

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

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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.

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

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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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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 *neural* 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 difficult/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 symbolic 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

Given the problem space two environments were created to validate the neuro-symbolic algorithms mentioned in the previous sections

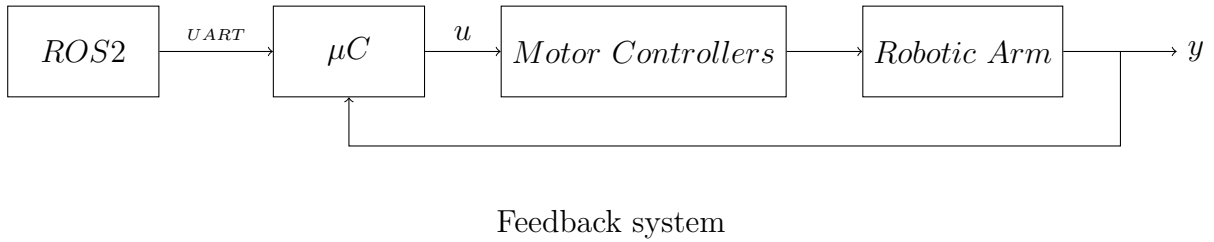
Custom real and coresponding simulated environments were created to demonstrate the possibilities of the Neuro-Symbolic Reinforcement Learning Methods presented in the previous chapter. The environment was set up for basic object manipulation tasks. The cooresponding dataset used to train the model that can be seen as an extension of the CLEVR dataset – which instead prompts the agent to act on the objects in the environment.

3.1 Real-Time Hardware Environment

The physical hardware used to test the algorithms is made up of a 6-axis robot arm communicating over serial (UART) with a PC running the algorithms in a ROS2 Jazzy workspace. The rigid components of the arm including gears and structural pieces are made of 3D-printed Polylactic Acid (PLA). The robotic arm uses stepper motors, belts, and pulleys to articulate the 6 joints. The first 5 joints (J1 to J5) use bipolar NEMA 17 stepper motors, while the last joint J6, responsible for manipulating the end effector, uses a bipolar NEMA 8 stepper motor. The belts and pulleys are "off-the-shelf" GT2 timing belts and pulleys of varying sizes, used to the torque applied to each joint (belts and pulleys connect every motor to a joint with the exception of J6). Ball and shunt bearings of verious sizes are also used

to reduce friction in the joints.

The electronic hardware is controlled by an ATmega328p microcontoller and 6 A4988 stepper motor drivers originally setup for controlling the stepper motors of a 3D-Printer. Custom firmware was written for the microcontoller to run the 6 stepper motor drivers simultaneously with a serial (UART) interrupt to recieve control commands from the host PC.



3.2 Virtual Environment

The environment consists of the same six axis robot arm described in the previous section set up in the Gazebo Robotic Simulator (using a ROS Universal Robot Description File and Gazebo Simulation Description File). Within the arm's working envelop various basic 3-D shapes (i.e. spheres, cubes, cylinders, etc.) are present.

3.3 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.

3.3.1 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.

3.4 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.

