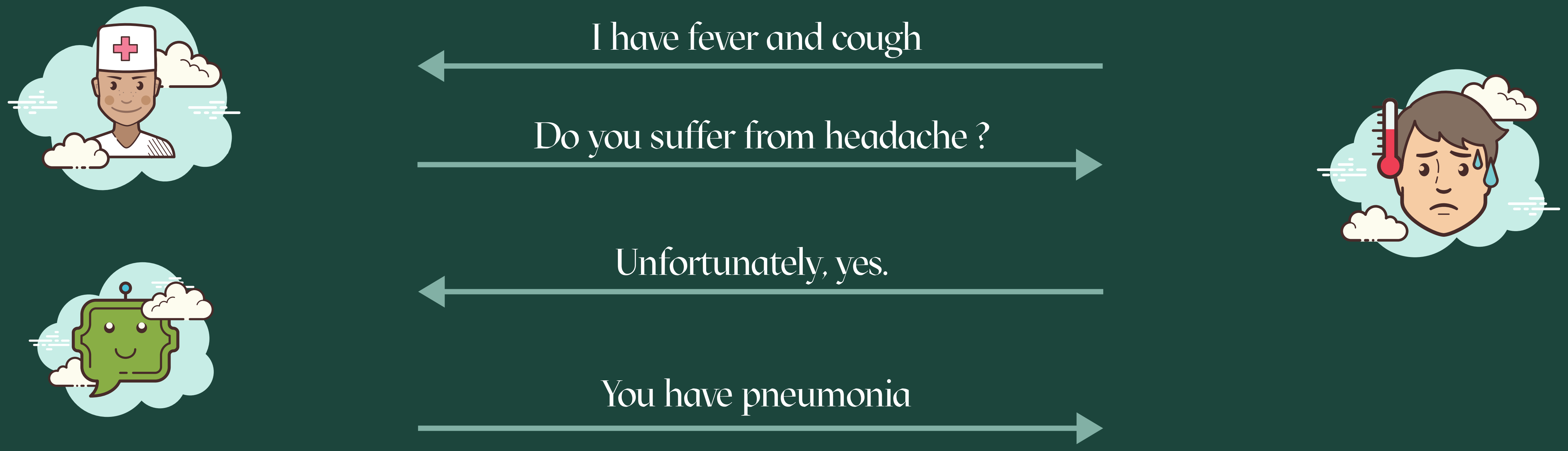
22 June 2024

Medical Diagnosis in Dialogue systems using Reinforcement Learning

Try Pitch

Introduction

Medical diagnosis is the process of identifying diseases and conditions based on symptoms, history, exams, and tests. It's crucial because it guides treatment, helps prevent complications, and improves patient outcomes.



Motivation

Early detection of disease using AI

- AI models can detect pancreatic cancer a median of 438 days before clinical diagnosis. (Med Xpress) (MIT News).

Lower the costs

- AI tools for diabetes management, such as continuous glucose monitors, educed the need for in-person appointments, also significantly lowered hospital readmission rates and overall healthcare expenditures. (Echelon Health).

Fast way to give you an idea on what clinic type to visit

- provide personalized recommendations on the type of clinic or specialist to visit based on the patient's specific symptoms(McKinsey & Company)

Different Ways of Medical Diagnosis

1. **Rule-Based Systems**

   They don't improve over time without explicit human intervention and updating of rules.

2. **Large Language Models**

   a. Generate output based on vast pre-trained *language* datasets

   b. Training and deploying LLMs require significant computational resources, making them costly and less accessible

3. **Reinforcement Learning**

   Learns from the environment based on a reward/penality

Actions

In our case, it is asking a patient about specific symptoms or diagnosing a disease.

States

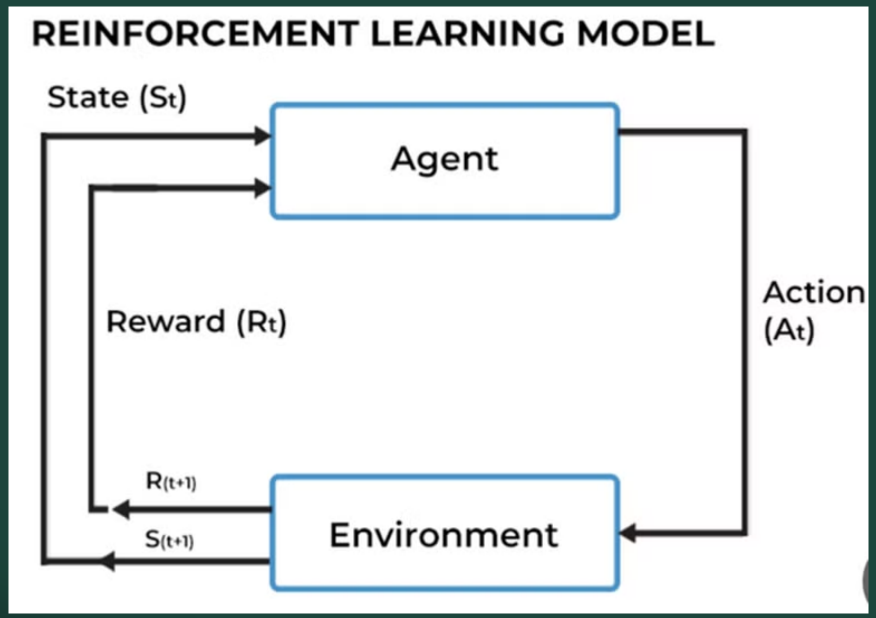
a state is the current set of symptoms that is known to agent.

