Statement of Purpose - Varshith Sreeramdass - Applying for PhD in CS/Robotics

The widespread adoption of robots demands robust control policies adaptable to diverse deployment scenarios. This includes settings such as driving or hospitals, where robots must function alongside and possibly collaborate with humans. However, human behavior is inherently variable and the variability is challenging to contain. Collected behavioral data mostly represents a limited view of the true variability. Thus, efficient algorithms that leverage limited supervision to learn human models and robot policies become crucial for effective human-robot collaboration. It is with this motivation that I seek to conduct research in algorithmic techniques for human-robot collaboration within the XXX program at YYY University.

Quantifying Model Knowledge: My early exposure to research was at IIT Bombay under the guidance of Prof. Sunita Sarawagi and Prof. Soumen Chakrabarti. Our first project delved into active learning for image classification and natural language entity recognition tasks. We investigated ways of quantifying the information embedded in a model, employing metrics for out-of-distribution detection to choose data points for label queries. In the subsequent project, we examined the adaptation of general-purpose cloud NLP services and found that their performance is limited in handling out-of-domain inputs. We proposed learning to substitute domain-specific tokens with general ones with Reinforcement Learning (RL), boosting the performance of the overall system. From these experiences, I learned the importance of understanding and quantifying what a model knows and doesn’t, which can be potentially used to devise effective interventions to improve out-of-domain adaptation. While I enjoyed academic research, I felt out of touch with real-world applications. Thus, after graduating from IIT Bombay, I chose to explore robotics in R&D.

Real-World Robotics: Joining Honda Robotics R&D in Tokyo, Japan helped me discover my passion for robotics. One of my main projects was deploying RL for real-world dexterous in-hand manipulation. Our focus was on algorithms capable of leveraging offline RL datasets and fine-tuning through online interactions. We successfully achieved robustness to noisy initializations of object poses in the real world. However, as we attempted to extend to more tasks, problems with deployed learning systems became more difficult to address. In-hand object pose estimation proved to be unreliable due to finger occlusions. Sparse reward specification made the RL optimization difficult. The process of reward shaping to attain favorable behaviors was an iterative cumbersome process. Consequently, my interest grew in investigating the incorporation of systematic biases into policy learning, to make it feasible for real-world applications.

Inductive Biases in Policy Learning: Applying insights gained from my experience in deploying real-world RL, I subsequently led two projects. In the first project, my focus was on integrating parameterizable low-level controllers, such as Dynamic Motion Primitives (DMPs) into policies for long-horizon in-hand manipulation. On the whole, the hierarchical policy structure proved useful in accelerating learning but hindered learning in scenarios requiring quick and reactive behaviors. In the second project, our objective was to enhance the robustness of a scripted base controller in a coke-can opening task. We employed residual actions to adjust commands from the base controller to accommodate for environment and initialization noise. While simulation results showed a significant improvement over the base controller and a policy learned without a base controller, real-world performance was limited by discrepancies between the simulation and reality. Factors such as noisy perception, intricate contact dynamics, and approximate resistance models for the pop-tab of the coke-can contributed to the limited performance. Nevertheless, through both projects, I understood the necessity of careful policy design for real-world robotics, emphasizing that the right inductive bias can make all the difference.

Return to Academia: While I wished to continue at Honda building robots for real-world applications, I recognized a substantial gap in my knowledge and research capabilities. Consequently, I decided to pursue a Master's degree in Computer Science at the Georgia Institute of Technology, specializing in Computational Perception and Robotics. I immersed myself in advanced-level research courses and delved into Human-Robot Interaction research under the guidance of Prof. Matthew Gombolay.

Human-Robot Teaming: I started looking into policy learning for robots aimed at effectively collaborating with human partners in doubles tennis. I considered broadcast videos of professional matches that provide information regarding various teaming strategies. These videos highlighted positions for partners to increase the likelihood of returning a ball or securing unguarded areas on the court. However, an effective robot partner must be capable of teaming with individuals who may have diverse preferences for receiving specific balls or occupying certain court positions. Adding to the complexity, such preferences cannot be explicitly encoded, necessitating the embedding of learned behaviors into a suitable latent space.

Capturing Diversity in Human Behaviors: Exploring the problem of learning from diverse demonstrations, I discovered that existing prior works often struggled to generalize to novel behaviors, i.e., interpolate or extrapolate from observed demonstrations. The latent vectors exhibited a tendency to overfit specific behaviors, lacking smooth variation to related ones. To address this problem of arbitrary diversity, I introduced a novel regularization scheme designed to encourage diversity relevant to the task. I illustrated its ability to enhance generalization to novel preferences beyond the dataset. This research resulted in a publication and an oral presentation at the workshop on Out-of-Distribution Generalization in Robotics, at CoRL, 2023. We are presently focused on improving the method and evaluating it with real-world object manipulation and returning to human-robot teaming in doubles tennis. This experience highlighted to me that in scenarios involving humans and limited data, data-efficient learning can be powerful.

PhD in HRI: My research experiences have grown my interest in robot learning and human-robot interaction significantly. I aim to pursue a PhD, focusing on building robot learning systems that facilitate effective collaboration with humans. My background involves understanding the epistemic properties of learned models, developing policy designs for practical robot learning, and addressing diversity in human behaviors. These experiences have equipped me with a distinctive skill set, preparing me for success in my undertaking. I am committed to putting in the necessary effort and dedication to learn and contribute influential research to this field.