Mult-Mosaics: Corpus Summarizing and Exploration using multiple Concordance Mosaic Visualisations

Shane Sheehan
shane.sheehan@ed.ac.uk
University of Edinburgh
United Kingdom

Saturnino Luz
s.luz@ed.ac.uk
University of Edinburgh
United Kingdom

Masood Masoodian
masood.masoodian@aalto.fi
Aalto University
Finland

Figure 1: Top left Concordance Mosaic displaying the primary keyword gold. Three secondary keywords (iron, bronze and silver) are presented and colored to highlight the most frequent context words from the primary Mosaic.

ABSTRACT

Researchers working in areas such as lexicography, translation studies, and computational linguistics, use a combination of automated and semi-automated tools to analyze the content of text corpora. Keywords, named entities, and events are often extracted automatically as the first step in the analysis. Concordancing – or the arranging of passages of a textual corpus in alphabetical order according to user-defined keywords – is one of the oldest and still most widely used forms of text analysis. This paper describes Multi-Mosaics, a tool for corpus analysis using multiple implicitly linked Concordance Mosaic visualisations. Multi-Mosaics supports examining linguistic relationships within the context windows surrounding extracted keywords.

1 INTRODUCTION

In many academic fields, corpus analysis is central to the study of texts. Computational tools have long been used for lexicography, corpus linguistics, and corpus-based translation studies [1, 3, 22], and new methods motivated by such tools have been more broadly applied to the study of policy in areas such as medicine [6] and politics [5]. One of the most popular techniques supported by computation is the indexing, retrieval and display of keyword-in-context. This technique dates back to at least the 1950’s with Luhn’s work on concordance indexing [15].

Corpus analysis using concordance and collocation provides a data-driven approach for corpus analysis – contrasting with more traditional scholarly work in these fields which requires close reading, researchers’ prior knowledge, and theoretical frameworks to interpret texts. Data-driven corpus analysis techniques are heavily influenced by the work of John Sinclair and Michael Halliday...
[13, 20], in which one usually starts by obtaining an overview of the data and exploring a much larger volume of text than would be practical to do by close reading of the texts. Visualization tools can aid this process by providing effective overviews and helping to identify patterns in the texts, as well as visual explanation of the analysis outputs [23].

Concordance Mosaic [16] is a visualisation tool which has been adopted by members of the corpus linguistic community for corpus analysis, and the presentation of their scholarly work [2, 5]. The visualisation provides an overview of the context words within a window of the selected keyword. Quantitative information – most often word frequency – is encoded using tile height allowing the analyst to identify positional collocation patterns around a single keyword.

This paper presents Multi-Mosaics, as an extension of Concordance Mosaic, to enable comparison of collocation patterns for multiple keywords. The design of Multi-Mosaics has been informed by observations, and requirements gathered using Concordance Mosaic. This paper also presents a user study where the Concordance Mosaic is compared to a traditional keyword-in-context textual display.

2 RELATED WORK
Keyword visualisations often take the form of networks or clusters of keywords[7, 11, 14]. While these visualisations are useful for identifying similar or connected keywords in a corpus, they do not provide any insight into the collocations of the keywords, and as such, they are not directly usefully for comparing the contexts in which these keywords appear.

Corpus Clouds [9] is a frequency-focused corpus analysis tool. A word cloud, based on the tag cloud visualisation [24], is used to encode the frequencies of all words returned by a corpus query. For quantitative tasks involving frequency estimation or comparison, the use of font size to encode value in cloud-based visualisations is a limitation [10]. Also, since positional collocations are not encoded in Corpus Clouds, the visualisation is of an entire context window.

TagSpheres [12] are word cloud based visualisation where keyword co-occurrences are encoded using an integral combination of color and radial position from the central keyword. The cloud layout places the same word from different positions close together to help identify strong collocation patterns. However, the linear structure of the text is removed making it difficult to identify multi-word collocation patterns.

