Special Section
Current and Emerging Methods in the Rhetorical Analysis of Texts

Closing: Toward an Integrated Approach

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Abstract: In this special section on Current and Emerging Methods in the Rhetorical Analysis of Texts, we have reported on the results of a project we undertook in order to better understand the costs and benefits of adopting particular approaches to the rhetorical analysis of texts. In the synthesis that follows, we begin with a brief review of the results of our researchers' analyses, then turn to examine their commonalities and variations. Finally, we conclude with the considerations that should be taken into account in choosing a method, as well as a discussion of the potential for integration. Overall, this synthesis will suggest that there is much to be gained by employing multiple methods for the rhetorical analysis of texts and outlines some of the design standards that can be used to support its development.

journal of
WRITING RESEARCH

Geisler, C. (2016). Current and emerging methods in the rhetorical analysis of texts - Closing: Toward an integrated approach. *Journal of Writing Research*, 7*(3)*, 511-526. doi: 10.17239/jowr-2016.07.03.09

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1. Brief Summary of Results

To begin our exploration of variations in the methods for text analysis employed by Karatsolis, by Kaufer, Ishizaki & Chi, and by Omizo & Hart-Davidson, we briefly review the results of their analyses.

1.1 By Level of Participant

In terms of what Karatsolis calls level of participation and Kaufer, Ishizaki & Chi call role, the analyses suggest few significant differences between the texts written by the PhD advisors and the advisees. While on average, advisees tended to use more references, more elaboration, and more evaluation than their advisors, individual variations were very large and kept these differences from reaching statistical significance.

This variety can best be illustrated, perhaps, by the results provided by Omizo & Hart-Davidson where we see that texts by the same advisor are no more alike than texts by different authors. For example, Chemistry Advisor 1's first text (CA1) is less similar to his second text CA2 with a similarity score of 5.98 than it is to Chemistry Advisor's first text (CAE1) with a similarity score of 2.81 (see Omizo & Hart-Davidson, this issue, Figure 3). Similarly, Materials Advisor first text (MA1) is less similar to his second text (MA2) with a similarity score of 48.56 than it is compared to Materials Advisee's first text MAE1 with a similarity score of 7.25 (see Omizo & Hart-Davidson, this issue, Figure 4). Given variations this large as well as the small number of texts, it is not surprising that the differences do not reach the level of significance.

There were a few small exceptions to this lack of significance for differences in level of participant. Kaufer, Ishizaki & Chi found a few significant differences by role. On the discourse-wide factor of negativity, they found that HSS advisees were more negative than their advisors while the opposite was true in Chemical Engineering. They also found one difference in the citation subdimensions. In this case, advisors used more numeric style citations than did their advisees. None of these differences by level of participant seem to add up to a broader account of the way level of participation affects citation use.

1.2 By Discipline

A very different story seems to unfold for the differences by discipline. Here we summarize the patterns discovered first by Karatsolis and then by Kaufer, Ishizaki & Chi. For simplicity, the patterns are visualized in Figure 1 (Omizo & Hart-Davidson did not analyze the texts by discipline).

