

# Trends in multi-modal behavioral state transitions for learners in a robot mediated human-human collaborative activity

Mortadha Abderrahim

Supervisors: Jauwairia Nasir, Aditi Kothiyal

## MOTIVATION

When embedded in a learning activity, an Intelligent Tutoring System (ITS) must intervene based on the perceived situation to support learners and eventually increase the learning gains. The situation is often evaluated based on learners' performance. Nevertheless, in activities that are exploratory by design, such as constructivist activities, performance could be misleading. Previous studies, with a collaborative learning activity called JUSThink mediated by a robot, found that behavioral labels, obtained by a classification analysis on multi-modal behaviors, are strongly linked to learning and seem to allow for better discrimination between high and low gainers.

However, in these papers, the authors treat all multi-modal behaviors as averages and frequencies over the entire duration of the task and do not consider the temporality of the data. In this project, we investigate how these behaviors evolve throughout the activity and if differences in the groups' behaviors exist at the temporal level.

## METHODS

We use HMMs to generate multi-modal behavioral profiles for all learners together, as well as for each type of learners; and investigate how these behaviors evolve throughout the interaction. Explicitly, each hidden state corresponds to a

behavioral micro profile that teams go through during the activity, while an observation corresponds to the set of multi-modal behaviors measured at a particular time window. The following methodology was adopted for all learners together and for each type of learners separately:

1. We normalize the behavioral features and time using a min-max scaler.
2. A Principal Component Analysis (PCA) is conducted to extract the principal components.
3. We cluster the observations based on the principal components using K-means. The number of clusters is optimized based on inertia and silhouette score.
4. We perform a Kruskal-Wallis analysis on each pair of clusters to confirm that they are significantly different in multi-modal behaviors.
5. The number of states is then chosen to be the number of obtained clusters.
6. The HMM model is trained using the Expectation-Maximization algorithm on the set of teams' sequences, where each sequence consists of all the observations of a team sorted in increasing order of time.
7. The average values of the multi-modal behaviors are computed at each state, and a Kruskal-Wallis analysis is performed on

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each pair of states to identify the significantly discriminating behaviors between each pair of states.

## RESULTS

The take-aways of the temporal multi-modal behavioral analysis we carried are:

1. Temporal behavioral micro profiles are generated for all learners together and for each type of gainers to investigate how learners' multi-modal behaviors evolve. The following figure summarizes these profiles.
2. The state of non-productivity, in any case, has the highest probability to start with and to stay in. However, once out of it, this state has the lowest probability to get back to.
3. Type 1 gainers and type 2 gainers do not exclusively adopt a global exploratory approach or a local exploratory approach, respectively, as suggested by the study conducted on the multi-modal behaviors as averages and frequencies over the whole activity. Temporal data reveal that both these gainer types adopt both these approaches and oscillate between them throughout the interaction.
4. The non-gainers transition between states of non-productivity and productivity in a smoother way when it comes to normalized time. In contrast, gainers' transitions are sharper, which could be explained by an AHA! Moment (eureka effect) occurring during the transition.

Such findings could be embedded in the robot's behavior to allow for more efficient interventions in the learning activity.

