Sequential Decision Making in Artificial Musical Intelligence

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Abstract

My main research motivation is to develop complete autonomous agents that interact with people socially. For an agent to be social with respect to humans, it needs to be able to parse and process the human cultural experience. That in itself gives rise to many fascinating learning problems. Music, as a general target domain, serves as an excellent testbed for these research ideas. Musical skills involve extremely advanced knowledge representation and problem solving tools. Creating agents that can interact richly with people in the music domain is a challenge that will advance social agents research and contribute important and broadly applicable AI knowledge. This belief is fueled not just by my background in computer science and artificial intelligence, but also by my deep passion for music as well as my extensive musical training. One key aspect of musical intelligence which hasn't been sufficiently studied is that of sequential decision-making. My thesis strives to answer the following question: **How can a sequential decision making perspective guide us in the creation of better music agents, and social agents in general?** More specifically, this thesis focuses on two aspects of musical intelligence: music recommendation and multiagent interaction in the context of music.

Introduction

In recent years, the application of algorithmic tools in cultural domains has become increasingly prevalent. Focusing on music, computers have accompanied both the creation and the analysis of music almost since they first came into existence. Over the last decade, many researchers have applied computational tools to carry out tasks such as genre identification (Burred and Lerch 2003; McKay and Fujinaga 2004), music summarization (Dubnov, McAdams, and Reynolds 2006), music database querying (Lu et al. 2001) and melodic segmentation (Pearce, Müllensiefen, and Wiggins 2008). My main long-term goal is the creation of large-scale autonomous musical agents, i.e., computational entities capable of high level musical reasoning. To achieve this goal, several crucial sub-problems must be dealt with. A key insight, which has not been sufficiently studied, is the roll of sequential decision-making and reasoning in the development of such musical agents. In my thesis, I am exploring how several key aspects of musical intelligence can be properly framed as sequential decision-making problems, and propose novel solutions that bring us closer to the creation of such complete musical agents.

Completed Work

As part of my current research toward the goal of large scale autonomous music agents, I have tackled several closely-related issues. I will now briefly survey two of them, which I consider completed work.

Autonomous Playlist Generation through Reinforcement Learning

A specific domain in which intelligent agents, music analysis, and preference elicitation connect is in the construction of musical recommender systems. To the best of my knowledge, most of these systems focus on predicting the preference of individual songs independently based on a learned model of a listener (see (Barrington, Oda, and Lanckriet 2009; Kreitz and Niemela 2010), for example). However, a relatively well known fact in the subfield of cognitive neuroscience which studies music cognition is that music is experienced in temporal context and in sequence. In two recent publications (Liebman, Saar-Tsechansky, and Stone 2015; Liebman et al. 2017), we focus on learning to adaptively build music playlists based on user interaction. We employ a reinforcement learning approach to music recommendation that does not recommend songs individually but rather song sequences based on a learned model of preferences for both individual songs and song transitions. To reduce exploration time, the algorithm actively initializes its model based on user feedback. The resulting agent has been tested on human participants and been shown to increase the expected enjoyment of listeners from the selected song sequence, compared to a greedy approach that only tries to select individual songs.

Learning to Model Responses to Musical Stimuli and Musical Preferences

One of the key issues in building a successful social agent with respect to music is its ability to model and predict human responses to musical cues. This motivation is central to a current research effort, in which we study how different music stimuli affect human decision making. To this end, we use the Drift-Diffusion model, a stochastic sequential model which decomposes observed decision behaviors into its underlying decision components. In our experiments, as an example "emotional" task, participants were requested to classify words as happy or sad while either happy or sad music was played. Results indicated that music affected people's a-priori tendency to classify words as happy or sad (Liebman, Stone, and White 2015). However, given a task of accepting or rejecting gambles based on the win-loss ratio, a different effect altogether was observed. Participants who listened to happy music were faster to make decisions, and the decisions they made were markedly better, than people who listened to music categorized as sad. Further analysis indicates there is a correlation between tempo and the speed and quality of decision making in this setting (Liebman, Stone, and White 2016).

Ongoing Work

Tracking Changes in Preference via Continual Model Update

The reality of music recommendation over time is such that tastes and fashion change, sometimes abruptly, both for individuals and collectively. Generally speaking, it is easy to see why such a shift in the underlying data structure constitutes a significant challenge to learning systems. In a forthcoming conference submission, we consider the problem of how to generically and adaptively adjust models to mitigate the risks of underlying changes in data. We refer to this challenge as *model retraining*, or model management. In our paper we propose a novel *reinforcement learning* (RL) approach, framing the model retraining problem as a sequential decision making task, and harnessing ideas from the RL literature to learn a robust policy for model update. We study our approach in multiple domains, both music and non-music related, and who it yields very promising results.

Multiagent Cooperation and Joint Improvisation

My work on modeling how human decision-making is affected by different kinds of music begs a follow-up question: can agents utilize their models of people's behavior in a musical context to improve their interactions with people in musical-influenced environments? This question is by no means trivial. Simply put, it is not enough to learn a model of people's behavior - it is crucial to learn strategies for how to act with respect to that information, under the assumption that the agent's actions also affect people's perception and behavior. This problem breaks down to two different aspects, then - first, how to model others' intentions and preferences effectively, and once a model is obtained, how to effectively plan and operate in a multiagent setting. I am currently actively exploring both aspects through two different settings. In the first setting, a group of agents, with *different musical aesthetic preferences*, learns to collaborate in a joint music generation setting without a-priori knowledge of each other's preference profiles. Studying this problem in a simulated environment with known preferences enables us to quantifiably study and compare algorithms. I am also currently looking the complementary problem of human-agent collaboration, and whether an agent can better collaborate with its human counterparts if it's actively trying to model their preferences, and how these preferences inform their overall behavior.

Final Notes

If we envision a future where intelligent artificial agents interact with humans, we should strive to give AI the ability to understand and communicate within cultural settings. In my thesis proposal, I unify the threads I have discussed in the previous section, focusing on the systemic and sequential nature of musical agents. I believe my dissertation research towards learning social agents in the music domain would make a valuable contribution to the AI community, with multiple real world practical benefits, ranging from recommender systems and business intelligence to negotiations and personalized human-computer interaction.

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