Evaluating and Predicting Collective Intelligence as a Latent Variable via Hidden Markov Models

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Abstract. Rapid growth in the reliance on teamwork in organizations, coupled with rapid advances in artificial intelligence, has fueled an increase in the use of Human Autonomy Teams (HATs) involving the collaboration of humans and agents to carry out work. Although there are many successful examples of HATs already in use, researchers and technology developers can see many more applications that would be possible if agents were better able to understand the mental states of humans to anticipate what a team is likely to do next. Creating such a capability requires creating models of team interaction that enable agents to interpret a team's current state and anticipate its future state. To build such a model, we draw on recent research on collective intelligence (CI), which has demonstrated that a team's capability to work together can be characterized by a latent collective intelligence factor, based on observations of their work across a range of tasks, and which is predictive of the team's ability to accomplish a wide range of goals in the future. We propose a method of evaluating and predicting CI by representing it as a latent variable represented by the hidden state in a Hidden Markov Model. By learning the set of hidden states representing a team's observed collaborative process behaviors over time, we can both learn information about the team's CI, predict how CI will evolve in the future, and suggest when an agent might make interventions to improve the team's performance.

Keywords: human-AI teaming · collective intelligence · human modeling

1 Introduction

During the past decade, rapid advances in computational science and artificial intelligence (AI) have given rise to *human autonomy teams* (HATs), or teams that involve at least one human working interdependently with at least one agent. While a fair amount of literature on human-computer interaction, including in HATs, has examined how humans respond to AI teammates [2], there is increasing recognition that humans and agents in HATs need to develop shared cognition to be successfully collaborative [9]. Such shared cognition requires agents to understand individual human mental states and predict their future behavior. Even further, to operate as a full collaborator in an HAT, an agent needs to understand the *team's* current collaboration state, and accurately predict future states in order to anticipate opportunities to contribute or intervene.

Recent work on collective intelligence (CI) provides a foundation for such modeling of collaborative states in HATs. Research on CI in human teams has identified a single latent statistical factor to describe the ability of a team to work together on a variety of tasks [6, 10]. To measure team CI, many existing studies use a performance-based measure calculated on the basis of teams' scores on a specific set of collective tasks. More recently, researchers have also identified observable metrics of collaborative processes that are strong predictors of CI and can be captured when teams work on almost any task, allowing unobtrusive and ongoing measurement of CI [3,6]. In addition to the quality of team collaboration, a second element that predicts future team behavior is the emotional state of individual team members. Two emotional states that have a large impact on performance are anxiety and anger. Recent work has also examined the potential benefits of anxiety [11] and anger in team performance [7].

Agents designed for collaborating in HATs must be able to judge how well a team is collaborating and anticipate what it might do next. Observable indicators of the quality of collaborative team processes that have been shown to predict collective intelligence include the appropriate team member *skill use*, the efficiency of *task strategy*, and the level of collective *effort* [6]. Interventions to improve targeted collaborative processes by automated agents can produce significant improvement [3]. In this work, we present a novel application of HMMs as a method for learning and representing collective intelligence levels based on sequences of team observations. We first collected data from a study in which human participants played a game involving a search and rescue mission over the internet with a prescripted agent. Next, we modeled collective intelligence as a latent (hidden) state related to observed collaborative process metrics through an HMM, which can help agents in HATs anticipate team behavior and perhaps decide when intervening in some way to improve team process could be helpful. After evaluating initial models trained with collaborative process metrics, we then consider how an understanding of human emotional state could further improve the ability of agents to predict the trajectory of CI in a group and inform decisions about possible interventions.

2 Method

We recruited 192 participants from Prolific.co, an online platform, to play a search and rescue game developed by [5] called Minimap. Participants were assigned to a team with an ostensible teammate (in reality a pre-programmed agent, heretofore referred to as the "teammate"), who played on the same two-dimensional map as the actual participant. Participants earned points for their team by rescuing victims that were worth either 10 or 20 points each.

2.1 Measures

Emotional States. Participants completed a brief 10-item measure of mood, similar in nature to the manner the Positive and Negative Affect Schedule is administered [8], before playing the game. *Anger* was measured as a composite of their response to the items *angry* and *mad* ($\alpha = 0.94$). *Anxiety* was measured by a composite of participants' responses to *anxious*, *nervous*, and *worried* ($\alpha = 0.90$). Finally, to facilitate comparison of different models, we also measured participants' positive emotion, using the items *happy*, *enthusiastic*, *inspired*, and *determined* ($\alpha = 0.85$).

