Reinforcement Learning Meets Logic Programming: Towards Explainable AI

1 Appendix

This appendix presents three detailed use cases that demonstrate the potential applicability of our neuro-symbolic framework in diverse real-world scenarios. These use cases have been carefully selected to illustrate the versatility of our approach in handling complex, dynamic environments across different domains. While we have not conducted experiments on these specific scenarios due to the scope of our current research, we believe they provide valuable insights into the broader applicability of our framework.

1.1 Use Case 1: Clinical Symptom Analysis in Patient Cases

In this use case, we consider a possible database containing a significant number of clinical cases. Each clinical case reports a *temporal sequence of symptoms* experienced by the patient. The system based on the proposed framework would analyze the sequence of symptoms present in patients and extract a set of rules modeling cause-and-effect relationships among the symptoms. Each clinical case is considered an episode that the agent will analyze. This approach allows the framework to learn from multiple patient histories, potentially uncovering complex relationships between symptoms that may not be immediately apparent to human observers. The potential benefits of applying our framework in this context include:

- Identifying patterns of symptom progression that could indicate specific diseases or conditions.
- Discovering unexpected relationships between seemingly unrelated symptoms.
- Predicting the likely occurrence of future symptoms based on current observations.
- Assisting in early diagnosis by recognizing symptom patterns in their early stages.

This application of our framework could provide valuable insights to healthcare professionals, potentially improving patient care through more accurate and timely diagnoses.

Use Case 2: Predictive Maintenance in Industrial Manufacturing

In this use case, we consider a large-scale industrial manufacturing environment where multiple machines operate continuously. The goal is to predict potential machine failures and optimize maintenance schedules.

The system based on the proposed framework would analyze *temporal sequences of machine sensor data*, *maintenance records*, and *failure incidents*. Each machine's operational history would be considered as an episode for the agent to analyze.

Potential propositional facts in this scenario could include: *HighVibration*, *AbnormalTemperature*, *ExcessiveNoise*, *OilPressureDropped*, *PowerConsumptionIncreased*, *MaintenancePerformed*, *MachineFailure*.

The framework would aim to extract cause-and-effect rules relating to these facts. For example, it might discover that a sequence of *HighVibration* followed by *AbnormalTemperature* often leads to *MachineFailure* if *MaintenancePerformed* is *False*.

Potential benefits of applying our framework in this context include:

- Predicting machine failures before they occur, reducing costly downtime.
- Optimizing maintenance schedules based on actual machine conditions rather than fixed intervals.
- Identifying complex patterns of sensor readings that precede failures, which might not be obvious to human operators.
- Continuously adapting to changing conditions as machines age or production processes evolve.

This application could significantly improve operational efficiency, reduce maintenance costs, and increase the overall reliability of the manufacturing process.

1.2 Use Case 3: Smart City Traffic Management

In this use case, we consider a smart city environment where various sensors and data sources provide real-time information about traffic conditions, weather, events, and public transportation. The system based on our proposed framework would analyze temporal sequences of traffic-related data across the city. Each day could be considered as an episode for the agent to analyze, with multiple data points collected throughout the day. Potential propositional facts in this scenario could include: i) *HighTrafficDensity*, ii) *PublicEventOccurring*, iii) *HeavyRain*, iv) *PublicTransportDelay*, v) *RoadworkInProgress*, vi) *RushHour*, vii) *TrafficAccident*.

The framework would aim to extract cause-and-effect rules relating to these facts. For example, it might discover that a combination of *HeavyRain* and *PublicEventOccurring* often leads to *HighTrafficDensity* if it coincides with *RushHour*. Potential benefits of applying our framework in this context include:

- Predicting traffic congestion before it occurs, allowing for proactive traffic management.
- Optimizing traffic light timings based on learned patterns of traffic flow.
- Improving public transportation scheduling to adapt to recurring traffic patterns.

- Identifying complex interactions between various factors affecting traffic, which might not be immediately apparent to human planners.
- Continuously adapting to changing city dynamics, such as new construction or changes in population distribution.

This application could improve urban mobility, reduce commute times, decrease air pollution from idling vehicles, and enhance overall quality of life for city residents. The interpretable nature of the rules generated by our framework would also provide valuable insights to city planners for long-term infrastructure development.