Tree-based visualisations of keyword-in-context have therefore been proposed as a technique for encoding quantitative information while maintaining the linear structure of the text [8, 16, 25]. In practice, however, displaying a large number of concordance lines, where font size is used to encode represent positional frequency, requires a trade off between frequency estimation and readability. The variable length of words also makes encoding frequency using font size challenging – since area is not as perceptually efficient as length for visualising quantitative information.

3 MULTI-MOSAICS
Multi-Mosaics was designed in collaboration with language scholars who work predominantly using corpus analysis techniques.

During this co-design process two of the researchers were asked to compile a list 20 questions which they would like to be able to answer about a corpus. They were asked to list them in order of importance, and after the lists were compiled they were used to discuss requirements for a potential visualisation prototype. This technique is a common means of requirements elicitation in human-computer interaction [18].

This process revealed a need for a tool which facilitated quantitative analysis of the words surrounding a keyword [17]. Concordance Mosaic was developed to address this need, where each mosaic visualization displays quantitative information – such as word frequency or collocation strength – in tiles representing words at positions relative to a keyword. The height of each word tile encodes the quantity, and the horizontal position of the columns represents word position relative to the keyword. In Figure 1 (top left) we see that the most frequent word occurring directly to the left of the keyword gold is the word of.

The language scholars also mentioned the need to investigate multiple keywords for similar patterns or to investigate lists of suggested keywords for a corpus. The following suggests that investigating collocation patterns of multiple words simultaneously would be useful “...if the keyword is a label used to describe a particular kind of political agent, we might be interested to look at what collective nouns are used to group and characterize these political agents (e.g. a mob of citizens, a tribe of politicians: LEFT -2).” Similarly it was suggested that automatically extracting related keywords would be useful to expand the analysis to include the collocations of these keywords “Are there other related keywords we might study in order to expand our investigation? Can the software suggest keywords that are important to these texts but which we might not otherwise have thought of?”. Using these observations the concept of multiple mosaics displayed together with linked contexts was presented to the corpus linguists and the design was refined to produce Multi-Mosaics.

3.1 Implementation
Multi-Mosaics is implemented as a single-page web application using the D3.js framework [4]. The interface displays a grid of Concordance Mosaics, generated from JSON files containing keyword-in-context data, and a single textual keyword in context window.

There is no theoretical limit to the number of Concordance Mosaic visualisations which can be displayed in Multi-Mosaics, as the interface is scrollable. Each mosaic displays a single keyword and four word positions to either side of the keyword. The Mosaic displayed in the top left position of Multi-Mosaics is considered the primary Mosaic, and all others are secondary Mosaics. Right clicking on a secondary Mosaic makes it the primary, and updates Multi-Mosaics. In Figure 1 the primary Mosaic for the keyword gold is selected.

Each mosaic is colored according to the 20 most frequent words in the 4-word context window of the primary mosaic. This colouring allows the corpus analyst to investigate each of the secondary Mosaic contexts in relation to the high frequency context words from the primary Mosaic. Words not in the 20 most frequent context
words of the primary Mosaic are colored grey. When looking at the contexts of secondary Mosaics, grey word tiles with high positional frequencies are also likely to be of interest, since they represent words which have high secondary keyword positional frequency, and low primary keyword positional frequency. In Figure 1, looking at the secondary mosaic for the keyword silver (bottom right), in relation to the primary Mosaic for the keyword gold, we can identify interesting collocation patterns. For instance, we can see that the word gold is a frequent collocate at position keyword – 2, and we can find silver in position keyword + 2 for the Mosaic of gold. The second most frequent word at position word key position – 2 is the word talents – this word is not in the 20 most frequent words in the context of the primary keyword gold so it is coloured grey.

In addition to the grid of Mosaics, a single textual keyword-in-context concordance window is also available, as shown in Figure 2. Initially this window displays the concordance lines from the primary keyword Mosaic. However, left clicking on any tile, in any of the Mosaics, switches the textual keyword-in-context window to display the concordance lines for the clicked keyword. The keyword from the selected Mosaic is displayed centrally and coloured Blue – in Figure 2 the Mosaic for the keyword silver was clicked. The tile which was clicked represented the word talents at the position keyword – 2, the concordance window is sorted alphabetically at this position and the lines containing the clicked word at the chosen position are highlighted in Cyan, the work which was clicked is coloured Pink. This enables quick investigation of the lines from the corpus which form the identified collocation pattern, in an overview and detail-on-demand interaction [19].

