Interpreting Probabilistic Models of Social Group Interactions in Meetings

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A major challenge in Computational Social Science [1–3] consists in modelling and explaining the temporal dynamics of human communications. Understanding small group interactions can help shed light on sociological and social psychological questions relating to human communications. Which interactions lead to more successful communication or productive meetings? How can we infer temporal models of interactions? How can we explain what these temporal interaction really mean? Current statistical analysis techniques do not explore the full temporal aspect of time-series data generated by interactive systems, and certainly they do not address complex queries involving temporal dependencies.

In [4] we investigated discrete-time Markov chains with rewards for human-human interactions in social group meetings. We identified various queries predicating over the temporal interactions between different roles, the impact of different sentiments in interactions or in decision making, causality between particular states, etc.. We used probabilistic computational tree logic with rewards [5, 6], which is a type of probabilistic temporal logic variant, to formalize these queries. We then used the PRISM tool [5], a symbolic probabilistic model checker, to analyse the formal queries and thus interpret the temporal interaction models. Probabilistic model checking [6] is a well-established verification technique that explores all possible states of a Markov model in a systematic manner and computes the probability of a temporal property of the Markov model to hold.

We analysed a dataset taken from a standard corpus of scenario and non-scenario meetings, the Augmented Multimodal Interaction (AMI) meeting corpus [7]. Each meeting group in the corpus consists of four people, and the group completes a sequence of four meetings where they are role-playing as members of a company that is designing and marketing a product. Each person in the group is assigned one of the fours roles: Project Manager, Marketing Expert, User Interface Designer, and Industrial Designer. Despite the artificial scenario and the assigned roles, the speech is spontaneous and unscripted, and each group is free to make decisions as they see fit.

Our main contribution in [4] was demonstrating the expressiveness of probabilistic temporal logic properties for formalising various probabilistic and reward-based queries about group interactions in meetings and then analysed them with the probabilistic model checker PRISM. Some of the queries analysed did not need probabilistic temporal logic properties to be asked on the initial data set. However all queries involving bounded time steps and in particular the steady-state properties cannot be expressed other way than as temporal property formulae. One subset of the queries validated our behavioral model as their results confirmed expected interactions, while another subset highlighted novel insight into the AMI dataset we analysed.

In [8] we analysed the Markov model inferred from state transitions counts in the data. For future work we will consider admixture models inferred from the data using classical Expectation-Maximisation algorithms [9] where each component (associated with a latent variable) in the admixture model models a particular pattern of behaviour. The challenge will be in identifying suitable classes of probabilistic temporal properties for characterising and discriminating between the patterns for the particular type of interaction data contained in the AIM corpus. In future work, we will also experiment with alternative state representations, particularly representations that are less specific to the AMI corpus scenario and its roles. For example, we will include demographic characteristics such as gender and the native language of the speaker. We will also apply this representation and methodology to other group interaction datasets such as the ELEA corpus [10].

References

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