Research Article

Mapping the Conversation: A Social Network Perspective on Intertextual Reading and Writing

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Structured Abstract

- **Background:** Research conceptions of adolescent writing development are increasingly focused on the socially situated, interactive quality of the composing process, and on the fundamental connections between reading and writing. Yet methods for analyzing classroom writing have not typically supported this wider and more intertextual account of how writing gets done. This study demonstrates the affordances of network analysis for studying written compositions as parts of larger systems of textual interaction.
- **Literature Review:** This interdisciplinary study draws together three bodies of literature as a basis for understanding student writing as a networked phenomenon: qualitative studies of the socially-mediated, intertextual quality of academic writing, studies of the role of writing prompts in student composition, and social network analysis of discourse communities, including co-citation literature. The review positions network analysis as a method capable of capturing aspects of the social context of writing production while employing large-scale data analytic techniques that might be replicated at scale on other corpora.
- **Research Questions:** The analysis focuses on the text referencing patterns of students and instructors in a rigorous college access program, guided by the following research questions:

1. How do the students in a pre-college seminar bring the curriculum texts together in their written work?
2. What programmatic features predict how students will bring the curriculum texts together in their writing? Specifically, what role do the prompts, student attributes, student groupings, and curriculum constraints play in the structure of the textual conversation?

- **Methods:** This study uses both descriptive and inferential network analysis techniques, including visual network projections and Exponential Random Graph Modeling.
- **Results:** The analysis reveals that, although the prompts played a significant role in the structure of the textual conversation, there were a number of other significant contextual features, including the progression of the curriculum and similarities in the thematic content and structure of course texts. In particular, the findings indicate that although the reading curriculum was curated to permit a wide variety of thematic connections across historical time, students tended to reference course texts that were assigned in close proximity to one another within the chronology of the course.
- **Discussion:** The results suggest some important lessons for curriculum design, program improvement, and writing research. First, they suggest the promising role writing prompts might play as brokers between disparate parts of the curriculum, drawing together otherwise separate portions of the course into closer dialogue. Second, given the significance of the curriculum structure and sequence in students' referencing practices, the findings highlight the importance of examining reading alongside writing in secondary and postsecondary research. More broadly, the findings hint at the value of network analysis for ongoing program assessment. While the current study was not focused on assessing student writing as an outcome of the course, one course-level outcome that might really matter for instructors is whether students are drawing the curriculum texts together in a wide variety of ways—precisely what network analysis is able to show.
- **Conclusion:** As a largely quantitative approach, network analysis offers a complementary, systems-level view of the interactive context of reading and writing activities. The method therefore functions as an intermediary between the qualitative literature on the social practice of writing and the large-scale data analytics of co-citation research. In particular, as Mike Palmquist (2019) has called for in this publication, this application of network analysis demonstrates

one option for applying data analytic techniques in service of improving course design and instruction.

Keywords: Composition, Writing Prompts, Reading Instruction, Intertextuality, Social Networks

1.0 Introduction

When Charles Bazerman (1980) advocated more than forty years ago for a conversational model to integrate the teaching of reading and writing, he noted that the connections between reading and writing seemed “so obvious as to be truistic” (p. 656). While an explicit focus on the reading and writing connection has gone in and out of vogue in the decades since, the basic metaphor of *textual conversation* has become utterly dominant in the guidance for secondary and postsecondary literacy instruction—encoded in major statements on policy and practice (Graham & Perin, 2007; IRA/NICHD, 2012; NCTE, 2016), in the titles of popular composition textbooks (Graff, Birkenstein, & Durst 2006/2018; Lunsford, Ruskiewicz, & Walters, 2004/2018; Palmquist & Wallraff, 2010/2017), and in the conceptual underpinnings of dialogic perspectives on literacy (see Graham, 2020 on rhetorical relations theory; also Bloome & Egan-Robertson, 1993; Olsen, et al., 2018; VanDerHeide, 2018; VanDerHeide & Juzwik, 2018). In her consideration of the role of reading instruction in college composition, Carillo (2015) commented that most of her first-year college students were already quite familiar with the notion of academic reading and writing as conversation.

The strong theoretical basis for the underlying cognitive similarities in reading and writing processes (Fitzgerald & Shanahan, 2000; Shanahan, 2016; Tierney & Pearson, 1983; Tierney & Shanahan, 1991) is also supported by a growing body of evidence that integrating reading and writing instruction improves comprehension, writing transfer, and content knowledge (Graham & Hebert, 2011; Graham et al., 2018; also Applebee, 2008; Lockhart & Soliday, 2016; Wiley & Voss, 1999).

Yet despite the general currency of the conversational model in our conceptions of reading and writing—and the growing evidence for teaching these processes in tandem—classroom research has not yet drawn on methodological tools that support this perspective (Graham, 2020). As I attempt to demonstrate in this study, the interactive quality of reading and writing activities poses a methodological challenge that network analysis (Wasserman & Faust, 1994) is well-positioned to address. Using descriptive and inferential network analysis, this study examines how various aspects of the social context in a pre-college seminar helped students make connections across the course readings. The study highlights the role of the writing prompt as an interface between the reading and writing curriculum, but also illuminates the wide range of other social interactions that constituted the context for student writing, including implicit parameters of the assignment, thematic overlap in the readings, and the sequence of the curriculum.

As a largely quantitative approach, network analysis offers a complementary, systems-level view of the interactive context of reading and writing activities. The method therefore functions as an intermediary between the qualitative literature on the social practice of writing and the large-scale data analytics of co-citation research. In particular, as Mike Palmquist (2019) has called for in this publication, this application of network analysis demonstrates one option for applying data analytic techniques in service of improving course design and instruction.

2.0 Literature Review

This study draws together two lines of work into a network analysis framework—research on writing as socially situated, intertextual practice, and research on the form and function of the writing prompt in composition. The analysis frames the writing prompt as a text occurring within a larger system of texts, one that responds to a conversation that has already been proposed in the curriculum, and that spurs subsequent textual responses. The methodological integration of these two literatures draws on research using social network analysis to illuminate the small discourse communities of classrooms and the large-scale discourse communities of scholarly networks.

2.1 Reading and Writing as Intertextual Social Practice

Qualitative work in a range of adjacent fields has drawn on the notion of *intertextuality* to characterize literate activity in secondary and postsecondary contexts (Bazerman, 1980; Bloome & Egan-Robertson, 1993; Olsen, et al., 2018; VanDerHeide & Juzwik, 2018). Though the studies are typically small-n, they have generally argued that intertextual practice is the defining feature of academic communities writ large (Bartholomae, 1986) and have focused on the social origins and implications of referencing practices in writing and discourse.

In their landmark study of intertextuality in the reading classroom, Bloome and Egan-Robertson (1993) argued that it is not within the texts that intertextual connections reside, but in the social activity that acknowledges and makes use of them. “People, interacting with each other, construct intertextual relationships by the ways they act and react to each other,” they wrote. “An intertextual relationship is proposed, is recognized, is acknowledged, and has social significance” (p. 311). Their micro-interactional discourse analysis of two students in a reading lesson analyzed the ways that the participants used intertextual referencing to define themselves as readers but not as dutiful students—and the extent to which this positioning was accomplished through the materiality of their interactions. Though the focus of their analysis was mostly on spoken discourse, the implications for social identity apply to written text as well, as a number of other studies have since argued (Nowacek, 2007, 2011; Olsen, et al., 2018; Prior, 1994, 1995; Roozen, 2010; VanDerHeide, 2018; VanDerHeide & Juzwik, 2018). These studies have focused most specifically on intertextuality within the larger social context of classroom discourse, and particularly the ways in which materials and processes may be traced to a wide range of textual materials in the instructional environment, including conversations with other participants. “As people make intertextual connections in writing," Olsen and colleagues (2018) wrote, "they are not only bringing texts together, they are bringing people together" (p. 84).

These fine-grained and largely qualitative inquiries contribute to a growing picture of how individual student writing develops over time and across contexts by accumulating and reworking other texts. They are also striking demonstrations of the ways in which intertextual activity is mutually constitutive with the social context—a feature that suggests a shift in the unit of analysis from the text as self-contained to the text as one of many in a larger interaction. Yet despite the intuitive appeal of intertextual perspectives on writing, we have few methodological tools that support this wider, more interactive, and collective perspective on literate activity.

2.2 The Writing Prompt in Composition Research

The role of the writing prompt has been of central interest in composition research for more than three decades, and studies from a wide range of perspectives have taken the prompt as a source of evidence for instructor expectations and as the immediate context for student writing (Bartholomae, 1983, Bawarshi, 2003; Crossley et al., 2013; Liu & Stapleton, 2018; Melzer, 2014; Wolfe, 2011). A key issue in all the research is the extent to which the prompt tends to elicit responses from students that match expectations, particularly when it serves a role in assessment and institutional gatekeeping (Aull, 2015; Beck & Jeffery, 2007; Grapin and Llosa, 2019; Horowitz, 1986a, 1986b; Leki & Carson, 1997; Moore and Morton, 2005). Important signals of context examined in this literature include the genre (e.g., essay, research paper, alternative assignment); the rhetorical function (e.g., comparison, explanation, argument); constraints around acceptable evidence (e.g., empirical research, primary sources, personal experience); and the expected object of inquiry (e.g., a phenomenon in the real world, an argument in a source text). Aull's (2015) study of placement test writing among incoming freshman referred to the latter distinction as "text-external" and "text-internal" points of departure, and noted that the specifications made a difference in terms of student attention to the existing scholarly conversation. Prompts that directed students to consider a perspective from the text rather than respond to an open-ended question elicited essays with higher frequencies of references to the source text and lower frequencies of personal markers.

But within a classroom context, where writing tasks are also framed by instructional practice and student interaction (Beck, 2006; Soliday, 2011), the writing prompt may also play the more situated job of commenting on the course readings, drawing together the curriculum into new configurations, and modeling the kind of intertextual connections that are endorsed within the class. This is one role of the writing prompt that has received almost no attention in the composition literature, despite the growing consensus around the importance of reading in writing instruction. In this perspective, the writing prompt is less a representative of a total context and more a single response to an already existing network of texts. In Bloome and Egan-Robertson's (1993) typology, the prompt offers an acknowledgement of a specific intertextual connection proposed in the gathering of the curriculum materials. It is one move in a larger conversation.

The present study extends this notion by using network analysis to examine the role of the prompt in the social activity of reading and writing in a classroom from the perspective of textual interaction. It considers the prompt as a text that interacts with the texts of the curriculum, drawing some closer together, neglecting others, and spurring (or not) corresponding connections in student texts.

2.3 Social Network Analysis in Discourse and Co-Citation Research

Unlike many other statistical methods, network analysis focuses not on individual observations of interest, but on the variety of relational structures that might exist between them: the flow of information and norms, the type and quality of connection, and the frequency of interaction (Scott & Carrington, 2011). The method assumes that observations of interest—people, government agencies, nations, scientific journals—are not independent of one another, but are configured in a variety of relational structures, that these relationships drive the flow of information and norms, and that they constitute an important object of study. The method has been applied in a wide range of research contexts, including studies of professional development networks in school districts (Jennings, 2010), co-authorship in scholarly publications (Yan & Ding, 2012), interracial friendships in classrooms (Cappella, et al., 2017), and, increasingly, in studies of classroom discourse (González-Howard, 2019; Grunspan, et al., 2014; Wagner & González -Howard, 2018).

Although much of the education research using network analysis has taken advantage of the ease of data collection in digital contexts (de Laat, et al., 2007; Sharma & Tietjen, 2016; Shea, et al., 2010; Thorpe et al., 2007), there are a growing number of studies examining more traditional classroom interactions, as well (Wagner & González-Howard, 2018). These are often descriptive attempts to elucidate the patterns of student interaction (Mameli et al., 2015; Yoon, 2011), the roles that students play in discussion (González-Howard, 2019), changes in interactions over time (Ryu & Lombardi, 2015), and the effects of discourse patterns on student performance (Buchenroth-Martin et al., 2017). Wagner & González-Howard's (2018) review of network analysis for discourse research suggested that the method could be particularly well-applied in studies drawing on a dialogic and interactional perspective because network analysis "shifts the focus of analysis from the unit of speech itself to the discursive interactions between persons" (p. 376).