Collaborative Process Metrics. In modeling and predicting latent CI states for human agent teams, we use the set of collaborative process metrics identified in existing research predicting collective intelligence [3, 6]. Collaborative process metrics are computed at 30-second intervals throughout a 5-minute search and rescue mission, resulting in 10 measurements. Let interval t denote minute i to $i + 30$ seconds, and $P = \{1, 2\}$ the set of teammates. (1) Team effort was calculated as the total distance traveled by all HAT members. Effort at interval $t = E^t = \sum_{p=1}^{|P|} \left[\sum_{h=i}^{i+30} \sqrt{(x_{h-1} - x_h)^2 + (y_{h-1} - y_h)^2}\right]$ where a player's position in second h is represented as (x_h, y_h). (2) Skill use was calculated as the number of messages communicated by each participant to their partner as a means of directing partner attention to tasks that were complete versus incomplete, as well as those they were uniquely equipped to handle. Skill usage at interval $t = U^t = \sum_{p=1}^{|P|} [\sum_{h=i}^{i+30}$ number of messages sent by player p via chat at second h]. (3) Task Strategy, or the efficiency of the team's coordination, is defined as the rate of progress throughout the task, here calculated as the number of victims triaged at each point in time. Task strategy at interval $t = S^t = \sum_{p=1}^{|P|} \sum_{h=i}^{i+30}$ number of victims triaged by player p at second h.

3 Analytic Approach

Hidden Markov Models. Hidden Markov Models (HMMs) are a formulation for learning probabilistic models of linear sequences. There are defined by state space $X = \{x_1, x_2, .., x_N\}$ and observation space $O = \{o_1, o_2, .., o_K\}$. $A = X \times X$ is a transition probability from hidden state x_i to hidden state x_j. In our HMM formulation, we consider transitions between hidden states as occurring between timesteps. $A_{ij} = \mathbb{P}(x_{t+1} = x_j | x_t = x_i)$. $B = X \times O$ is a transition probability from hidden state x_i to observation o_k. $B_{ik} = \mathbb{P}(o_t = o_k | x_t = x_i)$. p_0 is an initial probability distribution over hidden states.

State Featurization. In order to ensure rapid online computation of the HMM, we reduce the continuous observation space by discretizing the process metrics. The timestep t corresponds to data collected at the corresponding interval. The process metric value is converted to a binary value: 0 if the value is below the mean, and 1 if the value is greater than or equal to the mean. That is, the binarized effort $\hat{E}_k^t$ at time t for team k is defined as 0 if the effort is less than the mean across teams and 1 if the effort is greater than or equal to the mean across teams. Binarized strategy, $\hat{U_k^t}$, and skill, $\hat{S_k^t}$, are defined similarly. An observation at timestep t in a sequence is the condition of the team's effort, skill, and strategy at t. We lastly redefine each observation to include information from the previous timestep. The inclusion of the previous timestep in the HMM observation allows the HMM to reason about how the team's effort, skill, and strategy at timestep t may be influenced by its condition not only at time $t-1$, but also at time $t-2$. Each observation at time t, $o_t = (s_t, s_{t-1})$ is a tuple of the process metrics in the current time step and in the previous time step. An observation $o_t \in O \in \{0,1\}^6$ is represented as a six-length vector: [effort at time t, skill use at time t, task strategy at time t, effort at time $t-1$, skill use at time $t-1$, workload progress at time $t-1$] = $[\hat{E}^t, \hat{U}^t, \hat{S}^t, \hat{E}^{t-1}, \hat{U}^{t-1}, \hat{S}^{t-1}]$. s_t is the current-time component of observation o_t: $s_t = [\hat{E}^t, \hat{U}^t, \hat{S}^t]$. s_{t-1} is the previous-time component of observation o_t: $s_{t-1} = [\hat{E}^{t-1}, \hat{U}^{t-1}, \hat{S}^{t-1}]$.

