Social Navigation in the Emergency Department

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Video credit: Dr. Ryan McGarry, LA+USC Medical Center ED

Social Navigation in the Emergency Department

Goal: Design robots that socially navigate in safety-critical environments.

Taylor, A., Murakami, M., Kim, S., Chu, R., and Riek, L.D. (2022) Hospitals of the Future: Designing Interactive Robotic Systems for Resilient Emergency Departments. In Proc. of the ACM Conference on Computer Supported Collaborative Work (CSCW)

Taylor, A., Matsumoto, S., Xiao, W., and Riek, L.D. (2021) “Social Navigation for Mobile Robots in the Emergency Department." International Conference on Robotics and Automation (ICRA).

Taylor, A., Matsumoto, S., and Riek, L.D. Situating Robots in the Emergency Department. (2020) AAAI Spring Symposium on Applied AI in Healthcare: Safety, Community, and the Environment.

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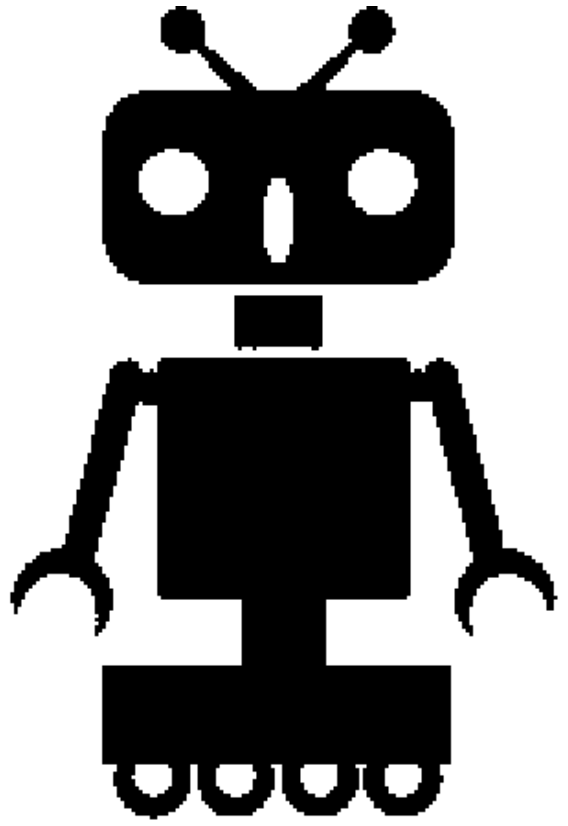
Context

A user (ED staff member) requests materials to be delivered a robot.

Request Delivery



Users

Deliver Materials

Robot

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Research Questions

1) How to model a patient's level of acuity while being treated by a team of clinicians?

2) How should a robot optimize its path to deliver supplies to clinicians treating patients with varying levels of acuity?

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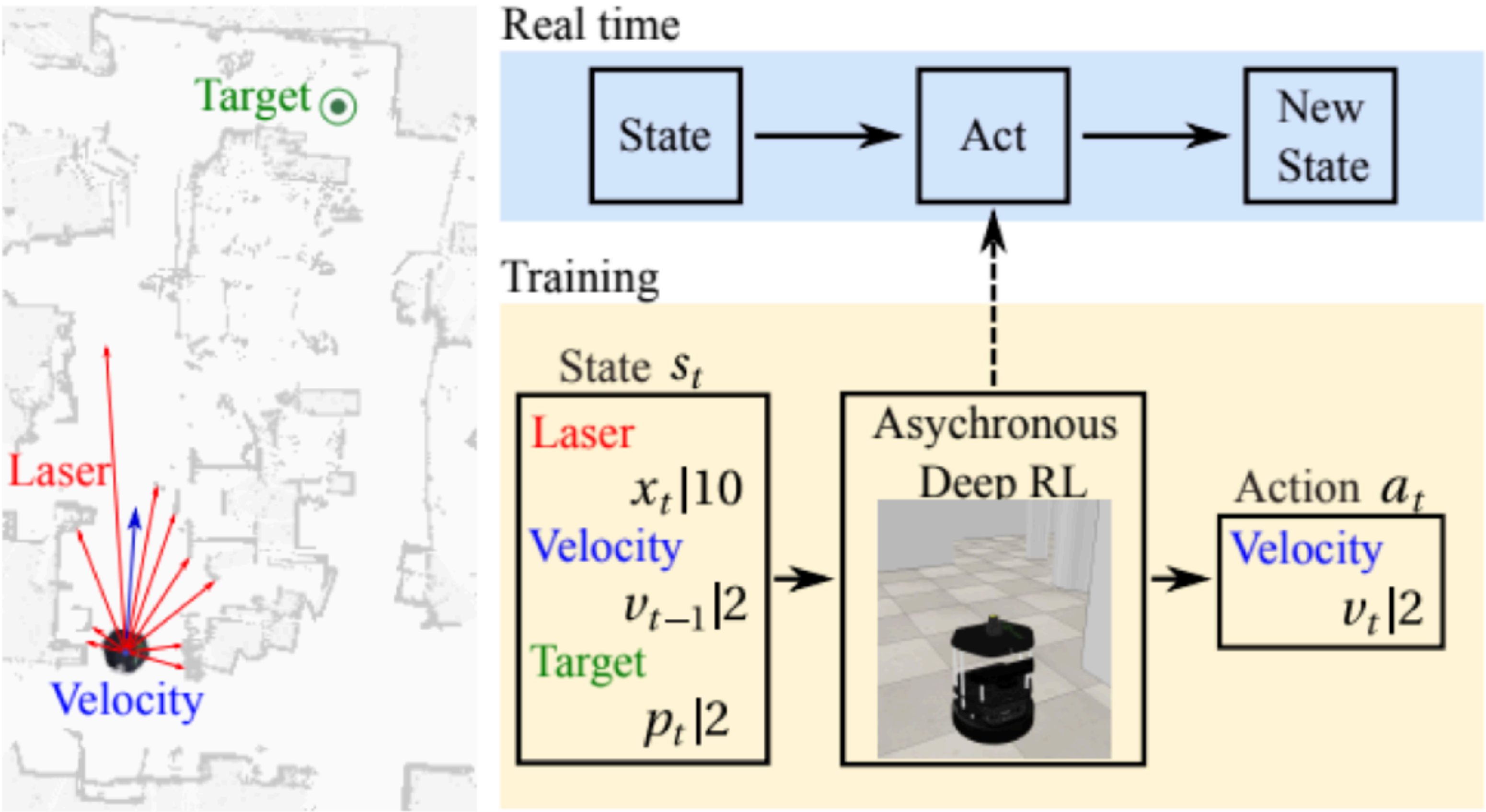
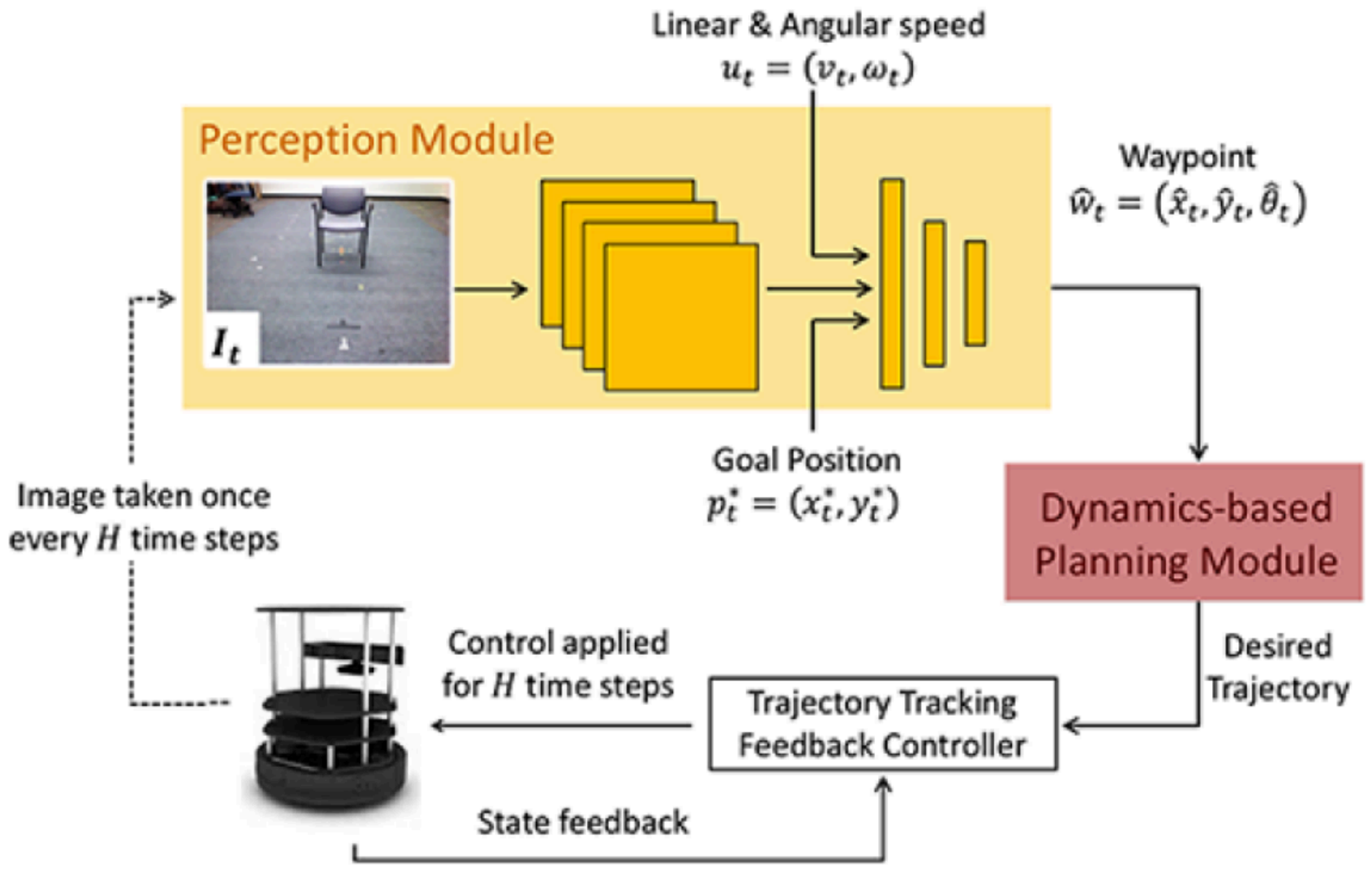
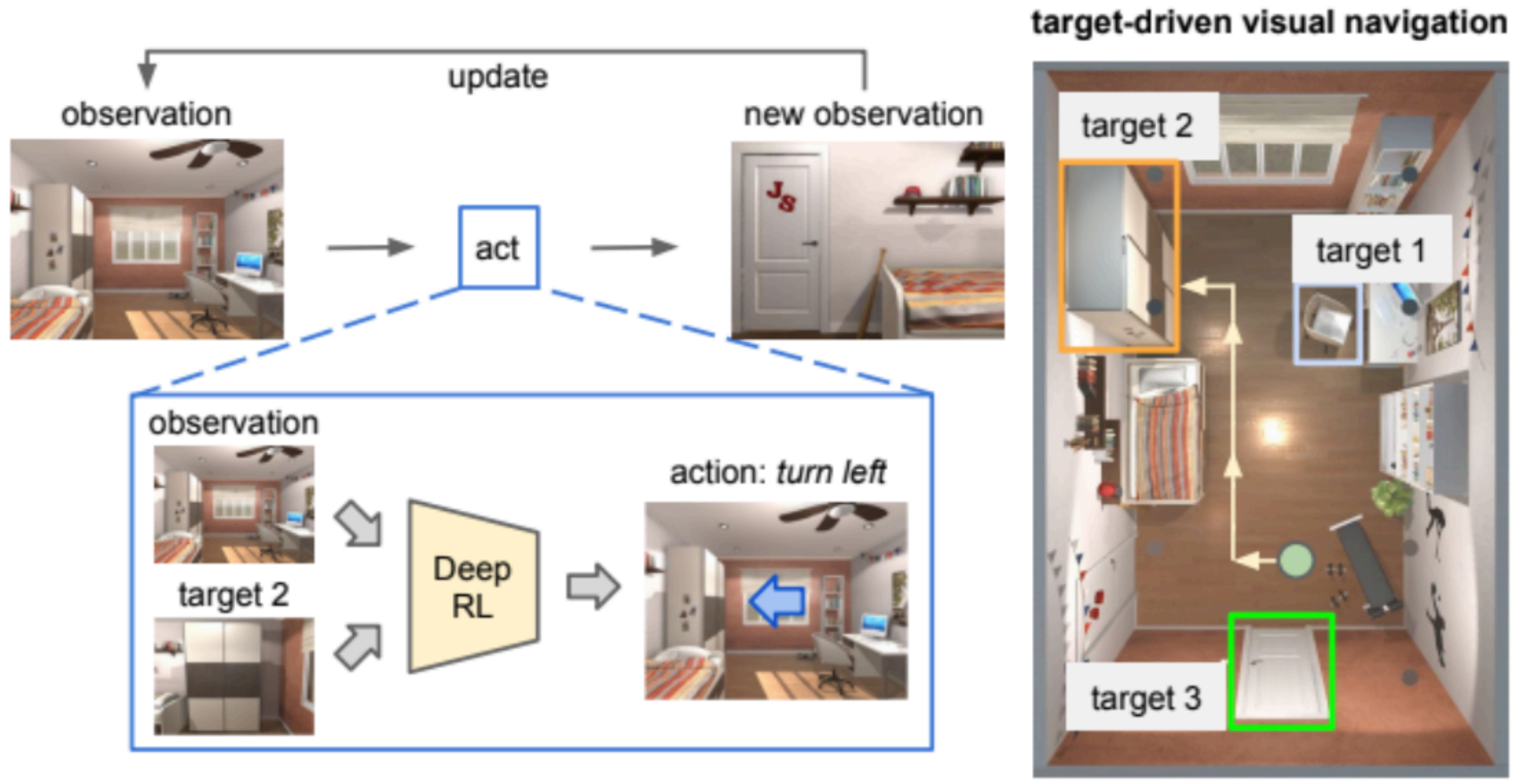
Prior Work



