Ordered Network Analysis

Yuanru Tan(✉), Andrew R. Ruis, Cody Marquart, Zhiqiang Cai, Mariah A. Knowles, and David Williamson Shaffer

Wisconsin Center for Education Research, University of Wisconsin, Madison, WI, USA
Yuanru.tan@wisc.edu

Abstract. Collaborative Problem Solving (CPS) is a socio-cognitive process that is interactive, interdependent, and temporal. As individuals interact with each other, information is added to the *common ground*, or the current state of a group's shared understanding, which in turn influences individuals' subsequent *responses to* the common ground. Therefore, to model CPS processes, especially in a context where the order of events is hypothesized to be meaningful, it is important to account for the ordered aspect. In this study, we present *Ordered Network Analysis* (ONA), a method that can not only model the ordered aspect of CPS, but also supports visual and statistical comparison of ONA networks. To demonstrate the analytical affordances and interpretable visualizations of ONA, we analyzed the collaborative discourse data of air defense warfare teams. We found that ONA was able to capture the qualitative differences between the control and experimental condition that cannot be captured using unordered models, and also tested that such differences were statistically different.

Keywords: Ordered Network Analysis · Collaborative Problem Solving · Directed Network · Network Visualization

1 Introduction

Collaborative Problem Solving (CPS) is often conceptualized as a process of constructing shared *cognitive* space through *social* interactions [8, 9]. Studies have found that successful CPS involves a large degree of mutual engagement, joint decision making, and discussions [12]. To model such socio-cognitive processes, the modeling approaches undertaken must not only account for the fact that events at any point in time are influenced by prior actions, but also that individuals make connections to the things their collaborators say and do [18]. However, current modeling approaches tend to either underrepresent or even neglect the *interactive* and t*emporal* nature of CPS by treating collaborations as a set of isolated events, or overrepresent the *interdependence* between CPS activities by assuming all events being equally related to each other.

In respond to such challenges, we introduce *Ordered Network Analysis* (ONA) in this study. ONA constructs directed network models of CPS by accounting for not only the interactive, interdependent, and temporal nature of collaborations, but also the *order of events* unfolding over time in CPS processes. We argue that ONA has three affordances for modeling CPS. First, ONA can model the order of events in CPS by tracking both

C. Damşa and A. Barany (Eds.): ICQE 2022, CCIS 1785, pp. 101–116, 2023.
https://doi.org/10.1007/978-3-031-31726-2_8

what units of analysis respond *with* and what they respond *to* as they interact with others in the group, and represent such connections in directed network models. Second, ONA supports comparison of network models at both the individual unit level and the aggregated group level. This enables the assessment of individual performance in group context and also statistical testing of differences between groups. Third, to facilitate the interpretation of analytical results, ONA visualizes models in network graphs that are intuitive to read and mathematically consistent with the model's summary statistics.

In what follows, we first discuss outstanding challenges in existing approaches for modeling CPS. Next, we describe ONA analytical procedures in detail and the rationale of ONA visualization design. Lastly, we demonstrate ONA using an example from a well-studied dataset documenting CPS in a context where the order of events is hypothesized to be meaningful. We conclude this paper with a discussion of contributions that ONA makes to Quantitative Ethnography (QE) research on CPS.

2 Background

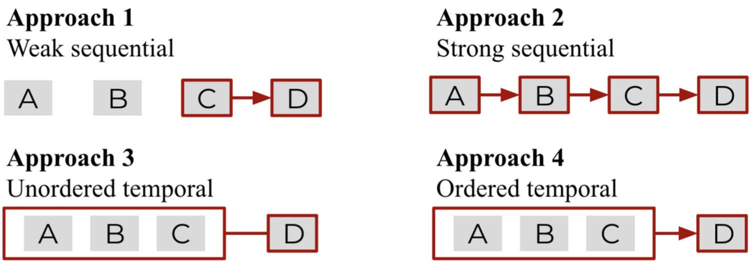
2.1 Collaborative Problem Solving

Working in numerous domains involves groups of people collaboratively solve complex or ill-formed problems, CPS is increasingly emphasized in educational curricula and assessment frameworks [6]. In educational contexts, students' proficiency in CPS can be measured by the extent to which students respond to requests and initiate actions to advance the group goals [2]. In military contexts where tasks are often cognitively demanding and have high stakes, for example, intensive interactions are needed between team members to solve problems that might outpace the capabilities of any one individual [17]. Regardless of context, CPS is fundamentally *socio-cognitive* that both cognitive engagement and social interactions are needed to solve problems [8, 10, 18].

As a result, there are three key features that models of CPS need to account for: *interactivity*, *temporality*, and *interdependence* [18]. First, CPS is *interactive* because team members solve problems by interacting with each other rather than independently. Second, CPS has an important *temporal* dimension because events at any point in time are influenced by prior actions that are within some recent temporal context [11]. For example, when one team member asks a question, other team members are likely to respond soon after; and each response may address not only the original question but also any prior responses to it. Third, CPS is *interdependent* because the contributions of a given individual are related to and influenced by the contributions of others. For example, Clark [3] argues that information is added to the *common ground*, or the current state of a group's shared understanding, as individuals interact with each other, which in turn influences individuals' subsequent *responses* to the common ground. This directional relationship *from* the common ground *to* response indicates that the *order* in which events unfold in CPS may reveal important differences in individuals' contributions to the collaborative processes.

