1 Executive Summary

One of the key challenges faced by current machine learning (ML) is its reliance on vast amounts of labeled data, which is often expensive to obtain. In our perpetually changing world, it is imperative that future ML systems are lifelong learners that adapt to change without requiring large new labeled data sets. To tackle this problem, my work studies knowledge composition as a means for reducing the amount of data needed to learn over a lifetime. Intuitively, decomposing the complex knowledge required to solve a task into simpler units enables adapting, recombining, and reusing these units as knowledge components to solve different tasks in the future. My dissertation has leveraged this idea to create an array of lifelong learning algorithms for supervised and reinforcement learning (RL), with applications to computer vision and robotics. Overall, these methods have demonstrated that compositional knowledge representations give rise to superior lifelong learning performance. My future research will study how to create socially impactful lifelong learning, with the vision of developing mechanisms that enable adaptation to changes such as social media trends, novel robot tasks, and new student cohorts. Beyond compositional knowledge representations, lifelong learners require versatile skills that enable actionable compositional behaviors, which I will target in my future work. As a part of this effort, I will leverage my experience on language learning to exploit human instructions that inherently encode the composability of skills. At a more fundamental level, my research seeks to understand the core principles of compositionality. This has led me to study connections between human and machine lifelong learning. While the scientific community has only grazed the surface of these connections, my future work will dive deeper into cognitive science by studying the mechanisms that humans use for learning the compositionality of language over their lifetimes. My research currently studies applications to robot platforms; I will complement this with applications to areas of social impact, such as education and climate change. My work will also study the broader impact and social implications of learning over a lifetime, including fairness and privacy.

2 Motivation

The grand vision of ML is to build artificial systems that can be deployed long-term in the real world to assist humans in solving difficult tasks. Traditional ML focuses on stationary tasks, yet in order to be deployed long-term, ML must be able to handle the one thing that is constant: change. Consequently, we need lifelong learners that can accumulate knowledge as they experience their environment, and reuse this knowledge to rapidly adjust to change. This capability to accumulate and reuse knowledge would dramatically improve the performance of ML systems in dynamic environments: hate-speech detection models could adapt to social media trends, search-and-rescue robots could handle novel disasters, and student feedback software could adjust to new cohorts.

Two fundamental challenges lie at the core of lifelong learning research (also called continual learning). First, the learning agent must discover knowledge that is reusable in the future before seeing what that future looks like. Second, the agent must retain knowledge from its past, both to maintain its ability to solve previous tasks and to leverage past knowledge when solving future tasks. My research has developed methods that tackle these two problems by decomposing complex knowledge (e.g., as expressed by deep neural networks) into simpler units that can later be recombined to reuse them in multiple ways [2, 4, 11, 5].

3 Foundational Work on Lifelong Learning of Compositional Representations

A central objective of lifelong learning is to create agents that continually learn to solve new problems, becoming better learners (e.g., more efficient or more accurate) over time. I posit that major
advancements in the creation of such agents will occur as we learn to understand and leverage the compositionality of knowledge. To this end, my work has proposed and addressed the novel question of how to learn compositional representations in a lifelong learning setting. My research developed the first general-purpose framework for lifelong discovery of compositional representations, which endows agents with the ability to autonomously discover reusable components as data arrives sequentially, in a manner agnostic to the specific algorithms and forms of representations [1]. Drawing from Piaget’s [9] conceptually appealing (yet by now debunked for humans) assimilation and accommodation stages of cognitive development, this framework embodies the benefits of dividing the lifelong learning process into two stages. In the first stage, the learner strives to model new data by combining components it has already acquired, maximizing knowledge reuse. The second stage uses discoveries from the new data to improve existing components and to construct fresh components. This process is illustrated in Figure 1, where each puzzle piece represents a knowledge component. This work combines practical algorithms with rigorous statistical theory [6, 4].

The framework of Figure 1 can incorporate various forms of compositional representations and mechanisms for updating components with new knowledge. My work developed nine algorithmic instantiations of the framework for supervised learning, using naïve adaptation, memory replay, and synaptic consolidation [8] as knowledge update mechanisms, as well as various forms of compositional model structures, including modular neural nets. These algorithms consistently outperform non-compositional baselines and even compositional baselines trained outside of the framework. In particular, when trained on a sequence of highly diverse tasks taken from various vision benchmarks, these algorithms were the only ones capable of learning tasks from all benchmarks. Moreover, the resulting components learned by the framework correspond to self-contained, reusable units.

My research has further developed these notions for RL with linear model combinations [1] and more general combinations of neural components [5]. The resulting algorithm was the first to display accelerated learning of complex and diverse robotic manipulation tasks in a lifelong RL setting, by leveraging accumulated knowledge from previously seen tasks (see video demonstrations at bit.ly/LPG-FTW). Moreover, this method avoids forgetting how to solve previously seen tasks, enabling the system to perform each task at any point, even long after having learned it. As an additional technical insight, this work drew a connection between lifelong RL and off-line RL that opened the door to future research leveraging past experiences to retain knowledge in lifelong RL.

