Neuro-Symbolic Reinforcement Learning: A Reinforcement Learning Platform & Neuro-Symbolic Agent

Hunter W. Ellis

Thesis submitted to the Faculty of the

Virginia Polytechnic Institute and State University

in partial fulfillment of the requirements for the degree of

Master of Science

in

Computer Engineering

Thinh T. Doan, PhD, Chair

Michael S. Hsaio, PhD, Co-chair

March 23, 2016

Blacksburg, Virginia

Keywords: Reinforcment Learning, Neuro-symbolic, Neuro-symbolic Concept Learner, Multi-task Reinforcement Learning, Robotics

Neuro-Symbolic Reinforcement Learning: A Reinforcement Learning Platform & Neuro-Symbolic Agent

Hunter W. Ellis

(ABSTRACT)

In recent years, neuro-symbolic learning methods have demonstrated promise in tasks requiring a semantic understanding that can often be missed by traditional deep learning techniques. By integrating symbolic reasoning with deep learning architectures the interpretability of the model's reasoning becomes more evident and can provide more control during deployment. This thesis aims to apply neuro-symbolic learning to the domain of reinforcement learning. First, a simulation environment for robotic manipulation tasks based on the Gazebo Harmonic physics simulator and ROS2 middleware suite is presented. In this environment an analysis of policy-gradient based reinforcement learning algorithm is given. Then, by leveraging the performance of deep learning with the semantic reasoning and interpretability of symbolically defined programming, a novel neuro-symbolic learning method is proposed to generalize tasks and motion planning for robotics applications using natural language. This novel neuro-symbolic can be seen as an adaptation of the Neuro-Symbolic Concept Learner (Mao et. al) developed by IBM Watson, in which images and natural language are first processed by convolutional and residual neural networks, respectively and then parsed by a symbolically reasoned program. Where the architecture proposed in this paper differs, is in its use of the Neuro-Symbolic Concept Learner for preprocessing of a given input task, to then inform a reinforcement learning agent of how to act in a given environment. Finally, the novel adaptation of the Neuro-Symbolic Concept Learner is introduced as a method of controlling multi-task agents.

Neuro-Symbolic Reinforcement Learning: A Reinforcement Learning Platform & Neuro-Symbolic Agent

Hunter W. Ellis

(GENERAL AUDIENCE ABSTRACT)

Neuro-symbolic learning is an area in machine learning that leverages user defined symbolic programming in addition to deep learning. This method goes against the typical approach of end-to-end training of models and instead hopes to benefit from the introduction of symbolic programs.

Dedication

This is where you put your dedications.

Acknowledgments

Thank you to Dr. Thinh Doan and Dr. Michael Hsiao for your guidance and expertise throughout my undergraduate and graduate studies.

Contents

List of Figures **viii**

List of Tables **ix**

1 Introduction **1**

1.1 Objectives 1

1.1.1 A sub-section 2

1.2 Applications 3

1.3 Challenges 3

1.4 Contributions 3

2 Background **5**

2.1 Markov Decision Process 5

2.2 Reinforcement Learning 5

2.3 Neuro-symbolic Architectures 5

2.4 Sim-to-Real 6

2.4.1 Transfer Learning 6

2.4.2 Multitask Learning 6

3 Reinforcement Learning Platform 7

4 Neuro-symbolic Reinforcement Learning Model 8

5 Simulations 10

6 Reality 11

7 Discussion 12

8 Conclusions 13

List of Figures

4.1 Overview of proposed architecture. 9

List of Tables

NLP is a field of computer science, artificial intelligence, and linguistics concerned with the interactions between computers and human (natural) languages.

σ is the eighteenth letter of the Greek alphabet, and carries the 's' sound. In the system of Greek numerals, it has a value of 200.

Chapter 1

Introduction

Neuro-symbolic learning methods and concepts have been used in recent years to achieve results that standalone deep learning and symbolic programming methods have not been able to achieve. [EXAMPLES]. The emerging developments in the field of neuro-symbolic learning has created opportunities to explore applications and adaptations of these methods. The field of Reinforcement Learning (RL) has also made advances – demonstrating the paradigms effectiveness in creating agents that can perform complex tasks autonomously. The intersection of these two research areas has led to developments that have allowed agents to perform tasks with with both programatic interpretability and learned performance. [EXAMPLES].

