Fig. 3: Feature selection editor (stop words)

This customisation will be discussed further below. Once the user has finished making an appropriate selection, the editor can be closed by clicking on ‘Commit selection’, which will update the feature list. Clicking on ‘Cancel’ instead will restore the original feature options list.
Below the controls for setting analysis options is the output window. Depending on the settings chosen above, different items of information will be shown here after starting the analysis.



Stopword filter: ./stop_en.fil
Statistics control object: ./stats.ctl
Document object: ./sample.txt
Unit for analysis: [✓ doc] para sentence | Unit number for paragraph or sentence option:
Feature selection: [✓ all] select | Stop word selection: [✓ all] select

```
Statistics for sample.txt:

headings                                  =>     1
paragraphs                                =>     3
sentences                                 =>     9

Type/token statistics raw|filtered:
types                                     =>     16       |  11
tokens                                    =>     72       |  44
ratio                                     =>     0.22     |  0.25

Mean sentence length raw|filtered:        =>     8.000    |  4.889
StdDev sentence length raw|filtered:      =>     0.000    |  0.314

Lexical density (tokens): 0.61
Lexical density (types): 0.69
Lexical density (ratio): 0.78

FOG index raw|filtered:                   =>     9.44     |  12.63

feature                                   =>     count    |  feat./sent.     |  feat./paras
------------------------------------------------------------------------------------------
commas                                    =>     2        |  0.22            |  0.67
coord. conjunctions                       =>     2        |  0.22            |  0.67
prepositions                              =>     8        |  0.89            |  2.67
definite articles                         =>     9        |  1.00            |  3.00
indefinite articles                       =>     1        |  0.11            |  0.33
demonstratives                            =>     9        |  1.00            |  3.00

No matches were found for the following features:
parentheses; dashes; subord. conjunctions; coord. conjunctions (initial); modals; modal hedging; existentials; 1
st person pronouns (subject); 1st person pronouns (object); 1st person pronouns (possessive); 2nd person pronoun
s; 2nd person pronouns (possessive); 3rd person pronouns (subject); 3rd person pronouns (object); 3rd person pro
nouns (neutral); 3rd person pronouns (possessive); reflexive pronouns; nominalisations; hedges (verbal); evaluat
ion.
```

Fig. 4: The output window, displaying analysis results for the included sample document

Interpreting the output

The previous figure shows the output for the complete short sample document included with the program, with all features of the initial (experimental) control file included. This output begins with a listing of some general descriptive statistics, namely:

- the number of headings, paragraphs and sentences recognised by the program for the particular document
- word types, tokens, and their ratio, calculated both for raw frequencies and stop word filtered frequency lists
- mean and standard deviation for sentence length, again for raw and filtered data
- Ure's LD, calculated for tokens, types, and ratio
- the FOG index, calculated for the whole document, both for raw and filtered frequencies

These general statistics will always be calculated when the whole document option is chosen. When the sentence or paragraph options are chosen instead, the sentence length options and FOG index are excluded because they only make sense for longer units, and the unit information pertaining to the whole document is also missing.

Below the basic statistics, feature counts of actually occurring features defined in the current statistics control file are displayed. When the whole document analysis is performed, these counts are also complemented by feature ratios to sentences and paragraphs. When the paragraph option is chosen, only the feature count and the feature/sentence ratio is given, and for the sentence option, only the raw feature count. Below these, a list of all non-occurring features defined in the control file is provided.

Multiple analyses can be run and output to the same window and when the 'Save Results' menu item is chosen, these will all we exported to a csv file, which can be analysed further using a spreadsheet or database. Any unwanted information can simply be deleted from the text window in the same way one deletes text in a word processor. In order to select the whole text in the window, the user can simply press 'Ctrl + a'.

One important feature to bear in mind for the word count is that, in order to perform the count efficiently and not to have to worry about sentence-initial uppercase words, all words are downcased automatically before being counted. This may actually lead to proper names being 'ignored' as such in the count, but this can be seen as a minor error that cannot be avoided without having access to a morphosyntactically annotated version of the text.

