Modeling the Dissemination of Misinformation Through Discourse Dynamics

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Abstract

With increased availability of information in modern societies, individuals are often faced with complex decisions regarding how to integrate and judge the veracity of available information. Generally, these issues have been approached using computational techniques to *detect* and *reduce* the spread of information across social media. However, few researchers have examined theoretically-grounded characteristics of misinformation. The purpose of this chapter is to examine this phenomenon through the lens of discourse processing theories, which emphasize interactions among features of the discourse, the reader, and the context. We describe a proof of concept on how dynamical systems modeling combined with computational linguistics has strong potential to reveal underlying characteristics of the spread of misinformation. Additionally, we discuss potential directions for future research,

as well as implications for interventions to help students accurately process information in the modern digital age. We call for research using a combination of computational linguistics, telemetry, and dynamical systems analytics in order to better understand the temporal organization of text and the spread of misinformation.

CHAPTER 9

MODELING THE DISSEMINATION OF MISINFORMATION THROUGH DISCOURSE DYNAMICS

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ABSTRACT

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Misinformation and Fake News in Education, pages 159–185

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The prevalence of online news and social media (e.g., emails, blogs, tweets, the 24-hour news cycle) in our modern society has dramatically increased individuals' access to information. One consequence of this cultural shift is that sources of information are widely varied in their quality and veracity; thus, individuals are often faced with complex decisions regarding how to evaluate and integrate these sources. Unfortunately, this task does not come easily to all. An estimated 17% of adults in the United States are illiterate (nces.ed.gov/surveys/piaac/results/summary.aspx), and the majority of students graduating from high school are ill-prepared to comprehend, integrate, and evaluate information from complex texts (NAEP, 2015; OECD, 2013). Thus, an important question facing both educators and researchers is how to train individuals to understand, learn from, and critically evaluate text content in the Internet-age (Braasch, Wiley, Geaeser, & Brodwinska, 2012).

One response to this issue has been an increase in research examining how individuals process information that is presented to them across multiple texts or documents (Braasch, Bråten, & McCrudden, 2018; Goldman, 2004; Goldman et al., 2016). This research is motivated by the widespread availability of texts in modern, technology-driven societies, as well as the abundance of daily tasks (e.g., dietary and medical decisions, evaluation of political views) that rely on processing and learning from multiple documents. Like single text comprehension, the process of comprehending multiple documents requires individuals to make connections between information contained within texts. The difference for multi-document comprehension lies in the additional task of generating links across the various documents. Given that individuals often lack sufficient knowledge and skills to understand single texts, their problems are compounded when they are faced with understanding and integrating multiple documents.

To further complicate and demonstrate the urgency of this issue, there has been a dramatic increase in the use of social media by political groups and individuals to sway public opinion through the dissemination of misinformation, rumors, and propaganda. For instance, botnets (i.e., networks of computers that have been programmed to automatically perform specific tasks) have been extensively relied on to spread misinformation across social media sites (Agarwal, Al-khateeb, Galeano, & Goolsby, 2017; Woolley, 2016). A recent report estimated that 8.5% of Twitter and 7% of Facebook accounts (over 50 million accounts) are fake (Lokot & Diakopoulos, 2016). Further, many of these fake accounts are run by highly sophisticated bots that try to mimic human behaviors, which makes their detection quite challenging.

Researchers have generally addressed this issue through the development of computational techniques to *detect* and *reduce* the spread of misinformation (e.g., Bajaj, Kavidayal, Srivastava, Akhtar, & Kumaraguru, 2016; Qazvinian, Rosengren, Radey, & Mei, 2011). For example, a common approach involves the identification of keywords within texts (e.g., headlines, texts, tweets) to develop algorithms that can detect misinformation. Although several of these approaches have been successful, a primary obstacle to their implementation is that the production of fake news content is consistently evolving in response to the development of these detection tools. Thus, individuals cannot simply be taught to identify misinformation based on specific features (e.g., linguistic properties) of texts, headlines, or social media accounts. Instead, it is important that researchers identify the specific cognitive processes that underlie the *evaluation* and *uptake* of material in fake news sources so that individuals can adapt with these evolving production strategies. This points to a significant gap in the field that remains to be addressed. Namely, few researchers have examined the factors involved in the spread and uptake of misinformation, such as the linguistic content of misinformation and the dynamics of the cognitive processes and strategies that are employed to detect false information in texts.

The purpose of this chapter is to examine these processes through the lens of discourse processing and dynamical systems theories, which together emphasize complex interactions among properties of discourse, readers, and contexts. We first provide an overview of these theories along with a review of state-of-the-art methods for automated text analysis. Next, we propose an integration and extension of these fields that accounts for how complex phenomena arise and unfold over time. In particular, we draw on theory and methodologies from dynamical systems theory to develop a proof of concept on how the spread and processing of misinformation might be modeled. Finally, we discuss potential directions for future research, as well as implications for educational interventions to help students accurately process information in the modern digital age.

Theoretical Accounts of Discourse Processing

Theoretical models of discourse describe comprehension as the process of interpreting and extracting meaningful information from text and discourse and linking that information to related knowledge in long-term memory. This process of connecting discourse information to prior knowledge allows readers to construct a *mental model* of the concepts in the text (Graesser, Singer, & Trabasso, 1994; Kintsch, 1988, 1998). A mental model consists of a network of propositions that reflect explicit information from the text, along with any generated inferences that establish how this content is interconnected and related to prior knowledge (Kintsch, 1988, 1998; Zwaan & Radvansky, 1998).

Readers generate inferences to establish how text constituents (e.g., propositions) are related to one another (Graesser et al., 1994; Kintsch, 1988). For example, bridging inferences establish how two elements of a text are semantically connected, whereas knowledge-based inferences involve the use of prior knowledge to elaborate on text content (McNamara & Magliano, 2009a, 2009b). In turn, the relations established by the reader can be at relatively shallow levels (e.g., overlap between words) or deeper semantic levels (e.g., causal, spatial-temporal; Wolfe, Magliano, & Larsen, 2005). These processes support the construction of a *coherent* mental model (McNamara & Magliano, 2009b).

