Towards Multimodal Characterization of Dialogic Moments On Social Group Face-to-Face Interaction

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Abstract. Multimodal data enables powerful methodological approaches to investigate social group interaction. This paper specifically focuses on dialogic moments, i. e., episodes of human communication with high mutual understanding. We present preliminary results of a pilot study, where we apply multimodal analysis of dialogic moments in the context of storytelling, for obtaining data-driven characterizations. We collected multimodal sensor data, including skin conductance, face-to-face proximity, and vocal non-verbal features of the participants, complemented by their subjective experiences collected via self-report questionnaires. Our first preliminary findings provide novel perspectives on different profiles of dialogic moments, characterized by objective and subjective features.

Keywords: Social Signal Processing, Multimodal Analytics, Dialogic Moment

1 Introduction

For analyzing group interactions, wearable sensors complemented by information from self-report questionnaires enable powerful methodological approaches for analysis, cf. e. g., [1–3]. This paper focuses on specific interaction episodes, so-called dialogic moments. These are characterized by a considerable level of mutual understanding, leading to the development of a sense of belonging to the group. During storytelling conversations, for example, such moments can be elicited efficiently [4,5]. In particular, dialogic moments occur when each participant aims to retain their "own truth" while acknowledging to a respective other "experienced truth", leading to mutual understanding.

The occurrence of dialogic moments can be useful for supporting collaborations and mediating conflict situations. Here, the detection and analysis of dialogic moments are important steps to understand the underlying mechanisms. In this paper, we take first steps towards the data-driven analysis and characterization of such dialogic moments during an immersive story-telling experience, focussing on face-to-face interaction. We investigated multimodal information of the participants while they were engaged in a group discussion that was based on fictional storytelling. The collected multimodal (sensor) data includes skin conductance, face-to-face proximity, vocal non-verbal features of the participants, and turn-taking interaction; here in addition, respective subjective experiences of the participants were collected via self-report questionnaires.

2 Related work

In this section, we briefly summarize related work on observing human group interactions and the idea of dialogic moments in such interaction contexts. Furthermore, we sketch time series analysis methods for the analysis of according sensor data.

2.1 Observing Human Group Interaction using Sensors

Based on collected sensor data we can construct social interaction networks which capture offline interactions between people [6–8]. Eagle and Pentland [9], for example, presented an analysis using proximity information collected by bluetooth devices as a proxy for human proximity. While this relates to face-to-face communication, however, the detected proximity does not necessarily correspond to face-to-face contacts [10]. Also, it does not cover vocal (non-)verbal aspects of communication. Another approach for observing human face-to-face communication is the Sociometric Badge.[1]. It records more details of the interaction, but requires significantly larger devices. The SocioPatterns Collaboration[2] developed proximity tags based on Radio Frequency Identification technology (RFID), which have been used in several ubiquitous and social environments, e. g., regarding educational/university contexts including scientific conferences [11–14] and schools [15]. In this paper, we apply the Openbeacon as well as the Rhythm badges [16], as a successor of the Sociometric badge, which provides a richer set of information. In addition, we complement the data collection using further sensors (e. g., skin conductance,cf. [17, 18]) and subjective questionnaire-based information.

Regarding dialogic moments, research has shown the importance of these but provides only few indications on how to predict or replicate a dialogical moment [5]. While dialogic moments have not yet been extensively studied, especially from a computational perspective, multimodal approaches to the study of social interaction are becoming more common [2, 19]. In this paper we target the multimodal characterization of dialogic moments focussing on social group face-to-face interaction.

2.2 Explicative Time Series Data Analysis

For the characterization of dialogic moments, explicative data analysis methods are important, because they provide interpretable and explainable approaches, in order to make sense of the data and the obtained patterns [20, 21]. For multimodal sensor data, time series data is recorded from multiple channels at the same time. Capturing the interplay of the different signals and using it for gaining relevant information from the data represents a challenge. In this context, several single time series techniques are used after different feature transformation procedures. One simple but quite effective transformation is the symbolic aggregate approximation (SAX), where a time series is initially transformed into a set of words through quantization using sliding windows [22]. Then, we can directly apply the interpretable symbolic representation towards the characterization of time series segments in the context of dialogic moments.

[1] http://hd.media.mit.edu/badges
[2] http://www.sociopatterns.org

3 Method

In the following, we first outline our research question for data analysis before describing the data collection context, measures, and methods in detail.