2.2 Existing Approaches to Modeling Collaborative Problem Solving

Currently, there exist different approaches that can be used to model CPS by accounting for interdependence, including the order of events. *Sequential* models and *temporal* models are two prevalent classes [19]. Figure 1 shows four common approaches that fall into these two classes. To illustrate the characteristics of the four approaches and how they differ from each other, considering the excerpt in Fig. 1 as an example, in which one commander and two coordinators who are on a navy ship are discussing whether a track's behavior is threatening. Each of them has a defined role to monitor ships and aircraft on radar, so that the team can collectively make an assessment as to whether its behavior is threatening.



Line	Role	Utterance	Code
A	Commander	Can I get an update on Track 13?	SEEKING INFORMATION
B	Coordinator 1	Track 13 descended to 12,000 feet altitude.	TRACK BEHAVIOR
C	Coordinator 2	Track 13 is a possible F-4.	DETECT?IDENTIFY
D	Commander	Issue a Level 2 warning to Track 13.	DETERRENT ORDERS

Fig. 1. Four common approaches to modeling CPS by accounting for the order of events.

In this excerpt, the Commander asks for an update on a track that is potentially threatening in line A and receives two relevant but different responses from two Coordinators in lines B and C. Coordinator 1 describes the track's behavior (a change in altitude that could signal preparation for an attack), and Coordinator 2 identifies that the track may be a fighter plane. Based on this information, the Commander decides to issue a warning in line D. That is, the commander's order in line D is a response to both Coordinators' contributions in lines B and C—and by extension, the commander's question in line A—which form the *common ground* for line D. Using this simplified example, we describe the affordances and limitations of the four main approaches to modeling collaborative interdependence.

Approach 1 represents sequential models that treat CPS processes as events that are weakly connected, such as Lag Sequential Analysis (LSA), where the sequential dependency is computed only between an event and its immediately preceding event. Such methods neglect the interdependent nature of collaboration and very limited temporal context is taken into account during modeling [4]. For example, the warning issued by Commander in line D is only considered as a response to its immediate precedent event line C in which Coordinator 2 identified what type of aircraft the track might be. In fact, the deterrent order issued in line D is because the track is likely a fighter plane (as indicated in line C) *and* its behavior is potentially threatening (as indicated in line B). Such conservative consideration of sequence undercounts the influence that Coordinator 1 has on the deterrent order.

Approach 2 is also a sequential method, but one that considers sequences of longer length. For example, Sequential Pattern Mining (SPM) is a common technique for the identification of frequent sequential patterns that emphasizes the specific local order of events. In SPM, every event is considered as a response to the immediately preceding event. This provides the most fine-grained information about the order of events. However, as Swiecki and colleagues [19] demonstrated, the micro-sequences that SPM produces are less effective predictors of collaborative performance than co-temporal models *even in contexts where order is hypothesized to matter*. In other words, SPM may overrepresent connections that are not meaningful. Although Approach 2 can count what is undercounted in Approach 1, i.e., the connection between A and B and between B and C, the example also shows that specific micro-sequences may introduce noise. For example, qualitative interpretation of the exchange in Fig. 1 would not change if the order of lines B and C were reversed, but SPM and other strong-sequential techniques will treat the sequences ABCD and ACBD as meaningfully different.

Approach 3 represents co-temporal methods, such as epistemic network analysis (ENA), that model the co-occurrence of Codes in common ground with Codes in the response [15]. ENA is sensitive to the order of events in the data, meaning changing the order of events changes which events are present in a given window, and thus changes the results of the model [19]. However, the order *from* common ground *to* response is not modeled in ENA. For example, an ENA model would not show that the warning the Commander issued in line D is a response to the common ground formed by lines A, B, and C; it would only show that there is a connection from D to each of A, B, and C. When the order of the connections is not modeled, the fact that the Commander issued a warning *after* gathering information from two Commanders can only be ascertained from qualitative triangulation. Consequently, it is difficult to compare how different Commanders might respond differently to similar situations.

In cases where the directionality of the connections from the common ground to response is hypothesized to be meaningful, techniques in Approach 4 can be applied. To our knowledge, the only extant technique that models CPS in this way is directed epistemic network analysis (dENA), a prototype technique presented at ICQE21 [5]. As Fig. 1 shows, the only difference between Approach 3 and Approach 4 is that the connection between common ground and response is unordered in Approach 3, and it is ordered in Approach 4. Adding such directionality makes it possible to model the influence of information *from* the common ground on individuals' response. For example, in line D where the Commander *responded with* DETERRENT ORDERS to the common ground formed by lines A, B, and C reveals important information about how the Commander's decision making is informed by his own question *and* the responses of the Coordinators. Compared to Approach 2 where ordered information is overcounted, and compared to Approaches 1 and 3 where ordered information is undercounted, Approach 4 is a relatively balanced approach to model CPS processes, especially in cases where the specific *local order* of collaborative discourse moves may be less important than their *local co-temporality*. For example, in ill-formed problem-solving scenarios where discussions do not strictly follow prescribed orders, such as in the example in Fig. 1, it may make little difference whether in a brief span of time the group talks about SEEKING INFORMATION, TRACK BEHAVIOR, and then DETECT/IDENTIFY, or any of the other possible ordering of those topics.

