Research Statement

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A remarkable characteristic of human intelligence is our ability to learn quickly. Most people can learn skills like tool-use and gameplay within just a few hours, and understand the basics of a new task after only a few attempts. This suggests that data-efficient learning may be a meaningful part of understanding broader intelligence. Over the last decade, deep learning and reinforcement learning (RL) have transformed the fields of computer vision, natural language processing, and simulated robotics. However, these algorithms are notoriously data hungry. Achieving superhuman performance on Atari with RL requires around 100M data samples, mastering Dota took 180 human years of simulated play, and the best performing robotic systems take hundreds of robot hours to train.

My overarching goal is to *transform scientific discovery through the adoption of artificial intelligence* (AI) across a broad range of domains. Efficient learning is crucial to achieve this goal. The fields of computer vision and natural language processing underwent a paradigm shift over the last decade, where manually engineered features and hand-specified pipeline approaches were superseded by end-to-end learning architectures such as Convolutional Neural Networks in vision and Transformers in language. However, domains where data is more expensive to procure and less standardized, such as robotics and the physical sciences, still largely rely on hand-designed pipelines. With breakthroughs in efficient learning, I believe robotics and the physical sciences can undergo a similar transformation to vision and language in the following ten years.

To this end, during my Postdoc at UC Berkeley, I investigated efficient control from pixels through three focus areas: (i) unsupervised representation learning, (ii) efficient algorithms, and (iii) effective architectures. For future research directions I plan to build on my prior work to (iv) scale RL to large and diverse datasets, (v) enable long-horizon decision making, and (vi) accelerate scientific discovery in the physical sciences with deep learning.

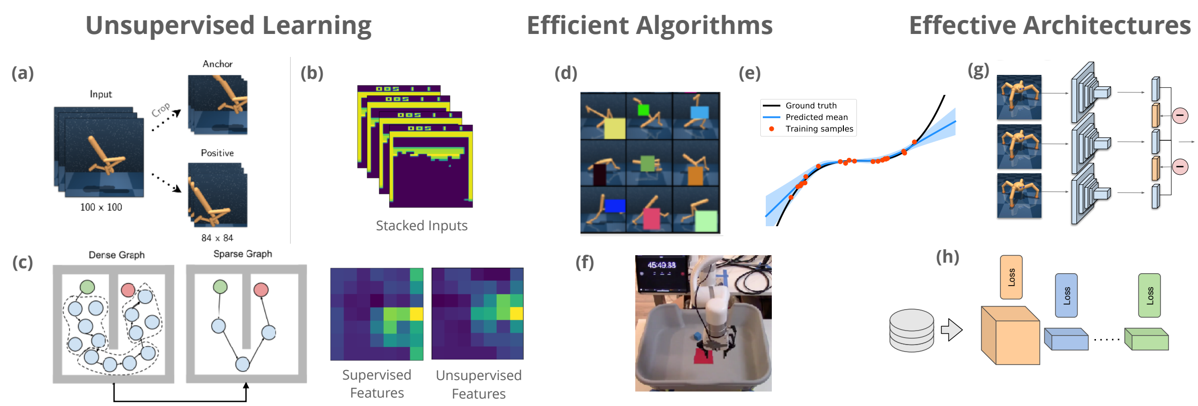

Figure 1: In my research, I investigated unsupervised representation learning for RL through (a) contrastive learning [1], (b) decoupling unsupervised representation learning from RL [2], (c) planning over state abstractions [3]. I developed efficient algorithms by leveraging (d) data augmentations [4] and (e) ensembles for RL [5]. These efforts culminated in (f) a framework for efficient robotic learning [6]. Finally, my research investigated new architectures for (g) RL by incorporating latent flow [7], and (h) for deep learning via local parallelism [8].

Unsupervised Representation Learning: Though standard datasets for vision and reinforcement learning rely on strong supervision signals in the form of image labels or dense rewards, in the real world labels and dense reward functions are costly and often infeasible to obtain. To develop widely applicable efficient learning algorithms, we must first have general methods for learning useful representations without supervision. My research investigated increasing the efficiency of RL through unsupervised contrastive learning [1], decoupling representation learning from control [2], and state abstractions for long-horizon planning [3].

Efficient Algorithms: Even if provided with an optimal representation, to maximally leverage information present in a dataset, we must make fundamental improvements at the algorithmic level. Additionally, for new algorithms to be widely adopted, they must not only be more efficient but also simpler and more scalable than alternative approaches. My research focused on simple efficient algorithms that scale by investigating the use of data augmentations [4] as well as ensembles [5] in RL, which resulted substantial efficiency gains in real-robot manipulation [6].

