Discovering Co-creative Dialogue States during Collaborative Learning

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Abstract. Many important forms of collaborative learning are co-creative in nature, with learners exchanging dialogue as they construct an artifact. AI systems to support co-creativity in learning are highly underinvestigated, and very little is known about the dialogue mechanisms that support learning during collaborative co-creativity. To address this need, we analyzed the structure of collaborative dialogue between pairs of high school students who co-created music by writing code. We used hidden Markov models to analyze 68 co-creative dialogues consisting of 3,305 total utterances. The results distinguish seven hidden states: three of the hidden states are characterized by conversation, such as social, aesthetic, or technical dialogue. The remaining four hidden states are characterized by task actions including code editing, accessing the curriculum, running the code successfully, and receiving an error when running the code. The model reveals that immediately after the pairs run their code successfully, they often transition into the aesthetic or technical dialogue state. However, when facing code errors, learners are unlikely to transition into a conversation state. In the few cases where they do transition to a conversation state, this transition is almost always to the technical dialogue state. These findings reveal the processes of human co-creativity during learning and can inform the design of intelligent co-creative agents that support human collaboration and learning.

Keywords: Collaborative learning · Dialogue · Co-creativity.

1 Introduction

There is growing interest in using AI to support collaborative learning. AI companions have the potential to improve learners' collaborative skills by, for example, encouraging "deep thinking" and initiative taking [10]. AIs have been developed for applications ranging from emotional learning companions that support elementary school children learning to code [14] to discussing Jane Austen books with learners [16]. AIs to support collaborative learning are underinvestigated, even though collaborative learning has been shown to increase learner interest in solving problems during online tutoring [2], decrease learner boredom [2], and improve critical thinking skills [8]. Researchers have begun to uncover features of strong collaboration, including gaze synchronization [22], the importance of proximity [4], and semantic similarity [21]. Substantial work has investigated collaborative processes with a variety of data sources including eye tracking [5][22], motion sensors [4][18][5], dialogue analysis [3][21], and speech features [24].

Research on the dialogue of collaboration has focused on detecting when students are off-task [3], supporting inquiry learning by analyzing the role of questions in collaborative computational modeling [23], and predicting problem-solving modes to support adaptive tutoring [19]. Research on collaborative learning within groups has used conversational agents to facilitate productive conversations [6] and dialogue features to identify trouble during collaboration [9].

Most research on virtual agents in collaborative learning has involved agents in a tutor or support role, but some work with agents as partners to human learners has demonstrated benefits including significantly higher levels of shared understanding, progress monitoring, and feedback [20]. Research on agents as partners has also investigated support for human-computer co-creation, a type of collaborative creativity in which responsibility for an artifact is shared between the human and computer [11]. To move toward systems that support collaborative co-creation during learning, we need to build an understanding of the dialogue mechanisms that characterize this process. Modeling human-human co-creative interactions is the fundamental starting point for building this understanding.

To address this need, this work makes a step toward characterizing the dialogue modes learners tend to enter as they engage in co-creative dialogue. We examined dialogue and system interactions between pairs of high school students learning to code through remixing musical samples. Using a hidden Markov model, we distinguished seven states, three characterized by conversation and four characterized by task actions. The model suggests that learners engaged in two types of discourse—aesthetic and technical—during this co-creative process. The *aesthetic* discourse pertains to musical style, taste, and expression, while the *technical* discourse pertains to writing code and task objectives. This work's contributions are a model of high school learners' collaborative interactions, insights about how aesthetic and technical discourse unfold during collaborative learning, and suggestions for adaptive systems supporting co-creativity. By modeling co-creative dialogue, we can move toward intelligent support of human collaboration and toward intelligent co-creative agents that support learning.

