Predicting the Temporal and Social Dynamics of Curiosity in Small Group Learning

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Abstract. Curiosity is an intrinsic motivation for learning, but is highly dynamic and changes moment to moment in response to environmental stimuli. In spite of the prevalence of small group learning in and outside of modern classrooms, little is known about the social nature of curiosity. In this paper, we present a model that predicts the temporal and social dynamics of curiosity based on sequences of behaviors exhibited by individuals engaged in group learning. This model reveals distinct sequential behavior patterns that predict increase and decrease of curiosity in individuals, and convergence to high and low curiosity among group members. In particular, convergence of the entire group to a state of high curiosity is highly correlated with sequences of behaviors that involve the most social of group behaviors - such as questions and answers, arguments and sharing findings, as well as scientific reasoning behaviors such as hypothesis generation and justification. The implications of these findings are discussed for educational systems that intend to evoke and scaffold curiosity in group learning contexts.

1 Introduction and Motivation

Profound transformations in employment may require increased socio-emotional learning (SEL) skills that improve the ability to learn new things throughout the lifespan. Curiosity, the strong desire to learn or know more about something or someone [19], is recognized as a vital SEL skill that leads to learning through constructing one's own understanding, rather than "being told" or "instructed" [1]. Curiosity is traditionally considered as a psychological state in individuals evoked by novelty, surprise, conceptual conflict and uncertainty [5]. Existing educational technologies that support curiosity through social means mainly focus on dyadic scenarios and are equipped with a limited set of curiosity elicitation strategies. We propose to investigate how curiosity is promoted or suppressed in groups and present here a social account of curiosity, adding to constructivist accounts of how knowledge may be actively constructed through social interactions in small groups [10]. The larger context of our research is to develop a virtual peer [6] that can evoke curiosity among human peers in group learning.

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Curiosity changes moment to moment in response to environmental stimuli [31] and underlying psychological states such as anticipation and satisfaction of knowledge seeking [25,28]. Although there has not been much study of how individuals' curiosity influences others, research shows that cognitive, behavioral and affective states in group members are not independent of one another. For example, convergence and alignment among individuals' dialogue, gestures, emotions and even learning are commonly seen during conversation and group work [26,35,36]. Previous work [33] developed a fine-grained theoretical framework to quantify and investigate curiosity at ten-second intervals. Still, there is a lack of studies that extract the underlying temporal and social *dynamics* of curiosity.

In this paper, we present a prediction model that describes social scaffoldings that evoke curiosity at both the individual and group level. To build the model, we extracted *instantaneous changes in individual curiosity* and *convergence of curiosity across group members*. We then used temporal association rule mining to identify sequences of multi-modal behaviors that predict these dynamics and condensed them into a small set of interpretable rule clusters. Behavioral sequences extracted from the model reveal distinct patterns of social interaction that predict curiosity increase and decrease in individuals, and group convergence to high and low curiosity. We observe that an increase in individual curiosity, and convergence at high levels of group curiosity, are predicted by behavioral sequences involving verbalizing and justifying ideas, followed by argument, question asking and uncertainty. In particular, behavioral sequences involving the most social of group behaviors (question asking, argument and sharing findings) and underlying science reasoning (hypothesis generation and justification) best predict the convergence of all group members to high curiosity.

The main contributions of the paper are threefold. First, the prediction model initiates the study of the temporal and social dynamics of curiosity at both, individual and group level, from sequences of verbal and non-verbal behaviors occurring in small-group learning tasks. Second, the behavior patterns extracted from the model serve as fine-grained heuristics of social scaffoldings that guide the design of educational technologies and pedagogical curriculum to support curiosity-driven learning. Third, our approach informs the combination of temporal and social dynamics analysis of underlying learning states that are subject to change in response to complex interpersonal activities.

2 Related Work

Curiosity motivates information-seeking and reasoning, even when external rewards for learning are absent. It is therefore a strong predictor of academic performance [34], and yet is often found to decrease with age and schooling [20]. For this reason, a number of studies examine how to trigger and sustain curiosity. Most research investigates the cognitive factors that trigger curiosity in an individual, such as uncertainty, incongruity, novelty and surprise ([19] for a review). These theories have led to the development of computational models for educational technologies such as curious virtual learners [38] and robots [14].