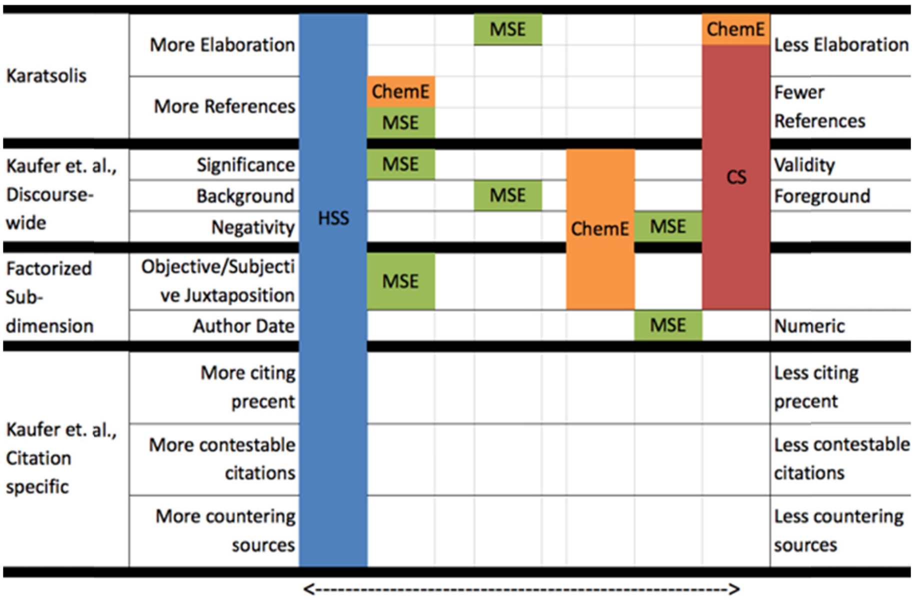


Figure 1: Visualization of significant results for discipline in Karatsolis and Kaufer, Ishizaki & Chi.

As shown at the top section of Figure 1, Karatsolis found significant differences by discipline in the use of elaboration and in the use of reference. The CS and ChemE texts contained significantly fewer instances of elaboration compared to HSS and MSE. The texts written by the computer scientists, in general, contained fewer references than did those written by authors in HSS, ChemE or MSE.

As shown in the rest of Figure 1, Kaufer, Ishizaki & Chi also found a variety of significant disciplinary differences. H&SS texts, represented in blue in Figure 1, were particularly distinctive. In terms of the discourse-wide factors, these texts focused more often on significance rather than validity, provided a high degree of background rather than foreground, and were generally negative. On the factorized subdimensions, HSS authors were significantly were more likely to use objective/subjective juxtaposition and more likely to use author-date citation style, advisees even more than advisors. The citation-specific analysis showed them to be more likely to cite precedent and use contestable citations and countering sources.

The CS texts, represented in red in Figure 1, were very different from the HSS texts. In terms of the discourse-wide factors, they focused very heavily on validity rather than significance, on foreground rather than background, and did not use much negativity. On the factorized sub-dimensions, they were less likely to use objective/subjective juxtaposition.

Kaufer, Ishizaki & Chi found the ChemE texts, shown in gold in Figure 1, to be more like the CS texts than the HSS texts. Their authors focused more on validity than significance; they placed some emphasis on foreground rather than background; and they did not use much negativity. Also like CS, they were less likely to use objective/subjective juxtaposition.

The MSE texts, shown in green in Figure 1, had a somewhat split profile in the analysis by Kaufer, Ishizaki & Chi. Like HSS texts, the MSE texts had a high focus on significance rather than validity, and were more likely to use objective/subjective juxtaposition. Unlike HSS texts, however, MSE texts had a balance of foreground and background, and not much negativity. The citation-specific analysis showed their authors were also the most likely to use numeric citation, advisees even more than advisors.

The overall picture in Figure 1 suggests some common patterns in the results of the analyses conducted by Karatsolis and by Kaufer, Ishizaki & Chi for HSS and CS. Specifically, HSS and CS appear to anchor the extremes both in terms of citation practices and discourse-wide practices. On the other hand, texts in the other two disciplines showed more irregular patterns. In Karatsolis' analysis, ChemE looked more like HSS texts in terms of numbers of reference but more like CS in terms of amount of elaboration; in Kaufer, Ishizaki & Chi's, ChemE looked more like CS. And the split profile of the MSE texts in Kaufer, Ishizaki & Chi was not as pronounced in the Karatsolis' analysis.

2. Commonalities in Analysis

Before we turn to examine the variation in analytic processes that lay behind the results just reviewed, it is important to recognize the overall analytic framework they had in common. Although the analytic process of the hand coding used by Karatsolis is well-documented (Geisler, 2004), there exist no handbook of procedures for the methods used by Kaufer, Ishizaki & Chi or Omizo & Hart-Davidson. Therefore, in order to better understand the analytic processes used by each of the sets of authors, I began by constructing step-by-step accounts of the methods used based on a careful reading of their manuscripts. I then sent these accounts to the authors and then followed up with phone interviews to review, correct, and clarify the process descriptions. The analysis of commonalities that follows is based on these corrected accounts.