Reward

are feedback given to the agent based on the effectiveness of its actions

Policy

the strategy or set of rules that the agent follows to decide its actions in each state



Proximal Policy Optimization

a. It is the state-of-art algorithm for reinforcement learning

b. Considered on-policy algorithm

c. Train the policy directly

Actor

Critic

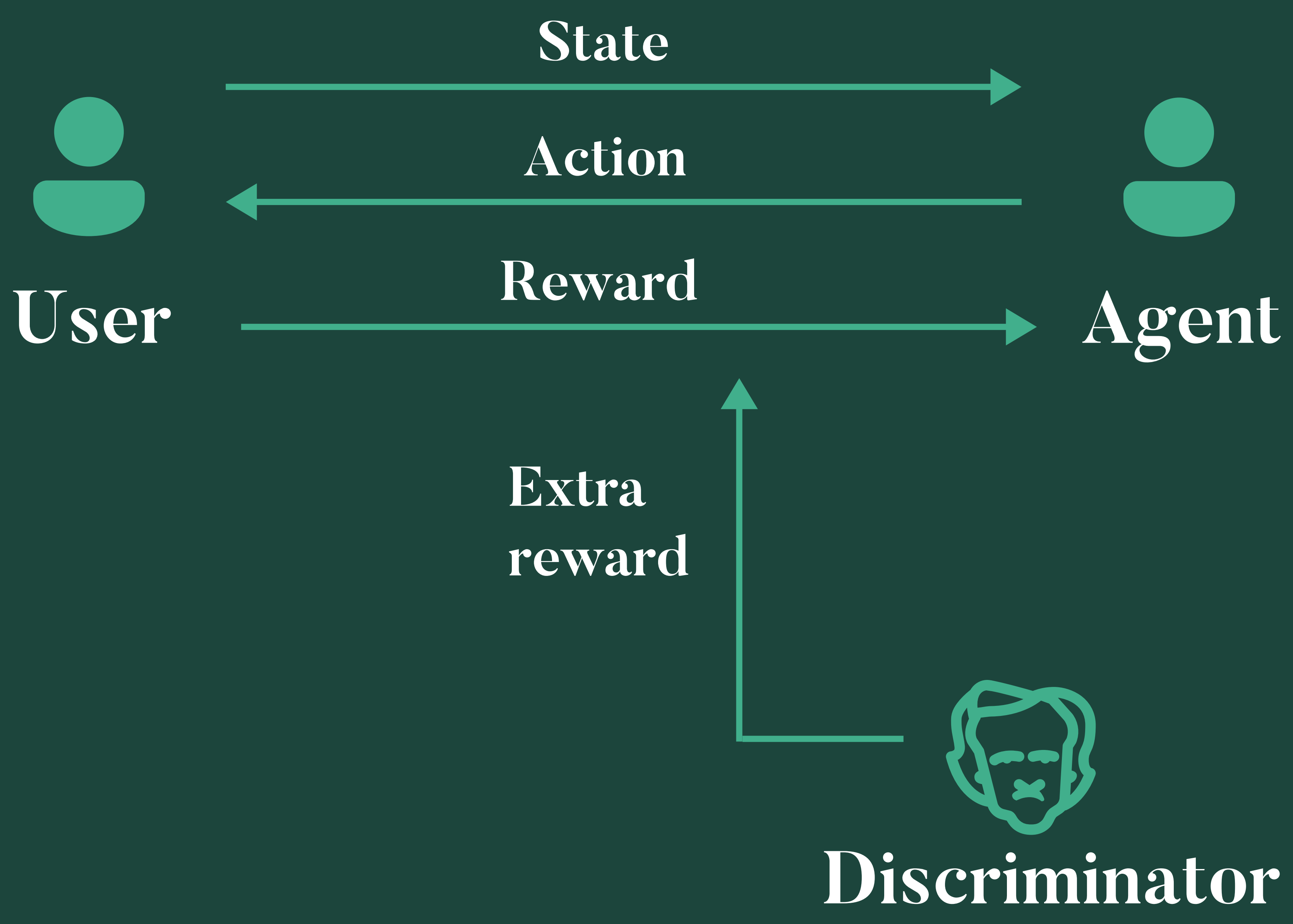
Related work

Hierarchical approach

Cheng Zhong, et al. (2022)

Related work

Adversarial approach



Ziming Li (2020)

Problem Formulation

Dataset - patient data

'explicit_inform_slots' : {'cough':True, 'vomit': True, 'fever': False}

'implicit_inform_slots' : {'headache':True, 'runny nose'': False}

'disease_tag' : pneumonia

State space

[0: 'cough', 1: 'vomit', 2: 'headache', 3:'runny nose', 4: 'anorxia', 5: 'expectoration', 6: 'Fever', ...]

state = [3, 3, 0, 0, 0, 0, 2, ...]

