“By the way, do you like Spider Man?” — Towards A Social Planning Model for Rapport

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Abstract

Interaction takes place not only on the propositional level but also on the social level. In this paper, we consider *rapport* as an important social phenomenon in interaction. Motivated by data from the tutoring domain, we hypothesize that (i) off-task episodes are triggered by a low level of rapport and (ii) such episodes are means of raising the level of rapport. We sketch a planning model that allows off-task episodes to be triggered by (low) rapport level, which we apply to two simple examples.

1 Introduction

Pursuing multiple goals is a common phenomenon in interaction (Tracy and Coupland, 1990). E.g., people use politeness strategies (Brown et al., 1987) to pursue social goals, while simultaneously conveying propositional meanings to the recipient. In task-oriented contexts, social goal fulfillment becomes an unspoken purpose underlying the surface interaction. In the literature on the relative importance of multiple goals (Fetzer, 2003; Cassell and Bickmore, 2003), evidence is provided of the interplay of propositional, interpersonal and interactional meaning of the speech acts.

Consider (1), an excerpt from an actual algebra tutoring interaction between a teen tutor (TR): and a teen tutee (TT).

(1)

TR: It should be k equals something. [1]
TT: yeah that’s right, I forgot about the k. [2]
TR: yeah so it wouldn’t be that it be this. [3]
TR: so the reason why I’m so tired today is that I was up until like twelve thirty working on this script all right. . . [4]
TT: oh. . . [5]
: (. . . 5 minutes of off-task talk)
TR: all right so let’s get back on topic to see what you’re doing here [6]
TT: yeah. [7]

In this example, the tutor digresses during the tutoring session to discuss why he was looking tired. He does not apologize, and returns to the task by reintroducing the original task—related topic. This interlude where the tutor engages in self-disclosure (Derlega et al., 1993) might help the two interlocutors to establish a closer social relationship and thereby helps the tutor achieve his task goals (Sinha and Cassell, 2015b).

This interleaving of on-task and off-task moves is common and is not random (Coupland, 2014) in human-human interaction and reflects the phenomenon of individuals pursuing multiple goals while interacting (Tracy and Coupland, 1990; Fishbach and Ferguson, 2007).

Rapport (Spencer-Oatey, 2005; Tickle-Degnen and Rosenthal, 1990; Zhao et al., 2014) also serves as an important factor of social communication. This off-task mode (e.g., referring to shared experience, deep self-disclosure) also helps to enhance and maintain rapport (Zhao et al., 2014), which has also been shown to have a positive relationship with task performance (Sinha, 2016).

The application of the phenomenon of human interactivity to agent design is an important philosophy. But how to use these off-task moves at the right time and in the right place is a problem that has not been sufficiently investigated to the best of our knowledge. So this paper attempts to present a planning model that helps an agent to perform the

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interleaving of task and social moves, in instances where we believe that the interlocutor may have picked up on low rapport accumulation over time.

The paper starts with a review of literature about rapport and its integration in dialogue systems. This leads us to formulate certain hypotheses about the relationship between off-task talk (OTT) and rapport. We then test these hypotheses using data from the peer tutoring domain. Building on this data, we sketch a model which provides rules for triggering off-task talk in natural conversation. We illustrate this model by analyzing two simple examples.

2 Related work

Rapport is described most fundamentally as a feeling of connection or harmony with another, and it has been shown to have important positive effects on communication and collaboration in a number of domains (Drolet and Morris, 2000; Bronstein et al., 2012; Bernieri and Rosenthal, 1991; Madaio et al., 2018). Some describe it as a calculus based on three essential components—mutual attentiveness, coordination and positivity (Tickle-Degnen and Rosenthal, 1990), while Spencer-Oatey (2005) describe it as based on behavior expectations, face sensibilities and interactional wants. Tickle-Degnen and Rosenthal (1990) shows that rapport is highly related to non-verbal moves. Moreover, verbal expression also influences rapport management (Zhao et al., 2014). Zhao et al. (2014) present a computational model for rapport management based on prior work and analysis of conversational data, and introduce different conversational strategies that enhance or maintain the rapport level. These conversational strategies include: self-disclosure, praise, violation of social norm, adherence to social norm, and hedging.