However, these studies are limited to modeling individual curiosity, while we know that knowledge is also acquired through social interaction [8]. What of a social account of curiosity during peer-peer interaction? Two recent studies shed light on how the interpersonal effects curiosity. One showed that a curious robot with a limited repertoire of social interactions (e.g. asking questions, making suggestions) can elicit curiosity in a child [16]. The other provided an elaboration of the interpersonal drivers of curiosity, based on fine-grained analysis of verbal and non-verbal behaviors occurring during small group learning, and it showed a strong influence of social interaction on curiosity [33]. In spite of these promising discoveries about curiosity in social contexts, learning in groups does not guarantee to lead to curiosity. For instance, curiosity rarely occurs while interacting with intelligent tutors [24], and is more frequent when the learning tasks are harder [18]. Sinha et al. [32] developed a preliminary approach to elicit multimodal behaviors for maintaining individual curiosity in response to real-time social interactions. This approach, however, does not model the instant change of curiosity over time and among different members of the group, which is an essential first step towards evoking curiosity during social interactions.

The larger scope of our work is to build a virtual child to engage in small group learning and elicit curiosity. So far, intelligent tutoring and scaffolding systems focus on promoting learning by adapting towards student's activities within a computer-based learning environment [3,23]. When students learn in a group, social interaction through verbal and non-verbal communication becomes a prominent learning resource [8]. The spontaneity and complexity of social interactions influence dynamic learning states such as curiosity. Previous work on socio-emotional states such as rapport [39] and attitude [9] reveals the advantages of using data mining technologies to capture the predictive relationship between real-time social interactions and underlying states. Furthermore, learning is a collective experience, and group performance is more complex than the simple aggregation of individual's performance [7,27,37]. Previous work has studied collective phenomena such as physical interactivity [12] and learning efficiency [21] in collaborative learning tasks. However, the collective aspect of socio-emotional learning states, curiosity in particular, has not been adequately studied in small-group learning.

In this paper, we initiate a study of the moment-by-moment change and collective aspects of curiosity by presenting a prediction model that uncovers the association between complex social interactions and curiosity dynamics at individual and group level.

3 Method

We collected audio and video for 12 groups of children (aged 10–12, 16 males and 28 females, 3–4 children per group, 44 in total)[1]. Each group collaboratively built a Rube Goldberg machine(RGM) for about 35–40 min. The RGM task included building creative chain reactions using a variety of simple objects such as rubber

[1] Experimental setup at https://tinyurl.com/experimental-setup.

bands, pipe cleaners, toy cars, clothespins, etc. We choose the RGM task since it enables collaborative hands-on learning and creative problem solving [29], and supports scientific inquiry for key science knowledge such as force, motion and energy transfer for students in 5th and 6th grades [2]. In our analysis, we used the first 30 min of the RGM task from the first 6 groups, that we annotated for curiosity and curiosity-related behavior.

3.1 Annotating Individual Curiosity

We used Amazon Mechanical Turk to quantify curiosity for every group member via the thin-slice approach [4]. We chose 10-s thin-slices, which showed the highest inter-rater reliability compared to 20 and 30-s in a pilot annotation. This corroborates with previous studies on detecting learning effects [18]. AMT workers were given the definition "curiosity is a strong desire to learn or know more about something or someone", and asked four naive annotators to rate every 10 s thin-slice of the video of every child on a scale of 0 (not curious), 1 (curious) and 2 (extremely curious). Slices were presented in random order. A single measure of inter-class correlation coefficient (ICC) was computed for each possible subset of raters for a particular HIT, and the subset that had the best reliability was retained[2]. The average ICC was 0.46 (Krippendorff's alpha)[3] and aligns with reliability of curiosity ratings in previous work [11].