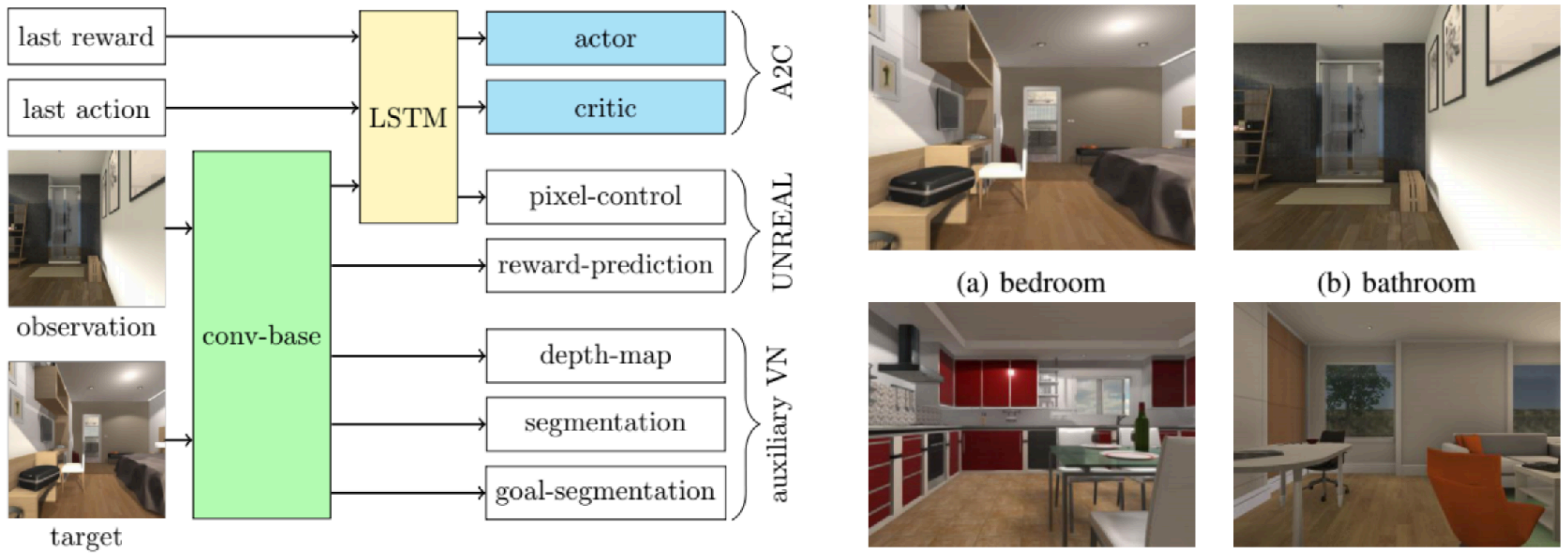
Tai et al., 2017



Tolani et al., 2020



Zhu et al., 2016



Kulhanek et al., 2019

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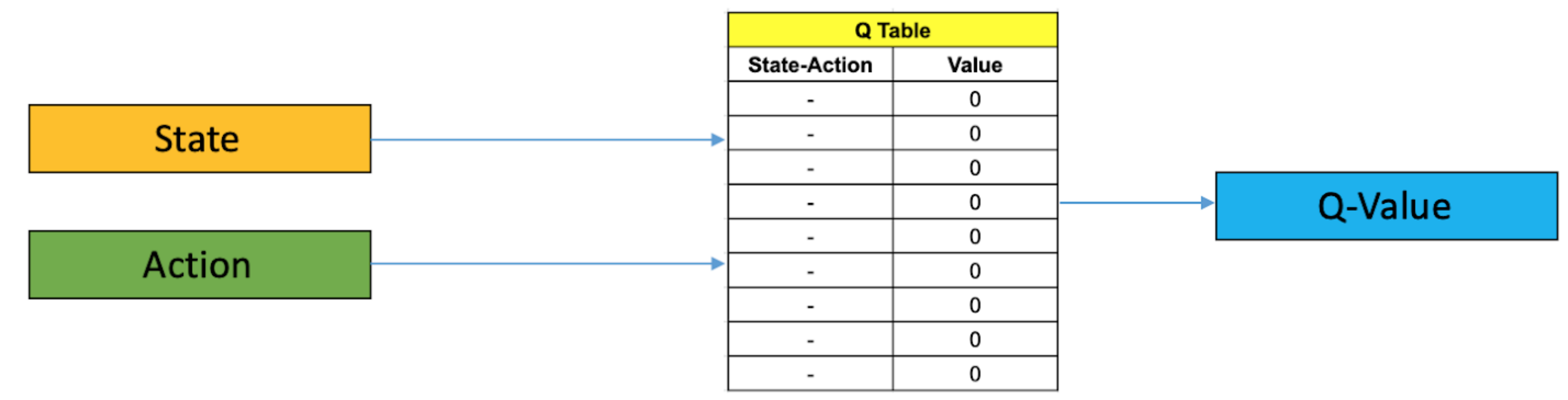
Deep Q-Networks

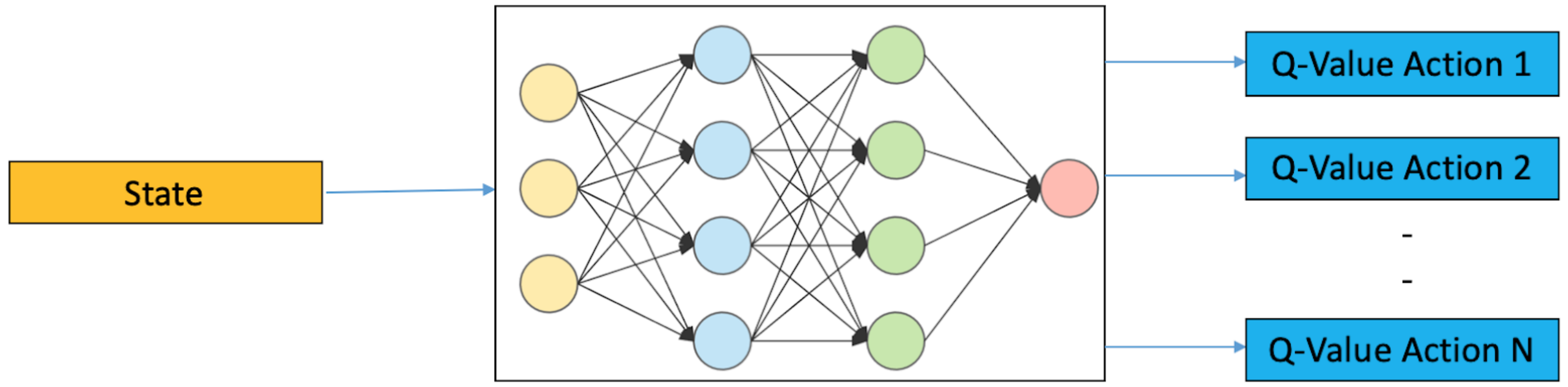
Experience Replay Memory:
- State
- Next State
- Action
- Reward

Episodes: collection of experiences

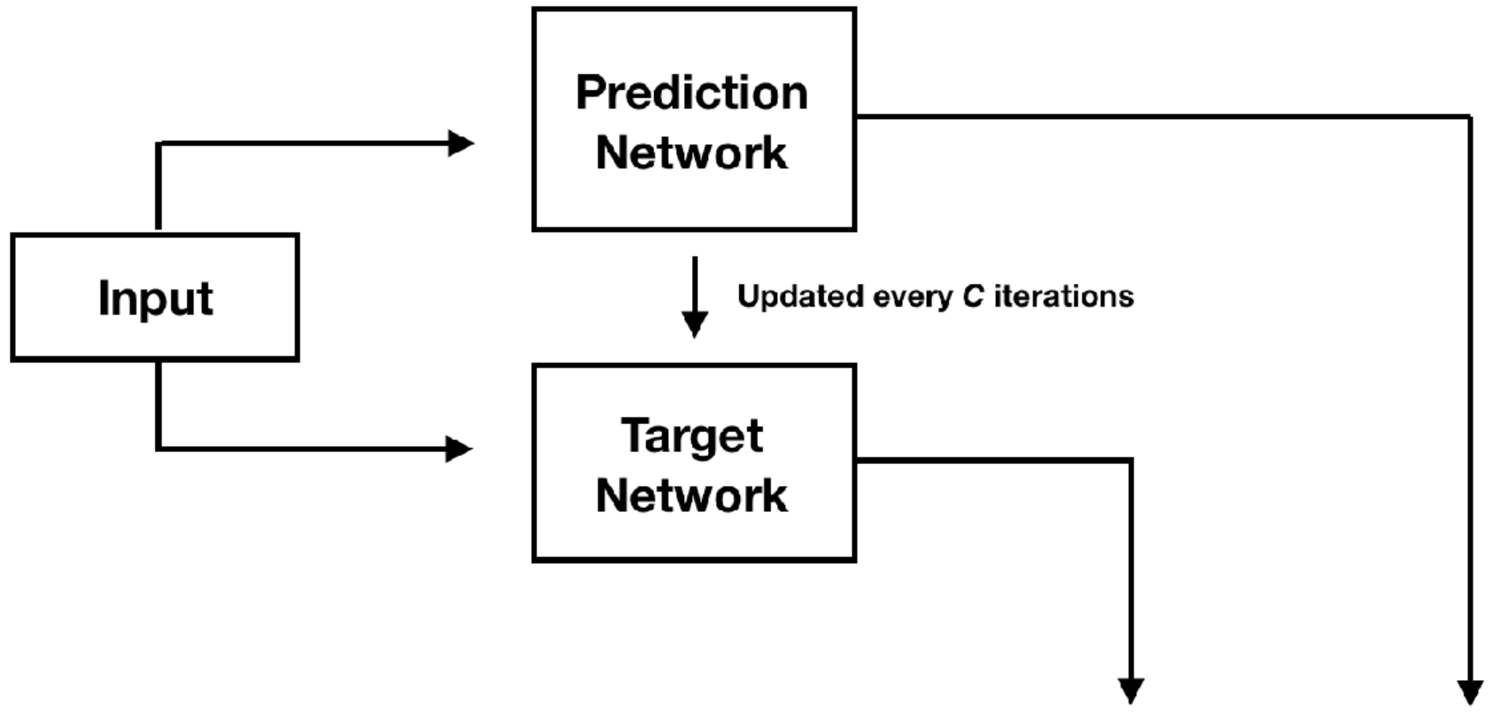
Exploration: ε-greedy, 0<ε<1



Q Learning



Deep Q Learning



$$L_i(\theta_i) \leftarrow \mathbf{E}[(r + \gamma \max_{a'} Q(s', a'; \theta_i^-) - Q(s, a; \theta_i))^2]$$

Mnih et al., 2015

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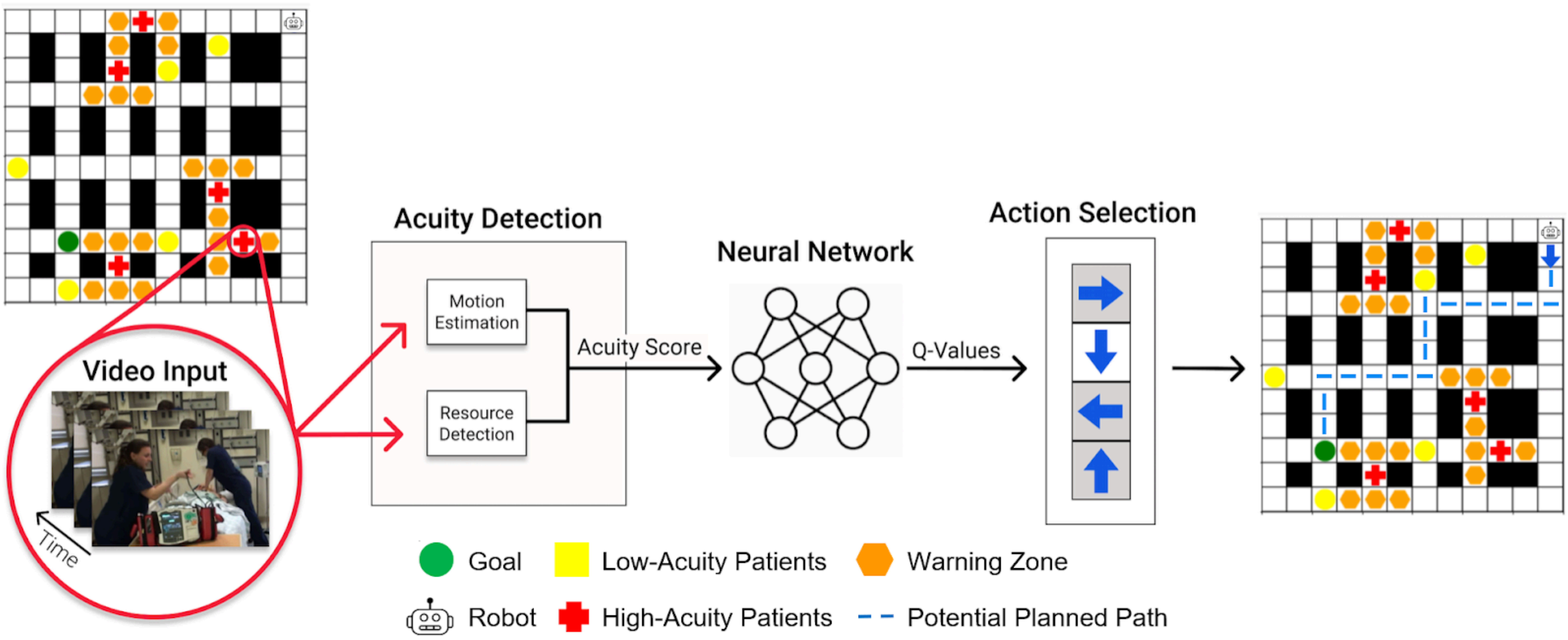
Safety-Critical Deep Q-Network (SafeDQN)



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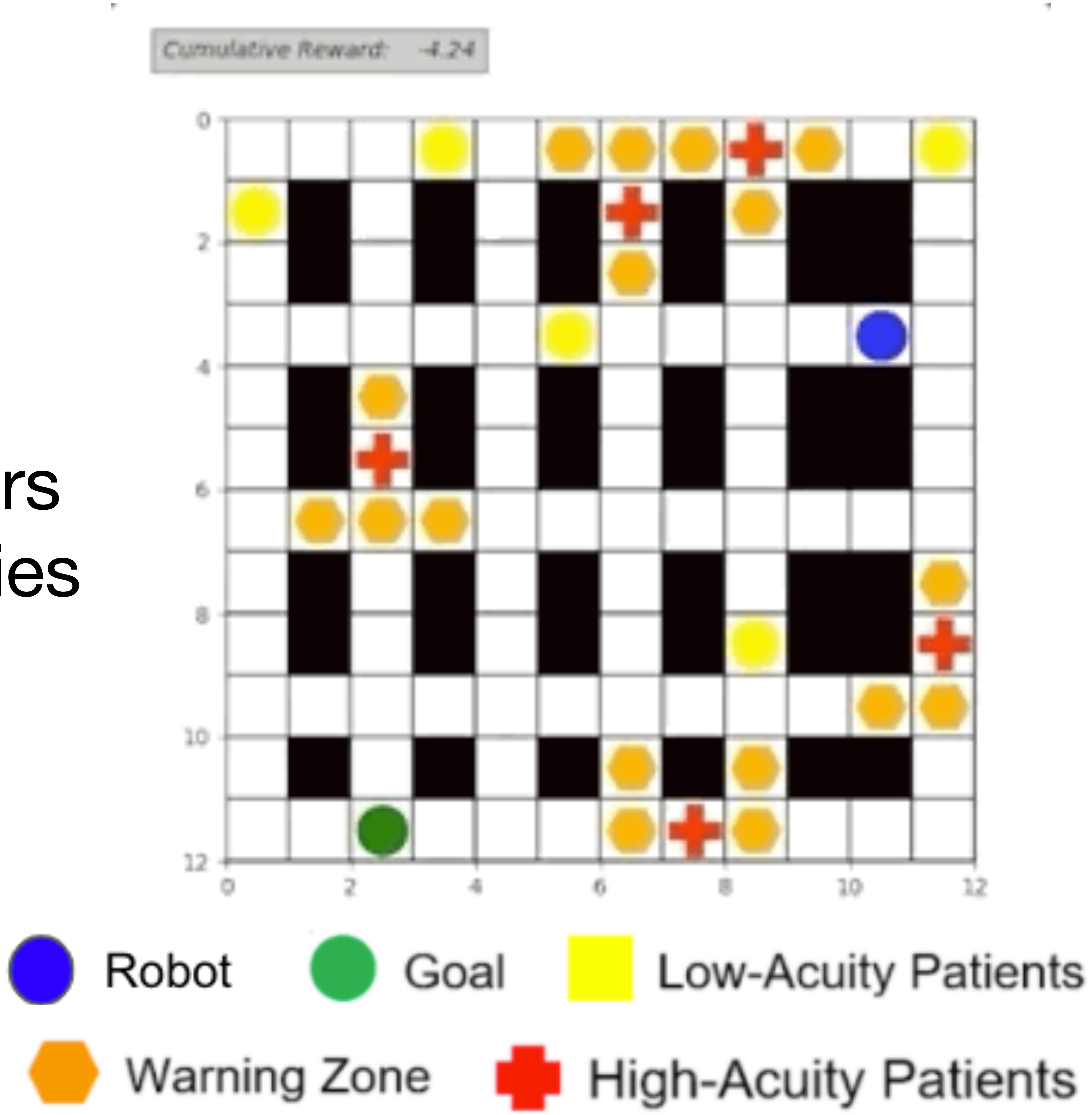
Assumptions

