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Abstract	Better conversational alignment can lead to shared understanding, changed beliefs, and increased rapport. We investigate the relationship in peer tutoring of convergence, interpersonal rapport, and student learning. We develop an approach for computational modeling of convergence by accounting for the horizontal richness and time-based dependencies that arise in non-stationary and noisy longitudinal interaction streams. Our results, which illustrate that rapport as well as convergence are significantly correlated with learning gains, provide guidelines for development of peer tutoring agents that can increase learning gains through subtle changes to improve tutor-tutee alignment.

Fine-Grained Analyses of Interpersonal Processes and Their Effect on Learning

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Abstract. Better conversational alignment can lead to shared understanding, changed beliefs, and increased rapport. We investigate the relationship in peer tutoring of convergence, interpersonal rapport, and student learning. We develop an approach for computational modeling of convergence by accounting for the horizontal richness and time-based dependencies that arise in non-stationary and noisy longitudinal interaction streams. Our results, which illustrate that rapport as well as convergence are significantly correlated with learning gains, provide guidelines for development of peer tutoring agents that can increase learning gains through subtle changes to improve tutor-tutee alignment.

1 Introduction

Accommodation [5], where participants in a conversation adapt (tendency to become similar over time) or differentiate (tendency to exaggerate their differences) their behaviors with time, has been shown to have powerful effects on collaboration quality [6], learning gain and task success [4], by the virtue of decreasing misunderstandings, attaining goals faster, building rapport and affiliation. In this work, we examine the nature of accommodation in dyadic peer tutoring conversations over time as a part of our research program on the social infrastructure of learning, with an eye towards implementing more effective intelligent peer tutoring systems. Following studies of joint action [9] that challenge the traditional assumption in cognitive psychology that higher-level cognitive processes can best be understood by investigating individual minds in isolation, in the current work the dyad is the unit of analysis. To fully understand what leads conversational partners to converge (adapt) or diverge (differentiate) in their behaviors over time, we therefore study the dynamics of interaction at a fine (30 second interaction segment) level of granularity to operationalize a metric for convergence, in contrast to prior work that has utilized coarse-grained division of the interaction into two or three sub-sessions to investigate effects of aggregated behavioral measures on longitudinal changes in accommodation. Moreover, the approach to accommodation in prior collaborative learning literature [7] has focused on joint construction activities that move the group towards problem solving goals and hence lead to members exhibiting knowledge convergence. Here we add an interactional perspective to the methodological toolkit for examining the effect of accommodation on learning.

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Study Context: We collected reciprocal peer tutoring data for 12 dyads of American English-speaking high school students (6 of whom were already friends), who tutored one another on procedural and conceptual aspects of an algebra topic, for 5 hourly sessions over as many weeks. Each session comprised two tutoring sessions (with role reversal between the tutor and tutee) sandwiched between three short social sessions. For the purpose of the current study, we selected a fairly balanced convenience sample of 9 dyadic conversational sessions (in terms of a)#friend versus #stranger dyads, b)session#).

2 Methodology

2.1 Operationalizing Features

Motivated by prior work [5] that has included speech rate, overlap (simultaneous speech frequency), laughing and smiling behaviors, we compute the following automatically harvestable features for each speaker for every consecutive 30 second segment from our peer tutoring conversations that have been transcribed and segmented into syntactic clauses: a)# words spoken, b)message density, which is the #independent clauses uttered, divided by the time difference between the first and last utterance, c)content density, which is the #characters spoken divided by the #independent clauses uttered, d)#overlaps, and e)#laughter expressions.

2.2 Operationalizing Convergence

We a)compute the difference in raw behavioral feature values for partner i and partner j engaged in the dyadic conversation for every 30 second slice (call this differenced series y), b)formulate the autoregressive model as $\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + ... + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t$, where α (constant term) is the drift or change of the average value of the stochastic process, βt is the deterministic time trend and p is the lag length (which is quantified as 3, similar to the prior influence computation), c)test the presence of unit-root in this time series framework using the Augmented Dickey Fuller (ADF) test at 1% LOS, following proposition 5 [2]. Intuitively, if the ADF test statistic is significant, we reject the null hypothesis that the differenced behavioral time series has a unit root and accept the alternative hypothesis that the variable was generated by a stationary process, which is an evidence for convergence (speakers become more similar to each other over the course of the entire conversation). Alternately, if ADF test statistic is not significant, we accept the null hypothesis of the presence of a unit root, in turn indicating that the process (change) is not stationary and the definition of convergence is violated. Thus, by moving beyond traditional Pearson correlation approaches between time and the absolute difference between a speaker and partner's behavioral feature value at an adjacent turn, we prevent ourselves from making falsifying assumptions about behavioral independence in the dyadic interaction. Finally, to construct a composite score for Convergence strength, we firstly scale the ADF test statistic for Convergence (call this x) along each feature dimension, between 0 and 1 using the formula $(x - minimum(x))/(maximum(x) - minimum(x))$, with an intuition to provide transparency and comparability. Secondly, in weighting across features, different feature dimensions are equally weighted (averaged).

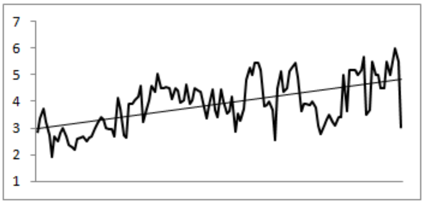

Fig. 1. Trend of increasing rapport for all dyadic sessions averaged over each 30 sec time slice. X axis: time on 30 second scale. Y axis: thin slice rapport rating (1-7).