3.2 Annotating Curiosity-Related Behaviors

We used semi-automatic (machine learning + human judgment) and manual (human judgment)[4] procedures to annotate every clause in our corpus for 11 verbal behaviors chosen from a combination of prior research and empirical observation. Verbal behaviors included: *Uncertainty* (Lack of certainty about ones choices or beliefs), *Argument* (A coherent series of reasons or facts to support or establish a point of view), *Justification* (showing something to be right or reasonable by making it clear), *Suggestion* (idea or plan put forward for consideration), *Question asking* (related to the task or unrelated), *Idea Verbalization* (explicitly saying an idea in response to own or others' actions), *Sharing Findings* (explicit communication of results, findings and discoveries to the group), *Hypothesis Generation* (Expressing one or more different possibilities or theories to explain a phenomenon by relating two variables), *Agreement* (Harmony or accordance in opinion or feeling), *Sentiment towards task* (positive, negative) and *Evaluation of other's actions* (positive, negative)[5]. Inter rater reliability (Krippendorf's alpha) for each of these was above 0.7. In addition, we used

[2] We remove raters who take less than 1.5 std. deviation time to rate and used inverse-based bias correlation to counter label over- & under-use.

[3] 0.72 Cronbach's alpha intra-class correlation.

[4] Outlined in [32].

[5] Coding scheme for verbal and non-verbal behaviors at http://tinyurl.com/codingschemecuriosity.

automated detection of facial-landmark features using *OpenFace* and a rule-based classifier to indicate the presence of the following expressions of affective states: *Joy, Delight, Surprise, Confusion* and *Flow (intense concentration)*[6].

3.3 Prediction Model

Our prediction model was developed in three steps. (a) We mined instances of temporal and social dynamics of curiosity, treated as discrete *events* occurring during the group activity. (b) We then mined temporal association rules [22] that employ sequences of multi-modal behaviors to predict the occurrence of these events. (c) finally, we use agglomerative clustering technique to group these association rules into distinct clusters that can serve as strategies for curiosity scaffolding in group learning tasks.

3.3.1 Detecting Moment-by-Moment Dynamics of Curiosity

We study curiosity dynamics along two orthogonal dimensions: (a) Temporal dynamics of one group member's curiosity as represented by the increase and decrease of its value in short intervals of time (b) Social dynamic of curiosity - instances of *convergence* of the curiosity values of all the group members. We chose convergence as it is a common measure of group reciprocal influence [35,36].

Temporal Dynamic of Individual Curiosity: We detect moment-by-moment increases or decreases in individual curiosity by modeling thin-slice curiosity data of each group member as a time series and using a sliding window-based outlier detection technique to extract discrete events. We use a moving window average to smooth the curiosity time series and reduce short-term noise. We track anomalous changes by segmenting the series into short overlapping intervals using a fixed-length sliding window and extracting intervals that end in an anomalous peak. Standard score (z-score), which is the signed number of standard deviations a data point is above the mean of the data series, is used to decide thresholds for outliers. For every segmented interval, we calculate absolute deviation of the last thin-slice from the interval average and select intervals where z-score of the deviation exceeds 2. Events can be further divided as (a) curiosity increase and (b) curiosity decrease.

Social Dynamic of Curiosity in the Group: To study curiosity convergence in the group, we focus on instances during the interaction when more than 3 members of the group simultaneously display high or low curiosity. We calculate the standard deviation of the smoothed curiosity signals of concerning group members and, as before, select segmented intervals of time where this deviation is consistently less than one Z-score to extract events of convergence. Convergence events are distinguished as either high or low based on the group average of

[6] Facial-landmark feature coding and classification heuristics at https://tinyurl.com/curiositynonverbal.

curiosity in the selected interval. Figure 1 shows the temporal and social dynamic events mined for individuals and the group, respectively[7].

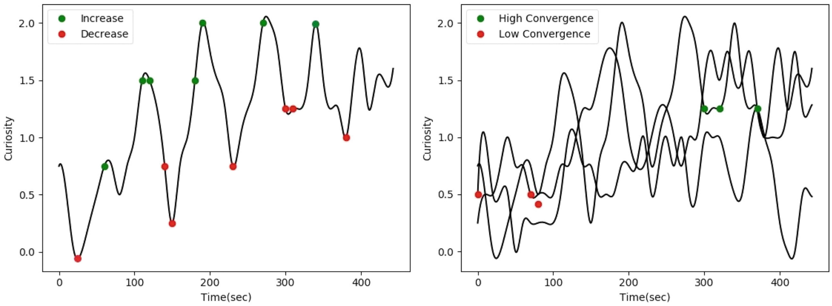

Fig. 1. (Left) curiosity increase and decrease events in Individuals. (Right) curiosity high and low convergence events in 3-member group