2 Methods

This work analyzes a corpus of textual student-student dialogue collected between November 2019 and March 2020 during computer science classes from eight public high schools in two districts in the southern United States, consisting of a total of 140 participants. More than half of the schools had a student population of majority (>50%) Caucasian students; one school was majority

Black; two schools had a substantial (>25%-35%) Latinx population; one school had a substantial Asian population. All students were in grades 10-12 (15-18 years old). Teachers placed the students into dyads, and students were placed at a distance in separate rooms or different areas of the same room to facilitate their communication through the textual chat interface (Figure 1). Students collaborated synchronously for an average of 48 minutes to remix musical samples and create an original song or ringtone. Some participants, 9 pairs, split their work across two class days. We included only the first day's dialogue for these pairs because concatenating two separate dialogues would change the natural beginning, middle, and end of the sequences; whereas including both dialogues for a pair would unevenly weight their patterns while training the hidden Markov models.

2.1 Learning Environment for Computational Music Remixing

This study was conducted in the EarSketch learning environment, an online interface for developing computational music (Figure 1). In prior studies, students that used EarSketch had significant positive results related to content knowledge and attitudes towards computing, especially in currently underrepresented groups in computing [13]. The EarSketch interface includes a code editor for Python or JavaScript and a digital audio workstation that allows users to access the music they have written [7]. The interface also features a content manager with samples (sound clips) that can be used to create music, as well as a curriculum tab that provides helpful resources associated with the class. Both students had access to all of the tools allowing both to contribute to the code simultaneously. In this study, the interface included a chat box to communicate with their partner. We logged all students' textual dialogue, all changes made in the code editor, all items accessed in the curriculum tab, and the results of the students running their scripts (such as successes or errors).

2.2 Dialogue Tagging

In cleaning the dataset, we removed 2 sessions that contained exclusively off-task, joking, offensive, or gibberish content. The remaining textual dialogue corpus contains 68 sessions (136 students) and 3305 utterances, with a mean of 48 utterances per session (SD=35, Min=4, and Max=214). We developed and applied a dialogue act taxonomy that included 16 labels, which three independent annotators applied with a kappa of 0.76, *substantial*, agreement [12]. Among the 16 original labels, 10 occurred with greater than 5% probability in the hidden states within the HMM reported here, and one more label appeared in an example excerpt in this paper's discussion section. These 11 relevant dialogue act labels are shown in Table 1.

2.3 Analyses

After compiling the lists of sequential observation symbols that represent the collaborative interactions, we implemented an HMM to analyze the learners'

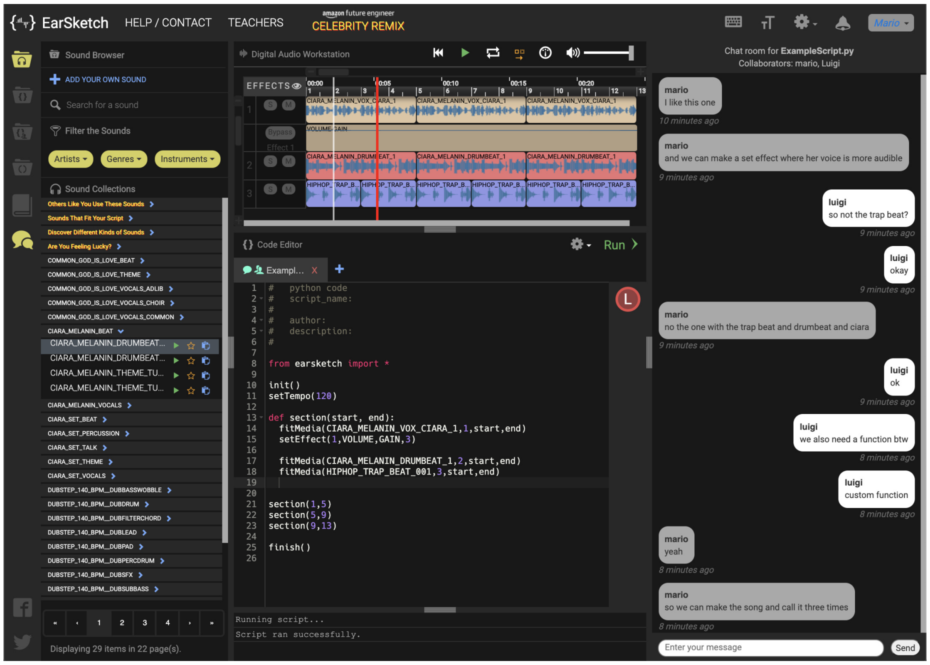


Fig. 1. The modified EarSketch environment with chat window used during the study.

interactions and model the co-creative sequences [17]. We chose this method because we were interested in the hidden discourse states. In an HMM, observable events such as textual messages and coding actions are represented by sequences of *observation symbols*. Influences upon those observation sequences are referred to as hidden states, and in an HMM each hidden state is characterized by its *emission distribution*, a probability distribution over observation symbols. Once the model is learned, every observation is modeled as having been "generated" by a hidden state, and each hidden state has a set of transition probabilities that indicates how likely the model is to either continue in that state or transition to another state.