The method has also played a central role in the much larger-scale analysis of co-citation networks (Yan & Ding, 2012), including in this publication (Swatek, et al., 2022). Like the classroom discourse literature, co-citation analyses have worked to illuminate clusters of scholarly activity (e.g., Tight, 2008), the influence of particular publications or authors (e.g., Newman, 2011), and changing academic and scientific affiliations over time (e.g. Smith, 2019; Swatek et al., 2022). Swatek and colleagues (2022) used network analysis to identify distinct clusters of scholarship in the second language writing field, and to examine how changing patterns of citation in the *Journal of Second Language Writing* might signal shifts in the relationship between composition and second language research. In all cases, the analysis of co-citation works to illuminate the social structures that underlie or are created by the references from one scholarly text to another—what Bartholomae (1986) referred to as the "network of affiliations that constitute writing in the academy."

While not a prominent method in classroom and scholarship research to date, studies in a range of fields have used Exponential Random Graph Modeling (ERGM) to simultaneously examine the role of individual attributes and local social interactions in the formation of larger networks (e.g. Goodreau et al., 2009; Lusher et al., 2013; Stephens et al., 2016; Wang et al., 2009, 2013). In an early demonstration of the utility of ERGMs, Goodreau and colleagues (2009) used the method to disentangle the extent to which students in the Add Health study were likely to make friends with those of similar age and background, or whether they were more likely to make friends with those who were friends with their friends. What the authors found was that friendships were governed by a complex interaction of these effects in relation to student attributes and school composition. This capacity to simultaneously model multiple dependencies between observations is what makes the ERGM process particularly relevant to the current study of student writing, which was produced in a classroom context with all the complexities of overlapping social influences.

3.0 Current Study and Research Questions

The present study uses the methods and assumptions of social network analysis to examine a system of texts from a quantitative perspective. The setting for the study is a highly regarded college access program held annually on the Columbia University campus. Although the curriculum is typical of many first-year general education courses in college, the compression and intensity of the program offer an unusual opportunity to examine how the students take up and reorganize the course readings in their writing. From a network analysis perspective, the arrangement of the curriculum readings, the connections indexed in the writing prompts, and the students' written responses all function as interactions in an unfolding conversation. Student choices about which readings to bring together are considered to be part of a larger interactive context, framed and influenced by other textual interactions around them.

As an analytic method for this perspective on intertextual work, network analysis has some notable virtues. Borgatti & Lopez-Kidwell (2011) have argued that network analysis is both "emically meaningful and fully mathematical" (p. 49). That is, the method is capable of representing social interactions in ways that accord with how participants experience the activity, while also supporting the more distant perspectives of quantitative analysis. In network analysis, activity is mutually constitutive with the context, a feature that is deeply aligned with our experience of reading and writing, but which has not always been well-represented in our methodological treatments of it.

This particular study takes as its basic unit of analysis the reference from one text to another. It examines how referencing is configured by the curriculum sequence, by the writing prompts, and by the grouping of students. The following research questions guided this study:

1. How do the students in a pre-college seminar bring the curriculum texts together in their written work?
2. What programmatic features predict how students will bring the curriculum texts together in their writing? Specifically, what role do the prompts, student attributes, student groupings, and curriculum constraints play in the structure of the textual conversation?

4.0 Methods

4.1 Instructional Setting

Freedom and Citizenship (F&C) is an annual pre-college seminar held for rising seniors from high schools around New York City. The four-week, residential program is designed to support low-income and first-generation high school students as they prepare to apply for college. The present study is drawn from a mixed methods case study of F&C during the summer of 2017. Although the full case findings are reported elsewhere (Black, 2020), the contextual framing and interpretations for the present study draw on this larger inquiry into the program. All data collection activities were completed within established guidelines for human subjects research and overseen by New York University's Institutional Review Board.

4.1.1 The Reading Curriculum

F&C's curriculum is focused around daily reading, writing, and discussion of canonical readings in political philosophy—from Plato in the beginning of the course to James Baldwin at the end. The faculty and program administrators gather each year to make slight adjustments to the sequence or to the contextual materials students might use (in the form of brief biographical sketches or historical context provided on the program's website), but the structure and primary readings of the curriculum are the same from year to year. The first week is devoted to classical texts, primarily Plato's *The Trial and Death of Socrates*, Aristotle's *Politics*, and Thucydides's *History of the Peloponnesian War.* The second week turns to political Enlightenment texts, with Hobbes, Locke, and Rousseau in the first half of the week, and readings by Jefferson, Frederick Douglass, and Lincoln in the second. The third week turns to a much wider range of readings about the American experience, including pieces from W.E.B. Du Bois, Saum Song Bo, Sojourner Truth, John Dewey, Martin Luther King, Jr., Ella Baker, and James Baldwin.

The syllabus is designed to parallel the second year of texts in Columbia University's Core Curriculum, though the readings are excerpted for this younger group of students and scaffolded with a wide range of supports. The compression and focus of the curriculum offer a particularly rich context for examining the role of various aspects of the context on students' text referencing; the readings were chosen generally for their similar thematic concerns and, more specifically, for their resonances with each other. Socrates's questions about the obligations of citizenship in the first week are taken up again by the social contract theorists in the second week, and again in Dr. King's reflections on civil disobedience toward the end of the program. Jefferson's *Declaration of Independence* finds a direct response both in Frederick Douglass's "The Meaning of July Fourth for the Negro" and in *The Declaration of Sentiments* from the Seneca Falls Conference. While this curriculum structure is not unique, the intertextuality of the readings may be more salient for students because of the program's compression. I provide a full list of the major readings from the year of the study in Table 1.

Table 1

Schedule of Freedom and Citizenship Readings and Short Names Used in the Figures

Week (Day)	Assigned Reading	Figure Name(s)
1 (1)	Plato: *Euthyphro in The Trial and Death of Socrates*	Euthyphro
1 (2)	Plato: *Apology in The Trial and Death of Socrates*	Apology
1 (3)	Plato: *Crito, Phaedo, and "Death Scene" in The Trial and Death of Socrates*	Crito Phaedo Death Scene
1 (4)	Thucydides: "Pericles' Funeral Oration" and "Account of the Plague" in *History of the Peloponnesian War*	Funeral Plague
1 (5)	Aristotle: *Politics*	Aristotle
2 (6)	Thomas Hobbes: *Leviathan*	Hobbes
2 (7)	John Locke: Second Treatise of Government	Locke
2 (8)	Jean Jaques Rousseau: "On the Social Contract"	Rousseau
2 (9)	Thomas Jefferson: Declaration of Independence *The Constitution of the United States of America* Frederick Douglass: Narrative of the Life of an American Slave and "The Meaning of July Fourth for the Negro"	Jefferson Constitution Narrative July 4th
2 (10)	Abraham Lincoln: House Divided Speech, First and Second Inaugurals, Address at Gettysburg, Fragment on Slavery	House Divided Inaugurals Gettysburg Fragment
3 (11)	W.E.B. Du Bois: "Of Our Spiritual Strivings" and "Forethought" from The Souls of Black Folk Saum Song Bo: "A Chinese View of the Statue of Liberty" "The Declaration of Sentiments," Seneca Falls Conference Soujourner Truth: "Ain't I a Woman?" Jane Addams: "If Men Were Seeking the Franchise"	Du Bois Saum Song Bo Sentiments Truth Addams
3 (12)	Franklin D. Roosevelt: "Four Freedoms Speech" John Dewey: "The Meaning and Office of Liberalism" Milton Friedman: "Capitalism and Freedom"	Roosevelt Dewey Friedman

3 (13)	Martin Luther King, Jr.: "Letter from a Birmingham Jail" and "Beyond Vietnam" Ella Baker: "Bigger than a Hamburger"	Birmingham Vietnam Baker

4.1.2 Faculty-Led Seminar

In the summer of 2017, when this study was conducted, F&C served 45 students, with 15 enrolled in each of three seminars conducted on Columbia University's campus. The course is structured much like a freshman seminar in college, with a two-hour classroom discussion led by an experienced faculty member, followed by a writing section led by an undergraduate teaching assistant. Seminar conversation typically focuses on concepts and extensions from the previous night's readings, as well as thematic connections across the course texts. Beyond supporting students' reading and writing development and their resilience for challenging, college-level work, the program is particularly focused on helping students to develop a robust sense of civic identity. Conversations in the seminar therefore highlight critical perspectives on the rights and responsibilities of citizenship, the boundaries of individual freedom within democratic societies, and ethical reasoning about contemporary issues of governance.

4.1.3 Undergraduate Teaching Assistants

In addition to the morning seminar, the students had a full schedule of activities designed to support their reading and writing tasks, including an hour-long writing section instructed by an undergraduate teaching assistant (TA), an evening study hall with a second undergraduate mentor (different from the teaching assistant), and a range of enrichment activities related to the curriculum. The TAs were responsible for the bulk of the explicit writing instruction in the program and typically designed the writing prompts. The extent to which these prompts were guided by the faculty member varied. In one seminar, for instance, the TAs had complete autonomy and would frequently develop the prompts based on how the conversation in the seminar unfolded. In another seminar, the faculty member specified that the TAs use an open-ended prompt focused on close reading activities. In all cases, however, the prompt was generally considered to be optional and was often intended to guide students' reading of the course texts.

In 2017, students lived in the dorms during the week (returning home on the weekends) and were almost continually engaged in social activity with others in the program. The undergraduate mentors served as residential advisors for the students and also supported them in a nightly study hall session. The study hall varied widely in its structure and approach, with open-ended discussions of aspects of the readings, silent reading and writing work, or opportunities for the mentor to make suggestions or edits to students' papers. Typically, the bulk of students would complete their writing assignments for the next morning during the study hall. Because students were generally arranged in different groups for their study halls than they were for their TA section, they also had opportunities to hear what students from other seminars had discussed and how they intended to respond to the readings.

4.1.4 Writing Assignments

Daily Informal Response. The daily writing assignment, which was expected to be a page to two in length, took the form of an informal response paper—a relatively under-researched genre (Black, 2020, 2022), but one that is ubiquitous across a wide range of disciplines at the college level (Melzer, 2014; Nesi & Gardner, 2012). In general, students were expected to respond to one or more course texts, including at least one from that particular night's reading list, and had wide latitude to incorporate personal experiences in their responses. The faculty members and TAs described this assignment as meeting a variety of goals they had for students, including helping them to make connections across the texts, rehearse ideas they could bring into the seminar classroom, and generate ideas for the longer and more formal composition at the end of the program. Most importantly, perhaps, the faculty saw the informal response as a medium for connecting the disciplinary and often contextually distant content of the readings with the students' own social and political lives.

Final Paper. The final paper was similar in form and function to a term paper that might be assigned in the midterm of a college course, though it was generally shorter, ranging from three to five pages. The genre was explicitly argumentative and was intended to bring together lines of thinking from multiple points in the curriculum. Students were typically directed to begin thinking of a topic as they entered their final week in the program and then worked with their TAs to develop a thesis and organizational outline. The only other guidance for the paper was that it include at least one reading from the first week of the program and one from the second or third week. In practice, students often focused on thematic similarities across three readings as part of their final work.

4.2 Participants

Twenty-eight of the 45 students in the program volunteered to participate in the research. They were all rising seniors in a variety of high schools throughout New York City and qualified for the program by either meeting the federally-established threshold for low-income households, or by being first-generation college-goers. Students in the program generally had higher grades than the city average, had high college aspirations, and qualified for the program through an application and essay process. The sample was racially, ethnically, and linguistically diverse. Fifteen students identified as Black/African American, five as Asian, four as Latinx/Hispanic, and two as Afro-Caribbean/Dominican. One student in the sample identified as White/Caucasian, and one as Mixed. Seven of the participants were men, a similar proportion to that of men in the program as a whole that year. In terms of home language, five students spoke Spanish or a mix of Spanish and English, three spoke Bengali, two spoke Mande languages, one spoke Mandarin, and one Arabic. The remaining 15 students spoke only English with their families. Two of the students were classified as English learners at the time of this study and attended a school specifically for new arrivals. Seventeen of the students would be the first generation in their families to complete college.

4.3 Data

The analytic data for the current study are drawn primarily from the set of texts used and produced during this program. These included the 29 primary course texts (Table 1), 78 writing prompts produced by the TAs, and the 340 informal responses (approximately 400 words each) and 25 final papers (approximately 1,000 words each) written by the students. Three students did not submit final papers.