The first commonality in analytic process for the methods used in this special section required that texts be preprocessed into appropriate format. In terms of format, many of the texts that Karatsolis collected from the participants in the original study were in pdf format that had to be converted into editable text. The other two groups required the data be put into the form of txt files. Preprocessing is a time consuming effort that many researchers new to these methods underestimate.

Next, all the methods used in this special section called for segmenting the preprocessed texts into smaller units. Karatsolis broke his data into sentences, a segmentation that Omizo and Hart-Davidson also adopted. Kaufer, Ishizaki & Chi, on the other hand, broke the original texts into separate paragraph-length txt files.

A third commonality among these studies was, as we'll see, reliance on coding schemes developed using interpretation. As we'll discuss more in the next section, the exact role that interpretation played in the analyses varied among the methods, but it is still true that interpretation played a role in all of the coding.

Finally, all of the studies used a two-stage analytic process. The first stage involved coding textual units. The second stage involved looking for patterns in that coded data using statistical exploration.

Recognizing this common analytic framework — preprocessing + segmentation + coding + pattern exploration — may be important to the question of integrating these methods, a topic to which we'll turn in our conclusions.

3. Variations in Analytic Method

Behind our authors' variations in results lie a number of important variations in analytic method.

3.1 Sequencing Information

As we noted above, all three of the methodologies in this special section segmented the texts in the common dataset. One consequence of fragmenting texts in this manner is the possible loss of sequencing information: Do we know — and can we analyze — the order in which the segments originally occurred?

Both of the studies that used the sentence in the segmentation stage — Karatsolis and Omizo & Hart-Davidson — also maintained and used information about sequence in subsequent stages. The hand coding used by Karatsolis built in sequencing information in the data coding stage. When analysts reviewed the data sentence by sentence, sequencing information was available to them. Sequencing information was more particularly relevant to their coding the data for Elaboration. Specifically, Karatsolis defined Elaboration as occurring "where the author elaborates on the information or ideas being presented from a cited source, even if the reference to this source appears in a previous or later t-unit." Elaborations, which may occur in a sentence preceding or following a citation, may provide details on a source, relate the source to a general category of thought, or note areas of agreement or conflict among multiple sources. Elaboration was one of two areas in which Karatsolis found major disciplinary differences, with both the HSS and ChemE authors using more elaboration than the CS authors. Without sequencing information, this potentially important disciplinary difference would not have been detectable.

Omizo & Hart-Davidson also preserved information about sequence at the coding stage, but then also went on to use it in pattern exploration. In coding, they transformed each text into a sequence of numeric codes, with each number representing one of their four coding categories: 0-no citation, 1-extraction, 2-grouping, and 3-author as actant. In the example they give, a four-sentence passage that contained an extraction citation in the second and fourth sentences would be represented as 0-1-0-1. They further annotated each of the nodes with a unique identifying number in order to preserve its identity as well as the order of its sequence, equivalent to representing the sample passage as 0_1-1_2-0_3-1_4, thus distinguishing between the first extraction (1_2) and the second one $_{(}1_4$).

Once they had represented texts as these numeric sequences, then they could explore them using techniques from graph theory, a branch of mathematics/ computer science designed to look at nodes and the edges connecting them, a representation specifically designed to capture sequence. All four of the features used to model the comparisons among the texts used this sequencing information. Of particular interest in rhetorical terms was the third feature, location and distribution of citational edges. Omizo and Hart-Davidson calculated whether each citational edge occurred at the beginning, middle, or end of the text, and they report that 48% of the citational edges appeared in the first 30% of the texts. While they do not report citational edge location data separately for each text, it was one of the contributing features that led texts to be or less similar to one another as represented in their sociograms.

As we noted earlier, Kaufer, Ishizaki & Chi worked at the paragraph level, breaking the original texts into paragraphs. Each paragraph was then saved in a separate txt file, which became part of the input to DocuScope. As a consequence, the sequence of paragraphs was not preserved for coding or pattern exploration.