Effective Architectures: Some of the most impactful research in the deep learning era, such as Residual Networks and Transformers, came from re-thinking learning architectures. New architectures often leverage inductive biases that enable further utilization of data or compute. My research in effective architecture design leveraged temporal inductive biases to accelerate the data-efficiency of RL [7] and local inductive biases to increase the compute-efficiency of training deep learning models, such as ResNets and Transformers [8].

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Research to date

My research to date has focused on developing fundamental building blocks for efficient learning from high-dimensional data – unsupervised representation learning, efficient algorithms, and effective architectures – which are essential components for pursuing the goal of transforming scientific discovery with AI.

Unsupervised Representation Learning

Today, deep RL algorithms are trained from scratch for each new task the agent encounters. This approach to training autonomous agents is fundamentally limited, because agents cannot re-use prior knowledge to learn a new skill. My research tackled this problem through unsupervised representation learning, which entailed learning representations from image data independent of the task at hand. We first showed that, by leveraging unsupervised contrastive learning as an auxiliary objective (see Figure 2), *RL algorithms from pixels could be as efficient as RL from coordinate state* [1]. Next, we showed that feature learning and RL can be decoupled entirely without hindering performance [2]. Finally, we investigated how representation learning could be leveraged for state abstraction, and showed that a hierarchical system that plans over abstract states can solve long-horizon navigation tasks robustly and efficiently [3].

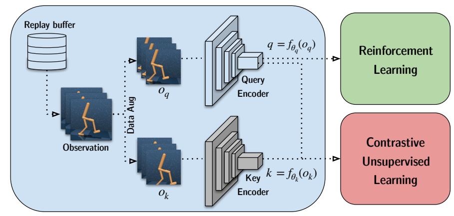

Figure 2: Contrastive Unsupervised Representations for RL (CURL) [1] optimizes an instance-based contrastive objective alongside the main RL task, which substantially improves the data efficiency of the learned policy.

Efficient Algorithms

In addition to learning general task-agnostic representations, progress towards efficient learning can be made through developing better algorithms. When it came to algorithm design, my goal was to develop broadly useful methods that were easy to implement and reproduce for other researchers. To this end, we provided the first extensive study into data augmentations within the context of RL [4]. Surprisingly, we found tsimple model-free RL with data augmentation was the most efficient algorithm on standard simulated benchmarks compared to both model-free and model-based state-of-the-art methods. Combining data augmentation with unsupervised representation learning subsequently enabled us to *train real robots to learn sparse-reward manipulation policies from pixels in just 30 minutes of training time* [6] (see Figure 3), substantially improving real-world learning efficiency, which before took hours or days of training time. Finally, we investigated how to utilize ensembles to improve stability and efficiency of RL, and showed that ensembles could be used to mitigate error accumulation in Q learning [5].

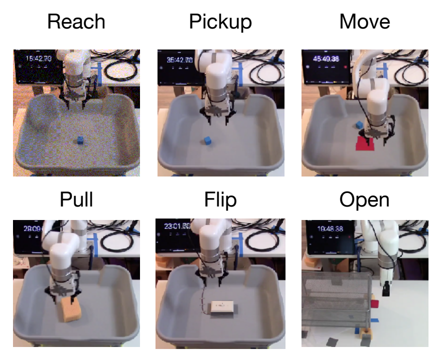

Figure 3: The Framework for Efficient Robotic Manipulation (FERM) [6] enables real robots to learn sparse-reward tasks from pixels in minutes.

Effective Architectures

Architecture plays a crucial role in the performance and efficiency of deep learning algorithms. In my research, we challenged fundamental architecture design assumptions in deep learning and RL, and produced highly effective alternatives. First, we replaced global backpropagation with a local variant where auxiliary losses are attached to intermediate layers of a deep neural network [8] (see Figure 4). This enabled an alternate form of parallelizing compute, which we called local parallelism. Local parallelism *increased the compute-efficiency of deep learning by up to* 10× when training Transformers and ResNets compared to backpropagation with data parallelism. For deep RL architecture design, we challenged the assumption that frame-stacking, which is used in nearly every off-policy pixel-based RL codebase, is the optimal way to pre-process observational input. Instead, we showed that a simple design change where frames are encoded individually and temporal information is incorporated through latent subtraction coupled with late fusion significantly improved learning efficiency on challenging continuous control tasks and Atari games [7].

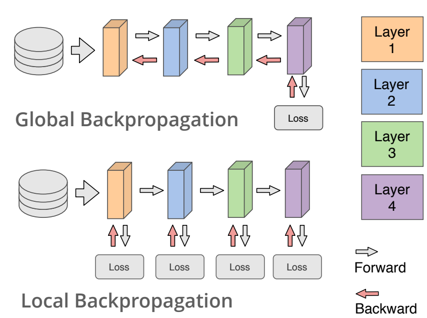

Figure 4: Local learning [8] parallelizes compute by training layers in a neural network asynchronously with local losses, and substantially improves compute-efficiency of training.