1.1 Objectives

Nam dui ligula, fringilla a, euismod sodales, sollicitudin vel, wisi. Morbi auctor lorem non justo. Nam lacus libero, pretium at, lobortis vitae, ultricies et, tellus. Donec aliquet, tortor sed accumsan bibendum, erat ligula aliquet magna, vitae ornare odio metus a mi. Morbi ac orci et nisl hendrerit mollis. Suspendisse ut massa. Cras nec ante. Pellentesque a nulla. Cum sociis natoque penatibus et magnis dis parturient montes, nascetur ridiculus mus. Aliquam tincidunt urna. Nulla ullamcorper vestibulum turpis. Pellentesque cursus luctus mauris.

1.1.1 A sub-section

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Ut purus elit, vestibulum ut, placerat ac, adipiscing vitae, felis. Curabitur dictum gravida mauris. Nam arcu libero, nonummy eget, consectetuer id, vulputate a, magna. Donec vehicula augue eu neque. Pellentesque habitant morbi tristique senectus et netus et malesuada fames ac turpis egestas. Mauris ut leo. Cras viverra metus rhoncus sem. Nulla et lectus vestibulum urna fringilla ultrices. Phasellus eu tellus sit amet tortor gravida placerat. Integer sapien est, iaculis in, pretium quis, viverra ac, nunc. Praesent eget sem vel leo ultrices bibendum. Aenean faucibus. Morbi dolor nulla, malesuada eu, pulvinar at, mollis ac, nulla. Curabitur auctor semper nulla. Donec varius orci eget risus. Duis nibh mi, congue eu, accumsan eleifend, sagittis quis, diam. Duis eget orci sit amet orci dignissim rutrum.

Nam dui ligula, fringilla a, euismod sodales, sollicitudin vel, wisi. Morbi auctor lorem non justo. Nam lacus libero, pretium at, lobortis vitae, ultricies et, tellus. Donec aliquet, tortor sed accumsan bibendum, erat ligula aliquet magna, vitae ornare odio metus a mi. Morbi ac orci et nisl hendrerit mollis. Suspendisse ut massa. Cras nec ante. Pellentesque a nulla. Cum sociis natoque penatibus et magnis dis parturient montes, nascetur ridiculus mus. Aliquam tincidunt urna. Nulla ullamcorper vestibulum turpis. Pellentesque cursus luctus mauris.

Nulla malesuada porttitor diam. Donec felis erat, congue non, volutpat at, tincidunt tristique, libero. Vivamus viverra fermentum felis. Donec nonummy pellentesque ante. Phasellus adipiscing semper elit. Proin fermentum massa ac quam. Sed diam turpis, molestie vitae, placerat a, molestie nec, leo. Maecenas lacinia. Nam ipsum ligula, eleifend at, accumsan nec, suscipit a, ipsum. Morbi blandit ligula feugiat magna. Nunc eleifend consequat lorem. Sed lacinia nulla vitae enim. Pellentesque tincidunt purus vel magna. Integer non enim. Praesent euismod nunc eu purus. Donec bibendum quam in tellus. Nullam cursus pulvinar lectus. Donec et mi. Nam vulputate metus eu enim. Vestibulum pellentesque felis eu massa.

Quisque ullamcorper placerat ipsum. Cras nibh. Morbi vel justo vitae lacus tincidunt ultrices. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. In hac habitasse platea dictumst. Integer tempus convallis augue. Etiam facilisis. Nunc elementum fermentum wisi. Aenean placerat. Ut imperdiet, enim sed gravida sollicitudin, felis odio placerat quam, ac pulvinar elit purus eget enim. Nunc vitae tortor. Proin tempus nibh sit amet nisl. Vivamus quis tortor vitae risus porta vehicula.

1.2 Applications

1.3 Challenges

1.4 Contributions

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Ut purus elit, vestibulum ut, placerat ac, adipiscing vitae, felis. Curabitur dictum gravida mauris. Nam arcu libero, nonummy eget, consectetuer id, vulputate a, magna. Donec vehicula augue eu neque. Pellentesque habitant morbi tristique senectus et netus et malesuada fames ac turpis egestas. Mauris ut leo. Cras viverra metus rhoncus sem. Nulla et lectus vestibulum urna fringilla ultrices. Phasellus eu tellus sit amet tortor gravida placerat. Integer sapien est, iaculis in, pretium quis, viverra ac, nunc. Praesent eget sem vel leo ultrices bibendum. Aenean faucibus. Morbi dolor nulla, malesuada eu, pulvinar at, mollis ac, nulla. Curabitur auctor semper nulla. Donec varius orci eget risus. Duis nibh mi, congue eu, accumsan eleifend, sagittis quis, diam. Duis eget orci sit amet orci dignissim rutrum.