3.2 Balance of Interpretation and Algorithm

One of the traditional arguments used against computer-aided text analysis has been its reliance on over-simplistic algorithms at the expense of interpretive richness. Admittedly, only human readers, relying on the power of linguistic intuition and contextualized understanding, can fully understand the rhetorical impact of a text. Nevertheless, in order to compare one text to another, to detect patterns that human readers may only unconsciously respond to, and to deal with large numbers of texts beyond human capacity, each of the computer-assisted methods used in this special section relied on computer algorithms as well as human interpretation. Understanding how each approach balanced algorithm with interpretation in the development and application of a coding scheme is critical to understanding their benefits and limitations.

Interpretation was at play throughout the hand coding used by Karatsolis. In the development stage, he created the coding categories by making repeated passes through a subset of the common dataset, using interpretation to create and refine the categories and their definitions. And, in the application of that coding scheme to the whole dataset, coders were also guided by their interpretations. For example, in coding for Evaluation, coders needed interpretative rather than algorithmic processes to apply the following definition:

> Code as Single Source Evaluation any sentence containing a reference where the author makes an evaluative statement or comment about a source by *noting the*

> *(established) value of the source/idea),* where the author points to the usefulness or positive impact of the source for the field, the specific project or the understanding of a new concept through phrases such as "another significant research was conducted by…" or "this methodology [4] provides the foundation/standard for …" or "this has been used extensively [5]" or "widely used" or verbs such as "the authors point out that."

With examples such as "another significant research was conducted by…," coders could gather a general sense of what Karatsolis had in mind, but they still needed interpretation to decide whether sentences like this one should be coded an Evaluation:

> RMW have concluded on the basis of orbital symmetry arguments that reaction 1 cannot be a concerted four-center reaction but has to involve a C202 complex.

In fact, coders would need to be familiar with the conventions of academic texts to know that providing an unqualified summary of an author's conclusions counts as an evaluation. Certainly Karatsolis provides no such rule or algorithm.

On first examination, it may appear that the coding methodology relied upon by Kaufer, Ishizaki & Chi was purely algorithmic. DocuScope uses a fast pattern-matching algorithm to search a given text to find matches of any arbitrary length to entries in its dictionary (Hu, et. al., 2010), without human intervention. Yet interpretation played a role at a much earlier stage in the process. In fact, long before the analysis reported here, Kaufer used interpretation to create the entries in the dictionary, identifying and classifying the rhetorical effect of patterns of language he encountered in the numerous corpora he worked with over more than a decade. As he has said elsewhere (MLA Committee on Information Technology, 2012), "The dictionaries are an innovative feature because they took so long to develop. But because they were produced by over-time theory and empirical observation and not by algorithm, they are considered more "art" than patentable method." Thus, as with Karatsolis, interpretation played a key role in the development of Kaufer, Ishizaki & Chi's coding categories.

For Kaufer, Ishizaki & Chi, interpretation also played a role in pattern exploration. Recall that they reported significant disciplinary differences for three discourse-wide factors as shown in the middle of Figure 1. As shown in Figure 2, each of these factors represents a selection from the default thirty-one discourse-wide dimensions built into DocuScope. So on Factor 1, for example, when the HSS texts were found to contain a high degree of significance, this meant that they contained an unusually high number of phrases that matched the sub-dictionaries marked with a + in the third column as well as an unusually low number of phrases that matched the sub-dictionaries marked with a – in that column. Each factor, then, was an amalgamation taken from the toolkit of discourse-wide dimensions. It was only by using DocuScope's visual interface to move from a map view to a single text view that allowed them to directly examine and interpret the language behind these amalgamations that Kaufer, Ishizaki & Chi were able to suggest generalizations behind the factors. Thus the amalgamation of discourse-wide dimensions into a factor was, in and of itself, only made meaningful by the researchers' careful reading and skill at interpretation. And, in fact, Kaufer, Ishizaki & Chi found some algorithmic-produced factors, such as objective/subjective juxtaposition (Factorized Subdimension 1) hard to interpret.

