The Impact of Punishment Sensitivity and Learning Rate on Anxiety: A Computational Modeling Approach in a Sequential Evaluation Task

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Key considerations

- Most computational anxiety research do not involve sequential evaluation, even though anxiety is an anticipatory response to uncertain future threats.
- While many studies with one-step experiments highlight an elevated punishment learning rate as key to anxious behavior, some suggest a lack of evidence in the role of punishment sensitivity, which contrasts with recent research that support anxiety is mainly an uncertainty disorder.

Anxiety Research from a Computational Perspective

Commonly symptoms across many anxiety disorders:

- Exaggerated threat appraisal.
- Fear generalization.
- Persistent avoidance behavior.
- Risk aversion.

Underestimation of coping resources

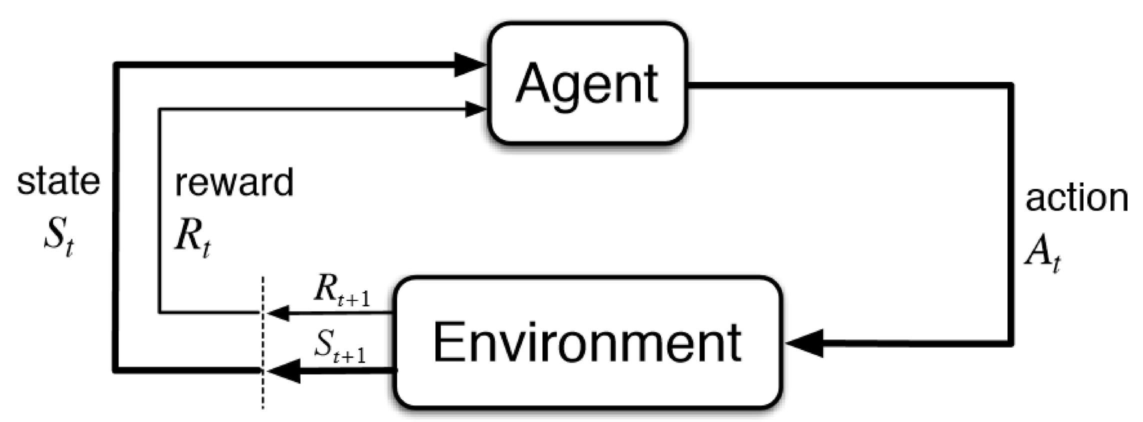
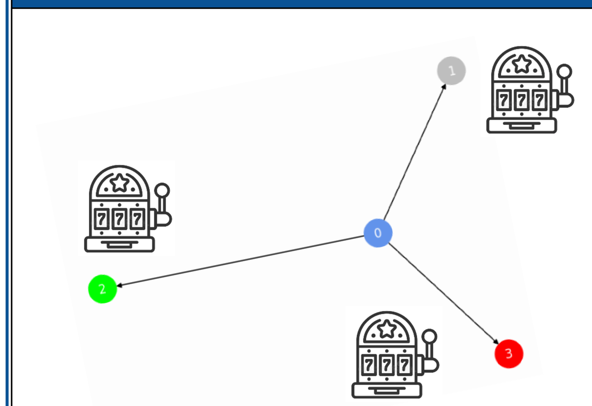
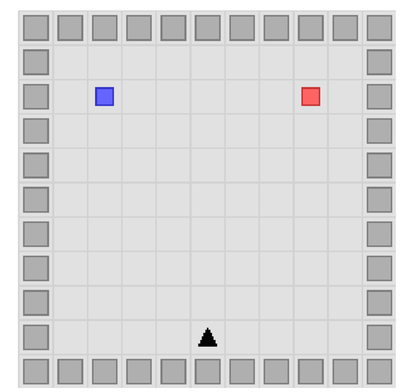


Figure 1. The agent–environment interaction in a Markov decision process.

One-step task	Sequential evaluation task
 **Figure 2.** Representation of a trial in a three-armed bandit task.	 **Figure 3.** A simple grid-world task environment.

Objective

To address the discrepancies regarding the impact of punishment sensitivity and punishment learning rate on anxiety, we developed two hybrid reinforcement learning (RL) models to explore how these parameters influence anxiety-related behaviors in a more natural context of anxiety.