4.4 Measures

The main unit of analysis was the reference to a course reading, which I coded in both student papers and in the TA prompts. I also used attributes of student papers, TA prompts, and course readings, in both the descriptive and inferential stages of the analysis.

4.4.1 Student Papers

References. Each student paper was coded for frequency of reference to course readings. This coding process was low-inference in that it encompassed only references that were explicitly signaled through parenthetical citations or evidential statements (e.g. *Aristotle argues*, *Du Bois writes*). In some cases, student papers referenced the same course text multiple times, and I counted these as multiple references only when they referred to different parts of the reading.

Attributes. I also noted the following attributes of each student paper: text type (informal response or final paper), day and week in which the paper was written, and the student's gender, assigned seminar, assigned TA section, and undergraduate tutor.

4.4.2 Writing Prompts

References. Each writing prompt was similarly coded for the reading(s) to which it referred. In many cases, these decisions were straightforward, as when a prompt directed students to reflect on the meaning of a term in particular text, for instance. In other cases, TAs posed more open invitations for students to generate their own connections from a set of options or did not specify readings at all. In these cases, I relied on the strong expectation in the program that students would focus their responses on the readings from that day, and considered the prompt to refer implicitly to that day's readings. I differentiated between this kind of implicit reference and more directed references by coding all ties as *explicit* or *potential*. This distinction is an important one because it speaks to the role of the prompt in directing student attention to particular texts. We would generally expect *explicit* references to create more standardized clustering among texts, with student papers all focusing on the same readings. Conversely, we would expect prompts offering *potential* ties to create more distributed networks, with papers referencing a wider range of choices. I illustrate how these categories worked in relation to a set of example prompts in Table 2.

Attributes. In addition to the type of reference (*explicit* or *potential*) and the readings to which they referred, I drew on two other aspects of prompt classification schemes that seemed likely to shape how students referenced the course readings in their papers: the rhetorical function of the requested response (e.g., *Explanation, Argument*) and the object of inquiry (*Text-External or Text-Internal).* In practice, these categories were substantially overlapped with the number and type of reference in the prompt. Prompts referring to a single reading, for instance, typically requested an explanation of an idea in the text in the form of a close reading. Prompts that took as their objects of inquiry concepts or ideas outside the text often indexed argumentation and invited students to choose from a number of potential readings. I describe how these categories worked and the resulting coding scheme using the examples listed in Table 2, with a full summary of all coding decisions by TAs in Table 3.

I categorized as *Close Reading* any prompts that directed students to focus primarily on an aspect of a single text as the basis for an explanatory response. *Close Reading* prompts might specify a text or permit students to choose their own, but they were focused very clearly on material in a single text as a starting point for the day's writing. Prompt (1), for instance, requested a close reading from any one of the Day 2 texts but did not specify which, so I coded it with potential ties to both *Phaedo* and *Crito*. I categorized as *Comparison* any prompts that elicited explanations of ideas with references to more than one text though, again, the prompt might specify two texts explicitly or permit students a degree of choice. Prompt (2) requested a comparison between "Pericles' Funeral Oration" by Thucydides, and any one of the sections from Plato's *Trial and Death of Socrates*. I therefore coded it with potential ties to the Plato sections and an explicit tie to "Funeral Oration." In some cases, the TA offered multiple prompt options to students, as in prompt (3), where the TA posed both a close reading and a comparison prompt. In such cases I used the option that signaled the largest number of references—comparison, in this case. I labeled as *Thematic Argument* any prompt that directed students to consider conceptual matter from a perspective outside the text. Thematic Argument prompts typically referenced the course texts only implicitly and therefore tended to invite a greater number of options for students to reference in their responses, as is the case in prompt (4).

As I had for the student papers, I also noted which day and week the prompt was assigned, as well as the TA's gender and their assigned seminar.

Table 2

Selected Examples of Coding Decisions for TA prompts

	Prompt Content	Coding
(1)	Select 1-3 sentences from one of today's texts. Write a 1-page reflection that 1) includes an explanation of what these sentences mean and how they fit into the larger context of the work, and 2) explains why these sentences are important, both to you and/or the work as a whole. [Day 3 – Crito and Phaedo]	**Close Reading** Potential ties to *Crito* and *Phaedo*
(2)	Comparing Socrates and Pericles, what makes a death honorable? Keep in mind how they both talk about laws/the state and the roles of citizens.	**Comparison** Explicit tie to "Funeral Oration" Potential ties to *Euthyphro*, *Apology*, *Crito, Phaedo*
(3)	If you're looking for something to write about, consider Locke's idea of nature. What is the law of nature? How does one leave the state of nature? Feel free to compare to Hobbes. Alternatively, take up Professor Montás' invitation to write a dialogue. It must include Locke.	**Comparison** Explicit ties to both Locke and Hobbes
(4)	Where does liberty come from? [Day 12 for which Dewey, Roosevelt, and Friedman were assigned as readings]	**Thematic Argument** Potential ties to Dewey, Roosevelt, and Friedman

4.4.3 Course Readings

As with the student papers and writings prompts, I coded the course readings by the day and week on which they were assigned. Although there are innumerable other features and aspects of texts that one might use as categories, I limited this initial analysis to those most related to the structure of the curriculum as a whole, namely, the timing and order of assignments.

4.5 Analysis

4.5.1 Descriptive Analysis

In network analysis, connections between the nodes—in this case, references made in student papers or TA prompts to the course readings—are prepared in a matrix using either '1' and '0' to indicate presence or non-presence of a connection, or a weighted value to indicate the strength of the connection. I used a bipartite network structure (Borgatti, 2009; Dormann et al., 2008; Wang et al., 2009) as the basis for all analysis, with the prompts and student papers constituting the first mode of data, and the curriculum readings constituting the second.

For the descriptive portion of this study, I created a weighted matrix with the number of references to each reading representing the weight of the tie. In line with network analysis conventions, I coded each of the explicit references in writing prompts with a '1' and the potential ties proportionally, as a way of capturing how likely students might be to take up any one of the references. On a day when the students read three course texts, for instance, a general request for a close reading might be considered a tie of 1/3 weight for each of the three possible texts. I also attached the set of attributes to each of the elements of the matrix, including the student information, assigned seminar, TA section and tutoring group, type of prompt, and the day and week in which the texts were assigned.

I used a combination of the *igraph* (Csardi & Nepusz 2006), *bipartite* (Dormann et al., 2008), and *tnet* (Opsahl, 2009) packages in R to calculate common network statistics, and I used the force-directed algorithm (Fruchterman & Reingold, 1991) to generate the network projection, or map. Force direction produces a relatively intuitive layout; nodes with more ties are closer together but are otherwise evenly distributed in the plot.

I used the network projection to address the first question in this paper from a descriptive perspective, drawing on more qualitative interpretations of the plot to understand how text referencing functioned in the program as a whole. This interpretive approach is particularly valuable for exploring “new or yet unexplored forms of networks, integration patterns, and network practices” (Hollstein, 2011; p. 406). It also provided some initial findings to guide the main quantitative portion of the analysis.

4.5.2 Exponential Random Graph Modeling

The descriptive findings guided the second portion of analysis, which tested the contribution of various aspects of the context on the entire structure of connections using an Exponential Random Graph Model (ERGM). I used ERGM for bipartite networks in the *Statnet* suite of packages for R (Goodreau et al., 2008; Handcock et al., 2018; Hunter et al., 2008). ERGMs are stochastic models using a series of Markov chain Monte Carlo simulations to produce a distribution of network graphs from which the target network could conceivably be randomly drawn. These data can then be used to test whether features of the original network are more or less likely to explain the configuration of ties than we would expect given this simulated distribution (Lusher et al., 2013). Positive parameter estimates indicate that a term plays more of a role in referencing patterns than might be expected, given the size and structure of the network, while negative estimates indicate that the parameters play less of a role in tie formation than would be expected. Although the process of building a model using ERGM can be complex, the resulting estimates are similar to those of logistic regression, with significance assessed using a p-value.

At its simplest, the ERGM includes a term controlling for the size and density of the target network. Any other features necessary to describe the network are then added in an iterative fashion, and the resulting model is assessed for the extent to which it fits the data (Morris et al., 2008; Statnet Development Team, 2019). Because the ERGM requires an unweighted matrix as the basis for analysis, I converted any non-zero value in the program-wide matrix into a ‘1,’ indicating simply the presence of a tie between the prompt or paper and a given course reading. I also included the following features of the program context in the model:

- **Role of prompt type**. This parameter tested whether, as we would expect, prompts or papers coded as comparisons and thematic analyses were more likely to reference a larger number of course readings.
- **Role of text type**. This parameter tested the expectation that final papers and TA prompts were more likely to reference a larger number of texts than the informal responses.
- **Explicit references in writing prompts.** This parameter tests whether explicit prompt references to particular course readings are more likely to generate student references to the same texts.
- **Role of student groupings.** This parameter tested whether particular groupings of students—the seminars, TA sections, and tutoring groups into which students were assigned—were more likely to make references to a larger number of course readings.
- **Role of gender**. In part because there were relatively fewer young men in the program than young women, I also tested whether they were generally less likely to make references to the course readings.
- **Similarity in referencing decisions within groups**. This parameter tested for the phenomenon of homophily among students in the same TA sections and tutoring groups. It indicated whether students who were grouped together for different portions of the day were more likely to reference the *same* texts as each other.
- **Similarity in referencing among course readings assigned in the same week**. This parameter tested whether two readings were more likely to be referenced together if they were also assigned in the same week. It might be thought of as indicating how the structure and sequence of the curriculum shapes student referencing practices.
- **Interactions of prompt type and week**. These terms were included to test for whether the type of prompt had different effects on referencing in different timeframes of the curriculum—whether a thematic prompt in the third week, for example, was more likely to trigger references in student papers than a thematic prompt in the first or second week. This set of parameters might be thought of as the role of one instructional decision in relation to the sequence of the curriculum.
- **References within a single day.** This term represents the basic constraints on referencing within the relatively short informal response paper that students wrote each day. It tests whether the daily response papers were likely to make only between one and six references when responding to the texts assigned that same night. In this particular context, the term is probably best thought of as a feature of the opportunity structure of the curriculum, given the length of the assignment and number of texts assigned on any given day. Papers responding to comparisons of course texts on multiple days, such as final papers, and the course texts themselves, were not constrained by this parameter.
- **Program-wide closure**: This term was included in the model to test whether there was a general tendency in the network for student papers to bring the *same pairs* of course texts together in their responses.

- **Closure around pairs of high-interest course texts**. The high-interest pairs were readings that received particular attention either as part of comparative prompts or as part of the classroom conversations during the program. They were included here not because they represented all of the important textual connections in the curriculum, but rather as examples of pairs of texts that had explicit thematic connections but were not assigned on the same day. These terms tested whether, regardless of the network-wide tendency toward closure, there was a tendency for students to reference the same texts when there were strong semantic or thematic overlaps between the texts.

In line with recommendations from the extant research (Goodreau et al., 2008, 2009), I used four criteria to determine the optimal specification of the ERGM: the Akaike Information Criterion (AIC); the autocorrelation plots of the model parameters; the alignment of the simulated degree distribution with the original text network; and the balance statistics for the simulated model terms and the edgewise shared partners as provided in the statnet package (Handcock et al., 2018; Hunter et al., 2008). I also examined the Bayesian Information Criterion (BIC) as a way of assessing the parsimony of the model. I disqualified any models that produced autocorrelation plots with visible trends in the parameter simulations, or that produced model statistics significantly different from those of the network. If the autocorrelation plots were acceptable, I prioritized the improvement of AIC, using BIC to adjudicate between models that were otherwise similar according to the other criteria.

5.0 Results

5.1 Descriptive Findings

Figure 1 depicts the configuration of references to course texts across the entire program, with course readings represented as large circles, student responses represented as small circles, and prompts represented as small squares. The force-directed layout (Fruchterman & Reingold, 1991) brings together spatially texts that are more frequently referenced together, while pushing apart texts that are infrequently referenced together. The map therefore shows the way the prompts and papers cumulatively position the readings of the curriculum, with several noteworthy results.