3.1 Research Questions

In our analysis, we focus on the following research questions:

1. Is it possible to observe certain traces of dialogic moments in the multimodal data of the participants?
2. Can we identify characteristic multi-modal features?
3. Can we identify conforming/deviating patterns among different moments and users, respectively?

3.2 Procedure

For the pilot study outlined below, we recorded a diverse set of data while participants were engaged in a storytelling-based discussion. In order to obtain ground-truth information about dialogic moments, we employed feedback from a domain expert for detecting and labeling the respective dialogic moments, also assessed by an independent annotator. In evaluating the data of the pilot study, we mainly resorted to basic statistical analysis and similarity assessment of the computed aggregated measurements, in order to identify characterizing features and patterns.

The participants (n=4, 2 female) were all university students. They received no incentives for their participation and gave informed consent for performing the experiment. The participants sat around a square table in an empty room and remained seated during the experiment. The experiment included 4 discussion sessions of 10 minutes each, with breaks of 2 minutes. All discussions were moderated by a storytelling expert. Each session was moderated to have either a negative or a positive valence. For the four discussion sessions, this was given with the order Negative – Positive – Negative – Positive, as follows:

Session 1 : Negative valence.
Session 2 : Positive valence.
Session 3 : Negative valence
Session 4 : Positive valence.

The moderator presented a fictional scenario to the group – the earth being inhabitable so that the group was seeking asylum on Mars. Valence was indicated by dilemmas or opportunities, respectively. The moderator could also choose to moderate interaction among the group, by directing attention to a less active member of the group, or by asking a direct question. After the discussions, the moderator, then indicated the critical moments where participants seemed to have come closer together, and potentially all shared a mutual understanding, as a subjective labeling of those moments. The strongest dialogic moments were then heuristically chosen, and additionally checked by an external observer.

3.3 Measurements

We utilized several sensors for collecting multi-modal data, including galvanic skin response, vocal non-verbal features and face-to-face interaction information, cf. [3, 16–18, 23, 24].

3.4 Multimodal Sensor Data

Galvanic skin response (skin conductance, GSR) of the participants were recorded using the Shimmer GSR+ wearable sensors, which are often applied in similar contexts, e. g., [17, 18]. Essentially, GSR indicates arousal [23]. Arousal can be calculated by subtracting the highest GSR in the period of interest and the average GSR in the 30 seconds prior to it. Besides that, we specifically focus on face-to-face interaction complemented by questionnaire information in our preliminary analysis. In addition, speaking volume and physical proximity of the participants were observed using the Rhythm Badge [16]. Given the speaking data from the Rhythm badge and the video recordings we investigated the speaking turns. We transcribed the content of participants' speech, and manually assessed and recorded their speaking turns. The recording of speaking turns assumes one speaker at a time. In a period of overlapping speech, a participant who spoke the longest was recorded as taking the turn. For observing face-to-face proximity, we utilized wearable sensors developed by the SocioPatterns consortium[3], as discussed above [24, 25]. The proximity tags are based on Radio Frequency Identification technology (RFID tags), capable of detecting close-range and face-to-face proximity (1–1.5 meters). The most significant advantage of using the SocioPatterns tags is that the human body acts as a radio-frequency blocker at the frequency used on the tags [24]. Therefore, only the signals that are broadcasted directly forward from the person wearing the tag will be detected by other tags.

3.5 Self-Report Assessment Information

In addition to collecting multimodal data, an Inclusion of Other in the Self (IOS) questionnaire was distributed to the participants to fill out at the baseline and after each discussion session (2-minute break each). In this break, they were asked to momentarily exit the fictional world and individually report (on a 7-point Likert scale) their perceived level of inclusion in the group in the preceding session. Here, we also applied the self-assessment manikin (SAM) [26] for estimating the affective dimensions of pleasure, arousal and dominance after each session. In general, SAM is an emotion assessment tool using graphic scales, depicting cartoon characters expressing the respective three emotion elements – pleasure, arousal and dominance – for the affective dimensions. In that context, pleasure refers to the happiness in a specific situation, arousal to the emotional arousal while dominance relates to the control of a situation. Low dominance, for example, relates to the feeling of lacking of control in a situation. A person with low dominance can present states, such as subordination, intimidation or withdrawal. In contrast, the participants with high dominance have control over a situation.