Prior domain knowledge can help to facilitate text comprehension, and particularly the process of generating inferences. Readers who have more knowledge about the topic of a text are able to process the information more quickly, remember more of the information, understand the information at a deeper level, and more effectively ignore irrelevant information (e.g., Alexander, Kulikowich, & Schulzse, 1994; Bransford & Johnson, 1972; Chiesi, Spilich, & Voss, 1979; Haenggi & Perfetti, 1994; McNamara & Kintsch, 1996; McNamara & McDaniel, 2004). When readers have limited prior knowledge of the topic, the construction of a coherent mental model can be hindered. Moreover, when the text is challenging (e.g., difficult vocabulary, complex syntax, low cohesion), the negative effects of knowledge gaps can be exacerbated (McNamara, O'Reilly, Best, & Ozuru, 2006).

Although there are ways of altering a text itself to make it more understandable (e.g., increasing cohesion, providing greater links to the world), in the real world students are faced with an abundance of challenging texts (McNamara, 2013). Texts with *cohesion gaps* are particularly challenging for students with lower knowledge of the domain (McNamara & Kintsch, 1996). Cohesion gaps occur when there are few repeated words and concepts and few cues (e.g., connectives) to specify the relations between ideas. These cues are often found lacking from individual texts, but there are even fewer cohesive cues to specify relations between multiple texts (Goldman et al., 2012; see also Stadtler, Scharrer, Brummernhenrich, & Bromme, 2013).

Research indicates that skilled readers more effectively tackle low cohesion texts primarily because they are more likely to use comprehension strategies. These strategies, such as comprehension monitoring, paraphrasing, and generating predictive, bridging, and elaborative inferences help students to connect information across a text (Magliano, Trabasso, & Graesser, 1999; McNamara & McDaniel, 2004; O'Reilly & McNamara, 2007a, 2007b). Prompting students to *self-explain* a text, that is, instructing them to explain the text to themselves as they read, has been shown to increase the use of comprehension strategies and, consequently, improve reading comprehension (Chi, de Leeuw, Chiu, & LaVancher, 1994). Further evidence indicates that students can be taught to use comprehension strategies (Brown, 1982; Palincsar & Brown, 1984). Similarly, the quality of students' self-explanations improves with comprehension strategy instruction and practice.

Comprehension of Multiple Documents

With the Internet now serving as a primary source of learning and information for individuals, there has been a dramatic increase in research on the factors that influence the comprehension of multiple documents (Braasch et al., 2018). The majority of this research has focused on how individuals critically evaluate the sources of information that are presented to them across texts. This is a particularly important issue, as a wealth of false information is now available across a wide variety of sources on the Internet. Source evaluation relies on a complex set of processes and skills that require the reader to process features of the sources (e.g., author, publication venue) to make informed decisions about the quality and accuracy of information in a given text or set of texts (Bråten, Stadtler, & Salmerón, 2017). Research has shown that actively attending to source information is crucial to the successful integration of information across documents (Brand-Gruwel, Wopereis, & Walraven, 2009; Britt, Rouet, & Braasch, 2013; Lawless, Goldman, Gomez, Manning, & Braasch, 2012; Perfetti, Rouet, & Britt, 1999; Rouet, 2006; Rouet & Britt, 2011). However, in the absence of domain expertise, individuals do not readily engage in these source evaluation processes (Wineburg, 1991), and the effects of source evaluation training have been mixed (e.g., Wiley et al., 2009).

Automated Analyses of Text and Discourse

One way that researchers have attempted to examine the text comprehension processes is to identify and model the linguistic properties of texts that influence comprehension. For instance, words that are more frequent in the English language tend to be more familiar to readers and are, therefore, processed more quickly and deeply by readers (Beck, McKeown, & Kucan, 2002; Haberlandt & Graesser, 1985; Perfetti, 2007). Automated measures of these linguistic properties provide researchers with the means to model these properties within texts and examine whether and how they influence comprehension processes. Researchers frequently rely on natural language processing (NLP) techniques to provide computational analyses of various aspects of language as they relate to particular tasks. NLP tools measure a variety of linguistic features that are important for understanding and producing text, including coherence, syntactic complexity, lexical diversity, and semantic similarity. One common approach is to analyze the incidence of individual words, or *n*-grams (i.e., groups of words where *n* refers to the number of *grams* included in the group; Jarvis & Crossley, 2012). These word and n-gram calculations allow researchers to examine the explicit content of a text. A different approach with a stronger potential to generalize involves the calculation of the linguistic features of the words and sentences in a text (McNamara, Allen, Crossley, Dascalu, & Perret, 2017). We have developed several NLP tools such as Coh-Metrix, which can be used to extract linguistic features of text across multiple levels.

Using NLP, we can derive features of students' constructed responses that are indicative of the cognitive processes that occur during learning (Graesser & McNamara, 2011). Over the past 2 decades, there have been substantial advances in the application of NLP techniques to support analyses of constructed responses (Landauer, McNamara, Dennis, & Kintsch, 2007; Shermis, Burstein, Higgins, & Zechner, 2010). These advances have been in the context of computer-based assessments of think-alouds and self-explanations (Gilliam, Magliano, Millis, Levenstein, & Boonthum, 2007; Magliano et al., 2011), grading of essays (Attali & Burstein, 2006; Burstein, 2003; Burstein, Marcu, & Knight, 2003; Landauer, Laham, & Foltz, 2003; Shermis et al., 2010), grading of short answer questions (Leacock & Chodorow, 2003), and intelligent tutoring systems and trainers that require students to produce responses during interactive conversations (McNamara, Levinstein, & Boonthum, 2004).