3.3.2 Extracting Rules Associating Sequences of Behaviors with Curiosity Dynamics

Multi-party interaction is dynamic, in that behaviors exhibited by some group members influence future behaviors exhibited by others. To capture this complex interaction of behaviors over time, we mine sequential multi-modal behaviors, which then serve as input features to predict the curiosity dynamic events we previously extracted. To this end, we use the Temporal Interval Tree Association Rule Learning (TITARL) algorithm [17] to mine frequently occurring association rules such as the one in Fig. 2. TITARL incorporates a degree of uncertainty in the interval between two behaviors in the sequential rule using a discrete probabilistic distribution over time. It then constructs a Random Forest Classifier that uses these sequences as input features for multi-class classification. We use TITARL to predict the occurrence of temporal change in individual curiosity (increase, decrease, no change) or social convergence (high, low and no convergence) events in a 20 s interval. We only mine TITA rules that have a minimum occurrence of 5% and prediction confidence of 50%. For curiosity change in one individual, we make the distinction between behaviors expressed by that individual (*target T*) and *other (O)* members of the group. For group curiosity convergence, we consider all members of the group as *targets*. To verify our hypothesis about the predictive power of sequential behaviors, we consider a baseline that treats every behavior as an independent feature to a Support Vector Machine classifier with an RBF Kernel ($\gamma = 2$, C $= 1$). To compare with other sequential models of prediction, we also implement a recurrent neural network baseline that

[7] Event mining is robust as we use z-score-based thresholds to select individual and group specific intervals.

models sequential inputs in a 20 s interval using 128 hidden dimensions to classify events. Figure 3 depicts the extraction of behavioral sequences and dynamic events of curiosity along the temporal and social dimension. We report the average performance on 5-fold cross validation for 100 runs, where association rule mining and fusion was done separately for each training fold.

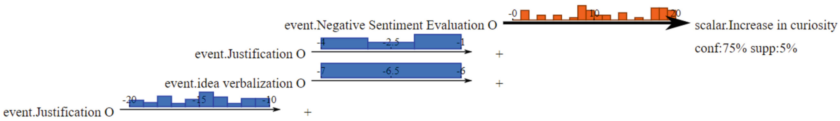

Fig. 2. A TITA rule. Between any two input behaviors, the temporal constraint is a discrete probability distribution over time (shown as a Histogram).

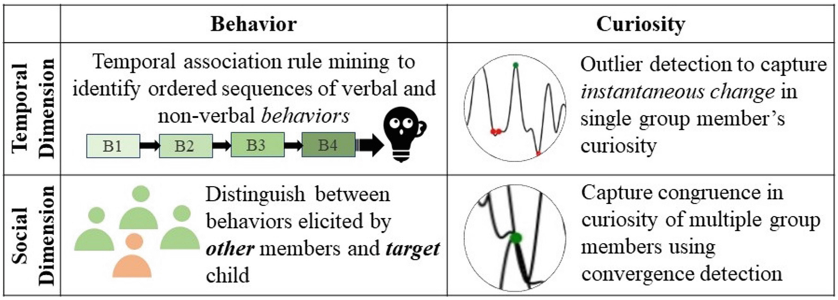

Fig. 3. Computational framework for prediction of curiosity dynamics

3.3.3 Extracting Predominant Clusters of Association Rules

TITARL results in a large set of rules that suffer from inter-rule temporal redundancies, making them hard to analyze and interpret. To counter this, authors employ supervised fusion that uses a training dataset of input behaviors and output events to learn correlation between TITA rules and fuse them. To further reduce the set of mined TITA rules into a feasible set that can be operationalized, we employ an edit-distance based hierarchical clustering technique to cluster rules with similar behavioral patterns. In the next section, we present TITA rules with the highest confidence categorized into their respective clusters.

4 Results and Discussion

4.1 Predicting Individual Curiosity Change

Table 1 shows the prediction performance of TITARL for anomalous change in individual curiosity and comparisons with baselines. TITARL outperforms the SVC baseline, increasing prediction recall. This indicates that it can model fine-grained behavioral associations that index social interactions and can consequently predict changes in curiosity more accurately. TITARL outperforms RNN on F1 measure. RNNs require a lot of training data and are hard to interpret and operationalize. This performance evaluation is promising given the relatively few occurrences of temporal dynamic events in the dataset (Class imbalance of 33%).