Cassell et al. (2007) presents a model where raising rapport may allow a conversational agent to model how people build friendships. Gratch et al. (2006); Huang et al. (2011) present a model that allows a virtual agent to produce verbal and non-verbal behavior appropriately to indicate rapport. Madaio et al. (2017) use such information to build a rapport estimator with temporal association rules. In (Pecune et al., 2018) the rapport scale is divided into seven levels from low to high (from 1 to 7); in the following discussion, we will follow this rapport scale to formulate our model.

Romero et al. (2017) create a social reasoner which takes a task reasoner's intention and rapport level as input and outputs a phrase that both attempts to achieve the task goals, and is phrased as one of the aforementioned conversational strategies, by using a spreading activation network (Maes, 1989). However, this model relies on a unidirectional relationship between the task and social reasoner—the social reasoner cannot affect the task reasoning. Concretely, such a model could generate an example similar to (1), such as "I'm doing a bad job because I'm so tired from staying up all night. . . " —a negative self-disclosure to mitigate the recipient's negative face in order to improve *rapport* and to continue the task plan without shifting to another topic and a resulting side sequence (one that ends normally with "let's go back to this question now" in order to continue the pending question). However, it could not generate the interleaving of utterances that only deal with social matters, such as those shown in (1).

A high rapport level contributes to effective task performance (Sinha and Cassell, 2015b), but when the current sub-task is performed with low rapport and this phenomenon lasts a certain period of time, it may not be viable to continue this sub-task. In contrast to the small talk function of (Cassell and Bickmore, 2003) (i.e., small talk helps the user modeling process with gaining the user's trust), in (Cassell and Bickmore, 2003) switching the topic is used to initiate an off-task mode characterized by a pleasant environment and positive valence in phatic communication like small talk (Coupland, 2003), jokes, and gossip, so that rapport can calibrate to a normal level to help the recipient comfortably continue the pending task. Zhao et al. (2014) introduce diverse conversational strategies which include referring to shared experience and self-disclosure. These strategies are the means of switching to off-task mode with off-task utterances that last longer than a clause. However, although off-task talk appears frequently, it is excluded from consideration given the architecture of the SARA system (Pecune et al., 2018). An as yet unresolved issue is whether off-task talk happens after low rapport occurs. Hence, we make the hypothesis:

H1: Off-task talk occurs after low rapport is observed within a certain window.

Off task moves are extensively used in real-life interaction (Jaworski, 2014; Holmes, 2014; Endrass et al., 2011). Kopp et al. (2005)'s museum guide agent can interact with the visitors using small talk, but these are controlled by rules triggered by specific interactional contents. By contrast, the REA model of Cassell and Bickmore (2003) uses an activation network to construct the discourse planner, which can choose new topics with entire off-task utterances, and these new topics are designed to gather the user's information in order to shape the user model (i.e., user's goal, plan and knowledge) to identify the users' cooperation level and establish the close social relationship — trust. This alternative planning serves the ultimate task goal. However, REA is not based on an investigation of the distribution of off-task episodes during the interaction (i.e., where people often use small talk). Sinha and Cassell (2015a); Sinha (2016) explain the relationship between the time series of rapport and task performance in peer tutoring setting. They conduct an in-depth analysis relating different conversational strategies (i.e., self-discourse, praise and reference to shared experience), different gender pair and learning gains across all periods (social and task periods) of interaction. The relationship between the OTT and the final learning gain is also a question worth exploring. Different conversational strategies have different effects on learning gains (Sinha et al., 2015). If OTT is widely present in real conversations, there is a natural question whether OTT can contribute to the completion of the task? This motivates a second hypothesis:

H2: Off-task talk helps to improve task performance (e.g., in the peer tutoring domain—learning gain).

3 Data Analysis

Our data consists of video recordings of reciprocal peer tutoring interaction taken from 14 dyads in which the age of the participants was on average 13, half were male and half were female. All dyads consisted of identically gendered participants. Each dyad interacted over two sessions. Before and after each session all participants were tested in order to measure their learning gains. A total of 24 interaction transcripts were manually annotated with tags relating to the off-task talk which we explain in more detail shortly. This yielded a total of 22709 clauses. Their interactions were split into 30 second slices whose rapport had been estimated by Amazon Mechanical Turk annotators.

3.1 Data Annotation

We classify the data into 4 types with respect to their content: 1) on-task talk, 2) off-task talk—side sequences involving topics that are distinct from the task, 3) clauses that reject or ignore off-task talk (e.g. P2's utterance in the following, which rejects P1's off-task talk invitation: P1: I watched Spider-Man yesterday. P2: let's add 5 to both sides.), 4) meta-task talk—clarification sequences concerning the task itself.

