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Social semantic networks: Measuring topic management in discourse using a pyramid of conceptual recurrence metrics

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Studies of conversational encounters typically employ manual discourse analysis methods to reveal participants’ topic management patterns, usually focusing on turn-by-turn interactions within a specific social context. These analyses, while powerful, are time-consuming to apply and can prove difficult to generalize. Recurrence analysis has recently been applied to discourse datasets to model how individual terms and concepts recur over whole conversation time scales and relate patterns of recurrence to topic management practices by individuals. In this paper, we propose a new multi-level quantitative method for modelling the topical interaction dynamics in conversation based on conceptual recurrence quantification analysis. The new protocol develops a hierarchy of speakers and their interactions, and partitions recurrence based on these groups. The new protocol is evaluated against expert human coding of television broadcast interviews. Our analysis reveals topic use patterns and networks of conceptual engagement (person-person and group-group) that show experts preferentially engaging with other experts rather than with laypeople, findings that are consistent with prior expectations for this discourse, although never before expressed as metrics. The studies provide a starting point for new computational protocols to provide fast, semi-automated methods for measuring the degree of conceptual interaction between individuals and groups. Published by AIP Publishing. https://doi.org/10.1063/1.5024809

I. INTRODUCTION

Group dynamics as a field of inquiry is concerned with understanding the dynamics, behaviors, and processes of social groups. Group dynamics’ central tenet is that the whole (group) is greater than the sum of the parts (individuals) (Hogg and Terry, 2001; Hogg and Williams, 2000) or as Gestalt psychologist Max Wertheimer (1938) proposed: “There are entities where the behavior of the whole cannot be derived from its individual elements nor from the way these elements fit together; rather the opposite is true: the properties of any of the parts are determined by the intrinsic structural laws of the whole.” Group dynamics research underpins much of our current knowledge and understanding of social systems, and with the emergence of computational social science which blends social and computer science methods and theories (Lazer et al., 2009), it is now possible to examine how aspects of group dynamics research can be enriched through the use of computational methods. This is not an entirely new perspective, with the work of Cooke et al. (2013) and Gorman et al. (2012) on interactive team (distributed) cognition providing strong evidence for the utility of dynamical systems methods in unpacking the complex group communication and interaction dynamics required for the completion of sequence-based tasks.

Topic management relates to the manner in which participants engaged in interpersonal communication negotiate and deploy concepts to achieve various communicative outcomes. As a core aspect of communication, studies of group dynamics often use topic management as a way of characterizing the dynamics of multi-participant fora (Lambrecht, 1996). The analysis of topic management is an important area of research in various communication contexts; however, in analyzing public discourse (broadcast interviews), it is particularly powerful in revealing the mechanisms through which hosts and guests manage and negotiate the topic of the moment, and ultimately how discourse can shape public opinion (Fairclough, 1992, 1993; and Hauser, 1999). To better inform analyses and understanding of public discourse, techniques are needed to quantify the topic management practices of discourse participants.

In this paper, we propose a multi-level quantitative method for modelling the topical interaction dynamics in
conversation based on a blending of recurrence quantification analysis (RQA) (Marwan et al., 2002; Webber and Zbilut, 1994; and Zbilut and Webber, 1992) and conceptual recurrence analysis (Angus et al., 2012a; 2012b). The method is based on a reformulation and decomposition of the RQA measure recurrence rate (RR) for systems that involve multiple interacting individuals, with optional and possibly varied group membership.

The original formulation of recurrence analysis was for single, individual channels/modalities (Thomasson et al., 2002 and Webber and Zbilut, 2005). The recurrence measures proposed in this paper extend RQA to conversations between individual, interacting agents, or groups of agents. By calculating recurrence elements within and between each agent, it is possible to attribute recurrence elements to single agents, groups of agents, or the interaction between these agents or groups. Such a hierarchy of calculations can provide numerical evidence as to the degree to which individuals repeat (or are repeated by) other individuals, the degree to which groups repeat topics from other groups, and which topics are discussed by influential individuals/groups. The evidence obtained through these various levels of granularity in the decomposition hierarchy allows different questions to be addressed, such as

- For each turn in a conversation, to what degree does the speaker engage with topics discussed in any other turn in the conversation, either matching their own topics or others?
- Over the whole conversation, what is the pattern of topic engagement between speakers: which speakers introduce topics; which speakers are on-topic with each other; and which speakers solely discuss topics tangential to the conversation?
- When speakers are members of identifiable groups, over the whole conversation, what is the pattern of topic engagement within and between these groups: do groups engage preferentially with topics of their own group members versus those of other groups within a conversation?
- To what extent is a conversation centered on a particular subset of topics?

We propose levels that span the general to the specific: total conceptual recurrence over all topics in a whole conversation (CRR: conceptual recurrence rate), recurrence between groups (G2G: group-to-group), recurrence between individual speakers (P2P: person-to-person), and recurrence between turns in a conversation (turn-by-turn). These levels can be expressed and visualized as a pyramid (see Fig. 1), with the aggregated single CRR value at the head of the triangle, and all individual recurrence values between all pairs of temporal elements at the base. Explanations of each of the metrics are offered in the following sections.