Hybrid models considerations

B-pessimistic module	α^+ | α^-
Dyna SR	

Methodology

Model design

Dyna ✚ SR

$$Q(s,a) = \sum_{s'} M(s,s',a)R(s')$$

$$R(s) \longleftarrow R(s) + \alpha(r - R(s))$$

$$M(s,a) \longleftarrow M(s,a) + \alpha\left(I_{[s=s']} + \gamma M(s',a^+) - M(s,a)\right)$$

Implemented Changes

Dyna β-pessimistic SR

$$a^+ = \arg\max_a Q(s',a')$$

$$a^- = \arg\min_a Q(s',a')$$

$$\delta^M = \omega M(s',a^+) + (1-\omega)M(s',a^-)$$

$$M(s,a) \longleftarrow M(s,a) + \alpha\left(I_{[s_t=s']} + \gamma\delta^M - M(s,a)\right)$$

Dyna α-SR

$$R(s) \longleftarrow R(s) + \alpha(r - R(s))$$

$$\alpha = \begin{cases} \alpha^+ & if\, r \geq 0 \\ \alpha^- & if\, r < 0 \end{cases}$$

Experimental Task

Cliff-Waling Task

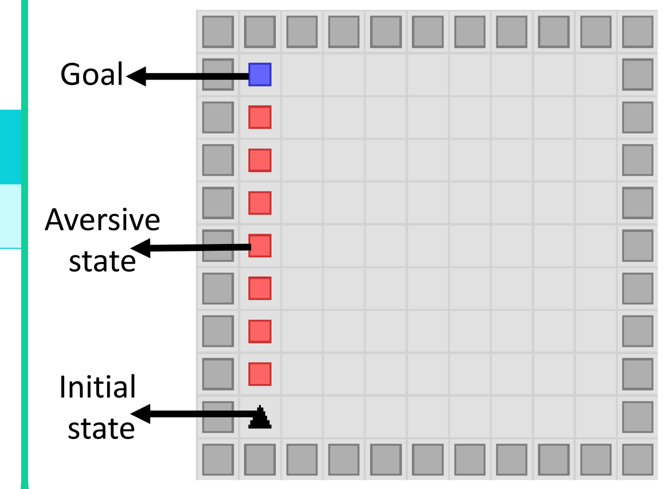


Figure 4. Cliff-Walking task environment.

Deterministic environment.

Stochasticity in action selection: **ε = 0.2**

Possible Agent's actions:

Total num. of episodes = **100**

Max. steps per episode = **100**

Agents		
Condition	Dyna β-pessimistic SR	
1	ω = 1.0	1 - ω = 0.0
2	ω = 0.5	1 - ω = 0.5
3	ω = 0.0	1 - ω = 1.0
Condition	Dyna α-SR	
1	α^+ = 0.1	α^- = 0.1
2	α^+ = 0.1	α^- = 0.15
3	α^+ = 0.1	α^- = 0.2

Table 1. Experimental conditions.

Results

Punishment sensitivity impact across different values	Punishment learning rate impact across different values
Dyna β-pessimistic SR	Dyna α-SR