There exist a number of automated systems and tutors that incorporate a variety of NLP tools and algorithms to assess constructed responses, and to make inferences about student comprehension, learning, and problem solving. For example, Magliano and colleagues have developed Reading Strategy Assessment Tool (RSAT; Magliano et al., 2011). RSAT involves having students produce open-ended responses to prompts intended to engender a think aloud or answer specific questions designed to tap into specific levels of comprehension. RSAT uses rudimentary (word-based) computer algorithms to analyze responses for evidence of comprehension processes, in particular paraphrasing, bridging inferences, and elaborative inferences. The algorithms exhibit construct (correlate with human coding of the protocols), convergent (correlate with independent measures of comprehension proficiency) and predictive (correlated with experimenter generated measures of comprehension) validity. McNamara and colleagues have

developed the Interactive Strategy Training for Active Reading and Thinking (iSTART; McNamara et al., 2004; Snow, Jacovina, Jackson, & McNamara, 2016) that uses a variety of NLP indices to identify and evaluate the quality of comprehension strategies in student-generated self-explanations. These algorithms also provide feedback to help students develop these strategies and produce higher quality self-explanations.

Indeed, computational linguistic techniques can serve as a powerful methodology for modeling individual differences and specific processes in which students engage (Rus, McCarthy, Graesser, & McNamara, 2009). To better understand the relations between linguistics and cognitive processes, we can first consider the notion that there are multiple linguistic features of texts that students comprehend and produce. These features impact the quality and readability of a given text as a function of the prior knowledge and skills of a given learner (Graesser & McNamara, 2011).

There are a multitude of linguistic features and dimensions to characterize text and discourse. Nonetheless, one heuristic is the consideration of two broad categories: surface-level and discourse-level features. *Surface-level* features relate to the characteristics of the words and sentences. Variations in these features can alter the style of the text, and influence its readability and perceived sophistication. For example, the frequency that a word occurs in English is linked to the *familiarity* of that word, as well as how quickly it is processed and how strongly it is linked to rich bodies of knowledge (Beck et al., 2002; Haberlandt & Graesser, 1985; Perfetti, 2007). Thus, texts that contain more frequent words will typically be easier than texts with less frequent words.

Discourse-level features go beyond the individual words and sentences, and reflect aspects of the mental model such as the degree of narrativity in the text and the strength of the relations (i.e., cohesion) between ideas across the text (Graesser & McNamara, 2011). These features influence the ease at which the text can be understood and recalled, even when controlling for variance associated with students' familiarity of the topic and the difficulty of the words (Haberlandt & Graesser, 1985).

Given the differential effects of surface- and discourse-level linguistic features on text *processing* and *comprehension*, it follows that these features might vary across constructed responses as a function of learners' individual differences. A variety of NLP measures are correlated with individual differences (Magliano & Millis, 2003). NLP indices have the capability of revealing various cognitive processes (Lintean, Rus, & Azevedo, 2012) and abilities, such as students' prior domain knowledge (Allen & McNamara, 2015), word knowledge (Allen & McNamara, 2015; Crossley, Allen, & McNamara, 2014), comprehension skills (Allen, Snow, & McNamara, 2015), and writing skills (Crossley & McNamara, 2012; Varner, Roscoe, & McNamara, 2013). These results suggest that NLP techniques can inform assessments and help to improve adaptivity in educational systems.

Dynamical Systems Theory and Discourse Processing

A caveat to the strength of NLP pertains to a limitation with regard to the detection of change over time. There are theoretical and practical limitations in that current NLP algorithms identify evidence of comprehension and skills, but do not provide information about how they occur in combination to support comprehension and learning, or how these processes dynamically unfold. We call for research that assesses the utility of computational techniques based on dynamical systems theory to analyze the temporal organization of students' responses to multiple texts (including authentic texts and texts with misinformation), potentially in conjunction with other relevant time-varying data (e.g., ratings of engagement or keystrokes during typing).

Importantly, dynamical systems theory subsumes a large analytical toolbox, which provides a novel means with which researchers can characterize *patterns* that characterize students' behaviors (e.g., language, system choices) during learning tasks. Traditional inferential statistics often aggregate variables across time, potentially discarding important information about learning and performance. In contrast, dynamic methodologies consider change over time to be a critical component of the analysis and explicitly seek to characterize temporal patterns. Thus, rather than treating behavior as a static process, these dynamic analyses have strong potential to more precisely account for the complex, changing nature of behavior. Although no studies have applied dynamic analyses to multiple text comprehension and misinformation detection, these techniques have previously been used across a wide variety of domains as a means to understand the complex patterns that manifest in individuals' behaviors over time (e.g., Anderson, Bischof, Laidlaw, Risko, & Kingstone, 2013; Dale & Spivey, 2005; Riley, Balasubramaniam, & Turvey, 1999; Shockley, Santana, & Fowler, 2003).

Dynamical Systems Theory

In order to illustrate the importance of dynamical systems theory, it is important to understand a number of the key concepts that are important to this line of research. *Dynamical systems theory* (DST) provides a principled theoretical framework for examining complexities associated with comprehension of complex information (Dale, Kello, & Schoenemann, 2016). Dynamical systems are composed of multiple components that interact over time (Kelso, 1995). Importantly, the complex patterns produced by these systems cannot be explained by simply reducing them to their component parts. Instead, these patterns emerge through a process of *self-organization*. That is, higher-level patterns emerge, stabilize, change, and dissipate as a natural consequence of local interactions among the system's components and constraints placed on the system. Constraints may be random fluctuations that come from the environment or so-called *nonspecific control parameters*, parameters of

the system which change continuously but lead to a noncontinuous, qualitative changes in the system's behavior—referred to as *phase transitions*. The DST approach to understanding human behavior is most well known in domains involving physiological networks and motor control, but it has also provided insight within the context of other relevant domains such as brain activity (Tognoli & Kelso, 2014), discourse (Fusaroli, Raczaszek-Leonardi, & Tylen, 2014), performance variability (Harrison & Stergiou, 2015), and team coordination (Gorman, Amazeen, & Cooke, 2010).