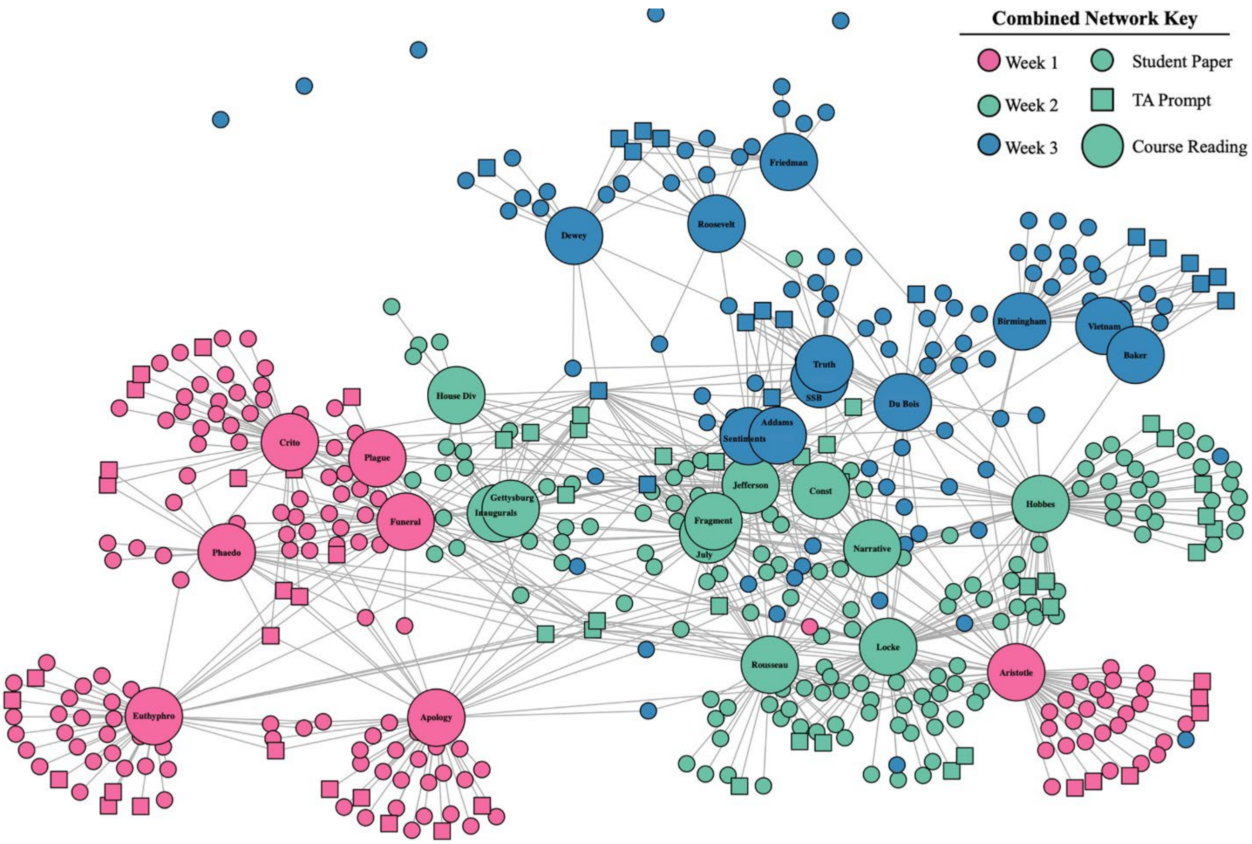
The most prominent feature of the network map is the strong clustering of references within week, as evident by the separation of colors. Week 1 course texts, with the exception of Aristotle, are particularly distant from the center of the map, which indicates that these early texts were less frequently referenced in the later papers. Also notable in terms of the chronological progression of the curriculum is the centrality of the Week 2 texts in connecting the readings of Week 1 with the readings of Week 3. Thematically and structurally, this finding is in line with what we would expect of a highly curated curriculum, but it is also notable given the heavy emphasis of political theory in the second week. Hobbes, Locke, and Rousseau, along with the Enlightenment texts of the early American Republic, form a core set of references for the program readings as a whole.

At the center of the projection, we also see some exceptions to the general clustering by week. The set of texts that students read at the end of the second week (Jefferson, Frederick Douglass, the *U.S. Constitution*, and Lincoln's fragment on slavery) and beginning of the third week (Du Bois, *Declaration of Sentiments*, Jane Addams, Sojourner Truth, and Saum Song Bo) are more closely connected than the rest of the map. These connections suggest that students and TAs were drawing on the foundational American documents of Week 2 to illuminate aspects of the drive for civil rights represented in the Week 3 texts.

There were also some notable clusters of texts which were situated in close proximity on the map but assigned on different weeks: Lincoln's speeches with Thucydides' *Funeral Oration* and *Plague* texts; Jefferson's *Declaration of Independence* with *The Declaration of Sentiments* from Seneca Falls; and Aristotle's *Politics* with four other texts dealing directly with the implications of slavery, namely Hobbes, Locke, Rousseau, and the *Narrative of the Life of Frederick Douglass*. In all three cases, the clusters represent important thematic and formal overlaps across the curriculum and are representative of the ways in which network analysis of referencing practices might capture aspects of semantic overlap in the curriculum. Whether these patterns were most related to the structure of opportunity for using the assigned readings, or to the TAs' writing prompts, or to students' interaction with peers as they wrote, are questions I address with the ERGM procedure.

Figure 1

Network of References Between Papers, Prompts, and Course Readings, Color-Coded by Week



5.2 Fitting the ERGM

Readers interested in the technical process of fitting the Exponential Random Graph Model can find those details here. Those who are more interested in the results may wish to skip to the section entitled Results of the Final ERGM.

The model was fit in 10 iterations, with increasingly complex terms included in each subsequent model. The first three models tested only the effects of the paper, prompt, and individual-level attributes, which by default are estimated directly using maximum pseudo likelihood estimation (Morris et al., 2008; Statnet Development Team, 2019). Beginning in Model 4, with the inclusion of more complex dependencies between the terms, all models were fit using Markov Chain Monte Carlo maximum likelihood estimation. Parameters that were non-significant and that did not improve the fit of the model were typically removed in the subsequent model.

5.2.1 Models 1-3

The baseline model included only an estimate for the overall density of the network. As is often the case, this estimate was negative because it was tested against an assumption of 50% network density. Model 2 included a set of main effects for paper attributes (including prompts) and course text attributes. Of the prompt and paper attributes, prompt type, week of the course, and text type all had positive, significant estimates. Papers responding to comparison prompts (b = .66, $p < .001$) and thematic analysis prompts (b =.31, $p < .05$) were both significantly more likely to feature references than papers responding to close readings. Final papers ($b = .6$, $p < .001$) and prompts ($b = .86$, $p < .001$) were both more likely to have references than daily papers. And papers written in Week 2 ($b = .256$, $p < .05$) and Week 3 ($b = .47$, $p < .001$) were both more likely to have ties than those written in Week 1, though the magnitude of the coefficient was much larger for the third week than for the second. Among the TAs, only the estimate for Samantha's section was significant, possibly driven by her own expansive approach to referencing in the prompts. The gender marker for male students and TAs was non-significant and was removed. For course texts, those from the third week of the program were significantly less likely to be referenced in comparison to those from the first week ($b = -.38$, $p < .0001$). The number of explicit TA references attached to particular course texts was positive and significant ($b = .15$, $p < .001$). In Model 3, I added interaction terms to test whether there were differences by week in the significance of the prompt types. These were all non-significant at the $p = .05$ level and were removed for the remainder of the models.

5.2.2 Models 4-7

Beginning in Model 4, I tested sets of homophily effects. Model 4 introduced a constraint on the number of references any given paper or prompt might make if it was written on the same day as the course texts it references (degree range by day homophily). This structural feature was the single largest effect ($b = 7.37$, $p < .001$) across all models, and its inclusion substantially improved the overall fit of the model with respect to AIC/BIC and degree distribution. This term represents the tendency for student papers to make between one and six references when responding to the night's texts. In this particular context, the term is probably best thought of as a feature of the opportunity structure of the curriculum, arising from both the kind of paper students were writing—short responses which could not realistically contain many references—in conjunction with the number of texts assigned as reading for any given day. Papers responding to comparisons of course texts on multiple days, such as final papers, and the course texts themselves, were not subject to this particular constraint.

Model 5 added a homophily term for TA, testing the extent to which papers and prompts were more likely to reference the same course text if they were in the same TA section. This term was non-significant, both in this model and in other slightly alternative specifications. By contrast, in Model 6, the term for homophily by tutor was significant ($b = .11$, $p < .001$), indicating that papers written by students in the same tutoring section were significantly more likely to have a tie to the same course text.

In Model 7, I tested homophily terms for course texts, specifically whether course texts were more likely to be connected through student papers or prompts to other texts from the same week. I tested separate terms by week in order to account for the differences that were evident in the combined network projection (Figure 3.11), using Week 3 as the reference. Both terms were positive and significant, indicating that Week 1 texts ($b = .76$, $p < .001$) and Week 2 texts ($b = .47$, $p < .001$) were more likely to be connected to other texts from the same week than were those from Week 3. The inclusion of these terms also improved BIC and AIC substantially though the autocorrelation plots were unacceptable. Inclusion of more than one homophily term in the model led to convergence problems, so I kept homophily by week rather than the term for tutoring.

5.2.3 Models 8-10

In Models 8 through 10, I continued to test structural effects in an attempt to optimize AIC. In Model 8, I added a term for the likelihood of dyads of prompts and papers sharing connections to course texts, a term that in a bipartite network serves as a measure of closure. This term was negative but non-significant in the two models in which it was included. However, because its inclusion improved AIC and was of theoretical interest, I chose to test it with various combinations of other terms. I also retained the term for TA Samantha because its inclusion improved AIC and BIC despite its overall non-significance.

In Model 9, I added a set of dyad-specific effects on closure based on the combined network map (Figure 3) and on the qualitative data collection described elsewhere (Black, 2020). These five terms represented pairs of texts that were located in different areas of the map and that received particular attention in the classroom conversations. The "Closure for Funeral-Gettysburg," for instance, tested whether having one paper reference both "Pericles' Funeral Oration" and *The Gettysburg Address* increased the likelihood of another paper also referencing both texts. All five terms were positive and significant with $b > 1.3$ and $p < .01$, indicating that the texts in each pair were significantly more likely to be referenced together than would be expected given the size of the network. The inclusion of these terms improved BIC and AIC but produced unacceptable autocorrelation plots and simulation of model terms.

In Model 10, I tested an alternative to the network-wide closure term in the hopes of producing better autocorrelation plots. Instead, I included a parameter estimating the degrees for papers and prompts, with a decay rate that corrects for the common problem of model degeneracy. This model was a substantial improvement over the others. From Model 1 to Model 10, AIC improved from 6080 to 3371, and BIC from 6087 to 3505. All autocorrelation plots for Model 10 were acceptable (Figure A-1 in the appendix), and the main terms included in the model were well within the recommended range for fit (Tables A-2 and A-3). Alignment of the degree distribution (Figure A-3) and structure of the simulated model were excellent (Figure A-

4). I therefore settled on Model 10, with coefficients reported in Table 3 and in the main text, below, where I describe the solution in greater detail.

5.3 Results of the Final ERGM

For the significant parameters remaining in the final Model 10, I report the log-odds estimates in parentheses but interpret the exponentiated coefficients, per Kruse et al. (2016). Of the main effects, text type was most important, with odds of references approximately three times higher for prompts (b = 1.2, p < .001) and final papers (b = 1.1, p < .001) than for the daily papers. Prompts and papers written in the second (b = 0.8, p < .001) and third weeks (b = 1.2, p < .01) of the program also had higher rates of referencing than those from the first week, with Week 3 papers having odds about 3.3 times higher than those written in week one. Finally, as expected, papers responding to both comparison prompts (b = 1.1, p < .001) and thematic analyses (b = 0.9, p < .001) had odds of referencing course readings between two and three times higher than those responding to close readings. The number of explicit prompt references was small but significant (b =0.1, p < 001). Each explicit reference to a course text in a prompt meant the odds of another reference to the same course text were about 1.1 times higher.

Among the structural features, the constraint on the number of references any given paper might make to texts from the same day was statistically significant (b = 7.4, p < .001), accounting for the single largest portion of network configuration. The two homophily terms for course texts by week indicated that the odds of Week 1 texts (b = 0.9, p < .001) being connected with other Week 1 texts were about 2.6 times higher than for being connected with Week 3 texts. Odds of Week 2 texts being connected within week (b = 0.5, p < .001) were about 1.7 times higher than for being connected with those in the third week.