Table 1. Cross-validation evaluation of TITARL and RNN, SVC Baselines for Prediction of *temporal* and *social* dynamics in curiosity, averaged over 100 runs

Dynamic	Method	Performance			
		Accuracy	Precision	Recall	F1
Temporal dynamic	**TITARL**	0.69	0.66	0.69	**0.67**
	RNN	0.74	0.60	0.75	0.64
	SVC	0.57	0.49	0.57	0.52
Social dynamic	**TITARL**	**0.81**	**0.78**	**0.82**	**0.79**
	RNN	0.79	0.74	0.81	0.77
	SVC	0.75	0.69	0.76	0.72

Table 2 lists examples of extracted temporal association rules that predict increase and decrease in curiosity. Rules have been grouped according to the clusters to which they belong, along with a few sequence of behaviors that make up the cluster. In Clusters 1, 2, 3 and 4 for curiosity increase, a recurring sequence of *Idea Verbalization(O)* followed by *Justification(O)* indicates that other group members (apart from target T) express an idea and justify its validity. Following this, a *Negative Evaluation* (Cluster 1) by another member indicates disagreement with the stated idea, exposing to the target child a conflict about the proposed solution and perhaps triggering a need to resolve this conflict (leading to increased curiosity). Clusters 2 and 3 show that the *Idea verbalization* -followed by *Justification* behavior of others may also trigger uncertainty or conceptual conflict about the stated idea in the target child (Cluster 3) or another group member (Cluster 2), which manifests as a *confused facial expression.* Confusion displayed by others (Cluster 2) may provide stimulus to the target child to think critically about the proposed idea. A knowledge-gap or conceptual conflict about the proposed idea may stimulate another group member to ask a question (Cluster 4), which in turn may trigger awareness in the target member of his/her own knowledge gap or conflict. In cluster 5, if evidence and validation is put forth by the target group member about a previously mentioned idea, and then another group member *argues* for a different view-point, the target is exposed to diverse aspects of the problem and that may stimulate critical thinking.

Sequences that predict decrease in curiosity include more behaviors carried out by the target group members themselves than others in the group. Prominent among these is *Agreement* and *Positive Sentiment evaluation* by the target of

Table 2. Rule examples for change in individual's curiosity

Rule Clusters that Predict Curiosity Increase
Cluster 1: Other's Idea Verbalization(IV), and Justification(J) followed by Negative Sentiment Evaluation(NSE)
1. $J(O) \rightarrow \{\ IV(O),\ J(O),\ NSE(O)\} \rightarrow NSE(O) \Rightarrow$ Increase
2. $\{J(O), IV(O)\} \rightarrow \{J(O), IV(O)\} \rightarrow NSE(O) \Rightarrow Increase$
Cluster 2 : Other's Justification(J), Negative Sentiment Evaluation(NSE) and Idea Verbalization(IV) followed by Other's Confusion(CONF)
1. $J(O) \rightarrow \{NSE(O), J(O)\} \rightarrow IV(O) \rightarrow CONF(O) \Rightarrow Increase$
2. $NSE(O) \rightarrow \{NSE(O), J(O)\} \rightarrow \{IV(O), J(O)\} \rightarrow CONF(O) \Rightarrow Increase$
Cluster 3: Other's Agreement(AG) followed by Idea Verbalization(IV)and Justification (J) followed by Target's Confusion(CONF)
1. $AG(O) \rightarrow AG(O) \rightarrow \{IV(O), J(O)\} \rightarrow CONF(T) \Rightarrow Increase$
2. $\{J(O), AG(O)\} \rightarrow \{IV(O), J(O)\} \rightarrow CONF(T) \Rightarrow Increase$
Cluster 4: Other's Idea Verbalization (IV), Justification followed by Other's Negative Sentiment Evaluation and Question Asking (QA)
1. $IV(O) \rightarrow \{IV(O), J(O)\} \rightarrow NSE(O) \rightarrow QA(O) \Rightarrow Increase$
2. $IV(O) \rightarrow J(O) \rightarrow NSE(O) \rightarrow QA(O) \Rightarrow Increase$
Cluster 5: Target's Justification(J) followed by Argument and/or Justification by Others
1. $J(O) \rightarrow \{J(O), J(O)\} \rightarrow J(T) \rightarrow Argument(O) \Rightarrow Increase$
2. $\{IV(O), Argument(O)\} \rightarrow \{J(T), Argument(O)\} \rightarrow J(O) \Rightarrow Increase$
Rule Clusters that Predict Curiosity Decrease
Cluster 1: Other's Idea Verbalization(IV) and Justification(J) followed by Target's Positive Sentiment Evaluation(PSE) and Agreement (AG)
1. $\{IV(O), J(O)\} \rightarrow \{PSE(T), IV(O)\} \rightarrow AG(T) \Rightarrow Decrease$
2. $IV(O) \rightarrow \{PSE(T), IV(O), IV(O)\} \rightarrow AG(T) \Rightarrow Decrease$
Cluster 2: Target's Justification(J), Idea verbalization(IV) or Positive Sentiment Evaluation (PSE) followed by Target's Agreement
1. $J(O) \rightarrow J(T) \rightarrow \{PSE(T), PSE(T)\} \rightarrow AG(T) \Rightarrow Decrease$
2. $\{J(T)\} \rightarrow \{PSE(T), PSE(T), IV(O)\} \rightarrow AG(T) \Rightarrow Decrease$
Cluster 3: Target's Idea Verbalization and Positive Sentiment Evaluation(PSE) followed by other's Agreement (AG)
1. $IV(O) \rightarrow \{PSE(T), IV(T), IV(T)\} \rightarrow AG(O) \Rightarrow Decrease$
2. $J(T) \rightarrow \{PSE(T), IV(T), IV(T)\} \rightarrow AG(O) \Rightarrow Decrease$