The observation symbols are the labeled dialogue and task actions in this model. There are 23 distinct possible observation symbols—19 dialogue act tags, of which 16 are represented in Table 1, and the following actions:

- **curriculum** - The student accessed the curriculum or moved between lessons.
- **edit** - Any consecutive insertion or removal of characters in the code editor.
- **success** - Each time the script was run successfully.
- **error** - Each time the script was run and any type of error was received.

We represented each of the 68 collaborative dialogues as a sequence of these observation symbols and trained an HMM on these sequences. We did not model time between actions, nor did we model which of the two students performed each action.

Table 1. Taxonomy of co-creative dialogue act labels. Tags that occurred with less than 5% probably in all hidden states and that do not appear in the examples presented in this paper are not included in this table.

Dialogue act label	**Relative Frequency in Corpus**	**Description**	**Examples**
Statement (**Stmnt**)	17.14%	Utterance of info or explanation, or something that exists in the coding workspace	*well we also have to make a loop*
Social (**Soc**)	14.11%	A general salutation, off-task comment, or display of remorse. Plays some social function not captured in the other tags	*how are you?*
Proposal (**P**)	12.32%	An assertion of creativity, related to code or music, for the partner to consider.	*we should do some beats in the background*
Directive (**Dir**)	11.55%	An utterance used to set task responsibilities for each or a single partner	*We should focus on the custom function first*
Confusion (**Con**)	10.41%	Seeking help, expressing confusion, lack of knowledge, or uncertainty	*What are those variables for?*
Acknowledgement (**Ack**)	6.35%	Accepting the content of the previous utterance or series of utterances	*yeah*
Passing Responsibility (**PR**)	6.17%	Passing creative or technical choice to partner	*Do you know what sounds you would like to use?*
Proposal Acceptance (**ProposalAccept**)	5.67%	Accepting a partner's addition or assertion to the co-creative mental model shared by both partners	*yeah jazzand dubstep sounds fine*
Positive Feedback (**PosFdbk**)	5.29%	Positive response relating to something the partner accomplished within the scope of the task	*I liked the piano thing you did*
Directive Acceptance (**DirAccept**)	3.97%	Response to a partner accepting the dictation of flow or direction of project	*ok i will figure out a makebeat*
Non-positive Feedback (**NPosFdbk**)	2.29%	Non-positive response relating to something incorrectly done by the partner within the scope of the task	*it doesnt sound as good as i thought it would*

3 Results

To select the best number of hidden states, we used leave-one-out cross validation and compared the average Akaike information criterion (AIC) score for each number of hidden states [1]. We compared models using 4-9 states, finding that the best AIC scores were consistently found for six and seven states. We then trained ten models for both six and seven states and compared the best models using log likelihood. The best models from each were nearly identical. One of the dialogue states for the six-state model split to become two dialogue states in the seven-state model, with the rest of the states remaining the same. We opted to move forward with the 7-state HMM.

The HMM analysis revealed that collaborative sessions contained the following seven hidden states (see Figure 2) which we interpreted as follows:

– **Social Dialogue:** In the this state, observation symbols are heavily (79%) *social* dialogue acts. Around 90% of sessions begin in this state.
– **Aesthetic Dialogue:** In the *Aesthetic Dialogue* state, *proposal* and *proposal acceptance* dialogue acts, which involve assertions and acceptances of creativity, constitute (51%) of observation symbols. The dialogue that belongs to this state usually involves discussing some aspect of the music.

