Avanessians Fellowship Application

Chia-Hao Chang, cc4626@columbia.edu

I am a third-year Ph.D. student in the Operations Research department at Columbia University. I am interested in *sequential decision making under uncertainty.* I am especially interested in *designing tractable and interpretable approximation algorithms* for them. Specifically, I am interested in *Markov decision process* (MDP), both in theory and applications. MDP is a widely used framework for sequential decision making. The applications of MDP are versatile, including finance, revenue management, queueing control, economics, and healthcare. A better understanding for MDP will allow us to gain insights in the essential trade-offs in sequential decision making problems. The focus of our work is to design a *tractable, interpretable and robust* policy for MDP with provable guarantees. The goal is not only theoretical but also practical. Understanding the approximability of different MDPs will help us better understand computational complexity theory. From a practical perspective, an efficient algorithm which finds an approximate policy for a MDP is also important. This is because in most applications, the state space and the action space for a MDP are often large, rendering the conventional approaches such as value iteration or policy iteration impractical. The problem parameters such as transition probabilities often can not be estimated precisely. The parameter uncertainty makes the robustness of an algorithm significant.

I have been working with Professor Vineet Goyal on the approximation of large scale MDPs. With Professor Goyal, we have been investigating the possibility of proactively transferring patients to the intensive care unit (ICU) in hospitals. ICU is a scarce resource in hospitals. By proactively transferring patients to the ICU, s/he receives better care and has a higher probability of recovering. On the other hand, proactive transfer may possibly block the urgent need from patients in severe health conditions. This trade-off is the key challenge in the problem. In our work, we formulate the problem as a MDP with an infinite state space and exponentially large action space. Specifically, the complex patient health condition is modeled by a score, with increasing scores reflecting more severe health conditions. The evolution of the health condition of a patient is modeled by changes in his/her scores. Due to the large state space and action spaces, value iteration or policy iteration face a computational challenge in our model. We propose an asymptotic fluid approximation for the stochastic system. In the fluid approximation, we are able to characterize the structural properties of the optimal policy. In particular, we show that in the fluid approximation, the ICU is maximally used; that is, an optimal policy will use up all the available ICU whenever possible. This is because the optimal policy tries to minimize the number of patients who are in need of an

ICU when no ICU is available. In fluid, both departures and arrivals to the ICU are deterministic. We can save the exact demand for the ICU in future periods while using up the rest of the ICU by proactive transfer. This is in contrast to the stochastic model, where the optimal policy will "underuse" the available ICUs to avoid future uncertainty. We also show that the optimal policy in fluid satisfies the following priority rule: It first transfers all patients in urgent need for the ICU. If there are remaining ICUs, it proactively transfers patients from the highest score to the lowest. With these structural insights, we design an algorithm which proactively transfers as many patients as possible while taking into account the future uncertainty of patients in urgent needs.

In the future, I would like to generalize our work on the ICU management problem. I want to study the *sequential resource allocation problem in a network with heterogeneous resources*. This model captures several applications, including healthcare and ride-hailing, since resources, such as therapies, are often heterogeneous and limited. An efficient allocation of resources not only increases the quality-of-service of agents in the network but also reduces the waste of resources (such as the idle time of a reusable resource). In particular, I am interested in designing an efficient scheduling algorithm which adaptively coordinates the on-hand resources and future uncertainty.

More generally, I want to work on *stochastic control problems, with an emphasis on healthcare applications*. For instance, with the increased data precision and availability, the dimension of the features of a patient may be huge. It may not be possible to summarize these features into low dimensions. I am interested in finding a simple and interpretable, such as an index-based policy, which provably approximates the optimal solution. More broadly, I would like to discern the conditions under which we can well approximate a MDP in a complex environment. More broadly, I would like to investigate stochastic control problems under parameter uncertainty, that is, the robust stochastic control problem. I am also interested in the reinforcement learning framework of these problems. Specifically, I would like to design algorithms which learn the optimal policy by exploiting the offline solution in an efficient way. Along the same line, I am interested in investigating sequential experiment design problems in high dimensions and with strong inter-temporal correlations, such as inference in Markov chains and inference in dynamic games. The goal is to design tractable and interpretable algorithms for them. With the insights from the analysis of MDPs from my current project, I hope I can put forward the analysis in these areas. Due to the generality of the stochastic control framework and the ubiquity of sequential decision making in real life, these works will have both theoretical and practical influences. In particular, I believe that these works have potential impacts on applications beyond healthcare. These works can serve as the precursor to algorithm design in complex environments with high-dimensional data, mirroring the goal of the Avanessians Fellowship.