ANALYZING TURN-TO-TURN CONVERSATIONAL DYNAMICS OF THEORETICALLY BASED ANALOGUE PSYCHOTHERAPY SESSIONS WITH CONCEPTUAL RECURRENCE PLOTS

by

JUNGSU OH

(Under the Direction of Alan E. Stewart)

ABSTRACT

Conceptual recurrence plotting (CRP) is a text analysis and visualization technique to analyze dynamics from a single conversation. This technique has been applied to various types of conversational settings, but its utility in analyzing psychotherapy transcripts has not been fully explored yet. To call researchers' attention to this innovative methodology, this exploratory study demonstrated how CRP can capture conversational dynamics from psychotherapy transcripts. The researcher selected and analyzed three psychotherapy transcripts from APA Psychotherapy Video Series listed in PsycTHERAPY, exploring their qualitative features revealed by CRP. The results from this study suggest that CRP was able to depict some important therapeutic dynamics, such as dominance in conversation or revisiting earlier concepts. Their corresponding quantitative features were also explored using MPR (Multi-Participant Recurrence) metrics, which demonstrated its utilities and limitations. The implications of this study in research and training settings were discussed in the end.

INDEX WORDS: Recurrence, Text analysis, Nonlinear dynamics

ANALYZING TURN-TO-TURN CONVERSATIONAL DYNAMICS OF THEORETICALLY BASED ANALOGUE PSYCHOTHERAPY SESSIONS WITH CONCEPTUAL RECURRENCE PLOTS

by

JUNGSU OH

B.A., Seoul National University, Republic of Korea, 2013

M.A., Seoul National University, Republic of Korea, 2015

A Dissertation Submitted to the Graduate Faculty of The University of Georgia in Partial Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

ATHENS, GEORGIA

2020

ANALYZING TURN-TO-TURN CONVERSATIONAL DYNAMICS OF THEORETICALLY BASED ANALOGUE PSYCHOTHERAPY SESSIONS WITH CONCEPTUAL RECURRENCE PLOTS

by

JUNGSU OH

Major Professor: Alan E. Stewart
Committee: Edward A. Delgado-Romero
Rosemary E. Phelps

Electronic Version Approved:

Ron Walcott
Interim Dean of the Graduate School
The University of Georgia
August 2020

ACKNOWLEDGEMENTS

I would not be able to complete this dissertation work and doctoral degree without support from many people. Dr. Alan Stewart’s genuine interest and encouragement on my work kept motivating me to be passionate, especially considering the unconventional nature of my research interests. Dr. Edward Delgado-Romero guided me through his practical and direct advices, which have been essential in my growth as a clinician and a researcher. Without the support and trust from Dr. Rosemary Phelps, it would have been much harder for me to adjust in the U.S. I also appreciate Dr. Bernadette Heckman, who gave me opportunities to broaden my knowledge and expertise in health psychology throughout this program. Lastly, I want to emphasize that my courage to survive this process grew from warmth and regard I was given by many others, including my family, friends, colleagues, and faculty members in this program.

TABLE OF CONTENTS

LIST OF TABLES

Page

LIST OF FIGURES

Chapter 1

INTRODUCTION

Statement of the Problem

Since the late 20th century, social science has been alternating between two different perspectives on the nature of knowledge. Borrowing Aristotle's concepts of *episteme* and *phronesis*, Flyvbjerg (2001) illustrated these conflicting views on how social science ought to look. According to Aristotle, *episteme* is universal and context-independent knowledge that holds its truth over time and space. *Episteme* is the foundation of modern natural science. For instance, the law of gravity is invariable regardless of where it is applied. If the mass of substances and the distance between them is known, then the attracting force between them can be predicted without considering other individual contexts. Meanwhile, *phronesis* denotes another type of knowledge not captured by *episteme*. It is practical wisdom for deliberate decision making in individual contexts. For instance, although one may be knowledgeable about general ethical principles, this does not guarantee that one can make the best ethical decision when facing an ethical dilemma. To make an ethical decision in an individual situation, one needs to keep applying their general knowledge into specific contexts. In this sense, *phronesis* not only requires general knowledge, but also encompasses context-dependent information.

For the most of 20th century, social science has tried to emulate the methodology and framework from the natural sciences. Therefore, *episteme* was prioritized over *phronesis*. To develop universal rules and laws independent from contexts, social science has relied on abstraction to explain and predict social phenomena. However, this abstraction does not correspond to how we become knowledgeable about the world. When one starts learning things, one strictly follows rules without allowing flexibility. On the other hand, as one become an expert, one makes decisions based on one's intuition and experience rather than rationality, as strict rules are not flexible enough to guide one in individual situations (Dreyfus & Dreyfus, 1986). Flyvbjerg (2001) argued that social science's attempt to imitate natural science reached a dead end, calling on researchers to engage in "phronetic social science" (p. 129) by integrating values and contexts into their research.

Although Flyvbjerg (2001)'s argument was developed based on the contrast between natural science and social science, it also sheds light on the controversial schism between research and practice in psychotherapy. Despite the wide adoption of the Boulder model (i.e., scientist-practitioner model), there is a constant controversy over whether the values and activities of researchers harmonize with those of practitioners (Weisz & Addis, 2006). Along the same line of reasoning, Addis (2002) described harmful yet popular stereotypes that researchers are "out of touch ivory-tower rat runners" and practitioners are "mindless true believers desperately in need of guidance" (p. 375). Baker, McFall, & Shoham (2008) also pointed out the clinician's deep ambivalence about research, which is attributable to lack of rigorous scientific training.

The concepts of *episteme* and *phronesis* serve as an informative framework to understand this gap between research and practice in psychotherapy: researchers want to develop generalizable theories using abstraction, while practitioners are attracted to uniqueness of individual clients. Researchers believe in the power of simplicity, while practitioners are more sensitive to the pitfall of reductionism. If this is the case, the scientist-practitioner model or evidence-based practice might be more challenging to achieve than previously believed. The issue is not just about mechanical integration of advantages from each side, but also about reconciling two conflicting paradigms on how knowledge can be gained and utilized. Without taking this challenge seriously, one may end up with strengthening unproductive stereotypes described by Addis (2002) earlier.

How can researchers narrow the gap between research and practice? Dattilio, Edwards, & Fishman (2010) provided one possible answer to this question. Criticizing the limitation of a positivist paradigm and its application of quantitative approaches, Dattilio et al. (2010) urged the necessity of a broader perspective on science. Dattilio et al. (2010) further argued that case studies within a mixed method design can be one of these examples, by providing more practical knowledge on individual cases and contributing to resolve the tension between researchers and practitioners. This suggestion is in line with earlier calls for more attention on case-based research, which emphasized its potential to become a foundation of evidence-based practice and its power to reveal intrasubject variability (Edwards, Dattilio, & Bromley, 2004; Hillard, 1993). However, despite these advantages, case-based research has been discounted in social science for a long time because of common misunderstandings attached to it, such as inability to generalize findings, a bias toward verification, and preference on theoretical knowledge over practical knowledge (Flyvbjerg, 2006). Although this is the case for social science in general, there is a parallel for psychotherapy research as well. Although it has been 35 years since the first case study on process and outcome research was published in the *Journal of Counseling Psychology* (Hill, Carter, & O'farrell, 1983), researchers continue to report the underuse of single case research design in counseling and psychotherapy research (Galassi & Gersh, 1993; Ray, 2015).

Despite the existence of two research outlets specifically devoted to case studies (*Clinical Case Studies* created in 2002, and *Pragmatic Case Studies in Psychotherapy* created in 2005), case studies are still marginalized within the major academic journals, because of its lack of ‘scientific’ rigor from the positivistic paradigm.

Although it is unfair to dismiss case-based research’s value solely from a positivistic viewpoint, this separation between positivism and single case design means that the research and practice gap will continue. To locate case studies within the mixed method framework as Dattilio et al. (2010) urged, there needs to be a methodological advancement to integrate quantitative approaches into case-based research. For example, Molenaar and Valsiner (2008) provided an interesting theoretical framework on how uniqueness of individual cases can be analyzed from a positivistic standpoint. The authors argued that quantitative research methods in psychology have heavily relied on a nomothetic approach, which assumes homogeneity among the similar group members. For instance, a regression model assumes that there is a certain pattern between independent and dependent variables that can be widely applicable across all research participants. In this framework, variance not explained by predictors is treated as error and participants whose responses are not accord with general patterns are treated as outliers. Although there are more sophisticated methods to include within-group differences within a model (e.g., hierarchical linear model), their power to analyze individual’s uniqueness is still very limited. The problem of a nomothetic approach is that generalized theories from this approach fail to explain a particular person’s behavior. This is because inter-individual variability (variability among individuals) is not interchangeable with intra-individual variability (variability within the same person). To make these two dimensions interchangeable, two rigorous conditions for ergodicity should be satisfied (i.e., homogeneity, stationarity), which is highly unlikely in most of the real-world cases (Molenaar & Campbell, 2009). As an alternative for a nomothetic approach, Moleanaar and Valsiner (2008) proposed an idiographic approach instead. This approach focuses on a particular individual of interest by gathering unique and relevant information and analyzing their longitudinal changes. Molenaar and Valsiner (2008) illustrated a short case example on how this approach can be applied into a psychotherapy research setting. In this case study 29 videotaped sessions between a female therapist and a 5-year-old boy were analyzed to track the pattern of self-reliance over time. Based on the cross-correlation values on self-reliance scores, the authors concluded that the therapist's implicit role modeling might enhance the self-reliance behavior of the client. This example is worth noting, as it demonstrated how an idiographic approach allows quantitative methods to analyze uniqueness of a single case.

Molenaar and Valsiner (2008) emphasized the power of an idiographic approach in psychotherapy research. However, this approach still has not received much attention from the field. Considering its potential to solve a conflict between positivism and case-based research, more attention is required to develop quantitative methods to reveal individual's characteristics and change processes. Instead of assuming that finding a universal law is the single most important purpose of research (*episteme*), an idiographic approach can provide a framework to capture context-dependent knowledge from a single case (*phronesis*), which will be a basis to bridge a longstanding gap between research and practice. Based on this theoretical and philosophical foundation, the current study aims to explore the potential of an innovative methodology that puts more emphasis on the uniqueness of individual cases.

Purpose of the Study

As not many studies have been done on how to use quantitative approaches to conduct idiographic studies, this study will introduce a methodology called conceptual recurrence plotting (CRP; Angus, Smith, & Wiles, 2012a), hoping to facilitate future research on this area. CRP is a way to visualize dynamics from a single conversation. It has been applied to analyze other types of conversations (e.g., Atay et al., 2015; Baker et al., 2015), but it has rarely been applied to psychotherapy transcripts. Considering the importance of a quantitative case study discussed above, it is worthwhile to introduce this novel methodology to the field of psychotherapy research.

Furthermore, by introducing CRP to psychotherapy research this study will also call attention to the role of innovative methodologies in revealing unique dynamics from a single psychotherapy session. For instance, a nonlinear analysis has great potential for quantitative case studies, as it is more sensitive to detect subtle dynamics existing in the microprocess level within a psychotherapy session. In addition, a computerized text analysis is a powerful and efficient way to handle microprocess data, which allows researchers to easily evaluate nonlinear dynamics from a psychotherapy transcript. As conceptual recurrence plotting is built upon a nonlinear analysis and computerized text analysis, exploring this plotting system will demonstrate the utility of these two innovative methodologies, which may encourage other researchers to adopt relevant methodologies in their future studies.

Definitions

Definitions used in this study are summarized in the following:

Autocorrelation: Correlation between a given time series and its lagged version.

Conceptual Recurrence Plot: An adapted version of a recurrence plot developed by Angus, Smith, and Wiles (2012a, 2012b), which visualizes the similarity of meanings across a single conversation.

Nonlinearity: A property of a system whose output is disproportionate to the input. Mathematically speaking, output from a nonlinear system cannot be represented by linear combination of its components.

Dynamic system: A system whose characteristics change over time. Changes in a dynamic system often refer to complex behaviors which are not explained by a linear trajectory.

Recurrence plot: Visual representation of a recurrence/similarity matrix. This plot visualizes how a certain time point is at the same state with the other points.

Stationarity: A property of a time series, which assumes that variance and autocorrelation is consistent over time.

Stop words: Words that are deleted during the text pre-processing, as they are not relevant to the purpose of a study.

Utterance: The smallest unit of speech in spoken language. In this study, utterance refers to the single talk-turn by a speaker.

Windowed Crossed-Correlation: A statistical technique to analyze correlation between two time series data. This technique is suited for analyzing non-stationary data, as it only assumes partial stationarity within a short period of time.

Chapter 2

REVIEW OF THE LITERATURE

Computerized Text Analysis on Psychotherapy

Analyzing therapeutic dialogue has been one of the major interests in psychotherapy research since Carl Rogers' innovative work using recordings and transcripts (Rogers, 1942). Rogers' revolutionary approach created a new genre of research, psychotherapy process research. By relying on transparent and organized data for analysis, researchers were able to focus on how specific interactions between therapist and client impact overall process of therapy. Although significant methodological development has been achieved within process research since Rogers' pioneering work, transcripts remain as the most important sources of data in process research.

Despite the widely acknowledged importance of transcripts for psychotherapy process research, analyzing transcripts has been a challenging and labor-intensive task for researchers. The most common approach to analyze psychotherapy transcripts is behavioral coding, for which raters evaluate verbal exchanges during the session to assign them into pre-defined categories. However, despite its popularity, behavioral coding is not very accessible to researchers, because of its time-consuming and labor-intensive nature (Tanana, Hallgren, Imel, Atkins & Srikumar, 2016); it requires training multiple coders for a specific coding system. In addition, coding a single 50-minutes session can take up to several hours, and a single case often involves multiple sessions, and a single study usually includes multiple cases. All things considered, the amount of effort for behavioral coding may discourage researchers from pursuing psychotherapy process research, which is discussed in Scheel et al. (2011) and Oh, Stewart, and Phelps (2017). In addition, behavioral coding tends to be vulnerable to researcher's biases, as it inevitably involves raters' subjectivities. Though reliability among multiple raters are examined and reported to minimize these biases, this still does not eliminate the possibility of subjective interpretation.

Considering these limitations of behavioral coding, computer-based text analysis has some potential to overcome these challenges. Unlike human judgment, computer-based techniques are free from human subjectivity (i.e., programs strictly follow predefined rules and algorithms) and demonstrate perfect reliability (i.e., always return the same result for the same dataset). Of course, computer-based techniques are limited by the programs that run them, that is, there may be errors in the programming. Efficiency is another advantage of computer-based text analysis over human rating. With the development of computing power, computers can analyze large number of documents within a very short amount of time, which may not achievable through human labor. These advantages of computer-based approach have attracted increasing number of researchers from various fields, including psychotherapy researchers. In the following section, some of these techniques and their applications are briefly reviewed.

In psychology, Linguistic Inquiry and Word Count (LIWC; Tausczik & Pennebaker, 2010) is arguably one of the most popular computerized text analysis tools. The developers of LIWC stated that they developed this tool to find a more efficient method to evaluate texts, after experiencing low reliability among human judges and high costs to conduct analyses. LIWC was a pioneering program when it was initially developed, as there was no computerized text analysis tool to evaluate psychology-related features from texts. A key feature of the LIWC program is the role of dictionaries (Tausczik & Pennebaker, 2010). After extracting individual words from the text, the LIWC program looks for dictionaries to determine categories into which each word falls. Within more than 80 categories in LIWC, some categories have more strict dimensions (e.g., grammatical features, such as ‘article’), while other categories have more subjective dimensions (e.g., emotional value, such as ‘positive’ and ‘negative’). With these categories, LIWC analyzes individual words from the text, generating summary statistics for the text.

Since its initial release in 1993, LIWC has generated much interest from various specialties in psychology, especially from language and social psychology. Using LIWC, researchers have successfully uncovered psychological dimensions of word usage, such as emotionality, social relationships, hierarchy, cohesiveness, and thinking styles (Tausczik & Pennebaker, 2010). As it has been widely validated by other specialties in psychology, an increasing number of researchers have been attracted to LIWC to study how word usages reflect process and outcome change in psychotherapy.

There are several studies using LIWC that explore linguistic exchange within psychotherapy sessions. For example, Kahn, Vogel, Schneider, Barr, and Herrell (2008) coded and extracted client disclosures from analogue psychotherapy sessions. The LIWC program generated the number of positive and negative emotion words from selected sections. Based on this analysis, Kahn et al. (2008) found that the level of disclosure and the number of positive emotion words were positively related to higher ratings of the session depth. McCarthy, Caputi, and Grenyer (2017) had human raters determine significant change events from psychotherapy transcripts, and words from significant change events and non-events were compared using LIWC to determine if there were significant differences between human raters and LIWC regarding the frequency of the identification of emotional and cognitive words. The results indicated that significant events contained more words within the five LIWC variables compared to non-events, among which four of them were affective features (i.e., positive emotion, negative emotion, anger, and sadness) and remaining one was a cognitive feature (i.e., insight). In both studies, LIWC was able to highlight linguistic characteristics of clinically significant moments, providing richer understanding on psychotherapy process as opposed to human raters.

Unlike LIWC, which is developed to analyze a wide variety of texts, some researchers have attempted to develop computerized text analysis methods specifically targeted for psychotherapy process research. The advantage of psychotherapy-specific text analysis methods is purposefulness: as their purpose is at detecting and investigating psychotherapy-specific phenomenon, it is easier for researchers to conduct theory-driven research using these methods. Although theory-driven research is not necessarily better than discovery-oriented research (Hill, 1990), it facilitates the integration between theory and research. Mergenthaler's (1996; 2008) therapeutic cycle model is an example of this approach. The therapeutic cycle model argues that there is a fluctuational pattern in emotion tone and abstraction within psychotherapy process. This emotion-abstraction pattern consists of five phases: relaxing, experiencing, connecting, reflecting, and relaxing. To detect this pattern from psychotherapy transcripts, Mergenthaler (1996) proposed a dictionary-based text analysis method. Using the emotion tone dictionary and the abstraction dictionary, Mergenthaler (1996) calculated the occurrence of words included in these dictionaries from psychotherapy transcripts. The results of text analysis supported the therapeutic cycle model's hypothesis, showing a fluctuational pattern across a series of psychotherapy sessions. Fertuck, Mergenthaler, Target, Levy, and Clarkin (2012) developed a computerized version of the Reflective Functioning scale (CRF). To develop the CRF, Fertuck et al. (2012) compared text samples with high reflective functioning and those with low reflective functioning, that is evaluated by the human-rated Reflective Functioning scale. From the comparison, the characteristic vocabularies which most differentiated two text samples were extracted. To test CRF's performance, these characteristic vocabularies were used to detect reflective functioning within the responses from the Adult Attachment Interview. The results verified robust performance of CRF compared to the original Reflective Functioning scale. Lastly, Automated Co-occurrence Analysis for Semantic Mapping (ACASM), proposed by Salvatore, Gennaro, Auletta, Tonti and Nitti (2012), detects contextual meaning from psychotherapy transcripts. ACASM utilizes a bottom-up approach to generate core themes from transcripts. More specifically, ACASM applies a cluster analysis into a term-document matrix whose terms are included in the ACASM dictionary. With generated clusters, researchers interpret their meaning and label them. According to the Salvatore and colleagues (2012), ACASM performed equally well when compared to human coders.

In recent years, computerized text analysis entered a new phase with the rapid development of machine learning/deep learning techniques in the computer science. With these techniques, computers can learn by themselves without being explicitly programmed. Although the theories behind these models have been around for decades, the models have gained increasing popularity with the drastic improvement of computing power and available training data (e.g., internet-based documents gathered by Google). Within the area of psychotherapy research, machine learning/deep learning techniques have just begun to be utilized by researchers. For example, research used topic models, a technique to infer underlying topics from a group of documents, to analyze 1,553 psychotherapy transcripts (Imel, Steyvers & Atkins, 2015). This exploratory analysis was able to demonstrate how this methodology can deepen the understanding of psychotherapy transcripts, by showing clinically relevant topics extracted from the model and visualizing discriminatory features across different types of therapy (i.e., Cognitive Behavioral Therapy, Psychodyanmic, Experiential/Humanistic, and Drug therapy).

Tanana, Hallgren, Imel, Atkins, and Srikumar (2016) provided another interesting example on whether machine learning techniques can be utilized to circumvent time- and labor-intensive nature of behavioral coding. Based on 341 transcripts on motivational interviewing, performances of two different automatic coding systems were compared (i.e., discrete sentence features model versus a recursive neural network model) to examine whether these models accurately generate behavioral coding consistent to that of human coders. The result indicated that the results from these models have high agreement with human raters for some behavioral coding categories, while they performed poorly on other categories. This advanced methodology is likely to draw more attention in the future, which will provide further evidence on its utility in analyzing psychotherapy transcripts.

Nonlinear Dynamics in Psychotherapy

A dynamic system is a structure whose characteristics change over time (Richardson, Dale, & Marsh, 2014). There have been increasing attempts to understand psychotherapy as a dynamic system, as change process in psychotherapy is inherently time-dependent (Hayes, Laurenceau, Feldman, Strauss, & Caradaciotto, 2007; Salvatore & Tschacher, 2012; Gelo & Salvatore, 2016). To analyze a dynamic system, it is important to remember that this system cannot be adequately represented by summary statistics such as mean and variance. In other words, these summary metrics are like a snapshot; though it provides general ideas on a relevant situation, it cannot capture the information on how it changes over time. Studying dynamic properties of a system requires researchers to pay close attention to longitudinal aspects of data. In psychotherapy research, researchers have realized the ability of dynamic properties to overcome the limitation of cross-sectional data (Braakmann, 2015). Within a decade or two, elaborated quantitative methods have been increasingly applied in process research, which greatly enhances our ability to depict the dynamic nature of psychotherapy (e.g., Frankfurt, Frazier, Syed, & Jung, 2016).

A simple way to represent time-dependent data is a linear model, such as $y = ax + b$. A linear model assumes that variable changes over time in a consistent manner; it only moves into a certain direction by a certain amount. However, a change pattern in a dynamic system does not necessarily follow a linear trajectory. Depending on its characteristics, nonlinearity may better at modeling change process of a dynamic system.

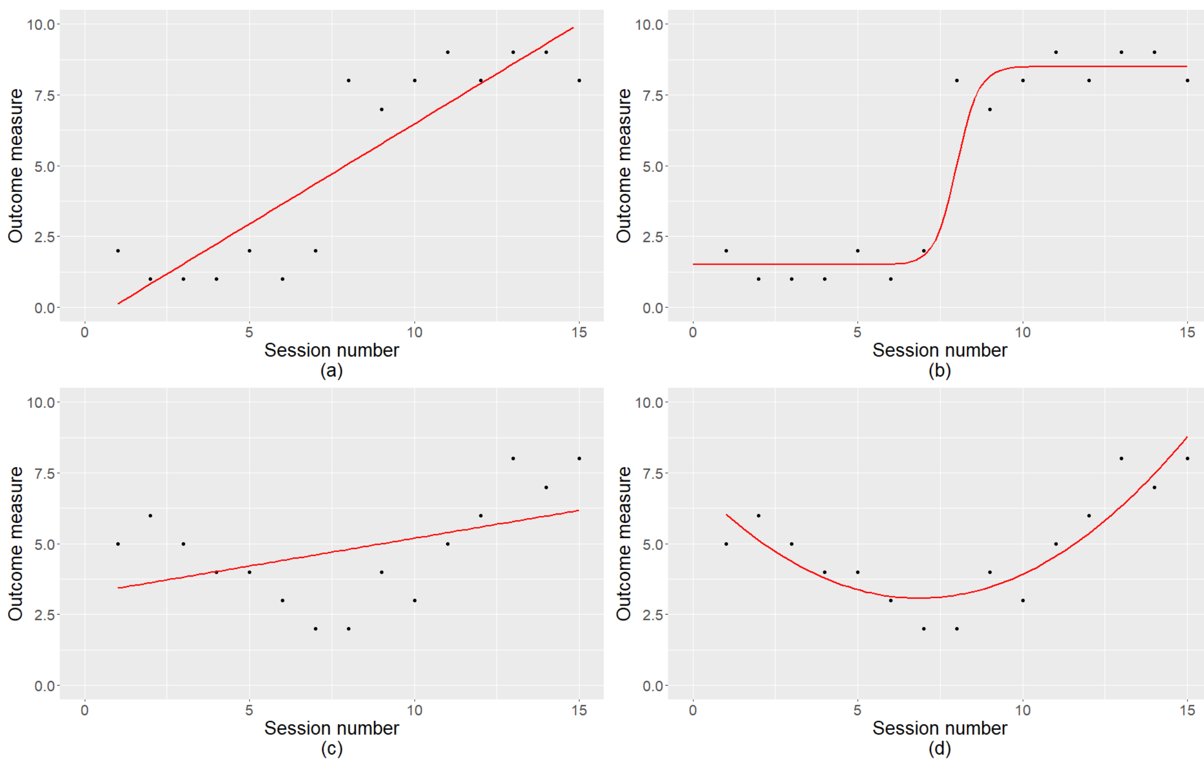


Figure 1. Comparisons between linear and nonlinear trajectories on imaginary psychotherapy outcome change over time

Figure 1 illustrates the value of a nonlinear model by comparing linear and nonlinear models on the same imaginary datasets. All four graphs, from (a) to (d), show how psychotherapy outcome changes over 15 consecutive sessions. Each black dot indicates a single data gathered after the session, and a red line represents a model to describe a change trajectory. By eyeballing the data points of Figure 1 (a) and (b), it is evident that an abrupt change occurred between session 7 and 8. Though a linear model of Figure 1 (a) partially captures a general trend of the data (i.e., improvement in the outcome measure), Figure 1 (b) is much better at describing the important dynamics of this process by using a sigmoid function. The same logic can be applied to Figure 1 (c) and (d); while Figure 1(c) depicts an overall upward change pattern, Figure 1 (d) (quadratic function) provides more useful information by illustrating a U-shaped trajectory. By and large these examples demonstrate why a nonlinear perspective can be useful in understanding behaviors from dynamic systems. However, it should be also noted that nonlinear models do not replace linear ones; it is rather complementary. Linear models are still useful tools to describe relatively simpler change patterns by using less information. Nonlinear models are viable options to consider when data do not fit well into linear models.