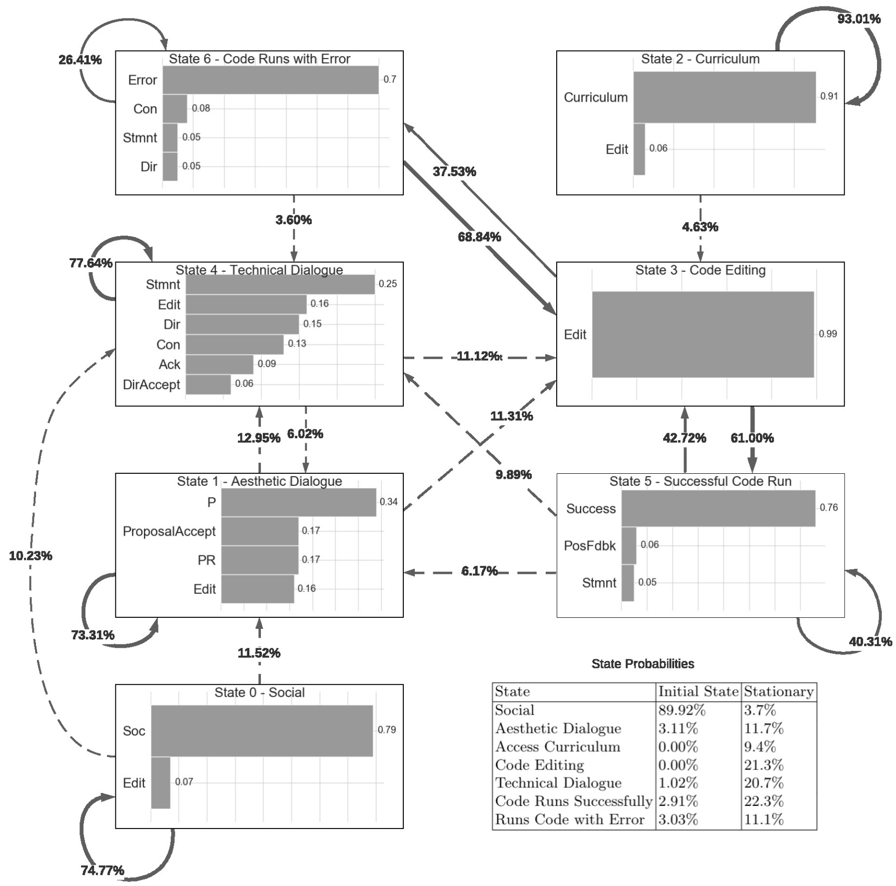
– **Curriculum:** The observation symbols from this state were almost exclusively (91%) from students accessing the curriculum.
– **Code Editing:** The observation symbols from this state are almost entirely (99%) code editing.
– **Technical Dialogue:** The dialogue acts that characterized this state involved *statement*, *directive*, *confusion*, *acknowledgement*, and *directive acceptance*. The dialogue that belongs to this state usually involves discussion of code features or task requirements.
– **Code Runs Successfully:** Mostly characterized by students running the code successfully, this state involves some *positive feedback* (6%) and *statement* (5%) dialogue acts.
– **Runs Code with Error:** Mostly characterized by students receiving an error when running the code, this state involves some *confusion* (8%), *statement*(5%), and *directive*(5%) dialogue acts.

This model revealed three distinct states of conversation that occur in these co-creative interactions: *Social Dialogue*, *Aesthetic Dialogue*, and *Technical Dialogue*. The *Social Dialogue* state usually occurs at the beginning of the interaction, but can occur throughout and usually includes some rapport building and off-task discussions. Utterances in the *Aesthetic Dialogue* state usually involved discussing different aspects of the music such as instruments, tempo, genre, and even what artist to emulate. Utterances in the *Technical Dialogue* state were typically about task requirements and code. This model also revealed four hidden states focused on coding: *Curriculum*, *Code Editing*, *Code Runs Successfully*, and *Runs Code with Error*. The sessions never begin in the *Curriculum* state, and no other states consistently lead to it. Every state, excluding the *Social Dialogue* state, has a significant chance to lead to the *Code Editing* state, and 21.3% of the actions occur in this state. This percent does not represent how much elapsed time learners spent editing the code, because we combined sequences of consecutive edits into a single *edit* observation symbol. *Code Editing* transitions to a *Success* or an *Error* state 98.53% of the time. The states the *Successful Code Run* state is likely to transition to are *Code Editing* (42.72%), *Technical Dialogue* (9.89%), and *Aesthetic Dialogue* (6.17%). The other state *Code Runs with Error* is most likely to transition to is *Code Editing* (68.84%), and the only other state is *Technical Dialogue* (3.60%).

