Neuro-Symbolic Reinforcement Learning: Natural Language Driven Multi-Task Agents

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: Natural Language Driven Multi-Task Agents

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: Natural Language Driven Multi-Task Agents

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

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

2.4 Sim-to-Real

2.4.1 Transfer Learning

2.4.2 Multitask Learning

Chapter 3

Neuro-symbolic Reinforcment Learning Model

Neuro

./images/architecture_overview.png

Figure 3.1: Overview of proposed architecture.

Chapter 4

Environment and Dataset

A custom simulation environment was created to demonstrate the possibilities of the Neuro-Symbolic Reinforcement Learning Methods presented in the previous chapter. The environment was set up for manipulation tasks that can be seen as an extension of the CLEVR dataset.

4.1 Overview

The environment consists of a six axis robot arm set up in the Gazebo Robotic Simulator. Within the arm's working envelop various basic 3-D shapes (i.e. spheres, cubes, cylinders, etc.) are present.

4.2 Robot Operating System

The Robot Operating System is a middleware suite used for robot software development. ROS workspaces consist of packages that interface with ROS libraries.

./images/architecture_overview.png

Figure 4.1: Overview of proposed architecture.

4.2.1 Description Package

The `arm_description` package is a ROS package that contains various files used to describe the physcial characteristics of the robot including its visual, collision, control, and forward kinematics.

The six-axis robotic arm model deployed in this package is a slightly modified version of an open source six-axis robot design with modfications made to some of the pulleys and end-effector design. The robot arm is made up of six joints (J1-J6) all described as revolute joints in the `arm_description`'s Universal Robot Description File (`.urdf`). Meshes for rendering the robot imported as `.stl` files and the meshes for collision areas are described by COLLADA (`.dae`) files. These meshes are linked together in the URDF in a kinematic chain to form the robotic arm manipulator. Control of the robot is accomplished through the ROS Jazzy control package.

4.3 Gazebo Robotics Simulator

Gazebo is a robotic physics simulator developed by Open Robotics which integrates the ODE physics engine, ORGE rendering engine, and support code for sensor and actuator control integration. This environment leverages Gazebo Harmonic (the latest release of Gazebo at the time of writing) to visually render and simulate the physics of the robotic manipulator and the objects in its environment.

4.3.1 Simulation Package

4.4 Dataset

Chapter 5

Simulations

Chapter 6

Chapter 7

Reality

Chapter 8

Discussion

Chapter 9

Conclusions