Action space

Action space = symptoms_set U disease_set

Action = 'runny_nose' (3)

new_state = [3, 3, 0, 2, 0, 0, 2, ...]

[3, 3, 0, 0, 0, 0, 2, ...]

3

[3, 3, 0, 2, 0, 0, 2, ...]

3: True
2: False
1: not-mentioned

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PPO Agent

Trajectory: state, action, old probability, value, reward, and done array

Memory

state, action, old probability, value, reward, and done array

state, action, old probability, value, reward, and done array

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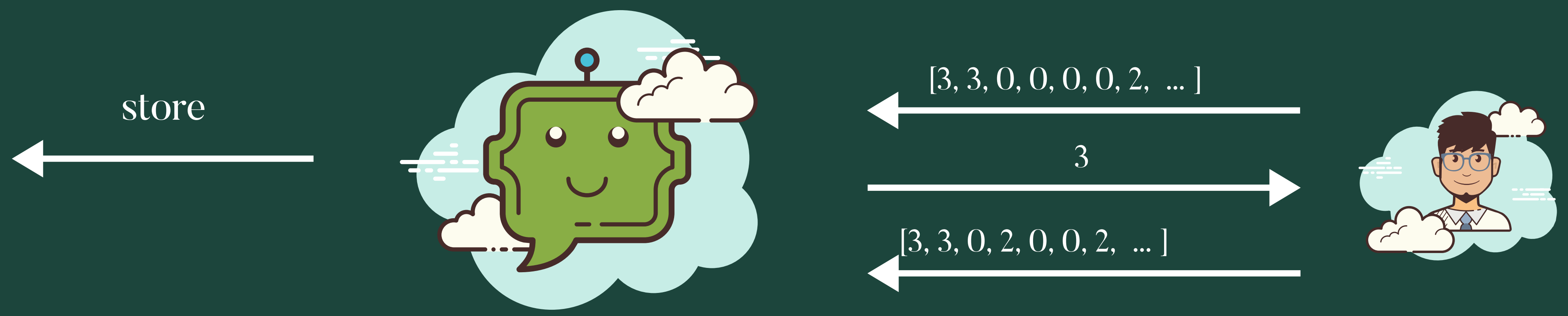
state, action, old probability, value, reward, and done array



PPO Agent

Learn()

1. Advantage Calculation
    2. For mini-batches
        3. Loss Computation

4. Actor Loss

min(policy_ration * advantages , clip(ratio, 1- e, 1 + e)* advantages)

5. Critic Loss

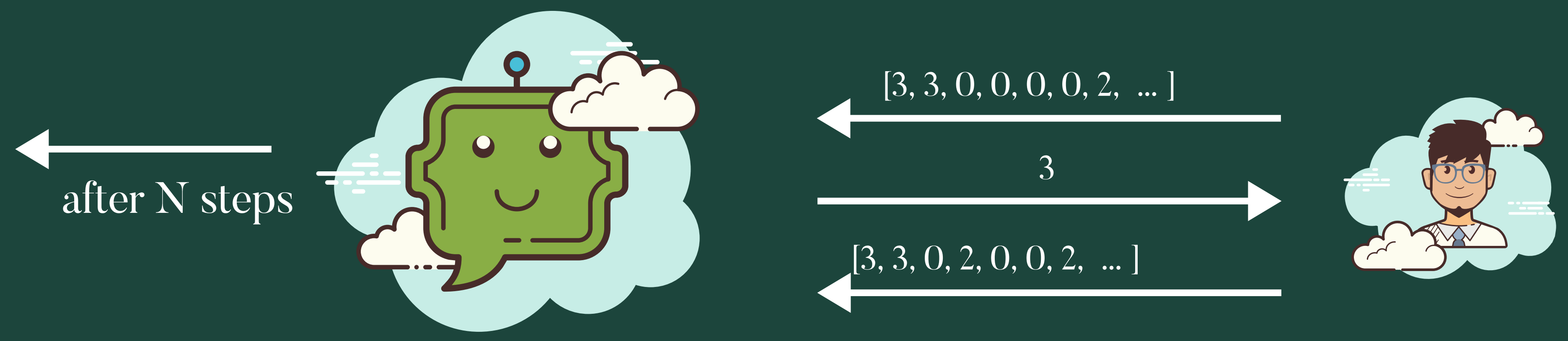
MSE(Value Estimates , Rewards)

6. Compute entropy

7. Total Loss

actor_loss + vf_coeff * critic_loss - entropy_coeff * entropy

8. Backpropagation



Auto Encoder

It consists of two main parts: an encoder and a decoder.

Encoder:

- Transforms the input data into a lower-dimensional representation (latent space).
- Captures the essential features of the input data.