2.3 Remaining Challenges and Proposed Solution

As a proof of concept, dENA provided empirical evidence that besides modeling the *interactive, interdependent,* and *temporal* aspects of CPS, accounting for the *order of events co-temporally* can reveal additional insights about CPS that otherwise remain unknown in the model. Despite its thorough theoretical foundation, there are still two unsolved analytical challenges.

1. dENA does not support statistical comparison of networks. While visual comparison is supported by superimposing network graphs with isomorphic nodes to show graphical differences, there is no statistical method to test whether the differences between groups are significant. This severely limits the kinds of analyses that researchers can conduct.
2. dENA network spaces contain redundant information that negatively affects both the interpretability of the visualizations and model fit. Each unit of analysis is represented by a combination of two vectors: one representing what the unit responding *to*, the other representing responding *with*. These two vectors contain the same information because one is the transpose of the other. Including such redundant information in modeling leads to less-than-optimal models.

In the following section, we introduce ONA and explain how it addresses the challenges with existing unordered and ordered co-temporal models (ENA and dENA, respectively), and we demonstrate the technique by analyzing a well-studied dataset for which there are published findings on CPS for [5, 18, 19].

3 Methods: Ordered Network Analysis

3.1 Dataset

We analyzed discourse data collected from U.S. Navy air defense warfare teams engaging in training scenarios. Each team's goal was to detect and identify tracks with uncertain identities, then make an assessment as to the tracks' threatening level. Based on these assessments, teams decide to issue a warning or engage them in combat. Each team consisted of two commanders and four support roles. The teams were divided into two conditions with eight teams in each condition. The conditions differed regarding the technological support and training provided to the commanders on each team. Commanders in the experimental conditions had access to more advanced technologies and additional trainings compared to commanders in the control conditions.

The transcripts were segmented into lines corresponding to turns of talk, for a total of 12,027 lines. Our units of analysis were the individual team members across different training scenarios. In total, the analysis included 94 individuals. In light of the experimental design, we grouped individuals according to their experimental condition and their duties on the team: command or support. We focused the analysis on the 29 individuals who held command roles—16 in the experimental condition and 13 in the control—because the experiment was designed to affect their performance directly.

We analyzed the transcripts using the codes in Table 1, which were developed by [18] using a grounded approach. All codes were validated at a kappa threshold of 0.65 and a rho threshold of 0.05 using the nCoderR package [7].

Table 1. Qualitative codes, definitions, and examples

Code	Definition	Example
DETECT/IDENTIFY	Talk about radar detection of a track or the identification of a track, (e.g., vessel type)	NEW BEARING, BEARING 078 APQ120 CORRELATES TRACK 7036 POSSIBLE F-4
TRACK BEHAVIOR	Talk about kinematic data about a track or a track's location	TRACK NUMBER 7021 DROP IN ALTITUDE TO 18 THOUSAND FEET
SEEKING INFORMATION	Asking questions regarding track behavior, identification, or status	WE'VE UPGRADED THEM TO LEVEL 7 RIGHT?
DETERRENT ORDERS	Giving orders meant to warn or deter tracks	CONDUCT LEVEL 2 WARNING ON 7037
DEFENSIVE ORDERS	Giving orders to prepare defenses or engage hostile tracks	COVER 7016 WITH BIRDS

3.2 ONA Analytical Procedures

The ONA algorithm begins by accumulating connections for each unit of analysis using coded and segmented data. For each unit, the ONA algorithm uses a moving window to identify connections formed from a current line of data (e.g., turn of talk), or *response*, to the preceding lines within the window, or *common ground*. We chose a moving window length of five for this data based on prior analyses of the same dataset [16].

During connection accumulation, ONA accounts for the order in which the connections occur by constructing an *asymmetric adjacency matrix* for each unit: that is, the number of connections from code A to code B may be different than the number of connections from B to A.

This method was also implemented in dENA [5], however, in dENA, this single asymmetric adjacency matrix is copied and transposed, such that each unit of analysis is thus represented by two accumulated asymmetric adjacency matrices: one representing its ground connections, i.e., what the unit *responded to*; the other representing its response connections, i.e., what the unit *responded with.*

In ONA, each unit is represented by the original asymmetric adjacency matrix, which contains the same information as the two matrices used in dENA, but represents that information in a more parsimonious fashion. ONA transforms this single matrix into a single high dimensional *asymmetric adjacency vector*. Each unit is thus represented by a single high dimensional vector (as opposed to two high-dimensional vectors in dENA), which results in a more succinct network space and allows flexibility in dimensional reduction and statistical comparison, as described below.