Researchers are increasingly aware of nonlinear properties of psychotherapy process in recent years (Hayes et al., 2007; Salvatore & Gennaro, 2015; Schiepek, 2009). As Schiepek (2009) and Schiepek et al. (2016) pointed out, psychotherapy process demonstrates some important properties of nonlinear dynamic systems, such as “deterministic chaos, non-stationary phase transitions, and nonlinear coupling between patient and therapist” (Schiepek, 2009, p.335). The concept of deterministic chaos is crucial in understanding the behaviors of dynamic systems. Though a behavior from a certain variable may look like totally disorganized, the aggregated behaviors of interacting variables can be regular and predictable. For instance, Schiepek et al.

(2017) proposed a model consists of five variables (i.e., emotions, problem intensity, motivation to change, insight, and success) and simulated how interactions among these variables generate chaotic and complex behaviors over time. This nonlinear perspective actively acknowledges time-dependent nature of change process. As it is illustrated in Figure 1, change processes cannot be fully understood without considering its longitudinal aspects. Accordingly, in psychotherapy, timing is as important as contents. In other words, psychotherapy is not only about what is said or how it is said, but also about when it is said (Gennaro, Gonçalves, Mendes, Ribeiro, & Salvatore, 2011).

A dynamic system theory has been applied to several studies to investigate change process in psychotherapy. For instance, Two-Stage Semiotic Model (TSSM) is an example of the application of a dynamic model (Gennaro, Salvatore, Rocco, & Auletta, 2017). TSSM views psychotherapy as a sense-making process. Clients seeking for psychotherapy are usually stuck with a rigid way of interpreting their own experiences (e.g., the concept of 'schema' or 'core belief' in a cognitive-behavioral therapy). Without dealing with this maladaptive sense-making system, therapy can hardly be effective. Therefore, within the frame of TSSM, the therapist first aims at deconstructing this problematic sense-making process. After disrupting existing maladaptive system, the therapist moves on constructing a new system to better regulate a sense-making process. Though these two stages (i.e., deconstruction and reconstruction) are not mutually exclusive, overall psychotherapy process can be conceptualized with these two steps in TSSM. This idea nicely illustrates how nonlinearity plays a key role in understanding psychotherapy process; rather than viewing psychotherapy as a linear and gradual process, TSSM suggests that it may be more fruitful to understand it as a quadratic change. TSSM is empirically tested by a method called Discourse Flow Analyzer, which was able to demonstrate

U-shaped trajectory of sense-making process (Gennaro, Gonçalves, Mendes, Ribeiro, & Salvatore, 2011; Salvatore, Gelo, Gennaro, Manzo, & Al Radaideh, 2010).

Schiepek et al. (2016) demonstrated another way of applying a dynamic system theory to psychotherapy. This study highlighted the potential significance of gathering data from daily assessment, as it allows researchers to better capture nonlinear dynamics in psychotherapy process without missing time-dependent information. This feasibility study found that respondents were highly compliant on frequent data gathering regardless of their severity of symptoms. In addition, Schiepek et al. (2016) claimed that data gathered by high-frequency monitoring will deepen our understanding on dynamic qualities of psychotherapy process, such as nonlinearity and self-organization.

Compared to relatively high attention on nonlinear dynamics existing in the between-session level, not much attention has been paid to nonlinearity in the within-session level. In other words, microprocess research, whose interest is at examining temporal dynamics within a session, was relatively slow in adopting the idea from the dynamic system theory, except some rare exceptions (e.g., Kowalik, Schiepek, Kumpf, Roberts & Elbert, 1997). A sequential analysis is a good example of how microprocess research has relied on a linearity assumption. A sequential analysis is a method that reveals temporal pattern of events by examining conditional dependencies among events (Lichtenberg & Heck, 1986; for empirical applications of the sequential analysis, refer to Wampold & Kim, 1989; Sexton, Hembre, & Kvarme, 1996; Rosenberger & Hayes, 2002). Lichtenberg and Heck (1986) reviewed and summarized three different methods of sequential analysis, which are Markov chain modeling, lag sequential analysis, and information theory analysis. In this section, only Markov chain modeling is discussed because it clearly articulates a linearity assumption behind a sequential analysis, but differences among these methods are not substantial (Wampold, 1986). Markov chain models are based on two central assumptions: (a) the probability of current state is contingent upon recent past states, (b) the sequence of events is stationary, meaning that the contingent relationship between current and past states do not change over time (Lichtenberg & Heck, 1986). The second assumption of stationarity shows that the Markov chain model expects a linear structure of contingency within a system. One empirical study found that this second assumption of the Markov chain model explained the data well, indicating that "The two Markov chain conditions were satisfied, that is, the sequences of talk were found to be highly stable (stationarity) and predictable (first-order dependence)" (Friedlander & Phillips, 1984, p.139). Although this illustrates the point that linear models can be a useful tool to reveal the underlying structure of turn-by-turn psychotherapy process, the linearity assumption might be too strict to detect more complex dynamics of psychotherapy.

In recent years innovative strategies have been developed to analyze the nonlinear nature of psychotherapy. These innovative approaches have two basic tenets in common to overcome obstacles of applying the nonlinear perspective into microprocess research (Salvatore & Gennaro, 2015). The first principle of these approaches is use of micro data (small segments of observed behaviors during a session, such as talk turn, body movement, vocal pitch) as units of observation; in the past, and even until now, it has been a challenging task to analyze these micro data, because of its labor-intensive and time-consuming nature (e.g. behavioral coding, which is introduced in the previous section). However, innovations in data gathering methods have provided a breakthrough to this challenge. For example, Villmann, Liebers, Bergmann, Gumz, & Geyer (2008) conducted a preliminary study on how physiological variables measured from therapists and clients during a single session can be analyzed by a nonlinear approach.

Videotapes and audio recordings are another way of collecting data. These can be especially promising methods for psychotherapy process research because they are widely used in real-world practice settings. The Vocalization-Silence Dynamics Patterns (VSDP) method is an example of how audio recording data can be used in analyzing temporal dynamics (Tomicic, Pérez, Martínez, & Rodríguez, 2017). By capturing nonlinear synchrony dynamics from audio recordings, the VSDP method examines vocal coordination patterns between therapist and client. Last but not least, a computer-joystick method is also an interesting approach to gather microprocess data (Lizdek, Sadler, Woody, Ethier & Malet, 2012). With this method, an observer can make real-time, moment-by-moment ratings with the direction and movement of a joystick while watching a recorded interaction on the screen. Thomas, Hopwood, Woody, Ethier, and Sadler (2014) applied this method to analyze the *Gloria* films with two-dimensional interpersonal circumplex (Dominant - Submissive / Cool - Warm), demonstrating its applicability in psychotherapy process research.

The second principle of innovative methodologies is consideration on how micro units interact with each other over time. While the first principle is related to data collection, this second principle deals with a concern about data analysis. With the increasing attention on the dynamic systems theory, psychotherapy process research began to adopt nonlinear analysis methods whose focus is at loosening the linearity assumption of traditional methods. For example, windowed cross-correlation is one of those attempts developed to analyze a pair of temporal data (Boker, Rotondo, Xu, & King, 2002). Instead of assuming stationarity over the entire time series, it only assumes local stationarity within segmented windows. By using cross-correlation values calculated from each pair of windows, this method depicts the pattern of association between two time series. To exclude the possibility of getting a spurious correlation by chance, pseudo-correlation can be calculated as well by randomly shuffling the temporal structure of windows while preserving the structures within the windows. Using this method, Ramseyer and Tschacher (2011) investigated nonverbal synchrony in psychotherapy. The study found that nonverbal synchrony, automatically measured by body movements from videos, is related to both process variable (relationship quality) and outcome variable (symptom reduction).

In addition to the windowed cross-correlation, recurrence analysis is another promising way of exploring a nonlinear structure from data. More thorough explanation will be provided in the next section.

Recurrence Analysis

As the characteristics of nonlinear processes cannot be illustrated by traditional statistics such as means and variance, different approaches are needed to reveal a nonlinear layer of longitudinal data. Recurrence analysis is one of these techniques developed for analyzing nonlinear time series. Around the 19th century, mathematicians found that recurrence is a fundamental property of a nonlinear dynamic system (Marwan, 2008). However, it was only after the rapid growth of computing power that recurrence was seriously studied by researchers, as calculating recurrence is a computation-heavy process; for instance, analyzing a recurrence pattern from a 10 minutes of body movement measured at every 1 second requires 360,000 calculations (600 * 600 = 360,000); the number increases exponentially for longer time series.

Eckmann, Kamphorst, and Ruelle (1987) introduced a recurrence plot, visual representation of a recurrence/similarity matrix. It was originally used as an exploratory tool to describe time series' nonlinear properties. However, as researchers became more interested in quantifying the characteristics of these plots, several measures of recurrence were developed and proposed, which was developed into recurrence quantification analysis (Zbilut & Webber, 1992; for more thorough explanation on recurrence quantification analysis, refer to Webber & Zbilut, 2005).

Although it was not long ago that recurrence analysis gained interests from researchers, the intuition behind this idea is simple. In brief, recurrence means self-repetition of a dynamic system. In other words, the major focus of recurrence analysis is at discovering the pattern of how each point on a time series revisits its own state. For instance, let's say that we measured the speed of a bus running around a city for an hour. At a certain time point t_i, assume that the observed speed of the bus was 0 (i.e., the bus was stopping). In this case, we can say any time point with the speed of 0 is at the same state of t_i; in other words, recurrence with t_i was observed with those time points. The same logic can be applied for any other amount of speed.

The comparison with more traditional time series analysis would aid in the understanding of the property of recurrence analysis. A linear approach to time series analysis describes the relationship between different time points with the concept of autocorrelation. For any time point t, an autocorrelation function represents its relationship with later time points, $t + h$ (h is a lag/delay, which is greater than 0). For a stationary time series, a time series whose structure does not change over time, autocorrelation is a nice and concise measure to describe its pattern. However, if a time series is not stationary, which means that autocorrelation between t and $t + h$ is not the same as autocorrelation between $t + i$ and $t + i + h$, it can be misleading to aggregate relationships between different time points. Boker et al. (2002)'s windowed cross-correlation, introduced in the previous section, is one approach to overcome this limitation by dividing a time series into smaller chunks, each of which is likely to be more stationary than entire time series. Recurrence analysis takes another route to deal with nonlinear time series, by not relying on the stationary assumption. Instead of assuming that the relationship between lagged time points is stable over time, recurrence analysis captures the relationship at every observed time point. With this methodological advantage of analyzing nonlinear data, recurrence analysis is becoming more popular in a wide variety of field, such as social and personality psychology and group research (e.g., Richardson, Dale, & Marsh, 2014; Knight, Kennedy, & McComb, 2016). Though there has been little attention on applying recurrence analysis in psychotherapy research, it is a promising approach considering the nonlinear nature of psychotherapy process discussed in the earlier section.

Cross-recurrence analysis is an interesting extension of recurrence analysis. Like recurrence analysis, cross-recurrence analysis does not rely on the linearity assumption. However, unlike recurrence analysis, cross-recurrence analysis examines the pattern of visitation between two different time series rather than the pattern of visitation from a single time series. In other words, while recurrence analysis explores how a time series revisits states from itself, cross-recurrence analysis depicts how two different time series visits the same state (Coco & Dale, 2014). Cross-recurrence analysis is suitable to analyze synchrony between two dynamic systems whose patterns follow nonlinear trajectory. For instance, Shockley, Butwill, Zbilut, and Webber (2002) reported that cross-recurrence analysis better captures characteristics of subtle nonlinear behaviors. Due to this advantage, increasing number of researchers use cross-recurrence analysis to examine interpersonal coordination, including body movement, eye movement, and verbal communication (Shockley & Riley, 2015; Abney, Paxton, Dale, & Kello, 2015; Richardson & Dale, 2005).

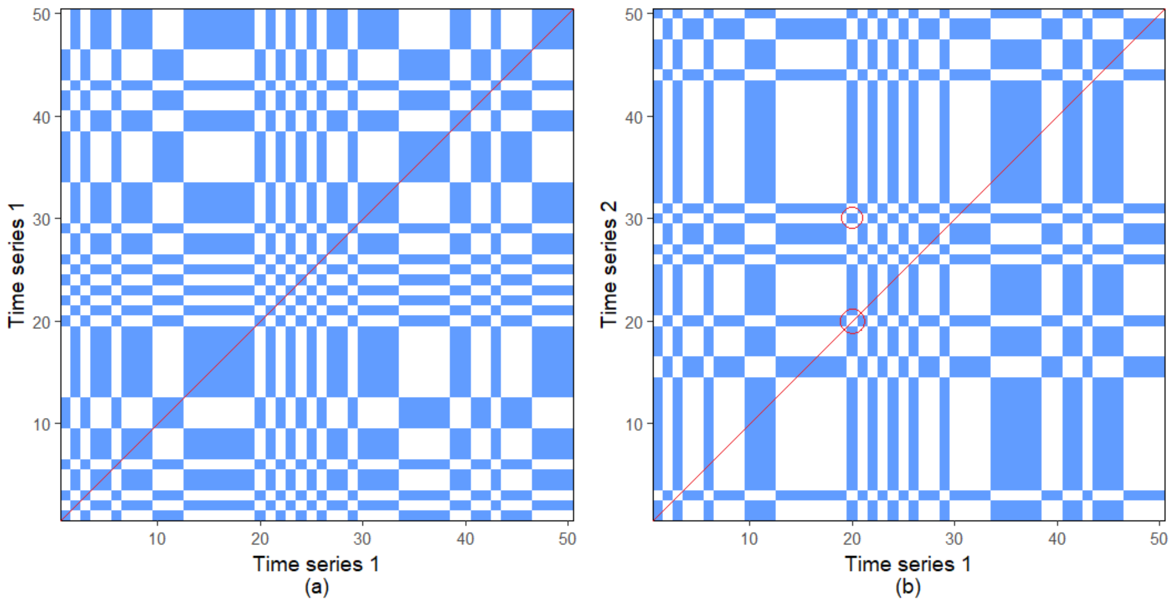


Figure 2. Example of recurrence/cross-recurrence analysis. These examples are generated by the '*simts*' function in R '*crqa*' package (Coco & Dale, 2014).

Figure 2 is provided here to illustrate difference between a recurrence plot and a cross-recurrence plot. Figure 2(a) is a recurrence plot of 'Time series 1,' which consists of 50 time points. Figure 2(b) is a cross-recurrence plot of 'Time series 1' and 'Time series 2,' both of which consist of 50 time points as well. The points marked as blue dot/squares mean that the two time points from x- and y-axis visit the same state, while the points left as blank indicate that they are not at the same state. For instance, let's say $t_{i,j}$ as 'Time series *i*'s j^{th} time point.' In figure 2(b), $t_{1,20}$ and $t_{2,30}$ are at the same state, while $t_{1,20}$ and $t_{2,20}$ are at the different state (these points are highlighted as red circles). In addition, as one can see from both plots' diagonal lines (highlighted as red lines), diagonal points in Figure 2(a) are all filled in, while those in Figure 2(b) are not; in a recurrence plot, diagonal points represent self-repetition of itself, and every point is always at the same state with itself. Meanwhile, the same time points from different time series do not necessarily exist at the same state. It is also notable that Figure 2(a) is symmetric with respect to the diagonal, but Figure 2(b) is not. This is also a property of recurrence plots; if point '*a*' is at the same state with point '*b*,' as a corollary, '*b*' is at the same state with '*a*.' By eyeballing these plots and calculating quantitative measures from them, one can better understand nonlinear properties of a single time series (Figure 2(a)) and coordination between two different time series (Figure 2(b)).

Application of Recurrence Analysis on Conversational Data

Although recurrence analysis has been mainly applied to physical/physiological phenomenon, several studies used this technique to analyze linguistic features of human communication. A dot plot, presented by Church and Helfman (1993) and Helfman (1994), are some of those earlier efforts. Although they did not make any explicit connection in their articles, a dot plot can be seen as a direct application of a recurrence plot on textual data. In a dot plot, a single character or word consists of a single point in an axis; for instance, if the word 'to' appeared in a 3rd element and 7th element in a document, these two elements are considered to be at the same state. It can describe self-similarity of a single document (like a recurrence plot) or similarity among different documents (like a cross-recurrence plot).

Unlike Church and Helfman (1993) and Helfman (1994), Dale and Spivey's (2006) analysis is theoretically based on cross-recurrence analysis. Using recurrence analysis, Dale and Spivey (2006) investigated dyadic patterns in child-caregiver interactions. As the main interest of this study was at syntactic coordination between child and caregiver, the study did not consider individual word matching as recurrence. Instead, it borrowed a simple natural language processing technique to measure recurrence; after identifying grammatical elements from sentences, they examined bigram correspondence of these elements. For example, if child stated, “I ate it!”, and caregiver responded “Yes, you ate the cake,” then “I ate” and “you ate” are considered as recurring bigrams, as both of their word class are ‘noun + verb.’ With this recurrence pattern, Dale and Spivey (2006) analyzed the conversational data with some quantitative measures, such as ‘overall recurrence,’ ‘diagonal-windowed recurrence,’ and ‘leading versus following.’ By analyzing these measures, the study revealed how patterns of leading or following conversation vary with the child’s level of development, demonstrating applicability of cross-recurrence analysis on child’s language acquisition. Within the same line of research, Fernández and Grimm (2014) proposed a different model of applying cross-recurrence analysis. Specifically, Fernández and Grimm (2014) used not only categorical convergence used by Dale and Spivey (2006), but also measured conceptual convergence using latent semantic analysis (the meaning of conceptual convergence will be further explained in the following paragraph). This study is also different from above mentioned studies, in a sense that it assigned a continuous value to each recurrence point (i.e., any real value between 0 and 1), instead of binary ones (i.e., either 0 or 1). With this approach, the study was able to compare difference in recurrence rates across conversations from different groups.

A conceptual recurrence plot is an interesting extension of recurrence and cross-recurrence plots on conversational data (Angus, Smith, & Wiles, 2012a). While a recurrence plot and cross-recurrence plot visualize only within-subject recurrence or between-subject recurrence respectively, a conceptual plot can represent both information in a single plot, by using a different plotting system. Instead of assigning a single time series to one axis like it is in recurrence or cross-recurrence plots (e.g., in figure 2 (a) and (b), x- or y-axis only represents information from a single time series, ‘Time series 1’ or ‘Time series 2.’), x- and y-axis of conceptual recurrence plots represent the information from all relevant time series (note that the number of time series that can be represented by conceptual recurrence plots can be bigger than two). Based on this conceptual recurrence plotting system, a research team at the University of Queensland developed a python-based computer program called ‘Discursis’ (Figure 3; Angus, Smith, & Wiles, 2012a; Angus, Rintel, & Wiles, 2013). It allows users to interactively explore a recurrence structure of conversation, by providing options to zoom in and out, adjust color schemes, and choose a visibility level. It is also possible to see similarity values and similar concepts between each utterance by hovering over and clicking on each recurrence point.

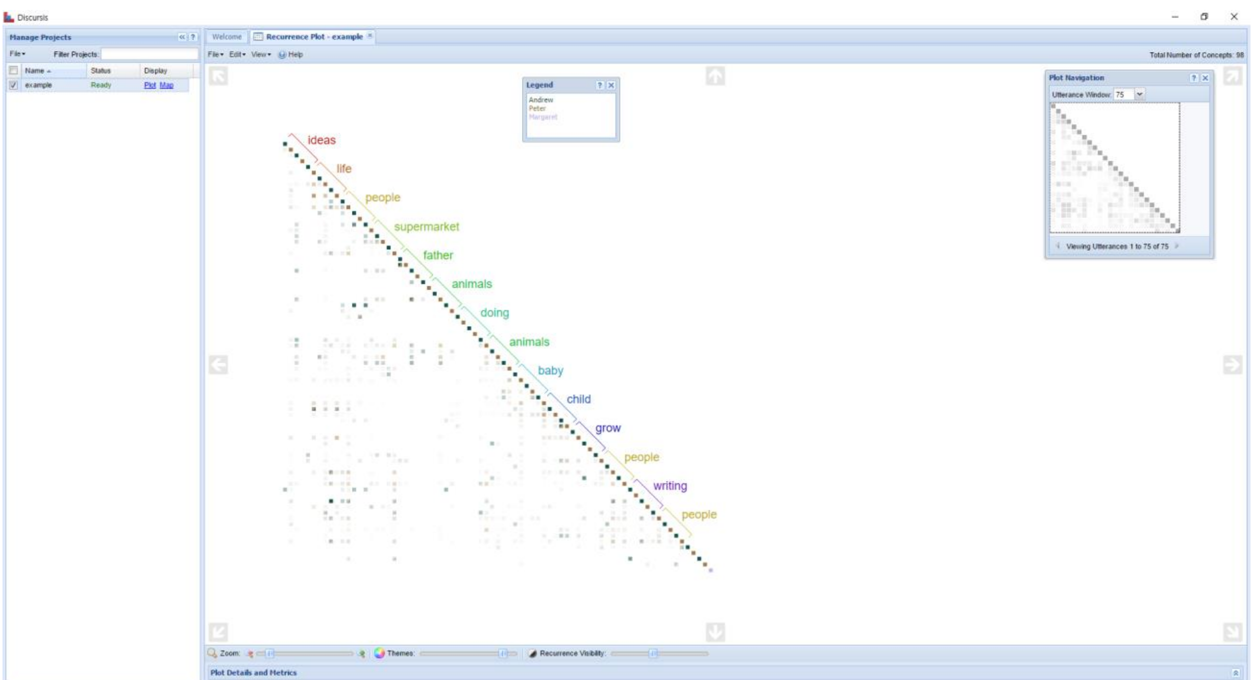


Figure 3. A screenshot from the Discursis software

A conceptual recurrence plot has been used to analyze conversational data in various contexts, including health care settings (Angus, Watson, Smith, Gallois, & Wiles, 2012; Watson, Angus, Gore, & Farmer, 2015), communication from people with dementia (Atay et al., 2015; Baker et al., 2015), broadcast interviewing (Angus, Fitzgerald, Atay, & Wiles, 2016), team communications (Tolston et al., 2017), and teacher-student discourse (Salamanca et al., 2012). These studies demonstrate the utility of a conceptual recurrence plot in revealing conversational structures. This technique has rarely been applied to psychotherapy settings except a recently completed master's thesis (Crompton, 2017). Using the Discursis software to analyze transcripts from psychotherapy sessions, Crompton (2017) introduced a conceptual recurrence plotting technique and demonstrated its utility to better understand moment-by-moment process of psychotherapy. As Crompton (2017) mainly focused on the utility of the Discursis software instead of methodology itself (i.e., conceptual recurrence plot), it would be meaningful to further explore the potential of this technique in psychotherapy research, with added methodological rigor.

Chapter 3

METHODOLOGY

Overview

This study aims at demonstrating the utility of CRP in analyzing conversational dynamics in psychotherapy. As stated earlier, CRP (Angus, Smith, & Wiles, 2012a) is a visual text analytic tool that provides insight into underlying structures of conversation. Specifically, it allows analysts to understand how participants use and share similar concepts over the development of discourse. As this method has only begun to be applied to psychotherapy settings (Crompton, 2017), this study will demonstrate how this method can be utilized to reveal turn-to-turn conversational dynamics of psychotherapy process. This is a meaningful contribution to existing text analysis studies on psychotherapy, considering that there has been scant research on analyzing within-session level dynamics except some rare exceptions (e.g., Lepper & Mergenthaler, 2008). In addition to investigate qualitative features from visualization, this study also examined the usefulness of quantitative metrics of conceptual recurrence plots proposed by Angus, Smith, and Wiles (2012b). As the early study (i.e., Crompton, 2017) only qualitatively interpreted data from the visualizations, examining the utility of these quantitative metrics would be an interesting area to explore.

