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2010

Siirtola, H, Räihä, K-J, Säily, T & Nevalainen, T 2010, Information visualization for corpus linguistics: Towards interactive tools. in S Liu, M X Zhou, G Carenini & H Qu (eds), First International Workshop on Intelligent Visual Interfaces for Text Analysis : Proceedings. ACM, New York, pp. 33-36, First International Workshop on Intelligent Visual Interfaces for Text Analysis (IVITA), Hong Kong, China, 07/02/2010. https://doi.org/10.1145/2002353.2002365

http://hdl.handle.net/10138/136254
10.1145/2002353.2002365

acceptedVersion

Information Visualization for Corpus Linguistics: Towards Interactive Tools

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ABSTRACT
In this paper linguists and researchers of visual data analysis outline the requirements and benefits of an information visualization approach for corpus linguistics. Over the years, the information visualization community has come up with a number of methods to visualize text, but the majority of these techniques do not serve the needs of the linguistic community. This is evident in the over-simplification of the linguistic problems and generally caused by a poor understanding of the domain. We started a joint research effort with linguists, data miners, and information visualizers to design and produce better data analysis tools for corpus linguistics. This work is still in its early stages, but we have a shared vision of what needs to be done.

Author Keywords
corpus linguistics, information visualization

ACM Classification Keywords
H.5.2 Information Interfaces and Presentation: Miscellaneous

INTRODUCTION
Corpus linguistics is the study of language use by means of large electronic text collections, or corpora [2]. These are carefully compiled to ensure representativeness across desired features such as time, genre and the social status of writers/speakers. Nowadays corpora are often annotated for, e.g., part of speech or sentence structure; however, there is a lack of sophisticated tools for visualizing and analyzing such tagged and parsed data.

Information visualization is about using external tools to amplify cognition. Often these external tools are visual as more information is acquired through vision than via all the other senses combined [15, p. 2]. Visual and interactive representations of data improve problem solving and acquisition of insight.

http://doi.acm.org/10.1145/2002353.2002365

Text as data is more challenging to visualize than numerical, nominal or categorical data. Text is high-dimensional and, e.g., equality tests are complicated because of multiple meanings and complex relations. Often the non-linguistically motivated text visualizations take shortcuts by ignoring the ordering relationships within the text, and by stemming the words (i.e., reducing them into their roots).

Here we will discuss our linguistically motivated visualizations for corpus linguistics. Although general-purpose visualization techniques provide a good starting point, techniques that dig deeper into the structure of the documents in the corpus, and work bottom-up from the texts, are needed to gain insight into linguistic variation and change.

Our work is based on the part-of-speech or POS-tagged version of the *Parsed Corpus of Early English Correspondence* (PCEEC) [9]. It is used as a running example in this paper whenever the copyright allows. The corpus consists of 4,968 letters written between the years 1415 and 1681, and has 2,155,446 words. The part-of-speech tagged text has each word marked up according to its definition and context, e.g., 'Hopkins_NPR' denotes that 'Hopkins' is a 'proper noun'. Although PCEEC is relatively small as a corpus, it is challenging to analyze because of the variations over time. In cases where the PCEEC copyright would be compromised, the freely available plain text version of *The Adventures of Sherlock Holmes* [3] by Sir Arthur Conan Doyle is used as example material.

TEXT VISUALIZATION
Text data comes in many forms: articles, books, novels, letters, web pages and blogs, just to name a few. In addition to texts created by a human author there are many computer-generated text genres as well, such as log files and other outputs from computer programs.

Text visualization is popular, both as an object of research and among the 'consumers of visualizations'. About one third of the user-created visualizations on the *Many Eyes* [8, 4] collaborative visualization service are related to text visualization, and media both in print and on the web routinely use such techniques as tag clouds and thematic maps to illustrate their texts (see, e.g., [12]).

The Many Eyes service has four text visualization modules in its selection (Figures 1 to 3 below). They provide a rep-

resentative sample of how the visualization community generates insight into text documents. Figure 1 shows a *Wordle* [5] visualization that illustrates the occurrence of words in PCEEC. In a Wordle visualization, the size of a word is determined simply by its frequency, and the placement of a word does not convey any additional information.