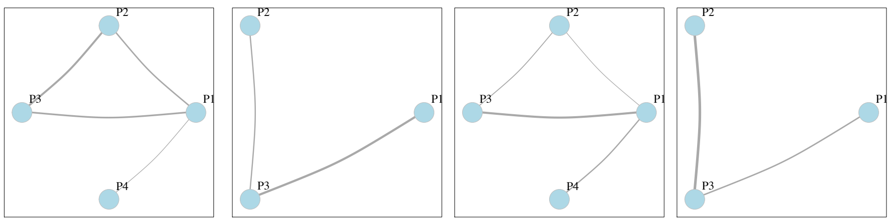
[3] http://www.sociopatterns.org

4 Results and Discussion

In our first exploratory analysis, we provide preliminary results focussing on face-to-face interaction, in particular, face-to-face proximity contacts, turn taking and the IOS questionnaire information. After that, we present initial results on the collected GSR data. It is important to note, that due to the exploratory nature of this study and the small number of participants, insights and conclusions are regarded as preliminary exploratory results, which we aim to extend on in future work.

4.1 Global Group Interaction Behavior: Session Face-to-Face Proximity

In the following, we briefly discuss insights on face-to-face proximity contacts of the participants during the individual sessions. Overall, the collected contact data was relatively sparse. Below, we focus on indications of proximity contacts between the participants, where especially the existance of a "non-contact" vs. "some contact" is interesting. Figure 1 shows an overview of the contact behavior during the different sessions in different graphs. In particular, the figures for the different sessions (Session 1 – Session 4) indicate the participants (as nodes of the respective graph) and proximity contacts (as edges of the respective graph) between those. An edge between two nodes (participants) is created if at least one signal between the tags of the participants was received, where the width of an edge is proportional to the number of proximity signal contacts.



(a) Session 1 **(b)** Session 2 **(c)** Session 3 **(d)** Session 4

Fig. 1: Face-to-Face proximity networks of the different sessions (Session 1 – Session 4). Participants are denoted by nodes of the respective graphs, an edge between two nodes is created if there is at least one signal between the tags of the participants; edge width is proportional to the number of proximity signal contacts.

Overall, we can distinguish different face-to-face proximity contact situations. Session 1 and Session 3 are quite similar, with participants P1, P2, and P3 in a triangle, and a weakly connected participant P4. Also, Session 2 and Session 4 indicate quite similar situations. The interesting feature that is common to the two pairs of sessions is the equivalence in the topological graph structure, as well as their valence, since Session 1 and Session 3 were negative, while Session 2 and Session 4 are positive regarding their valence. We will also investigate this further in the following sections.

4.2 Group Interaction Behavior: Turntaking

In total, 6 moments were selected as dialogic moments. Content-wise, moment 4 was when participants engaged in a heated dispute about the ethical way to choose which people on Earth were to be evacuated first. Conversely, the other 5 moments evolved around rather non-provocative sharing such as during moment M1. As shown in Figure 2 (left) for the overall turntaking behavior (shares), turntaking is not completely balanced. Participant P1, for example, tended to dominate during sessions 2-4.

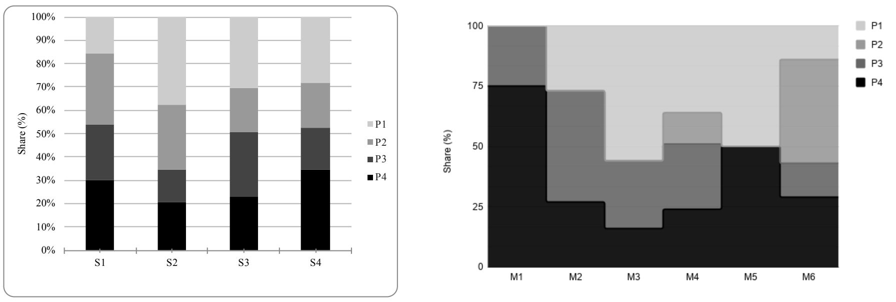


Fig. 2: Turn-taking of the participants (P1–P4) in each speaking session (left) and their turn-taking in each specific dialogic moment (right). Share (%) indicates the respective speaking turns per session and moment, respectively. Moment M1–M3 belong to Session S2; Moment M4 belongs to Session S3; the moments M5 and M6 belong to Session S4.