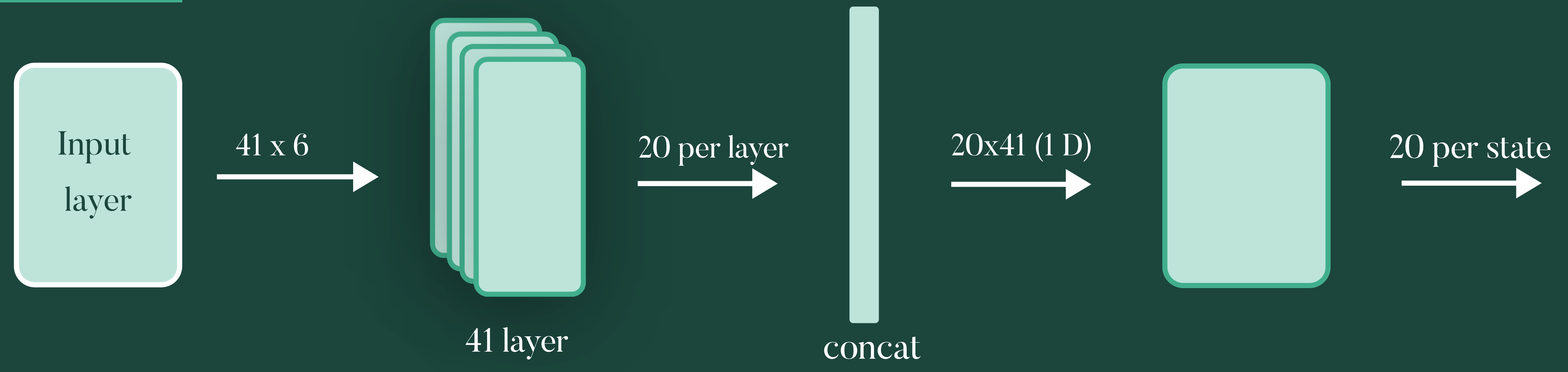
Decoder:

- Reconstructs the input data from the lower-dimensional representation.
- Aims to make the output as close as possible to the original input.

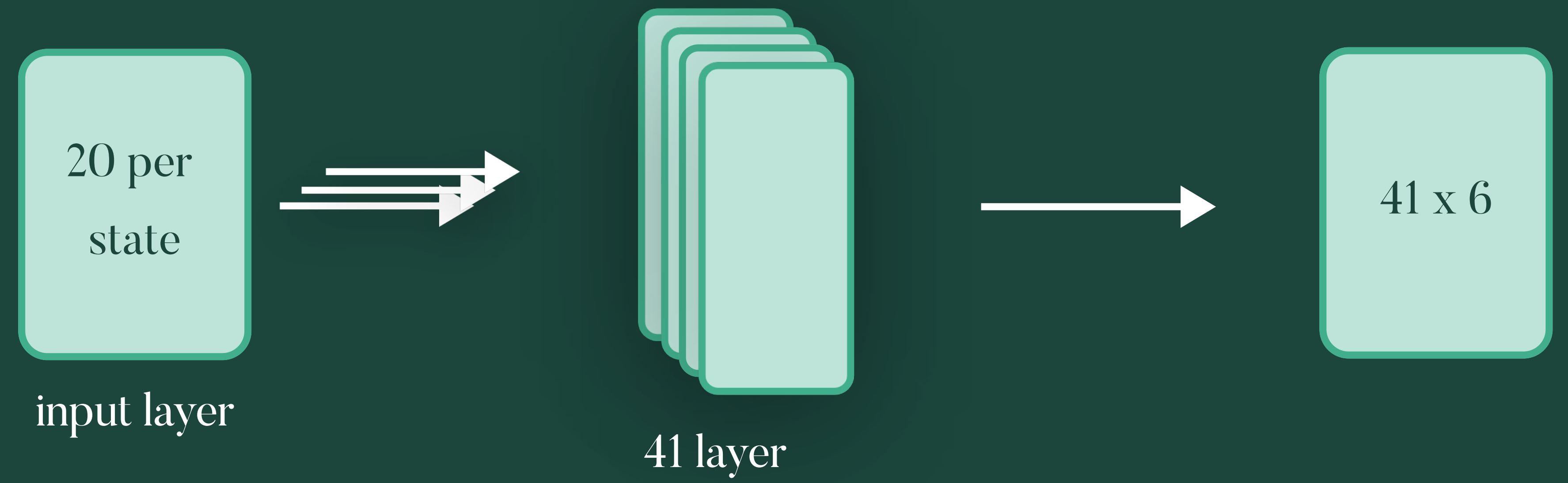
Minimize the difference between the input data and the reconstructed output.

