Learning Transferable Representations for Non-Stationary Environments

Doctoral Consortium

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ABSTRACT

For intelligent agents to become fully autonomous, they need to perceive and adapt to the changes in environmental dynamics. In addition, they need to devise a strategy to acquire new knowledge while retaining the past learned ones. Humans can acquire, retain and transfer knowledge over their lifespan. In a similar vein, intelligent agents are becoming capable of acquiring and transferring knowledge but not retaining it. Towards reaching these goals, we have proposed algorithms that address multiple aspects of machine intelligence, from robot perception, allowing robots to accurately model human intent and predict human motion, to knowledge retention, allowing robots to retain past knowledge without forgetting. Our proposed algorithms have attained state-of-the-art performances for robot perception and overcoming catastrophic forgetting in perception-based tasks. Our current and ongoing work builds upon our completed works to explore knowledge retention in more challenging domains, particularly robot control, and investigate multi-agent collaboration as a precursor for human-robot collaboration.

KEYWORDS

Motion Prediction; Continual Learning; Representation Learning

ACM Reference Format:

Mohammad Samin Yasar. 2023. Learning Transferable Representations for Non-Stationary Environments: Doctoral Consortium. In *Proc. of the 22nd International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2023), London, United Kingdom, May 29 – June 2, 2023*, IFAAMAS, 3 pages.

1 INTRODUCTION

Recent advances in machine intelligence and learning have significantly enhanced robot perception and decision-making, enabling their adoption across a variety of applications from healthcare and manufacturing settings to autonomous vehicles [5, 7, 10, 23, 24]. Despite significant advances in robot learning, robots' capabilities and actions are often limited in scope and require strong assumptions about the environment. As such, robots are mostly confined to their proverbial cage, limited by their inability to model the stochastic nature of dynamic environments [26].

For robots to become fully autonomous and reliable, they need to perceive and adapt to the changes in environmental dynamics [4, 11, 20, 28]. Along this line, progress has been made in robot perception in detecting changes and generalizing to new environments [8, 9, 12, 13]. However, adapting to dynamic environments remains an open challenge for robot decision-making, and closed-loop control [6]. Furthermore, robots have to adapt and interact with their environment using a continuous stream of observations, which requires that representations be learned in a continual manner [17]. However, continual learning does not suit current learning paradigms, which involve training Deep Neural Networks with the assumption that the training distribution is stationary and that the data samples are independent and identically distributed (i.i.d.) [14].

Proc. of the 22nd International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2023), A. Ricci, W. Yeoh, N. Agmon, B. An (eds.), May 29 – June 2, 2023, London, United Kingdom.

2 OUR WORK TO DATE

Toward reaching our goal of learning robust representations for robots, our works have furthered the state-of-the-art in *motion prediction* [25, 27, 28, 30] to allow robots to understand and anticipate human behavior, *robot control* [31] to interleave anticipation and prediction with planning and control and *continual learning*, to allow robots to acquire knowledge efficiently without forgetting [29].

2.1 Motion Prediction:

Human motion prediction is widely considered one of the essential parts of robotic intelligence that would enhance robot perception. Towards this end, we have made several architectural contributions. Firstly, we proposed a novel sequence learning framework that is scalable and interpretable, allowing us to forecast over long-term horizons [27]. We extensively evaluated our framework on single-agent, multi-agent, and human-robot collaboration datasets and have significantly outperformed all other evaluated approaches. In our latest work, IMPRINT, we focused on utilizing the multimodality of robot sensing to obtain a holistic representation of the environment [30]. In IMPRINT, we explicitly modeled a) the interactional dynamics of human and robot team members; and b) the multimodal context from different data modalities and fused them adaptively to predict human motion in team settings. We extensively evaluated IMPRINT across various benchmarks from multi-agent human-human and human-robot collaboration datasets. In Table 1, we present our results for human-robot collaboration, where we predict human motion conditioned on robot motion. Our results suggest that IMPRINT outperformed all other approaches.

2.2 Robot Control:

While forecasting future motion allows robots to perceive their environment better, they still need to perform actions that will impact the environment. Recent advances in deep RL have enabled

Table 1: MSE (in cm^2) of different multi-agent motion prediction methods on the KTH-HRC Dataset (Lower is better).

Approaches	Frames					
	5	10	20	30	35	40
Zero-Velocity [19]	0.11	0.34	1.18	2.38	3.07	3.81
Seq2Seq [19]	0.14	0.36	1.09	2.17	2.81	3.49
Seq2Seq-SPL [1]	0.17	0.42	1.20	2.33	2.98	3.66
Scalable + Interpretable [26]	0.06	0.20	0.72	1.61	2.21	2.91
IMPRINT (ours)	**0.06**	**0.18**	**0.63**	**1.36**	**1.85**	**2.42**

robot agents to achieve remarkable performance on tasks ranging from robotic locomotion to manipulation [3, 15, 16, 21, 22]. However, these algorithms have been developed and trained in environments where the goal state is static, and only the robot itself can bring changes into the environment [18]. For robots to reliably take action, they need to perceive and predict any environmental changes and accordingly take action. Our proposed algorithm, LASSO [31], allows the robot to learn a robust representation of its environment by forecasting future states and minimizing the distance between the current state and the desired goal state. Using state space forecasting on top of the hindsight experience replay buffer, our algorithm allows the robot to learn the expected future states of the environment. Compared to strong baselines (SAC and DDPG) LASSO performed favorably across multiple manipulation tasks, as shown in Fig. 1.