- Discrete 2D environment
- Videos are used for map actors
- Observations: video of activities
- Stationary actors



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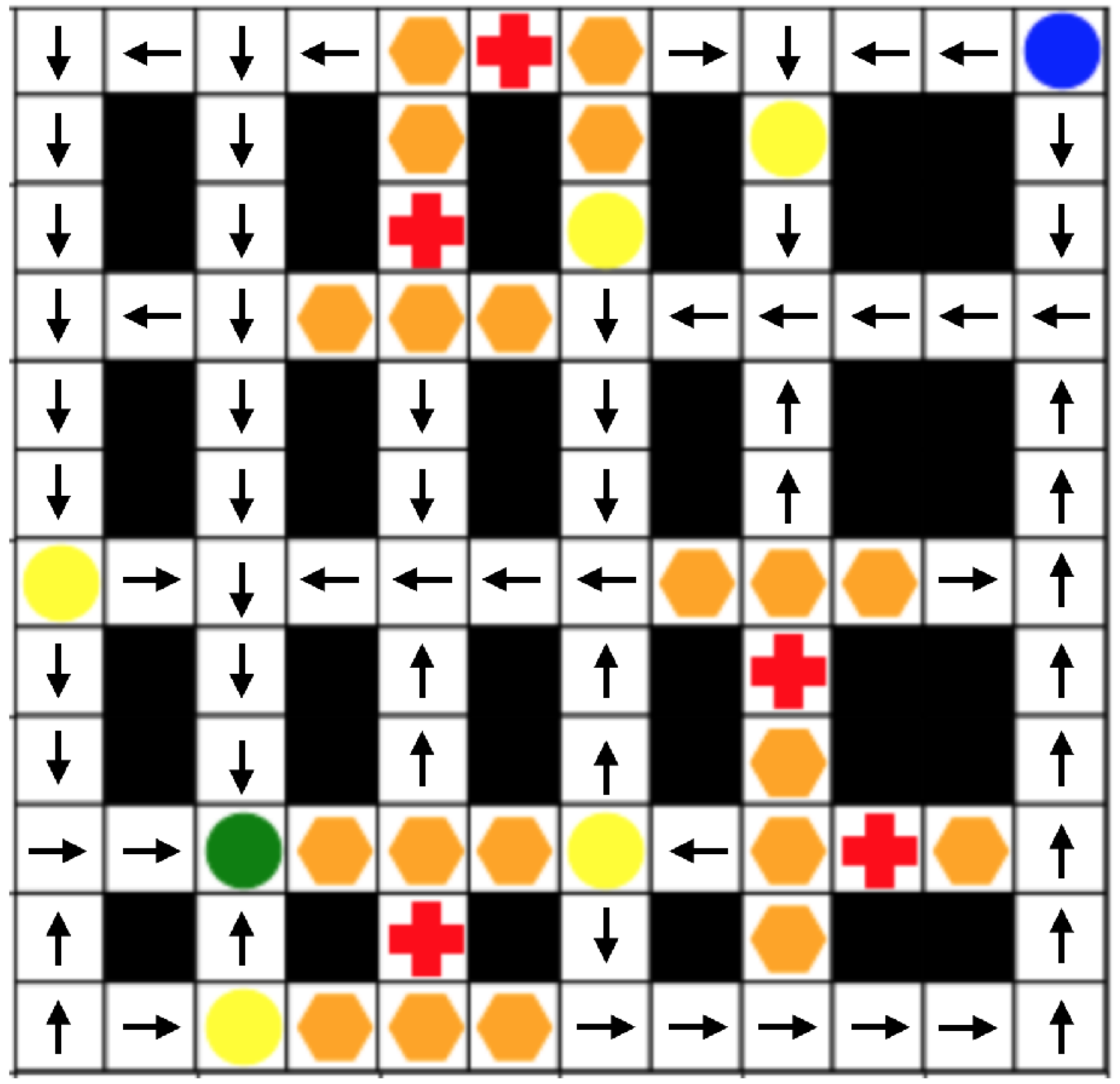
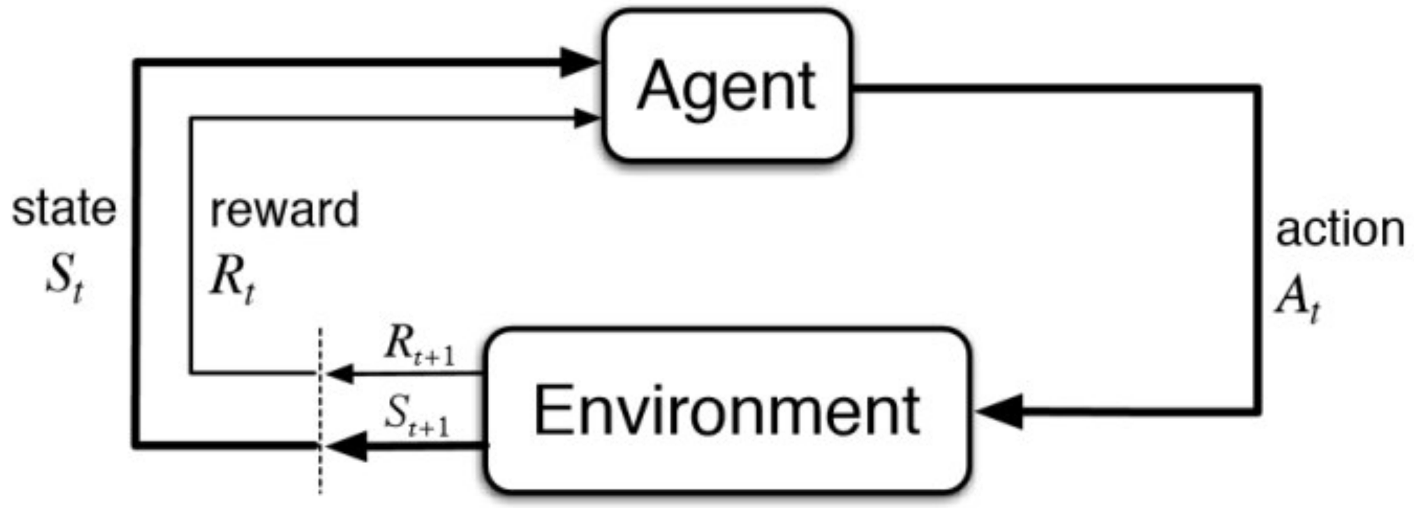
Safety-Critical Deep Q-Network (SafeDQN)

Use reinforcement learning to explore paths that take patient acuity level into consideration

- States **S** are locations on the map
- Actions **A** are the move from one location on a map to another location
- Reward **R** encodes the level of patient acuity
- Bellman Equation:

$$Q^*(s_t, a_t) = \mathbf{E}_{s_t \sim S}[r_t + \gamma \max_{a_t} Q^*(s_t, a_t)|s, a]$$





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Safety-Critical Deep Q-Network (SafeDQN)

Patient Acuity Detection

High-Acuity patients

- Result in chaotic, dynamic motion
- Require more resources than low-acuity patients

High-Acuity Patient

Low-Acuity Patient

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Safety-Critical Deep Q-Network (SafeDQN)

Patient Acuity Detection

Acuity Score (AS) ∈ [0,1]

Inspired by Term Frequency Inverse Document Frequency (tf-idf) from NLP.

$$AS \leftarrow \vec{v}\,\frac{|P|}{1+|T|}$$

- $\vec{v}$ average velocity of all image frames from a motion estimation method in a given video.
- $|P|$ is the maximum number of people in a given video.
- $|T|$ number of patients being treated in the ED.

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Safety-Critical Deep Q-Network (SafeDQN)

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Created New Emergency Department Dataset

- Collected videos of clinical work in real EDs
  - Representing various levels of patient acuity
  - 689,000 segments videos
- Computed *AS* across all videos

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Safety-Critical Deep Q-Network

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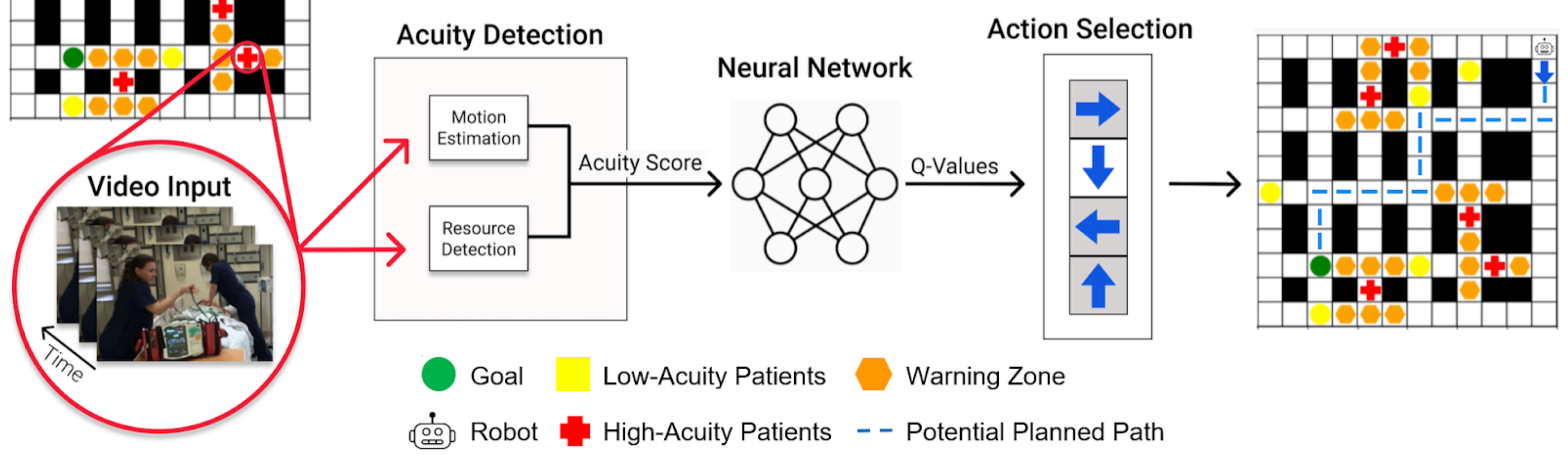
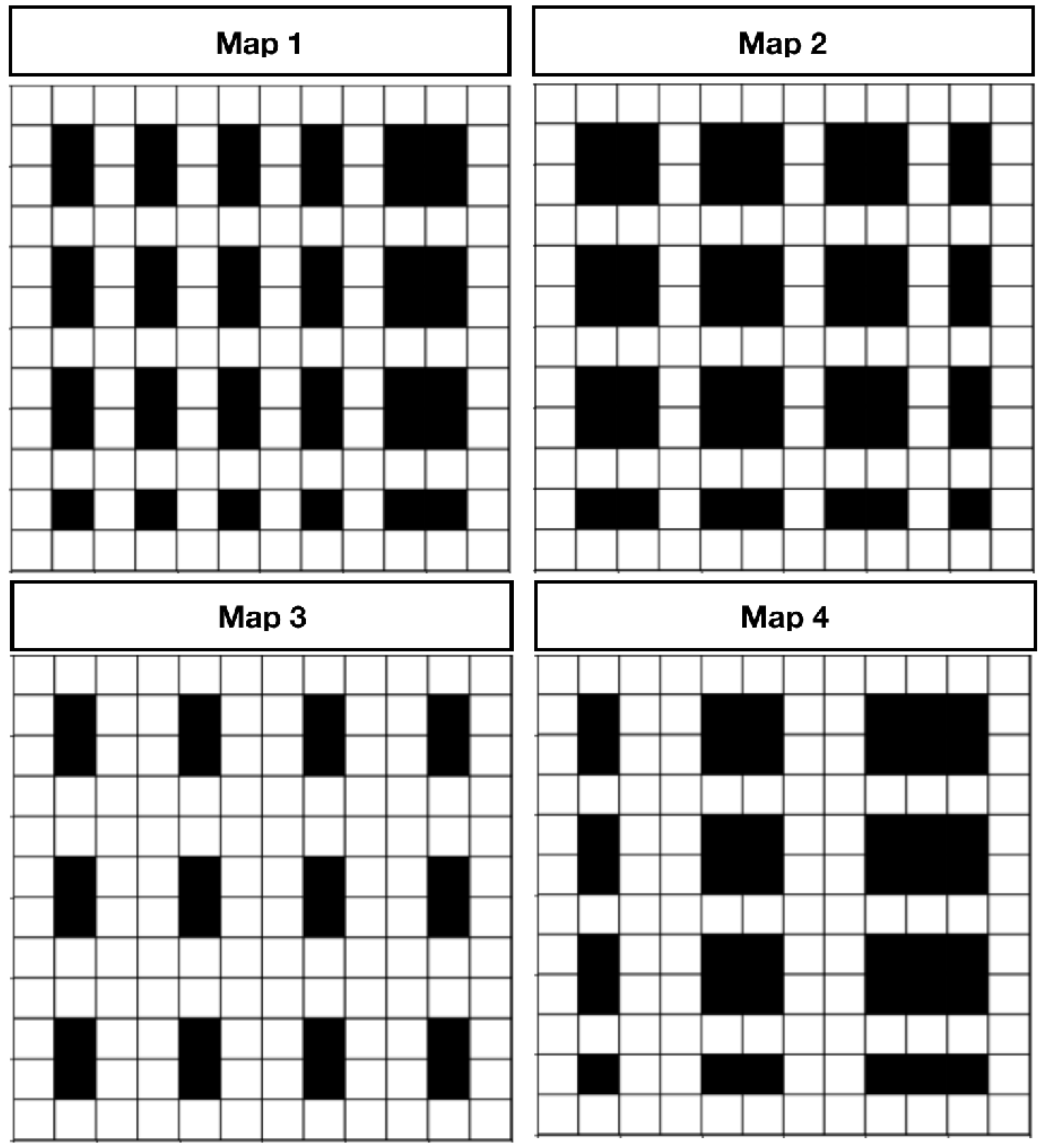
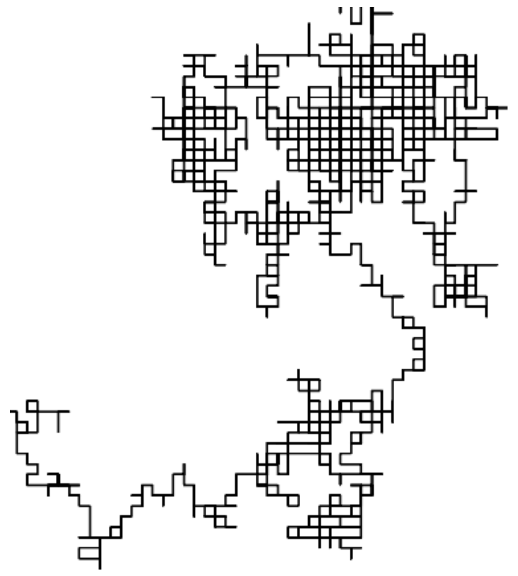
Evaluation