ENHANCEMENTS/CHANGES IN THE SCORE/INDEX REPRESENTATIONS

As can be seen from the list of general descriptive statistics above, the original methods of index calculation were modified to some extent, mainly through the addition of calculations based not only on raw counts, but also stop word filtered counts. Furthermore, all calculations can now easily be performed on larger units than the original 100-word passages used as a basis in Ventola (1996). The stop word filtered counts may in many cases actually be more reliable indicators than pure ratios/indices based on raw frequency counts because they tend to filter out many of the high-frequency items, such as function words, that represent the 'grammatical glue' of any text. However, when using stop word filters, we always need to bear in mind that it may also be exactly this type of 'glue' which accounts for important relationships within the text, and it may equally well be these relationships that make up the 'texture' and could hence also be responsible for the complexity of the text.

A case in point would be the occurrence of prepositions, which, on the one hand, may be of little influence in terms of their semantic/lexical content, but, on the other, be very important in helping us to identify the number of prepositional phrases, a feature that can easily increase the complexity of a text through numerous occurrences of pre[1]- or post-modification. On the content plane, though, these same prepositional phrases may also make a text more comprehensible by providing important 'disambiguating' information or be very important *domain indicators* when they express relations between different phrase types. However, the difficulty in deciding exactly which type of content may or may not be relevant to an analysis is somewhat alleviated by the configuration and selection options incorporated into the Text Feature Analyser because through them, it is easy to run similar, but slightly modified analyses and obtain different results in case there are any doubts as to the status or relevance of individual stop word items.

A further important feature that has been integrated into the Text Feature Analyser is the ability to count the number of syllables in a word automatically and with a fairly high degree of accuracy. This feature is essential to actually being able to calculate the FOG index in the first place, and is achieved via a relatively simple mechanism that tries to identify and count *syllable nuclei* (c.f. Hyman 1975: 188; Clark & Yallop 1995: 60,411).

CONFIGURING THE TOOL

The Text Feature Analyser can be configured in two major ways. First, by selecting or modifying an existing stop word filter list (file), and secondly, but perhaps most importantly, by doing the same thing with the statistics control file, where the user-defined analysis features are labelled and defined. The two types of control files have a slightly different format, so we will discuss both of them in turn, as well as looking at the general approach behind them.

The basic design of the control files is relatively simple. Just like the documents to be analysed by the tool, they have to be in plain text format[2]. Any line that starts with a hash symbol (#) is ignored when the data is read in by the program, which makes it easy to incorporate comments into the feature definitions, as well as to switch off individual features temporarily. This latter feature, for example, is directly exploited in the mechanism that allows the user to de-select options through the feature selection editor built into the program. For a more permanent change in the configuration options, the user can modify the original feature definition file externally or simply choose a specific (pre-defined) feature file before running an analysis.

Each feature definition begins with a user-defined label, separated from any specification options by a space + double colon + space (i.e. ‘ :: ‘). The use of the two possible additional options depends on the specificity/exactness of the following feature definition, as well as the knowledge of the user in terms of specifying appropriate patterns in terms of *regular expressions* (c.f. Friedl, 2002). In other words, users who are inexperienced in the use of such patterns should not ‘mess with’ certain predefined patterns, whereas it will be relatively easy for them to specify simple ones. Advanced users, on the other hand, will be able to specify very precise and highly flexible patterns, almost similar to ‘miniature programs’.

In order to make this easier to understand, let’s take a look at some sample definitions from the statistics control file:

```
(1) commas :: n :: ([\(\)]|\p{Dash}|\w),\p{isSpace}

(2) subord. conjunctions :: y :: but_however_therefore_so_additionally_[Ii]n
    addition

(3) 1st person pronouns (possessive) :: y :: my_mine_ours?
```

In example (1), we can see the definition of what represents a comma. For the computationally naïve user, a comma may seem like an extremely easy thing to define, but if we simply counted every comma in a text, we might obtain some surprising results, especially if the given text may contain many different large numbers, where – in English – the comma would usually serve as a thousand separator and not as a comma in the traditional sense at all. Thus, our definition above explicitly tells the computer to only count those commas as punctuation mark tokens that are preceded by a word character (letter), brackets or dashes, and followed by a space. The ‘n’ option (between the label name and the feature definition) tells the program routine in the statistics control object that compiles the corresponding instructions to use these instructions without any further modifications. In other words, we're here telling the program that we have specified an exact pattern.