Tendency toward closure in the network was highly clustered around sets of texts, as indicated by the estimates for the five pairs of course texts, all of which were positive and significant in explaining the overall likelihood of ties in this network, with estimates of b > 1.4 and p < .001 across the board. The pairs were between 4 and 12 times as likely to feature multiple shared references as would be expected given the size of the network as a whole. These local closure effects were in striking contrast to the non-significance of network-wide closure, a finding which I address in greater detail in the Discussion section.

Table 3

Estimates and Definitions for Final Model 10, with Coefficients Reported in Log-Odds

	Estimates			Definitions
	b	SE	sig	
Edges/Density	-7.131	(0.32)	***	Controls for the number of references in the whole network
TA: Samantha	0.202	(0.12)		Controls for number of references in prompts or papers from Samantha's section
Prompt: Compare	1.137	(0.18)	***	Likelihood of comparison or thematic papers having a tie in comparison to close reading papers
Prompt: Theme	0.869	(0.19)	***	
Week 2 Paper/Prompt	0.843	(0.20)	***	Likelihood of papers and prompts in weeks two and three having a tie, in comparison with week one papers and prompts
Week 3 Paper/Prompt	1.187	(0.22)	***	
Text Type: Prompt	1.201	(0.15)	***	Likelihood of prompts and final papers having a tie in comparison with daily papers
Text Type: Final Paper	1.085	(0.18)	***	
Explicit TA References	0.120	(0.02)	**	Likelihood of additional ties given each explicit TA reference
Degree Range by Day	6.307	(0.34)	***	Constraint on number of references a daily paper may make to the night's texts
Homophily by Week - 1	0.940	(0.05)	***	Likelihood that any two course texts that are co-referenced in a paper or prompt were assigned the same week in the program
Homophily by Week - 2	0.543	(0.04)	***	
Weighted Degrees	3.112	(0.56)	***	Overall estimate of ties for papers and prompts, with a decay rate to stabilize the model
Funeral-Gettysburg	1.693	(0.51)	***	Closure around particular pairs of course texts – likelihood of these two texts being referenced by the same paper or prompt
Aristotle-Narrative	1.660	(0.45)	***	
Locke-Rousseau	1.381	(0.30)	***	
Jefferson-Sentiments	2.511	(0.40)	***	
Constitution-Du Bois	2.349	(0.49)	***	
BIC	3505			Information criteria indicating overall fit of the model to the observed network in comparison with edges only model of BIC= 6087 and AIC=6080
AIC	3371			

Note: $p < .001$: *** $p < .01$: ** $p < .05$: * $p < .1$ +

6.0 Discussion

This study used network analysis to understand the dynamics of text referencing in a rigorous college access seminar. In particular, it sought to examine the extent to which the writing prompt, student groupings, and curriculum structure contributed to students' overall conversation with the curriculum. It revealed, broadly, that although the prompts played a significant role in students' textual conversations with the course materials, they were just one of many features of the context that helped to explain the structure of references. The structure of the curriculum over time and the underlying similarities in the themes of course texts also played significant roles in how students engaged in the core academic practice of text referencing. I discuss here some of the interpretive complexities posed by these findings, as well as some of the implications of using network analysis to support improvements in curriculum design and writing instruction.

6.1 Implications for Adolescent Writing Instruction

6.1.1 Writing Instruction and Writing Curriculum

Positive and significant coefficients for comparison prompts and thematic analyses indicated that the students' referencing choices, as we might expect, were at least partially explained by the types of prompts their instructors posed. But the non-significant coefficient on homophily by TA (Model 5) indicated that students were not particularly likely to reference the *same* course texts as other students in their TA sections. This may have been because the TAs often gave students wide latitude in which texts to examine, but it may also have been the case that other aspects of the program context were simply more salient for students as they were writing. The positive, significant coefficient for explicit references also suggests, for instance, that a more general, program-wide focus on particular texts played a role in which texts students chose to address. One potential mechanism for these program-wide patterns may have been students' interactions with other students outside the seminar, where they would have learned about other TA assignments. In this case, then, the students' uptake of the prompts would have been mediated in part by their interactions with other students.

These findings also provide some empirical support for the notion that writing prompts may play very different roles vis-à-vis the curriculum and student writing. Certainly in this situated classroom context, the prompt seems to have a less expansive role than it might in direct assessments, where the prompt may be the sole representative of the social context for the writing. Although the F&C prompts did have a role to play in how students used texts, they were really just one of many textual interactions in the environment, and not even the most important.

The overarching guidelines for the writing assignments played significant roles as well, as indicated by the magnitude of the coefficients on final papers and the degree range-by-day constraint. The latter was the single largest effect across all models, and it represented the strong tendency for daily papers to refer to texts from that particular night's readings. The prompts seemed to generally reinforce this existing day-by-day structure, even when they requested that students make comparisons or take a more thematic perspective. This finding emphasizes the role of the prompt as an interaction in an already existing system of texts.

6.1.2 Reading Curriculum

Two aspects of the ERGM analysis point to the role of the designed reading curriculum in how students referenced texts: homophily of course texts by week, and the findings on closure around particular pairs of texts. The strong clustering of course texts by week mirrors the chronological and thematic arrangement of the curriculum—with classical texts in the first week, Enlightenment texts in the second, and more contemporary American reflections on issues of democracy in the third. It is not clear whether the clustering by week is a function of this thematic similarity or whether prompts and papers are simply more likely to co-reference texts that are assigned in close proximity to each other.

The pattern of findings around closure in this network also hints at the importance of semantic and thematic overlap of the course texts. Although the coefficient for network-wide closure (Models 7 and 8) indicated that student papers typically did not share references to course texts, the coefficients on the five pairs of course texts indicated that closure was, in fact, a significant factor locally. In other words, while student papers were generally unlikely to reference the same pairs of course texts, they were significantly more likely to do so when there were substantial semantic or thematic connections between those texts.

What is notable about these particular texts is that four of the five pairs were assigned in different weeks, so their incidence of co-reference was otherwise unaccounted for in the homophily by week terms. Three of these pairs were also referenced by TAs in their prompts. This pattern of inter-week referencing was not especially common in the prompts, but these few examples hint at the promising role prompts might play as brokers between disparate parts of the curriculum, drawing together otherwise separate portions of the course into closer dialogue. This attention in both student papers and TA prompts to underlying similarities between course texts, regardless of when they were assigned, is also precisely what we would hope for with a highly curated curriculum. This analysis was not focused on assessing the writing as a kind of outcome of the course, but one course-level or program-level outcome that might really matter for instructors is evidence of the course texts being drawn together in student writing in a wide variety of ways—precisely what network analysis is able to show.

What the method cannot disentangle, is whether these patterns are the result of underlying semantic similarity in the texts or the result of shared student attention to these matters—because the relationship between course texts in this bipartite network is mutually constitutive with the relationships between papers and prompts. Proximity between texts is created through the social activity of the classroom, through the social recognition and interpretation of the latent intertextuality of the course texts (Bloome & Egan-Robertson, 1993). Other network approaches might be better able to separate matters of semantic overlap from matters of shared attention, a possibility I discuss more fully in the section on limitations and next steps. But this interconnection between social activity and intertextuality is probably best thought of here as an affordance rather than a limitation, as aligned as it is with our theories about how writing practice works.

6.1.3 Progression of Time

This analysis did not fully account for the longitudinal quality of the data, but I did account for some aspects of time in the week-by-week effects for student papers and course texts (in Model 6 and before). These indicated that papers in Week 3 were much more likely to reference course texts than were those in Week 1, even when controlling for the kind of prompts TAs made during those timeframes; the inverse was true for the course texts. Texts assigned in the first week of the program were most likely to be referenced in student papers and prompts, while texts assigned in third week were far less likely to be referenced.

The coefficients on homophily of course texts by week also showed the role of time, with texts from Week 1 and Week 2 significantly more likely to be co-referenced with other texts from their same week than those from Week 3. By contrast, Week 3 texts were more likely than either of the first two weeks to be connected to texts from other weeks, likely a feature of the opportunity structure, as well as the presence of the much longer final paper in week three. Both of these patterns are more or less to be expected given the increasing range of texts available for student use as the course progresses; students have more texts to work with later but more time to reference those assigned earlier.

What is less clear is whether this pattern might also be a function of other aspects of course progression—students learning they were expected to reference more texts, for instance, or differences in the number of texts assigned in each week. Week 1 featured only seven short texts, four from Plato's *Trial and Death of Socrates*, while Weeks 2 and 3 each featured eleven texts from mostly different authors. I discuss the potential benefits of longitudinal approaches to disentangle some of these issues in the section on next steps.

Most importantly, perhaps, these findings highlight the fundamental challenge of disentangling the effects of time from those of instructional design, which is naturally crafted within the constraints and chronology of a course. The F&C curriculum is designed with the progression of learners in mind, moving from relatively few, highly readable texts per day, to more challenging texts the following week, to clusters of three or four texts focused on similar ideas in the third week. The curriculum is also, notably, chronological in terms of the historical timeline, which is a feature of coursework that is so ubiquitous as to be almost beyond notice. But any student papers that take up issues of historical progression may be more likely to reference earlier papers from the course as they address the later ones. It is not just the opportunity to do so that directs student attention to the earlier texts; they form a kind of baseline for student understanding of the course material.

Similarly, the interaction coefficients tested in Model 3 were non-significant in part because the types of prompts were not evenly distributed across the weeks; close readings dominated in the first week, comparisons in the second, and thematic analyses in the third. This approach to prompt writing was not accidental but was itself a response to the type and number of course texts assigned in each week. Another important implication of this analysis, and one that has not been studied to my knowledge, is the important role of the prompt in relation to the passage of time in the course—the extent to which the prompt moderates or reinforces the chronological progression of the curriculum.

6.2 Methodological Limitations and Next Steps

The data for this study are limited in some ways that make it inadvisable to generalize findings beyond this particular context without confirmatory testing. First and perhaps most importantly, the completeness of the information in the bounded network is well below the 90% that is typically recommended for complete network analysis. Within the study sample, I have more than 90% of each student's textual network and 100% of the course texts and prompts. But because only 28 of the 45 program students participated in the research, I have only 472 of 737 possible texts/nodes in my network, which represents about 64% of the entire program texts during the year of this study. Despite these limitations, this study offers an unusual opportunity to examine network structure in a new context and with data that are relatively difficult to come by. Given the potential to learn something new about how the method might work in this context, I've chosen to proceed with the complete network analysis, with the important caveat that any analytic inferences should not be applied outside of this sample without confirmatory work.

There were also some aspects of these data that might be better modeled using a different approach, such as a longitudinal, multilevel, semantic mapping approach. A longitudinal perspective would allow us to understand the extent to which the effects we observe in the model are related to chronological interaction of referencing, rather than the way that course texts were assigned. The fact that there were differences in referencing by week, as well as clustering of course texts by week, suggests that there are at least some features of the longitudinal quality of these data that require more attention. These effects are unlikely to be straightforward, given the pattern of coefficients discussed earlier, and are complexities that only a longitudinal modeling process could sort out.

Second, there were aspects of the student social relations that were not fully captured in the attributes of TA and tutoring sections. For instance, many of the students attended the same high school or roomed together during the program, and these social groupings may have been more salient in which texts they chose to reference than either their assigned TA or tutoring section. A more robust way of handling these complex, overlapping social groups would be to treat the relationship of students to each other as a unimodal network, with multiple ties possible between the same students, and to model the text relations and student relations in a multilevel context. One benefit of this approach would be that it allows for additional, perhaps more realistic, sources of social variation to play a role in the model.

Finally, it seems clear from the findings on closure around specific pairs of course texts that the semantic overlap between texts, otherwise accounted for only in the structure of the curriculum, played a crucial role in the likelihood of students referencing the same pairs of texts. Another approach that allows for simultaneous modeling of semantic relations and social relations, such as epistemic network analysis (Shaffer, 2017), might support a more robust exploration of student text referencing.

7.0 Conclusion

Despite these limitations, however, this study offers several potentially fruitful avenues for using social network analysis to understand student writing as an interaction among the many other texts in a classroom. As other studies have noted (Grunspan et al., 2014; Wagner & González-Howard, 2018), network visualizations offer an efficient perspective of class-level or program-level curriculum use, and therefore have uniquely pragmatic applications for instructors and program administrators. The method not only provides a snapshot of how students use and connect texts in their writing—how the curriculum is taken up, reorganized, and connected over time—but also how the social configurations of students might guide these choices.