SafeDQN

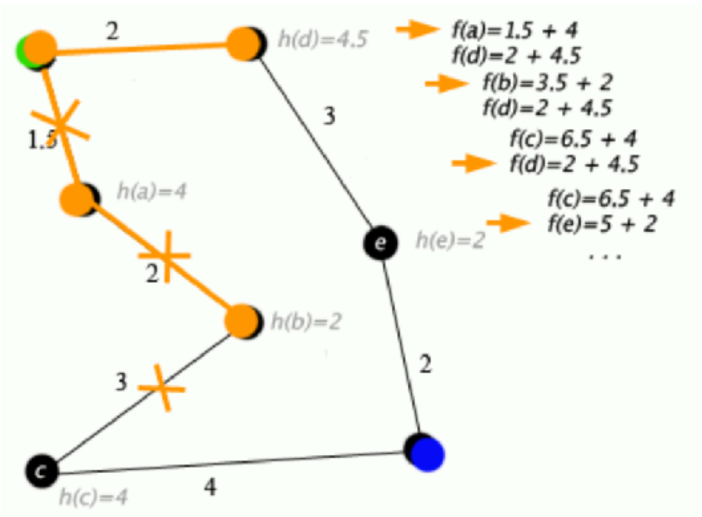




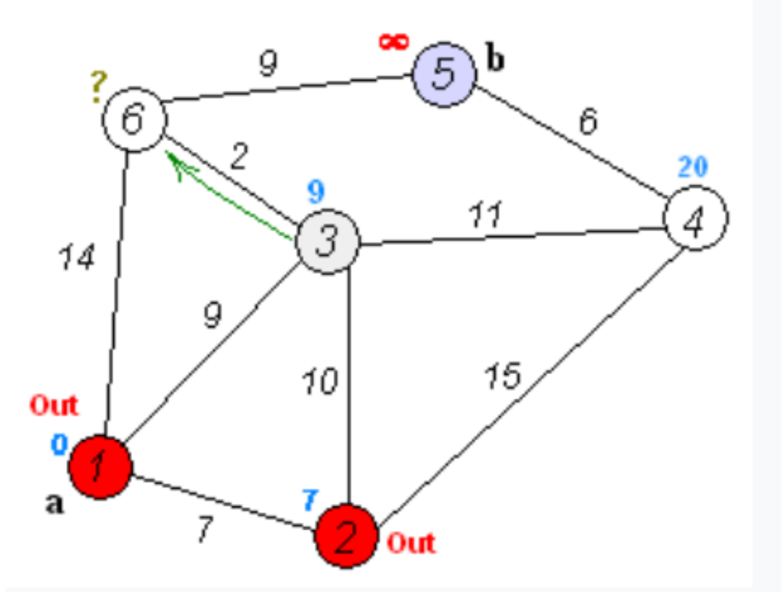
vs.



Random Walk



A* Search



Dijkstra

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Results

Method	Map 1 Avg. Path Length ↓ OF	Map 1 Avg. Path Length ↓ KD	Map 1 Avg. HA Penalties ↓ OF	Map 1 Avg. HA Penalties ↓ KD	Map 2 Avg. Path Length ↓ OF	Map 2 Avg. Path Length ↓ KD	Map 2 Avg. HA Penalties ↓ OF	Map 2 Avg. HA Penalties ↓ KD
Random Walk	243.6	231.0	5.9	5.6	231.6	240.6	3.1	10.9
A*	12.6	11.7	0.1	0.2	11.2	11.9	**0**	0
Dijkstra	11.6	10.4	0.1	0.3	12.0	12.0	0.1	0
SafeDQN	**11.3**	**9.4**	**0**	**0.1**	**17.2**	**10.6**	0.1	0

Method	Map 3 Avg. Path Length ↓ OF	Map 3 Avg. Path Length ↓ KD	Map 3 Avg. HA Penalties ↓ OF	Map 3 Avg. HA Penalties ↓ KD	Map 4 Avg. Path Length ↓ OF	Map 4 Avg. Path Length ↓ KD	Map 4 Avg. HA Penalties ↓ OF	Map 4 Avg. HA Penalties ↓ KD
Random Walk	247.9	215.9	6.7	2.1	225.6	215.8	4.7	10.4
A*	10.9	11.7	0	0.1	11.6	**10.7**	0.1	1.0
Dijkstra	10.2	11.4	0	0.1	11.6	12.3	0.1	1.5
SafeDQN	**10.1**	**10.6**	0	**0**	**10.5**	11.5	**0**	**0.3**

***SafeDQN performed best** at avoiding high acuity patients.*

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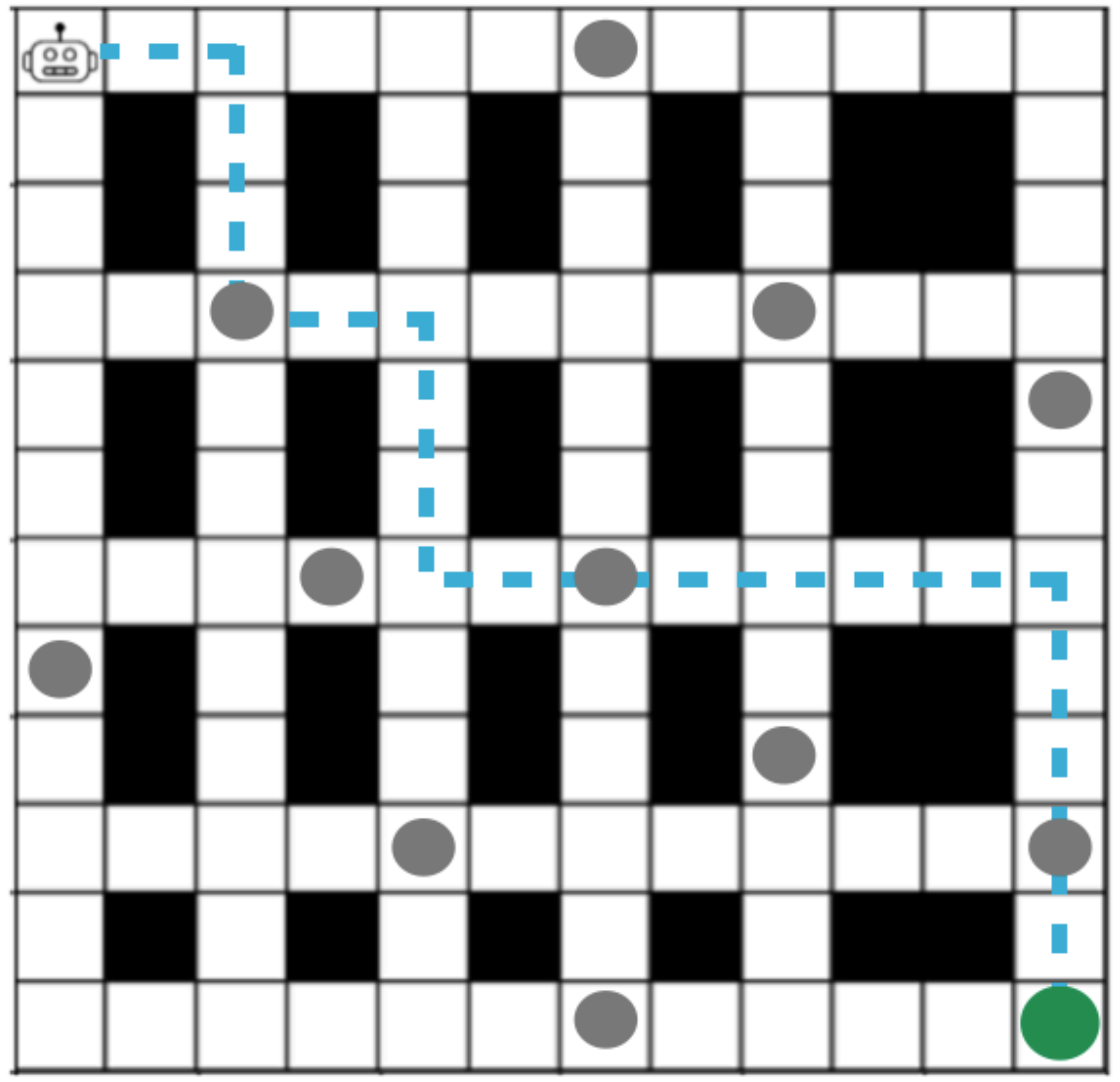
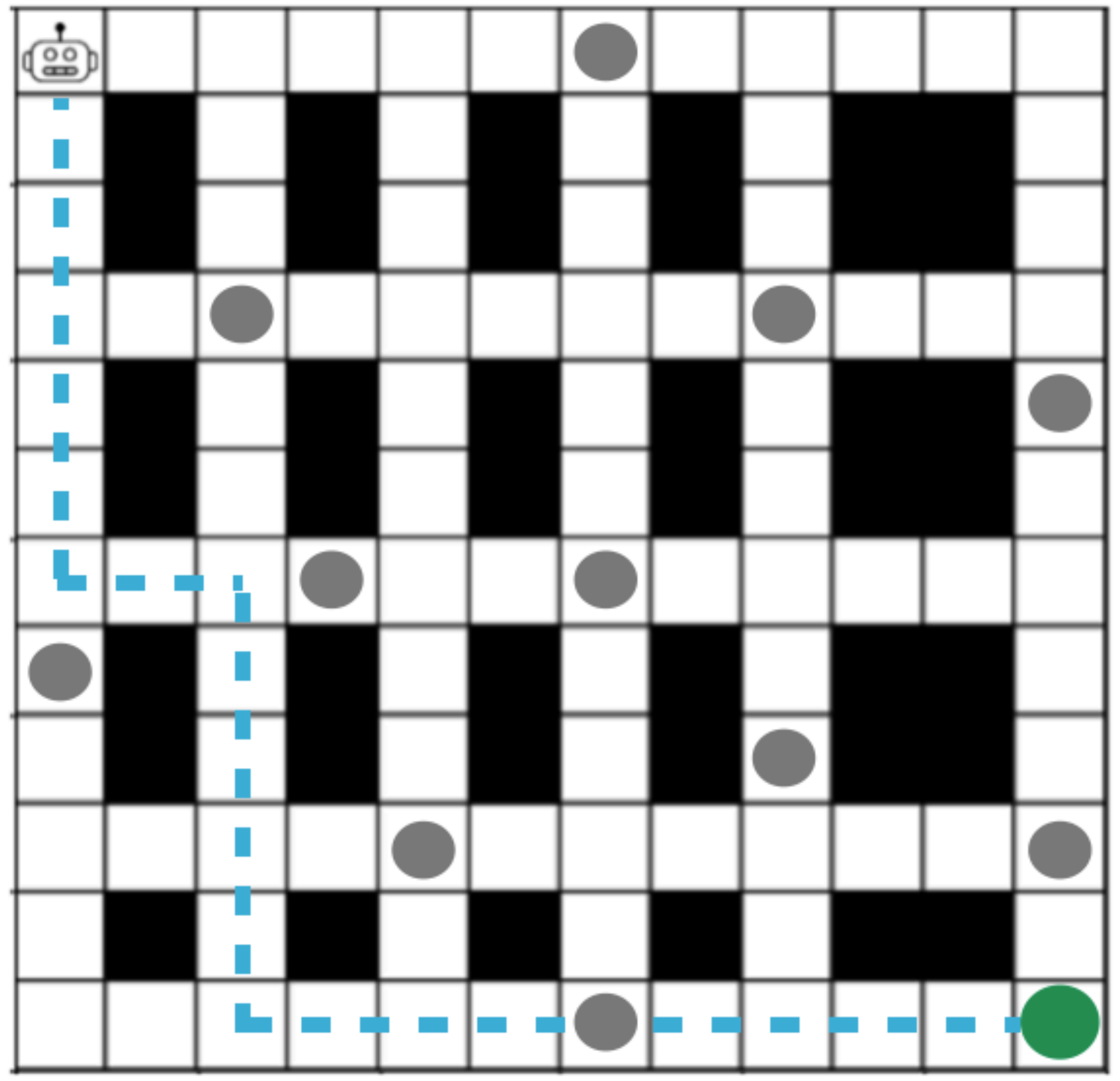
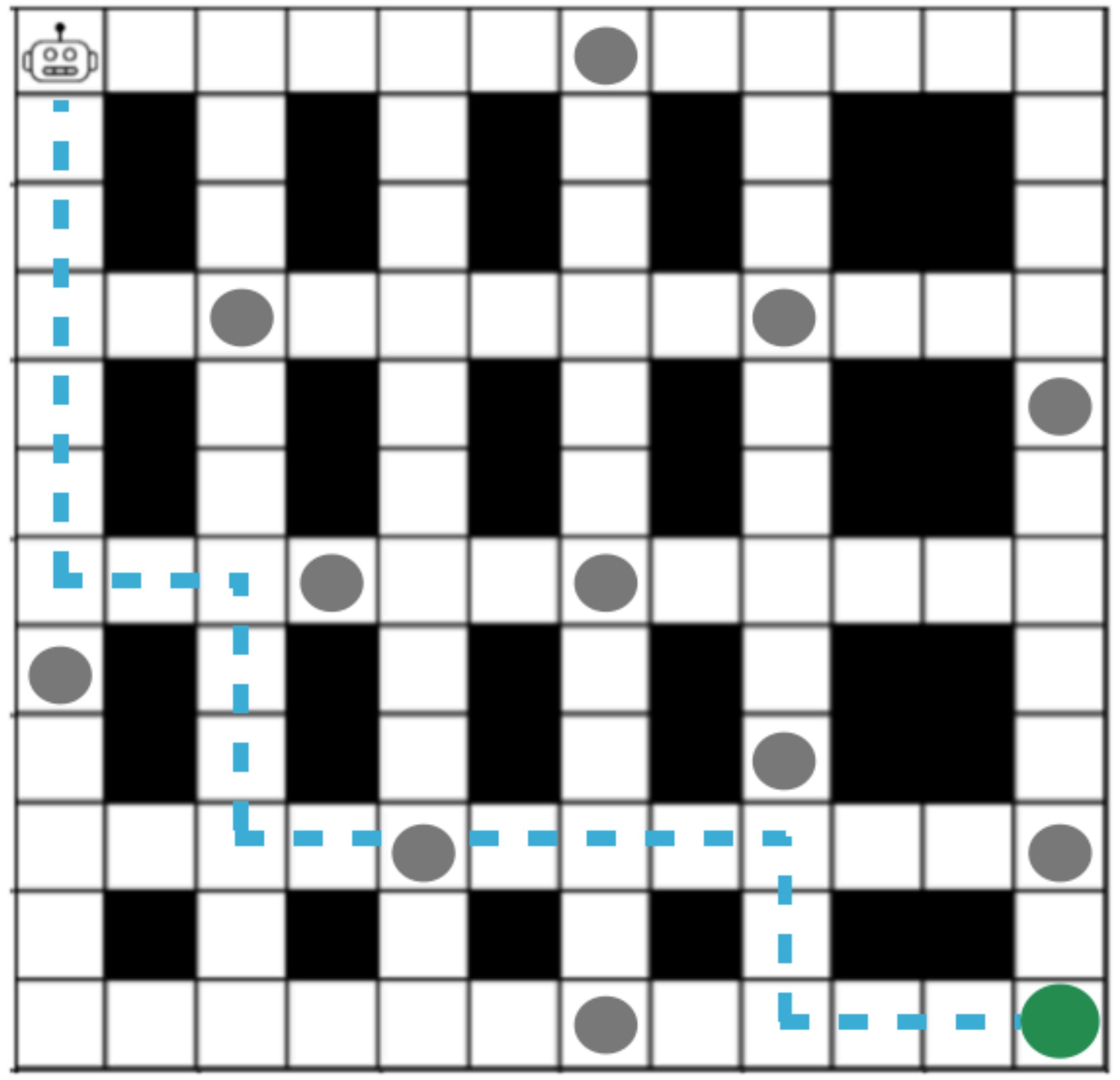
Results - Example 1