Collective Intelligence Modeling via HMM. Teams transition between levels of collective intelligence, which is not observed. We model CI using a latent variable whose dynamics is learned through the HMM. The transition matrices we learn through Baum-Welch [4] inform how teams transition between levels of collective intelligence based on their observations, as well as what observed process metrics are likely given teams of a certain collective intelligence level. The number of CI levels is also a tunable hyperparameter: the number of discrete hidden states in the HMM. The number of hidden states in our HMM is $N = 6$, which we selected by maximizing the likelihood of observation sequences, searching over $N \in \{1, 3, 6, 9\}$ hidden states. We also apply the Viterbi algorithm [1] to identify the most likely sequence of hidden CI states for each team based on their average observation value. In order to try to better understand the semantic meaning of the latent states, we propose to understand them by way of ordering the values of the probable emissions from each latent state. This allows us to order hidden states, mapping $f : \{x_1, ..., x_6\} \to \{c_{(1)}, ..., c_{(6)}\}$ from low collective intelligence of the team, $c_{(1)}$ to high collective intelligence, $c_{(6)}$. For online prediction, we use the state transition matrix to predict the level of collective intelligence at the next minute for a team.

3.1 Online Prediction of Process Metrics

Let H_J represent an HMM learned through Baum-Welch [4] over a set J of team observation sequences. The learned state transition probabilities, A_J, and emission probabilities, O_J, are matrices. The agent observes a given team briefly until timestep m, gathering a sequence of process metric observations up to time m: $\{o_1 = (s_1^1, s_1^0), ..., o_m = (s_t^m, s_t^{t-1})\}$ (Line 1 of Algorithm 1). The agent's objective is to predict process metrics for the given team online at each subsequent timestep until the end of the mission, T. The Viterbi algorithm [1] is run over the sequence of observations up to t to compute the maximum likelihood sequence of hidden states $\{c_1, ..., c_t\}$ that generate $\{o_1, ..., o_t\}$ (Line 3 of Algorithm 1). Prediction of process metrics is made by first determining the most likely hidden CI state in the next timestep, $\hat{c}_{t+1}$ (Line 4 of Algorithm 1). Next, the observations

Algorithm 1 Online Process Metric Prediction

Require: Set of Team Observations J, where Team $j \in J$
Require: HMM $\mathcal{H}_J = (A_J, B_J)$
1: $\{o_1 = (s_1^1, s_1^0), ..., o_m = (s_t^m, s_t^{t-1})\} \leftarrow$ sequence of process metric observations up to time m
2: **for** $t = m, ..., T$ **do**
3: $\quad \{c_1, ..., c_t\} \leftarrow VITERBI(\mathcal{H}_J, \{o_1, ..., o_t\})$
4: $\quad \hat{c}_{t+1} \leftarrow \arg\max_{c_i} \mathbb{P}(c_i|c_t) = \arg\max_{c_i} A_J(c_i|c_t)$
5: $\quad$ Set $Q \leftarrow \{o_i = (s_i^r, s_i^{r-1}) \in O : s_i^{r-1} = s_t^t\}$
6: $\quad \hat{s}_{t+1}^r \leftarrow \arg\max_{o_i \in Q} \frac{\mathbb{P}(o_i|c_{t+1})}{\sum_{o_k \in Q} \mathbb{P}(o_k|c_{t+1})} = \arg\max_{o_i \in Q} \frac{B_J(o_i|c_{t+1})}{\sum_{o_k \in Q} B_J(o_k|c_{t+1})}$
7: $\quad \hat{o}_{t+1} \leftarrow (\hat{s}_{t+1}^r, s_t^t)$
8: **end for**

that can be emitted from the hidden state are pruned, removing the candidate observations where the process metrics in the previous timestep do not match the process metrics in the current timestep (Line 5 of Algorithm 1). The probabilities of each observation in the pruned set are normalized. The maximum probability observation is selected and serves as the predicted observation, $\hat{o}_{t+1}$ (Line 6 of Algorithm 1). The $t+1$ component of the selected observation, $\hat{s}_{t+1}^r$, is the predicted set of process metrics for the team at the next timestep (Line 7 of Algorithm 1).

