



# Optimizing Patient Scheduling Using Reinforcement Learning: Prioritizing Urgent Cases

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# Background

Public health facilities in Uganda often struggle with long queues, inefficient patient flow, and manual scheduling.

Patients arrive with varying urgency levels categorised in to two in this project:

- ☐ Urgent (Red) patients that should be served soon.
- ☐ Non-Urgent (Yellow) patients who can wait.



# Problem statement

- ❑ Approaches that are commonly used in health facilities such as first-come-first-served ordering often result in;
- ❑ Delays for urgent patients
- ❑ Overcrowding
- ❑ Inefficient use of medical staff

Reinforcement Learning (RL) offers a dynamic solution to this problem.



# Main Objective

To develop a Reinforcement Learning-based patient scheduling system that:

- ☐ Dynamically selects which patient to serve next
- ☐ Minimizes overall waiting times
- ☐ Prioritizes Red cases appropriately
- ☐ Adapts to changing arrival patterns



# Hypothesis

## ❑ Null Hypothesis ( $H_0$ ):

The reinforcement learning agent **does not significantly reduce** average waiting times compared to a baseline policy (such as random or first-come-first-served assignment of patients).

## ❑ Alternative Hypothesis ( $H_1$ ):

The reinforcement learning agent **significantly reduces** average waiting times compared to a baseline policy.



# Markov Decision Process (MDP) Problem Formulation

## □ State Space (S)

The State includes the current triage categories, accumulated waiting times, queue size as well as the number of available clinicians and their ongoing service durations.

## □ Action Space (A)

The agent's action is to select which patient to serve next from the queue.



# MDP Problem Formulation Cont'd

## □ Reward Function (R)

Reward encourages the agent to prioritize urgent patients while minimizing waiting times for all categories.

**Priority reward:** Red = 40, Yellow = 30,

**Threshold bonuses:** If a patient is served within the waiting-time threshold (Red  $\leq 15$  min, Yellow  $\leq 30$  min), a positive reward is applied: Red = 40, Yellow = 30.



# MDP Problem Formulation Cont'd

## ☐ Transition Dynamics (P)

After the agent selects a patient basing on the category;

- ☐ Service time is sampled for the selected patient and doctor.
- ☐ Simulation clock is advanced by minimum service time.
- ☐ Waiting times for of all the other patients is updated.
- ☐ Served patient is removed from queue.
- ☐ New arrivals are added based on stochastic process.
- ☐ Rewards computed.
- ☐ New observation and rewards are returned.





# Algorithm Choice

Deep Q-Learning (DQN) is selected because the patient scheduling problem is a discrete-action, high-dimensional, and has a model-free environment.

- ❑ The scheduling decision of choosing which patient category to serve next forms a discrete action space, making DQN more suitable than continuous-action methods such as PPO or SAC.
- ❑ The environment involves stochastic patient arrivals, varying service times, and dynamic queue states, which cannot be modeled analytically; therefore, a model-free RL method is required.



# Justification for Choosing the DQN Algorithm

- ❑ DQN's neural network function approximator allows it to handle the complex, multi-feature state space representing waiting times, urgency levels, and doctor availability.
- ❑ Additionally, DQN's value-based framework aligns with the objective of optimizing cumulative performance
- ❑ Techniques like experience replay and target networks stabilize learning
- ❑ These characteristics make DQN the most appropriate algorithm for optimizing patient flow.



# Simulation & Training

## Environment Setup

- ❑ The project uses a custom-built simulation environment in Python. The environment models the outpatient department as a time-driven system with the following components:
- ❑ **Dynamic queue:** containing the waiting patients, their urgency level, and waiting time.
- ❑ **Multiple doctors:** Each doctor has a service status (“free” or “busy”) and a remaining service time counter.
- ❑ **Variable service times:** Each patient category has an average service duration. The model uses approximate average service times for each category. Red ≈ 15 minutes, Yellow ≈ 10 minutes
- ❑ To implement randomness in service duration, these average values are modelled using a lognormal distribution.