an idea or solution proposed by other group members (in Table 2, Clusters 1,2). Both behaviors are indicators that the target child approves of the solution. This may be an indication of closing an information-gap, which may lead to curiosity decrease. In general, we observe that sequences predicting curiosity increase have more behaviors elicited by other group members than the target member (35% more), which corroborate with findings in [32] that interpersonal interactions have a larger influence on positive curiosity than intra-personal behaviors.

4.2 Predicting Group Curiosity Convergence

Table 1 also summarizes the performance of TITARL for convergence of group members' curiosity to high and low values. Again, the model outperforms baselines and performs comparatively better predicting individual curiosity change ($F1_{TITARL} = 0.69$), despite group convergence events occurring half as frequently during the group activity as individual change events.

Table 3 lists examples of extracted temporal association rules that predict convergence of curiosity to high and low values, respectively. Rules that cause several group members' curiosity to simultaneously converge to high values tend

Table 3. Rule clusters for convergence in group members

Rule Clusters for Convergence to High Curiosity
Cluster 1: Sharing Findings(SF) followed by Idea Verbalization(IV) and Justification(J) or Negative Sentiment Evaluation(NSE)
1. $IV \rightarrow \{SF, NSE\} \rightarrow IV \Rightarrow High$
2. $\{NSE, IV\} \rightarrow \{SF, J\} \rightarrow IV \Rightarrow High$
Cluster 2: Suggestions(SUGG), Arguments(ARG) and Idea verbalization (IV) in that order
1. $SUGG \rightarrow ARG \rightarrow IV \rightarrow J \Rightarrow High$
2. $SUGG \rightarrow \{IV, ARG\} \rightarrow \{IV, J\} \Rightarrow High$
Cluster 3: Uncertainty(UNC) followed by Idea Verbalization(IV) and Hypothesis Generation(HG)
1. $\{J, UNC, UNC\} \rightarrow IV \rightarrow HG \Rightarrow High$
2. $UNC \rightarrow \{UNC, IV\} \rightarrow HG \Rightarrow High$
Cluster 4: Question Asking(QA) followed by Uncertainty(UNC) and Idea verbalization(IV)
1. $\{QA, J\} \rightarrow UNC \rightarrow IV \Rightarrow High$
2. $Confusion \rightarrow QA \rightarrow UNC \rightarrow IV \Rightarrow High$
Cluster 5: Arguments(ARG) followed by Idea Verbalization(IV), Justification(J) and/or Negative Sentiment Evaluation(NSE)
1. $\{IV, ARG\} \rightarrow \{IV, J\} \Rightarrow High$
2. $ARG \rightarrow \{IV, IV, J\} \Rightarrow High$
Rule Clusters for Convergence to Low Curiosity
Cluster 1: Question Asking(QA) followed by both Negative and Positive Sentiment Task (PST, NST) and Confusion
1. $\{QA, Confusion\} \rightarrow \{PST, NST\} \rightarrow Confusion \Rightarrow Low$
2. $\{QA, NST\} \rightarrow \{PST, NST\} \rightarrow Confusion \Rightarrow Low$
Cluster 2: Justification(J) and Agreement(AGREE) followed by both Positive and Negative sentiment task(PST, NST) followed by Confusion
1. $\{J, AGREE\} \rightarrow \{PST, NST\} Confusion \Rightarrow Low$
Cluster 3: Confusion and Idea Verbalization(IV) followed by more confusion
1. $\{IV, Confusion\} \rightarrow \{IV, Confusion\} \rightarrow \{IV, Confusion\} \Rightarrow Low$
Cluster 4: Uncertainty(UNC) and Idea Verbalization(IV) followed by more uncertainty
1. $UNC \rightarrow \{IV, Confusion\} \rightarrow UNC \Rightarrow Low$
2. $UNC \rightarrow \{IV, IV\} \rightarrow UNC \Rightarrow Low$