	Dimension	Factor 1: significance/ validity	Factor 2: background/ foreground	Factor 3: negativity
1	academic	-		
2	citation		+	
3	cohesion			
4	comparison			
5	contingency			
6	description	-		
7	directing			
8	emotion-negative			+
9	emotion-positive			
1	exposition	-		
1	facilitate			
1	first-person			
1	forceful	+		
1	future	+		
1	inquiry			
1	interactive			
1	linguistic			
1	narrative			
1	opposition			
2	past		+	
2	persons		+	
2	place		+	
2	privy			
2	public		+	
2	reasoning		-	
2	relations-positive	+		
2	relations-negative			
2	reporting			
2	strategic	+		
3	values-negative			+
3	values-positive	+		

Figure 2: Contribution of DocuScope dimensions to the three discourse-wide factors.

The coding process employed by Omizo & Hart-Davidson involved the most complex interplay between interpretation and algorithm. The three modules that make up their preprocessing and coding were entirely algorithmic. In the first module, a set of searches for author names and dates were used to mark the sentences containing citations. In the second module, words were replaced with tags — author names, for example, being replaced by the tag AUTHOR. In the third module, an algorithm was used to code the tagged sentences: Those citations that contained three or more PUBYEARs were coded as Grouping (code 2). Those that contained AUTHOR as grammatical subject or object were coded as Author(s) as Actant(s) (code 3). Then the remaining uncoded citations were coded as Extraction (code 1).

Although Omizo & Hart-Davidson's modules made use of algorithmic tools from the Natural Language Processing toolbox, it's important to understand that the choice of these tools relied on a process of interpretation. Specifically, these researchers would apply each algorithm and then read the results sentence by sentence to see if the results made sense. The final three modules they eventually used were thus the result of numerous interpretations and changes in tools, overall an interpretive bricolage.

3.3 Scope of the Analysis

The final variation in analysis that I want to call attention to concerns the relative scope of the analyses.

In his original hand coding, Karatsolis was specifically interested in how authors used citations. His coding schemes thus first looked for citations and then asked how those citations were used: Were they evaluated? Were they elaborated? Were they placed in relation to the author(s) current project? These are special-purpose coding schemes built to detect a specific phenomenon and, as a consequence, the results diagramed in Figure 1 only relate to citation use. If there were other differences among these texts, Karatsolis' methods would not have noticed.

The coding approach taken by Omizo & Hart-Davidson was similarly narrow in scope. Limiting their focus to citation-related patterns, they picked out sentences containing citations and sought to develop an analytic process that would produce comparisons similar to that created by Karatsolis' hand coding. When we look at the their results, then, we are looking only at representations of similarity and difference with respect to citation use. Both methods, then, can be understood as special-purpose sieves designed specifically to strain out and save citation-related phenomenon.

The scope of the analyses conducted by Kaufer, Ishizaki & Chi was generally broader. Although DocuScope includes citation as one of its thirty-one dimensions (see Figure 2), the remaining dimensions cover a broad spectrum of language phenomena that have been found to be useful in analyzing news reports, political speeches, even Shakespeare (Kaufer, undated). Furthermore, in the analyses employed for this special section, this citation-specific dimension was included in only one of the three-discourse-wide factors.

It is true that Kaufer, Ishizaki & Chi did pull out and use the citation-specific dimension in the two other analyses they conducted, shown at the bottom of Figure 1. But the results largely confirmed patterns of difference among the disciplines rather than adding anything new to what they found through the discourse-wide analysis.

These discourse-wide results, visualized in the middle of Figure 1, suggest a set of disciplinary differences broader in scope than simple citation use. HSS texts and CS texts showed discourse-wide tradeoffs between significance and validity, between background and foreground, and in the use of negativity in addition to citation-specific differences. Further work would be required to examine the nature of the interplay between these discourse-wide phenomena and citation use, but it is only through the addition of a general-purpose sieve like DocuScope that we would even notice this interplay.

4. Conclusions

In concluding, we return to the two questions that motivated the work reported in this special section: How can we best understand the costs and benefits of adopting a particular approach? Are they simply alternatives or can they be integrated?

In addressing these questions, it is important to keep in mind the limitations of this project. To begin with, the size and composition of the data set was not consistent across the three studies. If hand coding is included as one of the alternatives, a comparison of methods will inevitably suffer from inconsistencies in data set size. In our case, the original data set was limited to what could reasonably be hand coded, which caused problems for the use of text mining methods used by Omizo & Hart-Davidson. In the KWALON Experiment (Evers, et. al, 2011), the size of the data set was a much larger corpus, which caused problems for the human coding in the CAQDAS packages.