Total patients: 11

A* Search	Dijkstra	SafeDQN
		

SafeDQN encounters

3 patients Length = 22	1 patient Length = 22	1 patient Length = 22

Robot Patient Goal Robot Path

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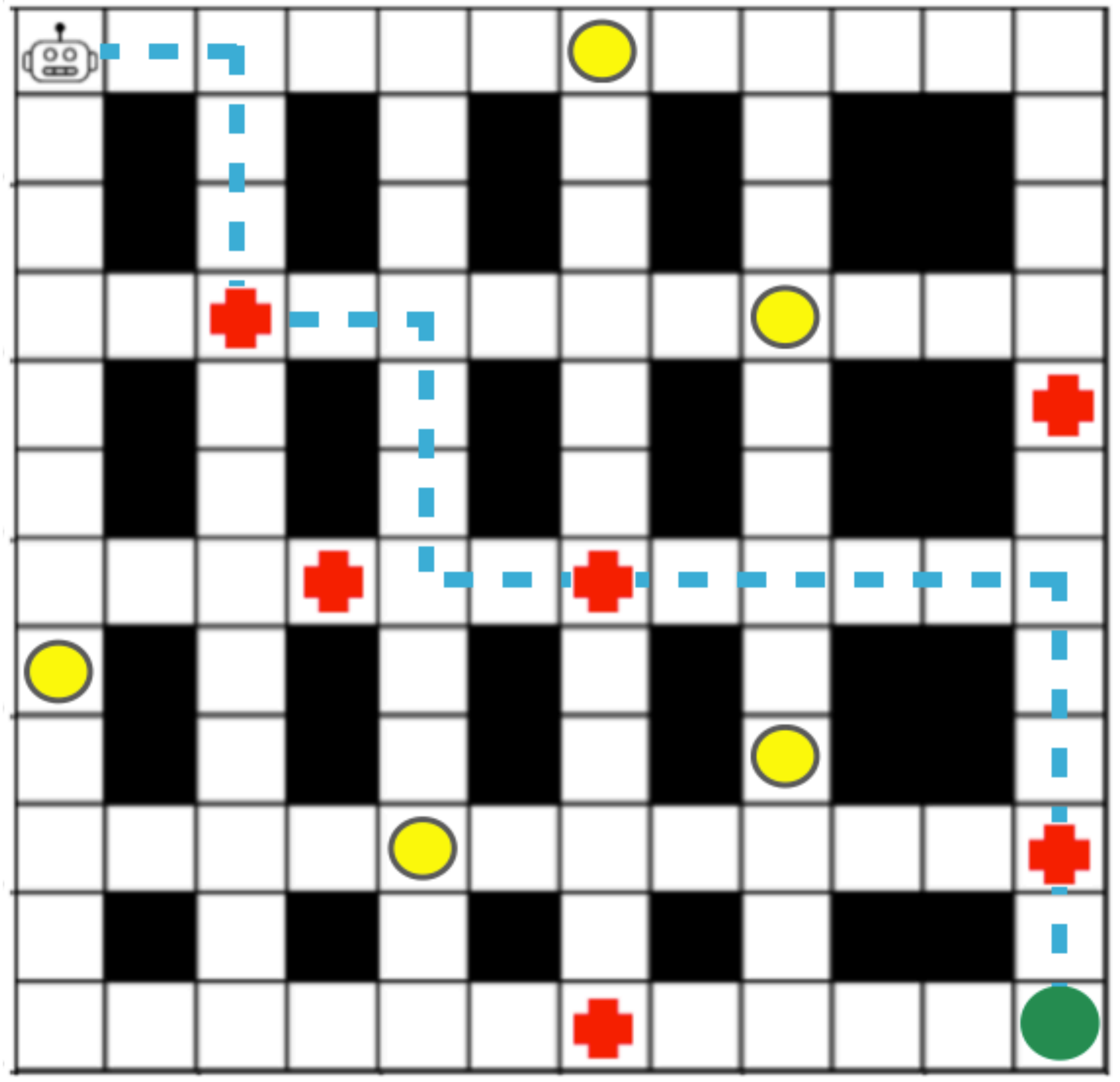
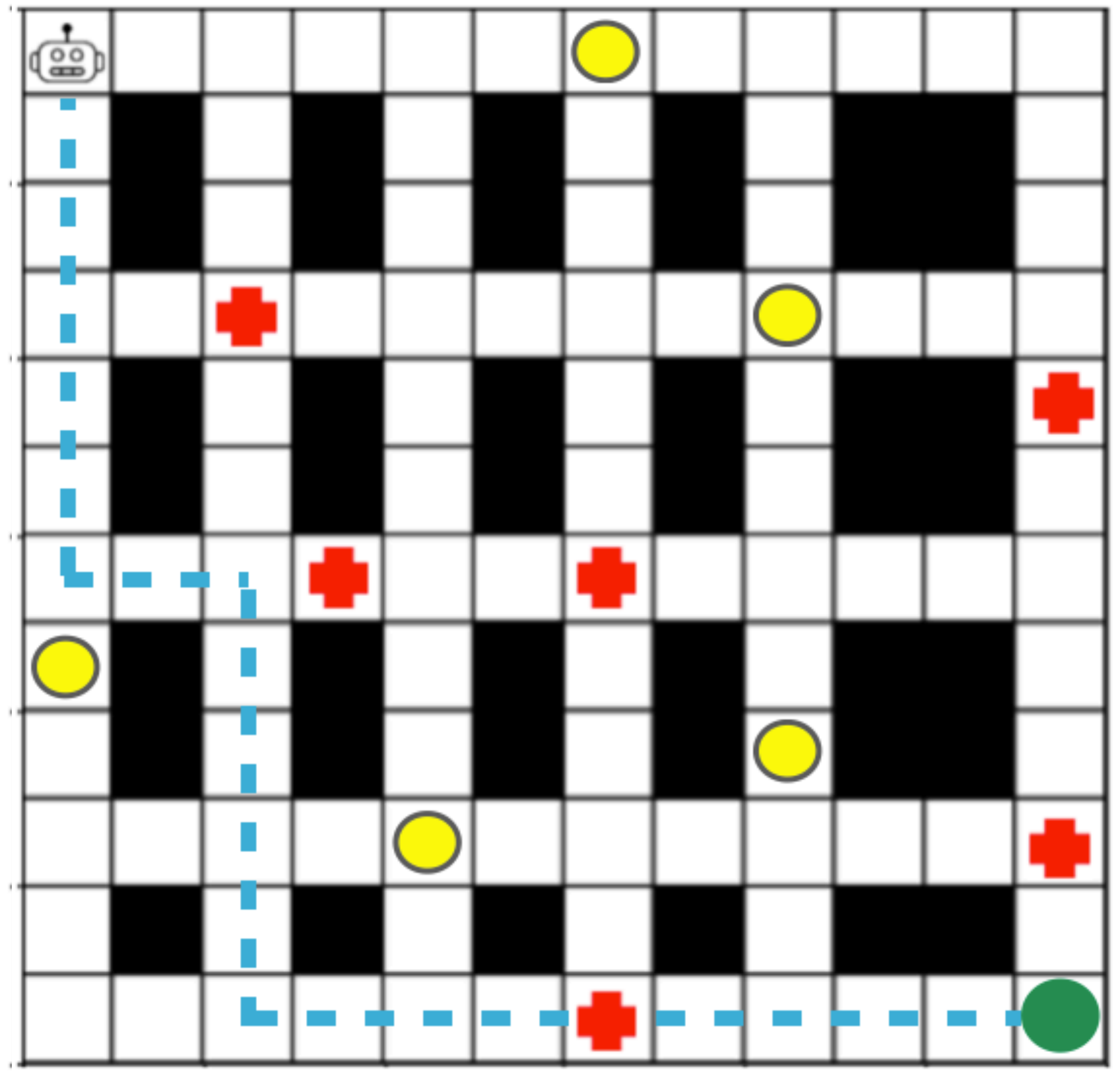
Results - Example 1