Architecture

Encoder



Decoder



Motivation

1. Tackles categorical data issues

Proximal Policy Optimization (PPO) benefits from continuous action spaces as they allow for smooth policy updates

2. Robust to hyperparameter

PPO algorithm's performance is highly sensitive to its hyperparameters, through extensive experiments, we showed that AutoEncoder is robust to hyperparameters

3. Reward sparsity

State is not informative enough, and the reward the agent receive is sparse

Typical solutions and Experimental results

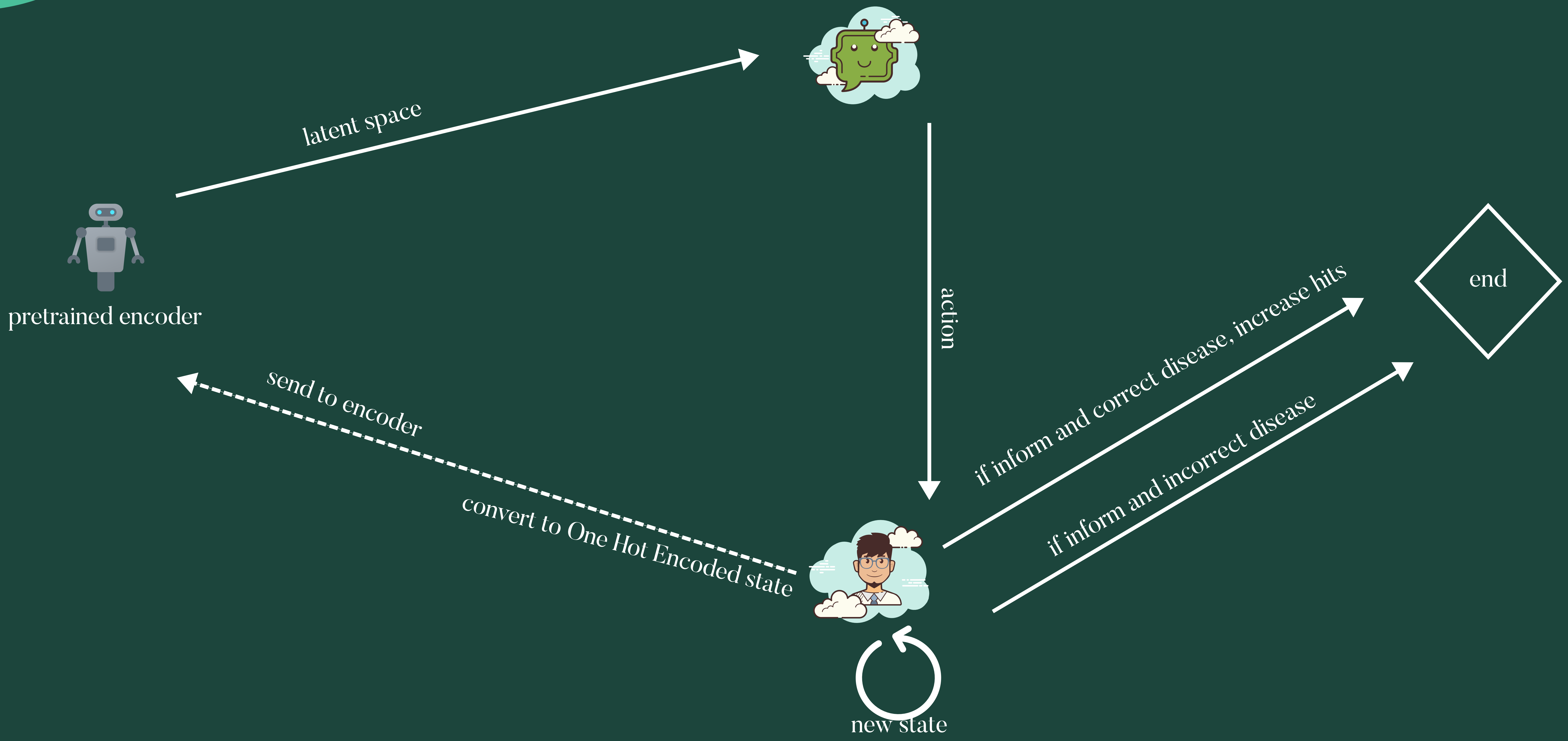
PPO One Hot Encoded Accuracy: ~ 33%

Will be discussed later

PPO with State Tracker Accuracy: ~45%

PPO with Extra Reward Accuracy: ~35%

Proposed Framework



Evaluation

We evaluate by calculating the hits the agent gets when he informs for a disease.

The dataset is already divided with 104 episodes(dialogues) for testing and 422 for training.

We calculate accuracy by dividing the number of hits over the number of episodes

$$\text{Accuracy} = \#\text{of hits} \div \#\text{of episodes}$$

Evaluation

We put the following research questions:

