Statement of Purpose

Dear Admissions Committee,

My name is _________ and I received my bachelor's degree in Electrical Engineering in 2015 from _________. Since then, I have been working towards my master's degree at the same institute. Currently, I am writing my master's thesis at _________. My research interests include **machine learning**, **control theory**, and their application to **human-robot interaction.**

Research Experience

In my bachelor's thesis, I worked on *pseudo-Boolean optimization*, more specifically, finding quality measures to estimate how difficult it is to optimize a pseudo-Boolean function. This topic stems from the previous research at _________ in *Markov Logic Networks* (MLNs) that inference in MLNs can be formulated as optimization of pseudo-Boolean functions. Although pseudo-Boolean optimization problems are NP-Hard in general, certain types of them can be solved efficiently. I proposed to identify such tractable problems with graph-theoretical properties: pseudo-Boolean optimization can be formulated as *maximum stable set problems* in a *conflict graph*. I also proposed several heuristics to improve a classical algorithm called *struction* for the maximum stable set problems.

The experience during my bachelor's thesis made me want to continue to participate in research projects to embrace the intellectual challenges. I then joined a team working on human-robot collaboration at _________, where I investigated how robots can communicate with the human collaborator through nonverbal behaviors.

This ability is important, as human-robot collaboration is susceptible to the imperfect memory of the humans. How can a robot *remind* its human collaborator of the true task goal nonverbally? I modelled the problem as a *hidden goal Markov decision process* (HGMDP), a special case of *partially observable Markov decision processes* (POMDPs). Solving HGMDP is PSPACE-complete even for deterministic systems. To find good approximate solutions, I resorted to the theory of *legibility* and introduced an auxiliary reward function promoting legible actions, which are not necessarily efficient but convey the task goal more clear to the human by exaggeration. The experimental results confirm that this approach indeed improves the human-robot collaboration compared to a greedily efficient policy. I published this work as the first author at _________.

This year, I joined _________ to investigate ways of integrating high-dimensional tactile sensor measurements into *Dynamic Movement Primitives* (DMPs). DMPs have the advantage that the learned movements can be modified reactively according to the sensor signals by introducing a *coupling term*. However, designing such coupling terms is a nontrivial task, as a model that relates the movements and the sensory events is missing. In this project, I proposed to learn this model with Mixtures of Factor Analyzers (MFA), which has the advantage of performing dimensionality reduction and data clustering concurrently. Once this sensory model is available, designing the coupling terms for DMPs becomes a control problem: if we augment the DMP with the learned sensory model, we can control both the positional and the sensory trajectory. We do this with a *model predictive controller* (MPC) to minimize a quadratic cost function induced by the positional and sensory errors.

Research Interests

I am applying to the Ph.D. program at the Robotics Institute of Carnegie Mellon University due to its leading position in the robotics research. I find the work of **Prof. Henny Admoni**, **Prof. Oliver Kroemer** and **Prof. Illah Nourbakhsh** particularly relevant to my research interest.

Physical human-robot interaction (pHRI) can be seen as an application of contact-rich manipulation on two levels. First, robots manipulate objects in the environment without direct contact with the human collaborator, yet change the human mental states indirectly: when a household robot cooks with humans, it conducts mostly conventional manipulation tasks. However, such manipulation tasks alone are already notoriously hard for today's robotic systems. For example, cutting food requires adaptive motion according to the different elastic modulus and friction coefficients of the food. To plan motions that include contacts—which is inevitable and even desirable—a dynamics model of the task-relevant objects and its environment will be explicitly or implicitly required. Hand-designing such models can be hard and tedious; therefore**, the first goal of my future research is to further develop learning frameworks for contact-rich manipulation tasks as the cornerstone for complex human-robot collaboration.**

Second, when a robot tries to touch or hug its human partner, all aforementioned difficulties remain and are exacerbated by the safety concerns. Even running at low speeds, many robots can exert forces more than sufficient to hurt a human. Thus, safe learning methods are necessary, which often draw inspiration from control theory: for instance, risk-sensitive control that uses exponential utility functions to account for the cost variance, or robust control which explicitly considers model uncertainties. **Note that the notion of safety or its opposite, risk, is predefined in those settings**, as it is straightforward to measure physical risks in human-robot interaction. However, another interesting topic may be learning the metrics of mental risks, as they vary from person to person, and even physically safe actions may still mentally affect the human collaborator in a negative way. For instance, consequential sound generated by mechanical actuation of the robot may be considered unpleasant to some people. **Therefore, I would also like to explore various safe learning methods that are able to learn and respect safety constraints which might be unknown beforehand.**

Finally, humans are more than an object to be manipulated: they reason, they react and they adapt. Thus, human mental states should be taken into account in such interactions. At first glance, it can be tackled with the same learning paradigm as in manipulation tasks, however, the large amount of human-involved data required may render the task infeasible. For example, disabled users who need assistive robots, might not be able to perform demonstrations themselves. To alleviate this problem, my final research goal can be decomposed into two subtasks: **(1) Develop mechanisms to learn from partial data by actively probe or inquire the human only when it is necessary. (2) Enable the robot to learn human cognitive models from other sources, for example from human-human interactions existed in the abundant video content in the internet.**

I am convinced that with the help of the extraordinary minds, the top research environment at CMU RI, and my strong motivation for research, I can make a meaningful contribution to the endeavor of human-robot interaction.