Total patients: 11

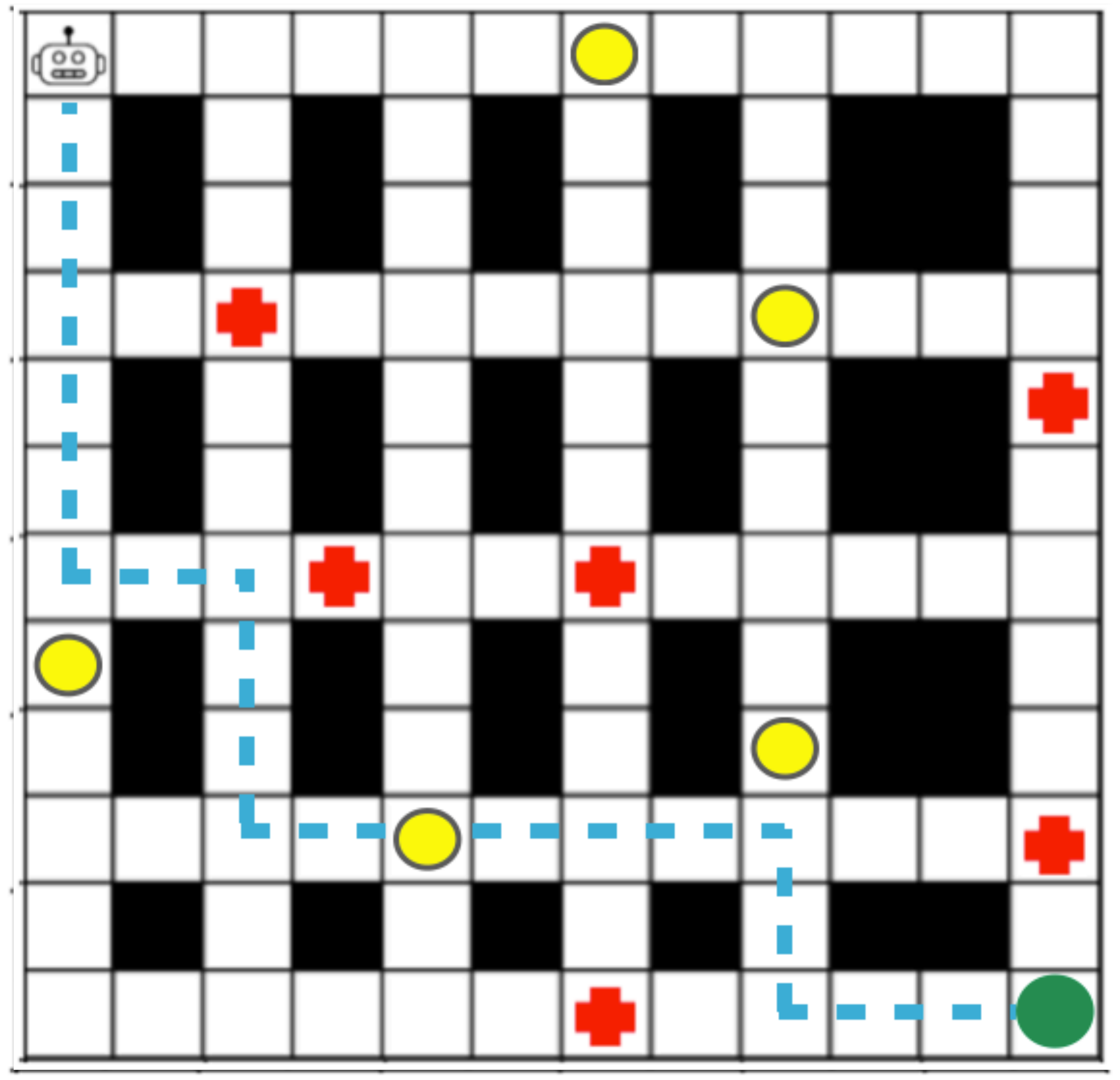
A* Search



Dijkstra



SafeDQN



SafeDQN encounters

3 high-acuity patients
Length = 22

1 high-acuity patient
Length = 22

1 low-acuity patient
Length = 22

Robot   Low-acuity patient   High-acuity patient   Goal   Robot Path

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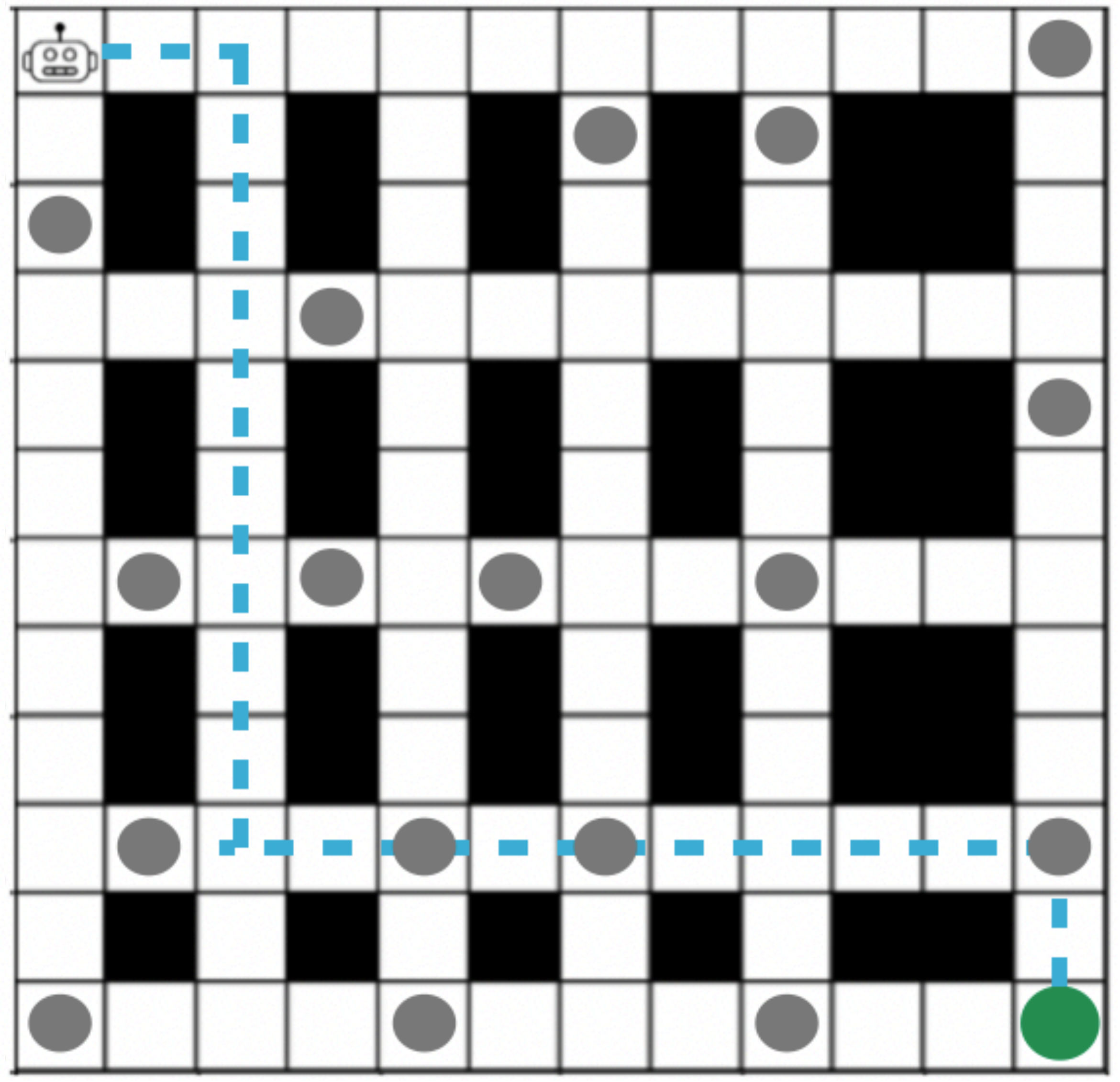
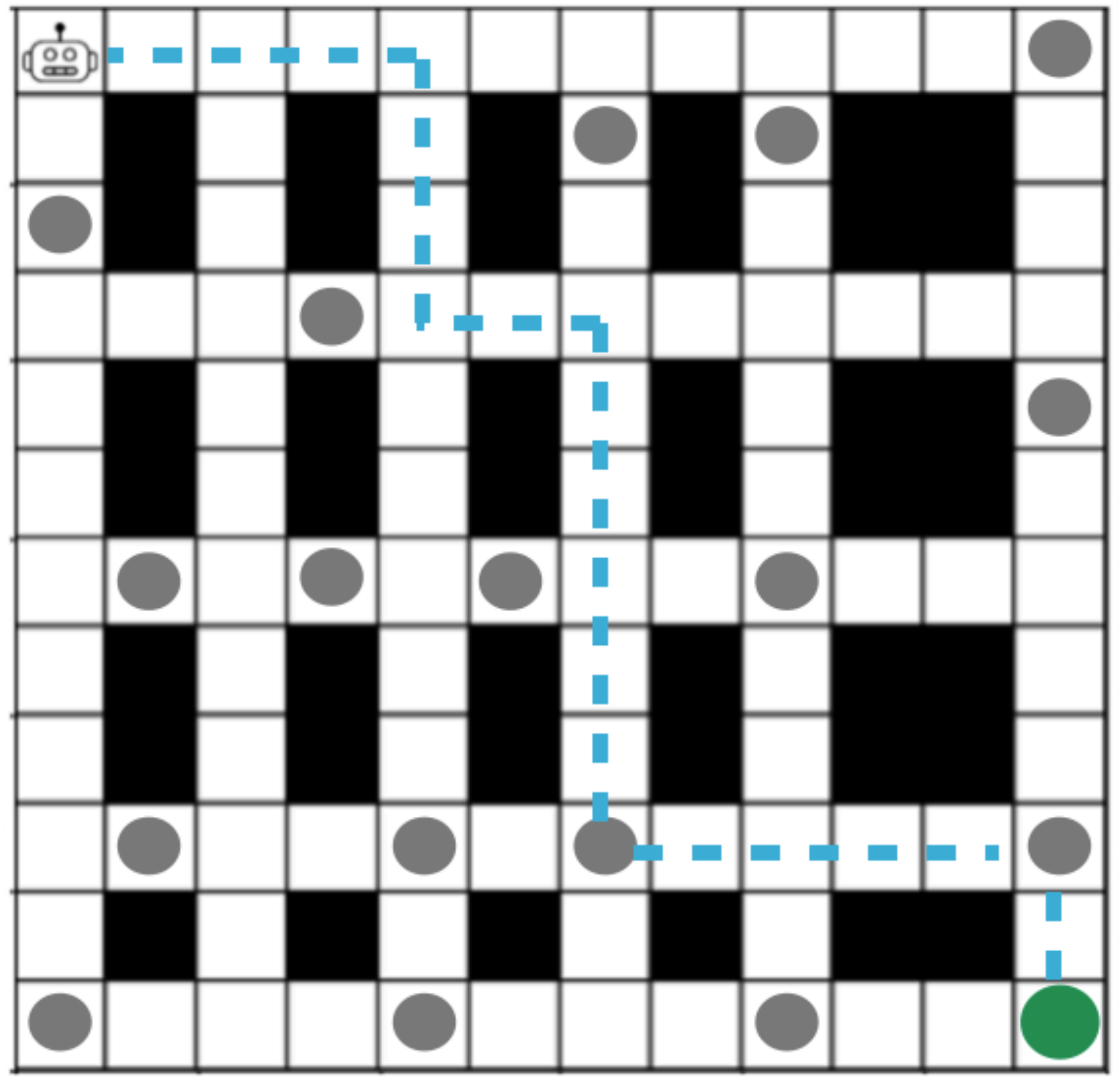
Results - Example 2

Total patients: 17

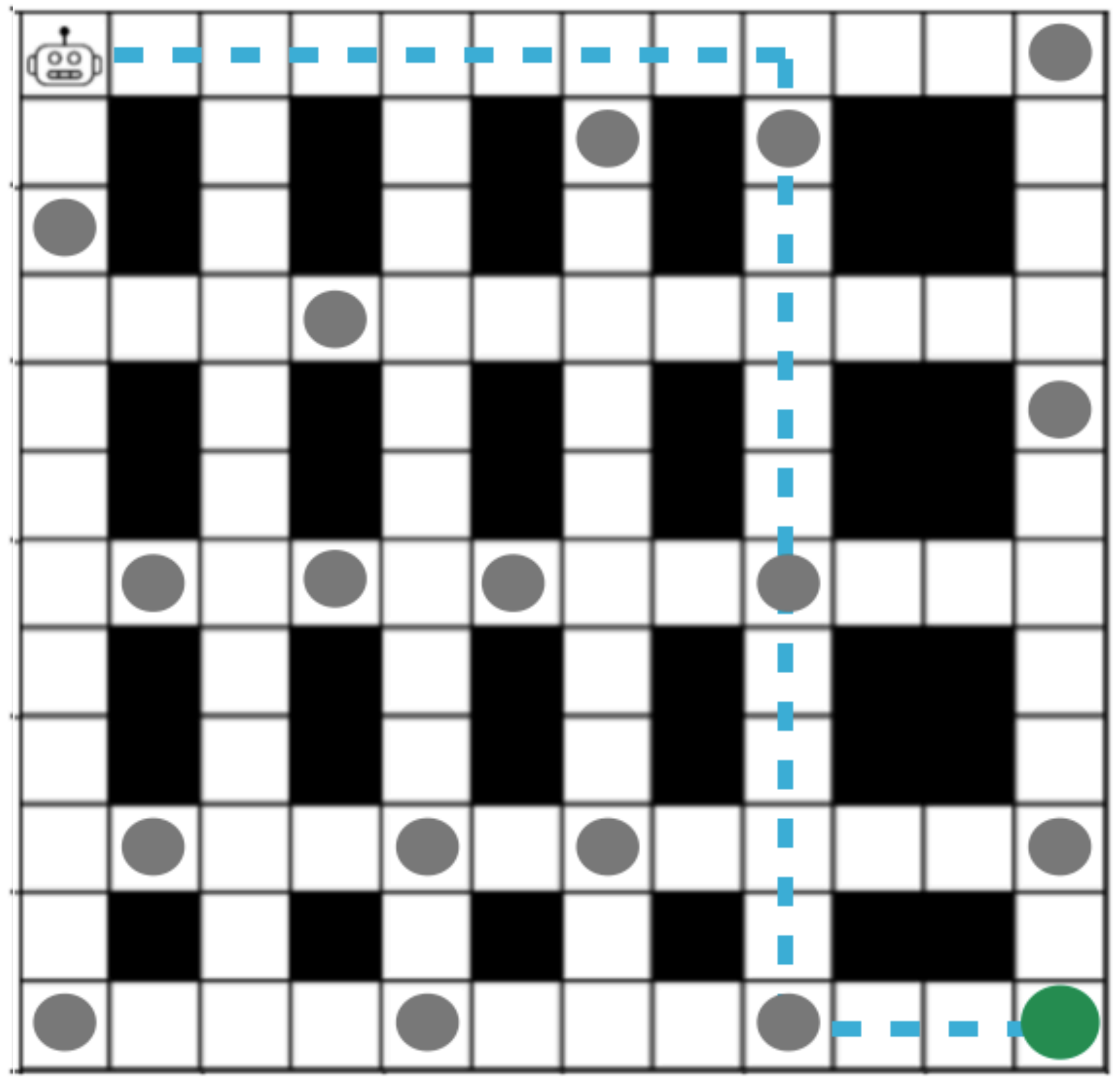
A* Search



Dijkstra



SafeDQN



SafeDQN encounters

3 patients
Length = 22

2 patients
Length = 22

3 patients
Length = 22

Robot Patient Goal Robot Path

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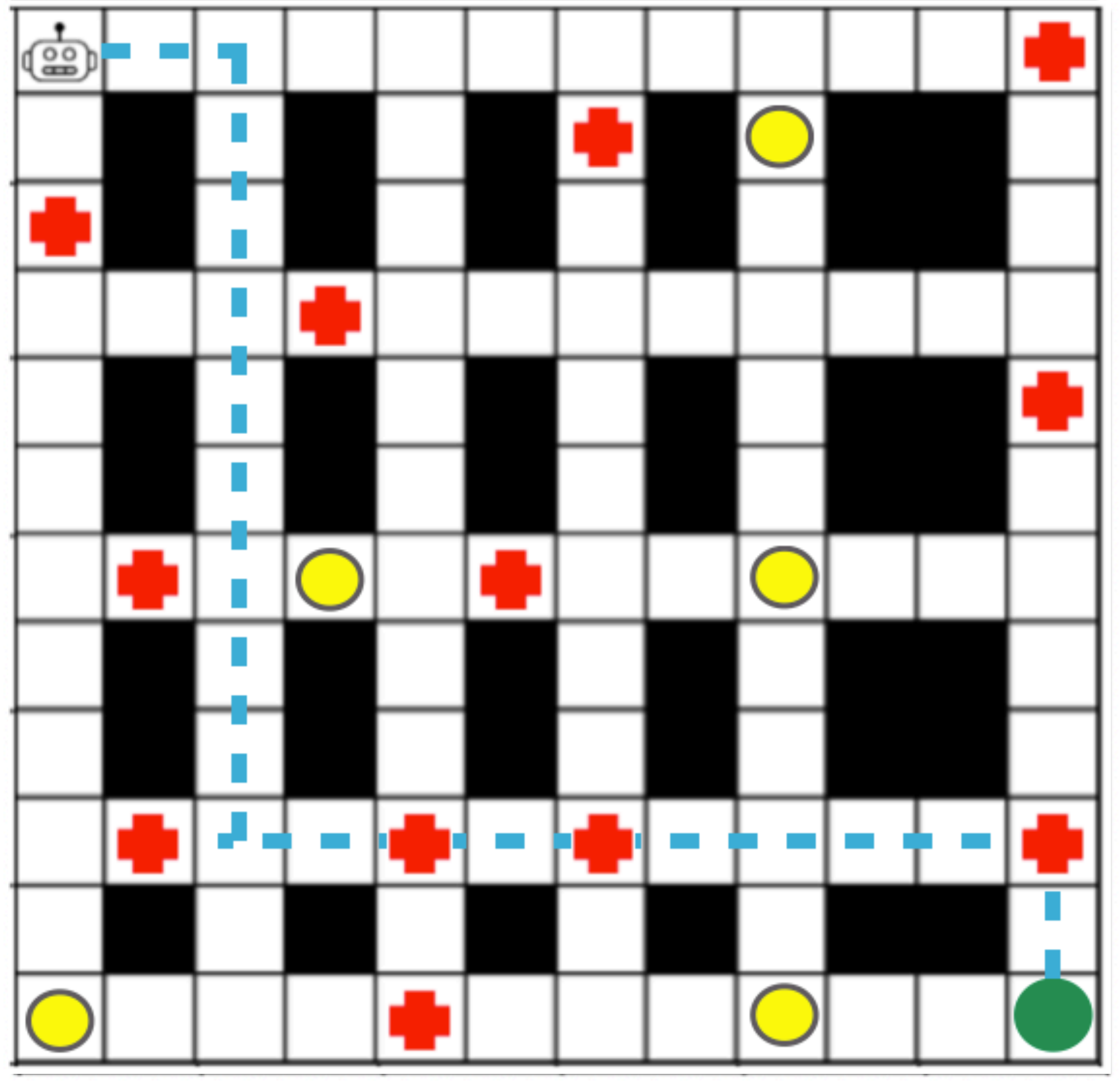
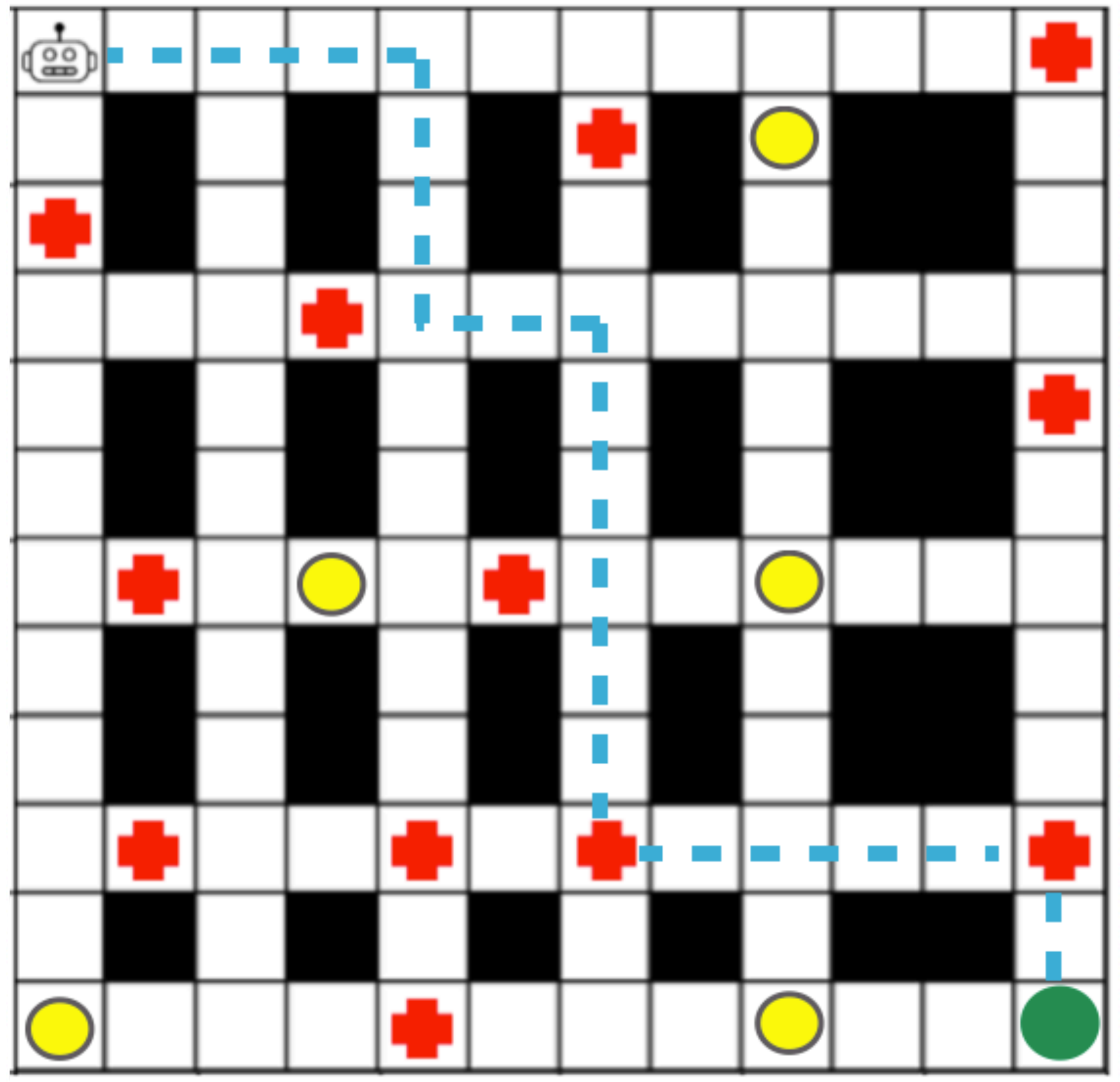
Results - Example 2