Conceptual Similarity Measure

To build a conceptual recurrence plot, conceptual similarity values between utterances need to be calculated. Following the example of Angus, Smith, and Wiles (2012a, 2012b), this study calculated conceptual similarity by using a similarity algorithm proposed by Salton (1989).

Angus, Smith, and Wiles (2012a, 2012b) provided detailed explanation on how Salton's similarity algorithm works. First, stop words and punctuations are removed from a document (*D*; in this case, a document is a transcript from a single psychotherapy session). With this pre-processed document (D'), a term vector ($\boldsymbol{T}$) of length $\boldsymbol{T}_{\text{size}}$ is generated, which consists of every unique term (t_i) appears within D'. D' is decomposed into *N* sentence windows, each of whom contains *w* sentences in it (*w* can be 1 or more; in this study, $w = 2$). An occurrence vector ($\boldsymbol{O}$, whose dimension is $\boldsymbol{T}_{\text{size}} \times 1$) is generated by counting how many sentence windows contain t_i. In addition, co-occurrence vector ($\boldsymbol{C}$, whose dimension is $\boldsymbol{T}_{\text{size}} \times \boldsymbol{T}_{\text{size}}$) is constructed by calculating how many times two terms (t_i, t_j) co-occur within a single sentence window. For calculating occurrence and co-occurrence vector, duplicated occurrence of a term within a single sentence window is treated the same as a single occurrence within a sentence window.

Salton (1989)'s similarity algorithm, which is used by Angus, Smith, and Wiles (2012a, 2012b) assigns bigger value when both terms co-occur, $P(t_i, t_j)$, or neither term occurs, $P(\bar{t}_i, \bar{t}_j)$, while giving a penalty when only either one of terms occur, $P(\bar{t}_i, t_j)$, $P(t_i, \bar{t}_j)$. The term similarity, $S(t_i, t_j)$ can be obtained as follows:

$$S(t_i, t_j) = \frac{P(t_i, t_j) \times P(\bar{t}_i, \bar{t}_j)}{P(\bar{t}_i, t_j) \times P(t_i, \bar{t}_j)}$$

$$P(t_i, t_j) = \boldsymbol{C}_{t_i t_j} / N$$

$$P(\bar{t}_i, \bar{t}_j) = \begin{cases} 1, & \text{if } \boldsymbol{O}_{t_i} + \boldsymbol{O}_{t_j} = \boldsymbol{C}_{t_i t_j} + N \\ \left(N - \boldsymbol{O}_{t_i} - \boldsymbol{O}_{t_j} + \boldsymbol{C}_{t_i t_j}\right) / N, & \text{otherwise} \end{cases}$$

$$P(\bar{t}_i, t_j) = \begin{cases} 1, & \text{if } \boldsymbol{O}_{t_i} = \boldsymbol{C}_{t_i t_j} \\ \left(\boldsymbol{O}_{t_i} - \boldsymbol{C}_{t_i t_j}\right) / N, & \text{otherwise} \end{cases}$$

$$P(t_i, \bar{t}_j) = \begin{cases} 1, & \text{if } \boldsymbol{O}_{t_j} = \boldsymbol{C}_{t_i t_j} \\ \left(\boldsymbol{O}_{t_j} - \boldsymbol{C}_{t_i t_j}\right) / N, & \text{otherwise} \end{cases}$$

(N = number of sentence windows; $\boldsymbol{O}_{t_i}$ = occurrence of t_i, which is i^{th} element of $\boldsymbol{O}_{t_i}$; $\boldsymbol{C}_{t_i t_j}$ = co-occurrence of t_i and t_j, which is (i, j) th element of $\boldsymbol{C}_{t_i t_j}$)[1]

The term similarity is used to calculate the utterance similarity. An utterance, in the context of conversational data, means a single talk-turn from a speaker. It can be either a single or multiple sentence(s). To compute the utterance similarity, D' is decomposed into an utterance list (***U***) of length $\boldsymbol{U}_{\text{size}}$.

A list of key terms (***K***) can be generated by selecting $\boldsymbol{K}_{\text{size}}$ most frequent terms from ***T*** (in this study, minimum of $\boldsymbol{K}_{\text{size}}$ is 50; note that it can be greater than 50 by including terms with the same number of smallest occurrence). After building ***K***, a similarity matrix (***S***, whose dimension is $\boldsymbol{K}_{\text{size}} \times \boldsymbol{T}_{\text{size}}$) is constructed by calculating similarities between terms in ***K*** and ***T***. A Boolean matrix (***B***, whose dimension is $\boldsymbol{T}_{\text{size}} \times \boldsymbol{U}_{\text{size}}$) contains information on whether individual terms occur in utterances or not (i.e.1 = a term occurs one or more times within an utterance, 0 = a term

---

[1] Though the similarity value of the identical terms (i.e., $S(t_i, t_i)$) can be calculated using this algorithm, it does not make much sense; intuitively, the similarity value of the same term should be at least as large as the maximum possible value of all the other similarity values (i.e., $S(t_i, t_i) \geq S(t_i, t_j)$, for $i \neq j$). However, it is not the case for this algorithm. As Angus, Smith, and Wiles (2012a, 2012b) did not mention how to handle this issue, this study set the similarity value of the identical terms as the maximum value of all the other similarity values (i.e., $S(t_i, t_i) = \max S(t_i, t_j)$, for all $i \neq j$)).

does not occur). With these matrices, the feature matrix ($\boldsymbol{V}$, whose dimension is $\boldsymbol{K}_{\text{size}} \times \boldsymbol{U}_{\text{size}}$) can be calculated as follows:

$$\mathbf{V} = \boldsymbol{S} \times \boldsymbol{B}$$

Each column of $\boldsymbol{V}$ ($\boldsymbol{V}_{*,j}$) contains information on the weighting of key terms on utterance *j*. The similarity of two utterances *i* and *j* is defined by the cosine similarity of corresponding column vectors of $\boldsymbol{V}$; mathematically, it can be represented as $\boldsymbol{V}_{*,i} \cdot \boldsymbol{V}_{*,j} / \left|\boldsymbol{V}_{*,i}\right| \cdot \left|\boldsymbol{V}_{*,j}\right|$.

Conceptual Recurrence Plots

With the calculated conceptual similarity values, a conceptual recurrence plot can be constructed. From *n* utterances, $n(n-1)/2$ similarity values can be calculated, which can be assigned into a lower triangular area of a recurrence plot. To better visualize the similarity between utterances by giving less emphasis on low similarity values, this study rescaled the values by using a nonlinear transformation with $\textit{rescaled similarity} = \textit{similarity}^2$.

Conceptual recurrence contrasts with term-based recurrence. While term-based recurrence only treats the use of the exact same term as recurrence (1 = presence of recurrence, 0 = absence of recurrence), conceptual recurrence can consider occurrence of conceptually similar terms as well (continuous values between 0 and 1 represents the degree of conceptual similarity). Unlike binary approach to visualize term-based recurrence, conceptual recurrence plots can visualize this conceptual similarity by using a level of shading which represents the degree of similarity between utterances. In addition to shading, it is also notable how conceptual recurrence plots use different colors to differentiate the source of similarities. In this study, blue and red are used to represent similarity between utterances from the same speaker, while black is used to indicate similarity between utterances from different speakers.

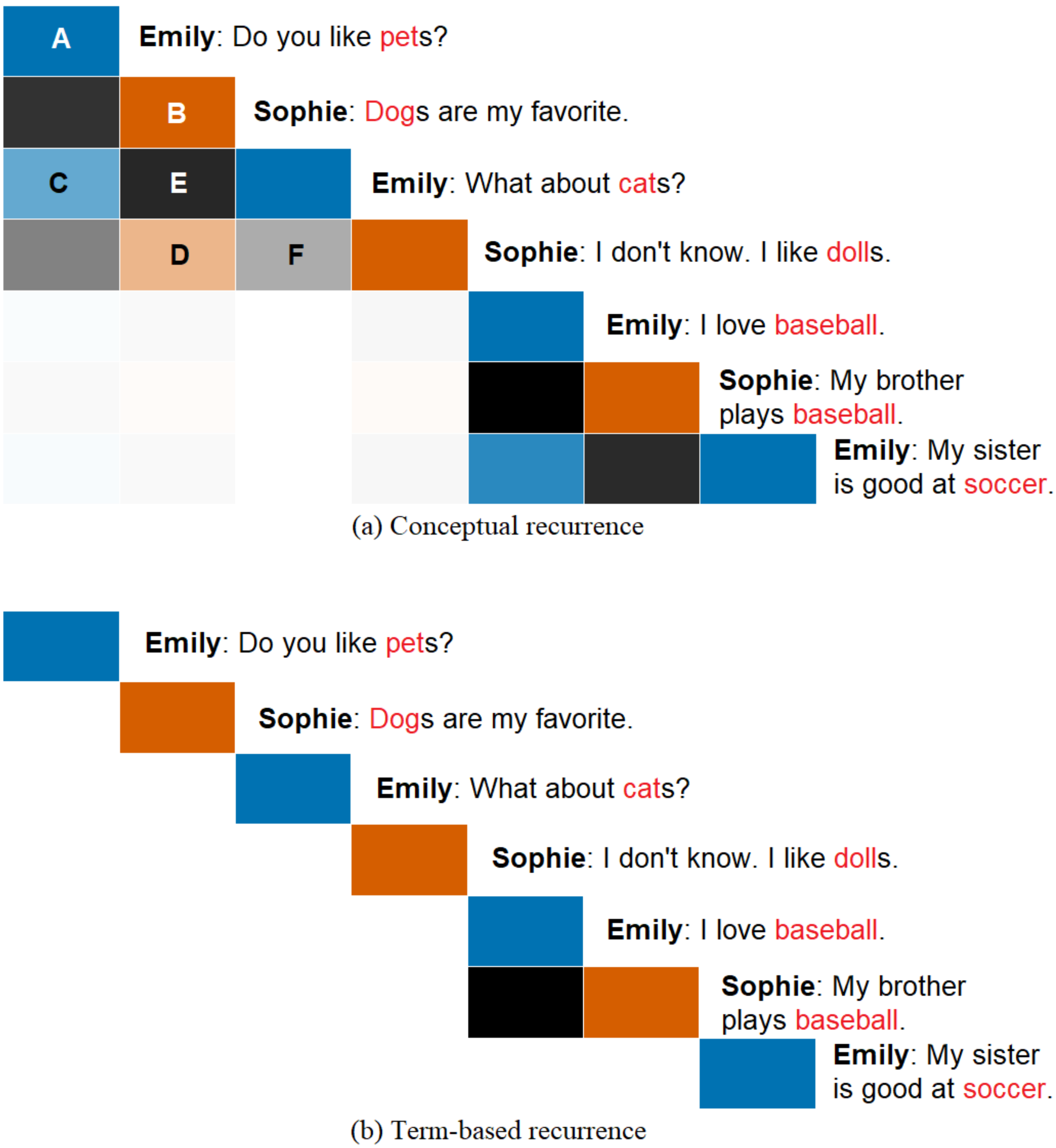


Figure 4. An example of a conceptual recurrence plot and term-based recurrence plot

To help better understand how conceptual recurrence plots work, a toy example is provided here. Let's imagine two kids have a following conversation:

Emily: Do you like pets?

Sophie: Dogs are my favorite.

Emily: What about cats?

Sophie: I don't know. I like dolls.

Emily: I love baseball.

Sophie: My brother plays baseball.

Emily: My sister is good at soccer.

A conceptual recurrence plot generated from this conversation is illustrated in Figure 4 (a). A term-based recurrence plot is provided in Figure 4 (b) for comparison. To make this example easier to understand, utterance similarity is measured based on only one key term from each sentence, which is highlighted as red in Figure 4. In other words, all the other terms except these key terms are treated as stop words which are removed during the pre-processing. Therefore, in this simplified case, utterance similarity is the same as word similarity. The word similarity is calculated by using Wu-Palmer similarity algorithm based on python Wordnet (Wu & Palmer, 1994).

In Figure 4 (a), one may notice that all utterances from two speakers are plotted in a single time sequence regardless of which axis one focuses on. Several points are marked with different alphabets to illustrate how to interpret a conceptual recurrence plot. First, the diagonal represents each utterance; A and B are illustrated with different colors as they are from different speakers, with blue representing Emily's utterance and red representing Sophie's one. A lower triangle area under the diagonal line visualizes the similarity between each pair of utterances and the color of each point indicates the origin of its recurrence. For example, C is colored as blue because it represents the similarity between Emily's utterances (i.e., "Do you like pets?" and "What about cats?"). By the same logic, D is marked as red, because it illustrates the similarity between Sophie's utterances. E is marked as a different color (black), as it represents how similar the utterances between Sophie and Emily are. As it is mentioned above, this conceptual recurrence plot includes information about both recurrence and cross-recurrence: C and D are the information that can be visualized with a recurrence plot, while E represents the information about cross-recurrence. Meanwhile, E and F are both black (or on the grayscale spectrum), showing utterance similarities between different speakers, but E is darker than F. It is because the similarity value between 'dog' and 'cat' (E) is greater than that of 'cat' and 'doll' (F) within the Wu-Palmer similarity algorithm.

Comparison between Figure 4 (a) and (b) allows us to see the advantage of conceptual recurrence over term-based recurrence. In a term-based recurrence plot, only one utterance pair was marked to be similar ("I love baseball." / "My brother plays baseball."), as it requires the exact word matching to detect utterance similarity. On the contrary, conceptual recurrence was able to capture the similarity between similar, but not identical words. As a result, Figure 4 (a) could illustrate conversational dynamics by visually grouping similar utterance clusters.

MPR (Multi-Participant Recurrence) Metrics

Multi-participant recurrence (MPR) metrics were proposed by Angus, Smith, and Wiles (2012b) to quantify properties of conceptual recurrence patterns. Angus, Smith, and Wiles

(2012b) demonstrated that these metrics could be useful in identifying conversational structures by applying them to several case examples.

MPR metrics are defined in three steps (i.e., dimensions, primitives, and metrics), which advances from basic concepts to more complex ones (Angus, Smith, & Wiles, 2012b). In brief, dimensions are basic foci of attention that serve as building blocks of primitives; primitives are all possible combinations of these three dimensions; metrics are statistics calculated from primitives, which is used to reveal the characteristics of conversational dynamics. These three stages are further described below.

A. Dimensions

Dimensions are basic building blocks of primitives. There are three principal dimensions: Time scale, Direction, and Type. Figure 5 is presented here to visually illustrate what these three dimensions mean.

Time Scale:

- Short ('1' in Figure 5(a)): the single closest similarity value of interest.
- Medium ('2' in Figure 5(a)): similarity values within a medium range (t_{med}; in this study, $t_{\text{med}} = 5$; note that t_{med} was set to 2 in Figure 5(a) for concise illustration).
- Long ('3' in Figure 5(a)): all similarity values relevant to current utterance.

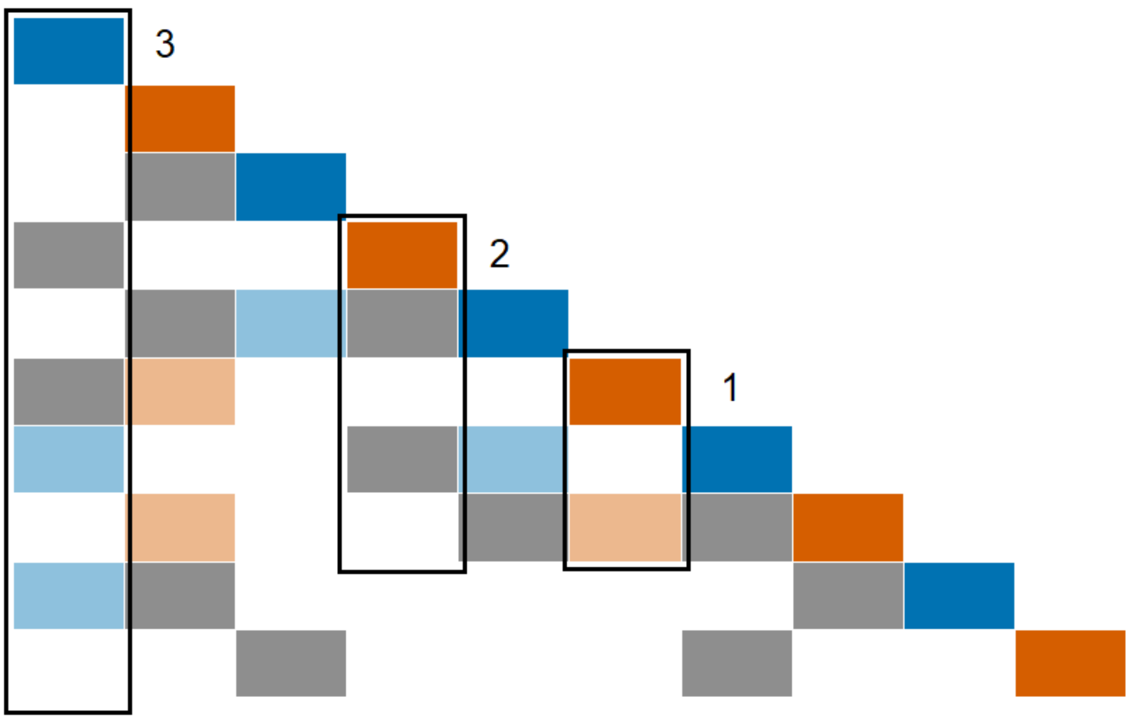
Direction:

- Forward ('1' in Figure 5(b)): similarity values between the current utterance and previous utterances.

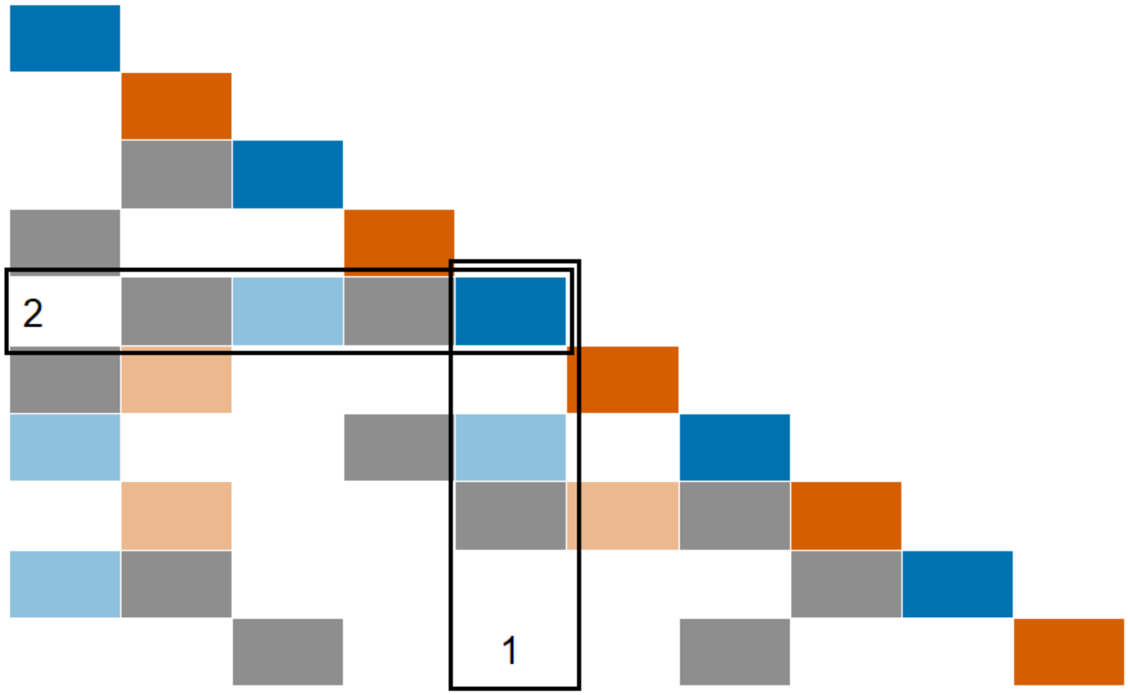
- Backward ('2' in Figure 5(b)): similarity values between the current utterance and later utterances.

Type:

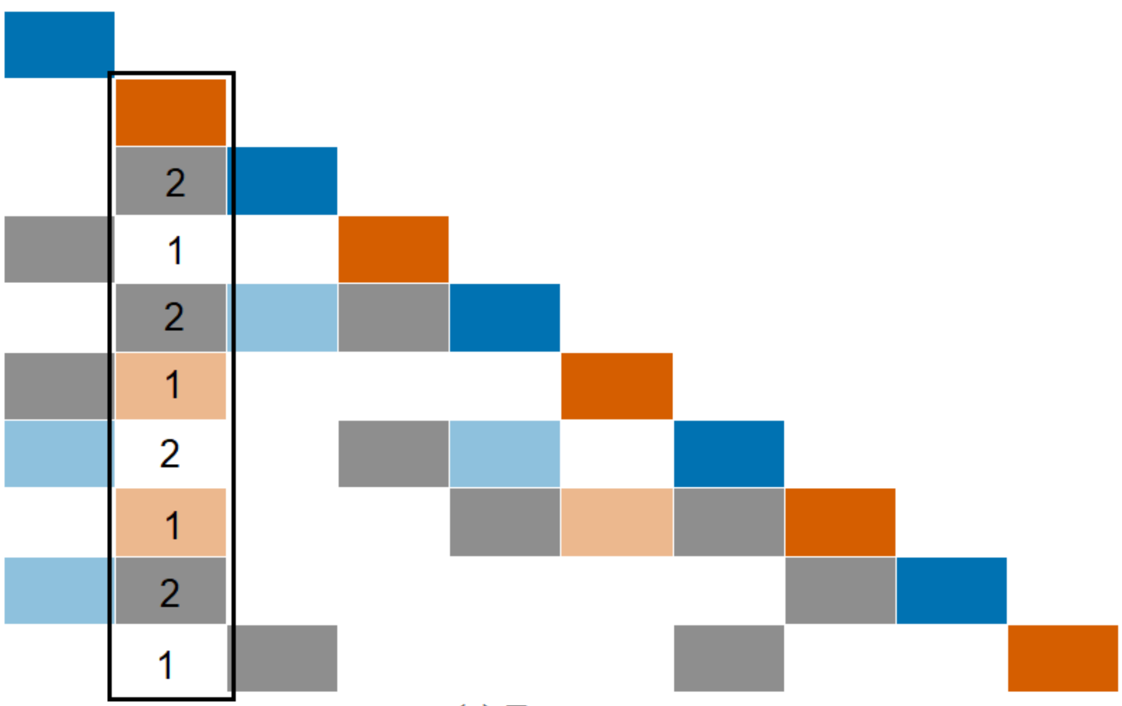
- Self ('1' in Figure 5(c)): similarity values between the current utterance and utterances from the same speaker
- Other ('2' in Figure 5(c)): similarity values between the current utterance and utterances from another speaker.



(a) Time scale



(b) Direction



(c) Type

Figure 5. An illustration on three dimensions of recurrence

B. Primitives

Twelve primitives can be generated from all possible combinations of the above three dimensions (3 × 2 × 2 = 12). Each primitive is named after its dimensional elements. For instance, Figure 6 illustrates one possible combination of three dimensions. Its dimensional characteristics are long (as it includes all similarity values of the current utterance), backward (as it contains similarity values from prior utterances), and self (as it focuses on similarity values of the same speaker). Therefore, this primitive is called 'Long Backward Self,' which can be abbreviated as 'LBS.' LBS value of the utterance marked as a star shape can be calculated by summing up the similarity values marked as heart shapes. The second column of Table 1 summarizes mathematical representations of all twelve MPR primitives.