Example (2) demonstrates the (more or less) simplest pattern options that can be specified. These consist of either individual words, or multi-word units (MWUs), each separated from the next by an underscore. In the case of this definition, the 'y' option is chosen, which means that the program will perform a few additional steps in order to produce a more suitable pattern. Creating this new pattern is necessary for two different reasons, the first being that (especially) short words may often occur as part of longer words, when they actually semantically have nothing in common with these, but computer simply look blindly for patterns of characters. Thus, e.g. the two short conjunctions *but* and *so* from the above pattern may occur in such completely unrelated words as ***but**ton*, ***but**ter*, *soda*, *al**so*** or ***so**phisticated*. In order to prevent this from being mis-matched by the program, each single word is always surrounded by word boundary markers (\b) automatically, which tell the program that no word characters may occur around the word. The second reason for extending/modifying the pattern is that most words that may be relevant in our context are words that can potentially also occur at the beginning of a sentence, and hence with an initial capital letter. The modified pattern after both operations have been performed for the word *but* would then look like this: '\b[Bb]ut\b'. This combination of one uppercase and one lowercase letter in square brackets actually looks rather similar to the beginning of the final MWU in example (2). In the above-mentioned *regular expressions*, a way of specifying variable patterns in programming languages, listing individual characters in square brackets like this represents a way of specifying alternative letters in specific positions.

This is also what we find in the MWU at the end of the feature definition, which represents the MWU *in addition*, with both initial capital and lowercase letter. The special thing about MWUs like this in the Text Feature Analyser architecture is that, unlike the single words, these are not transformed into a version of themselves surrounded by boundary markers, but rather left as is, apart from one change, which is that all spaces occurring in the MWU are replaces by Unicode compatible regular expressions that symbolise different types of *whitespace*. Thus, the MWU from above would actually be represented inside the running program as 'in\p{isSpace}addition' for pattern matching. However, this is something that the user need not think about. The only thing necessary for creating a suitable sentence-initial or -medial pattern is to specify the alternatives at the beginning of the MWU.

In our final example, we find another form of specifying a relatively simple regular expression, something even a computationally naïve user can easily learn. This is the use of the question mark after a single letter, in our case after the 's' in the word *ours*. This question mark indicates that the preceding character may or may not occur and helps us to specify the two alternative words *our* and *ours* as one single expression. For the user who wants to be more explicit, though, it is still possible, albeit redundant, to specify example (3) as ‘my_mine_our_ ours’.

The compilation of the stop word list works in a similar way, only that here, there is no need to retain the labels during analysis. In other words, all stop words (or also ‘stop phrases’) are simply joined into one large regular expression and everything contained in this is then removed from the text before the text/unit is split into words and a word count is performed. At the moment, also no word boundary markers are added to the individual constructs, but this is done for the whole expression inside the substitution step where the items are deleted.

PLANS FOR FUTURE ENHANCEMENTS

Although the Text Feature Analyser already contains a number of important analysis features and provides a convenient and easy way to extend the different types of built-in analysis, there are many additional features that would be worth while adding. First and foremost amongst these would probably be the ability to perform more in-depth grammatical analyses by making recourse to tagged data. This, however, would either involve writing a completely new *tagger* or to add an interface to a freely available one, such as the *Stuttgart Tree Tagger*[3].

In the somewhat more immediate future, the plan is to enhance the program by adding a small *concordancing* facility, which would allow the user to verify the results of the feature analyses. Clicking on the name of a feature in the analysis window would then run another search for the individual feature in the relevant file/unit and display all the results in a separate window, with each individual found item highlighted for ease of reference.

SAMPLE COMPARISON OF TWO TEXTS

The two texts chosen for comparison here are both from the domain of physics and deal with the topic of *wormholes*[4]. The first, entitled “Spot the stargate”, is taken from the print edition of the *New Scientist* (NS) magazine and the second, “On the possibility of an astronomical detection of chromaticity effects in microlensing by wormhole-like objects”, from the online open-access science archive *arXiv.org*[5] (ArXiv), housed at Cornell University. The difference in the register and intended readership immediately becomes obvious when comparing the two titles, where the first clearly shows a more popular orientation than the second. Further differences in style readily become apparent when looking at each of the introductory paragraphs in turn.