Total patients: 17

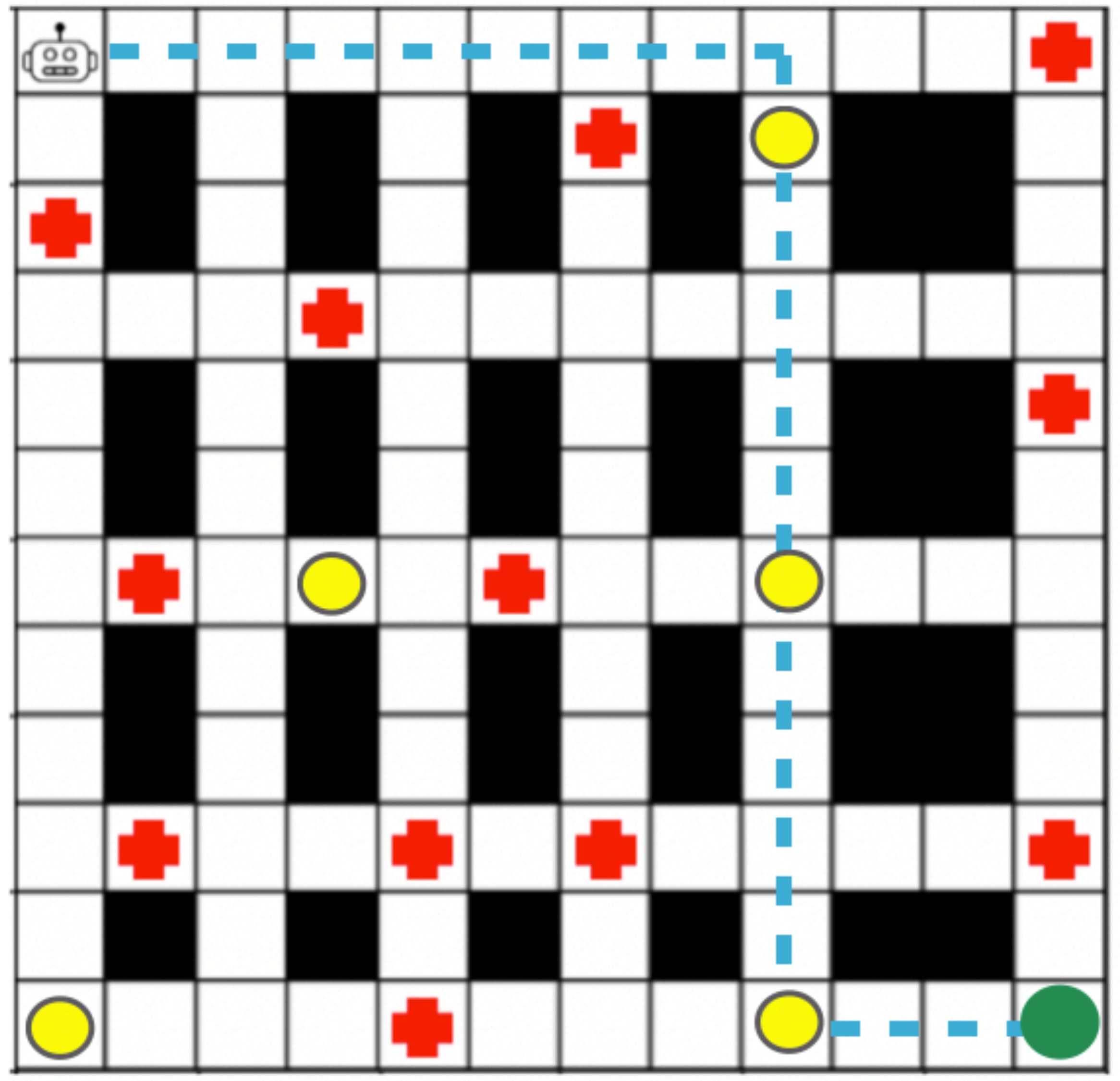
A* Search



Dijkstra



SafeDQN



SafeDQN encounters

3 high-acuity patients
Length = 22

2 high-acuity patients
Length = 22

3 low acuity patients
Length = 22

Robot   Low-acuity patient   High-acuity patient   Goal   Robot Path

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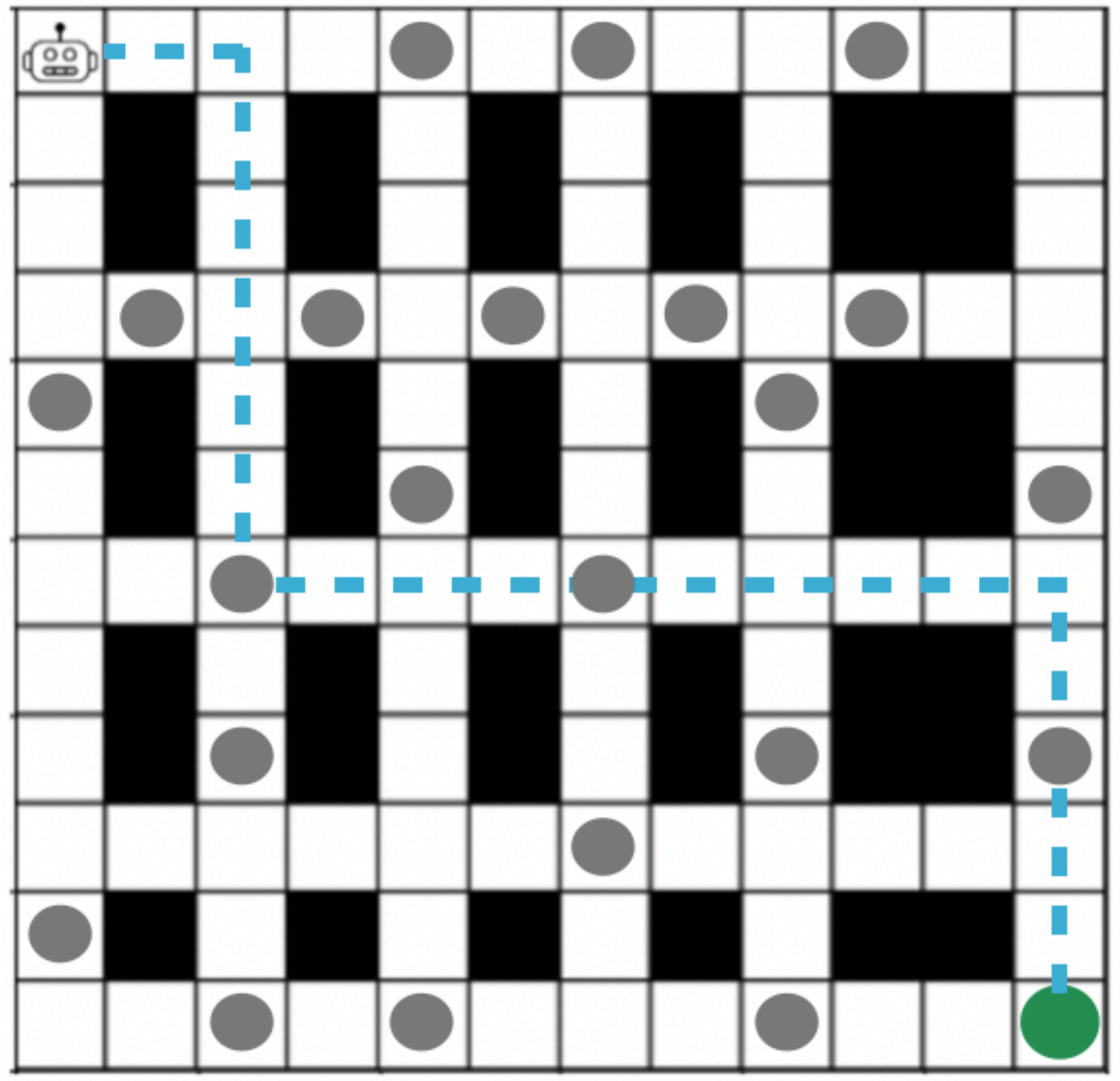
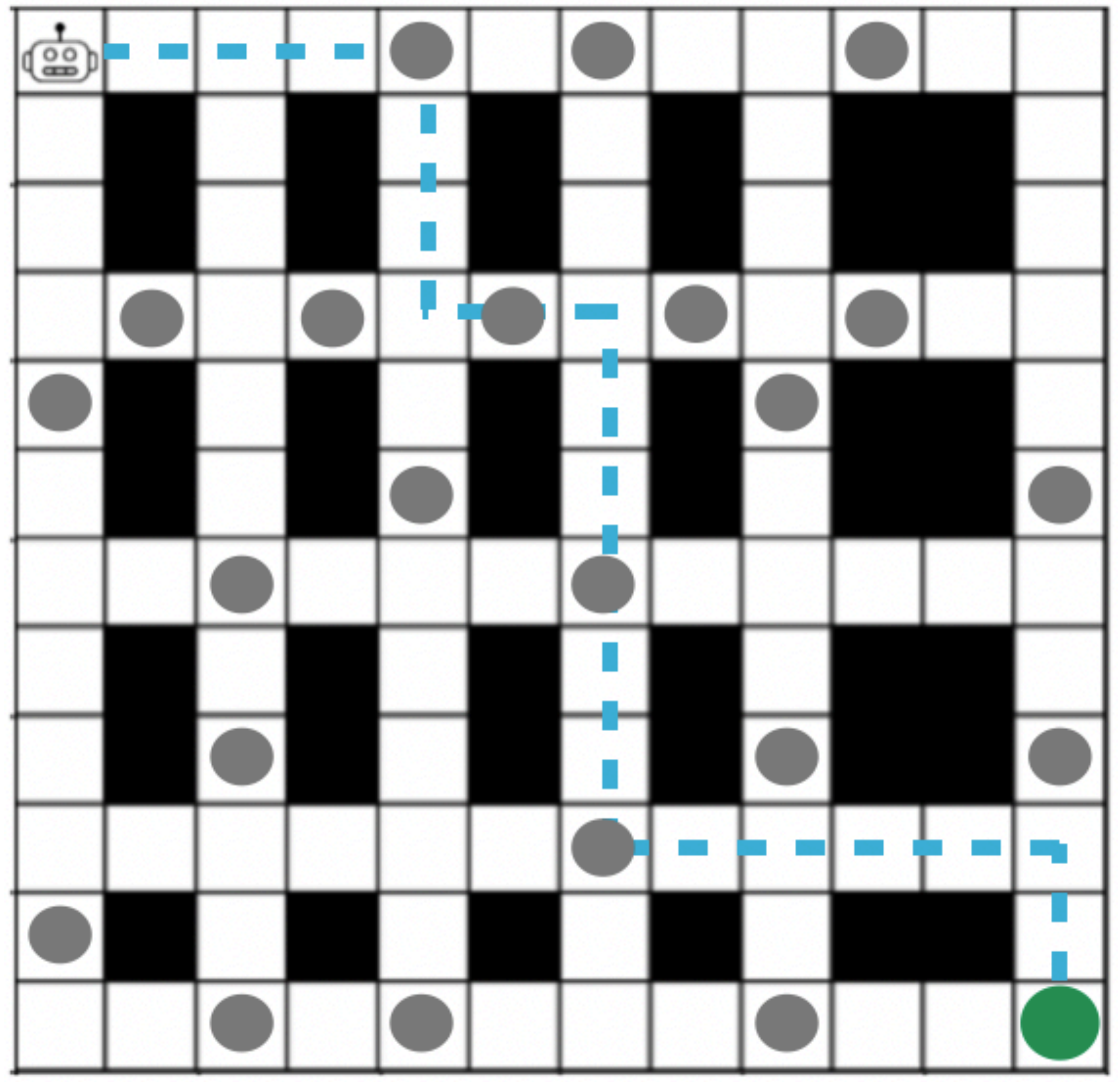
Results - Example 3