A simple illustration can help to make these ideas more concrete. A commonly referenced system in the motor control literature is one that emerges with alternating swinging of limbs, such as fingers, arms, and legs (Amazeen, Amazeen, & Turvey, 1998; Haken, Kelso, & Brunz, 1985; Kugler & Turvey, 1987). At slow speeds, two patterns dominate, an *inphase* pattern where the angle between the limbs is 0°, and an *antiphase* pattern where the angle between the limbs is 180°. However, faster speeds result in a *phase transition* such that only one pattern, 0°, remains stable. In this simple example, the phase relations between the limbs are the higher-order patterns that emerge from the local interaction of the systems' components—here, the limbs. The singular control parameter is the speed at which the limbs are moving. When the speed of the limbs' movement reaches a critical point (i.e., a critical speed), the system exhibits a qualitative change in behavior: the elimination of the 180° pattern and the movement towards the inphase pattern. This simple system captures several properties of a dynamical system (e.g., control parameters, phase transitions; Gilmore, 1981; Kelso, 1995). This example is not provided as a template for the dynamics expected to emerge from either students' natural language patterns, as these processes generate patterns that are far more complex (e.g., Allen, Perret, Likens, & McNamara, 2017; Dale & Spivey, 2005; Likens, Allen, & McNamara, 2017). Nonetheless, the example tacitly emphasizes the importance of how higher order patterns emerge as a result of how dynamical systems change over time, a feature that plays an important role in the identification and analysis of patterns in students' natural language responses.

Importantly, the processing and integration of information within and across texts does not consist of uniform processes; the nature of these processes changes as a function of the features of the text, metacognitive states of the reader, and the relevant prior knowledge that can be used to generate explanations about the text content (Kendeou & van den Broek, 2007; McNamara & Magliano, 2009a). We argue that a DST approach will contribute to a better understanding of the complex cognitive processes that underlie the evaluation, processing, and production of information. Our argument follows the assumption that language comprehension and production are driven by complex, dynamical systems with interacting components and complex emergent properties.

An underlying assumption of DST is that similar dynamics can emerge from systems with different compositions (Kelso, 1995). This has been referred to as *dynamical similitude*. One objective of DST is to examine the presence and degree of dynamic similarity between systems that may appear to be different based on static measures (e.g., different material substrates within the context of engineering). For instance, the Haken-Kelso-Bunz (HKB) model (Haken et al., 1985) was developed to characterize the rhythmic coordination of index fingers on the opposing hands of a single individual. The main predictions of the HKB model were informally presented earlier in the discussion of hallmark properties of a dynamical system, namely, the presence and stability of 0° and 180° coordination patterns. Given that the same neuromuscular system that moves the fingers also moves the wrists and legs, it is not surprising that the HKB model has been generalized to other limbs within a single individual (see Amazeen, 2018; Amazeen et al., 1998; for reviews). The HKB model has also been extended to phase synchronization patterns observed in brain dynamics (Bressler & Kelso, 2001).

More remarkably, however, the HKB model has been generalized to settings where the coordinated elements do not share a common nervous system. For example, Schmidt, Carello, and Turvey (1990) demonstrated that the stable patterns (0° and 180°) and accompanying phase transitions (annihilation of the 180° pattern) predicted by the HKB model also hold when two people rhythmically coordinate the swinging of their limbs. The number and variety of instances in which this model has been applied is extensive and well beyond the scope of this chapter. These examples provide only a hint of its generality. We emphasize this point because the HKB model's ability to characterize complex forms of coordination stands as a paramount example of the principle of dynamical similitude—systems ranging from clusters of neurons to clusters of people exhibit similar dynamics.

Despite the remarkable utility of the HKB model, we do not wish to give the impression that it is *the only model* in the DST toolbox. After all, the model was designed to characterize rhythmic movement patterns, which are only a small subset of the many behaviors typically found in human performance. Another example of dynamical similitude comes from the application of *fractal analysis*, a form of dynamic modeling that has been used to model complex systems emerging from the interaction of multiply-nested time scales (Ihlen & Vereijken, 2010). The systems that have been studied with approach extend over several orders of magnitude, ranging from individual neurons (Schroter, Paulsen, & Bullmore, 2017) to geomagnetic radiation (Picoli, Mendes, Malacarne, & Papa, 2007). Fractal analysis primarily focuses on examining whether time series exhibit *long-range autocorrelations* and *scale dependence*. When a time series is said to exhibit long-range autocorrelations, an observation made at a specific point in time will be related to subsequent observations in the future (Beran, 1994). Similarly, scale dependence means that time series measurements (e.g., variability) differ as a function of the temporal scale at which they were measured (Mandelbrot & Van Ness, 1968). Fractal analyses have been used to model numerous cognitive phenomena, such as speech patterns (Kello et al., 2010), engagement (Likens, Fine, Amazeen, & Amazeen, 2015), reaction times (Van Orden, Holden, & Turvey, 2003), and eye movements (Aks, Zelinsky, & Sprott, 2002). In our own research, we have found that fractal patterns observed in the inter-keystroke intervals (i.e., the time between keystrokes during essay writing) predict essay quality (Likens et al., 2017). In addition, we have found that fractal patterns that characterize student choices predict performance in an intelligent tutoring system. Importantly, researchers generally suggest that variability in fractal properties of a time series reflect the flexibility and adaptability necessary to complete cognitive tasks that require the coordination of information across multiple time scales (e.g., Van Orden et al., 2003; Stephen, Anastas, & Dixon, 2012).