4 USER STUDY

This study was designed to compare the performance of the two visualisation tools, the Concordance Mosaic and a textual Keyword-in-Context interface (KWIC). A third option was also tested, in which both the Concordance Mosaic and KWIC were available side-by-side. The evaluation was performed on concordance analysis tasks for which the Concordance Mosaic was designed. These tasks have been identified from analysis of the corpus methodology [17], described by John Sinclair [21].

An initial heuristic evaluation and a pilot study were used to refine the visualization tools and test their usability prior to the main user study. During this study we found that tasks requiring analysis of multiple context words or positions were difficult for non-expert users to understand. Based on this we limited the evaluation to five simple quantitative analysis tasks, only one of which required looking at multiple positions.

Each participant attempted to answer five questions using each of the 3 visualisation options – the order in which the options were presented was randomised and balanced across participants for every possible combination of option orderings. Similarly, for each visualisation option a different keyword was required per question, and the keyword per option was balanced.

Question 1 was, for example, “For the keyword KEYWORD, what is the most frequent word at position keyword – 1?". The three possible keywords chosen for this question were Wealthy, Daylight and Massive. These were chosen to ensure a consistent number of concordance lines were returned from the corpus used for this study, and that the difficulty level of the questions was consistent. For question one these keywords all returned a concordance with approximately 300 concordance lines – the most frequent word at position keyword – 1 occurs with a frequency of between 26–27%, and the second most frequent word at position word key position – 1 occurs with a frequency of 20–22%. Question 2 was the same as the first one, but the frequencies of the most common and second most common words at position keyword – 1 were approximately 40%
and between 5–10%, respectively — thus making this task more difficult.

The remaining three task questions were, Question 3: “For the keyword KEYWORD, what is the most frequent descriptive adjective at position keyword = 1?”, Question 4: “For the keyword KEYWORD, focusing only on concordances that contain the word CONTEXT-WORD at position keyword = 1, what word is most frequent at position keyword = 2?”, Question 5: “Estimate which word has the highest collocation strength at position keyword = 1”. For the last question, collocation strength was described as high frequency at a position but low frequency in the corpus.

The participants were shown how to access the corpus frequency lists prior to the study. It was possible to switch the MOSAIC to collocation strength mode, in which the tiles were scaled according to this metric.

The null hypothesis in this study was that: there is no significant difference in performance between the three visualisation options, on concordance analysis tasks. Performance was measured using the speed and accuracy with which participants completed tasks.

For this study we recruited 36 participants from the student population through our online university noticeboard and a mailing list. Since the study evaluated performance on quantitative tasks, we decided that previous experience with concordance tools or corpus analysis would not be a prerequisite for participation.

4.1 Results

Table 1 shows the results of an ANOVA for the dependent variable time, to complete a task (in seconds), with respect to the categorical variables: the question being answered (q), the visualisation being used (i), the participants assigned visualisation option ordering (iOrder), the participants assigned keyword set ordering (qOrder) and a binary variable representing a correct or incorrect answer (isCorrect). The results of the ANOVA where a significant difference (p < .05) was found are also shown.

Table 1: ANOVA results for the dependant variable time, where p < .05

| Independent Variable | F Value | P Value |
|----------------------|---------|---------|
| q                    | 26.9388 | < 2.2e-16 |
| i                    | 135.5089 | < 2.2e-16 |
| isCorrect            | 4.3170  | 0.03894 |
| q:i                  | 8.6946  | 1.428e-3 |
| i:iOrder             | 2.6226  | 0.00261 |
| i:qOrder             | 3.5232  | 0.008239 |
| q:isCorrect          | 2.4258  | 0.04070 |

Since the main effects q, i and isCorrect all feature in significant interactions, we have focused our post-hoc analysis on these interactions instead of the main effects. We conducted Tukey’s post-hoc tests (HSD) to analyse the different groupings of each interaction effect, again using p < .05 to test for significance.