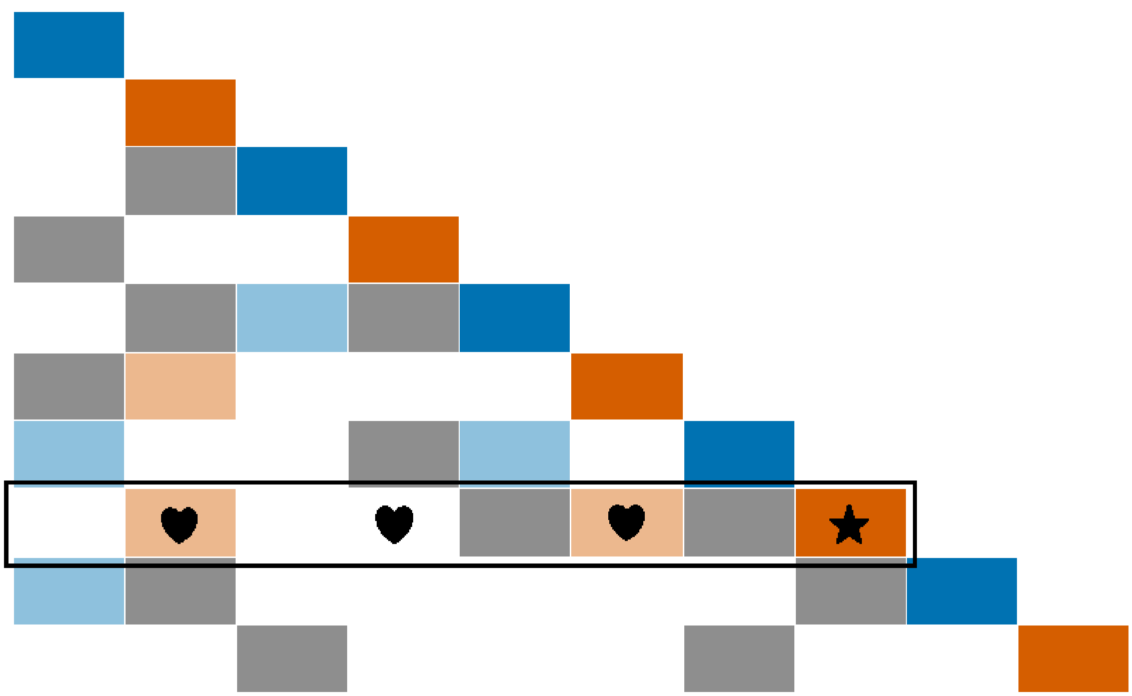


Figure 6. An example of Long Backward Self (LBS)

In many cases, it is useful to normalize primitive values so that they have values between 0 and 1. This can be done by dividing primitives by maximum possible values which are referred as normalization factors. For instance, *MFS'*, the normalized primitive of *MFS* (Medium Forward Self), can be calculated by

$$MFS'(t) = \frac{MFS(t)}{(count\{i \in [t+1, t+t_{med}] : A(t) = A(i)\})}$$

where the *count*(x) function refers to the number of similarity values included in its primitive. Normalization factors for each primitive are summarized in the last column of Table 1. These primitives function as building blocks for various metrics, which will be introduced in the next section.

Table 1

MPR primitives and their normalization factors (Angus, Smith, & Wiles, 2012b)

Primitive	Equation	Normalization factors
Short Forward Self	$SFS(t) = S(t, \text{next}(t))$	1
Medium Forward Self	$MFS(t) = \sum_{i=t+1}^{t+t_{med}} \text{self}(t,i)S(t,i)$	$count\{i \in [t+1, t+t_{med}] : A(t) = A(i)\}$
Long Forward Self	$LFS(t) = \sum_{i=t+1}^{t_{max}} \text{self}(t,i)S(t,i)$	$count\{i \in [t+1, t_{max}] : A(t) = A(i)\}$
Short Forward Other	$SFO(t) = \text{other}(t, t+1)S(t, t+1)$	1
Medium Forward Other	$MFO(t) = \sum_{i=t+1}^{t+t_{med}} \text{other}(t,i)S(t,i)$	$count\{i \in [t+1, t+t_{med}] : A(t) \neq A(i)\}$

Long Forward Other	$LFO(t) = \sum_{i=t+1}^{t_{max}} \text{other}(t,i)S(t,i)$	$count\{i \in [t+1, t_{max}] : A(t) \neq A(i)\}$
Short Backward Self	$SBS(t) = S(t, \text{last}(t))$	1
Medium Backward Self	$MBS(t) = \sum_{i=t-t_{med}}^{t-1} \text{self}(t,i)S(t,i)$	$count\{i \in [t-t_{med}, t-1] : A(t) = A(i)\}$
Long Backward Self	$LBS(t) = \sum_{i=1}^{t-1} \text{self}(t,i)S(t,i)$	$count\{i \in [1, t-1] : A(t) = A(i)\}$
Short Backward Other	$SBO(t) = \text{other}(t,t-1)S(t,t-1)$	1
Medium Backward Other	$MBO(t) = \sum_{i=t-t_{med}}^{t-1} \text{other}(t,i)S(t,i)$	$count\{i \in [t-t_{med}, t-1] : A(t) \neq A(i)\}$
Long Backward Other	$LBO(t) = \sum_{i=1}^{t-1} \text{other}(t,i)S(t,i)$	$count\{i \in [1, t-1] : A(t) \neq A(i)\}$

C. *Metrics*

Researchers can construct MPR metrics by combining 12 primitives introduced above. MPR metrics are used to quantify conversational dynamics represented in conceptual recurrence plots. This study will rely on eight metrics proposed by Angus, Smith, and Wiles (2012b), which are further described below.

Immediate Topic Repetition (ITR): The ITR metric measures how often and how many concepts were immediately repeated by another speaker. Topic repetition is a widely observed phenomenon in different types of conversations. In psychotherapy settings, the topic repetitions of therapists may reflect the use of restatement or reflection of feelings. Meanwhile, topic repetition from clients may be related to client's conformity to therapist's intervention. ITR at time *t* can be calculated as follows:

$$\mathrm{ITR}(t) = SBO'(t)$$

Topic Introduction (TI): The TI metric measures how much a speaker contributes to a topic, which are not referred by the immediate prior utterance from another speaker. TI at time *t* can be calculated as follows:

$$\mathrm{TI}(t) = MFO'(t) \times (1 - SBO'(t))$$

The TI metric is greater when similar concepts are repeated by another speaker during the successive utterances within the medium range ($MFO'(t)$). $1 - SBO'(t)$ is a weighting term to assign a greater value when topic of the current utterance is less relevant to that of the immediate previous utterance from another speaker.

Topic Reiteration (TR): The TR metric measures how much an utterance contains concepts previously mentioned by another speaker. TR at time *t* can be calculated as follows:

$$\mathrm{TR}(t) = MBO'(t) \times SBO'(t)$$

The TR metric is greater not only when an utterance is relevant to topics appeared in the immediate previous utterance from another speaker ($SBO'(t)$), but also when it contains topics in some earlier utterances from another speaker ($MBO'(t)$).

Topic Consistency Other (TCO): The TCO metric measures how much a speaker repeats concepts mentioned by preceding and successive utterances from another speaker within a medium time range. TCO at time *t* can be calculated as follows:

$$\mathrm{TCO}(t) = MBO'(t) + MFO'(t)$$

High value of the TCO metric implies that the topic appeared in the current utterance is shared by another speaker during the time frame of interest.

Topic Consistency Self (TCS): The TCS metric measures how much a speaker repeats concepts mentioned by their own utterances within a medium time range. This measure is similar to TCO, other than the fact that it focuses on self-repetition. TCS at time *t* can be calculated as follows:

$$\mathrm{TCS}(t) = MBS'(t) + MFS'(t)$$

Long-term Topic Novelty (LTN): The LTN metric measures how novel concepts appeared in the current utterance are and how much they are repeated in later utterances from another speaker. LTN at time *t* can be calculated as follows:

$$\mathrm{LTN}(t) = LFO'(t) - LBO'(t)$$

As the value of LTN is dependent on its position in conversation, this metric may require normalization if needed.

Long-term Topic Consistency Other (LTCO): The idea behind LTCO metric is similar to that of TCO, except its time frame of interest; while TCO considers a medium time range, LTCO focuses on entire time frame of conversation. High LTCO values mean that concepts in the current utterance are repeated by another speaker throughout the whole conversation. LTCO at time *t* can be calculated as follows:

$$\mathrm{LTCO}(t) = LBO'(t) + LFO'(t)$$

Long-term Topic Consistency Self (LTCS): Like LTCO, LTCS is an extended version of TCO metrics; it reflects the degree of concept repetition by oneself throughout the entire conversation. LTCS at time *t* can be calculated as follows:

$$\mathrm{LTCS}(t) = LBS'(t) + LFS'(t)$$

Data

This study applied a CRP technique to three psychotherapy transcripts from the APA Psychotherapy Video Series listed in PsycTHERAPY (American Psychological Association, 2012)[2]. This video series was designed to support clinical training and education for therapists, and each video covers various therapeutic approaches and client concerns. This video series effectively serves the purpose of this study for the following reasons: 1) the videotaped sessions are very similar to real-world psychotherapy, in terms of time frame (40-50 minutes) and contents, 2) as each video represents particular theoretical orientations and/or client concerns, comparison between different sessions is likely to generate distinctive results, 3) as it is available for researchers whose institution has site license for this database, readers of this study may access to the sessions used for this study to have better understanding on how the plotting technique works.

The researcher received permission from the APA permissions department for using this video series for the research purpose. The researcher chose the three demonstration videos from the website whose processes exhibit distinctive characteristics with each other. The transcripts of these three selected videos were downloaded and entered into .csv file with separation between utterances. A brief description of these videos is provided in Table 2[3].

---

[2] Copyright © 2018 American Psychological Association, Used with permission.

[3] To protect participants from being identified, demographic information of therapists and clients is not disclosed here. One can find this information from the website (https://psyctherapy.apa.org/browse/title), provided they have access to this database.

Table 2

Summary of the videotaped sessions used in this study

Title	Transcript Number	Therapeutic approach	Therapy topic	Length
- A Psychodynamic Approach to Spirituality in Psychotherapy	1	Psychodynamic Psychotherapy	Divorce	43 mins
- Treating Social Anxiety with Cognitive Behavior Therapy	2	Cognitive Behavior Therapy	Timidity	47 mins
- A Divorced Mother Tries to Balance School and Childcare Responsibilities	3	Multicultural Counseling	Stress	44 mins

Note. Transcript numbers are used to indicate each transcript for the remaining part of the study.

CHAPTER 4
RESULTS

Data Analysis Steps

Data analysis was conducted as follows. First, stop words and punctuation were removed from transcripts, so that analysis can only focus on meaningful concepts. In the following step, conceptual similarities were calculated using the similarity algorithm explained in the previous section (Salton, 1989). Based on these conceptual similarity metrics, conceptual recurrence plots were generated for each transcript. In addition, corresponding MPR metrics were also calculated. With qualitative information from plots and quantitative information from MPR metrics, each psychotherapy transcript was thoroughly reviewed by the researcher to explore how CRP techniques capture and describe unique features of each transcript. Because of its exploratory nature, this analysis focused on revealing idiosyncratic dynamics of individual cases, rather than conducting formal statistical analyses, such as significant testing.

Instead of using Discursis, a python-based GUI program for conceptual recurrence plotting, R (R Core Team, 2017) was used for the entire process of this analysis. R is a freely available, yet powerful program for statistical and textual analyses. Though Discursis is an excellent program which is highly accessible to many researchers who are not familiar with programming languages, some researchers may benefit from more flexible control on their work flow (e.g., implementing their own similarity algorithm). An R script can be one of the options that allows this flexibility to researchers.

Characteristics of Transcripts

Number of utterances and words used in three psychotherapy transcripts are summarized in Table 3 and 4. Table 3 shows that total number of utterances in Transcript 1 is smaller than that of other transcripts. Considering that length of the actual sessions and total number of words included in each transcript are comparable in all three transcripts, this difference in total number of utterances suggest that, in average, each utterance contains more words in Transcript 1 than Transcript 2 and 3. Table 4 also provides important information on conversational dynamics: while the client used more words than the therapist in Transcript 1 and 3, the number of words used by the therapist is about 4 times more than that used by the client in Transcript 2.

Table 3

Number of utterances in each transcript

Transcript	Total utterances	Number of utterances by each speaker	
1 - Psychodynamic	205	Therapist	103
		Client	102
2 – CBT	329	Therapist	165
		Client	164
3 - Multicultural	317	Therapist	159
		Client	158

Table 4

Number of words used in each transcript

Transcript	Total words used	Number of words used by each speaker	
1 - Psychodynamic	6855	Therapist	2318
		Client	4537
2 – CBT	7235	Therapist	5876
		Client	1359
3 - Multicultural	6462	Therapist	2460
		Client	4002

Figures 7, 8, and 9 visualize how the number of words used by the therapist and client changed over time. This fits with the information provided in Table 4. For instance, Figure 8 illustrates a clear pattern that the therapist used more words than the client throughout the session in Transcript 2. At the same time, this graph also provides additional information on how conversational dynamics changed over time in these transcripts. Although the client generally used more words than the therapist both in Transcript 1 and 3, Figure 7 and 9 illustrates different word usage patterns: in Figure 7 (Transcript 1), the number of words spoken by the therapist was increasing toward the end, while that spoken by the client was decreasing over time. In contrast to Figure 7, no clear changing pattern is observed in Figure 9 (Transcript 3).

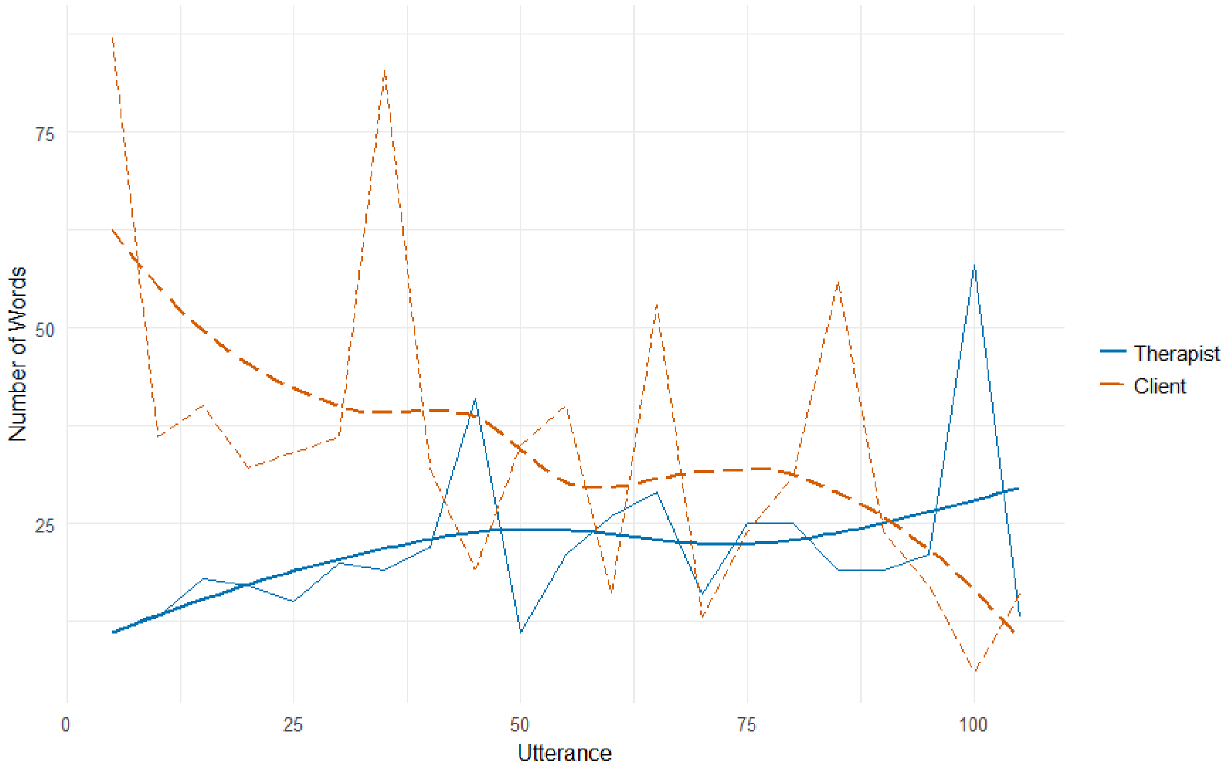


Figure 7. Number of words used in Transcript 1. Note that every 5 turns were aggregated into 1 point for better visualization. Trend lines were also provided.

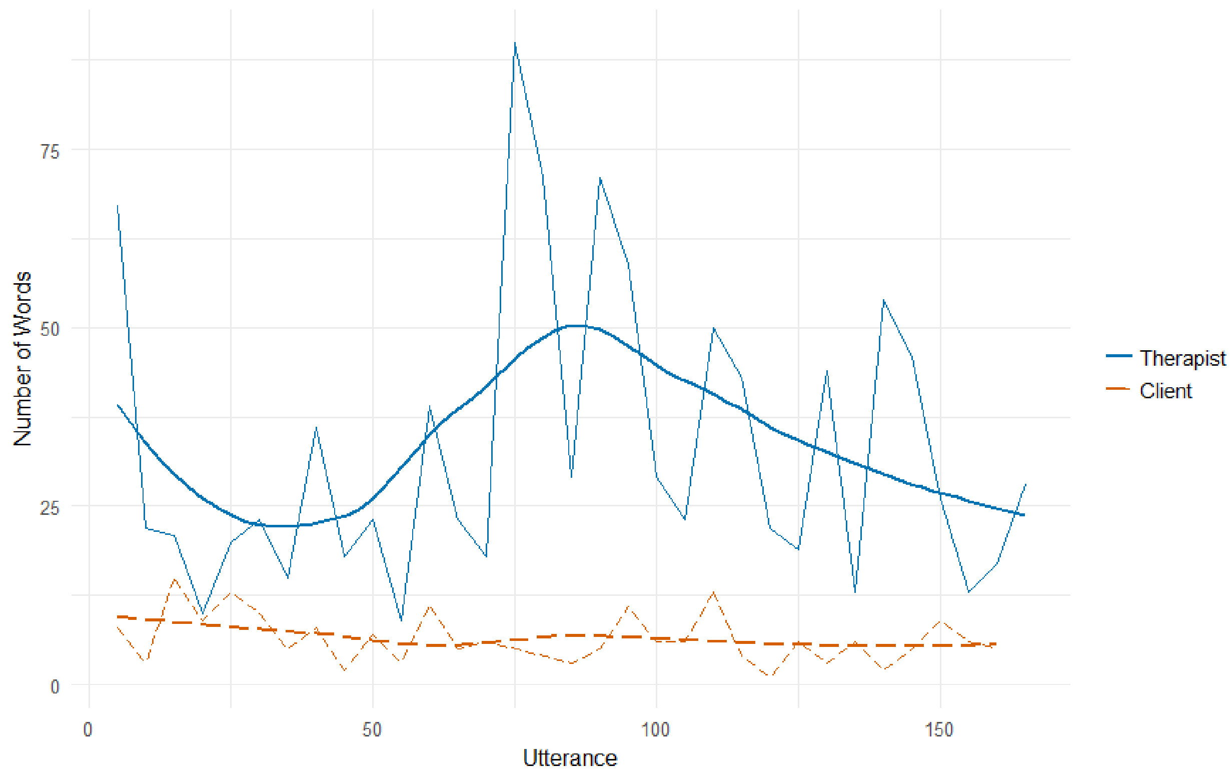


Figure 8. Number of words used in Transcript 2.

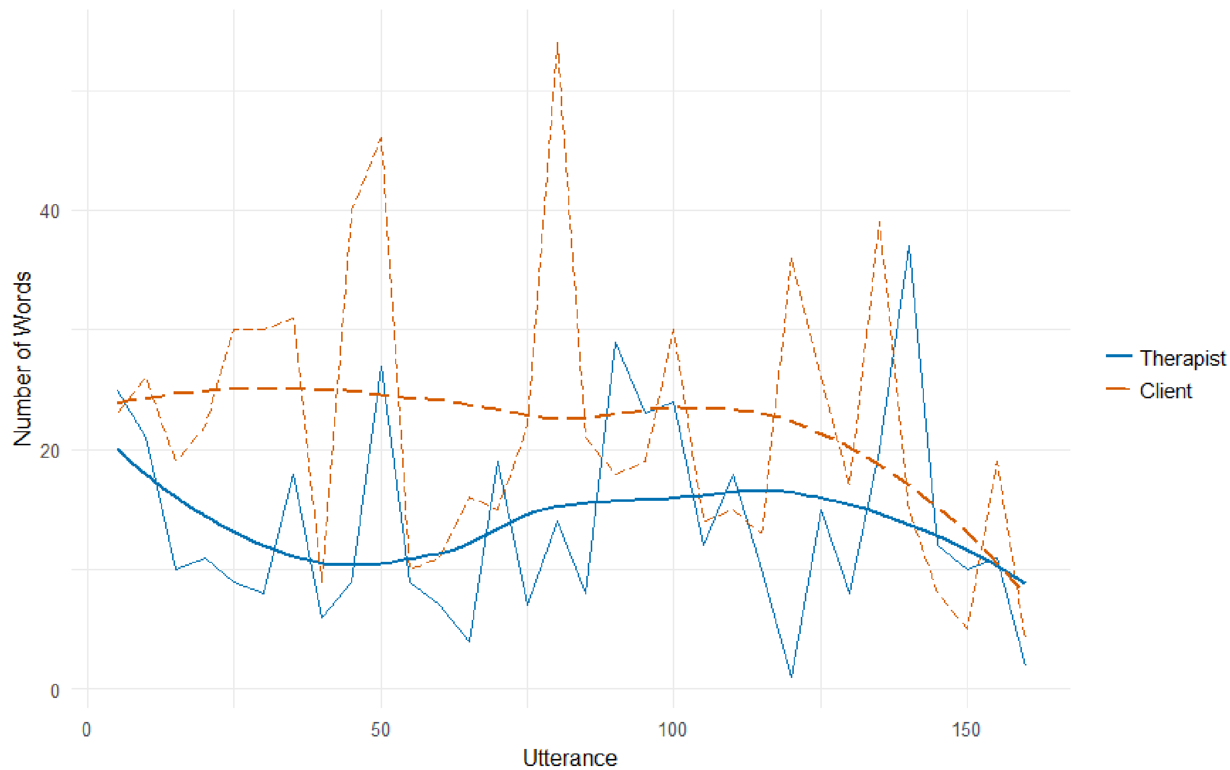


Figure 9. Number of words used in Transcript 3.

Table 5 presents average conceptual similarities in each transcript. As it is shown in Table 5, total average similarity is somewhat higher in Transcript 1 than others. Average conceptual similarities can be divided into three subcategories – similarity between therapist's utterances and therapist's utterances (marked as blue in conceptual recurrence plots), similarity between client's utterances and client's utterances (marked as red in plots), and similarity between therapist's utterances and client's utterances (marked as black in plots). An interesting pattern is observed in Table 5: while average similarities between therapist's utterances and client's utterances is the lowest among three in every transcript, similarities between therapist's utterances and therapist's utterances is higher than similarities between client's utterances and client's utterances in Transcript 1 and 2, whereas the opposite pattern is observed in Transcript 3. The implication of this result will be discussed later.

Table 5

Average conceptual similarity in each transcript

Transcript	Average similarity in total	Average similarity by type	
1	.020	Therapist-Therapist	.038
		Client-Client	.022
		Therapist-Client	.011
2	.012	Therapist-Therapist	.027
		Client-Client	.011
		Therapist-Client	.006
3	.014	Therapist-Therapist	.013
		Client-Client	.028
		Therapist-Client	.007

Qualitative Exploration of Transcripts Using Conceptual Recurrence Plots

In this section, qualitative features of each transcript are reviewed using conceptual recurrence plots. Conceptual recurrence plots can be drawn in two different ways: each block size can be adjusted proportional to the number of words in the corresponding utterance, or it can be set uniform across all utterances. In this study, all plots are drawn in the former way for the following reasons. First, Due to its relatively large number of utterances included in a single psychotherapy transcript, each block in a uniformly sized plot is too small to convey visual information. In addition, a uniformly sized plot can be misleading because of its tendency to overemphasize conceptual similarities in certain situations. It will be further discussed in the later part of this chapter.

Conceptual recurrence plots of all three transcripts are presented in Figure 10, 11, and 12. As explained in the previous chapter, a diagonal area represents utterances from two speakers (in this study, therapist's utterances are marked as blue and client's utterances are marked as red) and the length of each square's side reflects the number of meaningful terms included in the utterance. A lower diagonal area visualizes the conceptual similarities between two utterances: conceptual similarities between therapist's utterances are marked as blue and conceptual similarities between client's utterances are marked as red, while similarities between therapist's utterance and client's utterance are represented as black. Further analyses on these plots are presented in the following subsections.