The asymmetric adjacency vectors for all units are then normalized and centered and the algorithm performs a dimensional reduction. ONA currently implements *singular value decomposition* (SVD) and a *means rotation* (MR)[1] similar to the dimensional reductions in ENA.[2] In contrast, in dENA, some dimensional reductions (including SVD and MR) produce degenerate solutions when applied to the full set of high-dimensional vectors because each unit is represented by two vectors, one of which is the transpose of the other.[3] As a result, in dENA users had to choose to rotate by either the ground vectors or response vectors when applying SVD. To our knowledge, dENA has not yet provided users with recommendations on when to choose ground or response matrices to apply SVD or other dimensional reductions. Moreover, as a result of this mathematical limitation, dENA models suffer from low goodness-of-fit.

In contrast, by representing each unit's directed connections with a single vector, the dimensional reductions in ONA produce models with higher goodness-of-fit that are easier to interpret.

The dimensional reduction process results in an ONA score for each unit of analysis in the lower-dimensional space. The ONA scores are visualized by plotting them in the lower dimensional space resulting from the dimensional reduction. For each unit, its ONA score is represented as a point in the network space as shown in Fig. 2. Unlike the paired vectors (ground and response) used to represent units in dENA, the ONA scores are single points and thus can be used to conduct statistical tests or as predictors in regression models.

The ONA algorithm co-registers units' directed network graphs and projected points in the low-dimensional space.[4] As a result, the network graph visualizations meaningfully reflect the mathematical properties of the projected points that represent each network in the projected space. For each unit, its graph shows the strength and directionality

[1] MR is a dimensional reduction that can be applied when the units are divided into two discrete groups. The resulting space highlights the differences between groups (if any) by constructing a dimensional reduction that places the means of the groups as close as possible to the x-axis of the space. MR is frequently used in ENA analyses [1].

[2] Because each unit is represented by a single, high-dimensional adjacency vector, ONA can use any dimensional reduction technique that can be used with ENA.

[3] The mathematical proof that including vectors and their transpose cause degenerate solutions under SVD and other rotations is beyond the scope of this paper; however, we are happy to provide it upon request.

[4] The mathematical details of co-registration are beyond the scope of this paper and can be found in the work of Bowman et al. [1].

of the connections it made. Network nodes in ONA are positioned in the space using the same optimization routine used in ENA [1]: the algorithm minimizes the distance between the ONA scores and the centroids of the corresponding networks. As a result, the ONA metric space can be interpreted based on the locations of the nodes. Units with ONA points on the right side of the space have more frequent connections between the codes on the right side of the space. Similarly, units with points on the left have more frequent connections between the codes on the left side of the space.

3.3 ONA Visualization Design

Building on the graphic design principles used in ENA visualizations [20], in ONA, the node size is proportional to the number of occurrences of that code as a *response* to other codes in the data, with larger nodes indicating more responses. The color and saturation of the circle within each node is proportional to the number of *self-connections* for that code: that is, when a code appears in both the response and ground of a given window. Colored circles that are larger and more saturated reflect codes with more frequent self-connections. For example, Fig. 2 suggests that roughly 40% responses made with code A were responding to code A.

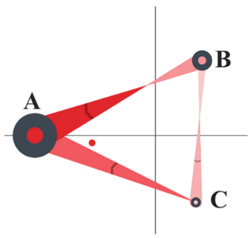


Fig. 2. Sample unit's ONA network. The overall size of the nodes represents the relative response strength with each code. The red dot in the middle of code A represents self-connections. Thicker and more saturated triangles represent stronger connections. The chevrons on the triangles indicate the order from common ground to response. The network is summarized by an ONA score, shown as a point. (Color figure online)

The directed connections in ONA are represented by edges between nodes, visualizing as a pair of triangles. Note that unlike most ordered network visualizations, which use arrows or spearheads to indicate directionality, ONA uses a "broadcast" model, where the source of a connection (ground) is placed at the apex of the triangle and the destination of a connection (response) is placed at its base. To facilitate interpretation, the dark chevrons place inside the triangles indicates the directionality of the connection from ground to response.

For example, in Fig. 2, between codes A and B, the thicker and more saturated triangle with a chevron on it represents the unit's *response with* code A to code B. In other words, code B is in the common ground that code A is a response to. Similarly, the thinner and less saturated triangle between A and B represents the unit's *response with* code A to code B. The dark chevron pointing towards A from B helps viewers identify that A is more often a response to B than the other way around. Between any pair of codes, if there is a bidirectional connection, the chevron only appears on the side with stronger connections. This helps viewers differentiate heavier edges in cases such as between codes B and C, where the connection strengths from both directions are similar. When the connection strengths are identical between two codes, the chevron will appear on both edges.