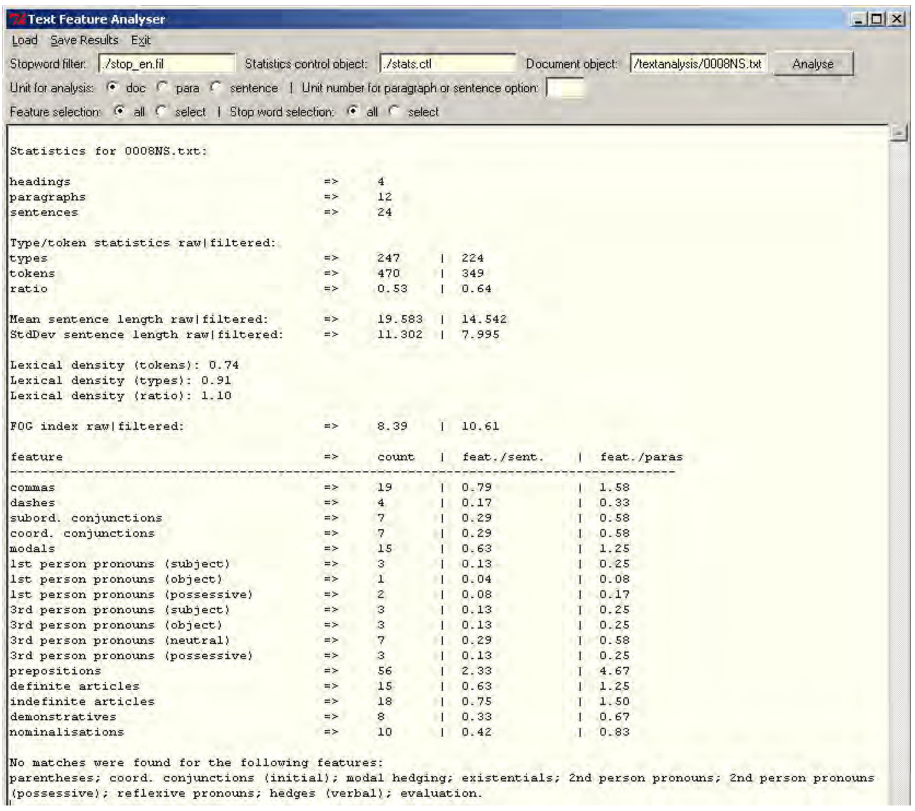
> IF SOPHISTICATED aliens are commuting across the Galaxy using a superfast transport network, we should be able to spot the terminuses. A multinational team of physicists has shown that "wormholes" - gateways to distant regions of space - should stamp a coloured

> hallmark on light from distant stars as it travels past them on its way to Earth. (NS)

Here, the introductory paragraph is relatively short, consisting only of two sentences, a pattern that is repeated throughout the whole article, as the average paragraph length is only 2.5 sentences. The article itself is also rather short, comprising only 24 sentences. In contrast to this, the ArXiv article is much longer, consisting of 248 sentences , with an average paragraph length of 5.88 sentences, as can be seen below.

> This paper continues our study on the possible observational effects that struts of negative masses would produce if they are isolated in space [1]. Since wormhole structures require the violation of some of the most sensitive energy conditions at the wormhole throat, wormholes are natural candidates – if they exist at all – for stellar size negative mass objects. Different wormhole solutions have been presented in the literature after the leading work of Morris and Thorne [2] (see for example Refs. [3]). Many of these solutions actually present a negative energy density and open the possibility of having a total negative mass. However, only a few works deal with the problem of developing observational tests for the existence of wormhole-like objects. Our aim in the present series of papers is to turn the speculation on macroscopic amounts of negative masses into an experimental question, one whose answer could be reached by current astrophysical observations. (ArXiv)

The frequent references also give the second article a somewhat more scholarly/scientific direction, which may initially lead us to believe that this article should equally well show a higher degree of complexity, as this is often associated with ‘scientificness’. However, proving this may actually be easier said than done, once we start looking at the textual features of both articles using the Text Feature Analyser. For ease of reference, I will first show two screenshots, detailing the results of the analysis for both text below, before discussing the differences and potential indicators of complexity.