In short, the findings of the social network analysis point to the complexity of this writing context, a complexity which is accounted for in our theories of writing but not particularly well accounted for in our methods for studying it. One of the affordances of network analysis, then, is that it offers a fuller contextual account of how writing gets done because it can model the way the object of analysis—textual interaction—becomes a part of the ongoing context for other texts in the same system. It makes literal the metaphor of conversation that has become so dominant in our conceptions of reading and writing in academic contexts.

Most importantly, perhaps, the goals and assumptions of network analysis are deeply consonant with our theories about textual practice. To the extent that participation in academic life is fundamentally conversational, network analysis is a valuable tool for understanding the structure of that activity and the ways we might open up the conversation to newcomers.

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Appendix

Table A-1

ERGM Estimates – Models 1-3

	Model 1			Model 2			Model 3		
	est	SE	sig	est	SE	sig	est	SE	sig
Edges/Density	-2.691	(0.04)	***	-3.948	(0.14)	***	-3.798	(0.12)	***
Gender: Male				-0.012	(0.09)				
TA: Ryan				0.126	(0.15)				
TA: Tessa				0.264	(0.14)	+			
TA: Helena				0.215	(0.13)				
TA: Samantha				0.373	(0.13)	**	0.183	(0.10)	+
TA: Carlos				0.220	(0.13)	+			
TA: Blair									
Prompt: Close Read									
Prompt: Compare				0.656	(0.10)	***	1.264	(0.32)	***
Prompt: Theme				0.307	(0.13)	*	0.595	(0.26)	*
Week 1 Paper									
Week 2 Paper				0.256	(0.10)	*	-0.056	(1.07)	
Week 3 Paper				0.466	(0.13)	***	0.160	(0.26)	
Text Type: Prompt				0.856	(0.08)	***	0.859	(0.08)	***
Text Type: Final Paper				0.600	(0.16)	***	0.627	(0.16)	***
Text Type: Daily Paper									
Week 1 Texts									
Week 2 Texts				-0.087	(0.08)		-0.087	(0.08)	
Week 3 Texts				-0.383	(0.12)	***	-0.384	(0.12)	***
Explicit TA References				0.146	(0.01)	***	0.146	(0.01)	***
Week 1 - Close Reading									
Week 2 - Close Reading							0.397	(1.08)	
Week 3 - Close Reading							0.188	(0.32)	
Week 1 - Comparison							-0.671	(0.37)	+
Week 2 - Comparison							-0.319	(1.05)	
Week 3 - Comparison							NA	0.00	
Week 1 - Theme							NA	0.00	
Week 2 - Theme							0.056	(1.06)	
Week 3 - Theme							NA	0.00	
BIC		**6087**			**5731**			**5759**	
AIC		**6080**			**5611**			**5617**	
Degree GOF		N/A			N/A			N/A	
Model Terms GOF		N/A			N/A			N/A	
Edgewise Shared Partner GOF		N/A			N/A			N/A	
Autocorrelation Plots		N/A			N/A			N/A	

Note: *p* < .001: *** *p* < .01: ** *p* < .05: * *p* < .1 +

Table A-1 (continued)

Models 4-6 (interactions replaced with structural terms)

	Model 4			Model 5			Model 6		
	est	**SE**	**sig**	**est**	**SE**	**sig**	**est**	**SE**	**sig**
Edges/Density	-5.741	(0.20)	***	-5.830	(0.21)	***	-6.036	(0.21)	***
Gender: Male									
TA: Ryan									
TA: Tessa									
TA: Helena									
TA: Samantha									
TA: Carlos									
TA: Blair									
Prompt: Close Read									
Prompt: Compare	1.438	(0.16)	***	1.430	(0.16)	***	1.406	(0.16)	***
Prompt: Theme	0.723	(0.18)	***	0.709	(0.18)	***	0.690	(0.18)	***
Week 1 Paper									
Week 2 Paper	0.725	(0.18)	***	0.733	(0.18)	***	0.741	(0.18)	***
Week 3 Paper	1.132	(0.19)	***	1.143	(0.20)	***	1.143	(0.19)	***
Text Type: Prompt	1.611	(0.11)	***	1.611	(0.11)	***	2.085	(0.15)	***
Text Type: Final Paper	1.470	(0.18)	***	1.476	(0.18)	***	1.528	(0.18)	***
Text Type: Daily Paper									
Week 1 Texts									
Week 2 Texts	0.183	(0.12)		0.179	(0.11)		0.165	(0.11)	
Week 3 Texts	-0.446	(0.17)	**	-0.420	(0.16)	**	-0.448	(0.15)	**
Explicit TA References	0.123	(0.02)	***	0.101	(0.03)	***	0.075	(0.02)	***
Degree Range by Day	7.371	(0.34)	***	7.342	(0.32)	***	7.465	(0.35)	***
Homophily by TA				0.028	(0.03)				
Homophily by Tutor							0.113	(0.02)	***
Homophily by Week - 1									
Homophily by Week - 2									
Degree for Papers									
Dyad Shared Partners									
Funeral-Gettysburg									
Aristotle-Narrative									
Locke-Rousseau									
Jefferson-Sentiments									
Constitution-Du Bois									
BIC		**3738**			**3741**			**3734**	
AIC		**3656**			**3652**			**3645**	
Degree GOF		acceptable			low peak, high at 7			good except at 7	
Model Terms GOF		acceptable			acceptable			acceptable	
Edgewise Shared Partner GOF		acceptable			acceptable			acceptable	
Autocorrelation Plots		problematic			problematic			minor problems	

Note: $p < .001$: *** $p < .01$: ** $p < .05$: * $p < .1$ +

Table A-1 (continued)

Models 7-8

	Model 7			Model 8		
	est	SE	sig	est	SE	sig
Edges/Density	-5.741	(0.16)	***	-5.395	(0.26)	***
Gender: Male						
TA: Ryan						
TA: Tessa						
TA: Helena						
TA: Samantha				0.131	(0.08)	
TA: Carlos						
TA: Blair						
Prompt: Close Read						
Prompt: Compare	0.928	(0.15)	***	0.892	(0.15)	***
Prompt: Theme	0.579	(0.17)	***	0.565	(0.16)	***
Week 1 Paper						
Week 2 Paper	0.646	(0.16)	***	0.609	(0.16)	**
Week 3 Paper	1.019	(0.17)	***	0.983	(0.17)	***
Text Type: Prompt	0.932	(0.10)	***	0.894	(0.11)	***
Text Type: Final Paper	0.872	(0.15)	***	0.828	(0.14)	***
Text Type: Daily Paper						
Week 1 Texts						
Week 2 Texts						
Week 3 Texts						
Explicit TA References	0.128	(0.02)	***	0.209	(0.05)	***
Degree Range by Day	7.379	(0.33)	***	7.478	(0.33)	***
Homophily by TA						
Homophily by Tutor						
Homophily by Week - 1	0.782	(0.04)	***	0.755	(0.04)	***
Homophily by Week - 2	0.493	(0.03)	***	0.469	(0.03)	***
Degree for Papers						
Dyad Shared Partners				-0.019	(0.01)	+
Funeral-Gettysburg						
Aristotle-Narrative						
Locke-Rousseau						
Jefferson-Sentiments						
Constitution-Du Bois						
BIC	3530			3534		
AIC	3448			3437		
Degree GOF	very high			high		
Model Terms GOF	acceptable			problematic on one		
Edgewise Shared Partner GOF	acceptable			good		
Autocorrelation Plots	unacceptable			unacceptable		

Note: $p < .001$: *** $p < .01$: ** $p < .05$: * $p < .1$ +

Table A-1 (continued)

Models 9-10

	Model 9			Model 10		
	est	SE	sig	est	SE	sig
Edges/Density	-5.396	(0.21)	***	-6.544	(0.27)	***
Gender: Male						
TA: Ryan						
TA: Tessa						
TA: Helena						
TA: Samantha	0.135	(0.09)		0.202	(0.12)	
TA: Carlos						
TA: Blair						
Prompt: Close Read						
Prompt: Compare	0.801	(0.13)	***	1.137	(0.18)	***
Prompt: Theme	0.590	(0.15)	***	0.869	(0.19)	***
Week 1 Paper						
Week 2 Paper	0.578	(0.16)	***	0.843	(0.20)	***
Week 3 Paper	0.902	(0.17)	***	1.187	(0.22)	***
Text Type: Prompt	0.851	(0.11)	***	1.201	(0.15)	***
Text Type: Final Paper	0.808	(0.14)	***	1.085	(0.18)	***
Text Type: Daily Paper						
Week 1 Texts						
Week 2 Texts						
Week 3 Texts						
Explicit TA References	0.145	(0.04)	**	0.120	(0.02)	***
Degree Range by Day	7.376	(0.34)	***	6.307	(0.34)	***
Homophily by TA						
Homophily by Tutor						
Homophily by Week - 1	0.835	(0.04)	***	0.940	(0.05)	***
Homophily by Week - 2	0.461	(0.03)	***	0.543	(0.04)	***
Degree for Papers				3.112	(0.56)	***
Dyad Shared Partners	-0.006	(0.01)				
Funeral-Gettysburg	1.366	(0.46)	**	1.693	(0.51)	***
Aristotle-Narrative	1.400	(0.40)	***	1.660	(0.45)	***
Locke-Rousseau	1.233	(0.30)	***	1.381	(0.30)	***
Jefferson-Sentiments	2.363	(0.40)	***	2.511	(0.40)	***
Constitution-Du Bois	2.181	(0.51)	***	2.349	(0.49)	***
BIC	3515			3505		
AIC	3381			3371		
Degree GOF	high			slightly high		
Model Terms GOF	unacceptable			acceptable		
Edgewise Shared Partner GOF	slightly high			slightly high		
Autocorrelation Plots	unacceptable			acceptable		

Note: $p < .001$: *** $p < .01$: ** $p < .05$: * $p < .1$ +

Figure A-1

Autocorrelations Plots for Model 10 – Terms 1-4

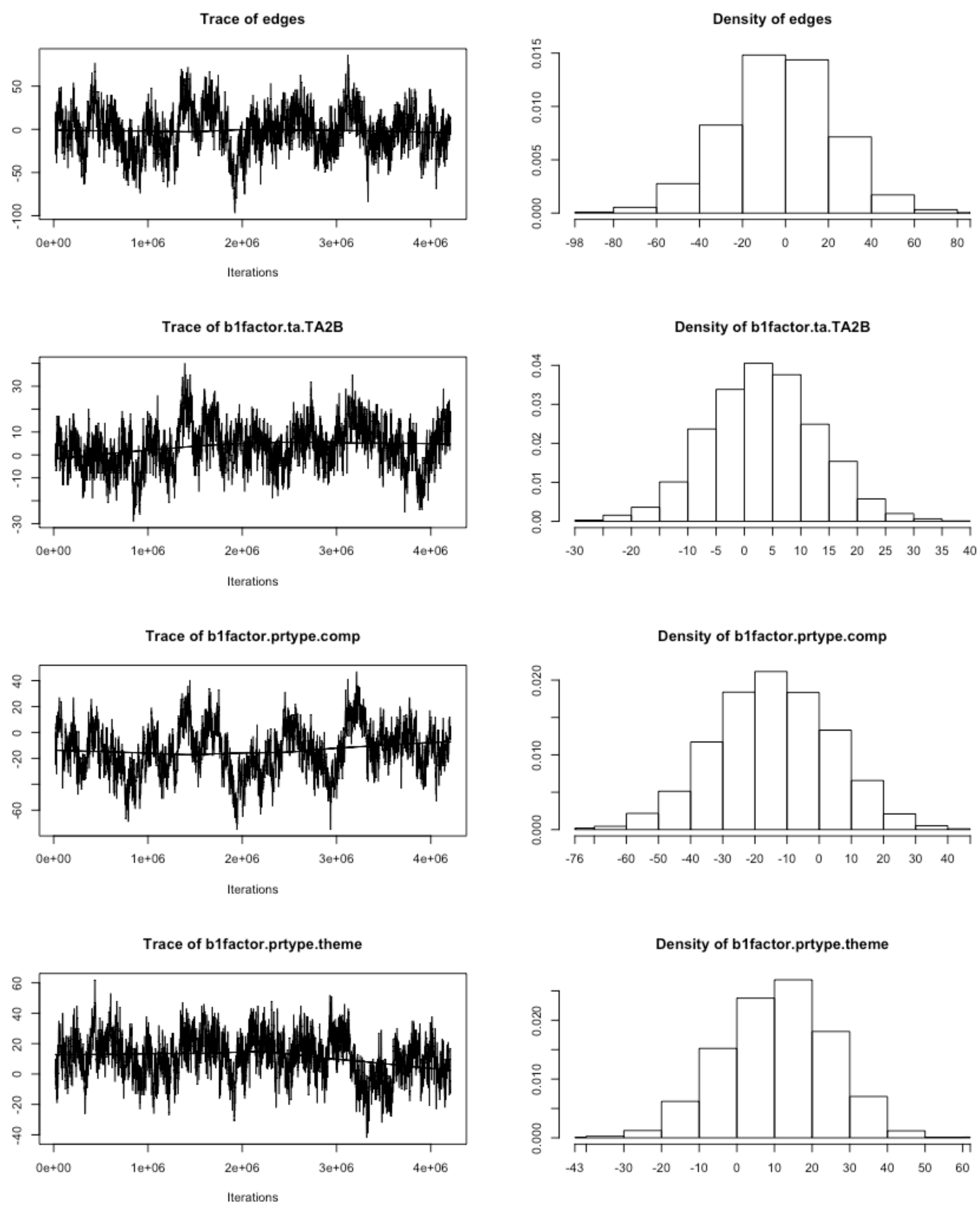


Figure A-1 (continued)