2.3 Continual Learning:

Despite significant improvements in robot perception and control, robots are seldom expected to be trained only once and never require retraining. Instead, robots are expected to interact and learn from their environment using a continuous stream of observations, which requires that representations be learned in a continual manner. However, Deep Neural Networks are trained with the assumption that the training distribution is stationary and that the data samples are independent and identically distributed (i.i.d.) from a stationary distribution. Current optimization strategies for training these networks focus on learning a representation from current data and do not account explicitly for past observed data, resulting in catastrophic forgetting when the network forgets representation salient to the past task/data distribution. To mitigate this while maintaining performance, we proposed CoRaL, a Continual Representation Learning approach for overcoming Catastrophic Forgetting that unifies Representation Learning with Continual Learning (CL). Our approach tackles CL problems from two aspects: learning effective representations that can be retained, refined, and transferred in incremental settings; and encouraging the model to retain its past responses using a memory buffer. The results in Table 2 underline CoRaL's effectiveness in addressing catastrophic forgetting, as it consistently outperformed all evaluated CL algorithms.

3 ONGOING AND FUTURE WORK:

Our work to date has established a foundation for the three thrusts of my thesis: Motion Prediction, Robot Control, and Continual Learning. The goal of my ongoing and future research is to develop algorithms that are at the intersection of these thrusts. Robot control at present is centered around having a single robot interacting with the environment. However, robots are expected to work in groups, potentially with other robots or even humans. An obvious use-case of this is in the manufacturing industry, where we expect

Table 2: Performance comparison (averaged across 10 runs) of various CL methods on different scenarios (Accuracy in %)

Method	IL-Task		IL-Class	
	S-CIFAR10	S-Tiny-ImageNet	S-CIFAR10	S-Tiny-ImageNet
JOINT	98.31 ± 0.12	82.04 ± 0.10	92.20 ± 0.15	59.99 ± 0.19
SGD	61.02 ± 3.33	18.31 ± 0.68	19.62 ± 0.05	7.92 ± 0.26
DER [2]	91.40 ± 0.92	40.22 ± 0.67	61.93 ± 1.79	11.87 ± 0.78
DER++ [2]	91.92 ± 0.60	40.87 ± 1.16	64.88 ± 1.17	10.96 ± 1.17
CoRaL (Ours)	**92.01 ± 0.32**	**41.37 ± 0.91**	**65.24 ± 1.09**	**14.06 ± 0.57**

robots to perform overly repetitive and potentially dangerous tasks and humans to perform the more "dexterous" tasks or tasks that require a higher level of decision-making. Another use case in the manufacturing industry could be robots collaborating to perform assembly tasks, which could improve efficiency and productivity.

In line with these requirements, my future work will focus on scaling robot control from single to multiple robots. My research will focus on developing algorithms that can create collaborative strategies for robots. We plan on taking a hierarchical approach to collaborative policy learning for each robot, where robots perceive their environments and decide what action category to take, say "Pick an object," "Screw the gear," or "Handover an object to another robot." This is followed by a low-level action at the robot's joint space. Such a hierarchical structure will allow the algorithms to be modular, explainable, and potentially more generalizable.

In a concurrent vein, we are actively working on closing the simulator-to-real gap in robotics, where algorithms that are trained in simulation do not generalize to the real world. To achieve this, we have collected a large-scale dataset of human-robot collaboration tasks comprising one robot and two humans. To the best of our knowledge, this is a first-of-its-kind effort, as our findings suggest a need for more human-robot teams datasets. The data is collected and aggregated from multiple modalities, ranging from RGB, Depth, Egocentric view, Eye-gaze, Skeleton, and finally, robot data, thus providing a rich array of sensing. We plan to use the data collected to develop learning models to predict human motion and develop robot policies. We plan to release the dataset along with our findings.

The contributions of this research are composed of three parts, all geared to scenarios involving multiple humans. The first part aims to improve the state-of-the-art in robot perception by developing frameworks that allow robots to anticipate human motion while being scalable and interpretable. The second part aims to interleave robot perception with control by developing algorithms that can be trained end-to-end and built on top of our completed human motion prediction work. Finally, the third part aims to develop training schemes that allow robots to learn without forgetting.

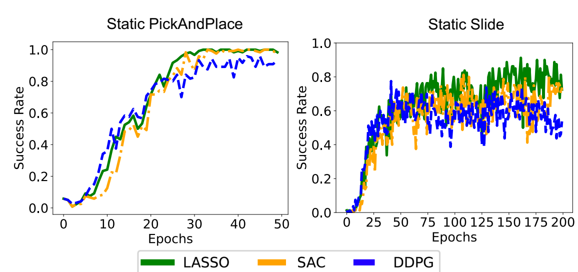

Figure 1: Performance comparison of all evaluated benchmarks

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