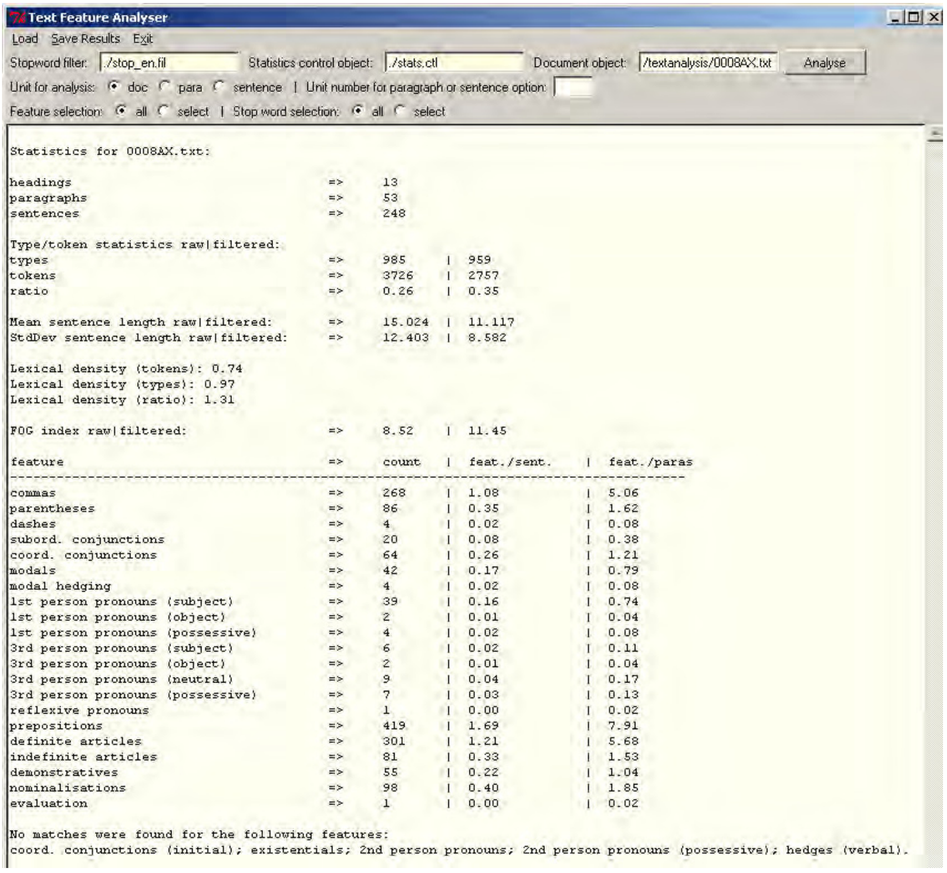
Stopword filter: ./stop_en.fil Statistics control object: ./stats.ctl Document object: /textanalysis/0008NS.txt

Unit for analysis: [✓ doc] para sentence | Unit number for paragraph or sentence option:

Feature selection: [✓ all] select | Stop word selection: [✓ all] select

```
Statistics for 0008NS.txt:

headings                                 =>      4
paragraphs                               =>      12
sentences                                =>      24

Type/token statistics raw|filtered:
types                                    =>      247     |  224
tokens                                   =>      470     |  349
ratio                                    =>      0.53    |  0.64

Mean sentence length raw|filtered:       =>      19.583  |  14.542
StdDev sentence length raw|filtered:     =>      11.302  |  7.995

Lexical density (tokens): 0.74
Lexical density (types): 0.91
Lexical density (ratio): 1.10

FOG index raw|filtered:                  =>      8.39    |  10.61

feature                                  =>      count   |  feat./sent.      |  feat./paras
------------------------------------------------------------------------------------------
commas                                   =>      19      |  0.79             |  1.58
dashes                                   =>      4       |  0.17             |  0.33
subord. conjunctions                     =>      7       |  0.29             |  0.58
coord. conjunctions                      =>      7       |  0.29             |  0.58
modals                                   =>      15      |  0.63             |  1.25
1st person pronouns (subject)            =>      3       |  0.13             |  0.25
1st person pronouns (object)             =>      1       |  0.04             |  0.08
1st person pronouns (possessive)         =>      2       |  0.08             |  0.17
3rd person pronouns (subject)            =>      3       |  0.13             |  0.25
3rd person pronouns (object)             =>      3       |  0.13             |  0.25
3rd person pronouns (neutral)            =>      7       |  0.29             |  0.58
3rd person pronouns (possessive)         =>      3       |  0.13             |  0.25
prepositions                             =>      56      |  2.33             |  4.67
definite articles                        =>      15      |  0.63             |  1.25
indefinite articles                      =>      18      |  0.75             |  1.50
demonstratives                           =>      8       |  0.33             |  0.67
nominalisations                          =>      10      |  0.42             |  0.83

No matches were found for the following features:
parentheses; coord. conjunctions (initial); modal hedging; existentials; 2nd person pronouns; 2nd person pronouns
(possessive); reflexive pronouns; hedges (verbal); evaluation.
```