to contain a sequence of behaviors uttered with the purpose of (a) evaluation of the proposed approach/solution by the group (Table 3, Clusters 1, 2) or (b) resolution of conflicts, knowledge gaps or opposing beliefs amongst different group members (Cluster 3, 4, 5). In particular, *Sharing Findings* (Cluster 1) or *Suggestions* (Cluster 2) made by one group member followed by *Negative Sentiment Evaluations* or *Argumentative* evaluations by other group members appears to lead to engagement and constructive debate in the group that stimulates critical thinking of alternative solutions and conflicting beliefs. Similarly, in Clusters 3, 4 and 5, when one group member reveals a knowledge-gap through the expression of *Uncertainty* (Cluster 3) or *Question Asking* (Cluster 4), or *Argues* (Cluster 5) for an alternative point of view, this knowledge-gap or conflict may be perceived by the group and jointly resolved through the use of ideas and supporting evidence (*Idea Verbalization*, *Justification*) or by building different possibilities and theories using a creative thought process (*hypothesis generation*).

A general explanation for these results is that the importance of a member's lack of knowledge is intensified through (i) explicit demand for response via sharing findings and question asking; (ii) high engagement with other's ideation through argument; and (iii) science reasoning involved in hypothesis generation [30]. These behaviors may lead to increased joint attention towards the information-gap, and thereby a high level of curiosity among group members [15]. This indicates that both cognitive and social engagement in conversation and group work plays an important role in joint curiosity at the group level and has previously been shown to produce a positive impact in edX MOOCs [13]. Rules where members' curiosity converges to low values contain the common theme of unresolved *Uncertainty* and *Confusion* in several members, revealing an unsolved knowledge-gap or conflict. This confusion is further exacerbated with the combination of both, *Positive* and *Negative* evaluations of the task (in Table 3, Clusters 1 and 2). Specifically, when curiosity converges at a low value across members, we observe more non-verbal behaviors (e.g. facial expressions of confusion, surprise) than verbal behaviors. The prominence of more non-verbal than verbal behaviors is indicative of low interactivity among group members (Table 4).

In summary, we observe that rules that predict a positive dynamic of curiosity (Increase and High Convergence) contain behavioral sequences where a possible solution to a problem is expressed with supporting evidence and is either critically evaluated through negative sentiments and arguments or triggers awareness of a knowledge gap leading to uncertainty and question asking. This is indicative of the desire to resolve conflicts arising from the critical evaluation or to bridge the perceived knowledge gap and is perceived as a positive scaffold for curiosity. Another interesting finding that contrasts curiosity as a group phenomenon with an individual state is that, compared to sequences that predict individual curiosity increase, sequences for high convergence contain a)more behaviors such as sharing findings and on-task question asking that elicit others' response and b)verbal behaviors with higher-order of reasoning such as justification and hypothesis generation. This is in spite of the rare occurrence of hypothesis generation, which emerges later compared to other scientific reasoning skills such as

Table 4. Examples of group conversations where association rules for curiosity increase and convergence are triggered