Taken together, ONA visualizations emphasize what the units of analysis *respond with*, rather than what they respond to. In other words, ONA visually emphasizes the units of analysis' active choice of reactions to what already happened in the common ground. To achieve such visual emphasis, we make sure that all the design elements (e.g., nodes, edges) and their attributes (e.g., size, saturation) in the visualizations consistently emphasize response strength. This is achieved by 1) using node size to represent the relative frequency of a code being present in a *response*, 2) using edge thickness and saturation to represent the relative frequency of a code being a *response* to the code it is connected to, and 3) using the chevron to represent the order of information flow from ground *to response.*

4 Results

In this section, we present the results of applying ONA to analyze the U.S. Navy air defense warfare teams discourse data that there are published findings for [5, 18, 19]. We compare ONA results against qualitative analysis results and ENA results, we found that ONA was able to capture qualitative differences between groups that were not shown in ENA model.

4.1 Qualitative Results

Qualitative analysis revealed both similarities and differences of the teams' CPS activities in the control and experimental conditions. In both conditions, teams were highly interactive, and individuals responded to and built upon the contributions of others as they pass information, make decisions, and take actions. However, commanders in the control and experimental conditions contributed to their teams in different ways. Specifically, in the experimental condition, since commanders in this condition had access to more advanced support system and were trained with additional curriculum materials, they did not need to acquire information verbally or hold it in their memory, so they were able to focus less on processing the tactical situation and more on contributing to and acting on that situation, such as issuing warnings in time. In contrast, commanders in the control condition, who only had access to standard technology support, often needed to clarify the tactical situation by asking questions. Consequently, they were often less able to take timely and appropriate actions toward tracks due to the increased burden of information management.

The following two excerpts illustrate such differences. The first excerpt is from a conversation between commanders and support roles from the control condition.

Line	Speaker	Utterance	Code
6241	CO	TAO CO, LET'S GO AHEAD AND ISSUE A THREAT LEVEL FOR THE PUMAS 13, 14, 15	DETECT IDENTIFY
6242	EWS	TAO, EW TRACK 012 IDENTIFIED AS F-4	DETECT IDENTIFY
6243	TAO	LEVEL 4, AYE	
6244	TAO	SAY AGAIN TRACK NUMBER F-4?	SEEKING INFORMATION
6245	EWS	14. CORRECTION 12, BEARING 094	TRACK BEHAVIOR
6246	TAO	TAO, AYE	

In line 6241, the CO asks the TAO to DETECT IDENTIFY the threat posed by the Puma helicopters. The TAO (line 6243) classifies the tracks as "level 4" threats, meaning that they are potentially hostile tracks that the team should monitor. Notice, however, between when the CO asks for a threat assessment and the TAO replies, the EWS (line 6242) reports another contact identified as an F-4 jet. The TAO then has to SEEKING INFORMATION by asking the EWS (line 6244) to repeat the information because they were busy making the threat assessment. The EWS repeats the track number of the F-4 and also adds additional information about TRACK BEHAVIOR (line 6245). The TAO acknowledges this message in line 6246.

As this excerpt shows, the members of this team were able to quickly distinguish similar sounding information (e.g., 14, level 4, F-4, 94). However, the commander (i.e., TAO) were often receiving new input while they were communicating decisions based on previous information. This means that they frequently had to request clarification by SEEKING INFORMATION from supporting members of the team to maintain an understanding of the tactical situation.

The next excerpt is from a conversation between commanders and support roles from the experimental condition. Typically, tracks are detected and reported by the supporting members of the team such as in the control condition, but the availability of the decision support system enabled the commander in the experimental condition to access this information directly, as the following excerpt illustrates.

Line	Speaker	Utterance	Code
9773	CO	OK 07 IS MOVING TOWARDS US SO WE'VE GOT TO COVER WITH GUNS OR BULLDOGS ON 07	TRACK BEHAVIOR DEFENSIVE ORDERS
9774	EWS	NEGATIVE	
9775	TAO	TIC GO OUT WITH LEVEL ONE QUERY ON 07 AND COVER WITH BULLDOGS	DEFENSIVE ORDERS DETERRENT ORDERS

The CO reports the detection of track 7, letting the team know its TRACK BEHAVIOR (line 9733). In the same turn of talk, the CO issues DEFENSIVE ORDERS to "cover with guns or bulldogs [anti-ship missiles] on 07". After adding an order to issue a level 1 warning to the track, the TAO passes the CO's orders to the TIC (line 9775). Thus, commanders on this team are reacting to the developing tactical situation by contributing new information about the TRACK BEHAVIOR (line 9733) and immediately responding to it with early actions from the detect-engage sequence: warning the track and covering it with weapons (lines 9733 and 97753).

As this excerpt shows, commanders in the experimental condition did not only contribute to their teams' understanding of the emerging tactical situation by passing information about tracks, also responded to these situations in a timely manner with appropriate decisions and actions. Although there were multiple simultaneous conversations that team members were participating it, but unlike the previous example, this did not lead to confusion because the commanders were not getting critical information only from the team.

4.2 ONA Results

Individual Unit Network. We first compared the individual network of one commander from the control condition (red, top) and another commander from the experimental condition (blue, bottom) as shown in Fig. 3.