To motivate the conceptualization of a new multiscale conceptual recurrence quantification analysis (cRQA) pyramid model, the paper begins with a discussion of RQA and previous literature using recurrence approaches to study language and communication. The new multiscale cRQA pyramid model is then defined, demonstrated, and evaluated using transcripts from a television audience discussion program that have been assessed by an independent discourse analysis expert. The paper concludes with a discussion of the implications of the new metrics for communication research, limitations of the metrics and analysis, and plans for future work.

II. RECURRENCE ANALYSIS

The recurrence plot technique was introduced by Eckmann et al. (1987) as a way to display and identify patterns from time series data, specifically data from high-dimensional dynamical systems. The recurrence plot is a 2D

![Figure 1](https://example.com/figure1.png)

**CRR**

Conceptual Recurrence Rate

**G2G**

Group-based Recurrence

**P2P**

Person-Person Recurrence

**Discursis Plot**

Turn-turn recurrence

FIG. 1. The multiscale cRQA pyramid for analysis of conversations. The scalar metric CRR is decomposed into multiple scales, the $g \times g$, $p \times p$, and $n \times n$ matrices, where $g \leq p \leq n$. Note that the $n \times n$ matrix is equivalent to the conceptual recurrence (developed for Discursis, see Sec. II B for details).
plot where the horizontal and vertical axes represent time series data, and individual elements of the plot indicate times where the phase space trajectory of the system visits the same region of the phase space.

While visual inspection of recurrence plots is useful for revealing the structure and dynamics of dynamical systems, recurrence quantification analysis (RQA) extends this technique by specifying a set of metrics designed to capture specific features of recurrence plots (Marwan et al., 2002; Webber and Zbilut, 1994; and Zbilut and Webber, 1992).

In the 25 years following the original work of Eckmann et al. (1987), recurrence analysis has been applied across diverse areas (we refer interested readers to http://www.recurrence-plot.tk/ for an extensive list of recurrence analysis studies), including financial analysis, neural recordings, engineering, earth science and chemistry, and an authoritative review being that of Marwan et al. (2007).

Recurrence plots have also been used to analyze communication data, using lexical, symbolic, and syntactic approaches that measure recurrence of single words or alphabetic characters (Angus et al., 2012b; Church and Helfman, 1993; Dale and Spivey, 2005; 2006; Orsucci et al., 1999; and Webber and Zbilut, 2005). Leonardi (2012) summarized these approaches and offered a detailed treatment of the use of recurrence quantification analysis to study language and conversation, discussed in further detail in Sec. II B. The major findings of Leonardi (2012) were that these various recurrence analysis approaches are effective because they are tailored to specific analytical tasks, rather than trying to act as general analytical frameworks/methods.

A. The Discursis recurrence analysis technique

One specific communication recurrence approach, the conceptual recurrence plot (Angus et al., 2012a, 2012b), now known as Discursis (Angus et al., 2012c), extended existing language recurrence plot approaches by mapping recurrence in language at the conceptual (semantic) level. The Discursis technique builds a statistical language model using word occurrence and co-occurrence statistics and tags text segments (turns in a conversation; paragraphs in a document) based on each segment’s conceptual content. As an example, if the words dog, ball, pet, and food are strong evidence for the concept dog, then if enough of these terms appear in a text segment, the concept dog will be tagged against that segment. The more evidence and more selectively words appear together, the stronger such associations become.

Unique concepts are generated (usually ~100 concepts) for any input text, and every individual text segment is assigned its own unique concept vector that indicates the degree of evidence for each of these conceptual dimensions. After assignment of these concept vectors, a full pair-wise cosine similarity comparison is made between the concept vectors of all text segments to construct the conceptual recurrence plot. Unlike traditional recurrence plots, no threshold is applied to the resultant distance/recurrence plot; instead, recurrences are retained as floating point numbers between 0.0 and 1.0 and displayed using varying opacity to represent the degree of the recurrence.

The Discursis plot arranges conversational turns as colored squares along a diagonal line, with the length of each turn (word count, or real timing data if known) reflected through the size of the square. The color of each diagonal square is determined by the channel, usually attributed as individuals or groups of conversational participants. Recurrences which appear below the diagonal are colored according to whether they correspond to a recurrence by the same channel or between different channels, using the same color for a single channel, and splitting the recurrence element rectangle into two triangles for recurrences between different channels, using each of these different channels’ colors (for an example, see Fig. 2).

While Discursis has historically employed the aforementioned bag-of-words natural language processing approach, it is entirely plausible to substitute other language processing approaches. The key principle of using recurrence to compare utterances for their semantic overlap can be achieved using a number of conventional language processing toolkits. We have recently developed a version of Discursis using the top-down ontologically driven paraphrase model

![Example conceptual recurrence plot. Four turns are shown as squares along the diagonal by the speakers Jordan Candlish (green), Jenny Brockie (red), and Susan Candlish (blue). The second and third turns repeat earlier concepts shown by the colored rectangles below the diagonal. The last turn by Jenny Brockie repeats the concept “appendix” which is also present in Susan Candlish’s turn (blue/red recurrence). The bottom left corner has no recurrence elements as no concepts are shared between the first two turns and the last turn by Jenny Brockie.](image-url)
A full discussion of the strengths and weaknesses of different language models is beyond the scope of this study; however, the measures proposed could be feasibly deployed using a variety of such models.