The result of the HSD test for the i and qOrder interaction (i:qOrder) showed a significant difference between two groupings. In this case, the data set was split into nine groups by the combinations of the 3 visualisation options and the 3 circularly shifted keyword set orderings. The HSD groupings simply combined these groups into data points where the KWIC option was being used, and a grouping of all data points where either the MOSAICs or combined visualisations were being used. This indicates that the interaction can be interpreted as i, and that qOrder can be safely ignored, as it does not feature in any other significant interactions or as a main effect. This result shows, as expected, that our choice of keywords has not had a major effect on time to complete within each question.

The mean response times of the i:qOrder groupings in which the KWIC option was used were all greater than 67 seconds, while the remaining groups containing the MOSAIC and combined option all had mean response times under 30 seconds. This is evidence of visualisation options having a large effect on response time.

The discovery of an interaction between q and i (q:i) is of great interest since our null hypothesis states: there are no significant differences between the interfaces on a per question basis. Analysing the groups created by splitting the data by visualisation options and questions, the Tukey HSD test found a number of significant groupings. For each question there is a significant difference in response time between the KWIC and both the MOSAICs and combined options. This is enough evidence to reject our null hypothesis for each question.

5 CONCLUSIONS

In this paper, we introduced Multi-Mosaics, a visualisation tool consisting of multiple linked Concordance MOSAICS and a textual keyword-in-context window. Multi-Mosaics is designed to support the analysis of collocation patterns for multiple keywords simultaneously. By encoding the most frequent collocations from the primary keyword MOSAIC onto all secondary MOSAICS similar and differing patterns of collocation can be identified in the secondary keywords. In addition, linking the MOSAICS to a textual keyword-in-Context concordance display allows for quick investigation of the lines of text making up the identified collocation pattern. Our user study evaluating the effectiveness of the visualisation tool shows that Concordance MOSAICS perform better than a textual keyword-in-context tool on a selection of quantitative corpus analysis tasks.

ACKNOWLEDGMENTS

REFERENCES

[1] M. Baker. 1993. Corpus linguistics and translation studies: Implications and applications. Text and technology: In honour of John Sinclair 233 (1993), 250.
[2] M. Baker. 2020. Rehumanizing the migrant: the translated past as a resource for refashioning the contemporary discourse of the (radical) left. Palgrave Communications 6, 1 (2020), 1–16.
[3] S. Bernardini and D. Kenny. 2020. Corpora. In The Routledge Handbook of Translation Studies, M. Baker and G. Saldanha (Eds.). Routledge, 110–115. In press.
[4] M. Bostock, V. Ogievetsky, and J. Heer. 2011. D3 Data-Driven Documents. IEEE Transactions on Visualization and Computer Graphics 17, 12 (Dec. 2011), 2301–2309.
[5] J. Buts. 2020. Community and authority in ROAR Magazine. Palgrave Communications 6, 1 (2020), 1–12.
[6] J. Buts, M. Baker, S. Luz, and E. Engebretsen. 2021. Epistemologies of evidence-based medicine: a plea for corpus-based conceptual research in the medical humanities. Medicine, Health Care and Philosophy 24, 1 (2021), 1–12.
[7] Jinho Choi and Yong-Sik Hwang. 2014. Patent keyword network analysis for improving technology development efficiency. Technological Forecasting and Social Change 83 (2014), 170–182. https://doi.org/10.1016/j.tfs.2013.07.004
[8] C. Culy and V. Lyding. 2010. Double Tree: An Advanced KWIC Visualization for Expert Users. In Information Visualisation (IV), 2010 14th International Conference. 98–103. https://doi.org/10.1109/IV.2010.24
[9] C. Culy and V. Lyding. 2011. Corpus Clouds - Facilitating Text Analysis by Means of Visualizations. In Human Language Technology: Challenges for Computer Science and Linguistics. Lecture Notes in Computer Science, Vol. 6562. Springer Berlin Heidelberg, 351–360. https://doi.org/10.1007/978-3-642-20095-3_32
References:

[10] Cristian Felix, Steven Franconeri, and Enrico Bertini. 2018. Taking Word Clouds Apart: An Empirical Investigation of the Design Space for Keyword Summaries. IEEE Transactions on Visualization and Computer Graphics 24, 1 (2018), 657–666. https://doi.org/10.1109/TVCG.2017.2746018

[11] Petra Isenberg, Tobias Isenberg, Michael Sedlmair, Jian Chen, and Torsten Möller. 2017. Visualization as Seen through its Research Paper Keywords. IEEE Transactions on Visualization and Computer Graphics 23, 1 (2017), 771–780. https://doi.org/10.1109/TVCG.2016.2598827

[12] Stefan Janicke and Gerik Scheuermann. 2017. On the Visualization of Hierarchical Relations and Tree Structures with TagSpheres. In Computer Vision, Imaging and Computer Graphics Theory and Applications, José Braz, Nadia Magnenat-Thalmann, Paul Richard, Lars Linsen, Alexandru Telea, Sebastiano Battiato, and Francisco Imai (Eds.). Springer International Publishing, 199–219.

[13] Jacqueline Léon. 2007. Meaning by collocation. In History of Linguistics 2005. John Benjamins, 404–415.

[14] Huajiao Li, Haizhong An, Yue Wang, Jiachen Huang, and Xiangyun Gao. 2016. Evolutionary features of academic articles co-keyword network and keywords co-occurrence network: Based on two-mode affiliation network. Physica A: Statistical Mechanics and its Applications 450 (2016), 657–669. https://doi.org/10.1016/j.physa.2016.01.017

[15] H. P. Luhn. 1960. Key word-in-context index for technical literature (kwic index). American Documentation 11, 4 (1960), 288–295. https://doi.org/10.1002/asi.5090110403

[16] S. Luz and S. Sheehan. 2014. A Graph Based Abstraction of Textual Concordances and Two Renderings for their Interactive Visualisation. In Proceedings of the International Working Conference on Advanced Visual Interfaces (Como, Italy) (AVI ‘14). ACM, New York, NY, USA, 293–296. https://doi.org/10.1145/2598153.2598187

[17] Saturnino Luz and Shane Sheehan. 2020. Methods and visualization tools for the analysis of medical, political and scientific concepts in Genealogies of Knowledge. Palgrave Communications 6, 1 (2020), 1–20.

[18] G. E. Marai. 2018. Activity-Centered Domain Characterization for Problem-Driven Scientific Visualization. IEEE Transactions on Visualization and Computer Graphics 24, 1 (Jan 2018), 913–922. https://doi.org/10.1109/TVCG.2017.2744459

[19] Ben Shneiderman. 1996. The eyes have it: a task by data type taxonomy for information visualizations. In Proceedings the IEEE Symposium on Visual Languages. 336–343. https://doi.org/10.1109/VL.1996.545507

[20] John Sinclair. 1991. Corpus, Concordance, Collocation. Oxford University Press.

[21] John Sinclair. 2003. Reading concordances: an introduction. Pearson/Lonergan.

[22] Jan Svartvik. 2011. Directions in corpus linguistics: proceedings of Nobel Symposium 82 Stockholm, 4-8 August 1991. Vol. 65. Walter de Gruyter.

[23] Edward R. Tufte. 1990. Envisioning information. Graphics Press, Cheshire, CT, USA.

[24] F.B. Viégas and M. Wattenberg. 2008. Tag clouds and the case for vernacular visualization. Interactions 15, 4 (2008), 49–52.

[25] Martin Wattenberg and Fernanda B Viégas. 2008. The word tree, an interactive visual concordance. IEEE Transactions on Visualization and Computer Graphics 14, 6 (2008), 1221–1228.