1. How is the performance of proposed approach compared to Baseline PPO?

2. What is the effect of hyperparameter tuning on both implementations?

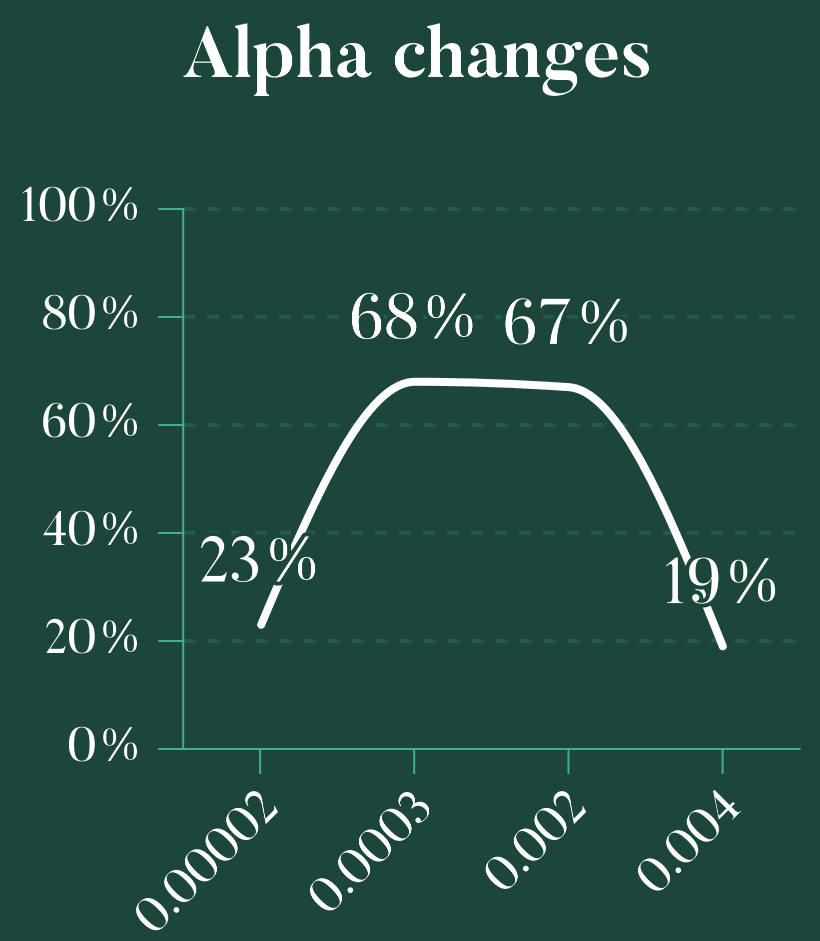
3. What is the effect of different parameters on both implementations?