4 Discussion

4.1 Dialogue States

These results revealed ways in which co-creative dyads moved among collaborative dialogue states characterized by conversation and task actions. Of the seven hidden states identified by the HMM, three were composed primarily of dialogue acts. *Social Dialogue* was the most likely state for students to start in, primarily composed of greetings and off-task dialogue. This is a typical feature of collaborative dialogue, prefacing discussion with periods of rapport building in



State	Initial State	Stationary
Social	89.92%	3.7%
Aesthetic Dialogue	3.11%	11.7%
Access Curriculum	0.00%	9.4%
Code Editing	0.00%	21.3%
Technical Dialogue	1.02%	20.7%
Code Runs Successfully	2.91%	22.3%
Runs Code with Error	3.03%	11.1%

Fig. 2. The co-creative dialogue states' emission and transition probabilities.

which the partners become more familiar with each other [15]. After leaving this initial *Social Dialogue* state, we found that the conversation was nearly twice as likely to move directly to the *Aesthetic Dialogue* state (60%) as to the *Technical Dialogue* state (31%). In the *Aesthetic Dialogue* state, students brainstorm and exchange dialogue related to the musical piece they are constructing. The *Technical Dialogue* is where students begin planning how to accomplish their creative goals. In the excerpt in Table 2, the students set their goal of creating a dubstep song and then debate how they would accomplish that in their code. While the transitions can move from either the *Technical Dialogue* state to the *Aesthetic Dialogue* state or vice versa, the transitions from *Aesthetic Dialogue* to *Technical Dialogue* were much more likely, 12.95% versus 6.02%, than the reverse. This observation suggests most pairs tend to decide on what they want to make before they move on to making it.

Table 2. Excerpt 1: Learner conversation transitioning from Aesthetic (State 1) to Technical (State 4) Dialogue State. Each dialogue state was determined automatically using the HMM presented in this work.

State	Action	User	Text
1	PR	**Student 1**	what you want to do
1	P	**Student 2**	lets do dubstep cause its fire
1	PA	**Student 1**	i feel you
4	C	**Student 1**	what did she say how many variables
4	STMNT	**Student 2**	3
4	D	**Student 1**	ok lets do this
4	C	**Student 2**	ngl im kinda lost already so im sorry
4	C	**Student 1**	i dont know what to do
4	C	**Student 2**	me either ima ask for help

4.2 The Debugging Process and the Conversation it Inspires

The remaining four states are mostly focused on actions in the interface: reading the curriculum and tutorials on code constructs (state 2), editing the code (state 3), having coding errors (state 6), and successfully compiling their code (state 5). The transitions between states 3, 5, and 6 demonstrate the movement between collaborative states that occur during debugging, and they offer insights about how co-creative conversations unfold. The editing state (state 3) primarily transitioned to the compile states (Error or Success), with no transitions to any of the dialogue states. After entering the success state, students were most likely to go back to the editing state, but they also sometimes transitioned back into the *Technical Dialogue* or *Aesthetic Dialogue* states. Table 3 illustrates this transition.

The *Success* state seems to be an inflection point in the co-creative process, in which the group may start to renegotiate some of the creative aspects of their code. In contrast, the *Error* state only transitions to *Editing* or *Technical Dialogue* suggesting partners who encounter errors focus on resolving their problems rather than discussing new ideas (*Aesthetic Dialogue*).