The session is divided into 4 periods, first period is the first social period usually about the self-introduction, second period is the task period about the algebra tutoring, one becomes the tutor, another becomes the tutee, the third period is a five minute long break after which the participants switch roles to start the second task period. We focus on the off-task talk in the task period and do not annotate the social period clauses. The entire data annotation work was carried out by two annotators, and all disagreements were discussed and resolved.

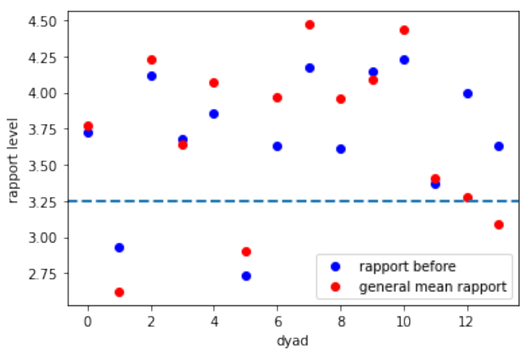
3.2 Results

The Pearson Correlation between the time spent per session off-task talk and the dyad average learning gain is 0.3558, ($p = 0.08 > 0.05$). This suggests that there is a moderate positive correlation between the duration of the off-task talk and the learning gain. As off-task talk increases, it may help a dyad's task completion. However, due to the small size of our data set, our results are not statistically significant. Nonetheless, this result does raise another reasonable question that needs to be investigated in future work: in a temporally-bounded task-oriented conversation, is too much off-task talk detrimental to task completion?

We mark the slices that appear to be off-task talk (OTT) and use the ten slices that do not appear to be OTT before these slices as reference objects. Means were calculated for each dyad and these were compared with the general rapport mean to perform a paired t-test. The result is: $t = -1.4587, p = 0.1470 > 0.05$. This result shows that rapport is lower compared to general rapport levels before the onset of the OTT, but the result is not significant. So we examined the data for each dyad as shown in the figure1.

We observe that 9 out of 14 dyads satisfy our **H1** hypothesis, that is, indicating that the rapport level is lower than the general level when OTT occurs. Moreover, when we filter out dyads with

Figure 1: Comparison by dyad between general rapports and rapports before OTT



lower levels of general rapport (less than or equal to 3.25), 9 out of 10 satisfy **H1**. This provides some justification for the truth of hypothesis **H1**, which drives our model of *social repair*, a concept we now turn to.

4 Tutoring: the interplay between task goals and social goals

4.1 A simple example

From the earliest days of AI to the present, Intelligent Tutoring Systems have remained as an important area, with its purpose to enable learners to learn better and more efficiently by using existent computer technologies to simulate what seems to be the most effective way to tutor, namely private tutors. Ritter et al. (1998) helps to improve a student's algebra performance based on the student's prior knowledge and experience. The Rapport-Aware Peer Tutor Assistant[1] is an anthropomorphic embodied social robot that maximizes student performance by improving rapport with students. This assistant incorporates a rapport estimator (Madaio et al., 2017) and uses a *social reasoner* to deduce the next conversational strategy and based on the communicative intent its task reasoner assigns to the recipient.

The assistant uses a top-down structure where the social reasoner accepts the task reasoner's intentions, but has no alternative means of influencing the manner in which the task reasoning proceeds, often causing the assistant to maintain rapport in a circumlocutory way, while fulfilling the tyrannical "commands" of the task reasoner. This approach tends to cause low rapport to build up slowly, causing the assistant's rapport level to slip in the opposite direction at some point. This is exemplified in (2):

(2)

AGENT: No that's not it. [1]
TEENAGER: I don't know. [2]
AGENT: So why did you do it that way sometimes I have a tough time explaining my thinking. [3]
TEENAGER: I wasn't right, so like. . . I don't know how to do it. [4]
AGENT: You want to get the x term by itself I hope I'm explaining this okay. [5]
TEENAGER: I. . . still don't know. [6]

This is a small extract from a lesson where the agent tries to help a student to complete a given algebra problem. The student is not able to complete the problem successfully perhaps because the difficulty of the question was beyond his current proficiency, though the agent uses different conversational strategies to perform face work (e.g., negative self-disclosure) in order to complete the task reasoner's "assignment" for this part and to maintain or enhance rapport.