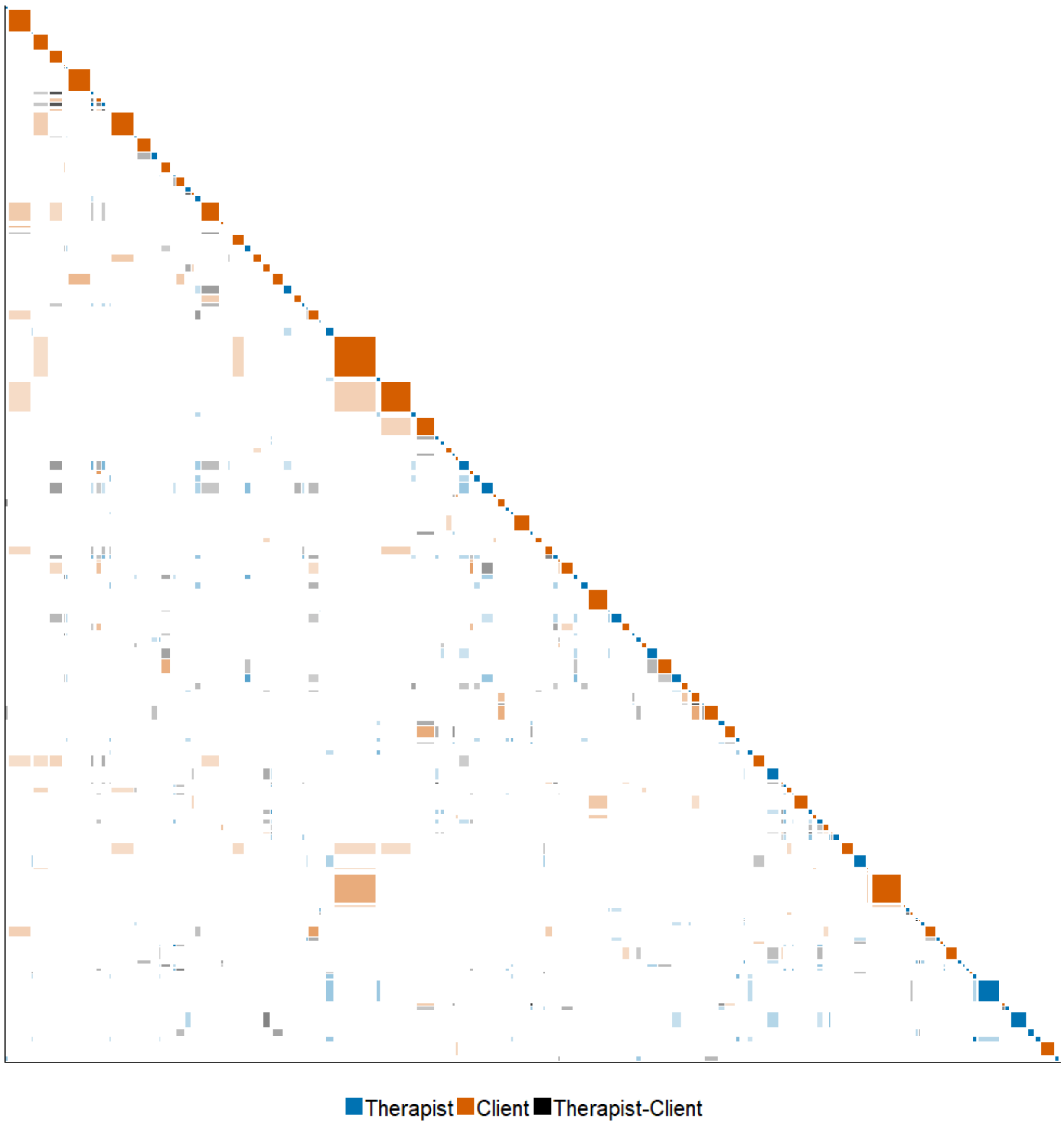


Figure 10. Conceptual recurrence plot of Transcript 1

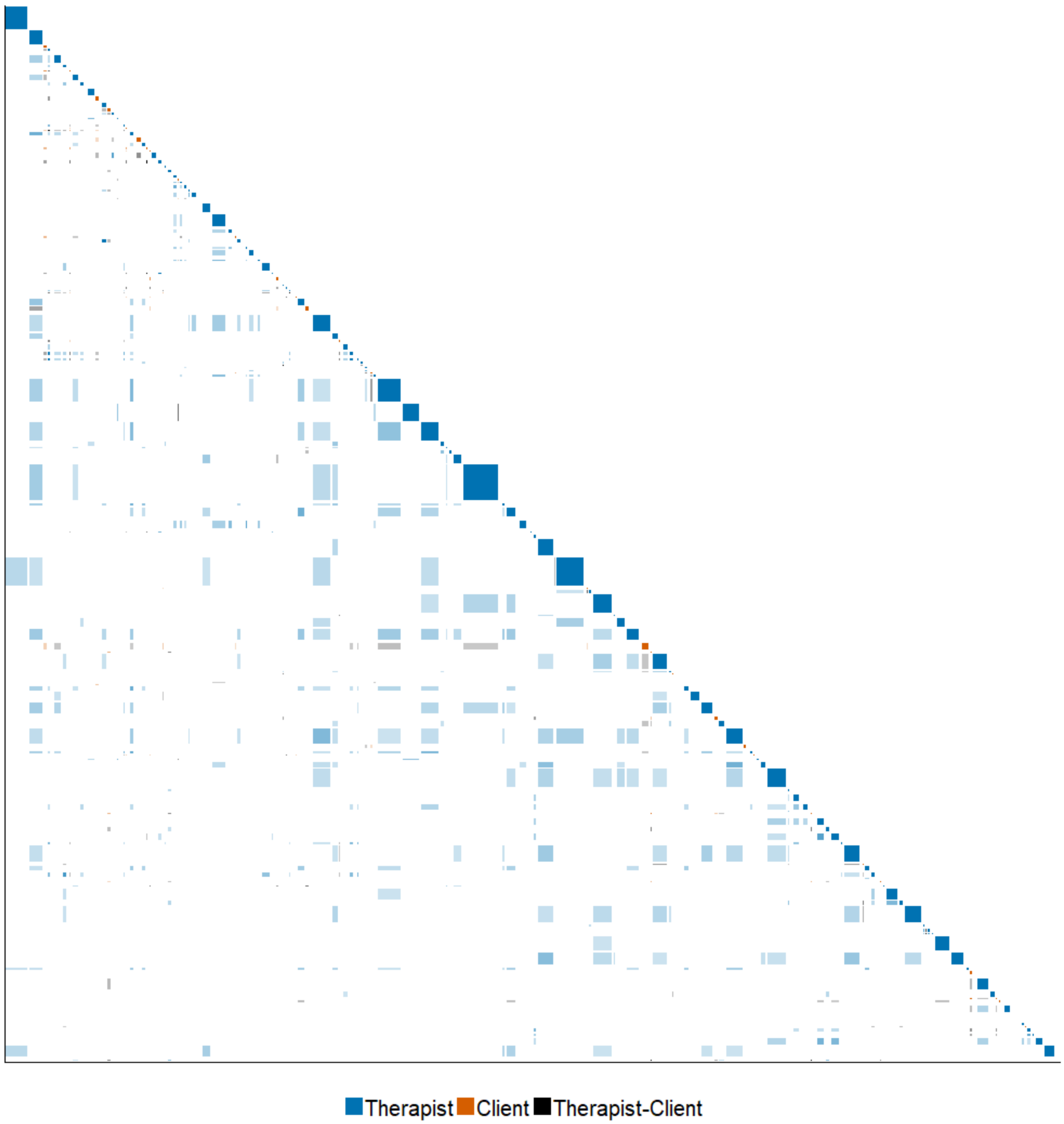


Figure 11. Conceptual recurrence plot of Transcript 2

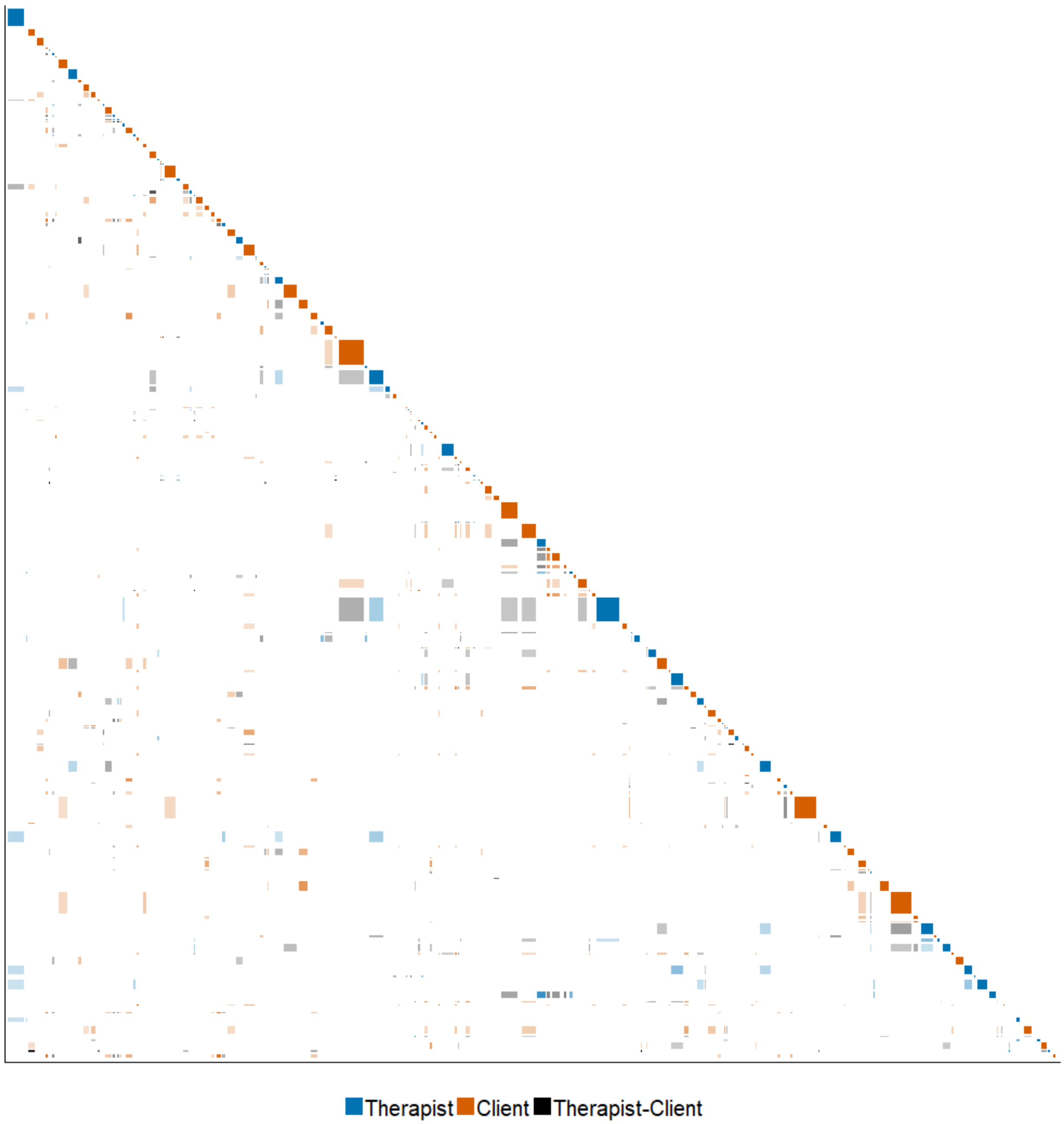


Figure 12. Conceptual recurrence plot of Transcript 3

Exploratory analysis on Transcript 1

An annotated conceptual recurrence plot of Transcript 1 is presented in Figure 13. Note that 'T(number)' and 'C(number)' each represents therapist's and client's utterance (for example, 'C34' in Figure 13 represents client's 34th utterance; note that utterance numbers were separately assigned to therapist and client, so that T1 is followed by C1, C1 is followed by T2, T2 is followed by C2, and so on), whereas lowercase letters represent multiple adjacent utterances and similarities.

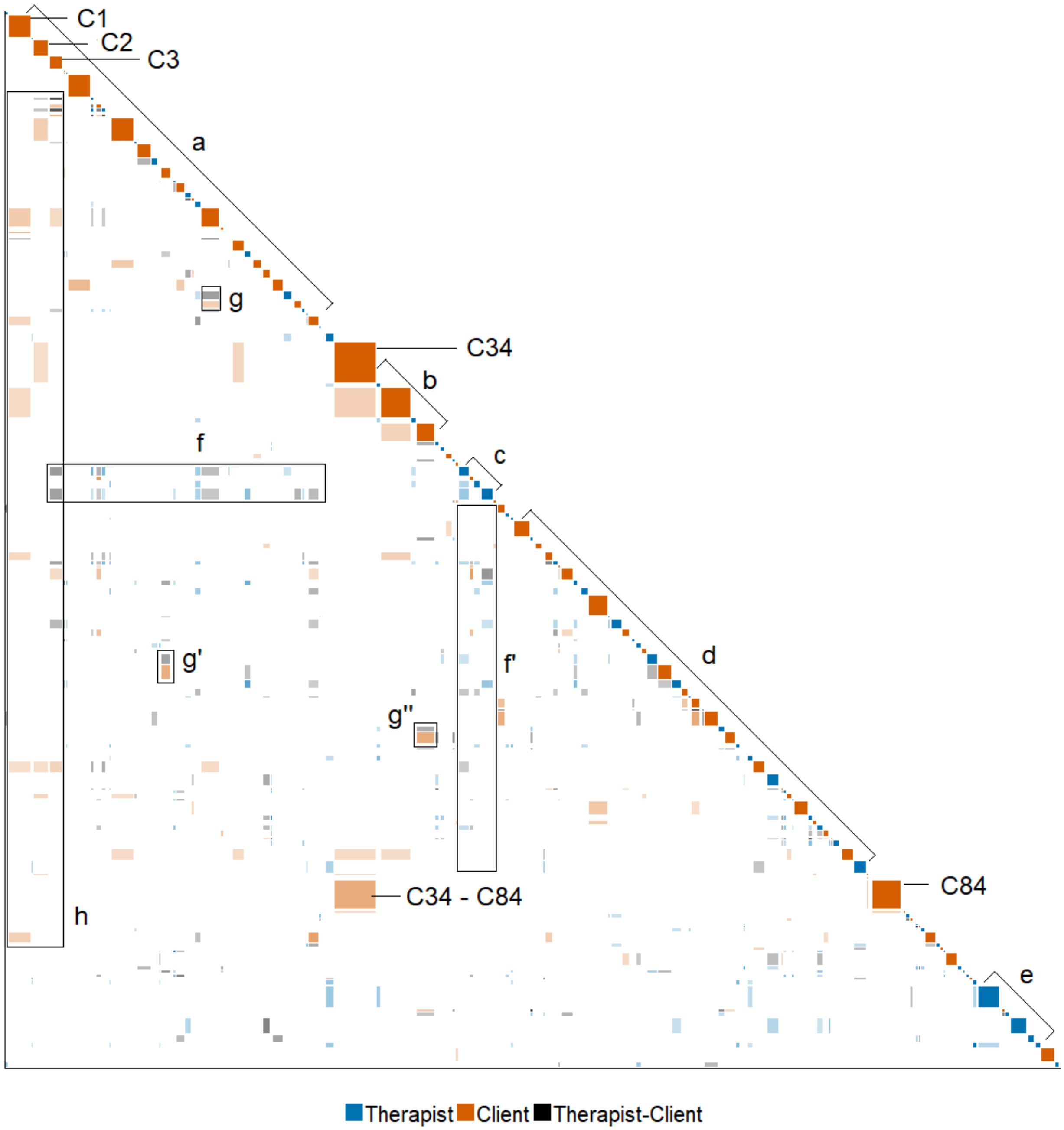


Figure 13. Annotated conceptual recurrence plot of Transcript 1

Figure 13 reveals some interesting dynamics from Transcript 1, as explained below:

a: At the beginning of the sessions (i.e., upper left corner of the visualization), the client started the conversation with relatively long utterances (C1 ~ C3) which contains the main concept that repeatedly occurs throughout the rest of the session (i.e., forgiveness, religious, marriage, daughter, church, and resentment). This is reflected in red rectangles in 'h,' which represents how much the client revisited concepts mentioned in C1 ~ C3 during the rest of the session. This openness reflects the client's high level of insight and readiness on her therapeutic concern. As the client was ready to open herself up, the therapist let the client lead the session in the beginning, mostly asking short questions to help the client to focus on the here-and-now emotions and experiences. This dynamic is illustrated as larger red squares compared to blue ones in the diagonal area, 'a.'

b: As the client's main concern was originated from the conflict between her religious values and her unresolved resentment toward ex-husband, the therapist invited the client to share how she learned her religious belief in her childhood. Responding to this invitation, the client shared her early experiences on religious life in C34, which is the longest utterance in this session. During the following utterances, the client actively participated in the process and willingly shared her experiences. This is represented as large red squares in the diagonal area, 'b.'

c: During the phase 'c' (T41 ~ T43), the therapist was more actively engaged in the verbal communication compared to the earlier part of the session. After exploring the client's religious history, the therapist connected the client's religious belief to her conflicted feeling toward forgiveness (i.e., feeling obliged to forgive vs. not wanting to forgive due to her resentment). During these short utterances, the therapist was able to summarize core concepts mentioned earlier (conceptual similarities with earlier utterances in the earlier phase ‘a,’ as shown in ‘f’) and introduce main topics that are discussed in the later part of the session (conceptual similarities with later utterances shown in ‘f '’).

d: During the phase ‘d,’ the therapist and client kept working on the client’s conflicted feeling toward forgiveness. Specifically, the therapist encouraged the client to find her religious strength and pointed out the client’s rigid belief about forgiveness which might cause her concern. This led to reduced level of resentment and increased level of forgiveness.

C34 – C84: At the end of the phase ‘d’ (T82), the therapist invited the client again to explore and share her spirituality. Responding to this invitation, the client further explored her religious history (C84) which was partly stated in C34. This is illustrated as a large red rectangle between C34 and C84 in Figure 13.

e: At the end of the session, the therapist took more active role and led the conversation, trying to wrap up the session. Relatively larger blue squares in the phase ‘e’ shows this dynamic.

g: Though conceptual similarity blocks are rather widely dispersed across the plot which makes it somewhat hard to detect clear patterns from it, there is an interesting conversational dynamic observed. There are a few sets of blocks that contain a black rectangle followed by a red one (‘g’, ‘g'’, and ‘g''’); In these blocks, the therapist invited the client to revisit concepts that are mentioned earlier, and the client responded to these interventions. This demonstrates the therapist’s effort to organize the session by connecting earlier conversations into the current ones. This also shows that somewhat dispersed similarity patterns in this plot is likely to be the indication of deliberate interventions of the therapist, rather than a sign of disorganization. One of excerpts among these blocks (‘g''’) is provided below to illustrate how this worked in this session[4].

> *C36 (the client’s earlier utterance)*: My sister, when she took my toy and broke it. *(omitted)* I was very, very upset so our mother came in and she was told what happened. *(omitted)* I told her, (sister’s name), I forgive you for breaking my toy and she says, well, I'm sorry, but by her saying she was sorry, and I just said, well, after I forgave her, I felt better. *(omitted)*
>
> (…)
>
> *T66 (the therapist revisited topics brought up earlier)*: I wonder, with your sister, you know, that how you felt every time you would look at the toy after that moment of forgiveness, how you felt when you would pick up your toy and the …
>
> *C66*: *(omitted)* I wasn't upset with her, but my toy was broken, and it wasn't the same. So, I was upset at that, that the toy was broken, and it couldn't be fixed but it was an accident, it wasn't anything she did purposely, so I didn't, never think, you know, hold it against her *(omitted)*.

Exploratory analysis on Transcript 2

An annotated conceptual recurrence plot of Transcript 2 is presented in Figure 14.

[4] Note that every excerpt cited in this study might be modified/partly removed to protect client’s identity.

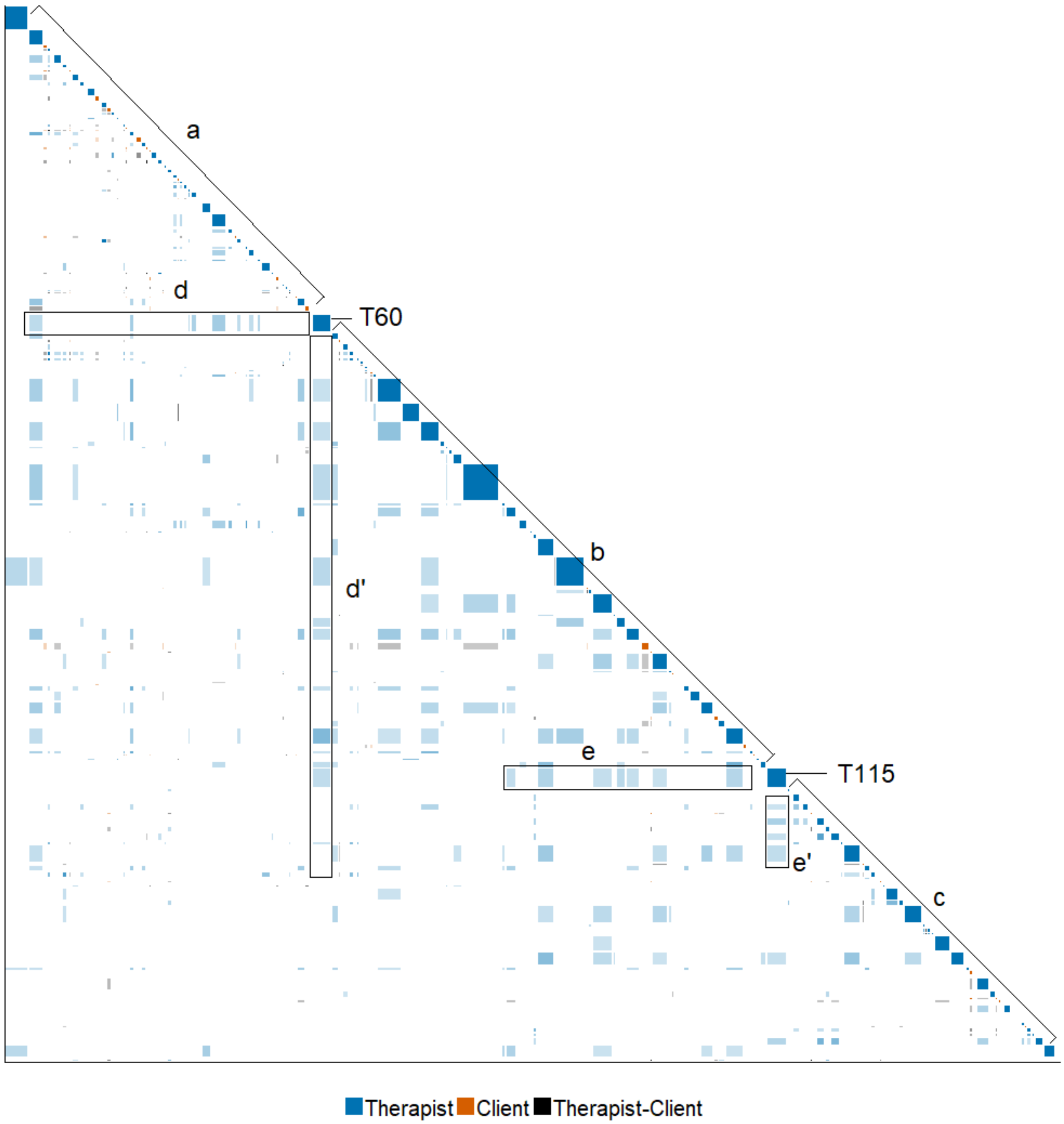


Figure 14. Annotated conceptual recurrence plot of Transcript 2

Unlike Figure 13, Figure 14 is mostly filled with blue squares and rectangles, with little red and black ones. This is because most of meaningful terms were spoken by the therapist, which is expected from Table 4 and Figure 8. In other words, the therapist took a leading role for the most part of this session, whereas the client mainly responded the therapist's questions with rather short and concise answers. Further analysis is provided below:

a: After providing a general overview of the session at T1, the therapist conducted clinical interview to assess the client's social anxiety. During the phase 'a,' the therapist asked a series of questions, such as the type of situations that are anxiety-provoking to the client, level of anxiety the client experiences in each situation, level of assertiveness, social resources, and symptoms of his anxiety. In this part, the therapist mainly used rather short questions, which is represented as comparatively small-sized blue squares in the diagonal area.

T60: In this utterance, the therapist wrapped up the information gathered from previous utterances (as shown in 'd'). The concepts appeared in this utterance kept reoccurring at the later part of this session (as shown in 'd″'), indicating that the later part of the session borrowed ideas from the information gathered earlier.

b: During this phase, the therapist provided psychoeducation on how CBT treats anxiety. The therapist also introduced how CBT framework can be applied to the client's specific situation. This phase is characterized by rather larger blue squares compared to the rest of the session, as psychoeducation requires somewhat larger utterances. In addition, compared to the phase 'a,' a lower diagonal area exhibits stronger conceptual similarities, as the main concepts used in this part mainly consist of the terms from CBT.