Fig. 5: Analysis results for the NS text



Stopword filter: ./stop_en.fil Statistics control object: ./stats.ctl Document object: /textanalysis/0008AX.txt

Unit for analysis: [✓ doc] para sentence | Unit number for paragraph or sentence option:

Feature selection: [✓ all] select | Stop word selection: [✓ all] select

```
Statistics for 0008AX.txt:

headings                                 =>      13
paragraphs                               =>      53
sentences                                =>      248

Type/token statistics raw|filtered:
types                                    =>      985     |  959
tokens                                   =>      3726    |  2757
ratio                                    =>      0.26    |  0.35

Mean sentence length raw|filtered:       =>      15.024  |  11.117
StdDev sentence length raw|filtered:     =>      12.403  |  8.582

Lexical density (tokens): 0.74
Lexical density (types): 0.97
Lexical density (ratio): 1.31

FOG index raw|filtered:                  =>      8.52    |  11.45

feature                                  =>      count   |  feat./sent.      |  feat./paras
------------------------------------------------------------------------------------------
commas                                   =>      268     |  1.08             |  5.06
parentheses                              =>      86      |  0.35             |  1.62
dashes                                   =>      4       |  0.02             |  0.08
subord. conjunctions                     =>      20      |  0.08             |  0.38
coord. conjunctions                      =>      64      |  0.26             |  1.21
modals                                   =>      42      |  0.17             |  0.79
modal hedging                            =>      4       |  0.02             |  0.08
1st person pronouns (subject)            =>      39      |  0.16             |  0.74
1st person pronouns (object)             =>      2       |  0.01             |  0.04
1st person pronouns (possessive)         =>      4       |  0.02             |  0.08
3rd person pronouns (subject)            =>      6       |  0.02             |  0.11
3rd person pronouns (object)             =>      2       |  0.01             |  0.04
3rd person pronouns (neutral)            =>      9       |  0.04             |  0.17
3rd person pronouns (possessive)         =>      7       |  0.03             |  0.13
reflexive pronouns                       =>      1       |  0.00             |  0.02
prepositions                             =>      419     |  1.69             |  7.91
definite articles                        =>      301     |  1.21             |  5.68
indefinite articles                      =>      81      |  0.33             |  1.53
demonstratives                           =>      55      |  0.22             |  1.04
nominalisations                          =>      98      |  0.40             |  1.85
evaluation                               =>      1       |  0.00             |  0.02

No matches were found for the following features:
coord. conjunctions (initial); existentials; 2nd person pronouns; 2nd person pronouns (possessive); hedges (verbal).
```

Fig. 6: Analysis results for the ArXiv article

Let’s start by discussing the general descriptive statistics. Here, both texts, apart from their obvious differences in overall and paragraph length, show surprisingly few differences. As a matter of fact, the values for the FOG and lexical density indexes are remarkably similar. The latter only seems to indicate that both texts are – in a sense – more or less equally academic, whereas the former seems to indicate that theses two texts are actually relatively low on the ‘diffuseness’ scale, with the ArXiv text exhibiting a slightly higher FOG index, especially once the stop words have been excluded from the calculation.

What seems to be slightly more relevant as a potential indicator of increased complexity in the ArXiv text is the fact that, although its mean sentence length is a little lower, possibly due to the relatively high occurrence of equations/formula, the standard deviation of sentence length is actually higher, perhaps indicating a higher degree of variability. This also seems to be supported by the lower type/token ratio, which indicates that the more scientific text uses a higher number of (low-frequency, content) words, thus making it more diverse, and possibly more specific.