4.3 Implications for Co-Creative Agents in Education

The findings of this research provide insights for modeling co-creative discourse, which can inform the design of AI to support learning based on human co-creative interactions. For example, after the initial rapport building phase, human pairs in our study usually moved on to establish aesthetic details, such as what kind of artifact they wanted to create or what elements to use, before they moved on to discussing the technical implementation of how to create the artifact as seen in Table 2. Additionally, certain milestones, such as completing a subtask or running the code successfully if it is a coding artifact, can be an opportunity to renegotiate or confirm aesthetic or technical decisions, as shown in the excerpt in Table 3. In contrast, when students encountered an issue, they

Table 3. Excerpt 2: Learners' successful code compilation (state 5) leading to Technical (state 4) and Aesthetic Dialogue (state 1). Each dialogue state was determined automatically using the HMM presented in this work

State	Action	User	Text
5	success	**Student 1**	
4	ACK	**Student 2**	oh
4	STMNT	**Student 1**	ohh its because they are 2 second each
4	STMNT	**Student 2**	each measure isnt exactly 2 seconds
4	STMNT	**Student 2**	its a little longer i think
4	STMNT	**Student 1**	but when another is added to the 30 it becomes exactly 2 seconds longer
4	STMNT	**Student 2**	measure 15 is at 28.5 seconds
4	success	**Student 2**	
1	P	**Student 1**	we can use a combination of sounds
1	P	**Student 2**	we should just leave it at 31
1	P	**Student 2**	i think that will be fine
1	PA	**Student 1**	yeah
...		...	...
5	success	**Student 2**	
1	edit	**Student 1**	\n
1	P	**Student 2**	we should put like a synth or something to that effect
1	P	**Student 2**	add some like futuristic noises or airhorns or something

usually continued with task-based actions, and any dialogue that occurred after was usually technical in nature and directly addressed the problem, as shown in the excerpt in Table 4. This finding suggests that a co-creative AI or collaboration support system should address the need for immediate focus on debugging before attempting to resume any aesthetic conversation. On the other hand, because dialogue can be such a powerful mechanism for identifying and resolving errors, an intelligent collaboration support system could foster productive dialogue in these instances where our data suggest learners may not engage in dialogue without scaffolding. This work could improve the design of AIED systems by identifying distinct phases of co-creative collaboration and identifying productive and unproductive patterns co-creative dialogues. These findings may inform co-creative agents inspired by human co-creativity that can support the different phases of collaboration.

5 Conclusion and Future Work

Co-creativity is important for many collaborative learning contexts, and understanding dialogue around these processes is important for supporting collaborative learning. In a study with 136 high school learners in 68 pairs co-creating music through programming, we analyzed learners' dialogue moves and contextual actions with a hidden Markov model. We uncovered three distinct dialogue states that included social, aesthetic, and technical dialogue. When the students

Table 4. Excerpt 3: Learners having a compilation error (state 6) and transitioning to *Technical Dialogue* (state 4). Each dialogue state was determined automatically using the HMM presented in this work

State	Action	User	Text
6	error	**Student 1**	Unknown Identifier
3	edit	**Student 1**	;
6	error	**Student 1**	Unknown Identifier
4	NPosFdbk	**Student 1**	bruh
4	C	**Student 1**	whats the error
4	error	**Student 2**	Unknown Identifier
4	STMNT	**Student 2**	vairable or function not defined makes sense
4	STMNT	**Student 2**	variable*
3	edit	**Student 2**	\n
6	D	**Student 1**	try fixing it idk what to do
6	error	**Student 1**	Unknown Identifier
6	DA	**Student 2**	okay

successfully ran their script, they transitioned into either aesthetic or technical dialogue, suggesting a renegotiation or planning phase. When the students encountered a coding error, they almost always returned to the code editing state and rarely transitioned to a conversational state. When they did transition to a conversational state, they only transitioned to *Technical Dialogue*. These findings revealed insights into co-creativity during learning and provide initial direction for developing co-creative agents for education.

The results point to several important directions for future work. For example, it is important not only to investigate what humans do during co-creativity, but how those actions are associated with outcomes. Such a research direction will identify not only what strategies are natural, but which strategies are most effective. Another direction for continuing this research is to examine the hidden states from the perspective of each student. Understanding these states from the perspective of each partner can inform the creation of agents as partners. Moving forward, we need to add co-creative AI to the ranks of pedagogical agents and other adaptive supports that are supporting learners in increasingly complex domains. These technologies have the potential to support engagement and learning for diverse students learning challenging material.

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