T115: The transition occurred in T115. In this utterance, while the therapist still borrowed some important ideas from the previous utterances (as shown in 'e'), the therapist set a new agenda of goal (task) setting here. Specifically, the therapist encouraged the client to come up with what the client wants to achieve in the next time he attends social gathering, which had been continuously discussed during the next few utterances (as shown in ‘e'’).

c: During the phase ‘c,’ the therapist kept setting a few homework practices the client can do within specific social settings. In addition, the therapist also pointed out several automatic thought patterns that might pose some challenges to homework practices.

Exploratory analysis on Transcript 3

An annotated conceptual recurrence plot of Transcript 3 is presented in Figure 15.

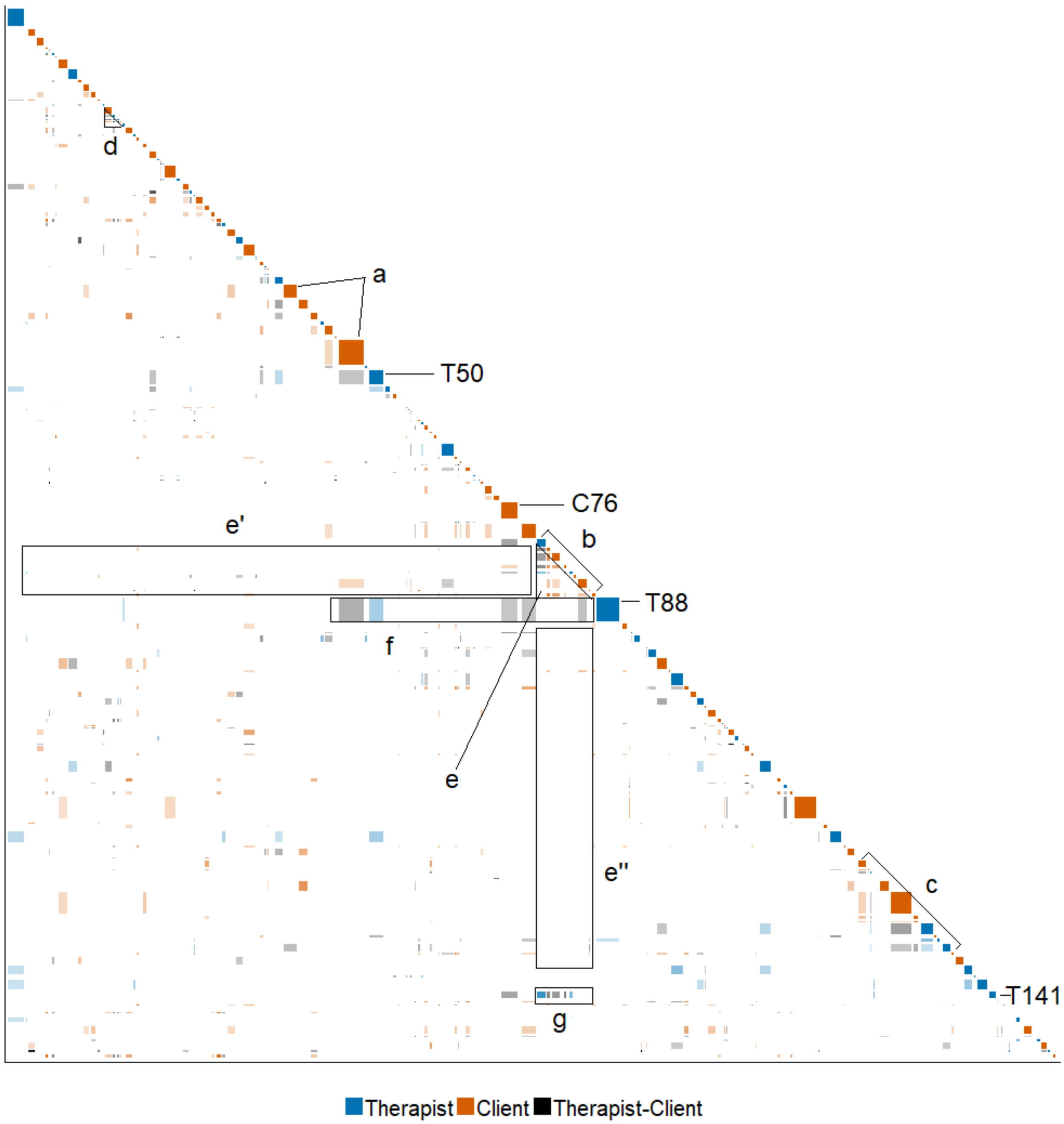


Figure 15. Annotated conceptual recurrence plot of Transcript 3

Figure 15 looks more similar to Figure 13 than Figure 14, in a sense that the therapist and client rather equally participated in the conversation in Figure 13 and 15. However, compared to

Figure 13, similarity blocks appear more sparsely, which makes sense based on the lower average similarity score shown in Table 5. More detailed analyses are provided below:

a: Compared to the client in Transcript 1, the client in this transcript was somewhat hesitant to share her concern in the beginning of the session. For example, in Transcript 1, the client provided detailed explanation on her concern in the first few utterances whose concepts repeatedly appeared throughout the session. In contrast, in the earlier part of Transcript 3, the client provided brief and factual accounts on her concern (i.e., balancing her dual role as a graduate student and a mother), rather than sharing her meaningful inner experiences. It was not until C41 and C48 that the client began to describe her experience with subjective terms (e.g., being anxious and upset about getting a grade below her expectation). However, concepts appeared in these utterances do not seem to be dominant in the later utterances from the client, which suggests that the client did not revisit these concepts later.

T50: As the client seemed to struggle in sharing her concern, the therapist took more active role in this utterance, which was represented as relatively larger squares compared to the therapist's utterances before (except T1, in which therapist provided general overview on how counseling works). In T50, the therapist restated what the client shared in C48 (shown as the black (gray) rectangle between C48 and T50 in Figure 15). At the same time, the therapist also encouraged the client to come up with more effective strategy to deal with her anxiety. Still, the client experienced a difficulty in following the therapist's lead. Due to this difficulty, not many meaningful utterances and conceptual similarities appeared until C76.

b: In C76, the client stated how she was able to find inner strength through her previous therapy, which helped her to overcome her earlier life challenge. In the beginning of the phase 'b' (T79), the therapist turned focus on the concept of strength and courage, about which the client responded well. In the next few utterances, conversation had been made around these concepts, which is reflected as dense conceptual similarity blocks in the triangular area of ‘e.’ This pattern of local concentration is noteworthy, as these concepts rarely appeared in the earlier (see ‘e'’) and later (see ‘e''’) part of the conversation. This means that the concepts discussed within the phase ‘b’ are distinctive from other concepts in the other parts of the session. Right after the phase ‘b’ (T88), the therapist encouraged the client to utilize the client’s strength and courage to make changes on her current concern (see how T88 revisited earlier concepts about the client ‘s concern and strength in ‘f’; also note that the conceptual similarities with the phase ‘b’ are mostly missing, which shows that the conceptual similarity algorithm does not perfectly catch the conversational dynamic here); however, the client’s hesitancy and ambivalence still prevented her from motivating herself.

c: In the beginning of the phase ‘c,’ the client brought up the issue of how her cultural value impacted her current work ethic, which is partly responsible for her current struggle of balancing her schoolwork and life. During this phase, the client and the therapist actively engaged in exploring this idea, which is represented as somewhat dense conceptual similarity blocks under ‘c’.

T141: As the client still remained hesitant to make changes, in this utterance, the therapist tried to give “the extra push” (*quoted from T141*) by revisiting the concepts of strength and courage and asking how the client can utilize these inner resources to make changes. This effort was represented as the similarity blocks in ‘g.’ As these concepts rarely appeared in the earlier conversation (see ‘e'''), this can be interpreted as a therapist’s intentional attempt to borrow earlier concepts to make a breakthrough in this therapeutic process.

d: Although the triangular area ‘d’ is not crucial in understanding process of this session, it shows the advantage of setting block sizes proportional to word counts over setting them uniform across the plot. In the triangular area ‘d,’ concentration of similarity blocks is observed, which makes sense given the content of corresponding utterances.

T15: Last fall, okay. And you are now full-time student?

C15: Yeah....

T16: Or part-time student?

C16: I am part-time student.

During this conversation, two main concepts (i.e., ‘time’ and ‘student’) are responsible for most of the contents, leading to higher conceptual similarities within this area. However, it is not that significant in understanding process of this session, as it is just a brief fact check. Fortunately, Figure 15 solves this problem by assigning smaller block sizes to them: although their similarity values are high, it is less noticeable in this visualization due to its small word count.

Quantitative Exploration of Transcripts Using MPR Metrics

While conceptual recurrence plots provide us qualitative understanding on conversational dynamics in psychotherapy, MPR metrics can add another layer of understanding by quantifying features underlying conceptual recurrence plots. In this section, among the various MPR metrics introduced in the previous chapter, several of them are chosen to demonstrate how MPR metrics can improve our understanding on conceptual similarity patterns of three transcripts. In addition, at the end of this section, a new MPR metric is proposed to explore its utility

ITR (Immediate Topic Repetition)

The ITR metric measures immediate repetition of concepts mentioned by another speaker. ITR is reviewed here, as it is expected to capture restatement and/or reflection of feelings, which are important techniques in psychotherapy. To explore ITR's utility in understanding psychotherapy transcripts, ITR of Transcript 1 and 3 are visualized in Figure 16 and 17.

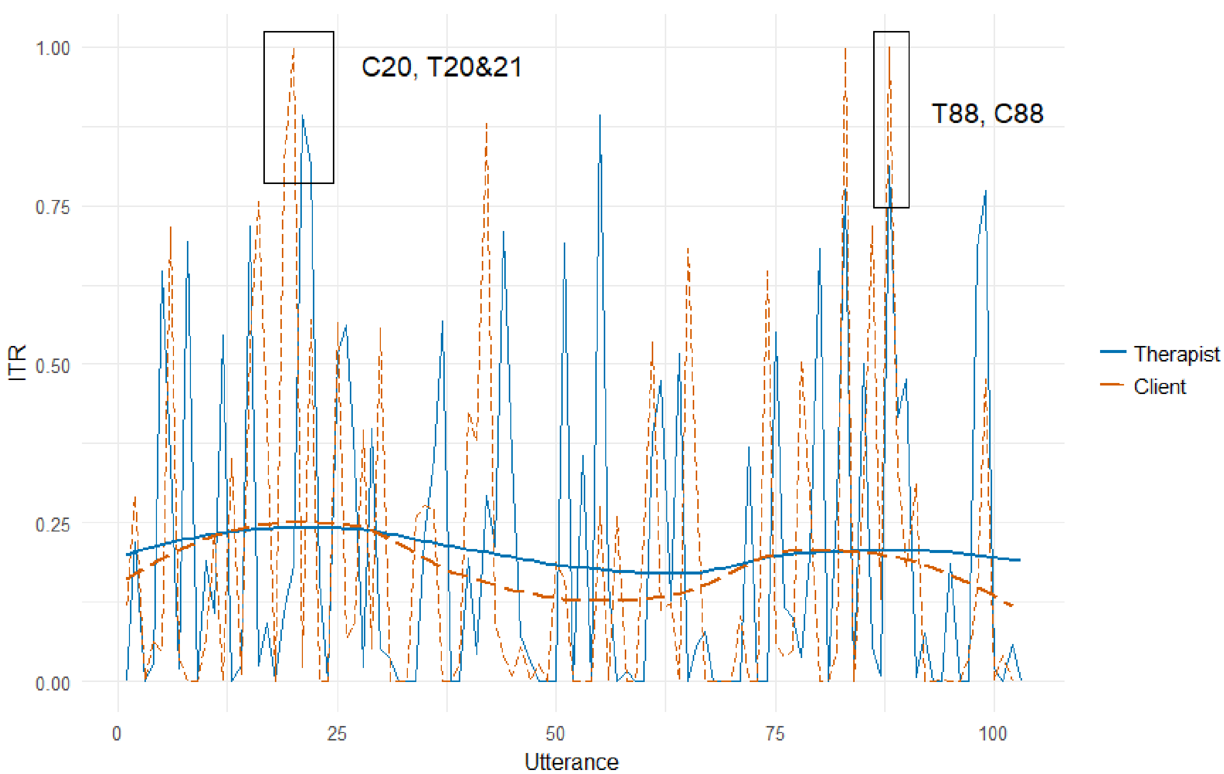


Figure 16. ITR of each utterance in Transcript 1

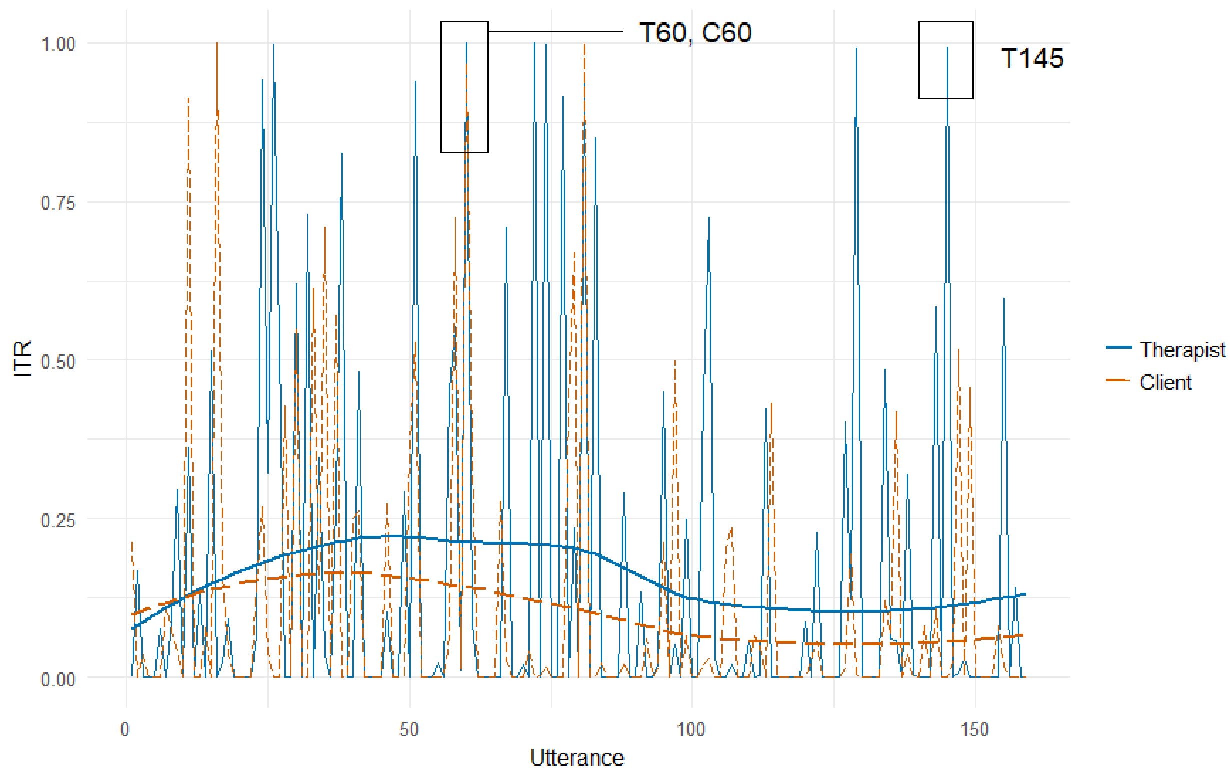


Figure 17. ITR of each utterance in Transcript 3

In these transcripts, some of the points with high ITR values are marked. Although all these points have similarly high ITR values, the reason behind it varies. For example, in T20 ~ T21 from Transcript 1, the same or similar concepts occurred repeatedly to do a simple fact check:

C19: When? Oh, not too long ago, not too long ago

T20: Within a year, within two years?

C20: Within a year.

T21: Within about a year? And your daughter is how old about?

Short questions and answers that borrow main concepts from the prior utterance also tend to exhibit high ITR value. An example is provided below (T88 and C88 from Transcript 1). In this example T88 borrowed the concept of ‘proud’ from C87, while C88 borrowed the concepts of ‘proud,’ ‘belief,’ and ‘relationship’ from T88:

T87: How do you feel when you say that?

C87: Proud. Proud.

T88: Proud of that belief and that relationship?

C88: Probably relationship, not so much the belief, but proud of my relationship.

T60 from Transcript 3 fits more into the restatement technique of psychotherapy.

C59: Yeah, we’ve been working on it.

T60: You are working on it, okay.

C60: I’m not sure I’m extremely successful, not yet anyway, but I’m still working on it.

In some cases, ITR fails to reflect immediate topic repetition. T145 from Transcript 3 can be an example.

C143: I guess, I will go home and write it down.

T144: Okay. And then,

C144: So, I will not forget it.

T145: Okay. That is good start.

Initially, ITR was expected to reflect restatement or reflection of feelings. Different from this expectation, the exploration of this study showed that ITR captured a few different kinds of conversational dynamics in psychotherapy transcripts as described above.

TI (Topic Introduction)

The TI metric measures the degree of introducing concepts that are not stated in the immediate prior utterance from another speaker. In Figure 18, TI of each utterance in Transcript 3 is visualized. Like the previous figures, points with high TI values are marked.

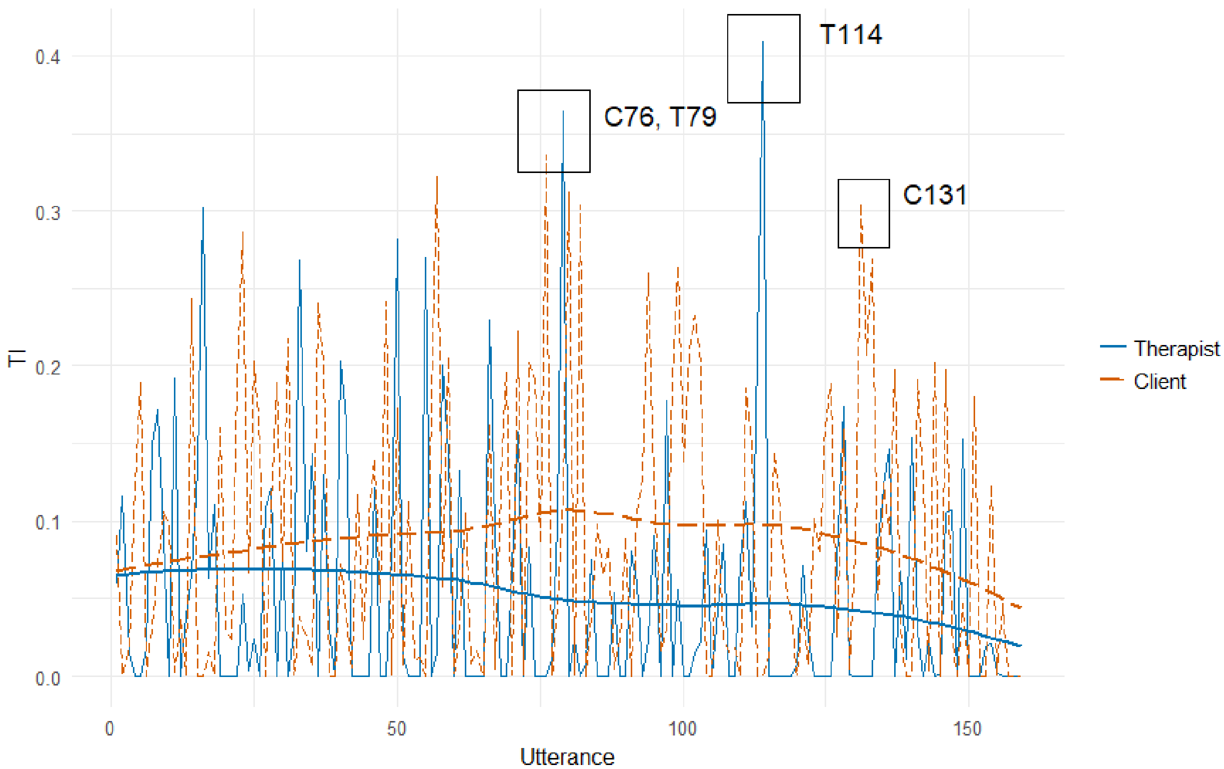


Figure 18. TI of each utterance in Transcript 3

As mentioned in Figure 15 and the following explanation, the therapist brought up the concept of strength and courage in T79, which had been revisited by the client's next few utterances. This demonstrates the sensitivity of TI metric in capturing the introduction of the new topic. However, at the same time, this also shows the limitation of TI. Again, as stated in the qualitative exploration of Transcript 3 (Figure 15), the concept of strength was not originally introduced by the therapist; it was the client who initially brought up this topic (in C76). However, C76 was not considered in calculating TI of T79, due to the way it is measured. As explained in Chapter 3, TI is calculated as follows:

$$\mathrm{TI}(t) = MFO'(t) \times (1 - SBO'(t))$$

TI only considers the immediate prior utterance of another speaker $(1 - SBO'(t))$ when determining a certain concept is new or not. Therefore, although ‘strength’ was initially mentioned by one of the near, but not immediate prior utterances (C76), TI of T79 did not take C76 into consideration and treated ‘strength’ as a new concept introduced by the therapist.

This can be especially misleading when the utterance is followed by a short or meaningless utterance. For instance, C76, T114, and C131 (marked in Figure 18) are all followed by simple statements like “Right,” “Yeah,” and “Okay.” In these cases, TI mainly measures the degree of topic sharing in the medium-term (measured by $MFO'(t)$), without considering whether it is initially introduced within that utterance. Accordingly, although high TI can indicate the emergence of a certain topic, the term ‘introduction’ might be misleading as it does not guarantee that the topic is initially introduced by the utterance.

TCS (Topic Consistency Self) and TCO (Topic Consistency Other)

TCS and TCO measures the degree of repeating concepts mentioned by utterances from oneself (TCS) or another speaker (TCO) within a medium time range. As it was illustrated by Angus, Smith, and Wiles (2012b), comparing average TCS and TCO metrics can provide useful information on the way two speakers contribute to the communication. Average TCS and TCO metrics of three transcripts are provided in Table 6.

Table 6

Average TCS and TCO

Transcript	Speaker	Average TCS	Average TCO
1	Therapist	.265	.228
	Client	.186	.230
2	Therapist	.253	.125
	Client	.055	.127
3	Therapist	.102	.177
	Client	.231	.178

In Table 6, average TCS metrics of the therapist is higher in Transcript 1 and 2 than in Transcript 3. This means that the therapists in Transcript 1 and 2 more frequently revisited their own topics than the therapist in Transcript 3, which is in line with the result from Table 5. This is also consistent with the finding from the earlier qualitative exploration. In Transcript 2, as this session was mainly about clinical interview and goal setting, the therapist's topics were formed around the CBT approach about anxiety, which resulted in high consistency around the therapist's own topics. In Transcript 1, the therapist could remain consistent in maintaining his facilitating role, as the client was ready to explore and share her concerns. Meanwhile, in Transcript 3, the therapist had to change her approach more frequently due to the difficulty of breaking the client's hesitation.

In addition to therapist's TCS, client's TCS metrics also reflect meaningful conversational dynamics of these transcripts. Table 6 shows that client's average TCS of Transcript 2 is the lowest among three, whereas that of Transcript 3 is the highest among them. Again, it corresponds well with what was discussed in the qualitative exploration section. In Transcript 2, the session was mainly led by the therapist and most of the client's utterances consist of short answers to therapist's questions. Accordingly, topic consistency of the client is expected to be low. In contrast, the client in Transcript 3 actively participated in the conversation, but she exhibited high level of hesitancy on making changes. Due to this hesitancy, topics raised and discussed by the client in Transcript 3 remained relatively more consistent than others.

In average TCO metrics, the most noticeable phenomenon is the similarity between therapist's and client's TCO across all three transcripts. This is neither coincidence nor the sign of synchrony. The overall trend of TCO metrics between two speakers are meant to be similar, as they share lots of similarity blocks in common by its definition (In Figure 19, TCO of Transcript 3 is provided as an example. See the almost identical trend lines). In Table 6, average TCO metric is smaller in Transcript 2 than Transcript 1 and 3. Similar to what has been discussed about TCS, this also reflects the characteristic of the session: in Transcript 2, the therapist mainly asked questions rather than reflecting what the client said, and the client mostly answered them with short answers without relying on CBT terms introduced by the therapist. Meanwhile, in Transcript 1 and 3, the therapist and client were more actively reflecting what each other said, which resulted in higher TCO values.