2.3 Outcome Measures

Learning Gains: Normalized learning gain for each individual in the dyad was computed using the formula: (Post-assessment - Pre-assessment)/(100% - Pre-assessment), while the composite learning gain for a dyad was calculated using the average of the individual learning gains. For the 9 dyadic sessions used in the current analysis, a paired t-test reveals trend towards significant difference in the pre-test and post-test scores (t = -1.8439, df = 17, p-value = 0.0827^{+})

Thin Slice Rapport: We employ "thin-slice" [1] judgments of interpersonal rapport for our work, where two annotators rate every 30 second video segment of the peer tutoring sessions using an 7 point likert scale, with the segments presented to the annotators in random order. We also employed an eye-tracker to assess which aspects of behavior contributed to the annotator judgments (Oertel et al., in preparation). The consensual accuracy of thin-slice judgments (composite ratings), computed using average measures for intra class correlations (ICC), is greater than 0.7 for all the sessions used in our study.

3 Results and Discussion

We compute Pearson correlation to find relationships between our joint constructs and the outcome measures described above, while testing significance of the correlation via two tailed t-test. Results reveal that higher convergence strength is positively associated with higher average learning gains for the dyadic sessions in our study (r=0.658, p-value=0.05), substantiating convergence as having a positive effect on learning. This leads us to believe that a virtual peer tutor that both mimics its human partner and evokes mimicry may be a more effective learning partner.

If students are to critique the ideas of their peers, offer tentative ideas and interpret others' critiques as valuable, they need to trust each other and feel a sense of warmth and belonging before they will engage willfully in collaboration and treat peer learning as a valuable experience. [8] emphasize that the social phenomenon of rapport builds up over time. Such long term assessment of rapport [3] has already been shown to have enhanced math performance. Figure 1 shows a linearly increasing trend for the average value of thin-slice rapport, for each 30 second slice of our hourly dyadic interaction data. It is thus legitimate to hypothesize that the deepening rapport in later sub-sessions might be more connected to greater learning. Therefore, to assess the relationship between perceived rapport (thin slice annotation) and learning gains, we divide each dyadic session into 5 equal sub-sessions ($\approx$ 10.2 minutes each) and compute Pearson correlation for the averaged perceived ratings for each sub-session. Indeed, our results reveal that perceived rapport for only the fourth sub-session from the start ($\approx$ 30th-40th minute) exhibits a trending positive correlation with learning gains (r=0.64, p-value=0.06). This roughly corresponds to the time where the reciprocal tutoring is approaching an end in the session (the 5th segment is a final social session).

4 Conclusion

These results give us a roadmap for integrating convergence into our dialog-based reciprocal peer tutoring virtual agent, in such a way as to detect cues of decreasing alignment between the tutor and student in real time, strategically scaffold instruction by regulating the tutee's problem solving pace and adjusting the balance between message density and content density, improve tutor-tutee alignment by entraining on overlapping behavior to signal acknowledgment or understanding of what the tutee says, and predict learning outcomes based on current level of convergence in the tutor-tutee interaction, so as to provide early scaffolding as opposed to delayed scaffolding at the end of the entire interaction. While some prior literature has suggested a cognitive explanation for the impact of convergence on learning, such that it indexes greater shared understanding, and hence leads to improved learning, other literature suggests that greater similarity is an index of increased interpersonal rapport which, in turn, leads to greater willingness to examine misconceptions, and hence to improved learning. Disambiguating these mechanisms remains a topic for future work.

References

1. Ambady, N., Rosenthal, R.: Thin slices of expressive behavior as predictors of interpersonal consequences: A meta-analysis. Psychological Bulletin (1992)
2. Bernard, A., Durlauf, S.: Interpreting tests of the convergence hypothesis. Journal of Econometrics **71**, 161–173 (1996)

3. Cassell, J., Gill, A.J., Tepper, P.A.: Coordination in conversation and rapport. In: Proceedings of the Workshop on Embodied Language Processing, pp. 41–50. Association for Computational Linguistics (June 2007)
4. Friedberg, H., Litman, D.J., Paletz, S.B.: Lexical entrainment and success in student engineering groups. In: SLT, pp. 404–409 (2012)
5. Giles, H., Coupland, N., Coupland, J.: Accommodation theory: communication, context, and consequence, pp. 1–68. Developments in Applied Sociolinguistics, Contexts of Accommodation (1991)
6. Schneider, B., Pea, R.: The Effect of Mutual Gaze Perception on Students' Verbal Coordination. In: Proceedings of the 7th International Conference on Educational Data Mining (EDM 2014), pp. 138–144 (2014)
7. Teasley, S.D., Fischer, F., Weinberger, A., Stegmann, K., Dillenbourg, P., Kapur, M., Chi, M.: Cognitive convergence in collaborative learning. Proceedings of the ISLS **3**, 360–367 (2008)
8. Zhao, Ran, Papangelis, Alexandros, Cassell, Justine: Towards a Dyadic Computational Model of Rapport Management for Human-Virtual Agent Interaction. In: Bickmore, Timothy, Marsella, Stacy, Sidner, Candace (eds.) IVA 2014. LNCS, vol. 8637, pp. 514–527. Springer, Heidelberg (2014)
9. Sebanz, N., Bekkering, H., Knoblich, G.: Joint action: bodies and minds moving together. Trends in cognitive sciences **10**(2), 70–76 (2006)