B. RQA for language and conversation

RQA metrics have been used to analyze language in a few cases (Angus et al., 2012b; Dale and Spivey, 2005; 2006; Orsucci et al., 1999; and Webber and Zbilut, 2005). These selected studies have looked at recurrences at the lexical, syntactic, and conceptual levels. At the lexical level, Orsucci et al. (1999) analyzed poems written in a variety of languages by comparing word stems of three letters using recurrence plots, and then applying RQA metrics to these plots to determine the structural qualities and rhythms employed in this poetry. Another study using lexical qualities of language was that of Webber and Zbilut (2005), who analyzed conversation by people with schizophrenia against control cases and found differences in the RQA measures for these groups, showing that the RQA metrics could be used as evidence for clinical diagnosis. Dale and Spivey (2005) used RQA to analyze child/care giver conversations, once again at the lexical level, and revealed structural differences captured through RQA that are indicative of language learning by children and increases in language competency.

At the syntactic level, (Dale and Spivey 2005, 2006) extended their study with children and care provider conversations from the CHILDES corpus by codifying their data according to the grammatical class of each word. They used the RQA measure, recurrence rate, to track grammatical coordination between speakers postulating that such coordination may be indicative of language learning.

At the conceptual level, Angus et al. (2012b) offered a series of RQA-inspired measures to track concept-use patterns in conversation. Angus et al. (2012b) applied these multiple participant recurrence (MPR) metrics to a series of interview contexts including flight transcript recordings and television interviews to show how their conceptual recurrence quantification model can be used to reveal dynamics of interaction and capture expected modes of behavior in these situations. In summarizing many of the aforementioned approaches, Leonardi (2012) suggested that the conceptual recurrence method represented a “promising direction for the future of RQA-type analyses in natural language research” (p. 178) given that concepts are central to human interaction. This said, the measures proposed in Angus et al. (2012b) only measure the degree to which a single conversational participant repeats their own or all other persons’ concepts. The measures do not discriminate between other participants, instead treating “other” as a single group, and therefore they cannot reveal the degree to which a single participant is repeating concepts of any other single participant, nor group to group. To better model these person-person topical interactions and ultimately inform about the aspects of topic management by individuals and groups of individuals, we require a concept-based RQA model that can model recurrences at these varied levels. In Sec. III, we propose such a model that extends the standard RQA measure of recurrence rate using conceptual recurrence as the base recurrence element.

III. MULTISCALE CRQA PYRAMID METRICS FOR THE ANALYSIS OF CONVERSATION

The standard definition of recurrence rate by Webber and Zbilut (1994) sums all binary recurrence elements and normalizes by the number of possible recurrence elements. RR is similar to the correlation sum used in chaos theory and is intended to capture the degree to which a system is located in a similar region of state space across time

\[
RR = \frac{1}{N^2} \sum_{i=j=1}^{N} R(i,j),
\]

where \(N\) is the number of observations and \(R(i,j)\) is the recurrence element corresponding to time points \(i\) and \(j\).

This formulation quantifies the degree of recurrence in a system, using thresholding where necessary. A high RR indicates that a dynamical system is persisting in or near a particular state, or revisiting a set of states. In terms of conceptual recurrence, CRR indicates the degree to which a conversation is persisting in a particular area of the conceptual space. CRR therefore provides a starting point for a set of metrics intending to capture the degree to which individuals in a conversation refer to sets of similar concepts.

To reveal the full breadth of topic management practice, conversation metrics are required that can reveal the meso-scale structure of a conversation, rather than just a single scalar measure of conceptual topic repetition (CRR) or the turn-turn conceptual overlap afforded by the existing Discursis plot. Decomposing the conceptual recurrence metric to reveal this meso-scale structure is challenging, given that conversations involve multiple interacting individuals and/or groups whose turns need not be ordered in time. The sequence of speakers’ turns could be highly regular and evenly distributed amongst speakers: A, B, C, A, B, C; or it could be irregular and unevenly distributed: A, C, B, A, B, A. Aggregates such as CRR and other crQA metrics do not naturally allow for decomposition based on such properties of the system under study.

Given the factors mentioned above, the current formulation of CRR is not sufficient to address questions concerning the degree of conceptual recurrence between individual agents or groups. In the following sections, we propose an extension of CRR for domains involving multiple interacting channels of information, where recurrence is defined as a continuous variable.

A. Conceptual recurrence rate (CRR)

The formulation of CRR for conceptual recurrence between multiple interacting agents differs from recurrence rate in a standard recurrence plot in that the source of the recurrence is not a binary plot, rather recurrence elements are represented as floating point values between 0.0 and 1.0. A second difference is that conceptual recurrence is only calculated for one half of the diagonal; therefore, the sum and
normalization take this factor into account

\[ CRR = \frac{2}{N(N-1)} \sum_{i=1}^{N} \sum_{j=i+1}^{N} R_{i,j}, \]

where \( N \) is the total number of utterances and \( R(i, j) \) is the recurrence element corresponding to time points \( i \) and \( j \) (defined below).

The basic element of conceptual recurrence \( R(i, j) \) is the cosine similarity between the concept vectors of utterances \( i \) and \( j \). For more information on how these concept vectors are created, we refer readers to Angus et al. (2012a; 2012b).