# Environment Setup

- ❑ **Random patient arrivals:** At each time step, a new patient may arrive based on a Poisson arrival rate  $\lambda$ . Each incoming patient is assigned a triage category:
  - ❑ Red (urgent)
  - ❑ Yellow (non urgent)



# Hyperparameter Tuning

## □ 1. Learning Rate ( $\alpha$ )

The size of steps taken to update the neural network weights (Q values) when it learns from new experience.

Value Used:

$\alpha = 0.0005$  (5e-4)



# Hyperparameter Tuning

## □ 2. Discount Factor ( $\gamma$ )

The discount factor determines how much the model values future rewards vs. immediate rewards.

$\gamma$  close to 1  $\rightarrow$  values long-term outcomes

$\gamma$  close to 0  $\rightarrow$  only cares about immediate reward

### □ Value Used:

$\gamma = 0.95$

The model should focus on long-term congestion reduction.



# Hyperparameter Tuning

## □ 3. Exploration Rate ( $\epsilon$ )

### $\epsilon$ -greedy strategy

It controls how often the agent explores new actions instead of choosing the best-known action.

### □ Strategy Used

$\epsilon_{\text{start}} = 1.0$  (pure exploration at beginning)

$\epsilon_{\text{end}} = 0.1$  (Mostly exploitation)



# Hyperparameter Tuning

## ❑ 4. Batch Size

Number of experience samples used in one training update.

### ❑ Value Used:

`batch_size = 64`

## ❑ 5. Replay Buffer Size

This is the memory that stores past experience (state, action, reward, next state).

### ❑ Value Used:

`buffer_size = 50,000`





# Hyperparameter Tuning

## ❑ 6. Target Network Update Frequency

The target network update frequency determines how often the weights of the online Q-network are copied into the target network.

### ❑ Value Used:

**target\_update = every 1,000 steps**

Smooths out Q-value updates, prevents divergence.



# Evaluation Metrics

## ❑ 1. Average Episode Reward

Average reward per episode: 1895.70

## ❑ 2. Average wait times

(Red, Yellow): 3.90, 5.86

## ❑ 3. Percentage served within thresholds

(Red, Yellow): 100.00%, 100.00%



# Evaluation Metrics

## ❑ 4. Convergence Speed

This refers to how quickly (after how many steps and episodes) the agent's learning stabilizes, meaning:

Q-values stop changing wildly

episode reward becomes stable

policy stops fluctuating

❑ At 0 timesteps → mean reward: 1940.10

❑ At 10000 timesteps → mean reward: 1869.30

❑ At 20000 timesteps → mean reward: 1874.40

❑ Model converged at ~20000 timesteps.



# links

The project includes training, inference, and deployment via a FastAPI endpoint.

For running the API locally:

<http://127.0.0.1:8000/docs>

For Web-based Testing:

<https://rl-hospital-api.onrender.com/docs>

Key libraries: numpy, gymnasium, stable-baselines3, torch, matplotlib, fastapi, pydantic, uvicorn



# Sample state vector for testing the FastApi inference API

```
{ "state": {  "free_doctors": 2,  "longest_wait_red": 8,  
"longest_wait_yellow": 12,  "red_queue_length": 4,  
"yellow_queue_length": 5,  "doctor1_busy_time": 0,  
"doctor2_busy_time": 0,  "doctor3_busy_time": 2  }}
```



# State vector for testing the FastApi inference API

Edit Value | Schema

```
{  
  "state": {  
    "free_doctors": 2,  
    "longest_wait_red": 8,  
    "longest_wait_yellow": 12,  
    "red_queue_length": 4,  
    "yellow_queue_length": 5,  
    "doctor1_busy_time": 0,  
    "doctor2_busy_time": 0,  
    "doctor3_busy_time": 2  
  }  
}
```

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# Test OutPut

## Details

### Response body

```
{  
  "action": "Serve Red",  
  "reward": 76,  
  "wait_time": 8,  
  "free_doctors": 2  
}
```

### Response headers



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