Learning of Symbolic Representations for Rescue Scenarios in Disaster Zones

BSc Defense

Ahmed Khaled

Department of Computer Science and Engineering
Faculty of Media Engineering and Technology
German University in Cairo

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Outline

Introduction and Overview

- Focus of this thesis

Findings and Personal Significance

- Potential of Reinforcement Learning (RL) and symbolic knowledge extraction
- Belief in the power of AI

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Improving Disaster Response Strategies

- Increasing frequency and severity of natural disasters
- Need for efficient and effective disaster response strategies
- Role of AI in improving these responses

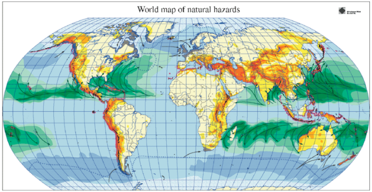

Figure 1: World Map of Natural Hazards

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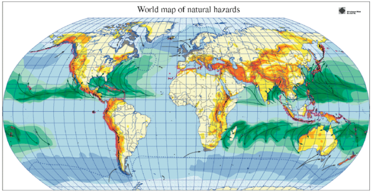

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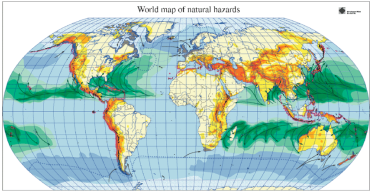

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Learning in Unknown Environments

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- Pushing the boundaries of AI adaptability and learning capabilities

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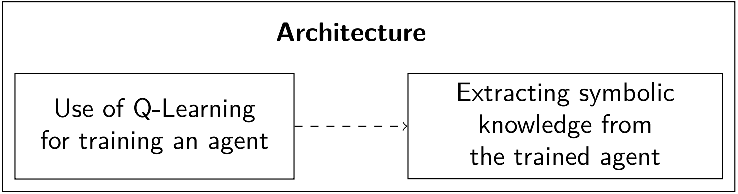
System Architecture



Remark

Each block of the system consists of other sub-systems.

Q-Learning

- Agent navigates a grid-based environment representing a disaster zone
- Agent learns to take actions that maximize its cumulative reward [1]

[1] Christopher JCH Watkins and Peter Dayan. Q-learning. Machine learning, 8(3-4):279–292, 1992.

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- Extraction of symbolic rules from numerical data

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Reinforcement Learning

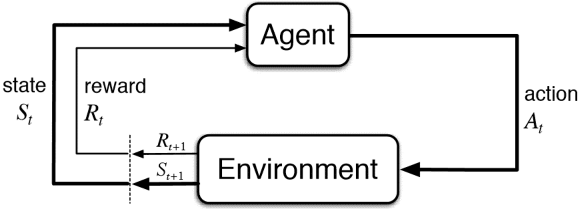

Figure 2: Reinforcement Learning

Definition

Reinforcement learning (RL) is an area of machine learning concerned with how intelligent agents ought to take actions in an environment in order to maximize the notion of cumulative reward. [a]

[a] Richard S Sutton and Andrew G Barto. Reinforcement Learning: An Introduction. MIT Press, 2018.

Q-Learning

- Explanation of Q-Learning
- Comparison of the learning process to a child learning to walk

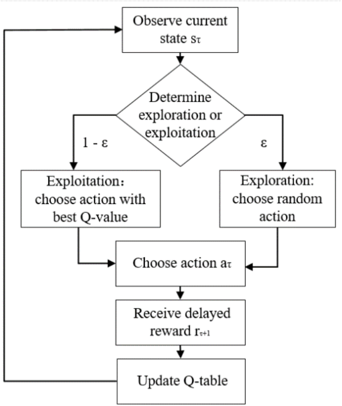

Figure 3: Q-Learning Algorithm

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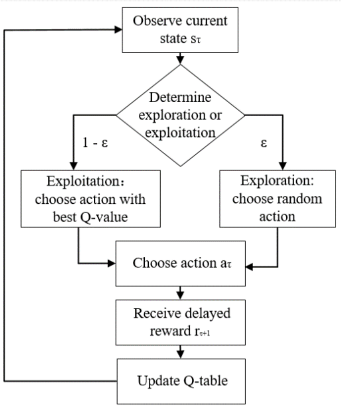

Figure 3: Q-Learning Algorithm

Environment

A		C	S
X	X		X
	S	C	X
X			S

- Grid representation of a disaster zone (`DisasterZone`) [3]
- Environment elements

[3] https://github.com/ahmillect/Learning-of-Symbolic-Representations-for-Rescue-Scenarios-in-Disaster-Zones