**B. Group-group (G2G)**

Some conversations involve multiple interacting agents that align to particular social groups. Group-to-group (G2G) decomposes recurrence rate according to whether recurrence is attributable to agents recurring with their own utterances and those of members of their group, or utterances by other social groups. The result is a matrix of recurrence sums where each element of that matrix is calculated according to

\[ G2G(a, b) = c(a, b) \sum_{i=1}^{N} \sum_{j=i+1}^{N} \left\{ \begin{array}{ll}
(\ i \in g^a \ & \ & (\ j \in g^b), \ R_{i,j}, \\
\text{else,} & 0,
\end{array} \right. \]

where \( c(a, b) \) is a single element of the normalization matrix (discussed in Sec. III D); \( g^a \) and \( g^b \) are vectors containing the time points of utterances by conversation agents \( a \) and \( b \), respectively; \( N \) is the total number of utterances; and \( R(i, j) \) is the recurrence element corresponding to time points \( i \) and \( j \). See Fig. 3 for a visualization of G2G and the other levels in the pyramid of cRQA metrics.

**C. Person-person (P2P)**

Person-to-person (P2P) recurrence is calculated in a similar manner as the G2G recurrence, the difference being that there are no social groupings, only individual relationships. P2P decomposes this aggregation of recurrence values such that there is a metric value for each pair of agents within the conversation; like G2G, it also assigns directionality to this recurrence such that agent \( b \) repeating agent \( a \) is summed into a different metric value to agent \( a \) repeating agent \( b \)

\[ P2P(a, b) = c(a, b) \sum_{i=1}^{N} \sum_{j=i+1}^{N} \left\{ \begin{array}{ll}
(\ i \in m^a \ & \ & (\ j \in m^b), \ R_{i,j}, \\
\text{else,} & 0,
\end{array} \right. \]

where \( c(a, b) \) is a single element of the normalization matrix (discussed in Sec. III D); \( m^a \) and \( m^b \) are vectors containing the time points of utterances by conversation agents \( a \) and \( b \), respectively; \( N \) is the total number of utterances; and \( R(i, j) \) is the recurrence element corresponding to time points \( i \) and \( j \).

**D. Normalization**

In the case of recurrence rate, normalization involves dividing the total recurrence sum (the sum of all below-diagonal recurrence elements) by the total number of possible recurrence elements. For G2G and P2P, normalization takes into account asymmetries in the summation of recurrence elements since later utterances can potentially recur with more utterances than those occurring earlier in a conversation.

---

**FIG. 3.** An example of a Discursis plot of a conversation between five people is presented in the left of this figure, each individual is represented by a unique color. The recurrence elements that represent the P2P value of the pink person repeating the blue person are highlighted and summed to produce one of the P2P values for this pair (step 1). The five people are then assigned into three groups (step 2), and the calculation of the G2G value for the dark red group (comprising one speaker) repeating the brown group (comprising two speakers) is shown (step 3). Finally, the sum total of the G2G matrix reveals the total conceptual recurrence of the conversation (step 4).
We introduce normalization factors in the form of a matrix, C, which scale the summed recurrence per person or group based on the total number of potential recurrence elements, taking a similar form to the formulation of G2G and P2P. Put simply, C contains the highest possible recurrence values for all element pairs. Each normalization element, \( c(a,b) \), calculates the number of recurrence elements between agent or group \( a \) and agent or group \( b \), given by

\[
c(a, b) = \sum_{i=1}^{N} \sum_{j=p^a}^{N} \left\{ \begin{array}{ll}
1, & (i \in p^a) \& (j \in p^b), \\
0, & \text{else},
\end{array} \right.
\]

where \( p^a \) and \( p^b \) are vectors containing the time points of utterances by conversation groups/agents \( a \) and \( b \), respectively, and \( N \) is the total number of utterances.

An alternative to the normalization above is to leave the recurrence sums un-normalized. Non-normalized values indicate the raw recurrence of turns, with those early in a conversation typically having higher values compared to those late in the conversation. In the following analyses, all scores presented are un-normalized unless explicitly stated otherwise.

**IV. USE CASE ANALYSES: MULTI-PARTICIPANT RECURRENCE ANALYSIS OF AUDIENCE DISCUSSION TELEVISION PROGRAMS**

**A. Aim**

Through application to publically available television transcripts, this study compares the new cRQA metrics to expert qualitative observations of these discourses. The aim is to determine the degree to which the proposed metrics correlate with known qualitative observations of the discourse. The use cases also serve a secondary purpose to showcase possible applications and analytical workflows for these new recurrence metrics.

**B. Background**

Television audience discussion programs are a form of panel discussion program that discuss current (often controversial) issues for the benefit of an over-hearing (at home) audience, often involving mixes of experts and non-experts (laypeople) arranged in a forum style seating arrangement, with the host and sometimes selected guests appearing on a stage. These discussion programs provide an important platform for the members of the society to contribute to the public discourse by entering into dialogues with a program host and other members of the audience (Tolson, 2006). At a surface level, communicative exchanges in these television shows typically resemble ordinary conversations; however, these conversational acts are guided by obligations to fulfill the interests of media networks, sponsors, audiences, and those of the respective institutions represented by the host and, if applicable, the guest.