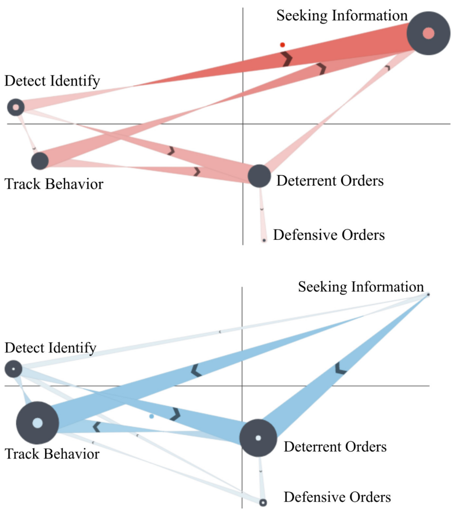


Fig. 3. Individual unit network for a commander from the control condition (red, top), and another commander from the experimental condition (blue, bottom). (Color figure online)

Both networks have strong connections between SEEKING INFORMATION and TRACK BEHAVIOR, as indicated by the relatively thicker and darker edges. However, ONA is able to show that the difference between how the two commanders made connections between TRACK BEHAVIOR and SEEKING INFORMATION was the *order* of the connections rather than their relative frequency. Such directional difference cannot be shown using ENA where the order of events is not accounted for. As the chevron indicates, in the network of the commander from the control condition, SEEKING INFORMATION is more commonly a response to TRACK BEHAVIOR. In the network of the commander in the experimental condition, TRACK BEHAVIOR is more commonly a response to SEEKING

INFORMATION. This difference in order is consistent with the qualitative findings. In the experimental condition, commanders were able to contribute to their teams' understanding of the emerging tactical situation by passing information about tracks supplied by the technological support system to which they had access to. Therefore, they were able to respond with TRACK BEHAVIOR when other team members SEEKING INFORMATION. In the control condition, due to the lack of support from the advanced technologies, SEEKING INFORMATION was the behavior commanders often initiated to ask for clarifications about TRACK BEHAVIOR.

Additionally, in the network for the commander in the experimental condition, there are two strong connections pointing towards DETERRENT ORDERS, one is from SEEKING INFORMATION, the other is from DETECT IDENTIFY. This means that orders to prepare defenses or engage hostile tracks are often issued *after* seeking information. In other words, the commander from the experimental condition was better able to use information to guide productive action, such as issuing orders, than the commander from the control condition.

Taken together, the SEEKING INFORMATION behavior in the experimental condition served as a common ground for commanders to respond to with productive actions such as issuing warnings through DEFENSIVE ORDERS and DETERRENT ORDERS. However, in the control condition, SEEKING INFORMATION was the behavior commanders initiated as a response to ask clarification questions about TRACK BEHAVIOR. In summary, compared to commanders in the control conditions, commanders in the experimental condition were thus better able to manage complex situations, ensuring that potentially hostile tracks were not lost from the tactical picture.

Group Comparison. Besides individual unit networks, we also compared the two conditions' aggregated mean ONA networks, as shown in Fig. 4 left. To illustrate the insights that ONA revealed about the group differences that otherwise remain unknown in unordered models such as ENA, we included an ENA network comparing the same groups, as shown in Fig. 4 right.

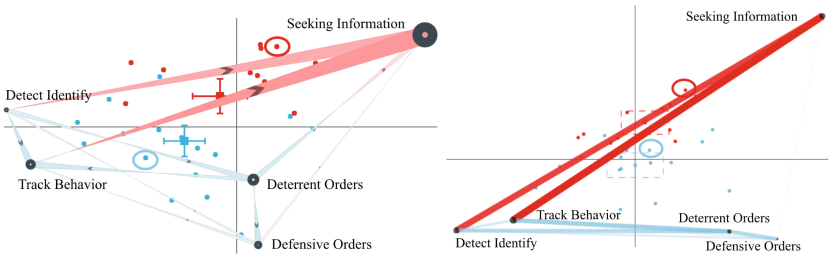


Fig. 4. Difference networks showing the most salient differences between the commanders in the control condition (red) and experimental condition (blue). Each edge is color-coded to indicate which of the two networks contains the stronger connection. Points represent ONA points (left) and ENA points (right), which summarize an individual unit network as a single point in the projection space. For example, the two individual networks shown in Fig. 3 are annotated in the network space in Fig. 4 using one red circle and one blue circle. (Color figure online)

Visual Comparison. By investigating ONA and ENA networks visually, we found that ONA contributed new insights to our interpretation of this dataset from two perspectives. First, for connections that have similar strength but differ in order, ONA preserved such directed connections while ENA counteracted it.

For example, in the ENA network, the connection between SEEKING INFORMATION and DETERRENT ORDERS is very weak, almost nonexistent. This means that there is very little or no difference in terms of how frequent those two codes co-occurred in the control and experimental conditions. However, recall that the qualitative results show that commanders in the control condition often had to request clarification by SEEKING INFORMATION from supporting members of the team to maintain an understanding of the tactical situation. In contrast, commanders in the experimental condition often responded to team members' SEEKING INFORMATION request in a timely manner with productive actions such as DETERRENT ORDERS. In other words, the differences in terms of how the two conditions made connections with SEEKING INFORMATION and DETERRENT ORDERS is not frequency, but *order*. ONA was able to capture such differences, representing by the chevron pointing from DETERRENT ORDERS to SEEKING INFORMATION.