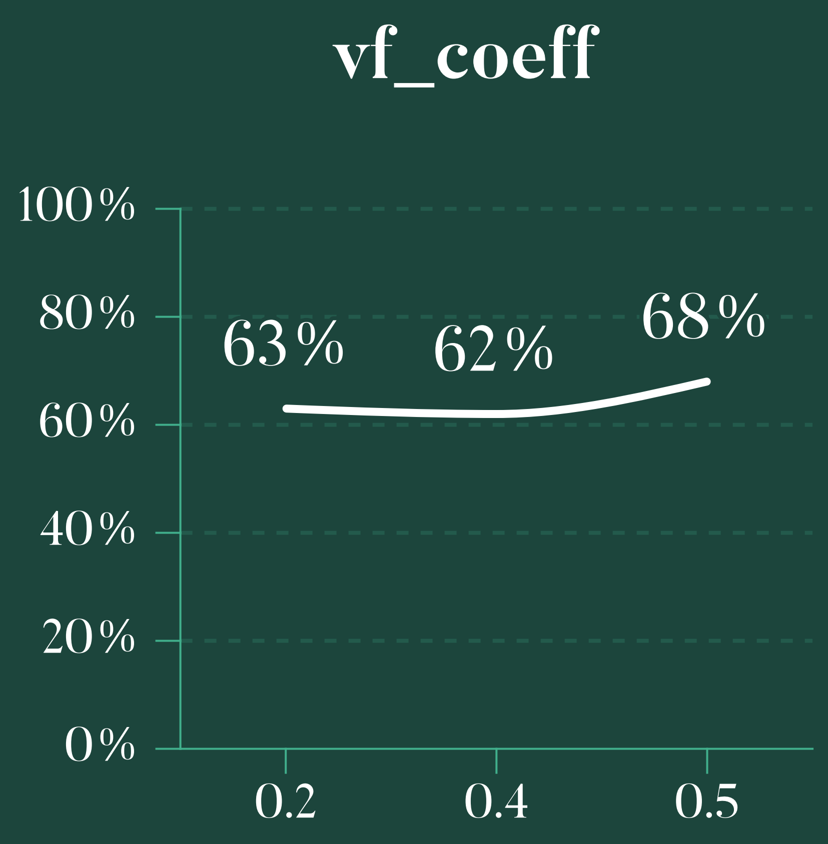
Results & Discussion

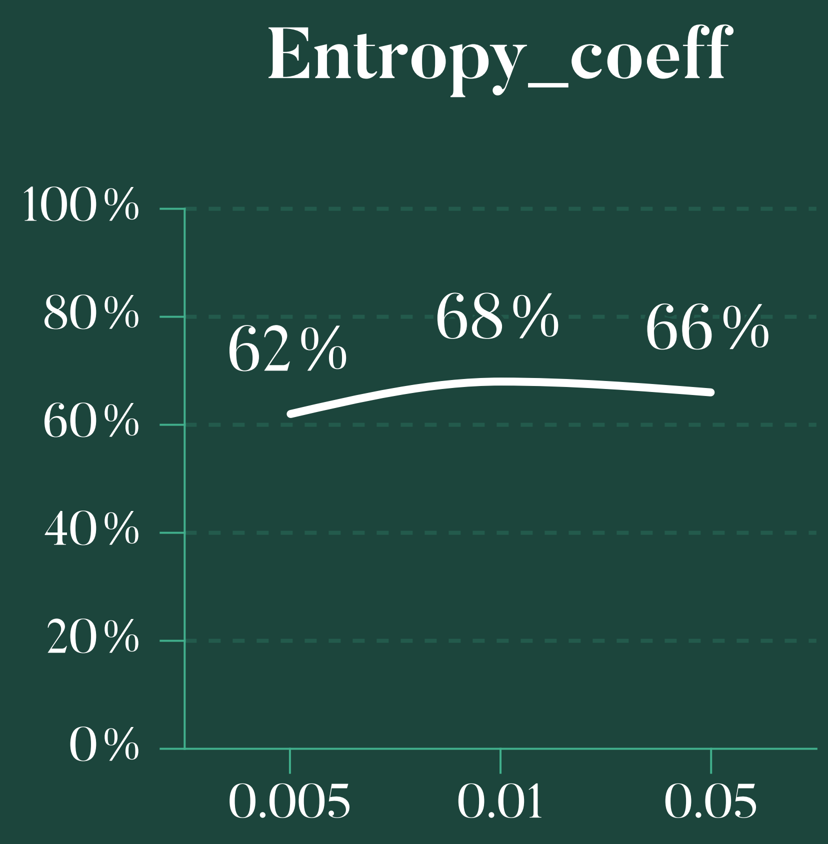
Implementation	Accuracy
PPO Baseline w/o hyperparameter tuning	~58%
PPO Baseline w hyperparameter tuning	~68%
PPO AutoEncoder w/o hyperparameter tuning	~72%
PPO AutoEncoder w Hyperparameter	**~81%**