Understanding the role that expertise plays in audience discussion programs is a critical issue in the field of media and communication studies, due to the democratization of speech that these programs claim to serve. For more than a decade, research into audience discussion programs has revealed how expert speakers appearing on such programs are attributed rank, status, and legitimacy through the conversational acts of the host, whereas lay participants typically do not have such status afforded to them, and have to establish their own credentials and claim the right to contribute to the discourse (Fitzgerald and Housley, 2002; Heritage and Clayman, 2010; Hutchby, 2005; and Thornborrow, 2001). A key finding from this work is that the marginalization of laypeople in these discourses is increased by expert guests’ use of interpretive repertoires (Potter and Wetherell, 1987), often in the form of anecdotes and vocabulary accessible to their colleagues but not by laypeople. In other words, experts engage more with their expert counterparts through the use of “expert” language and jargon that is difficult for laypeople to engage with.

**C. Method**

1. **Data: Special Broadcast Services (SBS) insight**

Three datasets are analyzed in this study, sourced from the Insight television program [full transcripts (including video) and program details are available at: http://news.sbs.com.au/insight/], an award-winning weekly panel discussion program that has been broadcast by Australian independent national broadcaster Special Broadcast Services (SBS) since 1999. Insight has an in-studio audience of approximately 40 people discussing controversial and/or socially relevant topics for 1 h each week. The audience often includes politicians, industry and academic experts, and other members of the public (laypeople) who are usually affected by the issue being discussed. The program host Jenny Brockie and her team of producers aim to maintain a civil discourse and discourage out-of-turn statements or interjections by audience participants during the program.

Brockie’s hosting style is to direct questions to particular audience members, often using their responses to frame follow-up questions to the same person or another member of the audience. At all times, Brockie acts to control the debate and choice of topic(s). Even though the audience is composed of around 40 people, the program’s time constraints mean that usually only about half of the audience contributes to the discussion, with preference often given to experts. Descriptions of each of the programs are provided in the following subsections, and a table of summary statistics on the number of speakers and turns in each program are provided in Table I.

a. **Program 1: Emergency**  Broadcasted on September 1, 2009, the SBS Insight program “Emergency” focused on the topic of under-resourced hospital emergency departments within Australia. The audience comprised doctors, nurses, and people who had recently had an experience at an Australian hospital emergency department. The show began with different laypeople giving personal accounts of recent negative experiences with hospital emergency departments, attributed mostly to lengthy waiting times before receiving medical attention.

b. **Program 2: The Science of Sexual Attraction**  Broadcasted on August 24, 2010, the SBS Insight program “The Science of
TABLE I. Summary statistics for the television programs under study. The statistics reveal how experts tend to speak for longer than laypeople, and that the host contributes mostly very short single sentence length statements.

<table>
<thead>
<tr>
<th>Group</th>
<th># of speakers</th>
<th># of turns (total)</th>
<th>Average turn length (content words)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Emergency</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Host</td>
<td>1</td>
<td>90</td>
<td>8.4</td>
</tr>
<tr>
<td>Laypeople</td>
<td>8</td>
<td>31</td>
<td>10.7</td>
</tr>
<tr>
<td>Expert</td>
<td>14</td>
<td>58</td>
<td>27.7</td>
</tr>
<tr>
<td>Total (avg)</td>
<td>23</td>
<td>179</td>
<td>(24.9)</td>
</tr>
<tr>
<td><strong>The Science of Sexual Attraction</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Host</td>
<td>1</td>
<td>109</td>
<td>5.9</td>
</tr>
<tr>
<td>Laypeople</td>
<td>17</td>
<td>83</td>
<td>7.6</td>
</tr>
<tr>
<td>Expert</td>
<td>4</td>
<td>38</td>
<td>37.1</td>
</tr>
<tr>
<td>Total (avg)</td>
<td>22</td>
<td>230</td>
<td>(13.7)</td>
</tr>
<tr>
<td><strong>Doctors and Drugs</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Host</td>
<td>1</td>
<td>100</td>
<td>7.2</td>
</tr>
<tr>
<td>Laypeople</td>
<td>5</td>
<td>9</td>
<td>13.4</td>
</tr>
<tr>
<td>Expert</td>
<td>18</td>
<td>96</td>
<td>21.0</td>
</tr>
<tr>
<td>Total (avg)</td>
<td>24</td>
<td>205</td>
<td>(19.7)</td>
</tr>
</tbody>
</table>

Sexual Attraction” discussed the science behind pair-bonding and sexual attraction in humans. The audience was composed of couples, and academics studying the science of attraction. The discussion began with commentary from several experts before including commentary from other audience members. This particular episode’s topic and audience composition allow it to be considered as an example of a non-contentious episode as it did not include conflicting viewpoints or opinions and is included in the study for this reason. By contrast, the other episodes selected present different conflicting viewpoints and accounts.

c. Program 3: Doctors and Drugs Broadcasted on May 26, 2009, the SBS Insight program “Doctors and Drugs” examined the relationship between pharmaceutical companies and health professionals, focusing on issues such as sponsorship of events, product placements in doctors’ surgeries, and free trials of pharmaceutical products. The audience comprised health professionals, pharmaceutical representatives, consumer advocates, and laypeople. This program was selected for analysis because unlike the programs analyzed previously, in this program the number of experts (18) vastly outweighed the number of laypeople (5).