Investigating the individual moments (see Figure 2, right), we also observe no balance of speaking contribution. Looking at the areas of speaking contributions, participant P1 and participant P4 tend to dominate the turn taking. The only moment with rather even share of speaking turns is moment M4 in Session 3. This already makes this moment special. While it had a negative valence at first, participants tended to become more "aligned" in a balanced way. Moment M4 also was the moment almost started by everyone, while the other 5 moments were started by a single member (a chief storyteller), who also took the most speaking turns, cf. Figure 2. Overall, we observed a trend towards more stable alignment on the "Inclusion of Others in the Self" self-reported scores, see Figure 3. Here, we can already see that moment M4 (session S3, respectively) seems special – observing a (positive) change in the overall IOS trend, while also the speaking contributions are more uniformly distributed.

We further investigated the differences among the moments M1-M3, and M5-M6, which indicated rather similar patterns. Figure 4 visualizes the similarities in turn taking behavior for Sessions 2 and 4, containing the respective dialogic moments M1–M3 and M5–M6. Specifically, for estimating the (dis-)similarity we applied a very simple measure; essentially, we computed the euclidean distance on the respective turntaking contributions (a darker color indicates more similarity). Here, moments M1 and M5 somewhat stand out, while M2, M3 and M6 are more conforming to the overall session contributions in terms of speaking turns.

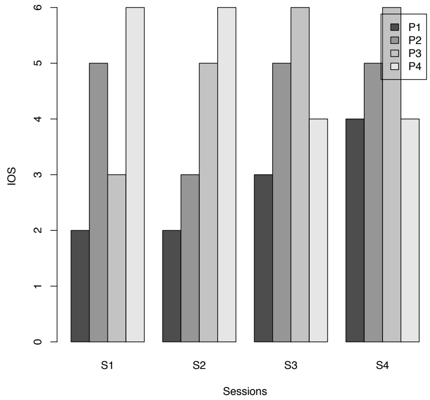


Fig. 3: Self-report scores of participants (P1–P4) of "Inclusion of Others in the Self" (IOS); 7 point Likert-scale after every session.

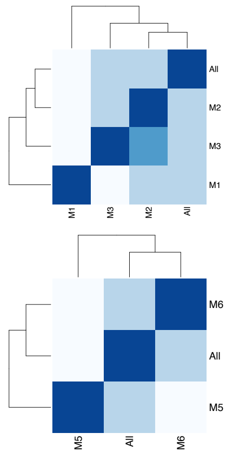


Fig. 4: Similarities w.r.t. turn-taking behavior among the moments (M1-M3, M5-M6) and enclosing sessions (S2, S4).

4.3 Self-Report Group Interaction: Self-Assessment Manikin

For obtaining a broader view on the affective dimensions after each session, we applied the self-assessment manikin (SAM) approach, cf. [26], as discussed above. Figure 5 outlines the results.

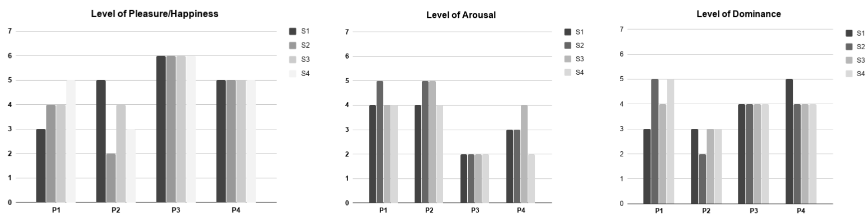


Fig. 5: Self-Assessment Manikin (SAM): Emotional state after each session.

Overall, we see that the scores remain relatively stable/similar for the individual participants, with a few exceptions (e. g., participant P2 which reported a more "dynamic" behavior). Specifically, the majority of participants reported to have a rather stable level of pleasure/ happiness, which implies a general satisfactory state. They also reported the level of arousal in a similar fashion: arousal was self-assessed to be unchanged or slightly decreased. This analysis of the self-report information provides some first indication on the dialogic moments; we aim to validate the observed trends in future studies, and to provide more context information on the affective states of the participants.

4.4 Group Interaction Behavior: Galvanic Skin Response (GSR)

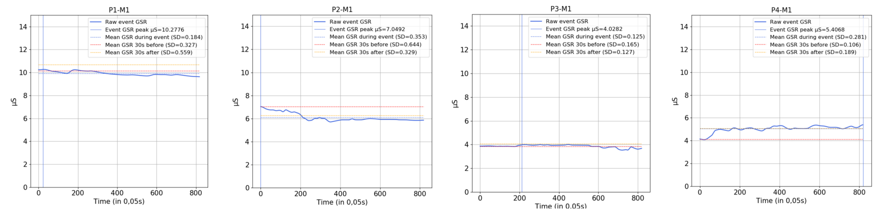


Fig. 6: Examples of two different GSR signal profiles during a dialogic period (M1): highly fluctuating signals (P2 and P4) vs. rather stable signals (P1 and P3).

