Research Statement

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September 2023

My (past and future) research concentrates on the advancement of deployable reinforcement learning (RL). I am particularly committed to addressing obstacles that may deter the practical application of RL algorithms in real-world decision-making scenarios, and I believe the most profound motivations come from real life. Specifically, I am interested in the following aspects of learning problems:

- Efficiency:
  - RL for tasks with sparse or delayed reward signals.
  - Agent exploration in high-dimensional state-action spaces.
- Reliability:
  - Explainable Deep RL systems.
  - Integration of RL and optimization techniques to enable robust and scalable decision-making.
  - Uncertainty/Constraint-aware RL algorithms.
- Generality:
  - Theoretical guarantee on the generalization capability of RL.
  - Skill-based RL for human-like decision-making and transferable temporal abstractions among tasks.
  - Life-long RL via pretraining and domain adaption.
  - Integration of RL with Large Language and Vision Models to achieve multi-modal learning.
- Data-Centric Study:
  - Offline RL capable of processing vast amounts of data.
  - Bridging online and offline RL.
  - Investigating the evolution of RL agent in relation to the data quantity & quality.

Turning to practical applications, RL, as a universal decision-making technique, has vast potential across various domains. However, this potential is accompanied by multifaceted challenges:

- Sim-to-real transfer.
- Underspecified or multi-objective reward functions.
- The inaccessibility or the high cost (in terms of time or resources) of simulations.
- Limitations on the volume or quality of offline data.
- Data scarcity in critical scenarios, which can yield biased policies.
- Safety-critical settings, which makes the deployment of unexplainable (block-box) policies challenging.
- The need for seamless integration with domain-specific foundational principles to ensure rationality.

With these considerations in mind, I am eager to explore greatly impactful RL applications tailored to the unique needs of various industries.

Notably, several types of research exist in this area, including theoretical analysis, intuition-based algorithm design, and application study. However, algorithms with superior theoretical guarantees often underperform on deep learning benchmarks or are not scalable at all, while those excelling in benchmark tasks usually lack robust performance in real-life applications. These disparities necessitate "full stack" RL research. Additionally, we should work on uncovering the root causes of these gaps and designing benchmarks to access the multiple aspects previously mentioned as efforts to bridge these disparities.

Overall, my research endeavors to advance the frontiers of RL algorithms, both in foundational designs and practical applications.