A second limitation in our work arises from the variation we allowed in the questions addressed. In the KWALON Experiment, researchers were asked to address the same set of research questions, but we recognized from the outset that limiting ourselves to the citation-specific interests that motivated Karatsolis would not lead to a fair exploration of the strengths of the other two methods. But because we allowed for this variation, we are not able to provide much direct insight into the way that the choice of research question fits one method better than another.

A third limitation in our work arises out of the limited and somewhat artificial way our work was framed. Karatsolis' original study (2005, 2011) included far more work and data than was included in this comparison, which allowed for a depth of investigation that cannot compare with the analyses undertaken by Kaufer, Ishizaki & Chi or Omizo & Hart-Davidson. Greater depth of analyses would have required these two sets of researchers not only to expand the size of their datasets, but also to pursue more analytic iterations. Kaufer, Ishizaki & Chi, on the one hand, would pursue additional analyses to better understand how the general disciplinary differences uncovered by Docuscope were related to (or distinct from) specific citational differences. Omizo & Hart-Davidson, on the other hand, would want to build further comparisons from their natural language processing data to see if there were differences by discipline in addition to differences by level of participant.

Finally, we must acknowledge the limitations of this analysis that arise from the evolving nature of the tools. While hand coding is a well-documented method for text analysis, albeit with important variations, both the dictionary methods used by Kaufer, Ishizaki & Chi and the natural language processing methods used by Omizo & Hart-Davidson are emerging methods in dramatic flux. Not only is Docuscope's general purpose dictionary constantly evolving in response to new data, but the tool also has the potential to be used with other and special purpose dictionaries. And methods in Natural Language Processing are evolving at rapid rate.

Given these limitations, what we have to say in the following about considerations in choosing an approach to textual analysis or about the potential framework for an integrated approach should best be understood as a set of temporary signposts on a road under construction: helpful, even necessary, for the present, but likely to be changed and refined in the future.

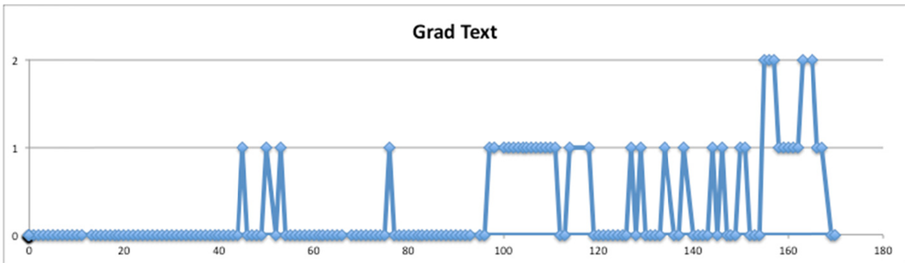
4.1 Considerations in Choosing an Approach

One of the primary considerations in choosing a method for analyzing rhetorical patterns in text is the size of the corpus to be analyzed. As Karatsolis points out, the common dataset used for this special section was not small by the standards of non-computerized hand coding, but both of the other research groups struggled to accommodate its small size. Kaufer, Ishizaki & Chi broke the data into paragraphs rather than dealing with whole texts as they usually do. Omizo & Hart-Davidson needed to use a corpus of 500 research articles from the SpringerOpen Journal archive to develop their approach before they could apply it to the common data. It almost goes without saying that researchers seeking to conduct analyses of rhetorical patterns in text need to consider the size of the available corpus.

A second consideration in choosing a methodology lies in the scope of the questions being asked. As we suggested earlier, both hand coding and text mining require the researchers to have a specific idea of what kind of differences they are looking for. The analyses conducted Karatsolis, Omizo & Hart-Davidson, as well as two of the analyses conducted by Kaufer, Ishizaki & Chi were citation specific. Dictionary-based approaches like DocuScope are more general-purpose, and can help the researcher discover unexpected language patterns with its discourse-wide investigations. The work by Kaufer, Ishizaki & Chi can be viewed as a model for how to look for significant variations with a large numbers of variables without the problems that accompany running multiple statistical tests and reaching significance on some of them purely by chance.