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Q-Learning Agent

- How the agent uses Q-Learning

Q-Table and State-Action Pairs

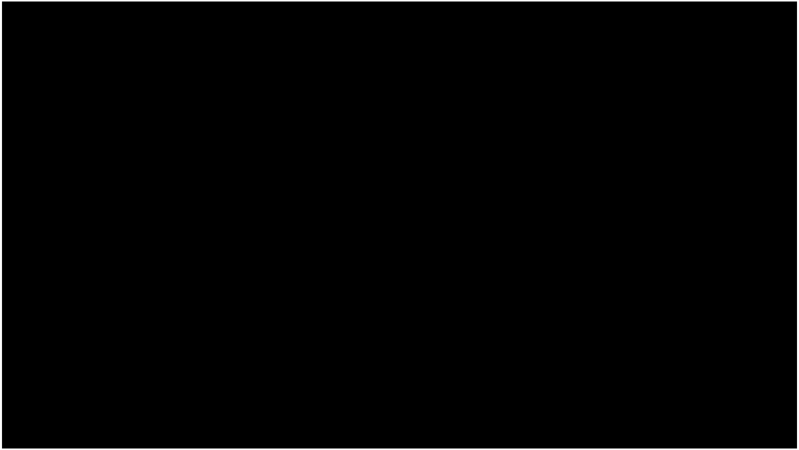
State/Action	Up	Left	Right	Down
State 1	$Q(s_1, \text{Up})$	$Q(s_1, \text{Left})$	$Q(s_1, \text{Right})$	$Q(s_1, \text{Down})$
State 2	$Q(s_2, \text{Up})$	$Q(s_2, \text{Left})$	$Q(s_2, \text{Right})$	$Q(s_2, \text{Down})$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
State M	$Q(s_M, \text{Up})$	$Q(s_M, \text{Left})$	$Q(s_M, \text{Right})$	$Q(s_M, \text{Down})$

Table 1: Sample *DisasterZone* Q-Table

States Set $\mathcal{S}$

$$s_M \in \mathcal{S} = \left[\overbrace{\begin{array}{|c|c|c|c|} \hline \text{A} & & \text{C} & \text{S} \\ \hline \text{X} & \text{X} & & \text{X} \\ \hline & \text{S} & \text{C} & \text{X} \\ \hline \text{X} & & & \text{S} \\ \hline \end{array}}^{s_1}, \overbrace{\begin{array}{|c|c|c|c|} \hline \text{S} & & \text{C} & \text{X} \\ \hline \text{X} & \text{A} & \text{S} & \text{X} \\ \hline & \text{X} & \text{C} & \text{X} \\ \hline \text{S} & & & \text{S} \\ \hline \end{array}}^{s_2}, \ldots, \overbrace{\begin{array}{|c|c|c|c|} \hline \text{C} & & \text{S} & \text{X} \\ \hline \text{S} & \text{X} & & \text{X} \\ \hline & \text{S} & \text{C} & \text{X} \\ \hline \text{X} & & & \text{A} \\ \hline \end{array}}^{s_M} \right] \tag{1}$$

Learning Process



Symbolic Knowledge Extraction

- Symbolic knowledge extraction explanation
- How symbolic knowledge extraction is used in this thesis

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Ron Sun's Approach

- Ron Sun's approach:
    1. Use of clustering techniques to group similar data together, which can then be used to generate symbolic rules
    2. provides a systematic and efficient way to extract symbolic rules from the numerical Q-values
    3. It's also been proven to be effective in various domains, making it a reliable choice for this task

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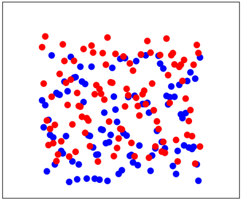
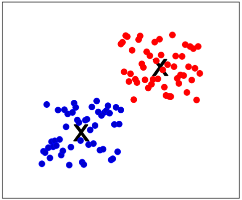
K-means Clustering

Before K-means



After K-means ($k = 2$)



- K-means clustering:
  1. A type of unsupervised machine learning algorithm used to categorize unlabeled data
  2. It works by partitioning the data into a set number of clusters, each represented by the mean of the data points in the cluster
  3. The algorithm iteratively assigns each data point to the cluster that it's closest to until the cluster assignments no longer change
  4. Simple yet powerful algorithm that can handle large datasets

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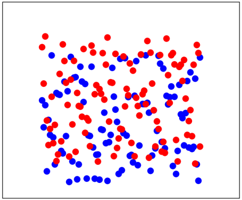

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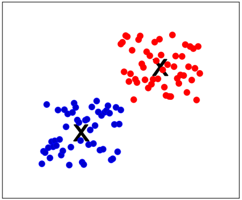

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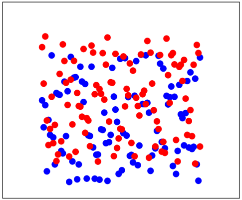

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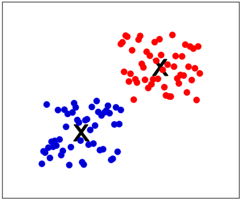

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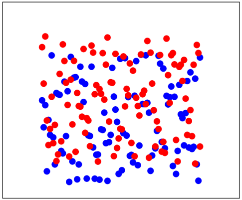