Importantly, analytic techniques have been developed that highlight the important role of time in complex systems. These techniques provide researchers the means to both visualize and quantify important temporal variability in data across multiple time scales. For instance, Figure 9.1

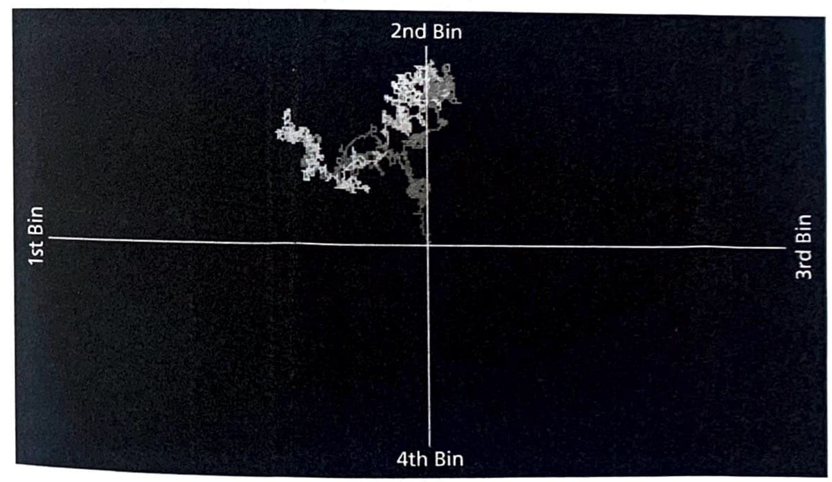

Figure 9.1 Example random walk representing one student's keystroke patterns over time (Bin 1 = quick bursts; Bin 2 = medium bursts; Bin 3 = slow typing; Bin 4 = slow typing with pauses). The bins represent four quadrants of interkeystroke interval speeds and the rainbow gradient represents the time that the keystrokes were produced. The dark blue represents the beginning of the essay and the red color represents the end of the essay typing process. This student typed relatively consistently throughout the essay as evidenced by their walk hovering near the second bin consistently.

depicts a *random walk* visualization of an individual's keystrokes while generating an essay. Random walk analyses are mathematical tools that are used to visualize patterns in data as they unfold across time (Benhamou & Bovet, 1989; Lobry, 1996; Nelson & Plosser, 1982). In this example, we first separated the intervals between keystrokes into four bins—1 being quick bursts of typing and 4 being long pauses. Each of these categories was then assigned to a vector along a basic scatter plot. Therefore, if an individual began typing very quickly, the random walk would first move towards the first bin, whereas if they then proceeded to slow down, they would move down toward the 4th bin. Once each keystroke interval had been assigned to a vector, we calculated a random walk for each student that began at the origin of the scatter plot (0, 0). For each subsequent interval between keystrokes, the walk "steps" in the direction is consistent with the assigned vector. The resulting walk represents each individual's keystroke patterns over time. We additionally colored the keystrokes points along a rainbow gradient to represent the time that the keystrokes were produced. Figure 9.1 represents a student who stayed relatively consistent in typing patterns over time, making small changes between bursts and

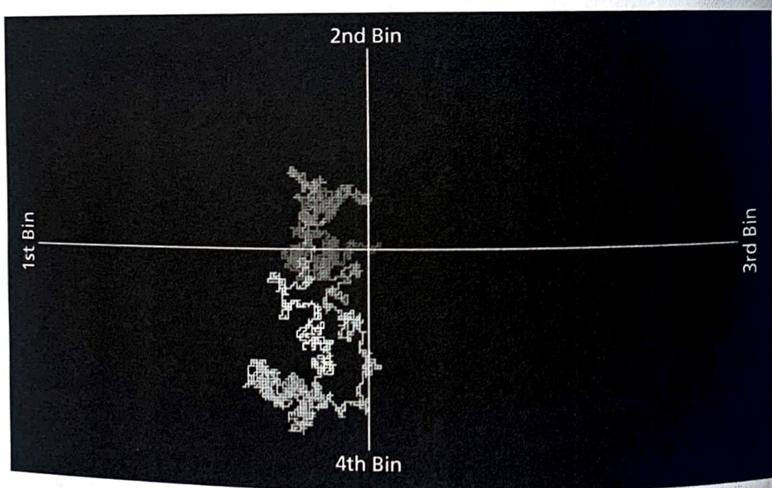

Figure 9.2 Example random walk representing one student's keystroke patterns over time (Bin 1 = quick bursts; Bin 2 = medium bursts; Bin 3 = slow typing; Bin 4 = slow typing with pauses). The bins represent four quadrants of interkeystroke interval speeds and the rainbow gradient represents the time that the keystrokes were produced. The dark blue represents the beginning of the essay and the red color represents the end of the essay typing process. This student went through different phases of quick burst typing and slow pauses as evidenced by the movement across the second and fourth bins.

pauses. On the other hand, Figure 9.2 represents a student who engaged in very different typing behaviors—moving over time between periods of pauses and slow typing to periods of time where they typed in quick bursts. These random walk images provide an example of a way in which dynamic methods of visualization can be used to reveal important structure in language production and comprehension over time.

Dynamical Systems Theory and Text Comprehension

We assume that comprehension processes fluctuate over time, and a comprehender may fluctuate between states of understanding and misunderstanding. Our hypothesis is that the transition from a state of misunderstanding to a state of comprehension will be preceded by critical fluctuations, and these fluctuations will be revealed through the *dynamic structure* of linguistic features of a student's constructed response. For example, the use of more familiar (frequent) words has been associated with lower levels of language proficiency and comprehension. Prior research has relied on averaging word frequency across all of a student's responses. However, fluctuations in word use may reveal when a student shifts between states of successful and less successful comprehension. Increases and decreases in word frequency may characterize shifts toward resolution of misconceptions by signifying that a phase transition is taking place.