A third consideration in the choice of method is the limitations of algorithmic models. Advances in Natural Language Processing make quickly obsolete any hard and fast rules about what can be detected with NLP algorithms, but the powers of human interpretation is still the gold standard for understanding rhetorical moves. It is no accident that all of the methods employed in this special section relied on interpretation for at least the development of their approach to coding. Nevertheless, researchers should keep in mind that it is fully possible that a given method may not be able to help them identify the rhetorical aspect of texts in which they are interested.

A final consideration that I want to call attention to is the importance of sequential information to the analysis of rhetorical moves. Much can be understood by taking a whole text view, asking, for example, how much elaboration does this text contain? How much evaluation? How much foregrounding? How much background? But if the texts in question have the kind of cultural integrity that earns them the status of a rhetorical object — a speech, an article, a blog, and so on — then the way rhetorical features unfold over the temporal dimension of the text will probably be important.



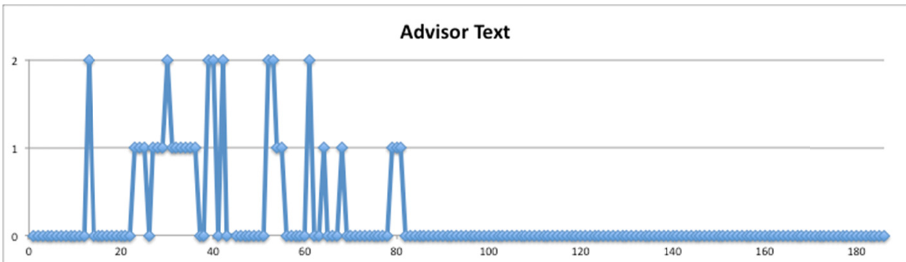


Figure 3: Temporal Graphs showing the sequence of sentences without citations (0), sentences with single citations (1), and sentences with multiple citations (3) in a text by a PhD advisee and his advisor.

Earlier we noted that some of the analytic approaches presented in this special section preserved sequencing information. If sequencing information is preserved in data segmentation and coding, then it can be analyzed in pattern exploration. The two temporal graphs (Geisler & Munger, 2002; Geisler, 2004) shown in Figure 3 illustrate how sequencing information from hand coding can reveal differences in the use of genre. The first text is by a PhD student in Chemical Engineering, the second by his advisor. Across the x-axis we find the sentences as they unfolded over time. On the y-axis are the kinds of citations used in those sentences: 0 for no citation, 1 for a single citation, and 2 for multiple citations. From these graphs we can see that citations are used differently over the temporal course of the two texts. Specifically, they are used to open the advisor's text whereas they are used almost exclusively towards the close of the advisee's text. These differences are most likely related to genre, as the grad text is a chapter from a PhD dissertation while the advisor's text is a published journal article. While it is possible to understand these patterns as simply an artifact of genre differences, it is also possible to question why PhD students attempting to learn the citation practices of their field are asked to produce textual genres that appear to work so different sequentially. But no matter how one chooses to understand the relationship between genre differences and level of participant, it is only by attending to sequencing information that these relationships can be noticed.

Temporal graphs like these show painstaking detail and cannot be used to analyze large datasets. But, as suggested earlier, the network graph structures built by Omizo and Hart-Davidson preserve sequencing information that can be used for later analysis. As a consequence these researchers were able to suggest that the location of citational edges (at beginning, middle, or close of the text) could be used to provide feedback to students trying to learn genre conventions. Researchers dealing with texts in potentially recognizable genre form may well want to insure that they preserve and analyze sequencing information.

4.2 Toward an Integrated Approach

The use of multiple methods for the rhetorical analysis of texts provides a kind of triangulation on the results of the analysis. Karatsolis undertook his research with the expectation that there would be significant differences between the PhD advisees and their advisors in their use of citation. Indeed, in the second half of the study reported here, he did find systematic differences in the kinds of rationales these authors offered to explain their citation choices. Nevertheless, the convergence of the multiple methods reported in this special section gives us confidence that systematic differences by level of participant did not exist at levels detectable in such a small corpus.

