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Statement of Purpose

I am broadly interested in autonomous robotics that address challenges in manufacturing, home assistance and space exploration. These interests have drawn me toward three research directions:

- **Task Planning:** design reconfigurable robots that can reason and plan themselves from natural language descriptions.
- **Continual Learning:** learn to accumulate new skills guided by task planner.
- **Safe and Efficient AI:** exploit control theory for safe and trustworthy learning algorithms in navigation and manipulation.

Task Planning Training a robot to generate plans based on human instructions is challenging due to the diversity and ambiguity of natural language. I am excited about overcoming this challenge as it is critical for widespread deployment of robots in human-centric environments. Two parallel lines of works have been studied: symbolic planner performs well for structured language but fails to capture the semantic meaning of open-ended languages; learning-based networks can generalize to various types of language but suffer from error propagation in planning. These limitations motivated us to design a neuro-symbolic planner which adopts the vision-and-language network to learn the goal symbol from the instruction, and then sends it to a symbolic planner for producing task-completing plans. I evaluate the effectiveness of the hybrid planner in the simulator AI2THOR through manipulation tests, and generate mid-level plans like "*grasp knife, cut tomato*" from commands "*Please cut me some tomato slices.*".

To further optimize the planning procedure, I also tried to plan the action sequence iteratively, instead of autoregressively, from the Masked Language Models (MLM). I train a MLM to capture the implicit energy function over action sequences, and formulate planning as finding a sequence of actions with minimum energy. By iteratively sampling and minimizing the estimated energy, I illustrate that this approach outperforms prior autoregressive planning which precludes sequential refinement of earlier steps.

Through this direction, I hope to further explore robotics reasoning and planning; for instance, using pre-trained large language models (LLMs) to decompose and sample plans effectively.

Continual Learning My impetus for pursuing this research comes from the assumption in high-level task planning that the robots have a complete set of pre-trained skills like "*grasp, cut*". However, it is impractical to prepare skills for all possible tasks. A robot must be able to grow its skill set on demand. Traditional reinforcement learning (RL) algorithms learn these skills by hand-engineering the reward function for each skill, which is prohibitively expensive. Instead, I consider training the skills in a self-supervised manner with the help of planner guidance: (1) regard the generated task plans as an autonomous curriculum to continuously learn skills and expand the capability of the overall system. (2) generate specified instructions from the planner given the current observation to guide the policy exploration. As a necessary initial step to self-supervised skill learning, I am using pre-trained LLMs to describe the details of target goal state, performing scene graph abstraction on the goal description and the current world observation, and guiding the skill learning by bridging the two scene graphs.

Safe and Efficient AI Another direction I have explored is using rigorous control theories to design reliable and efficient learning algorithms with formal guarantees. In my provably safe robotics course, I learned that the safety challenge prevents deploying deep learning (especially RL) in physical robots. Traditional learning algorithms only add soft constraints like reward penalties which can't guarantee 0-safety violations. Therefore, borrowing ideas from the control community, I adopted Lyapunov-based safe set algorithm (SSA) to provide hard constraints by monitoring and modifying the unsafe controls, and achieve significantly better safety for learning to navigate in crowded dynamic environments. Moreover, by encouraging policy exploration with safety constraints and treating SSA modified safe control as expert demonstrations, the policy training efficiency is further improved.

With the success in navigation, I wonder if we can develop dynamically-informed control and learning for dexterous robotic manipulation. The algorithmic efficiency of model-based control techniques frequently surpass the current state of learning-based control. However, they are often restrictive due to conservative assumptions; for instance, many approaches become un-amenable when non-smooth contact mechanics or objects with unknown geometry are encountered. Learning-based research contributions, on the other hand, have been boldly solving these manipulation problems in an aggressive end-to-end manner, producing impressive results, though with the aforementioned drawbacks relative to control theoretic solutions. Inspired by these challenges, I am interested in bridging learning and control theory and lead to innovative solutions that are robust and efficient for greater scopes of contact-rich manipulation tasks.