4 Ongoing Work

Compositional RL Benchmark In a collaborative effort, we created a robotic manipulation benchmark for evaluating functional composition in RL. The benchmark consists of hundreds of highly diverse RL tasks, constructed compositionally from a variety of robot arms, objects, obstacles, and objectives (Figure 2). The diversity and number of tasks push the capabilities of current multi-task and lifelong RL methods. Moreover, the compositional construction makes the relations across tasks fully interpretable, which permits extracting insights about the compositional nature of the solutions. Most critically, the benchmark constitutes a step towards reproducible RL research
Application to service robots One of the key motivators of my work is developing methods that have practical impact to real systems. Consequently, I am incorporating the methods created in my research for lifelong composition into physical service robots built atop a Freight base with Astra Pro RGB-D sensors. The robots will face a sequence of navigation tasks, including navigating crowded hallways, and will accumulate and reuse knowledge components to accelerate their training.

Task-free lifelong learning So far, my research has modeled changes in the environment as switching from one task to another. As a further step towards deployed lifelong learning, my work is moving to the more challenging task-free setting, in which time itself dictates change via a non-stationary process. In this setting, compositionality will still permit focusing knowledge updates to individual components that need adaptation, improving the capabilities of lifelong learners.

5 Future Work

Versatile skill learning with instructions As a community, we have become very good at reusing and adapting knowledge representations for diverse tasks, but we have struggled to decompose complex behaviors into reusable skills. Consider for example a robot in charge of multiple search-and-rescue operations. These missions will require common skills, such as finding injured people, navigating cluttered environments, and removing obstacles. My immediate research will leverage my experience in knowledge composition and lifelong transfer to discover such skills. This will incorporate techniques from off-line RL, and leverage high-level task instructions that implicitly encode the compositionality of skills, building upon my work on multi-task learning in language [3].

Cognitive science and natural language More broadly, my work focuses on obtaining a deeper understanding of the principles of compositionality and how they might be exploited to drive more efficient learning. A prime example of compositional learning is in human language learning, and so I will investigate how humans learn to navigate this vast combinatorial space throughout their lives. In particular, I will focus on how humans acquire language skills without access to a large stationary data set, but instead do so sequentially as they encounter new written and spoken words. This requires moving away from the typical task-based lifelong learning, and instead consider a smoother non-stationary process without artificial task boundaries, as I consider in my ongoing work.

Robotics As an application domain, robotics presents a wealth of potential impactful applications, including to search-and-rescue, agriculture, and health care. My work is inspired by the potential of creating autonomous robots that can be deployed long-term, continuously accumulating knowledge and improving their own performance over time. I will continue to use robots both as an inspiration for developing algorithms and as a test bed for evaluating their applicability.
Social good  I firmly believe that science has the responsibility of creating improvements for society. ML in particular has struggled in recent years to reconcile its often conflicting scientific and societal goals. I will contribute to the reconciliation of these goals in two ways. First, the methods I develop will be motivated by and applied to areas with social impact, such as education and climate change. Second, I will analyze the methods developed in my research under recent metrics for ethical ML [7]. Concretely, I will study the theoretical and empirical trade-offs of performance versus privacy and fairness in a lifelong setting. These metrics are typically defined over single data points, assuming that each point corresponds to an individual person. However, a common lifelong learning scenario considers an entire task to correspond to a single individual. Therefore, I will extend the common metrics for privacy and fairness to work over tasks.

6  Research Impact
One of the major factors limiting the widespread adoption of ML for a variety of applications is its need for vast amounts of (typically expensive) labeled data. The problem is further exacerbated by the fact that, once a traditional ML system has been trained, it is incapable of adapting to change, and therefore it must be trained from scratch whenever the environment changes. My research will create methods that learn with less data by leveraging the compositionality of knowledge accumulated over a lifetime, while guaranteeing the privacy and fairness of human users. In the future, these capabilities will enable the long-term deployment of systems such as hate-speech detection models, search-and-rescue robots, and student feedback programs.

7  Collaboration
I value research collaborations as a means for bringing forth diverse perspectives, increasing productivity, and making work more enjoyable, which is why I have sought out collaborations with academic and industrial labs. I look forward to working with faculty from the CS and other departments on creating physical learning robots and on exploring connections to cognitive science. I also plan to continue to collaborate with industrial labs, which will keep my vision focused on ML with real-world applications, and will also provide students in my group with connections outside of academia for their future careers.

8  Funding
My proposed work on lifelong learning for social good, with applications to language and robotics, will attract both industry and government agencies; similar works have recently been funded via faculty awards (e.g., Google and Facebook), hardware awards (e.g., NVIDIA), and grants (e.g., DARPA and AFRL). Beyond these funding sources, I will pursue early career awards such as NSF CAREER, the Packard Fellowship, and the Department of Energy Early Career Research Program. For this, I will leverage proposal-writing experiences gained during my Ph.D., winning 3rd place of the Two Sigma Diversity Fellowship and assisting my advisor in writing grant proposals.

References