2. Calculation and presentation of cRQA pyramid metrics

The cRQA pyramid metrics CRR, G2G, and P2P were calculated for each of the three Insight programs. The groups, expert, laypeople, and host, were used for the G2G metric calculation. Jenny Brockie was the sole person assigned to the host category, audience members afforded a professional title or introduction based on their professional expertise were assigned into the expert category, and all remaining audience members were assigned to laypeople.

To examine the structure of conceptual interactions in the Insight programs, social network diagrams were created, using the individual speakers as nodes and the non-normalized P2P metrics as edge weights. Herein, we refer to these social networks as social semantic networks to avoid confusion with social networks which are commonly constructed using relationship data derived from social network platforms. The ForceAtlas2 force-directed layout algorithm (Jacomy et al., 2014), as implemented in the Gephi 0.8.2 software package, was used to create the social semantic network diagrams. ForceAtlas2 attempts to co-locate participants with higher shared metric values to reveal clusters of television guests that are repeating each other’s content strongly. Edges are sized proportionate to the P2P values, and self-referential edges are sized based on the degree to which individual speakers repeat their own conceptual content.

3. Expert assessment

All three transcripts were analyzed by an independent expert discourse analyst to provide a qualitative ground truth, informed from current discourse analysis theory. Richard Fitzgerald from the Department of Communication, University of Macau, is an expert in the organization of cultural knowledge and identity in interaction and broadcast news and has published extensively in the areas of membership categorization analysis and discourse analysis. Fitzgerald was provided with transcripts of the three Insight conversations and also the original video and audio. He was not shown our cRQA calculations, analysis, or conclusions. The independent expert findings contained observations that were relevant for individual conversations, in addition to generally applicable findings for all three conversations (discussed in Sec. V).

D. Analysis

1. Turn-by-turn conceptual recurrence rate (CRR)

The turn-taking statistics reported in Table I reveal that “Emergency” had the second highest average turn length coupled with a relatively high number of turns taken by members of the expert group. This could be a reason for this program having the highest normalized CRR value of the three programs (see Table II). The “Science of Sexual Attraction” program has the lowest CRR value of the three, and also has the highest number of laypeople and turns taken by laypeople as a proportion of total turns of the three programs. The “Science of Sexual Attraction” also has the lowest average number of words per turn.

2. Person to person (P2P)

As per prior expectations, for all three datasets the P2P values reveal a lack of reciprocity between experts and laypeople. This finding is reflected in the lack of, or relatively thin edges that connect laypeople to others in Figs. 4–7.

TABLE II. Normalised CRR for all three programs.

<table>
<thead>
<tr>
<th>Program</th>
<th>CRR (normalized)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Emergency</td>
<td>0.09873</td>
</tr>
<tr>
<td>Science of Sexual Attraction</td>
<td>0.02860</td>
</tr>
<tr>
<td>Doctors and Drugs</td>
<td>0.05207</td>
</tr>
</tbody>
</table>
High P2P values occur when individuals directly repeat concepts of their interlocutors, whereas low values are when there is a lack of conceptual repetition. It is observed that in all social semantic networks, experts tend to cluster closely with each other and the host, and are connected by thicker edges. This observation suggests that experts are engaging more strongly with each other’s conceptual content, and that the host is also tending to repeat and be repeated by these experts.

While Figs. 3–6 utilize non-normalized P2P values, Fig. 7 showcases the effect of the normalization factor described in Sec. III D on the P2P social semantic network. The most prominent difference between Figs. 3 and 7 is that the centrality of the host is reduced in the normalized network; however, all other findings between these networks, particularly the different clustering of experts and laypeople, are commensurate.

One notable exception to the observation of laypeople and experts being in independent clusters in the “Emergency” program is layperson Susan Candlish, a mother who gave an account of her son’s acute appendicitis. Susan Candlish gave a lengthy account of her son’s traumatic experience which many experts referred back to as a particularly important real-world example of problems in emergency departments, specifically the concept “waiting” which refers to lengthy wait times experienced in some Australian health facilities. The median P2P value of experts repeating her content is 0.10 compared to the median P2P value for all expert-laypeople pairs of 0.05. A plausible explanation as to why experts repeated her content so strongly was that she recounted her story early in the program and the host encouraged its elaborate extension by experts, making it a powerful agenda setting device:

SUSAN CANDLISH: I felt frustrated, just sitting there waiting. We weren’t sure how long it was going to be. I asked a nurse here and there and they couldn’t really give me an answer and said the surgeons weren’t available they were either in theatre or you don’t see them around. We thought well, someone has to see him.

JENNY BROCKIE: Of course, you were waiting just to go to another hospital as it turned out and you didn’t know that.

FIG. 4. SBS Insight “Emergency” P2P social network. The clustering of expert (red) and laypeople (blue) nodes suggests that experts preferentially repeat concepts by fellow experts rather than those of laypeople. The social network also shows individual outliers in each group: Candlish is an outlier in the laypeople, being repeated by many experts; while McGhie clusters closer to several laypeople. Arrows indicate the direction of influence; A → B suggests that B repeats A’s concepts.