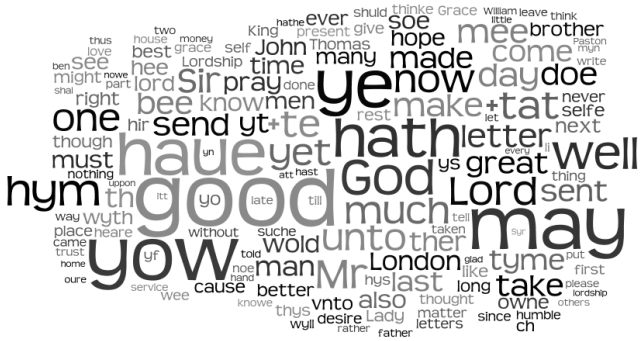

Figure 1. Wordle visualization of the two million words of the *Parsed Corpus of Early English Correspondence*.

The Wordle visualization in Figure 1 is impressive in that it manages to summarize almost 5,000 letters in just one picture. Although it is thought-provoking and entertaining, its worth from the linguistic point of view is questionable. As the designer of Wordle notes [14], a significant number of Wordle users do not even understand what the graphics are encoding, and a user might seek explanation for the proximity of certain words when they are just put together randomly. This is not to be taken as criticism of Wordle, as it does exactly what it was designed to do, and there are interesting applications for it. It has been used in the domain of text corpus visualization as well, to get an overview of Shakespeare's sonnets and plays. It might also be interesting to compare Wordle visualizations of PCEEC material per letter or per author, as in Feinberg's comparison of the inaugural addresses of the presidents of the United States [6]. In addition to Wordle, *Tag Cloud* is another word frequency visualization from the Many Eyes service. In a tag cloud the words of a text are laid out in alphabetical order and their size is in proportion to their frequency.

Figure 2 displays another text visualization, *Word Tree*, from the Many Eyes service which is a visual version of a traditional concordance (a list of words in their context). Instead of a traditional list view of such tools, the data is displayed as a tree. The primary difference besides the representation is that the tool displays only the right hand side of the current word's environment. However, selecting a word will permit exploration of the left hand side environment as well.

In a *Phrase Net* visualization, as seen in Figure 3, the user selects one of the pre-defined 'bigrams' or two-word patterns or creates a new one. The patterns define the elements that should appear between two words, and the tool creates a graph of all word pairs that match the pattern. Size is again used to encode frequency.

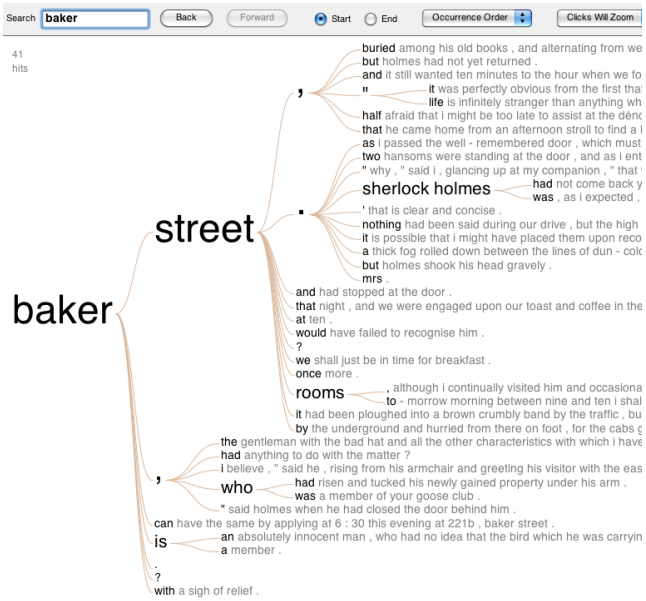

Figure 2. Word Tree visualization of *The Adventures of Sherlock Holmes* with focus on the word 'baker'.

SCENARIO

While Many Eyes can be a useful toolset for corpus linguistics, it is not designed to utilize annotation in corpora. This section presents a scenario of how the information visualization approach might be applied to solving a linguistically motivated problem in a POS-tagged corpus. Two open-source and freely available software tools are employed: the general statistical data-visualization system *Mondrian* [13] and the statistical system *R* [10].