4 Results

Evaluation of an Aggregate CI-HMM. Starting with our initial 192 trials of the human agent team, we split the data into a training set (168 trials) and a holdout test set (24 trials) to develop our model. First, we applied the HMM-based algorithm to model the progression of collective intelligence states of human-agent teams throughout the search and rescue mission. We trained a single HMM across a time-series of six intervals, estimating six hidden states (one at each time stage) during the trials in the training set. The number of hidden states represents the granularity by which the algorithm can model collective intelligence and be tuned manually based on the observation of the outputs. We will refer to this model as CI-HMM$_{aggregate}$, since it is just a single HMM estimating CI on all teams. We apply the Viterbi algorithm [1], a standard dynamic programming approach to calculate the maximum a posteriori probability estimate for the most likely hidden state sequence corresponding to a sequence of observations. This allows us to infer the level of collective intelligence of each team at each time step in the trial. In Figure 1, we visualize the development of CI over time for two teams drawn from the training set.

One way in which a model such as CI-HMM$_{aggregate}$ can be useful is for capturing what the model estimates to be a team's current CI state, but also what is likely to happen in the next time step. For instance, an autonomous teammate in team 1 might observe the rapid decline from where the team began

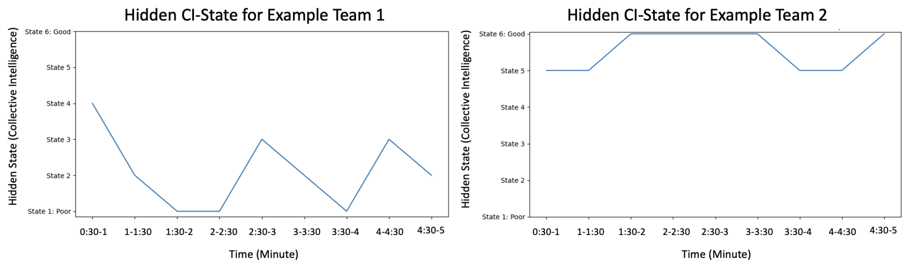

Fig. 1: The CI-HMM algorithm infers the team's collective intelligence level at each timestep. We visualize the progression of CI for two teams drawn from the training set. Based on the CI-HMM$_{aggregate}$ model we see that Team 1 (left) experiences some fluctuation but mostly lower levels of CI, while Team 2 (right) maintains high CI.

and look for opportunities to improve behavior, while in team 2 an autonomous teammate would observe a team achieving a consistently high level of CI. We can also interpret the dynamics of collective intelligence of the team from one state to the next from the state transition matrix for the CI-HMM$_{aggregate}$ model (Figure 2). The $(row_i, column_j)^{th}$ entries of the transition matrix in Figure 2 refer to the probability of transitioning from state i to state j, where darker red indicates a higher likelihood that a team in the CI state indicated by the value on the x-axis in one time period will be in the CI state corresponding to the value on the y-axis in the next time period. We can see that teams exhibiting poor collective intelligence states, being in State 1 or State 2, are likely to remain in those states. However, as teams begin to show higher collective intelligence, such as in State 3 and 4, they have higher probabilities of transitioning to even higher CI states, exhibiting increased CI. Teams exhibiting extremely high values of CI in State 6, are likely to maintain high CI in their collaboration, represented by a high likelihood of staying in state 6.

One way to evaluate the accuracy of our model in estimating CI at different timesteps is to evaluate how well the (latent) learned CI state predicts the observed variables of effort, skill use, and task strategy. Algorithm 1 proposes an online inference approach for predicting at timestep t a given team's collaborative process behaviors (effort, task strategy, skill use) for the next timestep $t+1$. The algorithm predicts the most likely next-timestep $t+1$ observation, with the constraint that model's prediction of its own prior timestep matches the current observation. Based on Algorithm 1, $\hat{o}_{t+1} \leftarrow (\hat{s}^r_{t+1}, s^t_t)$ is the predicted next observation, and $\hat{s}^r_{t+1}$ is the set of three predicted process metrics (effort, skill use, and task strategy) in the next timestep $t+1$. Let s^t_{t+1} represent the true metrics of the observed process in the next timestep. Let $s^t_{t+1}(i)$ equal the i-th value in the sequence of process metrics. For example, when $i = 1$, $s^t_{t+1}(i) = s^t_{t+1}(1)$ refers to effort: the first process metric in the sequence. We compute L1-loss for predicted observations on a given team. We simulate online predictions by using data up