Our aim here is to promote research on the topic of text comprehension (e.g., evaluation of sources) that leverages concepts borrowed from DST such as *dynamical similitude*. The motivating idea is that discourse processes can exhibit the hallmark properties of a dynamical system (e.g., complex patterns; Gilmore, 1981; Kelso, 1995). In particular, our objective is to leverage the assumption that we can observe and compare dynamic patterns across multiple time series in order to understand how complex systems unfold over time. In the context of fake news and misinformation, our ultimate objective is to explore the notion that dynamics of misinformation comprehension emerge in the form of complex, dynamic patterns across documents, constructed responses to these documents, and even lower level data produced during comprehension tasks, such as keystroke, reading time, and eye movement patterns. For instance, we assume that linguistic features, when extracted from complex texts or students' constructed responses, may provide suitable *observables*, which in turn can serve as important parameters in dynamical analyses. If so, they will have the potential to reveal themselves as a powerful lens through which to observe comprehension processes, particularly as they relate to the complex processes involved in *misinformation* comprehension. As mentioned earlier, one window to online comprehension is to elicit constructed responses to texts such as think-aloud.

One approach that has been used in the past is to examine the linguistic features of each think-aloud separately and then use averages across performance to glean the quality of comprehension. For example, Magliano and colleagues (2011) previously developed the RSAT, in which students produce think-aloud responses while reading. This tool uses algorithms based on the presence of particular key words to analyze responses for evidence of comprehension processes, including paraphrasing, bridging inferences, and elaborative inferences. The algorithms correlate with experts' coding of the protocols as well as independent measures of comprehension abilities. While RSAT algorithms provide indicators for the presence of paraphrasing, bridging, and elaboration during comprehension, they do not provide information about how they occur in combination to support comprehension, nor how those processes change over time.

As a proof of concept, we have combined linguistic and dynamic analyses to understand comprehension behaviors through analyses of the temporal organization of constructed responses. In a recent study (Allen et al., 2017), students generated constructed responses (i.e., self-explanations or think-alouds) while reading a science text and then answered comprehension questions. A dynamic methodology—Recurrence quantification analysis (RQA; Webber & Zbilut, 2005) was used to visualize and quantify the extent to which recurrent patterns in students' natural language text responses relate to their reading comprehension processes. Recurrence quantification analysis is a nonlinear data analysis technique that provides information about patterns of repeated behavior (i.e., the number and duration of recurrences) in a continuous or categorical time series. Like many techniques used in the DST framework, this methodology has been used in a variety of domains, both within and outside the realm of human behavior. For example, researchers have utilized RQA to examine patterns of heart rate variability, postural fluctuations, and eye movements (Anderson et al., 2013).

Beyond these physiological measures, RQA has the potential to provide important information about recurrence in the content of students' language. Dale and Spivey (2005), for example, have revealed that RQA can be applied to categorical data sets, such as the words in a particular conversation. This flexibility of the RQA technique (i.e., the fact that it can be applied to both continuous and categorical data sets) may be particularly salient for the study of natural language. In particular, recurrence can be measured at multiple levels of the text (e.g., word, semantic), rather than relying only on one level of analysis.

The starting point of RQA is the development of a recurrence plot, which is a visualization of a matrix wherein the individual elements represent points in a time series that are visited more than once (i.e., they recur).

In other words, this plot represents the times in which a dynamical system visits the same area in a phase space. Within this plot, each point represents a particular state that is revisited by the system. If multiple points occur continuously, they form diagonal lines, which represent times when the system is revisiting an entire sequence of states.

As a simple illustration, consider the following sentence: "The ice cream man brought ice cream on Friday." To generate a recurrence plot for this sentence, the words in the sentence are first placed on both the X and Y axes of a 2-dimensional plot (see Figure 9.3). Each time a word appears both the X and Y axes, a dot is placed in that location on the plot. Because this sentence is being plotted against itself, the recurrence plot is symmetrical with a diagonal line through the center—the line of identity (LOI). The points of interest in these recurrence plots are the points that do not occur on the main diagonal. Individual points off the main diagonal represent the times that a word is repeated later in the sentence. When multiple points occur simultaneously, these points form *diagonal lines* (e.g., "ice cream" in Figure 9.3), which represent *sequences* of words that are repeated in time.

Visualizing recurrent patterns is informative, but researchers also need to quantify the structure contained in recurrence plots. Recurrence quantification analysis offers multiple metrics that help to quantify recurrent patterns to allow for statistical comparisons of recurrence plots. Table 9.1

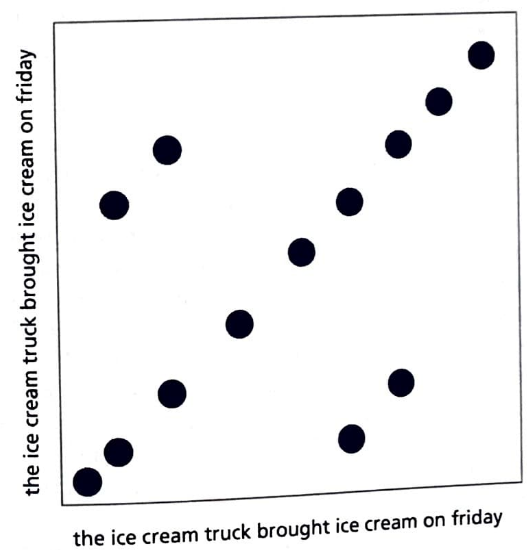

Figure 9.3 Example recurrence plot where a sentence is plotted against itself and the individual dots represent points where a word is repeated.

TABLE 9.1 Common Metrics Used in Recurrence Quantification Analyses

Recurrence Rate	A measure of the density of points represented in a recurrence plot. A recurrence rate is calculated by dividing the total number of points in a plot by the square of the length of the overall time series. This metric represents the overall amount of recurrence that is present in the recurrence plot, regardless of the distributions of the points.
Determinism	A measure of the number of recurrent points that tend to fall on diagonal lines (ignoring the LOI) in the recurrence plot. Thus, this metric provides information about the *distribution* of the recurrent points. Diagonal lines in recurrence plots reflect time periods when the system is revisiting a particular sequence of states. Thus, systems with low determinism can exhibit short moments of repetitive states; however, they are considered less ordered than highly deterministic systems.
Average Line Length	This metric calculates the average length of the diagonal lines in the recurrence plot. Thus, when the system repeats a sequence of states, this metric provides information about the typical length of those sequences.
Maximum Line Length	This metric calculates the length of the longest diagonal line in the recurrence plot. Therefore, this metric reveals whether a system revisits a long sequence of states at some point in time.
Entropy	Entropy is calculated as the Shannon entropy of the distribution of the line lengths in the recurrence plot. This metric quantifies the degree to which the trajectory of the system exhibits order. Thus, entropy will be higher if the system revisits a wider variety of state sequences over time. Dynamic systems that continually revisit the same, or similar, sequences of states, will have lower entropy.

describes the most commonly used metrics in recurrence quantification analyses.