Two shifts could take place at this point. The first one (*knowledge tracing*) is to change the current question to an easier one. This serves two purposes, one is not to remain blocked with the current question, and by doing the easier one, to accumulate experience which will enable solving the pending question. The second shift is to alleviate the teenager's negative face, so that the rapport may rise. This second shift involves changing the current direction of the dialogue by initiating unrelated topics (e.g., weather, hobbies, etc.), where small talk is proven to pull the relationship closer (Coupland, 2014). In this paper, we focus on the social reasoning part with the second type of shift rather than on knowledge tracing.

When the current discussion is not appropriate to be continued given a low level of rapport, it is imperative to change the current topic in order to *raise* the current rapport to an acceptable level. The assistant can digress (e.g., switch to talking about hobbies, sports and favorite movie stars) and wait until the rapport level returns to a baseline, then resume the questions that were just pending.

We dub these kinds of behaviors as *social repair*.

[1] http://articulab.hcii.cs.cmu.edu/projects/rapt/

4.2 Social repair

The purpose of communicative repair (Jefferson et al., 1977; Purver, 2004; Ginzburg, 2012) is to enable one interlocutor to fully understand their interlocutor's initially incompletely comprehended utterance and the associated intentions. In such cases, the problematic utterance is set aside until reference or mishearing etc are resolved. By analogy, what we call *social repair* concerns the need to restore social relations such as rapport, power, trust, to "appropriate" levels.

Social repair can happen in a single utterance that also attempts to achieve task goals, by using the different conversational strategies supported by rapport theory (Zhao et al., 2014; Spencer-Oatey, 2005; Tickle-Degnen and Rosenthal, 1990). However, people also perform off-task moves constantly during an interaction.

Zhao et al. (2014) introduce several conversational strategies as rapport enhancement and rapport maintenance, in order to keep the rapport level high enough to allow the task to proceed smoothly. They are initiated when the rapport falls below a certain level, or in the beginning of the dialogue to raise it to a certain level. Some of these strategies can be delivered within a single clause (e.g., praise, adherence to social norms, etc.) But here we focus on strategies that can involve more than one clause without mentioning the task (e.g., referring to shared experience, deep self-disclosure).

With the existence of a social repair function, the question arises when to trigger the social repair process. When we return to consider example (2), we observe that the student repeats his feeling that he doesn't know what to do next, and this statement also appears after the assistant gives him a hint how to solve the problem ([5]). The low rapport in the current interaction which accumulates over time as he moves from a simple "I don't know" to a self-defeating [4] to a direct statement that he still does not know.

4.3 Rapport Accumulation

As we already mentioned above, following (Madaio et al., 2017)'s rapport estimator, rapport is determined as a time series function where the value ranges from 1 to 7 (1 for lowest rapport level and 7 for the highest). We assume rapport persists and accumulates in one's *Cognitive State*, tempered by some notion of *decay*. Rapport is, then, given by a function over time $rp(t)$ modulated by γ, a postulated decay rate.[2] So we obtain the following for *rapport accumulation*:

$$\begin{aligned} r_a(t) &= rp(t_0) + \gamma * rp(t_1) \ldots + \gamma^{(\Delta t - 1)} * rp(t_0 - \Delta t)) \\ &= \sum_{t=t_0-\Delta t}^{t=t_0} \gamma^{t-t_0} * rp(t) \end{aligned} \tag{1}$$

5 Social Planning

In this section, we introduce a computational model that adjusts the current plan to maintain a reciprocal goal relationship based on the different low rapport accumulation to the task encountered, in order to maintain an efficient pattern of pursuing goals in tandem.

5.1 Cognitive States

We use KoS (Larsson, 2002; Ginzburg, 2012; Ginzburg et al., 2020) as a framework for representing the cognitive states of dialogue participants; the individual's perspective on the public aspects of the interaction are represented in the *dialogue gameboard* (DGB) whereas the private projection and interpretation of current events are presented in *private*, on which more below. Rapport estimation is mostly based on information originating in the DGB e.g., gaze, linguistic delivery, smiling etc, though we do not offer an account of how this gets computed here.