Suppose that the aim of the study is to investigate if the 'nouniness' of language is affected by the sociolinguistic background variables as manifested in the PCEEC corpus. Nouniness, or the proportion of nouns in a text, can be determined in a part-of-speech tagged corpus by computing the percentage of words tagged as nouns against the whole corpus. The question of which of the tags are regarded as nouns is a matter of definition and open to some debate.

The first concern in a study of a POS-tagged text is data integrity, to make sure that the phenomenon under study is correctly encoded in the corpus. In this case, it means checking that the words tagged as nouns are really nouns, and that tokenization (how the text is segmented into words) is handled correctly. With a historical corpus, this step may involve many manual operations and computer scripts that 'prune' the corpus, and the result is a refined version of the corpus. Suppose the result from this step is in the following form (only 6 out of 2,154,210 lines are shown):

```
       word  tag
1       Mr.  NPR
2   Hopkins  NPR
3       yow  PRO
4 discourse  VBP
5    wisely  ADV
6       and  CONJ
```

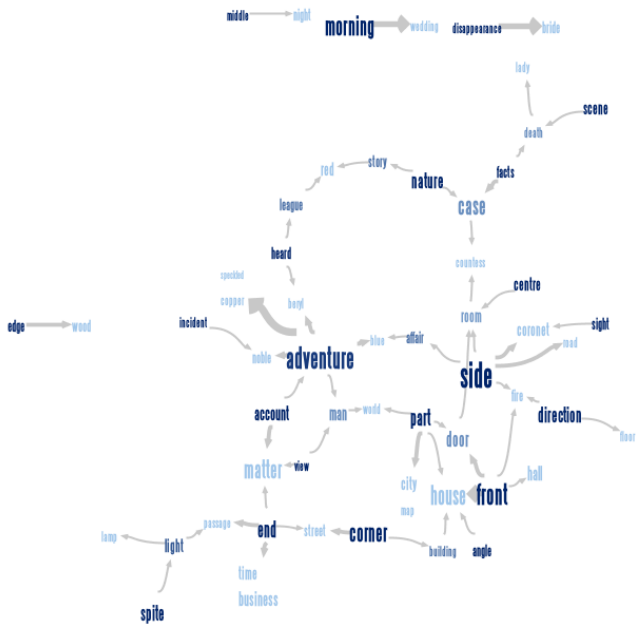

Figure 3. Phrase Net visualization of '* of the *' word patterns in *The Adventures of Sherlock Holmes*.

Once the word-category disambiguation is satisfactory, the corpus needs to be transformed into data tables for analysis. In this particular study, the text itself is not needed, only the frequencies of tags. The transformation can be done conveniently under R with the *reshape* package [16], which allows the user to 'melt' a data set into its components and then 'cast' it into a desired shape.

The desired statistical units in this study are letters, authors, years, time periods, and authors-by-time-periods. Summarizing the tag frequency data into these units can then be combined with the available sociolinguistic metadata, such as additional details about the authors and letters. Again, this can be carried out in R with its built-in relational operators and the aggregate function. After this step we will have the following tables:

```
pceecByText:  4968 obs.  of 101 variables
pceecByAuthor:  659 obs.  of 49 variables
pceecByYear:  243 obs.  of 26 variables
pceecByPeriod:  7 obs.  of 25 variables
pceecByAuthorPeriod:  729 obs.  of 50 variables
```

At this stage it is also trivial to extend the data tables with additional variables needed in the analysis, such as the word counts and the percentage of nouns.

As soon as the data tables exist, they can be explored with the Mondrian data visualization tool. Exporting the data tables in the current version of Mondrian is straightforward [13], and the forthcoming release can access R data frames directly from the R images.

A linguist might approach the data as follows. 'Nouniness' is a well-known indicator of formality in language use. Previous work in corpus-based sociolinguistics has shown that it varies depending on the gender of the speaker/writer: men tend to use more nouns than women [1, 11]. Furthermore, we know that people modify their language use depending on their interlocutors. Therefore, we might hypothesize that the linguistic formality of our material could vary depending on the gender of both the sender and the recipient of the letters. This hypothesis can be explored by looking at the histogram of the percentage of nouns in Mondrian, and then selecting the four possible combinations of the values of variables 'Sex.Sender' and 'Sex.Recipient' (Figure 4).