In order to be able to compare the two texts better in terms of the additional features, the logical thing to do is to compare the middle columns because they reflect the average number of each feature per sentence. Here, when looking at the text-structuring devices – such as commas, different types of parentheticals or conjunctions – first, we can observe that the ArXiv text employs a far higher number of commas, but apparently rather fewer subordinating conjunctions than the NS text. Although a higher use of commas should actually help to create an increased cohesive effect and often increase readability, the relative lack of subordinating conjunctions initially seemed to suggest that the information contained in the ArXiv text was simply more densely structured. As it turned out however, the initial definition I had used for cohesive markers had simply been too restrictive, and the text does indeed contain a few more of these, often in the form of enumerative devices, such as *firstly*, *secondly*, etc., so that the cohesiveness factor does increase a little once some modifications have been applied to the previous (experimental) categories. The number of co-ordinating conjunctions in both texts is relatively similar and therefore may not be a good distinguishing characteristic.

In terms of modality/stance, the NS text quite clearly demonstrates a higher degree of *hedging* than the ArXiv one. However, this is more an indicator of genre differences between the two texts, rather than of complexity, but confirms the common stereotype that the more scientific a text is, the more factual it tends to be. Similarly, when looking at the pronoun use, the more populist NS version also seems to be slightly more involved, inasmuch as the number of first person pronouns is higher and, conversely, the number of (more factual) third person pronouns lower.

The number of preposition in the NS text is higher, which – together with the previously noted higher incidence of commas – may indicate that the ArXiv text is structurally denser, containing more relative clauses or occurrences of postmodification. Surprisingly, though, the number of nominalisations is marginally higher in the NS text, although this is commonly assumed to be a feature of more scientific texts.

In terms of article usage, the occurrence of definite and indefinite articles seems to be reversed between the two types of 'genre'. The higher incidence of definite articles seems to underline the scientificness or factuality of the ArXiv text, whereas the NS article appears to be less factual.

CONCLUSION

In this article, I have discussed the main motivation behind the creation of the Text Feature Analyser and the analysis and configuration features it offers so far. However, the possibilities for textual exploration such a tool offers are not limited purely to attempts at identifying the individual features that may account for textual complexity. Through its simple extensibility and customisability, the tool should also provide an ideal means for exploring the features underlying different genres, or potentially even a way into learner error analysis, e.g. by identifying over- or under-use of specific features. For this, especially the planned new concordancing feature will be of utmost relevance because it will provide immediate access to features that may strike the user as being obvious candidates for further analysis. However, because of its interactive nature, the program should also be suitable for classroom analysis that goes beyond simple classroom concordancing techniques, and may help to raise learners' awareness of complexity in academic writing, as well as exploring argumentative structures, specific genre features, etc.

NOTES

1 Pre-modification in this case essentially in the form of deictic elements, such as sentence adverbials.

2 Although the tool actually assumes that the encoding of these files is UTF-8, a Unicode format. In practice, however, it hardly makes any difference to the user who is analysing English texts that primarily rely on ASCII characters.

3 http://www.ims.uni-stuttgart.de/projekte/corplex/TreeTagger/DecisionTree Tagger.html

4 Wormhole. (2007, April 4). In *Wikipedia, The Free Encyclopedia*. Retrieved 08:17, April 5, 2007, from http://en.wikipedia.org/w/index.php?title=Wormhole&oldid=120335350

5 http://arxiv.org/

References

Biber, D. (1988). *Variation across speech and writing*. Cambridge: Cambridge University Press.

Biber, D. (2006). *University language: A corpus-based study of spoken and written registers*. Amsterdam/Philadelphia: John Benjamins.

Clark, J., & Yallop, C. (1995). *An introduction to phonetics and phonology*. Oxford: Blackwell.

Ellis, R., & Hopkins, K. (1985). *How to succeed in written work and study*. London & Glasgow: Collins.

Friedl, J. (2002). *Mastering regular expressions*. Beijing, Cambridge, etc.: O'Reilley.

Halliday, M. (1985). *Spoken and written English*. Geelong, Victoria: Deakin University Press.

Hyman, L. (1975). *Phonology: Theory and analysis*. New York: Holt, Rinehart & Winston.

Ure, J. (1971). Lexical density and register differentiation. In Perren, G., & Trim, J. (Eds.), *Applications of Linguistics: Selected Papers of the 2nd International Conference of Applied Linguistics, Cambridge 1969*. Cambridge: Cambridge University Press, 443-451.

Ventola, E. (1996). Packing and unpacking of information in academic texts. In: Ventola, E., & Mauranen, A. (eds.), *Academic writing: Intercultural and textual issues*. Amsterdam: John Benjamins,153-194.