I seek admission into the Master of Science in Robotics (MSR) program at The Robotics Institute, CMU. With a solid theoretical background in CS and AI, with all the relevant coursework, diverse projects spanning NLP, Knowledge Graphs, CV, RL from my undergraduate studies at IIT Bombay; practical knowledge surrounding robot learning from my Research Engineer position at Frontier Robotics, Honda R&D; and aspirations for a research career in Academia, I believe I am an ideal candidate for this program. I intend to use this opportunity, if given, to build foundational knowledge in robotics that I currently lack, practice the research process meditatively, work on focused research projects with emphasis on publications, and build experience towards a PhD.

My research interests broadly lie in Robot Learning and Perception. More specifically, I believe that the effort towards improving robustness of robotic systems in the real world can benefit a great deal from incorporation of structure and appropriate inductive biases: to have a task-oriented perception of the interaction environment; and hybrid policy architectures, algorithms that are able to effectively exploit them for complex manipulation. I would be delighted to work with Prof Nancy Pollard on dexterity, Prof Shubham Tulsiani on structured perception, or Prof David Held on the intersection of 'perceiving' and 'doing'.

I believe that my background is well suited for research towards these topics. I have done thorough foundational coursework in Advanced Machine Learning (Graphical Models, probabilistic reasoning), Foundations of Learning Agents (Search, Q Learning, Policy Gradients), Organization of Web Information (Corpus models, deep representations of entities, knowledge graphs, querying). Despite my lack of publications, I possess relevant varied research experience.

The first part of my undergraduate thesis involved working on Out-of-distribution (OOD) and Active Learning under the supervision of my thesis advisor, Prof. Sunita Sarawagi. Our initial survey work provided me with valuable exposure to modeling neural networks in various purpose driven ways. An important insight gained from failing to effectively extend perturbation based OOD methods (ODIN), originally built for images, to actively learn language tasks, was with respect to how differently (and challengingly) the data distributions are structured across domains. Though we brainstormed various ways to accordingly structure the data distributions, and further, to learn an optimal active learner using RL, we eventually decided to move to a fresh and relevant topic, which was the next part of my thesis, titled 'Domain Adaptation of Cloud NLP Services through word substitutions'. We analysed SOTA models (at the time - BERT, ELMO) for weaknesses on particular client domains and observed that simple substitutions of domain specific OOV words with appropriate ones improved performance. This problem was an educational study in exploration strategies in large lexicons, utilizing task relevant tools, such as language models and sentiment-aware embeddings.

Independent study under Prof. Soumen Chakrabarti titled 'Augmenting Scene Graph Generation with knowledge from corpora' helped me appreciate the potential of structure - in this case, graphs - in enabling effective use of information across modalities. However, what proved to be a significant practical challenge was dealing with discrepancies across label spaces, specifically the presence of a NOTA class in the image domain. This entailed attempts to work around the problem using omission and inverse class ratios, which impaired the performance. A valuable insight was that even though modern NNs are quite expressive, they can sometimes be undesirably rigid. This motivates me to work on ways to make models modular and flexible enough to use across various scenarios.

While projects during my undergraduate studies were influential in my thinking, research work during my position as a research engineer at the R&D facility of Honda, are directly responsible for my interest in Robot Learning.

The project on Hierarchical Reinforcement Learning (HRL) dealt with learning motor primitive based policies for robot manipulation tasks. The approach attempted to do three things: harness the expressibility of NNs to be able to handle control with complex contact dynamics; use gating policies to explore in higher level subgoal and duration param spaces to practice structured exploration; employ dynamic motion primitives for reaching assigned subgoals with smooth trajectories. Though the several attempted variations performed only nominally better than their 'flat' counterparts, the implementation of DRL algorithms from scratch and the experimentation effort testing each aspect of the architecture across environments contributed a great deal to a practical understanding of deep reinforcement learning, its flexibility, generality, and more interestingly, its fickle nature.

In learning policies for InHand manipulation using data-driven DRL, working with real prototype hardware and learning setup was easily the most challenging and fascinating aspect of the effort. The in-house prototype robot hand (similar to Shadow Hand) and low level control software under active development meant dealing with various hardware aspects up close, such as manual calibration of the tendon systems, compliance control to avoid fingertip skin damage due to excessive contact forces, etc. The learning setup involved the use of motion capture for object pose recognition, involving complications with regard to occlusions and time-dependent noise/offsets. While designing and collecting demos for complex transitions among objects grasps was a challenging task in itself, doing so in the learning setup, so as to be able to reliably use behaviour-cloned policies and deploy DRL at later times proved to be an exercise in patience. This work imbibed in me a deep appreciation of the challenges that real robot learning faces, and motivates me towards making some of these tasks easier, through the use of structure, in perception and learning.

Reflecting on the experience working on various research projects, I find myself increasingly fascinated by the capacity of research methodologies in realizing seemingly abstract intuitions. While I am confident in my ability to materialize complex ideas as model/algorithm designs, what I believe I fundamentally lack is training in the research process, to be able to achieve reliable implementations of these designs. Until a year into my position at Honda, I found myself building complex monolithic frameworks, deploying learning algorithms, hyperparameter optimization frameworks and miserably failing. I have since understood the importance of breaking down a multifaceted hypothesis into its most basic components. Designing rigorous tests for each such component in isolation is crucial, not only to develop a reliable foundation for your method, but to also be able to withstand scientific scrutiny. A thorough exercise in precisely this, and laying groundwork of foundational concepts in a few fields of interest towards my PhD, is what I hope to gain from graduate studies.