Research Plan

Due to the generality of the framework and its effectiveness learning from high dimensional data, I believe reinforcement learning coupled with powerful deep learning function approximators is poised to transform scientific discovery in robotics and the physical sciences. My future research will pursue this paradigm shift in three ways. First, since data collection in robotics and the sciences is expensive, I propose to move away from the current paradigm where narrow single-task algorithms are trained from scratch and towards one where RL is trained on large multi-task datasets. Second, to be truly transformative beyond the domains of video games and simulated control, RL algorithms need to be equipped with long-horizon planning capabilities. Finally, we can start making substantial progress today by accelerating discovery in the physical sciences with deep learning through cross-disciplinary collaborations.

Reinforcement Learning from Large and Diverse Datasets

Today, most RL algorithms are trained online and evaluated in single task settings, such as Atari where the agent is trained to master a single video game. While effective for benchmarking performance, this task-specific approach to RL research results in algorithms with narrow applicability and requires data to be collected from scratch for every training run. However, in fields like healthcare, quantum computing, drug discovery, and robotics, data collection during every training run is impractical and for this reason it is preferable to collect large offline datasets in advance.

Much like Transformer architectures with unsupervised learning objectives like BERT and GPT enabled unprecedented capabilities in natural language generation and understanding, unsupervised representation learning will also play a critical role in learning effective policies efficiently from large data sets. With the ability to learn from large offline datasets, RL could be transformative for decision making across a broad range of domains including robotics, circuit design for quantum computers, and healthcare. My prior research in unsupervised representation learning [1, 2, 9], robotics [6], and physics [10, 11, 9] have equipped me with the cross-disciplinary expertise needed to pursue this research agenda.

Long-Horizon Planning Capabilities

Even if we could extract rich representations from large banks of diverse offline data, the resulting policies would still be limited by a fundamental shortcoming of today's RL algorithms – they can only solve short-horizon tasks. For example, in robotics it is simple to solve a block pushing task with RL, but slightly longer skills that seem simple to humans like stacking multiple blocks remain an outstanding challenge, while training home robots to help us with our chores is completely out of reach without environment specific manual feature engineering. How can we get RL algorithms to reason over multiple levels of temporal abstraction - from seconds, to hours, to days?

Answering this question would have substantial impact on the breadth of the applicability of RL in both robotics and the physical sciences. I will investigate two pathways for equipping RL agents with long-horizon capabilities – hierarchical reinforcement learning (HRL) and model-based reinforcement learning (MBRL). HRL provides an explicit framework for reasoning over multiple levels of temporal abstraction by automatically breaking a long-horizon task into a series of short-horizon subproblems. MBRL extracts policies based on sequential dynamics models, which can be capable of long-horizon planning if the deep learning architecture is expressive enough and there is sufficient structure in the data to extract long-range correlations.

Accelerating Progress in the Physical Sciences with Deep Learning

Though my research as a Postdoc has focused on developing general ML and RL algorithms, my PhD research focused on theoretical aspects of quantum statistical physics[1] [10, 11, 9, 12, 13]. I was trained as a theorist, but noticed that some of the greatest challenges in physics were rooted in understanding and acting on experimental or simulated data, which motivated me to change fields to machine learning. I believe machine learning can have out-sized impact on the physical sciences by transforming hand-designed pipelines into learning-based ones, similar to the transformation that happened in vision and natural language processing over the last decade.

For example, in an ongoing collaboration with the Quantum Nanoelectronics Laboratory group at Berkeley, we're designing machine learning methods for automatically generating quantum circuits. Today, quantum circuits are generated manually, similar to how feature extraction for vision was done before the deep learning era. Incorporating machine learning into the quantum circuit design process will result in faster timelines and more robust quantum computers. While quantum computing is one aspect where deep learning can accelerate scientific progress, its impact can be much broader with relevance to other important problems in the physical sciences like weather forecasting, analysis of cosmological data, and protein modeling.

[1] Authorship order is usually alphabetical in the Wiegmann theoretical physics group.

Why MIT

The MIT EECS Department and the Computer Science and Artificial Intelligence Laboratory (CSAIL) have a history of producing world-class research in robotics, perception, and machine learning. As a researcher with expertise in unsupervised learning, deep learning and reinforcement learning, I foresee fruitful collaborations with faculty who have complementary expertise, such as robotics (Leslie Kaelbling, John Leonard, Daniela Rus, Russ Tedrake), computer vision and perception (Ted Adelson, William Freeman, Phillip Isola), and machine learning (Costis Daskalakis, Aleksander Madry). As a trained physicist and given my overarching research goal of transforming scientific discovery through artificial intelligence, I am also interested in cross-disciplinary collaborations through the Center for Global Change Science, MIT Kavli Institute for Astrophysics and Space Research, and the McGovern Institute for Brain Research.

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