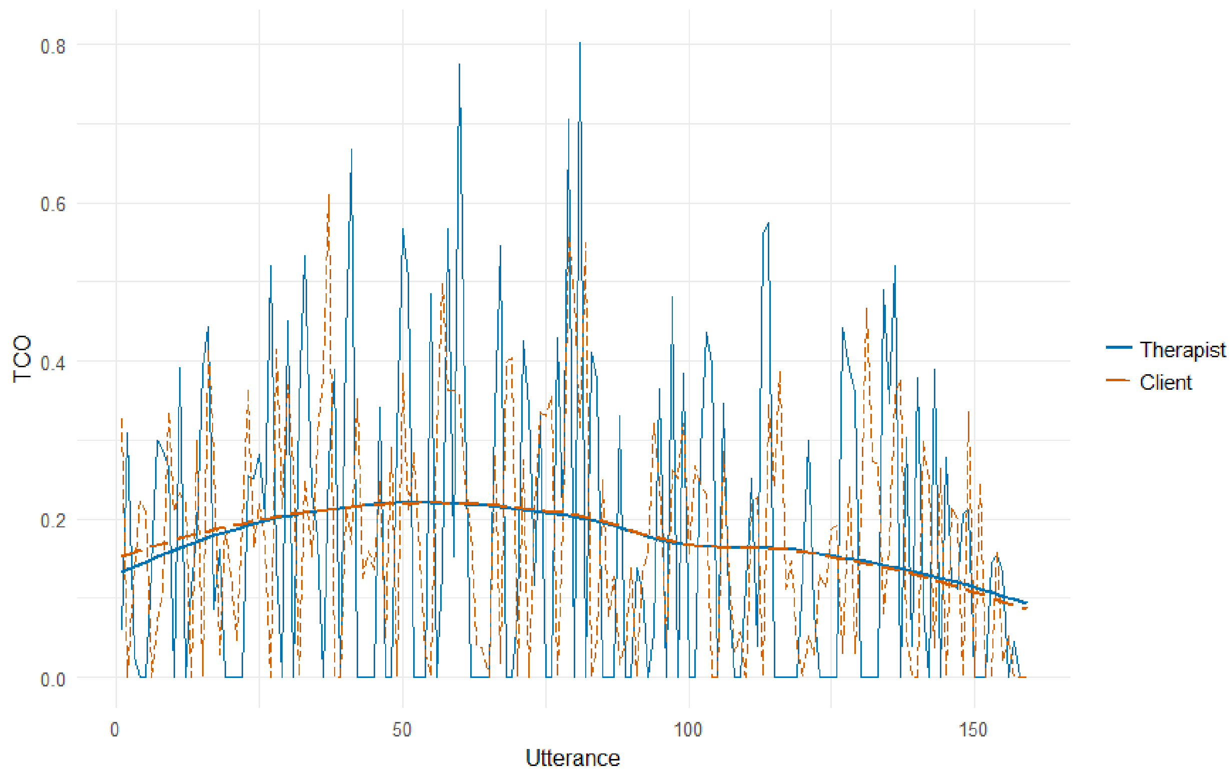


Figure 19. TCO of each utterance in Transcript 3

LTCS (Long-term Topic Consistence Self)

LTCS measures how much the concepts from the current utterance are repeated by oneself throughout the rest of the session (including both prior and later part of the session). Figure 20 and 21 presents LTCS metrics of Transcript 1 and 3.

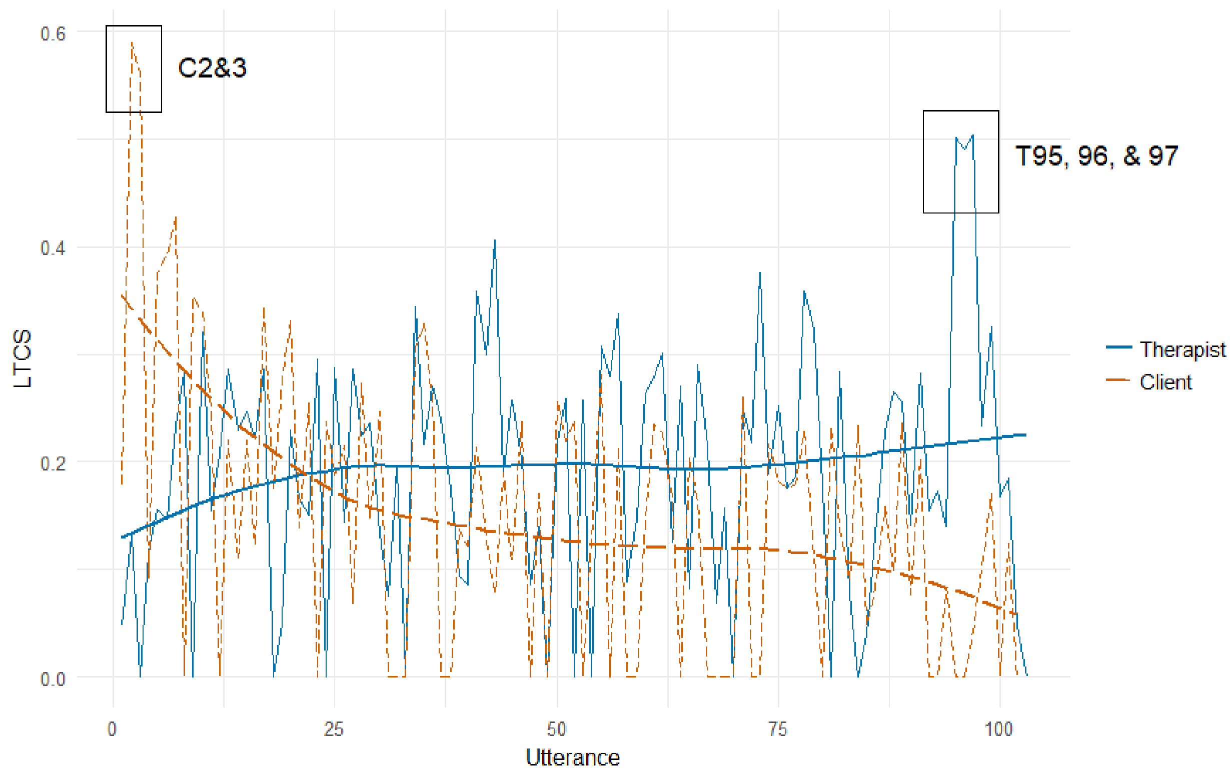


Figure 20. LTCS of each utterance in Transcript 1

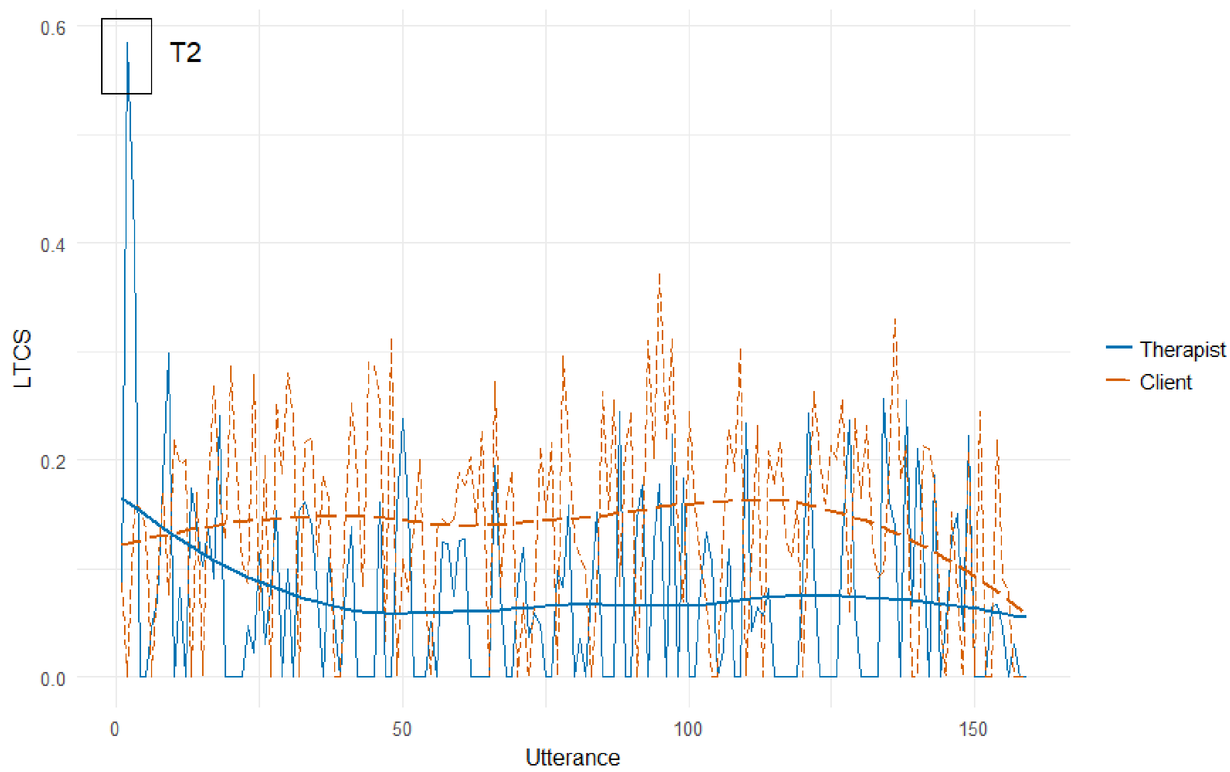


Figure 21. LTCS of each utterance in Transcript 3

In Figure 20 (Transcript 1), the highest LTCS value of client is observed at C2 and C3. As mentioned earlier, in these client's initial utterances, the client shared her main concerns that are revisited by the client herself throughout the rest of the session, so it makes sense these utterances have high LTCS values. Furthermore, at the end of the session, the therapist summarized the session, repeating concepts the therapist himself used at the earlier part of the session, which is depicted as the marked high peak in Figure 20.

In contrast, Figure 21 illustrates a different kind of dynamic. At the beginning of Transcript 3, the therapist provided a brief overview on the session, which the therapist revisited later part of the session. Meanwhile, different from the client in Transcript 1, this client's initial utterances do not contain core concepts that are used by her later utterances. This fits with the characteristics of Transcript 1 and 3 explored thus far (i.e., client's different level of readiness toward psychotherapy).

Local Engagement (LE)

Although Angus, Smith, and Wiles (2012b) originally proposed eight MPR metrics, Angus, Smith, and Wiles (2012b) also encouraged researchers to develop additional metrics to gain deeper insight on the conversation. Following this suggestion, this study proposes a new metric called Local Engagement (LE). This name is derived from the concept proposed by Angus, Smith, and Wiles (2012a), *Engagement Block*. According to Angus, Smith, and Wiles (2012a), "an engagement block is a section of connected recurrence that is strongly adjacent to the diagonal" (p. 10). The triangular area 'e' in Figure 15 is an example of an engagement block. In the area 'e,' the conversation between the therapist and client can be characterized by strong engagement around the concepts of strength and courage. Taking one step further, the area 'e' can be considered as 'local' engagement, as the recurrence occurs exclusively around diagonal area 'e' with little recurrence within 'e'' and 'e'''. To capture the emergence of local engagement in a conversation, this study created LE metrics which can be calculated as below:

$$\mathrm{LE}(t) = (TCS(t) + TCO(t)) \times (1 - (LTCS(t) + LTCO(t)))$$

The LE metrics is greater when a certain topic is consistently discussed by both speakers within the medium range $(TCS(t) + TCO(t))$. At the same time, $(1 - (LTCS(t) + LTCO(t)))$ is multiplied to put a negative weight if the topic is consistently discussed across the conversation, as the interest of LE metrics is at discovering engagement that only occurs locally.

Figure 22 demonstrates the utility of LE metrics. In this plot, the highest points are observed within the utterances between T79 and C82. This corresponds to the phase ‘b’ in Figure 15, which is attached to the triangular area ‘e.’ This shows that LE metrics successfully quantifies visual information from the plot.

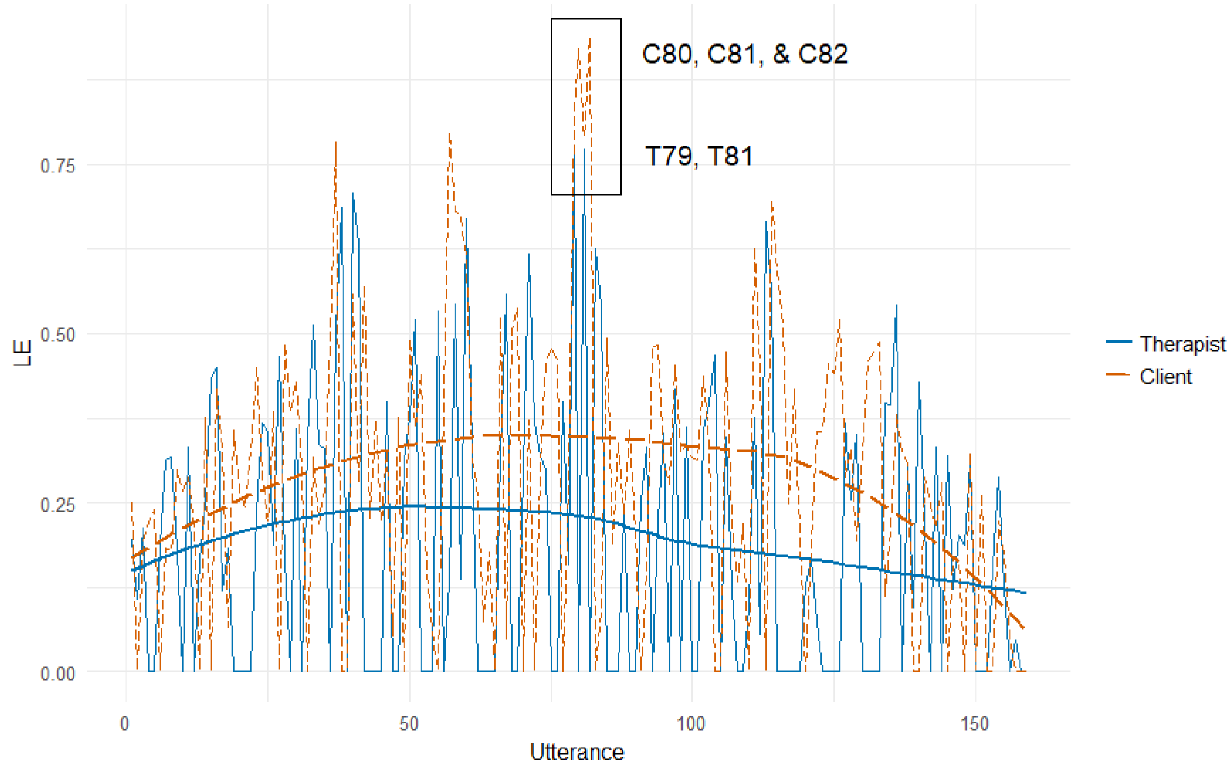


Figure 22. LE of each utterance in Transcript 3

Chapter 5

DISCUSSION

Summary

This study aimed to explore the utility of a CRP technique in understanding conversational dynamics in psychotherapy sessions. CRP is a visualization tool combined with a text analytic technique whose purpose is at discovering the changing pattern of conceptual similarities over the course of a conversation. CRP has demonstrated its utility in various conversational settings, but its potential has not been fully explored yet in psychotherapy settings. Considering the dearth of analytical tools that allow examining within-session level dynamics, CRP can be a meaningful contribution to the existing analysis techniques on psychotherapy process research.

To serve this purpose, this study applied CRP into three psychotherapy transcripts from the APA Psychotherapy Video Series listed in PsycTHERAPY. While these three transcripts are comparable in terms of their time frame (40-50 minutes) and format (one-on-one individual therapy), each of them represents unique dynamics that commonly appear in real-world therapy. Specifically, Transcript 2 demonstrated a typical first session from a CBT approach whose major focus is at clinical interview and goal (task) setting, during which the therapist actively led the session to structuralize the process. In contrast, while Transcript 1 (Psychodynamic approach) and 3 (Multicultural counseling) are more geared toward process-oriented approaches, these two sessions still exhibit distinctive dynamics: in Transcript 1, the client was ready to share her concern, so the therapist's role was mainly around facilitating exploration and helping the client to experience here-and-now emotions. Meanwhile, in Transcript 3, the client was more hesitant and remain ambivalent about making changes, so the therapist mainly focused on breaking the client's hesitancy by highlighting the client's strength.

This study showed that how these different dynamics are captured by both qualitative (conceptual recurrence plot) and quantitative (MPR metrics) features of CRP. For example, a conceptual recurrence plot of Transcript2 clearly shows that most of meaningful concepts were spoken by the therapist's utterances (represented as dominance of blue squares in the diagonal line). Furthermore, a careful look at the plot provides additional information on how conversational dynamics changed over time. As shown Figure 14, the whole session can be divided by three sections – a, b, and c. This structure was intentionally implemented by the therapist; in T60 and T115, located in the middle of these sections, the therapist summarized what was discussed in the earlier section (represented as 'd' and 'e' in Figure 14) and suggested new topics that were revisited in the later part of the conversation (represented as 'd'' and 'e'').

The therapist's dominant role in leading the session is also reflected in its MPR metrics. Table 6 shows that the therapist's Average TCS is much higher than that of the client, while Average TCO metrics of the therapist and client are lower than those from Transcript 1 and 3. The difference in Average TCS metrics between the therapist and client is an indication of the therapist's consistency in organizing main concepts across the nearby utterances, whereas the client's responses were rather short and unorganized. Meanwhile, low average TCO values mean that the therapist and client in Transcript 2 did not actively share and reflect concepts raised by another speaker compared to the therapists and clients in other transcripts, which makes sense considering the different dynamics of clinical interview and process-oriented therapy.

Different dynamics are observed in Transcript 1. Figure 13 illustrates how the client actively shared her main concerns that were repeatedly revisited during the rest of the session (represented as C1 ~ C3 and h). In contrast to Transcript 2, the client actively led the conversation especially during the earlier part of the session, which is shown both in the trend line of Figure 7 and the dominance of red squares in the phase ‘a’ and ‘b’ in Figure 13. However, this does not mean that the therapist remained passive throughout the conversation. For instance, during the phase ‘c,’ during a few relatively short utterances, the therapist was able to effectively summarize concepts mentioned earlier and proposed topics that were revisited later. In addition, the therapist kept connecting what was discussed earlier into the current conversation, which was illustrated as the black square followed by red one (‘g,’ ‘g',’ and ‘g''’ in Figure 13). Lastly, the therapist participated in the verbal communication more actively toward the end of the session, wrapping up what had been discussed in this session (shown in ‘e’). LTCS illustrated some of these dynamics by showing that the concepts brought up in the earlier part of the client’s utterances and the later part of the therapist’s ones were frequently revisited by other utterances from the same speaker across the conversation (see Figure 20).

In contrast to Transcript 1, the therapeutic work in Transcript 3 was less smooth. In Figure 15, different from Figure 13, no client’s utterance seems to be dominant and has a long-lasting effect throughout the session, which reflects this client’s lower level of readiness on therapy compared to that of Transcript 1. Facing this hesitancy, the therapist in this transcript kept trying to help the client and make a breakthrough. The most noticeable effort was observed during the phase ‘b’: in these utterances, the therapist paid attention to the concept of ‘strength’ brought up by the client in C76 and successfully invited the client to talk more about it. It is noteworthy that this topic was mainly communicated within these utterances (‘e’), without being discussed in the earlier or later utterances (‘e'’ and ‘e''’). In the later part of the session, the therapist intentionally revisited topics discussed in the phase ‘b’ to motivate the client (T141), which is represented as a group of similarity blocks in ‘g.’ These dynamics are generally well reflected in MPR metrics. For example, therapist’s average TCS is higher while the client’s average TCS is lower compared to those of Transcript 1. This echoes with the observation that the therapist in Transcript 3 changed her approach more frequently to break the client’s hesitation, whereas the client consistently maintained her hesitancy throughout the session. Moreover, a new MPR metric was proposed to capture the phenomenon of local engagement observed in the phase ‘b,’ which successfully captured this dynamic.

Although the findings of this study generally demonstrated CRP’s utility in understanding conversational dynamics in psychotherapy, it should be also noted that CRP is not perfect in capturing the characteristics of conversation. T88 in Figure 15 is one of these examples. Although T88 actually shares similar concepts with earlier utterances in the phase ‘b,’ this was not reflected in this similarity algorithm. Besides, though ITR is generally a good indicator of immediate concept repetition, T145 in Figure 17 shows that the algorithm may misinterpret similarities. These are not surprising observations, considering CRP relies on an automatic text analysis technique; although it is generally accurate enough to analyze overall dynamics, it does not guarantee perfect precision like thoroughly reviewed human coding. Apart from this innate shortcoming of a computerized text analysis, it is also worth noting that interpretation of MPR metrics can be misleading in some cases. For example, TI is supposed to measure the degree of topic introduction from the utterance, but this metric can be inaccurate when the utterance is preceded by a short and insignificant statement (e.g., “Yeah.”). Therefore, it would be important to consider the context where the utterance is located, rather than uncritically relying on a metric itself.

Implications

This study can make unique contribution to the existing literatures in the following ways. First, this study demonstrated how CRP can be utilized to perform case studies. Although research and practice are two fundamental building blocks of psychotherapy, the ultimate purpose of psychotherapy is at helping a real individual, instead of theorizing generalizable principles. This applied nature of psychotherapy requires practical and context-dependent knowledge, instead of generalizable and context-independent knowledge which is common in natural sciences. Responding to this special need of psychotherapy, researchers have urged to pay more attention on case-based research (Edwards et al., 2004; Dattilio et al., 2010). However, it has been a challenging task to promote case studies due to its conflict with the positivistic paradigm. Considering this challenge of case studies, CRP can be a nice addition to a researcher’s toolbox. Although there are several analytic tools that allow positivistic examination of individual cases (e.g., Mergenthaler, 1996; Salvatore et al., 2012), CRP is unique in a sense that it can provide information on within-session level dynamics with detailed visual information on turn-to-turn conceptual similarities. In addition, as this study demonstrated, not only is CRP well summarizes the conversational dynamics from the session using visualization, but also it generates quantitative information on the focal phenomenon, which fits nicely with the positivistic research paradigm.

Another strength of CRP is at the fact that it relies on a computerized text analysis. Due to its automatized process, once the algorithm is established through the computer program, one can easily generate conceptual recurrence plots and their corresponding MPR metrics on numerous psychotherapy transcripts only with minimal effort. Although nonlinear nature of CRP makes it an ideal technique to utilize in case-based research, its computerized analytic process also allows it to be easily applied in large-scale studies as Imel et al. (2015) argued. For example, researchers may run the program to generate average TCS and TCO metrics from more than 1,000 psychotherapy transcripts and compare these metrics among different subtypes of psychotherapy sessions.

Beyond utilizing CRP in a research setting, the recent development in technology opens the possibility of using it in a training setting as well. Traditionally, clinical supervision has been heavily dependent on trainee's verbal self-report on clinical issues (Amerikaner & Rose, 2012), complemented with occasional observation on recorded sessions. This approach assumes that therapist in training is knowledgeable enough to detect and verbalize clinically significant events, which might not always be the case. This constraint in clinical supervision mainly comes from supervisor's limited availability. However, as Imel, Caperton, Tanana, and Atkins (2017) well illustrated, adopting technological innovation in clinical practices can be a game changer. The rise of deep learning technology has led revolutionary improvement in the quality of speech recognition and automatic transcription. Once the sessions are automatically transcribed, CRP can also be automatically applied to these sessions. Based on generated conceptual recurrence plots and MPR metrics, supervisors can develop an initial hypothesis on the therapeutic processes, before gathering supervisee's self-report or watching entire videotaped sessions. Furthermore, once enough research evidence is accumulated on the relationship between CRP and important clinical issues (e.g., working alliance), a computer program may be able to automatically generate hypotheses on the sessions from the data. Although this may sound too futuristic, the results from this study suggest that it will be worthwhile to explore the potential of CRP in analyzing real-world psychotherapy sessions.

Limitations

Although this study is a meaningful contribution to the existing literatures on psychotherapy process research, it is equally important to be aware of the limitations of this study. The most fundamental limitation of this study comes from its exploratory nature. Unlike confirmatory studies which come with reliable methods to verify their results (e.g., significance testing), this study is heavily dependent upon researcher's subjectivity. For instance, the way how conceptual recurrence plots are interpreted in this study is not necessarily correct; one may find different ways to interpret conversational dynamics from those plots. Furthermore, this study only focused on three psychotherapy sessions to acquire in-depth knowledge of each transcript. This implies that what is discussed in this study is not necessarily generalizable to other similar transcripts; one may find another transcript from the clinical interview in a CBT approach whose conceptual recurrence plot exhibits different features from the plot of Transcript 2 in this study.

Another limitation lies at the fact that it does not capture dynamics from nonverbal communication. As previous studies adequately pointed out, nonverbal communication, such as body synchrony or vocal coordination (Ramseyer & Tschacher, 2011; Tomicic et al., 2017), plays a crucial role in understanding the process of psychotherapy. For example, therapist can reflect client's emotion without restating what client said in the previous utterance by utilizing their body language or vocal tone. Thus, CRP alone cannot describe the entire dynamic of psychotherapy sessions, without being complemented by other methodologies that can reflect dynamics from nonverbal interactions.