The visualization immediately provides strong support for our hypothesis. For instance, the letters sent by men to women (Sex.Sender='M' AND Sex.Recipient='F' – the highlight in the bottom right corner) have a clearly lower percentage of nouns than the letters sent by men to men (the top right corner). In fact, there seems to be a cline of formality: M2M $>$ M2F $>$ F2M $>$ F2F. This kind of analysis can be done rapidly in Mondrian-like interfaces by creating and combining persistent selections, or *selection sequences* in Mondrian terminology. The approach is based on a technique known as *brushing* [17] where the multiple, coordinated views propagate the selections of data items, thereby facilitating comparisons between the views.

In the mean time, back in the statistical system R, the findings from the explorative phase will undergo careful analysis to determine if a statistically significant difference exists, and the relevant graphics are re-created in print quality under R. The confirmed findings are then ready to be disseminated.

DISCUSSION

We have approached the information visualization needs and benefits of corpus linguists from two directions: from a sample of the 'state of the art' text visualizations, and from a scenario of how a linguistically motivated research problem might be tackled. Neither of these reflect realistically the current state of corpus-linguistic research as simple text concordancers and spreadsheet applications are still the prevailing tools. However, the use of the statistical system R is gaining popularity and is strongly endorsed by prominent computational linguists [7]. The downside of R is the steep learning curve and the dreaded command line interface.

What is crucial in visualization tools such as Mondrian from the linguist's standpoint is the chance for rapid and interactive exploration of data. It is known that interaction enhances discovery, and linguistic data visualizations are no exception. Generating "Aha! That's interesting!" exclamations may succeed with static data visualizations, such as Wordle tag clouds, but the chances are far better with interaction.

The problem we now have is how to make these tools more accessible to the linguistic community. With many extensive and versatile toolkits available, it makes sense to build on them instead of creating something from the ground up. In the case of R and Mondrian we are planning to improve the integration of the two systems and add new domain-specific data views as well.

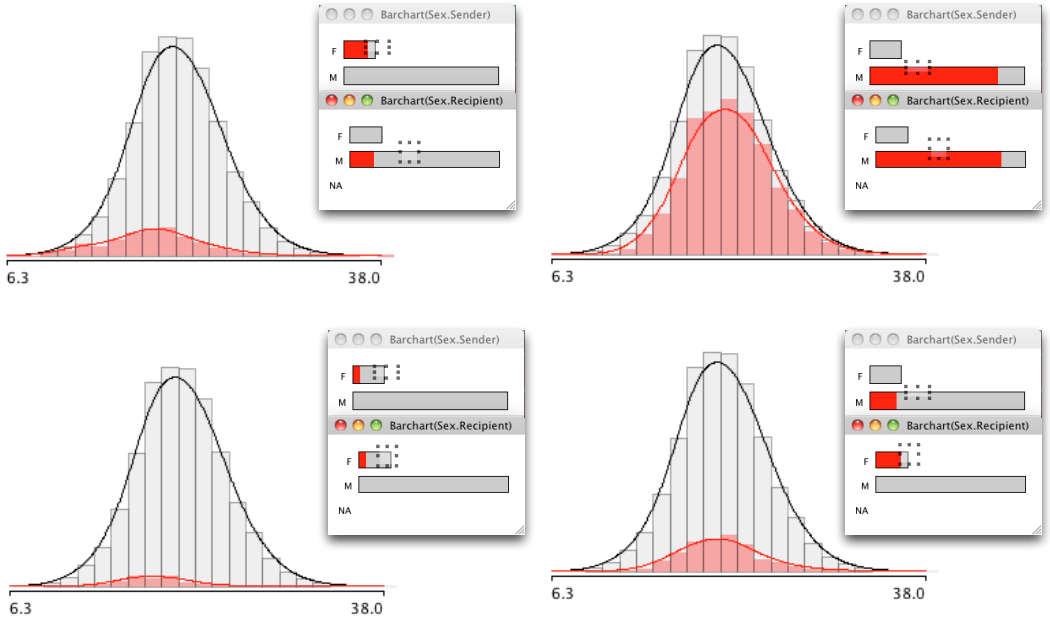

Figure 4. The effect of gender of letter sender/recipient on the 'nouniness' of text explored with the interactive data visualization system Mondrian.

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