FIG. 5. SBS Insight “The Science of Sexual Attraction” P2P social network. Even with far fewer experts than in “Emergency,” the experts still form a clique around the host due to the high P2P values connecting the host with experts, and experts to experts; the experts also show the highest self-recurrences.
FIG. 6. SBS Insight “Doctors and Drugs” P2P social network. Note the dense connectivity between the experts in this program.

SUSAN CANDLISH: In the end, after nine hours when we were told we were at the wrong hospital, we should be transferred and we were transferred, that way it was just ridiculous.

JENNY BROCKIE: Mike, you are a specialist emergency physician from WA which has some of the longest waiting times in the country in emergency for patients in emergency. A nine hour wait to get the information you are at the wrong hospital. I mean, how often does that sort of thing happen?

DR MIKE CADOGAN: Certainly, it’s not a frequent occurrence. But to have people come to the triage desk, that’s the place where we would initially make did some diagnosis of someone being too young or to actually be at my hospital and need to go to a children’s hospital. I guess you know, without going into the individual facts, trying to get somebody through the triage system, given appropriate treatment and care and then make the ongoing referral as part of what we have to do on a daily basis.

JENNY BROCKIE: And those long waits something like a nine hour wait is that happening frequently?

DR MIKE CADOGAN: Yes, we certainly are we have extensive waits for a number of different reasons. It can be waiting for the specific specialist on call to come and see them. It can be trying to get through the emergency department. It can be waiting in the waiting room to get into the emergency department. There are a number of different levels which we’re blocked.

When the number of experts relative to laypeople is low, as is the case for the “Science of Sexual Attraction” episode, the social semantic network still locates experts in close proximity to each other and the host due to the high P2P values connecting the experts to the host. Of note also is the high amount of self-repetition by individual experts in this program, reflected by the thick edges that loop back onto the same node.

The “Science of Sexual Attraction” episode involves couples as guests and also more direct interaction between guests rather than the host directing the flow of questioning. This manifests as more layperson-layperson edges within the social semantic network. Similar to the other episodes though, laypeople do not tend to engage with each other or experts’

FIG. 7. SBS Insight “Emergency” P2P (normalized) social semantic network. This normalized version of the P2P social semantic network shown in Fig. 4 reduces the prominence of the program host Jenny Brockie given her somewhat dominant number of turns and therefore large normalization factor and allows the layperson and expert clusterings to become more apparent.
TABLE III. G2G matrix for SBS Insight “Emergency” expressed as the percentage of total for all G2G values.

<table>
<thead>
<tr>
<th>Initiated by</th>
<th>Host (%)</th>
<th>Layperson (%)</th>
<th>Expert (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Host</td>
<td>21.8</td>
<td>7.1</td>
<td>14.7</td>
</tr>
<tr>
<td>Layperson</td>
<td>5.9</td>
<td>3.0</td>
<td>2.7</td>
</tr>
<tr>
<td>Expert</td>
<td>21.6</td>
<td>6.1</td>
<td>17.1</td>
</tr>
</tbody>
</table>

TABLE IV. G2G matrix for SBS Insight “Science of Sexual Attraction” expressed as the percentage of total for all G2G values.

<table>
<thead>
<tr>
<th>Initiated by</th>
<th>Host (%)</th>
<th>Layperson (%)</th>
<th>Expert (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Host</td>
<td>25.9</td>
<td>10.3</td>
<td>12.8</td>
</tr>
<tr>
<td>Layperson</td>
<td>9.4</td>
<td>9.5</td>
<td>5.0</td>
</tr>
<tr>
<td>Expert</td>
<td>11.0</td>
<td>5.3</td>
<td>10.9</td>
</tr>
</tbody>
</table>

TABLE V. G2G matrix for SBS Insight “Doctors and Drugs” expressed as the percentage of total for all G2G values.

<table>
<thead>
<tr>
<th>Initiated by</th>
<th>Host (%)</th>
<th>Layperson (%)</th>
<th>Expert (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Host</td>
<td>19.5</td>
<td>1.4</td>
<td>25.8</td>
</tr>
<tr>
<td>Layperson</td>
<td>0.9</td>
<td>0.3</td>
<td>2.0</td>
</tr>
<tr>
<td>Expert</td>
<td>16.3</td>
<td>1.7</td>
<td>32.0</td>
</tr>
</tbody>
</table>

concepts in this program at the same level that experts are engaging other experts and the host, reflected through their overall layout and edge thicknesses.

In the Doctors and Drugs episode, the P2P values for laypeople repeating or being repeated by others is low, like the previous examples. A similar pattern of host to expert interaction can be seen in addition to high P2P values connecting some experts with other experts.

In all episodes, the host is placed at the center of the non-normalized social semantic network by the graph layout algorithm, reflecting the high degree of conceptual repetition (P2P) flowing both ways (host-guest and guest-host). This central placement in the social semantic network is a reflection of Jenny Brockie’s hosting style. In the transcript from the Emergency episode above, it can be observed that Brockie tends to take a (short) turn between guests, acting as a conduit between guests, but perhaps also for the benefit of the at-home audience. This accommodative style which reframes and reflects the content of guests would naturally lead to elevated conceptual recurrence between host and guests. Even when normalized (Fig. 7), the host is still located near the center of the network.