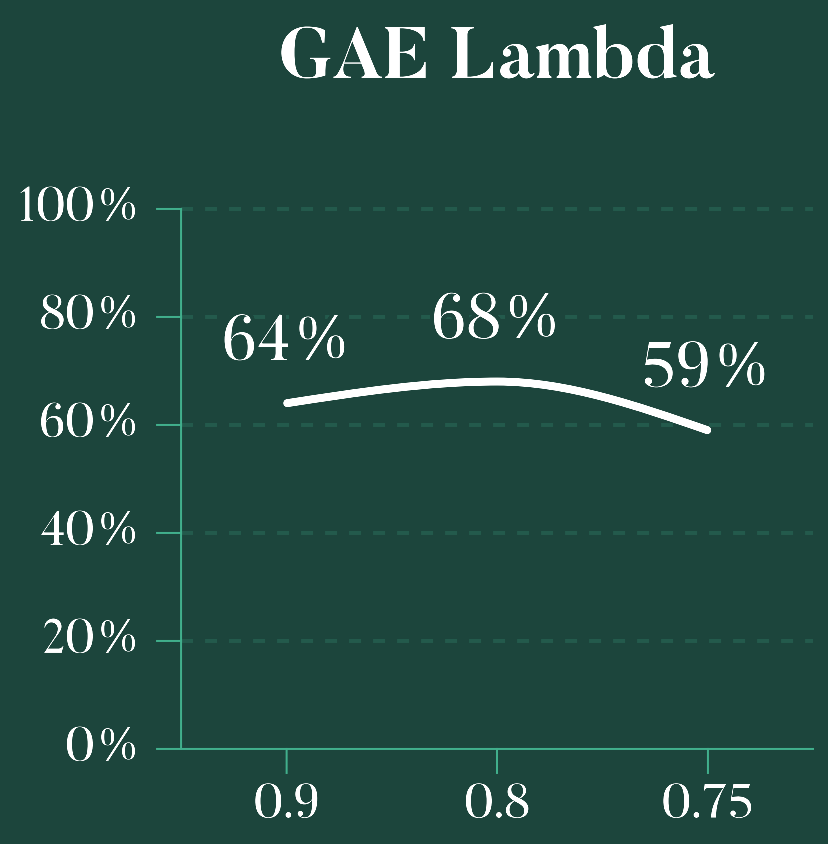
Results & Discussion

PPO Baseline



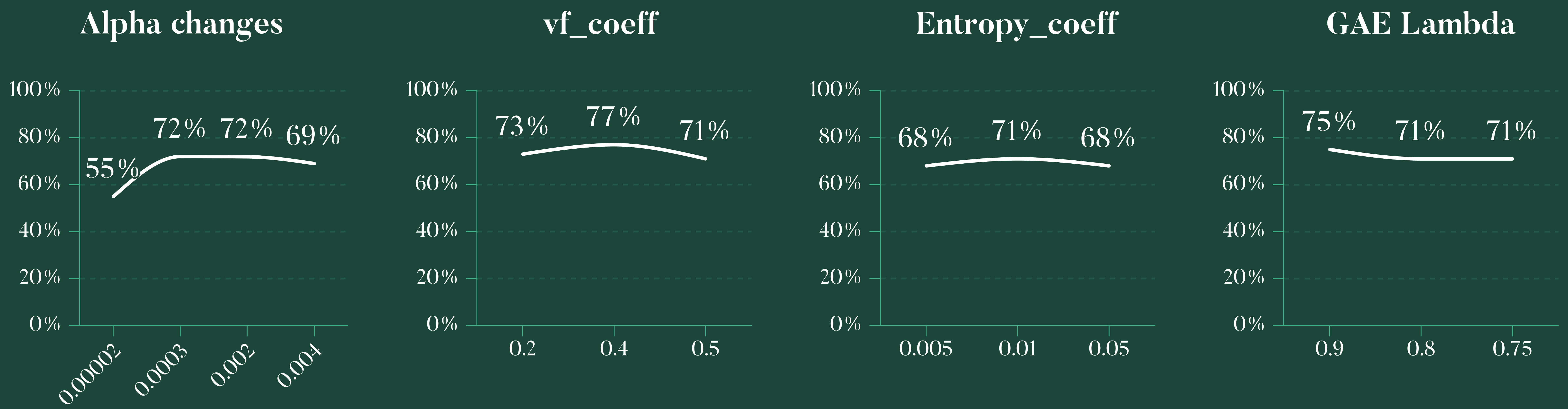




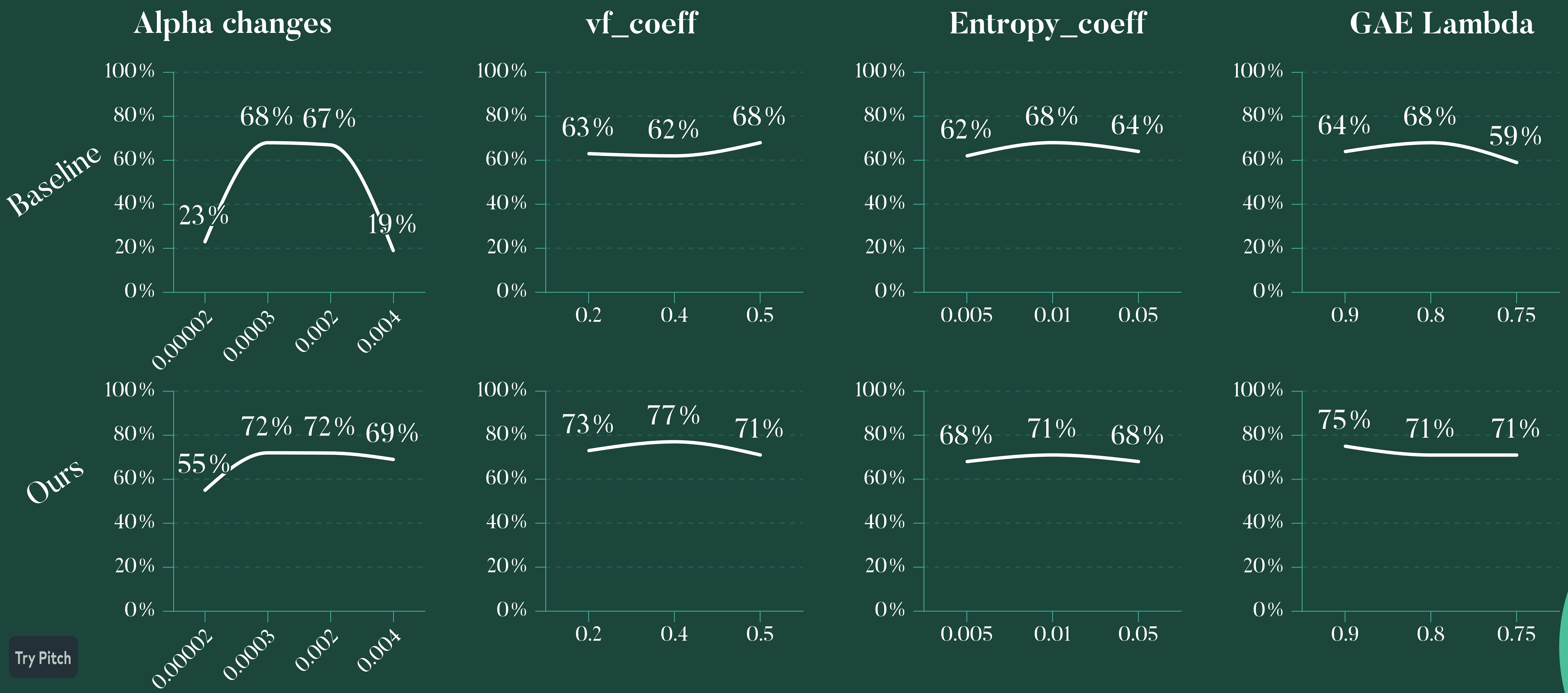


Results & Discussion

Our proposed framework



Results & Discussion



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