Looking into each individual's GSR, we distinguished different profiles, see Figure 6, mainly distinguishing between the signals that highly fluctuate, and those that remain rather stable. The figures manifest this diversity among the participants of a dialogic event, visualizing the mean of GSR signal 30 seconds prior to, during and 30 seconds after the event.

Interestingly, the signal during the event can be considered a marker of an overall persistent change in the level of arousal: the mean of GSR 30 seconds prior to the event (in red) is highly distinctive from the mean of GSR 30 seconds after the event (in orange). This phenomenon is prevalent among the moments and among the participants. The only difference is whether the blue line - the mean of a participant's GSR during the event - is closer to the red or the orange line. If the blue line is closer to the red one, the participant seemed to experience the "dialogic" impact at the end of the event: a late adopter. If the blue line is closer to the orange one, the participant seemed to experience the "dialogic" impact at the beginning of the event: an early adopter.

Additionally, there are half of the moments where its participants are mixed between late and early adopters, such as M1 in Fig. 6, The other half witnesses its participants unanimously falling into one categories of either early or late adopter, such as M3 in Fig. 7. Regardless when we can witness the impact of a dialogic period on each participant, we can assume that such impact exists and can be significant.

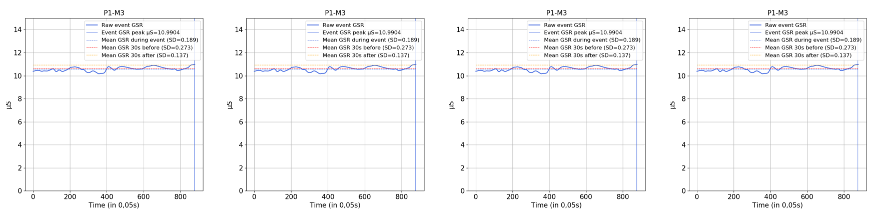


Fig. 7: Examples of a dialogic period, M3 that have all of its participants being "late adopters", experiencing the "dialogic impact" rather at the end of this period.

For the interpretation of time series data, explicative methods [20, 21] provide suitable approaches for making the analysis interpretable and explainable. One central idea is symbolic abstraction of the data, in order to make it easier to understand via feature reduction. One exemplary method for that is the piecewise aggregate approximation (PAA), which is employed in the SAX transformation. Applying that method, segments of a time series are mapped to an alphabet which can subsequently be processed to words, which – due to their symbolic nature – facilitate analysis and interpretation, in order to allow also explanation, e. g., by detailed inspection in a "drill-down" approach [27, 28] referring back to the detailed time series.

Comparing among individuals' arousal during dialogic events, as discussed before, SAX was applied on each of their GSR signals to transform them into a discrete and symbolic representation (a word, i. e., a sequence of characters). Then, the Levenshtein distance (also called edit distance) metric, e. g., [29] was employed to measure the difference between these sequence of letters, thus, allowing the calculation of the normalized similarity between each pair of string. Essentially, the Levenshtein metric estimates the distance between two character sequences (words), where intuitively, the distance between two sequences is the minimum number of single-character edits (i. e., insertions, deletions, or substitutions) which are required in order to transform one sequence into the other sequences.

In the beginning, the PAA components of SAX were set to 4, cf. Table 1, corresponding to each event's 4 statistical quartiles. Hence, there are total 256 permutations with replacement of the 4 letters a, b, c, and d; therefore there is approximately a chance of 0.016 that 2 participants have 2 or more of the same letters at exactly the same place. In other word, this means having a normalized similarity value of 0.5 or higher, Yet such values have been recorded in numerous occasions (Table 1), especially in the case of M2 and M4, the GSR signals of the participants fluctuates in a highly similar fashion. Overall, as can be seen in Table 2, M2, M4 and M5 appear to be the moments has the highest similarity in term of GSR fluctuation patterns among the participants, Content-wise, while the other moments emerged around a sharing of pleasant experiences or ideas, M2, M4 and M5 arose from disputes around moral-related issues. Likewise, in general, every participant tends to slightly "synchronize" during these moments, however, the level of pairwise "synchronization" varies. In other words, just looking at these tables, we could argue that the facilitator should have paid more attention to, for example, P3 and P4 in M3, The reason is even though, during M3, P3 and P4 vocally contributed to the discussion more than some of P1 and P2 (see Figure 2), it is more likely that P3 and P4 had felt less included in the group than the others: on average, the normalized similarity of GSR patterns of P3 and P4 to every other is 0.167, while those of P1 and P4 are 0.333. Furthermore, we applied the same analysis process onto the data again but increased the level of sensitivity by 5 times, setting PAA to equal to 20. This entails 20^{20} permutations with replacement of the used letters, making it highly unlikely for a random two symbol representations of participants' GSR signals to be similar. As predicted, Table 3 overall entails smaller values of normalized similarity than Table 2.