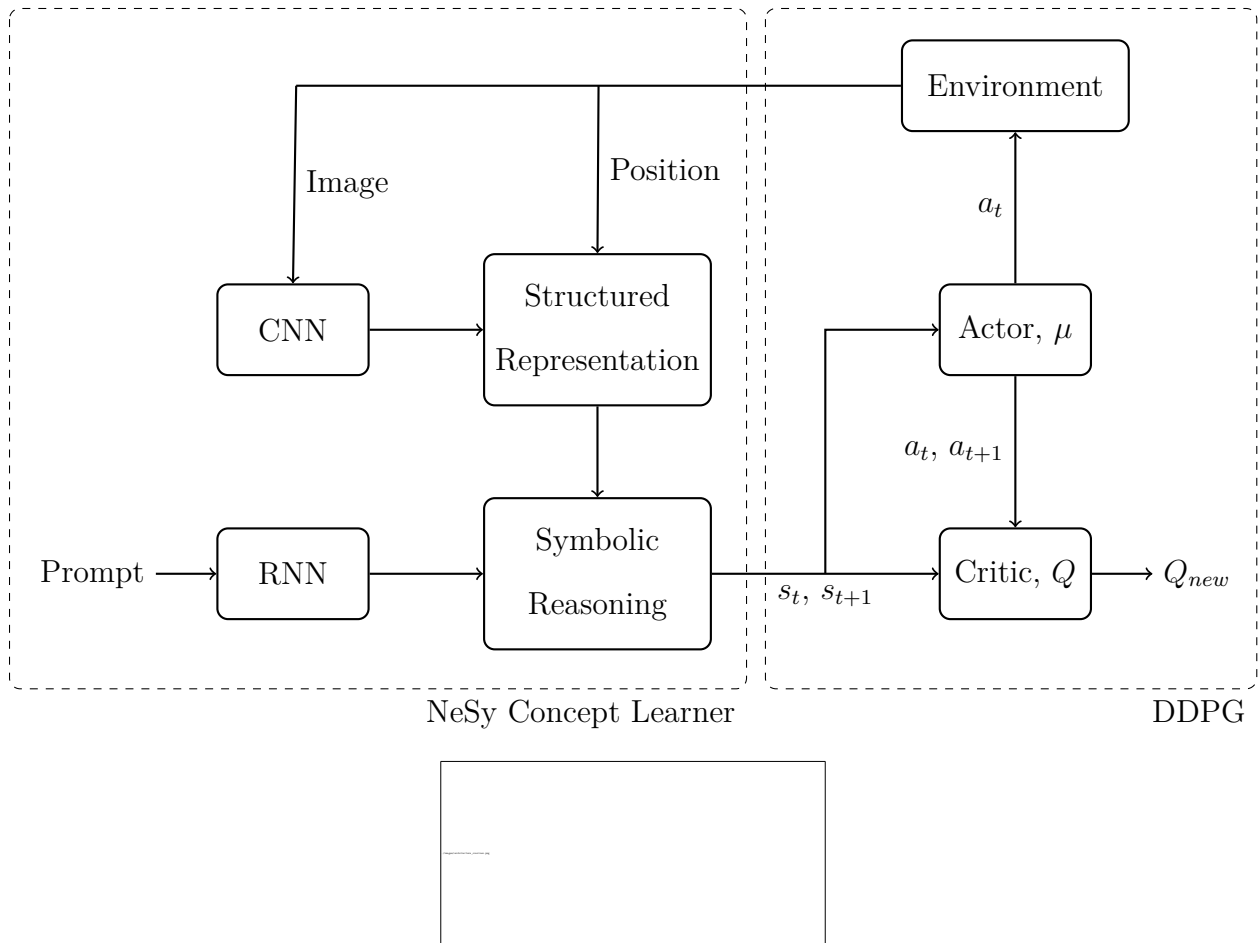
3.4.1 Simulation Package

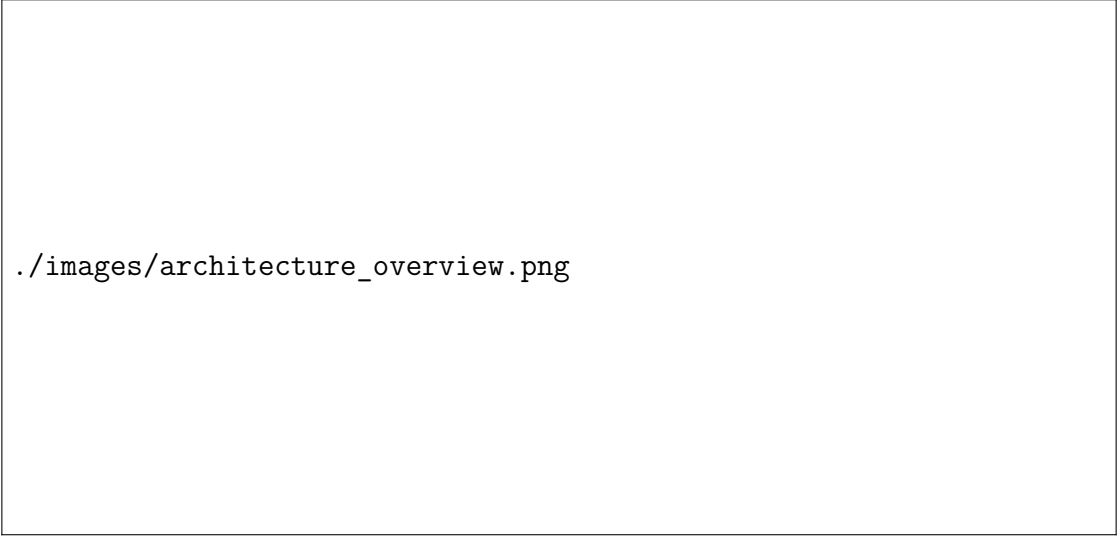
3.5 Dataset

Chapter 4

Neuro-symbolic Reinforcement

Learning Model





./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

Discussion

Chapter 7

Conclusions