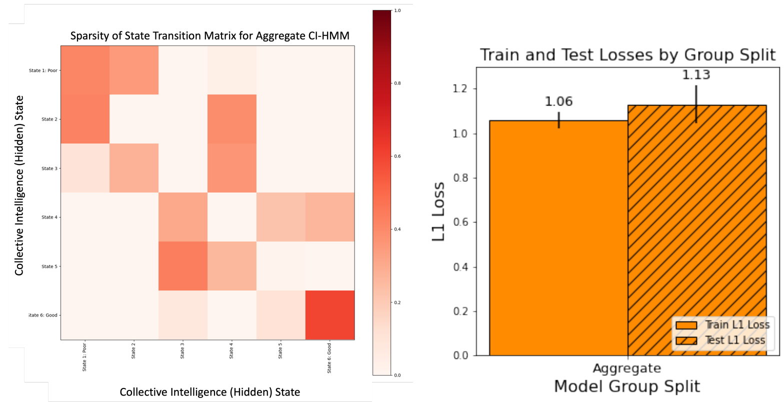

Fig. 2: **Left.** State Transition Matrix for CI-HMM$_{aggregate}$ Model. The transition matrix provides insight into the dynamics of the latent collective intelligence variable learned by the HMM. The $(row_i, column_j)^{th}$ entries of the transition matrix refer to the probability of transitioning from state i to state j. Extremely poor CI states (State 1 and 2) and extremely high CI states (State 6) have high likelihood of transitioning back to themselves, indicating that teams with extreme CI are likely to maintain those levels. Teams in the intermediate states (States 3, 4, and 5) have a higher spread in their probable transitions, and thus more uncertainty in how their CI will evolve. **Right.** The CI-HMM$_{aggregate}$ model achieves L1-loss of approximately 1, on the training set. The model achieves comparable, but slightly higher, loss on the holdout set.

to time t to predict the process metrics $\hat{s}^r_{t+1}$ at the next timestep $t+1$. Then, we continue using data up to time $t+1$, to predict observations for $t+2$, and so on. The loss is computed from the second timestep, as the model must receive observations in order to begin predicting next-step observations for a given team. For each team, we average the loss over each timestep in order to compute the final per-team L1-loss. $L_1 \in [0, 3]$. The maximum L1-loss is 3, since the accuracy of predicting each collaborative process metric is captured as binary variables (i.e. $1 =$ incorrect, $0 =$ correct), and thus the minimum loss is 0, if the model makes no mistakes in its prediction. $L_1(\hat{\mathbf{s}}, \mathbf{s}) = \frac{1}{T-1}\sum_{t=1}^{T}\left[\sum_{i=2}^{3}|\hat{s}^r_{t+1}(i) - s^t_{t+1}(i)|\right]$. L1 loss for CI-HMM$_{aggregate}$ is calculated on the teams in the training set and separately on teams in the holdout test set.

The CI-HMM$_{aggregate}$ on average makes one mistake in its prediction of the team's process metric observations, predicting one of effort, skill use, or task strategy incorrectly, but the remaining two correctly, overall supporting the utility of the model in predicting future collaborative behavior (see Figure 2 Right). This evaluation of CI-HMM$_{aggregate}$ demonstrates the use of Hidden Markov Models as a candidate approach to modeling collective intelligence, a latent factor that characterizes the quality of HATs and predicts its development over time.

Affect-Informed CI-HMM. Next, we explore how we might improve the accuracy of our HMM approach to predicting future CI states built on an aggregate model of human behavior by developing affect-informed HMM ensembles. Teams in training and holdout sets are first divided into four groups, based on a mean-split in participants self-reported levels of anger and anxiety: Group 1 = $anger \geq mean$, $anxiety \geq mean$, Group 2 = $anger < mean$, $anxiety \geq mean$, Group 3 = $anger \geq mean$, $anxiety < mean$, Group 4 = $anger < mean$, $anxiety < mean$. We then trained four hidden Markov models, one for each anger-anxiety group. We refer to this ensemble model as CI-HMM$_{anger-anxiety}$. As with the aggregate model, the models are also trained with six hidden states. Predictions for a given team are made by the model corresponding to the anger-anxiety affect group corresponding to the team's affective state. Using the learned latent variable dynamics, we again make predictions about the observed collaborative process metrics of the HATs, and directly evaluate the accuracy of those predictions by computing the L1-loss, as we did with the aggregate model. The L1-loss for CI-HMM$_{anger-anxiety}$ is compared to the model trained on the data in aggregate CI-HMM$_{aggregate}$ (see anger-anxiety and aggregate bars of Figure 3).