Autocorrelations Plots for Model 10 – Terms 5-9

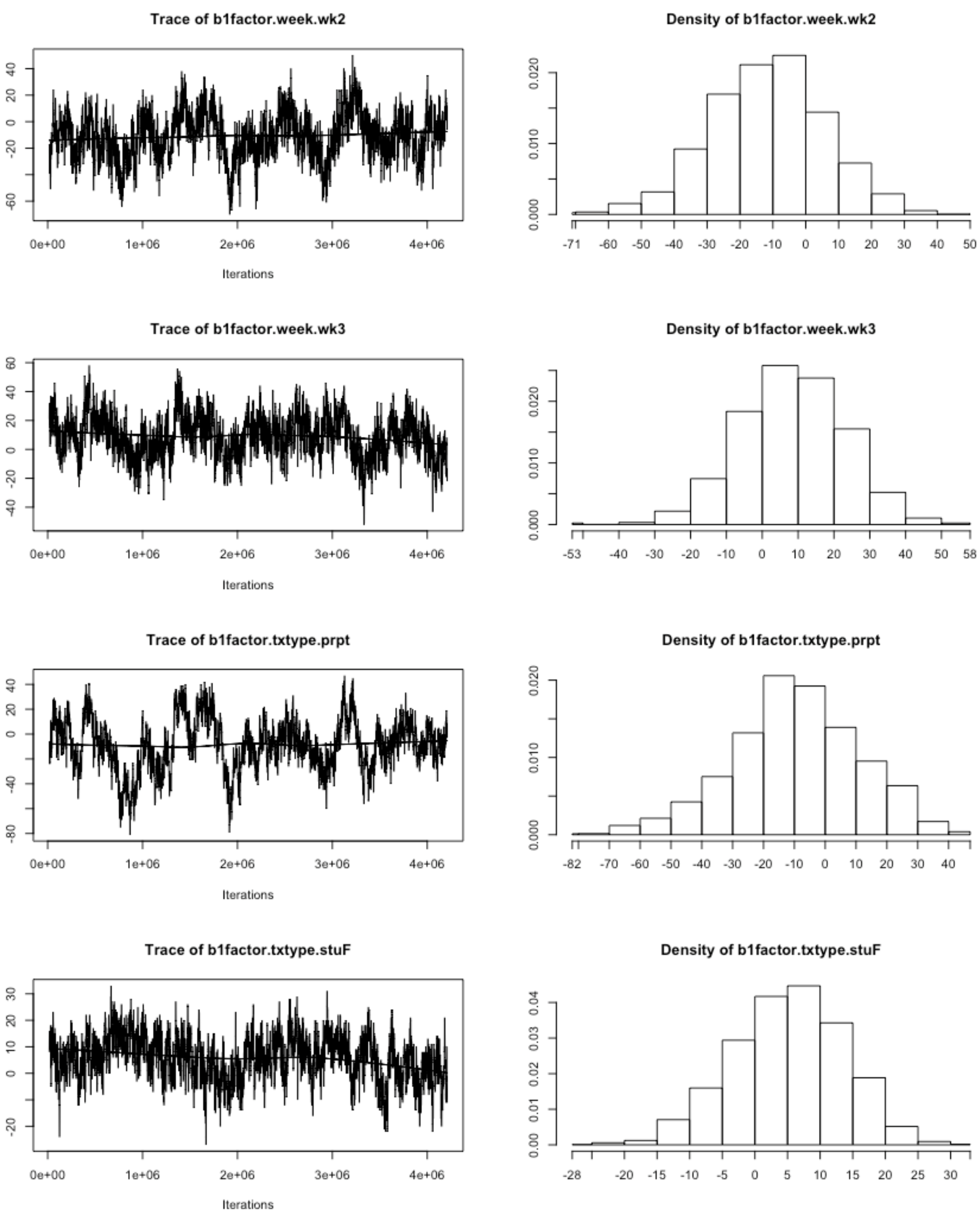


Figure A-1 (continued)

Autocorrelations Plots for Model 10 – Terms 10-13

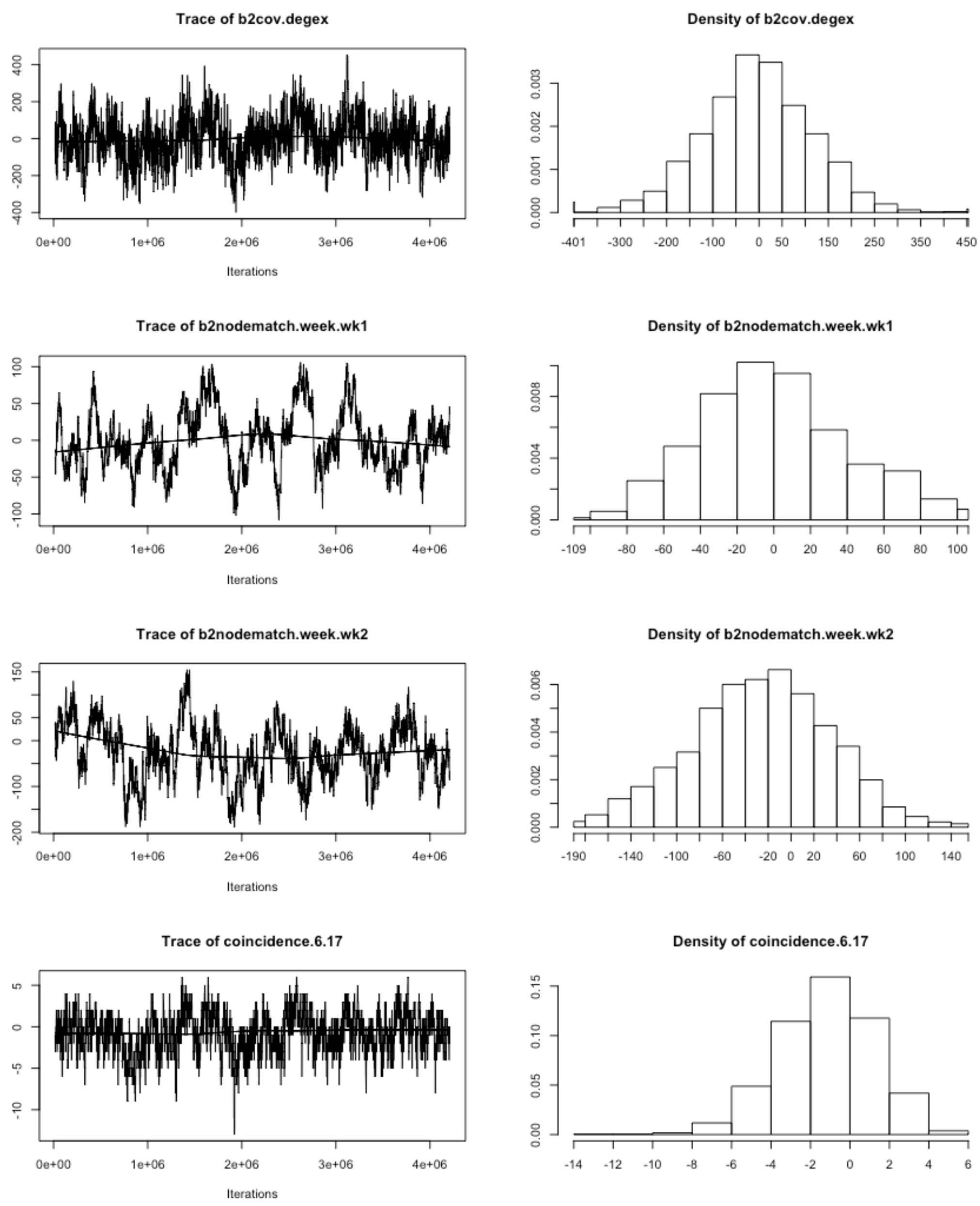


Figure A-1 (continued)

Autocorrelations Plots for Model 10 – Terms 14-17

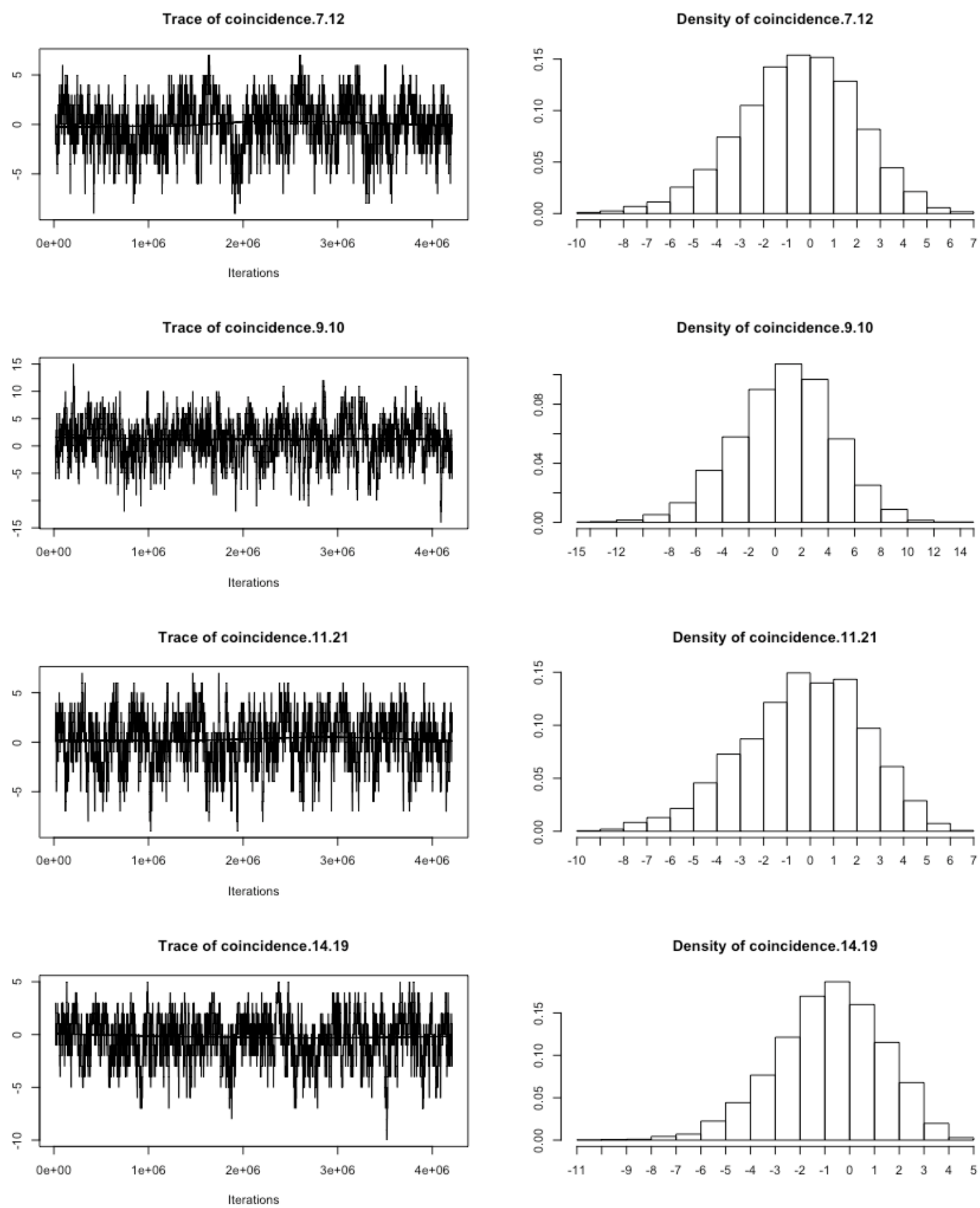


Figure A-1 (continued)