(3)

a. Total Cognitive State $=_{def}$
$$\begin{bmatrix} \text{dialoguegameboard : DGBtype} \\ \text{private : Private} \end{bmatrix}$$

b. DGBType $=_{def}$
$$\begin{bmatrix} \text{spkr: Ind} & \text{turn} \\ \text{addr: Ind} & \text{owner-} \\ \text{utt-time: Time} & \text{ship} \\ \text{c-utt: addressing(spkr,addr,utt-time)} & \\ \text{Facts: Set(Proposition)} & \text{shared assumptions} \\ \text{VisSit: } \begin{bmatrix} \text{InAttention : Ind} \end{bmatrix} & \text{visual field} \\ \text{Pending: list (locutionary Proposition)} & \text{ungrounded utts} \\ \text{Moves: list (illocutionaryProposition)} & \text{grounded utts} \\ \text{QUD: poset (Question)} & \text{qs under disc} \\ \text{Mood: Appraisal} & \text{face} \end{bmatrix}$$

[2] Thanks for an anonymous reviewer for SemDial for suggestions concerning the decay rate.

5.2 Plan Modification for Social Repair

A plan p can be represented by a sequence of episodes: $p = stack(\{ep_1, \ldots, ep_n\}) = stack(EP)$.

We hypothesize that low rapport accumulation is a trigger of task plan change. As the plan represents the dynamic representation of pursuing the goal(s), for simplicity we restrict the goal set here to two goals with same hierarchy: a task goal and a social goal. The task goal represents the task completion state, whereas the social goal is constituted by the end state attained by a social actor (e.g., maintaining high rapport).

We introduce Ω as a set of weights relating to the goals: $\Omega = \{\omega_1, \ldots, \omega_k\}$, Depending on the parameters, different goals have different levels of importance, which affects the judgment made by the agent based on the own threshold values. We simplify here to assume a simple goal set: $G = \{g_t, g_s\}$ (i.e., one task goal and one social goal) and the $\Omega = \{\omega_t, \omega_s\}$. Furthermore, we define r_{th} as the accumulated rapport threshold. From this, we obtain $\omega_s * r_{th}$ as the weighted rapport accumulation threshold. We also assume the existence of a *repair set* $REP = \{ep_1^r, \ldots, ep_n^r\}$ which is composed of several *repair actions*, which include actions construed as OTT.

Putting all this together, we assume the PRIVATE part of Total *Cognitive State* is typed as in (4).

(4) PRIVATE =

$$\left[\begin{array}{l} \text{Agenda:OpenQueue(Action)} \\ \text{Plan: OpenStack(PlanConstruct)} \\ \text{BEL:} \left[\text{Rapport} = \left[\begin{array}{l} \text{Cur} = rp(t) \\ \text{Accu} = r_a(t) \\ \text{Trd} = r_{th} \end{array}\right]\right] \\ \text{Goals:} \left[\begin{array}{l} \text{GoalsSet: List(Prop)} \\ \text{GoalsIpt} = \Omega\text{: List(Float)} \end{array}\right] \\ \text{RepairSet: Set (Plan)} \end{array}\right]$$

Rapport, as we have said above, is given by a function over time: $rp(t)$. r_{th} is the rapport threshold that triggers the task plan changes if $r_i^j < \omega_s * r_{th}$. r_{th} implies the agent's social sensibility during the interaction. If the threshold condition is reached, we infer that the next episode in the plan ep_{j+1} can be *deferred*. If one episode is *deferred*, an element of the repair set ep_i^r can be *inserted* before ep_{j+1}.[3]

Calculation of all the expected rapport raising actions for the episodes in the *repair set* and the subset $EP_{j+1,n}$ takes place according to the current *Total Cognitive State* s_i then a choice is made for the maximal one. This calculation process occurs after the precondition is triggered (i.e., $r_i^j < \omega_s * r_{th}$). The formal update rule (**Off Topic Triggering**) is given in (5):

(5) **Off Topic Triggering**

$$\left[\begin{array}{l} \text{Pre:}\left[\text{BEL.Rapport.Accu} < \text{BEL.Rapport.trd}\right] \\ \text{Eff:}\left[insert(ep_i^r, Plan.cur)\right] \end{array}\right]$$

Where ep_i^r is an episode selected from EP^r assumed to be maximal in rapport raising. We do not explicate this selection process in the current paper.

6 Examples

In this section, we apply our model of planning to example (2) and to a variant thereof.