Nam dui ligula, fringilla a, euismod sodales, sollicitudin vel, wisi. Morbi auctor lorem non justo. Nam lacus libero, pretium at, lobortis vitae, ultricies et, tellus. Donec aliquet, tortor sed accumsan bibendum, erat ligula aliquet magna, vitae ornare odio metus a mi. Morbi ac orci et nisl hendrerit mollis. Suspendisse ut massa. Cras nec ante. Pellentesque a nulla. Cum sociis natoque penatibus et magnis dis parturient montes, nascetur ridiculus mus. Aliquam tincidunt urna. Nulla ullamcorper vestibulum turpis. Pellentesque cursus luctus mauris.

Chapter 2

Background

2.1 Markov Decision Process

2.2 Reinforcement Learning

2.3 Neuro-symbolic Architectures

Neuro-symbolic models can be broadly defined as models which focus on merging both *neural* and *symbolic* AI approaches to add value to the system. The term *nerual* refers to the use of artificial neural networks and the term *symbolic* typically refers to approaches based on explicit symbol manipulation. (CITATION taxonomy.pdf) The fundamental desire of neuro-symbolic models is to leverage both neural and symbolic approaches in a way that is favorable to the strengths of each approach and unfavorable to their weaknesses. The strengths neural models would include the ability to leverage raw data that may be too dificult/complex to semantically reason about, while the weaknesses may include the challenges faced when attempting to reason neural models. Conversely, the strengths of symbolic models include their ability to be highly explainable and verifiable, but they may have weaknesses in their reliance human input/understanding of a system. Thus, the promise of a neuro-symbolic architecture is a system which would be robust from training data, symbolically explainable, and be able to leverage human expert knowledge in its design.

In recent years many different neuro-symbolic models have been designed and deployed. Because the intersection of these two approaches may be quite broad and models can take many different forms be it is important to make distinctions between the various incarnations of neuro-symbolic architectures. Henry Kautz, in a 2005 article presents ”six possible designs” patterns classifying each method in reference to their neural and symbolic interactions:(CITATION KAUTZ)

Neuro-symbolic Design Pattern	**Definition**	**Example**
Symbolic Neural symbolic	A symbolic input is fed into a neural network producing a symbolc output.	GPT
Symbolic[Neural]	A neural subroutine is evoked by a symbolic strategy.	AlphaGo
Neural[Symbolic]	A symbolic subroutine is evoked by a neural strategy.	ChatGPT accessing Wolfram for computations
Neural|Symbolic	A neural network converts a non-symbolic input into symbolic data to be symbolically processed.	Neuro-Symbolic Concept Learner
Neural:Symbolic $\rightarrow$ Neural	A symbolically represented dataset is used to train an neural network to predict a symbolic output	ANN-MPC
Neural_{Symbolic}	Symbolic rules are used to define the structures making up the neural network.	Logic Tensor Networks