3. Group to group (G2G)

The G2G values were calculated for all three groupings (host, layperson, and expert) and converted into a percentage against the total of all nine G2G values (see Tables III–V). The G2G values express the percentage share of conceptual recurrence between these pairings as a proportion of the total for that episode.

The analysis of P2P values in Sec. IV D 2 revealed the central role of the host in accommodating guests’ content and of reframing content for follow-up questioning and potentially the benefit of the at-home audience. Also, that experts tended to engage more strongly with other experts than they did with laypeople. These findings are also reflected in the G2G values which highlight the strong interaction between experts and host, as well as self-repetition by these two groups.

Laypeople tend not to repeat or be repeated by experts, or repeat their own group. The one exception being a slightly higher self-repetition by guests in the “Science of Sexual Attraction” episode. In this episode, guests do tend to repeat other guests, also seen to some degree via the couple’s interaction in the P2P social semantic networks. Another plausible explanation is that this episode had more layperson talk (83 turns for laypeople versus 38 for experts) and an outnumbering of laypeople (17) to experts (4). However, despite laypeople having twice the number of turns in this episode, the host-host, host-expert, expert-host, and expert-expert G2G values are still the top four recurrence values accounting for 60.6% of the total G2G score.

E. Expert assessment

The independent expert’s observations are reproduced in full here:

While these three programs have very different topics there is an evident orientation to particular discourses being privileged. There is a privileging of the discourse of knowledge over that of experience achieved through the individual experience always coming off or being taken back into the knowledge of the expert.

In the program on the Science of Sexual Attraction the experts are asked to speak first which then provides the framing for the discussion. The framing of the topic is of the study and research of sexual attraction. Following the expert the Host then invites a member of the audience to tell of their experience, i.e., a personal story. After this turn the host then addresses another expert. The pattern unfolds as Expert–Host–Lay–Host–Expert–Host–Lay etc. Not only does this structure the turn order but also the topical flow. The experts’ contributions are reproduced in the institutional voice referencing their knowledge to studies and research rather than personal experience. Following each of the expert contributions the host then picked up on one aspect for the audience member to then provide a personal anecdote. In many ways this resembles a classic research structure with individual case studies illustrating the points being made by the various authors.

In the program about the crisis in waiting for emergency care the organization of the participants is similar with two main groups reflected through turn taking organization is similar but begins with two detailed personal stories. Here the experts are those who work in hospitals, nurses, doctors and administrators, and researchers while the other group is made up of patients who had recently attended emergency rooms. A similar turn taking structure is adopted with the host mediating the turn transition and the topical flow. Again the privileging of the experts is achieved through the expert’s knowledge over the individuals experience and where this knowledge is given authority through the use of the institutional voice. In many ways this particular program resembles a policy inquiry where individuals provide the illustrative cases to highlight the problem.
V. DISCUSSION

The metric values obtained in all three cases highlight a general tendency for experts to engage more strongly with concepts of other experts and to engage more strongly with concepts of the host than concepts of laypeople. The host’s accommodative interaction style and use of question formulation drive her high values for self-recurrence and are also reflected in G2G and P2P recurrence values.

General observations made by the independent expert discuss how in every program analyzed, the expert’s contributions are privileged. The independent expert’s observations reinforce the notions of the experts engaging with each other to the near exclusion of lay people, which aligns with the values obtained for the P2P and G2P metrics, reinforced through the semantic social network layout which revealed tight clustering of experts with other experts.

VI. CONCLUSION

In this paper, a set of cRQA metrics were proposed to aid the analysis of topic management practice in naturally occurring conversations. The new metrics, CRR, G2G, and P2P, extend the existing multiple participant recurrence (MPR) model and the existing RQA measure, recurrence rate, over whole conversations, by partitioning recurrence based on different speakers and their interactions. Using a well-studied conversational context from the broadcast interview genre, the new cRQA measures of conceptual recurrence rate, person-to-person, and group-to-group were shown to capture the expected conceptual interaction dynamics of these conversations. The case-studies presented demonstrate how these new conceptual RQA measures allow analysts to work at multiple layers of complexity to unpack the topic management practices present in multi-party conversations.

Observations informed by the new metrics were contrasted against analysis by an independent expert discourse analyst, and in all cases similar insights were obtained. While the metrics are not intended to replace the role of the analyst, the use cases presented show that the metric values align with expectations of these discourses making them a potentially powerful tool in a discourse analyst’s toolkit.

Also demonstrated was how the new metrics allow for the detection of cases which fall outside the realm of expected conduct, as the analysis of the “Drugs and Doctors” program highlighted with respect to the laypeople repeating each other’s content.

Conceptual recurrence metrics cannot replace detailed discourse analysis, but they could provide a necessary first step in the analysis of big data. For example, CRR, G2G, and P2P metrics could be useful in studies of very large (1000+) datasets as a way of pre-screening data, particularly when the need to understand the total degree of conceptual consistency is critical.

In conclusion, the new metrics offer a simple and quick way for assisting the analysis of topic management practice in multi-party conversations. Future studies can continue to apply these metrics to other conversational contexts to further examine the robustness of the metrics and uncover new insight into topic management practices.

ACKNOWLEDGMENTS

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