Autocorrelations Plots for Model 10 – Terms 18-19

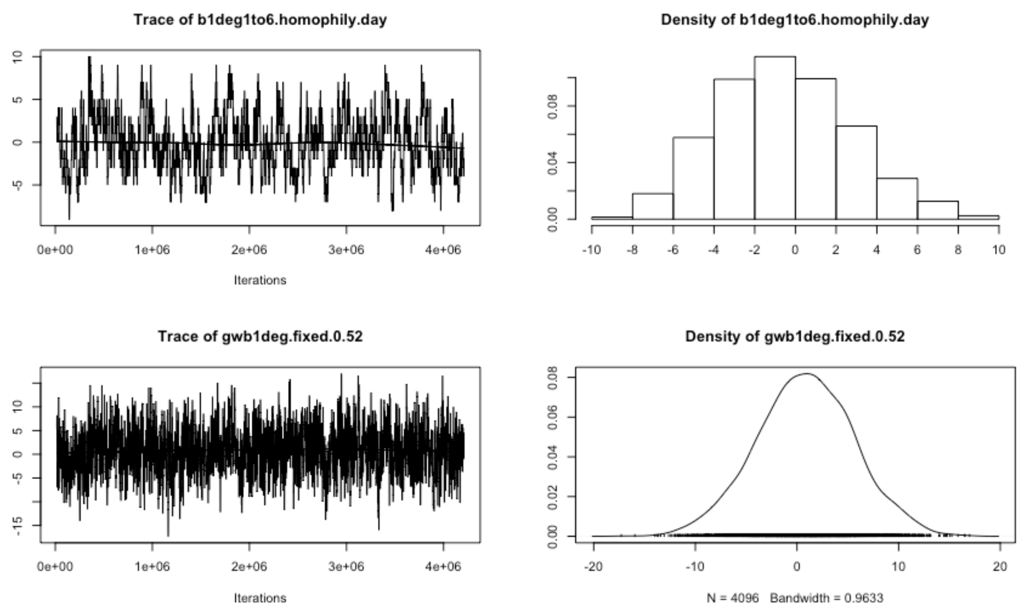


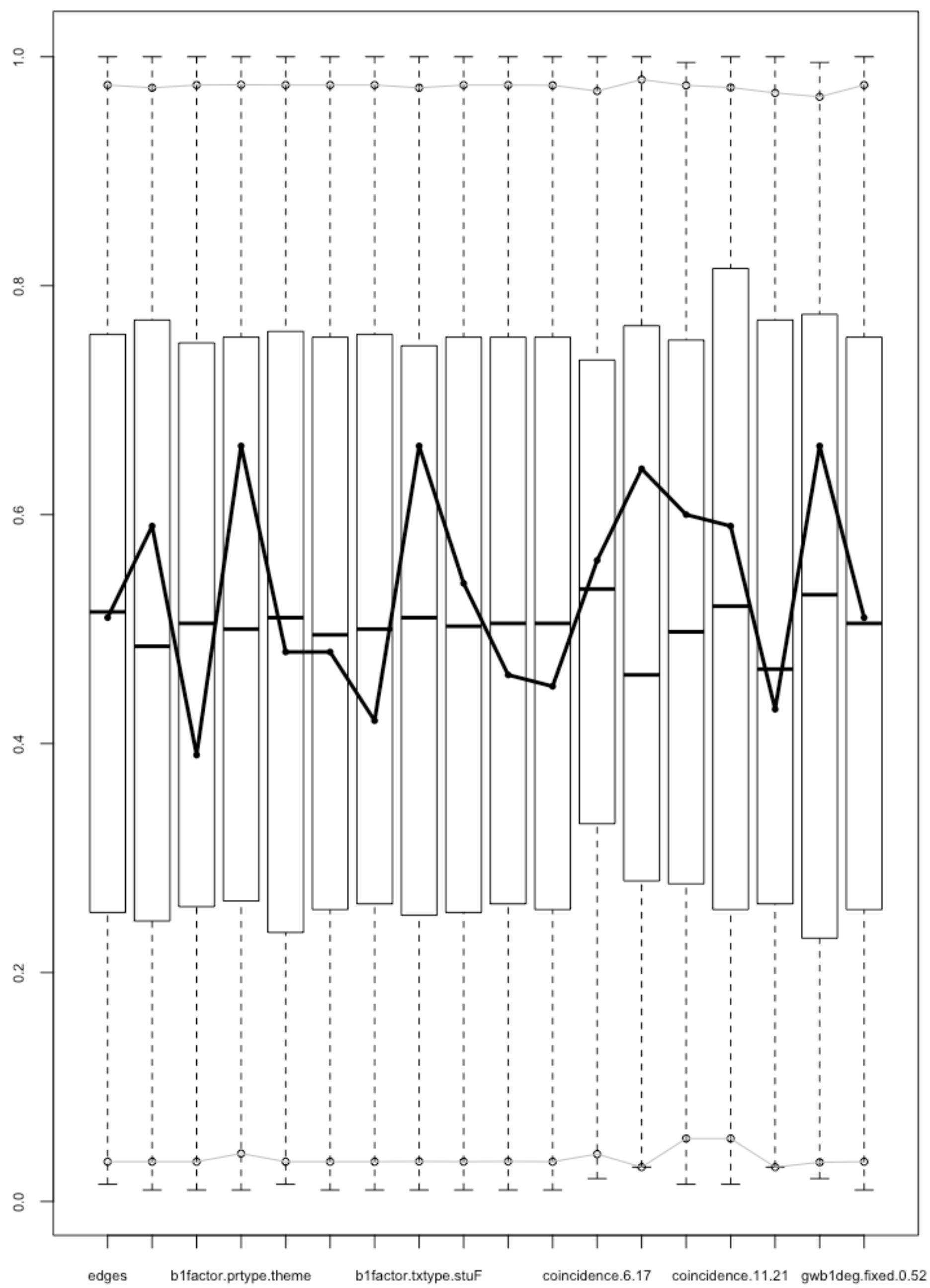
Table A-2

Goodness-of-Fit Statistics for Terms in Model 10

	Observed Network	Simulated Network			
		Min	Mean	Max	p-value
Edges	816	757	822.41	890	0.84
TA: Samantha	140	115	141.36	166	0.9
Prompt: Comparison	264	222	258.79	302	0.78
Prompt: Thematic Analysis	253	222	257.34	298	0.74
Week 2 Papers/Prompts	331	299	331.18	379	0.96
Week 3 Papers/Prompts	284	238	282.76	322	0.96
Text Type: Prompt	245	197	241.73	299	0.84
Text Type: Final Paper	76	52	79.14	102	0.82
Number of explicit TA references	3478	3200	3490.08	3800	0.92
Degree Homophily by Day	407	399	407.17	414	0.96
Homophily by Week – Week 1	179	78	175.32	280	0.92
Homophily by Week – Week 2	312	171	300.8	447	0.9
Closure at Funeral-Gettysburg	6	2	5.95	12	1
Closure at Aristotle-Narrative	8	3	8.42	15	1
Closure at Locke-Rousseau	23	16	24.08	34	1
Closure at Jefferson-Sentiments	8	3	7.85	14	1
Closure at Constitution-Du Bois	5	1	4.46	10	0.86
Geometric Weighted Degrees	532.5159	518.1214	532.5104	548.0572	0.98

Figure A-2

Goodness-of-Fit Plot for Terms in Model 10



Model Terms

Figure A-3

Comparison of Degree Distribution in Observed Network and Simulated Network in Model 10

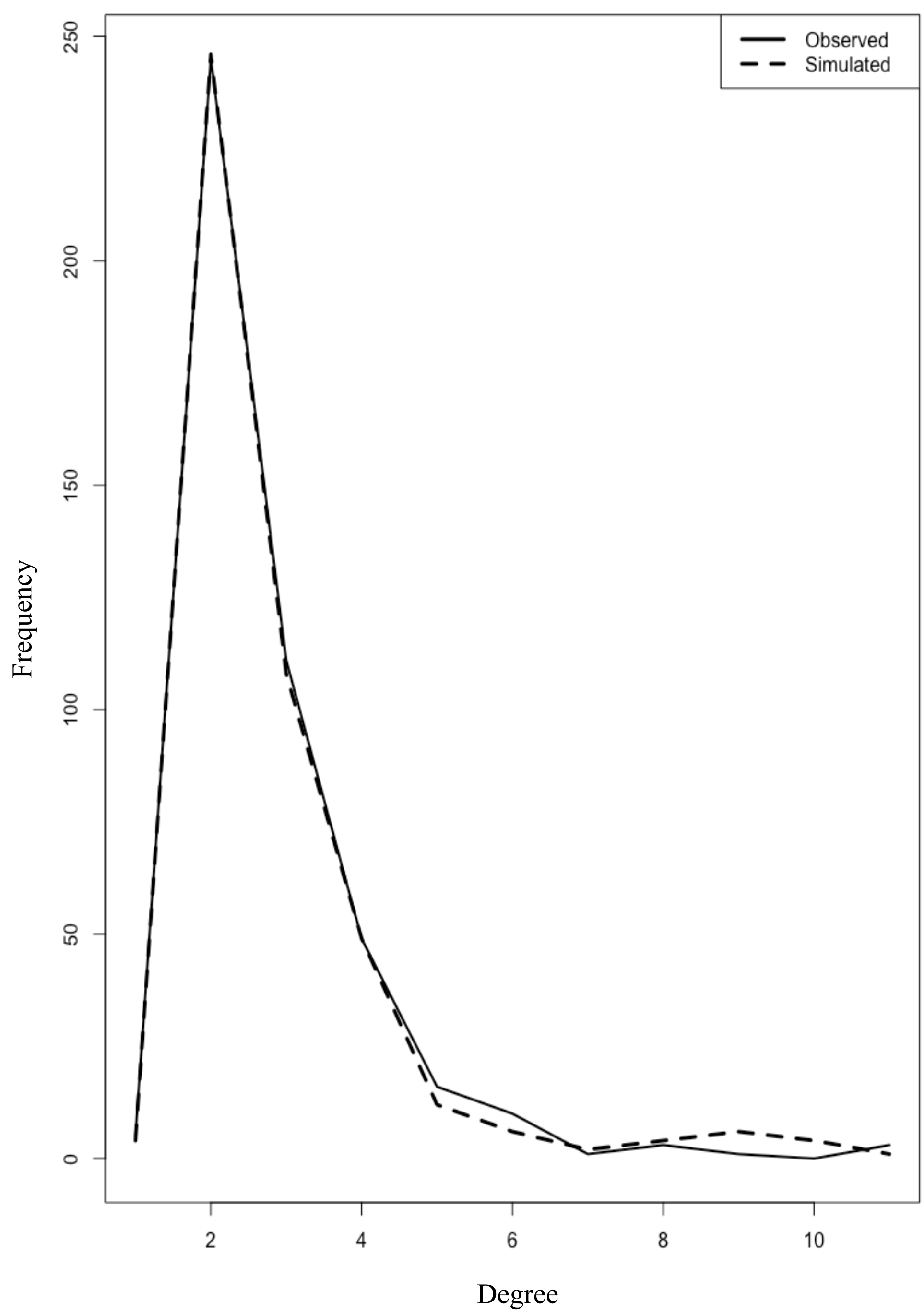


Figure A-4

Observed Network Plot (above) and Model 10 Simulated Plot (below)