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

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

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(GENERAL AUDIENCE ABSTRACT)				

Dedication

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Acknowledgments

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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.

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

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1.1.1 A sub-section

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1.2 Applications

1.3 Challenges

1.4 Contributions

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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

Neuro-symbolic Reinforcment Learning Model

Neuro

./images/architecture_overview.png

Figure 3.1: Overview of proposed architecture.

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 basic object manipulation tasks. The cooresponding dataset used to train the model that can be seen as an extension of the CLEVR dataset – which instead prompts the agent to act on the objects in the environment.

4.1 Environment 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.

4.2.1 Description Package

The arm_description package is a ROS package that contains various files used to describe the physical 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 modifications 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

Simulations

Reality

Discussion

Conclusions