As we see in Figure 3, the CI-HMM$_{anger-anxiety}$ on average makes less than one mistake in its prediction of the team's process metric observations. The model achieves an average L1-loss of 0.84 on the teams in the training set and an average L1-loss of 0.91 on the teams in the training set, both of which indicate the model is more accurate than the loss achieved by the aggregate model. The results demonstrate that when developing a model that predicts the observed behavior of human-agent teams, constructing more granular models that utilize additional information, such as the emotional state of team members, enables models to make better predictions of future behavior. The ensemble method is a candidate way of using affect to additionally parameterize the model.

Since the four affect groups contain a subset of teams, resulting in smaller datasets for each HMM, we also consider the possibility that improvements in model performance may be a result of overfitting to a smaller dataset. Thus, we also compare anger- and anxiety-based groupings with random splits of the data. Furthermore, we compare the anger-anxiety model CI-HMM$_{anger-anxiety}$ with ensemble HMMs constructed using only information about anxiety *or* anger variable. CI-HMM$_{anger-anxiety}$ is an ensemble of 4 groups. The anger-only model CI-HMM$_{anger}$ is an ensemble of 2 groups, based on a mean split (i.e. high anger vs. lower anger HATs). The same is true for the anxiety-only criterion. We also created another split based on positive emotion scores to provide another comparison. For the random model, teams are assigned to one of two groups, resulting in a 2-HMM ensemble. The aggregate model remains CI-HMM$_{aggregate}$. L1-loss is computed for the model trained under each affect-based criterion and is shown in Figure 3.

As we observe in Figure 3, there is variation in the L1-Loss scores across the models generated by the different approaches to dividing the sample into groups to train the models. To evaluate the magnitude of the differences, we

Fig. 3: The anger-anxiety model CI-HMM$_{anger-anxiety}$ achieves lower loss than the random model, and models trained using the data split on a single emotion. The random model does not perform as well as the models trained using the data split on a single emotion, but does outperform the aggregate model. The positive emotion model exhibits lower test loss than training loss, which may be due to lower variation in the test set. Bars represent std. error over participants.

Table 1: Pairwise Comparisons of Affect-Informed Training Models versus Aggregate Model.

Constrast	M_{diff}	***se***	***p***	**95% LLCI**	**95 % ULCI**
Anger-Anxiety vs. Agg	-0.22	0.06	< 0.001	-0.33	-0.11
Anger vs. Agg	-0.07	0.06	0.20	-0.18	0.04
Anxiety vs. Agg	-0.14	0.05	0.009	-0.25	-0.04
Positive vs. Agg	0.002	0.05	0.97	-0.10	0.11
Random vs. Agg	-0.05	0.05	0.36	-0.15	0.05

conducted a Repeated Measures ANOVA to compare L1-loss values across the different training sets, and we observed a significant effect: $F(_{5,163}) = 5.32$, $p < 0.001$, $np^2 = 0.14$, Cohen's $d = 0.81$. To more specifically evaluate where we see the biggest gains in accuracy, we compared each of the affect-based group split training models with the aggregate model. As shown in Table 1, the model based on the combined anger-anxiety split was significantly more accurate (as indicated by lower L1 loss) than the aggregate model. In addition, the group split based on anxiety only was also significantly more accurate than the aggregate model, while the group split based on anger only also showed improvement, but the difference compared to the aggregate model was not statistically significant.

Overall, these findings suggest that accounting for anger and anxiety in an HMM model is a candidate extension of HMMs which may produce more accurate predictions compared to models that do not account for these emotional states. In the current research, our HATs consisted of pre-scripted agents as teammates collaborating with one human participant. Our agent did not attempt to adapt its behavior in response to predicted team collective intelligence levels. However, we see several opportunities to leverage our CI models to inform agent behavior to make them helpful teammates in the future.

5 Conclusion

We propose a method for modeling and predicting collective intelligence of a team by representing CI as a latent variable whose evolution we model by using a Hidden Markov Model. The observations in the model are the team's effort, use of task-related skills, and the progress throughout the task. The hidden states represent levels of collective intelligence. We show that by learning the set of hidden states that represent the collaborative behaviors of a team over time, we can both learn information about the collective intelligence of the team and predict how the collective intelligence will evolve in the future, allowing agents to be better collaborators in HATs and possibly even make interventions to improve team performance.

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