In example (2), we assume that:

- The decay rate is 0.8.
- This conversation takes place in the j th episode.
- The rapport accumulation threshold is $r_{th} = 5$.
- We assume that at the completion of utterance [2], the rapport score (in ascending order from 1 to 7) is 4, and after [6], it is 2.
- The assistant's $\Omega = (\omega_t, \omega_s) = (0.5, 0.5)$. This means that equal importance is assigned to the task and social goals.
- $\Delta t = 1$. This means the turn span is one. We calculate the accumulation from [2] to [6].

From (1), r[2]: $r_2^j = \sum_{t=1}^{t=2} \gamma^{2-t} rp(t) > \omega_s * r_{th}^j$ and r[6]: $r_6^j = \sum_{t=5}^{t=6} \gamma^{6-t} rp(t) < \omega_s * r_{th}^j$

When [6] triggers the accumulation threshold condition, the assistant defers the current episode (i.e. the agent could say:"Let's take a break."); the assistant needs to select an episode that maximizes the rapport raising among the social repair set EP^r, inserting an off task topic (i.e., agent could say:"By the way, do you like Spider-Man?").

[3] There are also other operations we could envisage such as *replace*, *delete* or *swap*, but we will restrict ourselves to a simple account in the current paper.

We turn to another example. In this case we assume that the person helping the child is a strict parent. The parent's goal is to get the child to complete the given task quickly regardless of the rapport level.

Since the social relationship is established, we can naturally assume that the parent pays less attention to social needs. Hence, in the model we propose that the social repair function will be triggered less frequently in the process of interaction, which is followed by a continuation of the task plan. We consider the following constructed example:

(6)

PARENT: You should do this ... [1]
TEENAGER: I don't know. [2]
PARENT: What do you mean, you should understand, you should do exactly like this ... [3]
TEENAGER: Yes, but I still don't know how to do it. [4]
PARENT: You should do this and this! [5]
TEENAGER: OK... [6]

We assume that:

- The decay rate is 0.8.
- This conversation takes place in the j th episode.
- The accumulation threshold is $r_{th} = 5$.
- We assume that at the completion of [2], the rapport score (in ascending order from 1 to 7) is 3, and after [3], it is 1.
- The parent's $\Omega = (\omega_t, \omega_s) = (0.8, 0.2)$. This means that the parent's focus is more on task than on the social needs.
- Δt = 1. This means the turn span is one.

From (1), r[2]: $r_2^j = \sum_{t=1}^{t=2} \gamma^{2-t} rp(t) > \omega_s * r_{th}^j$ and r[5]: $r_5^j = \sum_{t=4}^{t=5} \gamma^{5-t} rp(t) > \omega_s * r_{th}^j$

After [3], since the rapport accumulation has not been lower than the parent's threshold, the social repair mechanism is less likely to be triggered than in the first example. Hence, the parent pushes the child to continue the task with [5].

7 Conclusions and Future Work

Interaction involves not only exchange resolving around propositional meaning, but also around different social phenomena. In task-oriented natural dialogue, we find that the participants not only initiate the dialogue as required by the task, but also intersperse this with different off-task moves which contribute to the achievement of social goals. In this paper, we sketch a model that places rapport as a central social phenomenon and segments tasks into episodes using the accumulated rapport as a mechanism for triggering off-task moves. We also apply this model to two examples.

We hope to spell out this model and apply it to more complex examples in future work.

Required refinements include:

- Certain conversational strategies in the rapport model proposed by Zhao et al. (2014) can improve rapport when social repair is required. How this and more generally how rapport estimation can be integrated into formal model of dialogue such as KoS remains to be worked out.
- We focus on the example of tutoring in this paper, but off-task mode exists in a wide variety of task-oriented conversational types in different forms. Furthermore, we plan to investigate how this mode differs across distinct conversational types.
- In our brief presentation, for simplicity, we assume that the individual's rapport accumulation threshold (r_{th}) is fixed. In reality, however, r_{th} changes dynamically in accordance with the dialogue context and conversational type. We would like to integrate the conversational type (Wong and Ginzburg, 2018) into the assessment of the rapport accumulation threshold.
- In our subsequent data analysis, we performed a t-test in the interval where OTT occurred and in the interval before it occurred, The result did not show a significant effect ($t = -0.5718, p = 0.5683$). This is probably because we do not have sufficient data. However, we hope to scale this up in the hope of proving hour basic hypothesis.

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