Second, the *common ground* and *response* metaphor that ONA has helped differentiate the role of the same code in different connections. For example, ENA network shows that TRACK BEHAVIOR co-occurred frequently with SEEKING INFORMATION in the control group, as indicated by the corresponding red edge; and co-occurred frequently with DETERRENT ORDERS in the experimental group, as indicated by the corresponding blue edge. ONA makes it clear that the role TRACK BEHAVIOR acted in the two conditions is different. In the control condition, TRACK BEHAVIOR acted as the *common ground* for SEEKING INFORMATION, as indicated by the chevron pointing from TRACK BEHAVIOR to SEEKING INFORMATION. This means that *after* being shared with information about TRACK BEHAVIOR, commanders in this group often needed to SEEKING additional INFORMATION from other members. On the other hand, in the experimental condition, TRACK BEHAVIOR acted as a *response* to DETERRENT ORDERS. This means that *after* warnings being issued through DETERRENT ORDERS, TRACK BEHAVIOR information is presented to commanders to ensure that potentially hostile tracks were not lost from the tactical picture. The different role that TRACK BEHAVIOR has can be used as one of the aspects to characterize networks of different conditions.

Statistical Comparison. Since each unit's network is summarized as an ONA point in the projection space, we can compare the distribution of the projected ONA points for commanders in the control and experimental condition. Since most points in red locate on the upper right side, the points in blue locate on the left lower side of the space, we assume that the two groups are different with respect to their positions on both the first and second dimension. To test whether these differences were statistically significant, we conducted two sample t test between distributions of the projected points in ONA space for commanders in the two conditions. We found a significant difference between the experimental group (mean = −0.24, SD = 0.28) at the alpha = 0.05 level from the control (mean = 0.07, SD = 0.31) on the first dimension, as well as a significant difference between the control (mean = 0.24, SD = 0.08) and experimental (mean = −0.08, SD = 0.16) point distributions on the second dimension. However, in ENA, significant difference was only found on the second dimension between the control (mean = 0.32, SD = 0.17) and the experimental (mean = −0.05, SD = 0.20), with a smaller effective size compared to ONA (Cohen's d = 2.67 in ONA, Cohen's d = 1.69 in ENA).

Taken together, ONA was not only able to visually represent network differences between groups, but also allow researchers to make statistical claims about such differences. Similar comparison had also been conducted in the previous dENA study using the same dataset visually by investigating the difference network [5]. However, dENA was not able to further test if such differences observed visually are statistically different. Besides the test we demonstrated above, researchers can also conduct other statistical analysis such as using ONA points as predictors in regression analysis.

5 Discussion

In this study, we presented *Ordered Network Analysis* as a solution to model CPS by accounting for not only the interactive, interdependent, and temporal nature of collaborations, but also the order of events unfolding over time in CPS processes. We demonstrated the three major analytical and visual affordances of ONA. First, ONA can model both what units of analysis *respond with* and what they *respond to* as they interact with others in the group. Second, ONA supports the comparison of network models at both the individual unit level and the aggregated group level. This allows researchers to make statistical claims about how different individuals or groups respond to certain common ground differently. Third, through the co-registration process and the intentional visual design, ONA network visualizations are not only mathematically consistent with its summary statistics, but also intuitive to read.

5.1 Comparison of Methods

To extend the discussion in Sect. 2.2 where we reviewed extant CPS modeling approaches, in Table 2. We compare three QE approaches (i.e., ENA, dENA, ONA) by comparing their affordances. In summary, given its analytical and visual advancements, we suggest that ONA is preferable to dENA in all cases. When modeling weak sequential or temporally ordered data, we suggest that ONA should be used instead of ENA or other sequential methods such as SPM. For readers to make methodological choices for their CPS modeling, Table 2 serves as a brief summary rather than a meticulous description of the three approaches. We recommend that readers should refer to additional literature such as [1, 5, 14, 15] for more in-depth description.

Table 2. Different affordances of ENA, dENA, and ONA

Affordances	ENA	dENA	ONA
Connection matrix	Symmetrical	Asymmetrical	Asymmetrical
Summary statistics	ENA points	Vectors	ONA points
Rotations	Singular Value Decomposition, Means Rotation, hENA[5]	Singular Value Decomposition	Singular Value Decomposition, Means Rotation hENA
Node positions	Deterministic	Deterministic	Deterministic
Comparison of networks	Statistical, visual	Visual	Statistical, visual
Goodness of fit	High	Moderate	High
Best for	Temporal unordered data	ONA is preferrable to dENA in all cases	Weak sequential or temporal ordered data

5.2 Limitations and Conclusions

Although the ONA analysis in this study was only conducted using a single dataset, the data we used was only meant to provide an example of how ONA can model CPS by accounting for the order of events. Given its analytical and visual flexibility, we argue that ONA can not only be applied to model CPS processes, but also broadly in any research questions in situations where patterns of directed associations in data are hypothesized to be meaningful. In future work, we are interested in applying ONA in QE research in different domains.

