Task-Oriented Dialog Agents Using Memory-Networks and Ensemble Learning
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Abstract

Task-oriented dialog agents are ever more relevant systems to engage with an user through voice or text natural language input to fulfill domain-specific tasks. Recently, neural based approaches are gaining popularity over traditional rule based systems thanks to promising results cited{hcn} in standard tasks cited{babi}. While most modern approaches follow an architecture based on a pipeline of components cited{pomdp, rasa, hcn}, there is still much room for design in these architectures, and many promising models that can be incorporated in the pipeline. One such pipeline architecture is the Hybrid Code Networks (HCN) cited{hcn}, which uses example human-bot conversations to train an LSTM cited{lstm} to track conversation state and predict the next action. Inspired by the promising results from cited{babi}, this thesis focuses on building an architecture similar to HCN but improving the action policy by using a Memory Network instead of an LSTM and then using an ensemble that combines both the Memory Network and the LSTM from HCN into a single action policy. By combining the benefits of the HCN architecture with the Memory Network and the ensemble policy, the model achieves perfect scores in bAbI task 5, almost 4% accuracy improvement over cited{babi} and almost 8% higher than the LSTM action policy from cited{hcn}, while the ensemble policy by itself proved responsible for more than 1% improvement over the HCN architecture on bAbI task 6. The final results prove not only the advantages of a Memory Network over an LSTM for some scenarios, but more importantly, the fact that both policies complement each other and benefit of working together, even when trained with the same data.