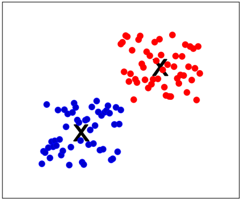

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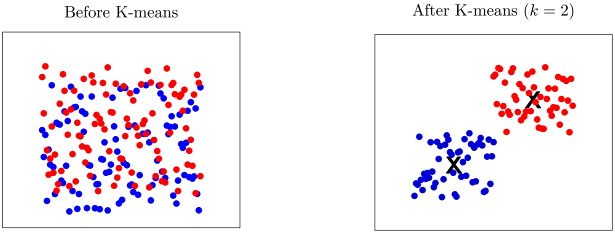

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Generating IF-THEN Rules

- How IF-THEN rules are generated

IF $\longrightarrow$

			X
X	A		S
	S	C	X
X			

$\longrightarrow$ THEN $\longrightarrow \downarrow$

Figure 4: Example of an IF-THEN rule

Evaluation Criteria

1. Training performance and cumulative reward of the agent
2. Quality of the extracted symbolic knowledge

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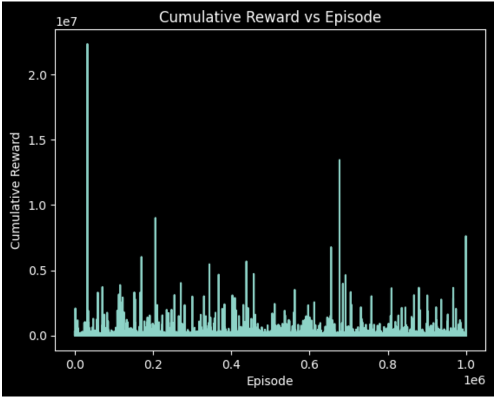
Agent's Performance



- Summary of the agent's performance
- A cumulative reward of **3758300** over **1** million training episodes

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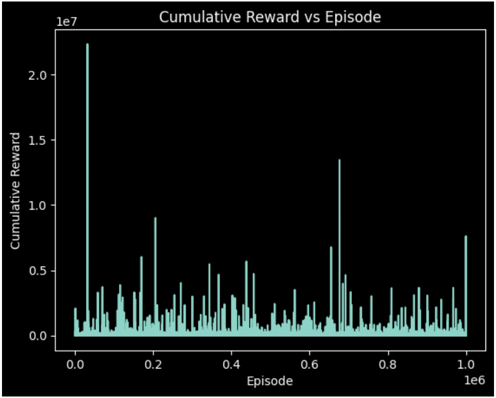

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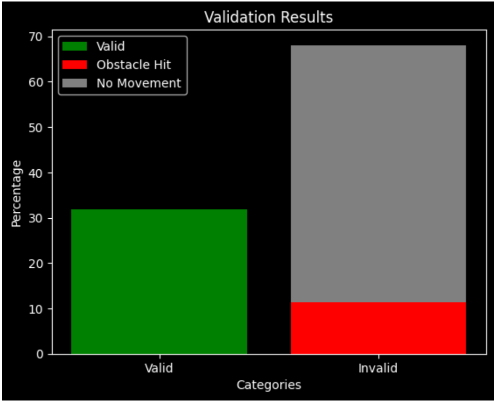
Quality of Extracted Symbolic Knowledge



- **20** million extracted rules
- **31.92%** valid, **11.38%** hit obstacles violations and **56.69%** no movement ones

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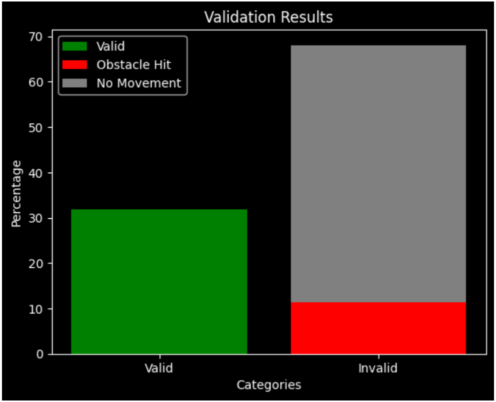

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Rule Validation (Valid)

```
Validating Rule:

IF

. . . C
A S . C
. C C .
X . . C

THEN Right

State-action pair is valid because it rescued a survivor.

Next State:

. . . C
. A . C
. C C .
X . . C

Reward: 3
```

Figure 5: Survivor Rescue

```
Validating Rule:

IF

. . . C
A C . C
. S C .
X . . C

THEN Down

State-action pair is valid because it moved to an empty cell.

Next State:

. . . C
. C . C
A S C .
X . . C

Reward: -1
```

Figure 6: Empty Cell

Rule Validation (Invalid)

```
Validating Rule:

IF

A . . C
X S . C
. C C .
X . . C

THEN Up

State-action pair is a violation because it didn't move.

Next State:

A . . C
X S . C
. C C .
X . . C

Reward: -3
```

Figure 7: No Movement

```
Validating Rule:

IF

. . S C
X C C .
A S S C
X C . S

THEN Down

State-action pair is invalid because it hit an obstacle.

Next State:

. . S C
X C C .
. S S C
A C . S

Reward: -7
```

Figure 8: Obstacle Hit

Implications and Insights

- Potential use of the trained agent in disaster response strategies
- Insights into the agent's decision-making process
- Potential contributions to the design of reinforcement learning algorithms
- Contribute to saving lives in real-world disaster scenarios

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