To visualize the temporal distribution of words in students' self-explanations, recurrence plots for each student were calculated using the procedure described in the previous sections. These recurrence plots varied considerably among the students and provided us a means to *qualitatively* analyze differences in the word recurrence in the self-explanations of students who received low and high scores on the comprehension test.

Figures 9.4 and 9.5 illustrate two recurrence plots that were generated using two students' actual self-explanations from the current study. Although the students' self-explanations had a similar total number of words (Figure 9.2 = 224; Figure 9.3 = 251), the plots demonstrate that these students exhibited different patterns of word recurrence throughout their self-explanations.

Figure 9.4 illustrates the recurrence plot of a student who received a score of 1 (out of 8) on the comprehension test (text-based comprehension score = 1; bridging comprehension score = 0). As illustrated in the plot, this student rarely produced self-explanations with similar words from

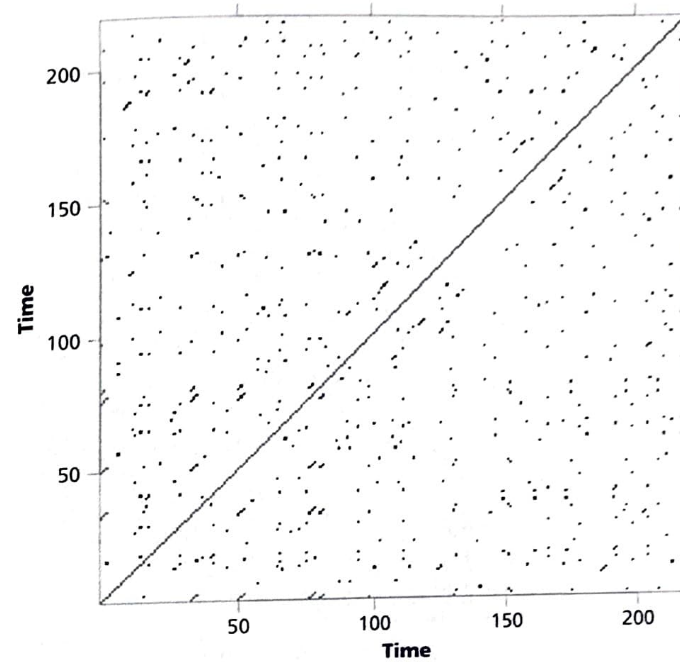

Figure 9.4 Recurrence plot for a student with a low text comprehension score.

their previous explanations. Additionally, in the situations when this student did exhibit word recurrence, the words tended to occur in isolation, rather than in sequences (diagonal lines) of words. In other words, the recurrence plot suggests that this student did not generate explicit connections between the information explained in different sections of the text.

In contrast, the plot depicted in Figure 9.5 comes from a student who received a perfect score of 8 on the comprehension test (text-based comprehension score = 4; bridging comprehension score = 4). Unlike the previous student, this student exhibited a high degree of recurrence across self-explanations. Additionally, many of the recurrent points fell on diagonal lines, suggesting that this student was repeatedly referring to sequences of words, rather than individual words. Thus, while reading through the text, the student continued to explain the new text information in connection with previously encountered text information.

Overall, these recurrence plots provide a means through which the comprehension processes of skilled and less skilled readers can be differentiated. Despite the fact that these two students generated a similar amount of text during the self-explanation procedure, the temporal distribution of

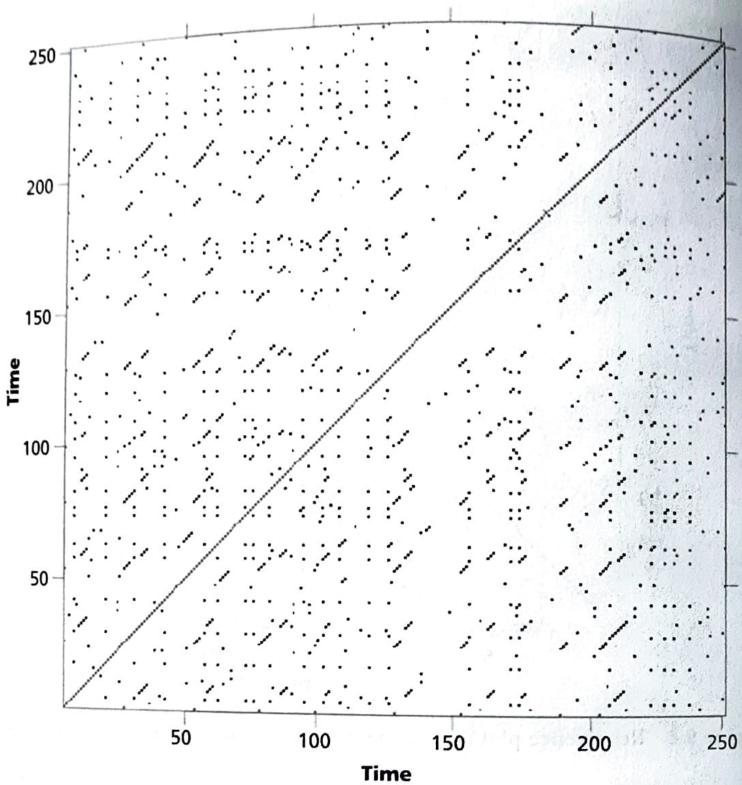

Figure 9.5 Recurrence plot for a student with a high text comprehension score.

the words they used varied widely. In particular, these plots reveal that the student who continuously repeated words and phrases while self-explaining ultimately developed a deeper comprehension of the text. In comparison, the student who rarely repeated information across self-explanations demonstrated low text comprehension.