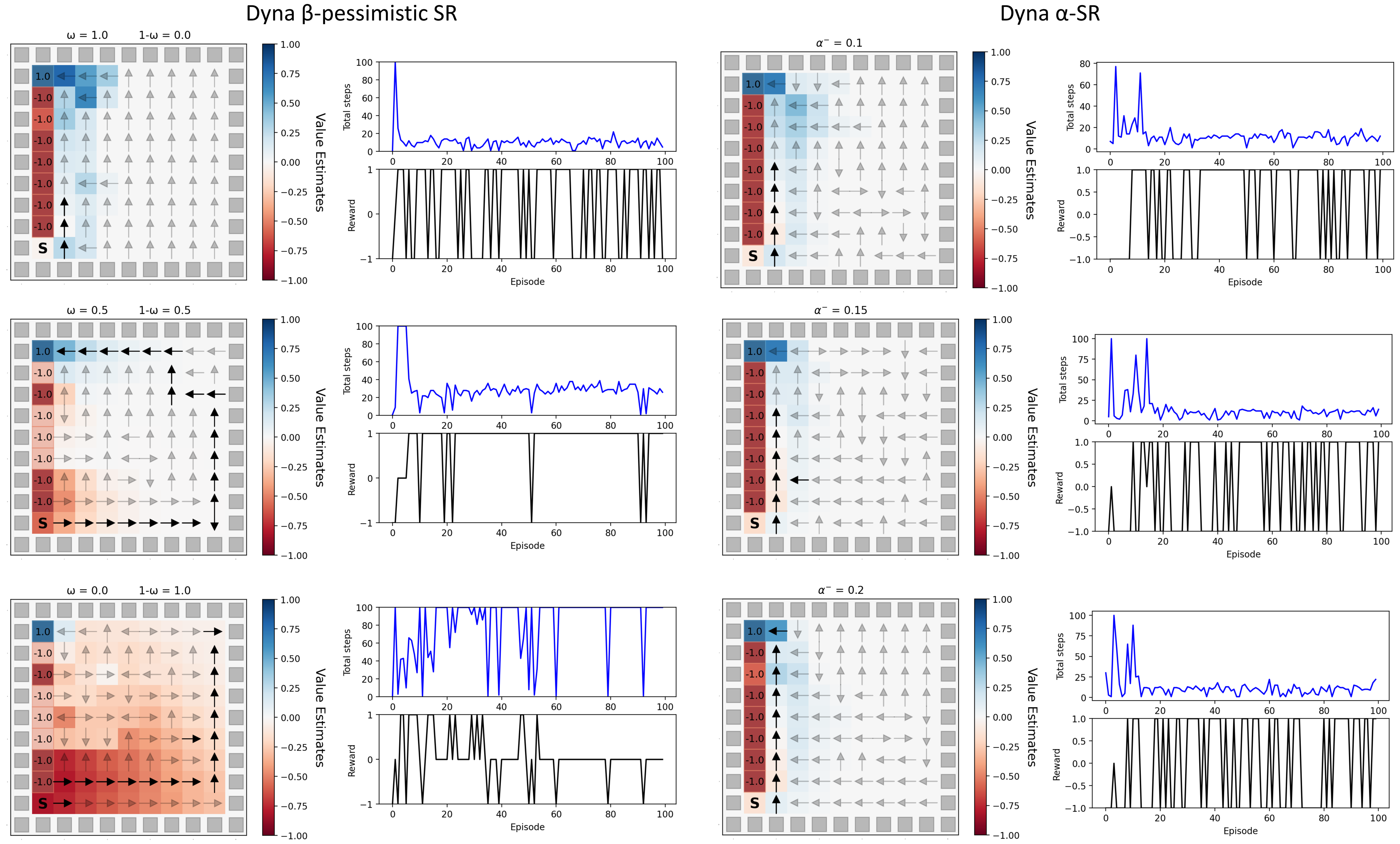


Figure 5. Graphs of the Dyna β-pessimistic SR Dyna (on the left) and α-SR (on the right) agents across condition 1 (at the top), 2 (in the middle), and 3 (at the bottom). The heat maps indicates the value estimates of each state after 100 episodes; the blue graphs shows the number of steps taken by an agent per episode, while the black graphs indicates the total reward gained per episode.

Conclusions

- Punishment sensitivity plays a central role in anxiety-related behaviors in tasks more closely related to anxiety, particularly where sequential evaluation is required.
- Unlike previous findings, this work suggests that the impact of estimated punishments on planning is more significant than the speed at which they are learned.
- Results differ from those obtained in one-step tasks, highlighting the importance of studying anxiety in contexts more natural to the phenomenon under study to make less biased inferences.
- Based on findings in the literature, it can be assumed that an elevated punishment learning rate for anxiety becomes more important in one-step tasks. However, we should also question what this parameter is actually capturing and what has been studied in such tasks.

Next Steps

1) Human data validation.
2) Study how a model of the environment is constructed in non-deterministic environments.
3) Compare competing models.

Contact Information

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