Note that the complete list of symbolic representations, based on which Table 3 was calculated, is not included in here due to its size. Also note that, we abstained from setting the PAA to be proportional to the various length of the events, because the

Table 1: Strings represent each participant's GSR signal used SAX conversion (PAA=4)

Participants	M1	M2	M3	M4	M5	M6
P1	dcaa	aacd	bbcc	dcba	aacd	bdca
P2	dbbb	aadc	ccca	ddab	bbdb	babd
P3	cdca	cacc	dcba	daad	dbca	ccca
P4	accc	abcc	abdc	bbad	abcd	dabc

Table 2: Pairwise Levenshtein normalized similarity between the pairs of strings (PAA=4).

M	P1-P2	P1-P3	P1-P4	P2-P3	P2-P4	P3-P4	Mean	SD
M1	0.25	0.5	0.25	0	0	0.25	0.208	0.188
M2	0.5	0.5	0.5	0.5	0.5	0	0.417	0.204
M3	0.25	0	0.50	0.5	0	0	0.208	0.246
M4	0.25	0.25	0.25	0.5	0.25	0.5	0.333	0.129
M5	0	0.25	0.75	0.25	0.25	0.5	0.333	0.258
M6	0.25	0.5	0	0	0.5	0	0.208	0.246
Mean	0.25	0.333	0.375	0.292	0.250	0.208		
SD	0.158	0.204	0.262	0.246	0.224	0.246		

Levenshtein distance algorithm is highly sensitive to the string's length. This means, if PAA is set to be proportional to the events' length, certain event will induce on average higher similar GSR patterns just because they are shorter than other event. In other words, by keeping the same PAA among the moments, we normalize their length, and thus, make it possible to compare between their enclosed pairwise similarity values. Interestingly, M2 is distinct to M5 in term of its length: M2 is the longest dialogic period (136 seconds) while M5 is the shortest period (23 seconds) (mean = 64.83, SD = 40.29). However, both of them entail the highest similarity in GSR among the participants regardless of PAA settings.

Table 3: Pairwise Levenshtein normalized similarity between each pair of strings (PAA=20).

M	P1-P2	P1-P3	P1-P4	P2-P3	P2-P4	P3-P4	Mean	SD
M1	0.301	0.051	0	0	0	0.051	0.067	0.117
M2	0.051	0.250	0.151	0.1	0.051	0.1	0.117	0.075
M3	0.051	0.051	0.151	0.250	0	0	0.084	0.098
M4	0.151	0.151	0.051	0.151	0.051	0	0.093	0.067
M5	0.1	0.051	0.250	0.051	0.151	0.151	0.126	0.076
M6	0	0	0.051	0	0.1	0	0.025	0.042
Mean	0.109	0.092	0.109	0.092	0.059	0.050		
SD	0.107	0.092	0.092	0.097	0.059	0.064		

5 Conclusions

The preliminary descriptive analysis of the data has shown great potential in studying dialogic moments computationally. Although all 6 moments in the pilot arguably fell into the category of dialogic moments, we observed different profiles regarding the agreement/similarity between their resulting multimodal data. In particular, moment M4 was quite distinctive. However, we were able to obtain characteristic indicators, considering turntaking, GSR data, as well as the questionnaire-based (IOS) information. We aim to complement the analysis further for enhancing these preliminary insights, and to provide a more comprehensive context for facilitating multimodal interpretation.

Overall, future research in the direction initialized by this pilot can help to create digital storytelling technology that has the ability to identify dialogic moments in conversation, quantifying an otherwise very subjective phenomenon. Potentially, understanding dialogic moments can even help us induce them in (otherwise) unproductive conversations, assisting in the context of difficult discussions and negotiations. Then, such factors can also be incorporated in the design process of affective systems.

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