Conversation 1: Others Show Idea Verbalization(IV), Justification(J) followed by Negative Sentiment Evaluation(NSE) ⇒ Curiosity Increase
P1: If we bring the ball down in here... **(J)**
P1: Alright, it would need more space. **(IV)**
P4: Oh! use this, use this.
P1: Oh ain't it better.. **(NSE)**
P1: No, no, no! i just- look, i just got it
P1: Just need to aim it a little bit better, see?
P2: what are you trying to do ? **(Person 2's curiosity increases)**
Conversation 2: Uncertainty(UNC) followed by Justification(J) or Idea Verbalization(IV) and Hypothesis Generation(HG) ⇒ High Convergence
P3: We could have made- we didn't actually need this. **(UNC)**
P2: P3 how's that?
P3: We could have put this here **(J) (IV)**
P1: Uh we really need to make it really like on it's edge **(IV)**
P4: And then the ball could have landed in the boot, kicking this, kicking another ball.**(J)(HG) (Everyone is now curious)**

evidence evaluation among primary school students [30]. This initial observation opens up a new direction for differential social scaffolding of curiosity at different social granularities, individual and group.

We present conversation examples from a group building the RGM where association rules for curiosity increase (Conversation 1) and convergence at high levels (Conversation 2) are triggered. These association rule clusters can serve as the base of the reasoning model that determines real-time social scaffoldings to evoke curiosity in response to sequences of interactions in small group learning.

5 Implications and Future Work

Curiosity is an important motivation for learning, and our work demonstrates the ways in which curiosity is heavily influenced by social interactions in small groups. Findings of this work lead us to conceive of curiosity as socially as well as cognitively driven, and to ensure that in small group learning, we look not just at individual members' curiosity, but also the curiosity of the group. Our prediction model lays the foundation for determining what kinds of social scaffolding can evoke an increase in curiosity at both the individual and group level. Technically, this can be realized by monitoring the social interaction stream, and estimating the likelihood of future behaviors that may lead to curiosity increase or convergence to a high level, and to them choose the most appropriate social scaffolding based on the real-time learning contexts. We aim to integrate this solution into a curiosity reasoner for an intelligent virtual peer, that can evoke curiosity in small group scientific inquiry. It can also, however, be employed by teachers as they monitor small groups in learning activities, and by those who develop curricula and serious games for group learning activities.

The computational model presented here identifies temporal and social dynamics as two essential aspects of the association between complex social interactions and dynamic learning states like curiosity. The temporal dynamics we investigated were sequential behavior patterns and anomalous curiosity changes. The social dynamics were sequential behaviors across group members and curiosity convergence among group members. Although the study only explores basic temporal and social dynamics, it reveals promising directions for the AIED community to develop future theories and adaptive technologies for learning in social contexts. The approach of combining temporal association rule mining and curiosity dynamics is a technique that can be applied to investigate the temporal and social dynamics of other socio-emotional learning states in group work. Our study is limited by sample size since multi-party data collection and human-annotation of behavior and curiosity is a resource-intensive process. However, the promising results obtained in this work will encourage the community towards the creation of larger datasets, fine-grained analysis of the dynamics of learning states and development of adaptive SEL technology for collaborative group learning. In the future, we plan to enhance the model with multi-modal information at the turn-level to add a higher resolution to the social dimension of behaviors. We will also, of course, take the next step and assess whether implementing these sequences raises, not just curiosity, but also learning gains.

6 Conclusion

To our knowledge, this work is the first attempt to understand and build a prediction model of the dynamic interpersonal nature of curiosity in small group learning contexts. The computational model associates temporal sequences of verbal and non-verbal behaviors displayed by children in small learning groups with curiosity change in individuals as well as curiosity convergence of the group. Our model reliably predicts these events and extracts rules with distinct sequential patterns for each dynamic, thus uncovering different social interaction influences that lead to different curiosity dynamics. We observe that an increase in curiosity is associated with behavioral sequences where a solution to a problem is expressed together with supporting evidence and is either critically evaluated or triggers awareness of a knowledge gap. Convergence of high curiosity in a group tends to be associated with both scientific discourse (such as hypothesis generation) and interpersonal discourse (such as sharing findings). The extracted association rules provide heuristics for educators and designers to develop curricula and educational technologies that support curiosity in peer-peer learning environments. Furthermore, our approach provides a way for future adaptive learning technologies to incorporate social and temporal dynamics of positive learning states in supporting peer learning in small group.

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