Recommendations for Future Research

Though the current study demonstrated that CRP can be an effective tool to analyze microprocess of psychotherapy, further studies are required to utilize its full potential. Specifically, it can benefit greatly from borrowing concepts and frameworks from the existing psychotherapy research and theories. Conversational dynamics of psychotherapy has been extensively studied by many researchers and practitioners since Sigmund Freud invented psychotherapy. This brings a unique opportunity and challenges in applying CRP into psychotherapy compared to other conversational settings, as it requires connecting features extracted from CRP into concepts originated from existing psychotherapy studies and theories which has been empirically validated by researchers. By investigating how psychotherapy phenomena manifest themselves in CRP, future studies can contribute to generate reliable research evidence, which is essential in the current evidence-based practice framework in psychology (APA, 2006).

In future studies, it would be also important to further examine the validity of the similarity algorithm used in this study (Salton, 1989). Although this algorithm has demonstrated its utility in previous studies (e.g., Angus, Smith, & Wiles, 2012a, 2012b), this is not the single best way to calculate conceptual similarities, as it is a challenging task to calculate semantic similarities between words (Gao, Zhang, & Chen, 2015). Although there are several popular similarity algorithms widely used in the field of text analysis, such as Latent Semantic Analysis and Latent Dirichlet Allocation, most of these techniques require large dataset to retrieve a robust outcome, which poses a challenge when analyzing a single psychotherapy transcript. Future studies may want to consider using other innovative similarity algorithms and comparing them with Salton (1989)'s algorithm used in this study.

Conclusions

The present study explored the utility of CRP in analyzing psychotherapy transcripts. This study illustrated that the results from CRP were able to reflect important dynamics in psychotherapy sessions. By doing so, this study aimed at expanding researcher's abilities to analyze psychotherapy process existing in the within-session level dynamics. This is a valuable finding, considering that our field is based on the scientist-practitioner model. This model assumes that our expertise can be maximized when we integrate our identities as a researcher and practitioner. However, the values of researcher and those of practitioners are not necessarily congruent; rather, they often clash with each other, which is conceptualized as the gap between *episteme* and *phronesis* in the introduction of this study. Thus, it is challenging yet crucial to produce general knowledge without sacrificing individual's uniqueness. My hope is that this study can be a small but meaningful step to achieve this goal.

References

Abney, D. H., Paxton, A., Dale, R., & Kello, C. T. (2015). Movement dynamics reflect a functional role for weak coupling and role structure in dyadic problem solving. *Cognitive processing*, *16*(4), 325-332. https://doi.org/10.1007/s10339-015-0648-2

Addis, M. E. (2002). Methods for disseminating research products and increasing evidence-based practice: Promises, obstacles, and future directions. *Clinical Psychology: Science and Practice, 9*(4), 367-378. https://doi.org/10.1093/clipsy.9.4.367

American Psychological Association. (2012). PsycTHERAPY. Retrieved from https://psyctherapy.apa.org/browse/title

Amerikaner, M., & Rose, T. (2012). Direct observation of psychology supervisees' clinical work: A snapshot of current practice. *The Clinical Supervisor, 31*(1), 61-80. https://doi.org/10.1080/07325223.2012.671721

Angus, D., Fitzgerald, R., Atay, C., & Wiles, J. (2016). Using visual text analytics to examine broadcast interviewing. *Discourse, Context & Media, 11*, 38-49. https://doi.org/10.1016/j.dcm.2015.11.002

Angus, D., Rintel, S., & Wiles, J. (2013). Making sense of big text: a visual-first approach for analysing text data using Leximancer and Discursis. *International Journal of Social Research Methodology, 16*(3), 261-267. https://doi.org/10.1080/13645579.2013.774186

Angus, D., Smith, A., & Wiles, J. (2012a). Conceptual recurrence plots: Revealing patterns in human discourse. *IEEE transactions on Visualization and Computer Graphics, 18*(6), 988-997. https://doi.org/10.1109/TVCG.2011.100

Angus, D., Smith, A. E., & Wiles, J. (2012b). Human communication as coupled time series: Quantifying multi-participant recurrence. *IEEE Transactions on Audio, Speech, and Language Processing*, *20*(6), 1795-1807. https://doi.org/10.1109/TASL.2012.2189566

Angus, D., Watson, B., Smith, A., Gallois, C., & Wiles, J. (2012). Visualising conversation structure across time: Insights into effective doctor-patient consultations. *PloS one, 7*(6), e38014. https://doi.org/10.1371/journal.pone.0038014

APA Presidential Task Force on Evidence-Based Practice. (2006). Evidence-based practice in psychology. *The American Psychologist, 61*(4), 271. https://doi.org/ 10.1037/0003-066X.61.4.271

Atay, C., Conway, E. R., Angus, D., Wiles, J., Baker, R., & Chenery, H. J. (2015). An automated approach to examining conversational dynamics between people with dementia and their carers. *PloS one*, *10*(12), e0144327. https://doi.org/10.1371/journal.pone.0144327

Baker, R., Angus, D., Smith-Conway, E. R., Baker, K. S., Gallois, C., Smith, A., ... & Chenery, H. J. (2015). Visualising conversations between care home staff and residents with dementia. *Ageing & Society*, *35*(2), 270-297. https://doi.org/10.1017/S0144686X13000640

Baker, T. B., McFall, R. M., & Shoham, V. (2008). Current status and future prospects of clinical psychology: Toward a scientifically principled approach to mental and behavioral health care. *Psychological Science in the Public Interest*, *9*(2), 67-103. https://doi.org/10.1111/j.1539-6053.2009.01036.x

Boker, S. M., Rotondo, J. L., Xu, M., & King, K. (2002). Windowed cross-correlation and peak picking for the analysis of variability in the association between behavioral time series. *Psychological Methods*, *7*(3), 338-355. http://dx.doi.org/10.1037/1082-989X.7.3.338

Braakmann, D. (2015). Historical paths in psychotherapy research. Foundations, process and outcome. In O. Gelo, A. Pritz, & B. Rieken (Eds.), *Psychotherapy research: General issues, process, and outcome* (pp. 39–65). New York, NY: Springer-Verlag. https://doi.org/10.1007/978-3-7091-1382-0_3

Church, K. W., & Helfman, J. I. (1993). Dotplot: A program for exploring self-similarity in millions of lines of text and code. *Journal of Computational and Graphical Statistics, 2*(2), 153-174. https://doi.org/10.1080/10618600.1993.10474605

Coco, M. I., & Dale, R. (2014). Cross-recurrence quantification analysis of categorical and continuous time series: an R package. *Frontiers in Psychology, 5*, 510. https://doi.org/10.3389/fpsyg.2014.00510

Crompton, E. A. M. (2017). Visualising the psychotherapeutic process: A computer-aided text analytics approach. (master's thesis). Queensland University of Technology, Australia.

Dale, R., & Spivey, M. J. (2006). Unraveling the dyad: Using recurrence analysis to explore patterns of syntactic coordination between children and caregivers in conversation. *Language Learning*, *56*(3), 391-430. https://doi.org/10.1111/j.1467-9922.2006.00372.x

Dattilio, F. M., Edwards, D. J., & Fishman, D. B. (2010). Case studies within a mixed methods paradigm: toward a resolution of the alienation between researcher and practitioner in psychotherapy research. *Psychotherapy: Theory, Research, Practice, Training, 47*(4), 427-441. http://dx.doi.org/10.1037/a0021181

Dreyfus, H. L., & Dreyfus, S. E. (1986). *Mind over machine: The power of human intuition and expertise in the era of the computer*. New York: The Free Press. http://dx.doi.org/10.1109/MEX.1987.4307079

Eckmann, J. P., Kamphorst, S. O., & Ruelle, D. (1987). Recurrence plots of dynamical systems. *Europhysics Letters, 4*(9), 973-977. https://doi.org/10.1209/0295-5075/4/9/004

Edwards, D. J., Dattilio, F. M., & Bromley, D. B. (2004). Developing evidence-based practice: The role of case-based research. *Professional Psychology: Research and Practice, 35*(6), 589-597. http://dx.doi.org/10.1037/0735-7028.35.6.589

Fernández, R., & Grimm, R. (2014). Quantifying categorical and conceptual convergence in child-adult dialogue. *Proceedings of the Cognitive Science Society, 36*, 463-468.

Fertuck, E. A., Mergenthaler, E., Target, M., Levy, K. N., & Clarkin, J. F. (2012). Development and criterion validity of a computerized text analysis measure of reflective functioning. *Psychotherapy Research, 22*(3), 298-305. https://doi.org/10.1080/10503307.2011.650654

Flyvbjerg, B. (2006). Five misunderstandings about case-study research. *Qualitative Inquiry, 12*(2), 219-245. https://doi.org/10.1177/1077800405284363

Flyvbjerg, B. (2001). *Making social science matter: Why social inquiry fails and how it can succeed again*. New York: Cambridge University Press. https://doi.org/10.1017/CBO9780511810503

Frankfurt, S., Frazier, P., Syed, M., & Jung, K. R. (2016). Using group-based trajectory and growth mixture modeling to identify classes of change trajectories. *The Counseling Psychologist, 44*(5), 622-660. https://doi.org/10.1177/0011000016658097

Friedlander, M. L., & Phillips, S. D. (1984). Stochastic process analysis of interactive discourse in early counseling interviews. *Journal of Counseling Psychology, 31*(2), 139-148. http://dx.doi.org/10.1037/0022-0167.31.2.139

Galassi, J. P., & Gersh, T. L. (1993). Myths, misconceptions, and missed opportunity: Single-case designs and counseling psychology. *Journal of Counseling Psychology, 40*(4), 525-531. http://dx.doi.org/10.1037/0022-0167.40.4.525

Gao, J. B., Zhang, B. W., & Chen, X. H. (2015). A WordNet-based semantic similarity measurement combining edge-counting and information content theory. *Engineering Applications of Artificial Intelligence, 39*, 80-88. https://doi.org/10.1016/j.engappai.2014.11.009

Gelo, O. C. G., & Salvatore, S. (2016). A dynamic systems approach to psychotherapy: A meta-theoretical framework for explaining psychotherapy change processes. *Journal of Counseling Psychology, 63*(4), 379-395. http://dx.doi.org/10.1037/cou0000150

Gennaro, A., Gonçalves, M. M., Mendes, I., Ribeiro, A. P., & Salvatore, S. (2011). Dynamics of sense-making and development of the narrative in the clinical exchange. *Research in Psychotherapy, 14*(1), 90-120. http://dx.doi.org/10.4081/ripppo.2011.44

Gennaro, A., Salvatore, S., Rocco, D., & Auletta, A. (2017). Deconstructive and constructive dynamics in the clinical process: A step further in the validation of the two-stage semiotic model. *Journal of Constructivist Psychology, 30*(2), 105-126. https://doi.org/10.1080/10720537.2016.1183536

Hayes, A. M., Laurenceau, J. P., Feldman, G., Strauss, J. L., & Cardaciotto, L. (2007). Change is not always linear: The study of nonlinear and discontinuous patterns of change in psychotherapy. *Clinical Psychology Review, 27*(6), 715-723. https://doi.org/10.1016/j.cpr.2007.01.008

Helfman, J. I. (1994). Similarity patterns in language. *Proceedings of the IEEE Symposium on Visual Languages*, 173-175. https://doi.org/10.1109/VL.1994.363626

Hill, C. E. (1990). Exploratory in-session process research in individual psychotherapy: A review. *Journal of Consulting and Clinical Psychology*, *58*(3), 288-294. https://doi.org/10.1037/0022-006X.58.3.288

Hill, C. E., Carter, J. A., & O'farrell, M. K. (1983). A case study of the process and outcome of time-limited counseling. *Journal of Counseling Psychology*, *30*(1), 3-18. http://dx.doi.org/10.1037/0022-0167.30.1.3

Hilliard, R. B. (1993). Single-case methodology in psychotherapy process and outcome research. *Journal of Consulting and Clinical Psychology*, *61*(3), 373-380. http://dx.doi.org/10.1037/0022-006X.61.3.373

Imel, Z. E., Caperton, D. D., Tanana, M., & Atkins, D. C. (2017). Technology-enhanced human interaction in psychotherapy. *Journal of Counseling Psychology, 64*(4), 385. http://dx.doi.org/10.1037/cou0000213

Imel, Z. E., Steyvers, M., & Atkins, D. C. (2015). Computational psychotherapy research: Scaling up the evaluation of patient–provider interactions. *Psychotherapy*, *52*(1), 19-30. http://dx.doi.org/10.1037/a0036841

Kahn, J. H., Vogel, D. L., Schneider, W. J., Barr, L. K., & Herrell, K. (2008). The emotional content of client disclosures and session impact: An analogue study. *Psychotherapy: Theory, Research, Practice, Training*, *45*(4), 539-545. http://dx.doi.org/10.1037/a0014337

Knight, A. P., Kennedy, D. M., & McComb, S. A. (2016). Using recurrence analysis to examine group dynamics. *Group Dynamics: Theory, Research, and Practice, 20*(3), 223-241. http://dx.doi.org/10.1037/gdn0000046

Kowalik, Z., Schiepek, G., Kumpf, K., Roberts, L., & Elbert, T. (1997). Psychotherapy as a chaotic process II. The application of nonlinear analysis methods on quasi time series of the client-therapist interaction: A nonstationary approach. *Psychotherapy Research, 7*(3), 197-218. https://doi.org/10.1080/10503309712331331973

Lepper, G., & Mergenthaler, E. (2008). Observing therapeutic interaction in the "Lisa" case. *Psychotherapy Research, 18*(6), 634-644. https://doi.org/10.1080/10503300701442001

Lichtenberg, J. W., & Heck, E. J. (1986). Analysis of sequence and pattern in process research. *Journal of Counseling Psychology, 33*(2), 170-181. http://dx.doi.org/10.1037/0022-0167.33.2.170

Lizdek, I., Sadler, P., Woody, E., Ethier, N., & Malet, G. (2012). Capturing the stream of behavior: A computer-joystick method for coding interpersonal behavior continuously over time. *Social Science Computer Review, 30*(4), 513-521. https://doi.org/10.1177/0894439312436487

Marwan, N. (2008). A historical review of recurrence plots. *The European Physical Journal-Special Topics, 164*(1), 3-12. https://doi.org/10.1140/epjst/e2008-00829-1

McCarthy, K. L., Caputi, P. & Grenyer, B. F.S. (2017). Significant change events in psychodynamic psychotherapy: Is cognition or emotion more important? *Psychology and Psychotherapy: Theory, Research and Practice, 90*, 377–388. https://doi.org/10.1111/papt.12116

Mergenthaler, E. (1996). Emotion-abstraction patterns in verbatim protocols: A new way of describing psychotherapeutic processes. *Journal of Consulting and Clinical Psychology, 64*(6), 1306-1315. http://dx.doi.org/10.1037/0022-006X.64.6.1306

Mergenthaler, E. (2008). Resonating minds: A school-independent theoretical conception and its empirical application to psychotherapeutic processes. *Psychotherapy Research, 18*(2), 109-126. https://doi.org/10.1080/10503300701883741

Molenaar, P. C., & Campbell, C. G. (2009). The new person-specific paradigm in psychology. *Current Directions in Psychological Science, 18*(2), 112-117. https://doi.org/10.1111/j.1467-8721.2009.01619.x

Molenaar, P. C., & Valsiner, J. (2008). How generalization works through the single case: A simple idiographic process analysis of an individual psychotherapy. *YIS: Yearbook of idiographic science*, *1*, 23-38.

Oh, J., Stewart, A. E., & Phelps, R. E. (2017). Topics in the *Journal of Counseling Psychology*, 1963–2015. *Journal of Counseling Psychology*, *64*(6), 604-615. http://dx.doi.org/10.1037/cou0000218

Ramseyer, F., & Tschacher, W. (2011). Nonverbal synchrony in psychotherapy: coordinated body movement reflects relationship quality and outcome. *Journal of Consulting and Clinical Psychology*, *79*(3), 284-295. http://dx.doi.org/10.1037/a0023419

Ray, D. C. (2015). Single-Case Research Design and Analysis: Counseling Applications. *Journal of Counseling and Development*, *93*(4), 394-402. https://doi.org/10.1002/jcad.12037

R Core Team (2017). R: A language and environment for statistical computing [Computer Software]. Vienna, Austria: R Foundation for Statistical Computing. Available from https://www.R-project.org/.

Richardson, D. C., and Dale, R. (2005). Looking to understand: The coupling between speakers and listeners eye movements and its relationship to discourse comprehension. *Cognitive Science*, *29*, 39-54. https://doi.org/10.1207/s15516709cog0000_29

Richardson, M. J., Dale, R., & Marsh, K. L. (2014). Complex dynamical systems in social and personality psychology. In H. T. Reis, & C. M. Judd (Eds.), *Handbook of research methods in social and personality psychology* (pp. 253-282). New York: Cambridge university press. https://doi.org/10.1017/CBO9780511996481.015

Rogers, C. R. (1942). The use of electrically recorded interviews in improving psychotherapeutic techniques. *American Journal of Orthopsychiatry, 12*(3), 429-434. https://doi.org/10.1111/j.1939-0025.1942.tb05930.x

Rosenberger, E. W., & Hayes, J. A. (2002). Origins, consequences, and management of countertransference: A case study. *Journal of Counseling Psychology, 49*(2), 221-232. http://dx.doi.org/10.1037/0022-0167.49.2.221

Salamanca, L. P., Carini, A. R., Lee, M. A., Dykstra, K., Whitehill, J., Angus, D., ... & Bartlett, M. S. (2012). Characterizing the temporal dynamics of student-teacher discourse. *2012 IEEE International Conference on Development and Learning and Epigenetic Robotics (ICDL)*, 1-2. http://dx.doi.org/10.1109/DevLrn.2012.6400840

Salton, G. (1989). *Automatic text processing: The transformation, analysis, and retrieval of information by computer*. Boston, MA: Addison-Wesley. https://doi.org/10.5860/choice.27-0351

Salvatore, S., Gelo, O., Gennaro, A., Manzo, S., & Al Radaideh, A. (2010). Looking at the psychotherapy process as an intersubjective dynamic of meaning-making: A case study with discourse flow analysis. *Journal of Constructivist Psychology, 23*(3), 195-230. https://doi.org/10.1080/10720531003765981

Salvatore, S., & Gennaro, A. (2015). Outlines of a general theory of the psychotherapy process. The clinical exchange as communicational field: Theoretical considerations and methodological implications. In O. Gelo, A. Pritz, & B. Rieken (Eds.), *Psychotherapy research: General issues, process, and outcome* (pp. 195-212). Springer Vienna. https://doi.org/10.1007/978-3-7091-1382-0_10

Salvatore, S., Gennaro, A., Auletta, A. F., Tonti, M., & Nitti, M. (2012). Automated method of content analysis: A device for psychotherapy process research. *Psychotherapy Research, 22*(3), 256-273. https://doi.org/10.1080/10503307.2011.647930

Salvatore, S., & Tschacher, W. (2012). Time dependency of psychotherapeutic exchanges: the contribution of the theory of dynamic systems in analyzing process. *Frontiers in Psychology*, *3*, 253. https://doi.org/10.3389/fpsyg.2012.00253

Scheel, M. J., Berman, M., Friedlander, M. L., Conoley, C. W., Duan, C., & Whiston, S. C. (2011). Whatever Happened to Counseling in Counseling Psychology? *The Counseling Psychologist, 39*(5), 673-692. https://doi.org/10.1177/0011000010380278

Schiepek, G. (2009). Complexity and nonlinear dynamics in psychotherapy. *European Review, 17*(2), 331-356. https://doi.org/10.1017/S1062798709000763

Schiepek, G., Aichhorn, W., Gruber, M., Strunk, G., Bachler, E., & Aas, B. (2016). Real-time monitoring of psychotherapeutic processes: Concept and compliance. *Frontiers in Psychology*, *7*, 604. https://doi.org/10.3389/fpsyg.2016.00604

Schiepek, G., Viol, K., Aichhorn, W., Hütt, M.-T., Sungler, K., Pincus, D., & Schöller, H. J. (2017). Psychotherapy is chaotic— (not only) in a computational world. *Frontiers in Psychology*, *8*, 379. https://doi.org/10.3389/fpsyg.2017.00379

Sexton, H. C., Hembre, K., & Kvarme, G. (1996). The interaction of the alliance and therapy microprocess: A sequential analysis. *Journal of Consulting and Clinical Psychology, 64*(3), 471-480. https://doi.org/10.1037//0022-006x.64.3.471

Shockley, K., Butwill, M., Zbilut, J. P., & Webber, C. L. (2002). Cross recurrence quantification of coupled oscillators. *Physics Letters A, 305*(1), 59-69. https://doi.org/10.1016/S0375-9601(02)01411-1

Shockley K., Riley M.A. (2015). Interpersonal couplings in human interactions. In C. L. Webber & N. Marwan (Eds.), *Recurrence quantification analysis* (pp.399-421). Springer International Publishing. https://doi.org/10.1007/978-3-319-07155-8_14

Tausczik, Y. R., & Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. *Journal of Language and Social Psychology, 29*(1), 24-54. https://doi.org/10.1177/0261927X09351676

Tanana, M., Hallgren, K. A., Imel, Z. E., Atkins, D. C., & Srikumar, V. (2016). A comparison of natural language processing methods for automated coding of motivational interviewing. *Journal of Substance Abuse Treatment, 65*, 43-50. https://doi.org/10.1016/j.jsat.2016.01.006

Thomas, K. M., Hopwood, C. J., Woody, E., Ethier, N., & Sadler, P. (2014). Momentary assessment of interpersonal process in psychotherapy. *Journal of Counseling Psychology, 61*(1), 1-14. http://dx.doi.org/10.1037/a0034277

Tolston, M. T., Finomore, V., Funke, G. J., Mancuso, V., Brown, R., Menke, L., & Riley, M. A. (2017). Effects of biasing information on the conceptual structure of team communications. In K. S. Hale, K. M. Stanney (Eds.), *Advances in neuroergonomics and cognitive engineering* (pp. 433-445). Springer International Publishing. https://doi.org/10.1007/978-3-319-41691-5_37

Tomicic, A., Pérez, J. C., Martínez, C., & Rodríguez, E. (2017). Vocalization–Silence Dynamic Patterns: A system for measuring coordination in psychotherapeutic dyadic conversations.

Revista Latinoamericana de Psicología, *49*(1), 48-60. https://doi.org/10.1016/j.rlp.2016.09.004

Villmann, T., Liebers, C., Bergmann, B., Gumz, A., & Geyer, M. (2008). Investigation of psycho-physiological interactions between patient and therapist during a psychodynamic therapy and their relation to speech using in terms of entropy analysis using a neural network approach. *New Ideas in Psychology*, *26*(2), 309-325. https://doi.org/10.1016/j.newideapsych.2007.07.010

Wampold, B. E., & Kim, K. H. (1989). Sequential analysis applied to counseling process and outcome: A case study revisited. *Journal of Counseling Psychology*, *36*(3), 357-364. https://doi.org/10.1037/0022-0167.36.3.357

Wampold, B. E. (1986). State of the art in sequential analysis: Comment on Lichtenberg and Heck. *Journal of Counseling Psychology*, *33*(2), 182-185. http://dx.doi.org/10.1037/0022-0167.33.2.182

Watson, B. M., Angus, D., Gore, L., & Farmer, J. (2015). Communication in open disclosure conversations about adverse events in hospitals. *Language & Communication*, *41*, 57-70. https://doi.org/10.1016/j.langcom.2014.10.013

Webber, C. L., & Zbilut, J. P. (2005). Recurrence quantification analysis of nonlinear dynamical systems. In M. A. Riley & G. C. Van Orden (Eds.), *Tutorials in contemporary nonlinear methods for the behavioral sciences* (pp. 26-94). Retrieved from http://www.nsf.gov/sbe/bcs/pac/nmbs/nmbs.jsp

Weisz, J. R., & Addis, M. E. (2006). The research-practice tango and other choreographic challenges: Using and testing evidence-based psychotherapies in clinical care settings. In C. D. Goodheart, A. E. Kazdin & R. J. Sternberg (Eds.), *Evidence-based psychotherapy:*

Where practice and research meet (pp. 179-206). Washington DC: American Psychological Association. https://doi.org/10.1037/11423-008

Wu, Z., & Palmer, M. (1994). Verbs semantics and lexical selection. *Proceedings of the 32nd annual meeting on Association for Computational Linguistics*, 133-138. https://doi.org/10.3115/981732.981751

Zbilut, J. P., & Webber, C. L. (1992). Embeddings and delays as derived from quantification of recurrence plots. *Physics letters A, 171*(3-4), 199-203. https://doi.org/10.1016/0375-9601(92)90426-M