In addition to these visualizations, the quantitative RQA indices generated from these recurrence plots were able to provide important information about students' comprehension performance. In particular, the results of correlation and regression analyses indicated that 32% of the variance in students' comprehension scores were accounted for using a combination of summative metrics of word use (i.e., *total number of words*, the *number of letters per word*, and the *type-token ratio*), as well as indices related to recurrent patterns of this word use (see Table 9.1). These analyses speak to the importance of accounting for temporal patterns in analyses of students' language. Analyses of students' language tend to rely on summative metrics of text

features; however, the results of the work by Allen et al. (2017) suggest that expanding these analyses to include temporality can provide critical information about students' learning processes.

Notably, the work in Allen et al. (2017) was the first of its kind to examine constructed responses from a dynamical systems perspective; however, several other studies have reported correlations between the dynamical properties of comprehension (Wallot, 2017; Wallot, O'Brien, Haussmann, Kloos, & Lyby, 2014; Wallot & Van Orden, 2011). In addition, the application of DST has been broadly applied in other psychological settings (Kelso, 1995; Thelen, Schöner, Scheier, & Smith, 2001; Thelen & Smith, 1994; Spivey, 2008) and educational domains (Koopmans & Stamovlasis, 2016). In combination with our own work (e.g., Allen et al., 2017), the success of the DST in various psychological domains leads to the hypothesis that the dynamical systems approach will reveal valuable information regarding comprehension processes, leading ultimately to improved measurement and interventions.

Our overall proposal is that we can extend these types of studies to examine students' responses to the types of multiple and conflicting texts that are readily encountered on the Internet. For instance, students could be provided with multiple texts that contain both true and fake news information and asked to provide constructed responses to the texts as they read. Our hypothesis is that the complex dynamics involved in evaluating, integrating, and processing conflicting sources of information can be revealed in the dynamics, such that they exhibit different patterns that can be quantitatively modeled. Through aggregate analyses of these responses, we may miss out on how students are switching amongst the texts and generating connections amongst the text concepts across time. Dynamic models, on the other hand, provide researchers the means to examine the specific parameters and processes that govern this complex comprehension system.

DISCUSSION

The ability to construct a coherent mental model from multiple documents is an essential skill for school and the workforce. This is particularly important in the Internet-age, as the texts presented to students often contain conflicting and even false information. Having a better understanding of the processes involved in these complex comprehension and production tasks will help us develop the instruction needed to combat misinformation and fake news in the modern age. We have argued that dynamic analyses of students' comprehension and production processes (in the form of constructed responses, keystroke patterns, text properties, etc.) can provide unique insights into the coherence-building processes underlying discourse production and comprehension. This is important because these processes are a keystone to learning as well as understanding how to properly identify and overcome misconceptions. Given that the strategies and features driving fake news dissemination are constantly evolving, it is important that we develop a deeper understanding of the complex *processes* involved in rejecting or accepting this information. Dynamical systems theory provides an avenue to consider a variety of processes without having to focus on the influence of one individual variable in isolation of other potentially relevant factors. Thus, our objective is to encourage researchers to combine current theories of comprehension and dynamical systems to provide a better understanding of how comprehension and discourse production unfold.

Importantly, visualizations and analyses similar to the ones presented throughout this chapter may be able to be used to improve tools for discourse instruction. In particular, educational technologies have been developed to provide instruction and feedback on a variety of discourse production and comprehension tasks. However, these tools often focus on summative metrics of language use and fail to consider how students' language and cognitive processes unfold dynamically. The methodological techniques from DST may serve as a useful addition to the technologies, by allowing researchers to provide visualizations and representations that consider how students are learning and processing information over time.

As a final note, in this chapter, we only focused on a small subset of the techniques that can be leveraged from the dynamical systems "toolbox." Additionally, in our analyses, we did not account for the wide variety of linguistic properties that can be calculated about a given text. We chose this approach because our objective is to provide a broad proof of concept about the power of the dynamic techniques when only surface-level features (such as words) are considered. However, these techniques are highly flexible and can be used to analyze any number of features of language. For instance, categorical recurrence quantification analyses, such as the one presented in this chapter, can be used to analyze recurrent patterns in the parts-of-speech or topics of multiple documents or students' constructed responses to those documents. Further, recurrence quantification analyses can be used to model continuous data, such as word frequency, keystroke patterns, or eye movements. Finally, these models can be combined using a number of different dynamical techniques to account for the way in which multiple features interact and unfold over time simultaneously. We urge researchers to conduct studies that build on prior research to account for the multidimensional properties of the language that students process and generate.

Overall, the aim of this chapter is to argue that the theoretical perspectives and methodological techniques afforded by DST can be used to inform both theory and practice related to misinformation processing. In particular, DST emphasizes a focus on complex systems that are not reducible to

the sum of their parts and which unfold in complex patterns over time. This theoretical perspective may provide key insights into the ways in which individuals process fake news, as this information is highly complex and contains multiple interacting variables that combine to influence comprehension and misconception resolution. Additionally, the field of DST has developed a number of techniques that can be used to guide both qualitative and quantitative assessments of students' comprehension processes. In particular, these techniques can be combined with current approaches to automated language analyses to model how individuals integrate and comprehend the wide variety of information presented to them on the Internet. Thus, our ultimate proposal is that these dynamic visualizations and analyses can be used as a step towards more adaptive educational technologies for literacy, as well as for any system that automatically models language.

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CHAPTER 10

A NATION OF CURATORS

Educating Students to be Critical Consumers and Users of Online Information

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ABSTRACT

Internet users encounter information from a wide array of sources with varying intents and standards of publication. The Internet, which is mostly unmoderated, has largely replaced sources curated by experts, such as books,

Misinformation and Fake News in Education, pages 187–206