Acknowledgement. This work was funded in part by the National Science Foundation (DRL-1661036, DRL-1713110), the Wisconsin Alumni Research Foundation, and the Office of the Vice Chancellor for Research and Graduate Education at the University of Wisconsin-Madison. The opinions, findings, and conclusions do not reflect the views of the funding agencies, cooperating institutions, or other individuals.

References

1. Bowman, D., et al.: The mathematical foundations of epistemic network analysis. In: Ruis, A.R., Lee, S.B. (eds.) ICQE 2021. CCIS, vol. 1312, pp. 91–105. Springer, Cham (2021). https://doi.org/10.1007/978-3-030-67788-6_7

[5] hENA, or Hierarchical Epistemic Network Analysis, is an extension to ENA that enables researchers to model nested effects of multiple grouping variables rather than one grouping variable using means rotation. Detailed description of hENA can be found in [13].

2. C. Graesser, A., Foltz, P.W., Rosen, Y., Shaffer, D.W., Forsyth, C., Germany, M.-L.: Challenges of assessing collaborative problem solving. In: Care, E., Griffin, P., Wilson, M. (eds.) Assessment and Teaching of 21st Century Skills. EAIA, pp. 75–91. Springer, Cham (2018). https://doi.org/10.1007/978-3-319-65368-6_5
3. Clark, H.H.: Using Language. Cambridge University Press, Cambridge (1996)
4. Csanadi, A., Eagan, B., Kollar, I., Shaffer, D.W., Fischer, F.: When coding-and-counting is not enough: using epistemic network analysis (ENA) to analyze verbal data in CSCL research. Int. J. Comput.-Support. Collab. Learn. **13**(4), 419–438 (2018). https://doi.org/10.1007/s11412-018-9292-z
5. Fogel, A., et al.: Directed epistemic network analysis. In: Ruis, A.R., Lee, S.B. (eds.) ICQE 2021. CCIS, vol. 1312, pp. 122–136. Springer, Cham (2021). https://doi.org/10.1007/978-3-030-67788-6_9
6. Graesser, A.C., et al.: Advancing the science of collaborative problem solving. Psychol. Sci. Public Interest **19**(2), 59–92 (2018)
7. Marquart, C.L., et al.: ncodeR: Techniques for Automated Classifiers (2018)
8. Miyake, N., Kirschner, P.A.: The social and interactive dimensions of collaborative learning. In: Sawyer, R.K. (ed.) The Cambridge Handbook of the Learning Sciences, pp. 418–438. Cambridge University Press, Cambridge (2014)
9. Roschelle, J., Teasley, S.D.: The construction of shared knowledge in collaborative problem solving. In: O'Malley, C. (ed.) Computer Supported Collaborative Learning, pp. 69–97. Springer, Heidelberg (1995). https://doi.org/10.1007/978-3-642-85098-1_5
10. Rosen, Y.: Computer-based assessment of collaborative problem solving: exploring the feasibility of human-to-agent approach. Int. J. Artif. Intell. Educ. **25**(3), 380–406 (2015). https://doi.org/10.1007/s40593-015-0042-3
11. Ruis, A., et al.: Finding Common Ground: A Method for Measuring Recent Temporal Context in Analyses of Complex, Collaborative Thinking (2019)
12. San Martín-Rodríguez, L., et al.: The determinants of successful collaboration: a review of theoretical and empirical studies. J. Interprof. Care **19**, 132–147 (2005)
13. Shaffer, D.: Hierarchical Epistemic Network Analysis (2021)
14. Shaffer, D.W., et al.: A tutorial on epistemic network analysis: analyzing the structure of connections in cognitive, social, and interaction data. J. Learn. Anal. **3**(3), 9–45 (2016). https://doi.org/10.18608/jla.2016.33.3
15. Shaffer, D.W., et al.: Epistemic Network analysis: a worked example of theory-based learning analytics. In: Columbia University, USA et al. (eds.) Handbook of Learning Analytics, pp. 175–187. Society for Learning Analytics Research (SoLAR) (2017). https://doi.org/10.18608/hla17.015
16. Siebert-Evenstone, A.L., et al.: In search of conversational grain size: modeling semantic structure using moving stanza windows. J. Learn. Anal. **4**(3), 123–139 (2017)
17. Smith, C.A.P., et al.: Decision support for air warfare: setection of deceptive threats. Group Decis. Negot. **13**(2), 129–148 (2004)
18. Swiecki, Z., et al.: Assessing individual contributions to collaborative problem solving: a network analysis approach. Comput. Hum. Behav. **104**, 105876 (2020)
19. Swiecki, Z., et al.: Does Order Matter? Investigating Sequential and Cotemporal Models of Collaboration, vol. 8 (2019)
20. Tan, Y., et al.: Epistemic network analysis visualization. In: Wasson, B., Zörgő, S. (eds.) Advances in Quantitative Ethnography, pp. 129–143 Springer International Publishing, Cham (2022). https://doi.org/10.1007/978-3-030-93859-8_9