2.4 Sim-to-Real

2.4.1 Transfer Learning

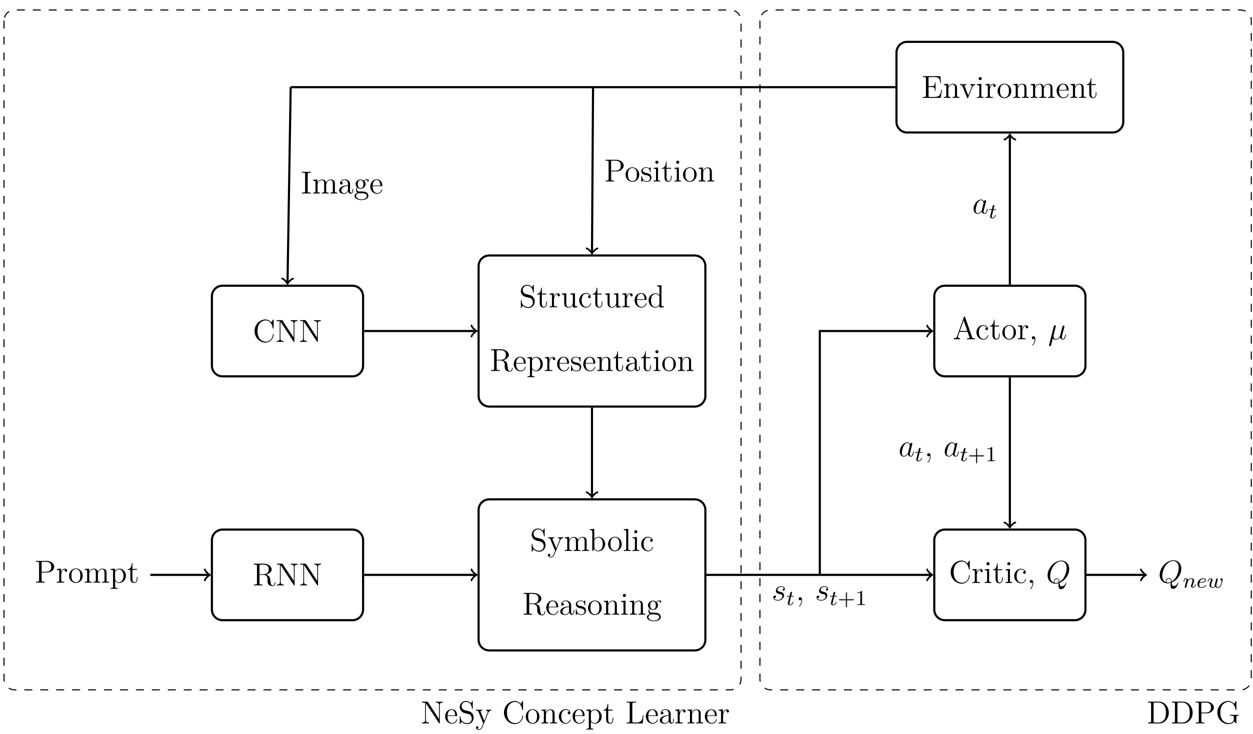
2.4.2 Multitask Learning

Chapter 3

Reinforcement Learning Platform

Chapter 4

Neuro-symbolic Reinforcement Learning Model



./images/architecture_overview.png

./images/architecture_overview.png

Figure 4.1: Overview of proposed architecture.

Shape	**Color** (r, g, b)	**Position** (x, y)	**Rotation** θ	**Velocity** (v_x, v_y, v_z, ω)
J1	(0, 0, 0)	(0, 0, 0)	0°	(0, 0, 0, 0)
J2	(0, 0, 0)	(0, 0.1, 0)	0°	(0, 0, 0, 0)
J3	(0, 0, 0)	(0, 0.2, 0)	0°	(0, 0, 0, 0)
J4	(0, 0, 0)	(0, 0.4, 0)	0°	(0, 0, 0, 0)
J5	(0, 0, 0)	(0, 0.4, 0)	0°	(0, 0, 0, 0)
J6	(0, 0, 0)	(0, 0.4, 0)	0°	(0, 0, 0, 0)
cube	(255, 0, 255)	(0.75, 0.75, 0)	0°	(0, 0, 0, 0)
cylinder	(255, 255, 0)	(-0.25, 1, 0)	0°	(0, 0, 0, 0)
rectangle	(0, 0, 255)	(0.5, 0.5, 0)	90°	(0, 0, 0, 0)
sphere	(0, 255, 0)	(0.6, -0.1, 0)	0°	(0, 0, 0, 0)

Label	**Color** (r, g, b)	**Position** (x, y)	**Rotation** θ	**Velocity** (v_x, v_y, v_z, ω)	**Symbol**
J1	(0, 0, 0)	(0, 0, 0)	0°	(0, 0, 0, 0)	null
J2	(0, 0, 0)	(0, 0.1, 0)	0°	(0, 0, 0, 0)	null
J3	(0, 0, 0)	(0, 0.2, 0)	0°	(0, 0, 0, 0)	null
J4	(0, 0, 0)	(0, 0.4, 0)	0°	(0, 0, 0, 0)	null
J5	(0, 0, 0)	(0, 0.4, 0)	0°	(0, 0, 0, 0)	null
J6	(0, 0, 0)	(0, 0.4, 0)	0°	(0, 0, 0, 0)	null
cube	(255, 0, 255)	(0.75, 0.75, 0)	0°	(0, 0, 0, 0)	null
cylinder	(255, 255, 0)	(-0.25, 1, 0)	0°	(0, 0, 0, 0)	avoid
rectangle	(0, 0, 255)	(0.5, 0.5, 0)	90°	(0, 0, 0, 0)	move
sphere	(0, 255, 0)	(0.6, -0.1, 0)	0°	(0, 0, 0, 0)	null
goal	(0, 0, 0)	(-1, 1, 0)	0°	(0, 0, 0, 0)	goal

Chapter 5

Simulations

Chapter 6

Reality

Chapter 7

Discussion

Chapter 8

Conclusions