On the other hand, the use of multiple methods gives confidence and depth to the finding of the systematic differences by discipline. The HSS texts and CS appear to anchor a whole host of disciplinary differences in the deployment of rhetorical moves that includes but is not limited to the use of citations. And, although Omizo and Hart-Davidson did not examine disciplinary differences with their analyses, their method holds promise of being able to uncover a temporal dimension behind these disciplinary differences as well.

If, as we suggest, there is a benefit to be gained by taking an integrated approach to the rhetorical analysis of texts, it remains clear that at the present time such integration requires an enormous investment in researcher time and knowledge. In particular, further work needs to be done to link the kinds of research questions asked with the kind of analytic tool chosen. Nevertheless, we find the possibility of integration promising enough to close this special section with a list of design standards that could be used to make such integration more than a distant promise:

1. *Adopt a common analytic framework*. Behind the variety of their descriptions of research process, we have found here evidence of a four-part analytic framework that may serve the purpose:

   preprocessing + *segmentation* + *coding* + *pattern exploration*.

   Being able to link a technique to its appropriate stage can help researchers begin to mix and match tools by stage rather than treating the selection of approach as an all-or-nothing decision.

2. *Support common preprocessing standards*. Hand coding requires very little pre-processing to prepare a text for human coders other than segmentation, but computer-assisted text analysis often requires moderate or even laborious data cleaning. In order to draw on an arsenal of tools for the rhetorical analysis of texts, researchers will need to use common preprocessing standards.

3. *Support flexible options in tool choice*. No single text analysis method is going to be useful for all research questions. Any integrated environment will need to allow researchers options in tool choice as well as an open architecture for adding new tools as they are developed.

4. *Provide for transparent inspection*. As Wiedemann (2013) has suggested, any rhetorically adequate process needs to support close interpretive reading as well as distant reading. All of the methods in this special section employed a process that cycled between algorithm processing and interpretive reading. Yet not all text analytics allow for easy return to the language behind an analytic generalization. The visual interface in DocuScope is an example of the way one tool allows researchers to move from a multiple text view to a single text view. Many mixed methods packages for computer-assisted qualitative data analysis also support toggling between coding generalization and coded text. But some of the current methods for Natural Language Processing do not support this level of inspection.

5. *Support selective hand coding*. In this special section, the original coding done by Karatsolis functioned as a hand-coding stage for the machine learning used by Omizo & Hart-Davidson. As we noted earlier, hand coding often plays a role in text analytics, providing the "expert" judgments that computers try to match. But even if researchers are not explicitly using a machine-learning framework, they often find a role for selective hand coding as they seek to develop their coding methodology. An integrated environment should support their efforts, allowing for easy movement between automated processing and hand coding tools.

6. *Suggest options as to when to hand code*. For the most part, hand coding has been used as an option in the early stage of coding, providing the judgments against which algorithms are tested. Lejeune's use of Cassandre (2011) is a good example of an alternative ordering. Here algorithm-based tools are used to produce a preliminary coding/selection of data that is then passed onto human coders for interpretive hand coding. Ending rather than starting with hand coding can capitalize on an algorithm's strength as a filter, leaving a small dataset to human interpretation for more complex and hard to automate judgments. Such a combination may help to overcome the limitations of purely algorithmic methods.

7. *Preserve sequencing information*. Not atypically, the analyses presented in this special section largely favored whole text generalizations. Yet if we want to examine the rhetorical nature of text as experiences that unfold over time, we should preserve sequential information in our segmenting and coding so that information is available for pattern exploration.

As the taxonomy presented in Figure 1 of the opening article for this special section suggests, the field of text analysis is far broader than the community of writing researchers. Yet writing researchers do bring to the text analytic table a more sophisticated understanding of the way texts work. As a consequence, the tools we need for the rhetorical analysis of texts may require more specific design standards like those suggested in this synthesis. Certainly the prospect of a more integrated approach to the rhetorical analysis of texts created excitement among the researchers on this project and we hope this this special section on Current and Emerging Methods in the Rhetorical Analysis of Texts has helped us share this excitement.

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