Total patients: 22

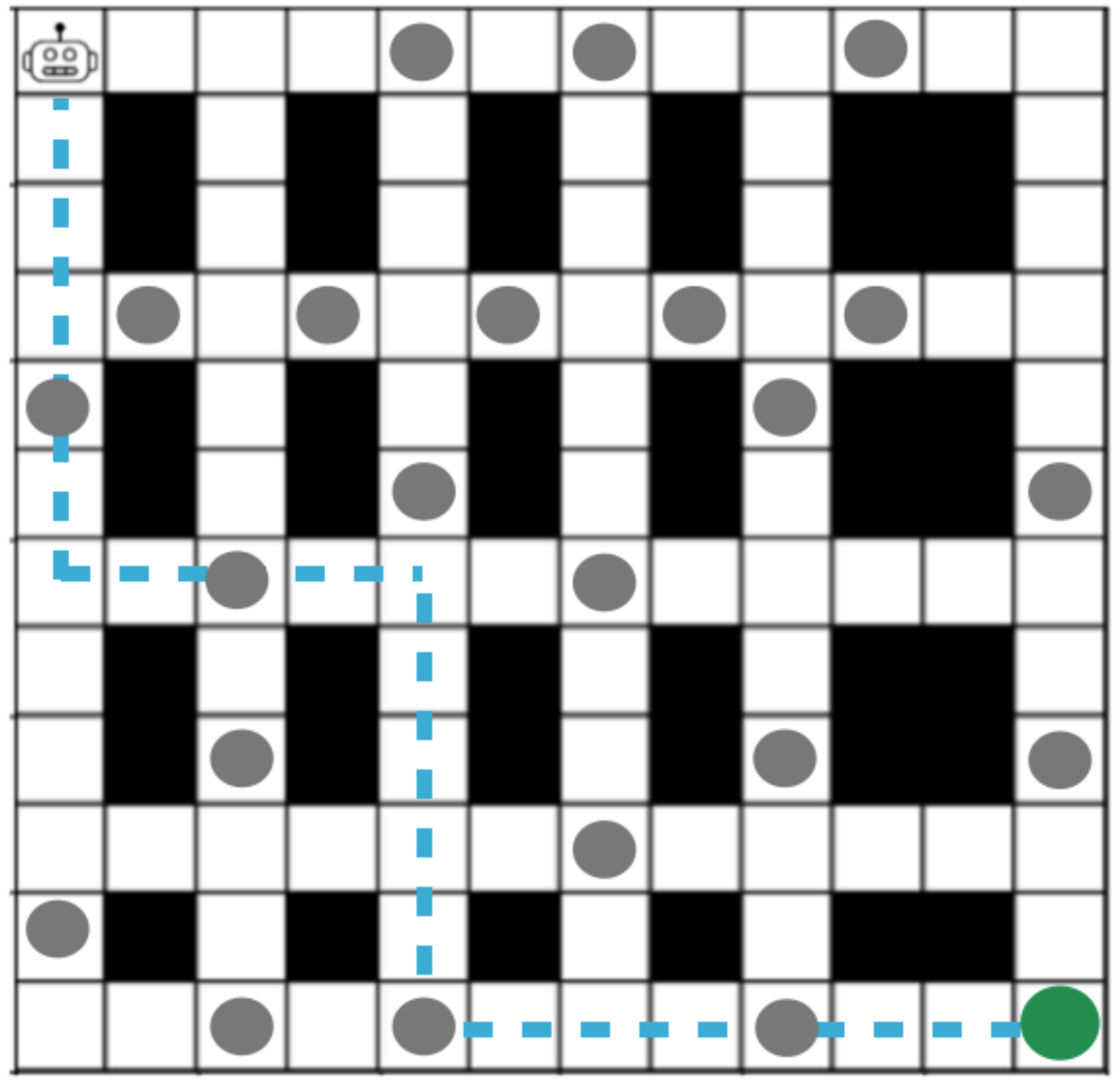
A* Search



Dijkstra



SafeDQN



SafeDQN encounters

3 patients
Length = 22

4 patients
Length = 22

4 patients
Length = 22

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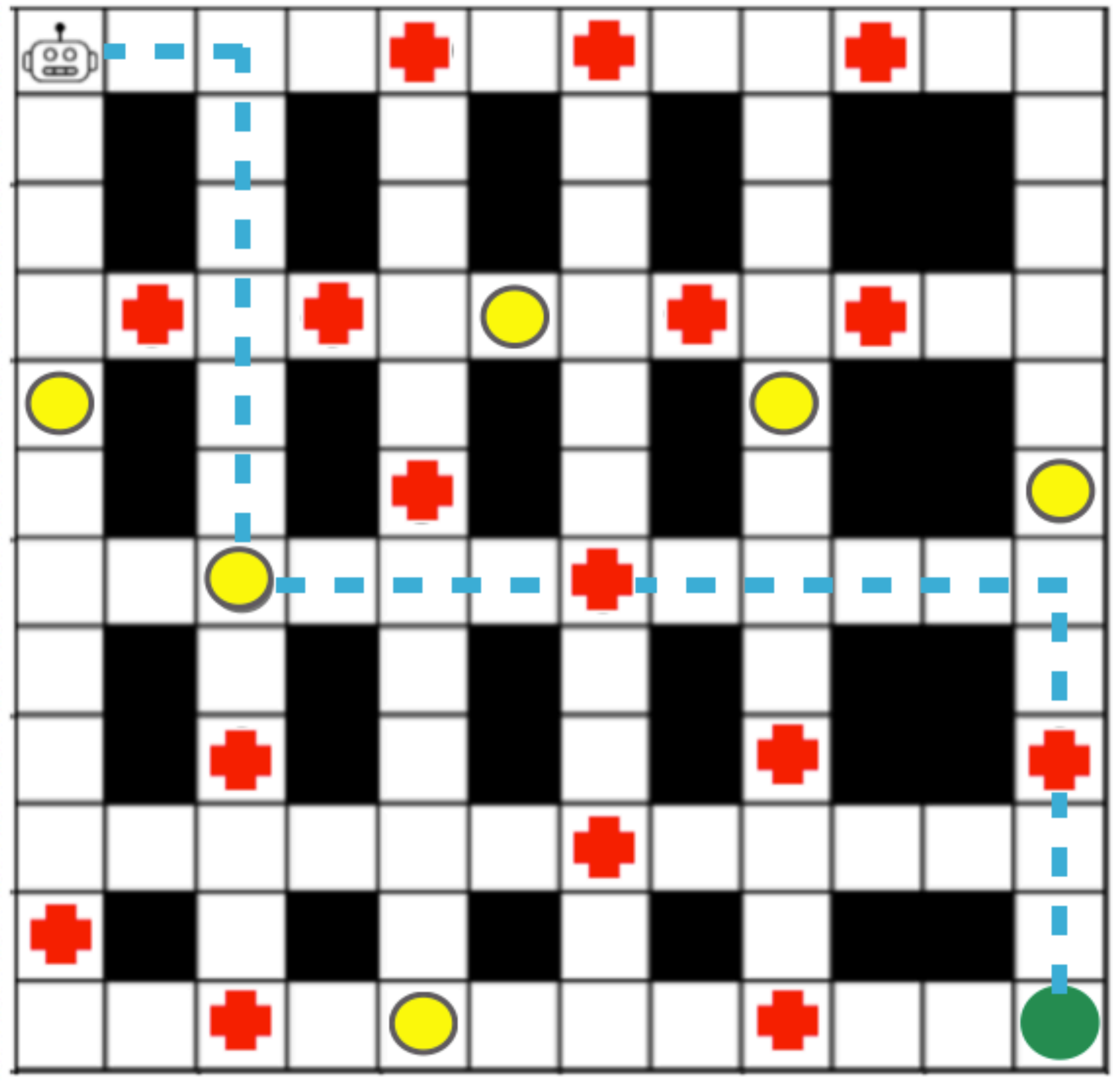
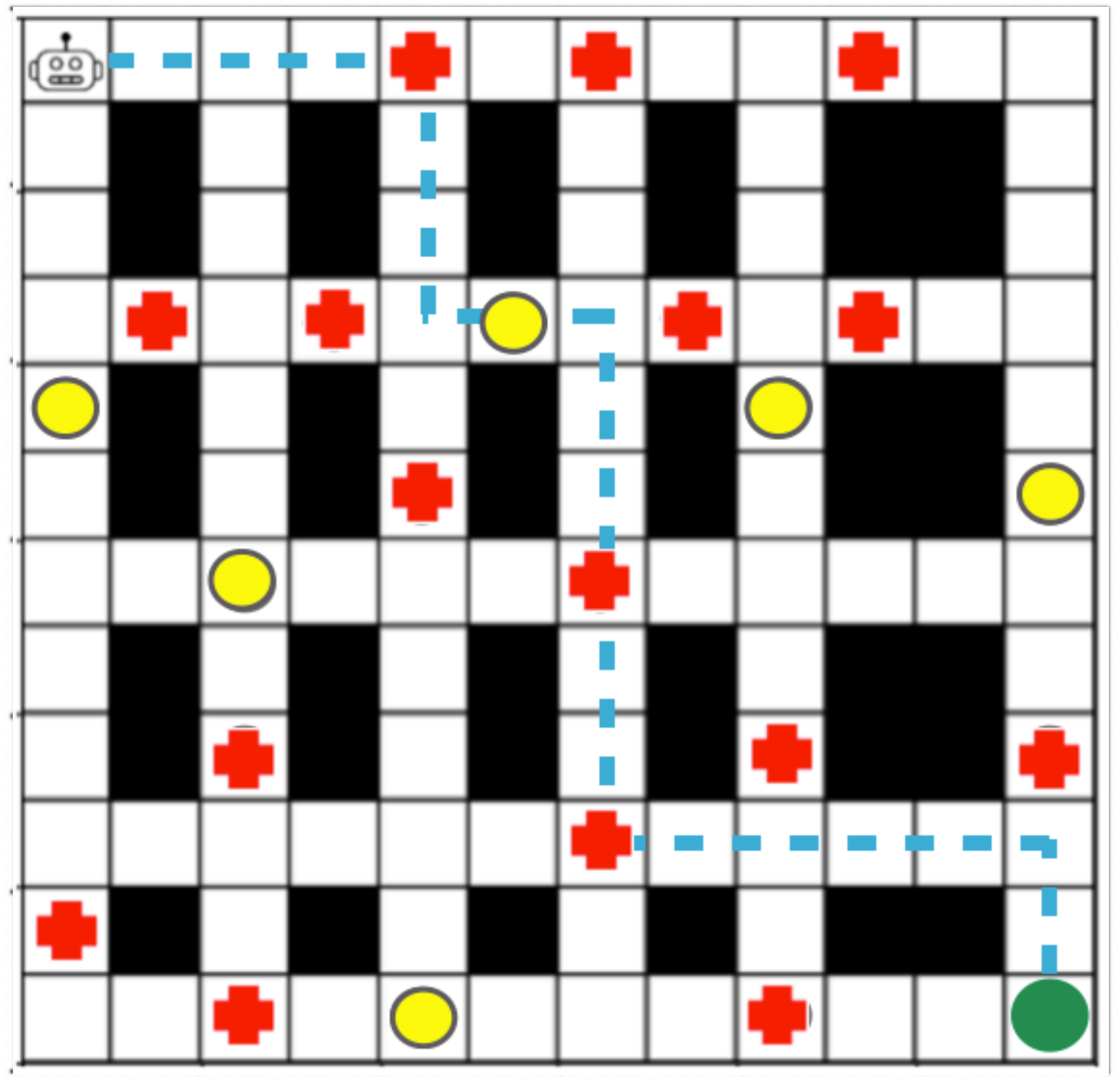
Results - Example 3

Total patients: 22

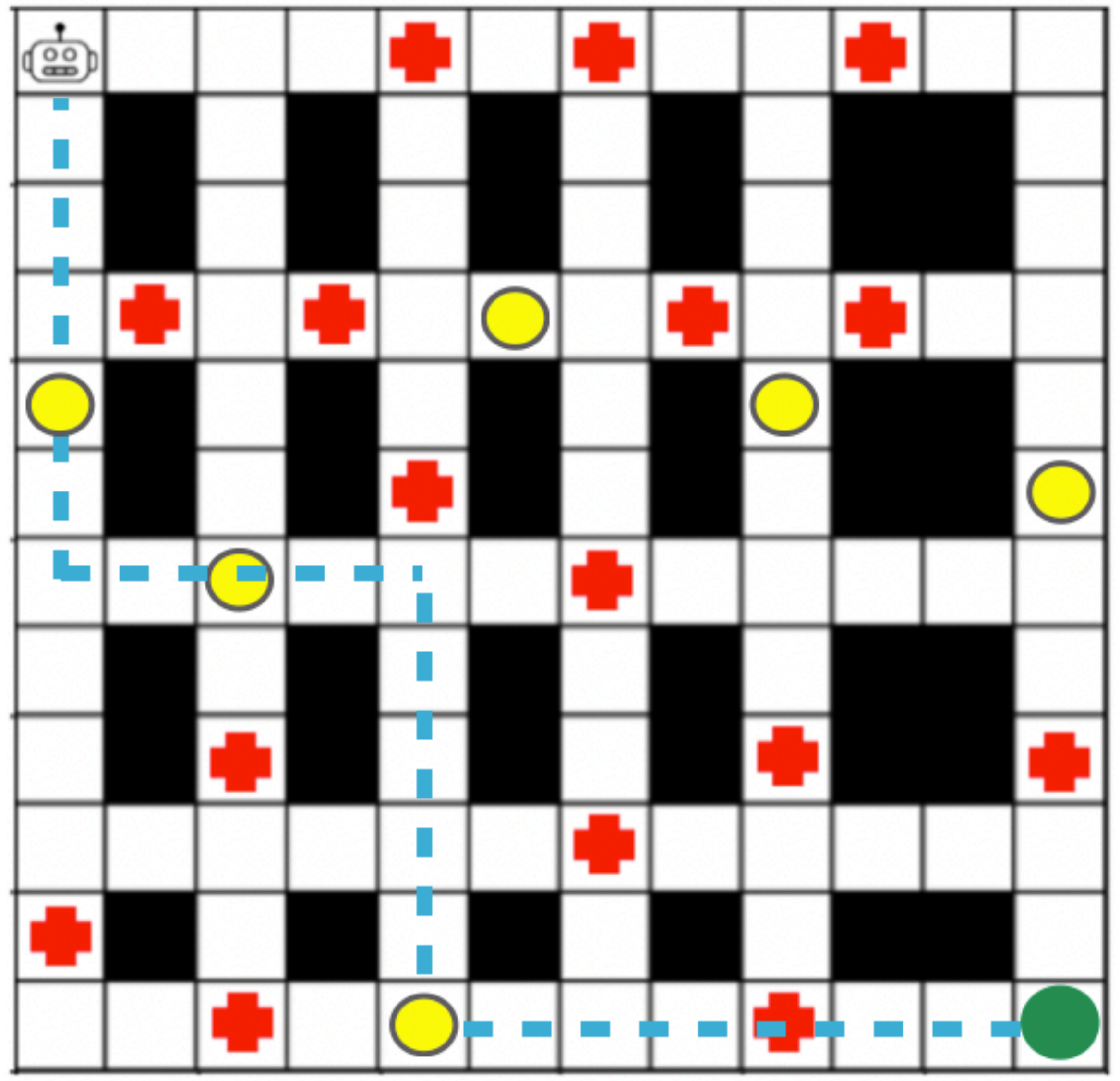
A* Search



Dijkstra



SafeDQN



SafeDQN encounters

2 high-acuity patients
1 low-acuity patient
Length = 22

3 high-acuity patients
1 low-acuity patient
Length = 22

1 high-acuity patient
3 low-acuity patients
Length = 22

Robot · Low-acuity patient · High-acuity patient · Goal · Robot Path

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SafeDQN: Future Work

Contributions & Impact

Developed an acuity-aware social navigation system for robots working in the Emergency Department to enable them to generate efficient, safety-compliant paths.

To the best of our knowledge, SafeDQN is the first method to explore robot navigation while considering patient severity.

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Social Navigation in the Emergency Department

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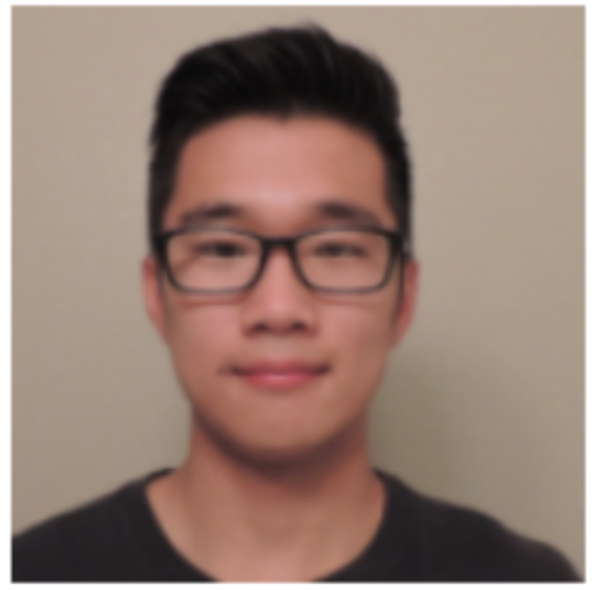
Sachiko Matsumoto



Wesley Xiao

Laurel Riek, Ph.D.

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