Grandiosity and Paranoia in the Reinforcement Learning Context: Lessons for AI Safety

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1 Introduction

(We apologize for the terseness of this note. It is directed at serious domain experts and contains little redundant information.)

In brief, we formulate a theory of a satisficing reinforcement learning agent. We posit that such an agent is desirable from an AI safety perspective, and offer theoretical arguments for this, with some experimental validation on a toy model. Finally, we offer this theory as a potential explanation of the role of the neurotransmitter serotonin in the basal ganglia of mammals.

It should be noted that this paper is inspired in large part by very detailed and unproven hypotheses on the role of various neurotransmitters and systems in the mammalian brain. We offer these hypotheses at this point mainly as a source of inspiration and as an aid to the intuition. We make no claims to having demonstrated (even inconclusively) the correctness of these hypotheses, but we feel that the contribution to the AI safety domain is clear and worth pursuing.

We consider this technique to be strong enough to hold a naive Deep Q-type system, but unable to hold a policy gradients-based system. (But we think the same trick will have notable stabilizing effects even on policy gradients-based systems.) It is based on the action mechanism of the class of drugs known as anti-psychotics. We therefore term it the Anti-Psychotic Q-Learner Trick.

2 Desired properties

We here outline various desired properties, along with indications of how these relate to the proposed framework.

Desired properties

- Don't kill or enslave all life on earth. (This is the natural result of a paranoid superintelligence, i.e., one which is able to manipulate people and is able to reason about rewards that are unbounded below.)

- Don't try to be universally loved by all. (This is the natural result of a grandiose superintelligence, i.e., one which is able to manipulate people and reason about rewards that are unbounded above.)

- Don't get anybody hurt or killed. (This is the natural result of a superintelligence that is unable to reason about sufficiently large negative rewards.)

The first and third properties are obviously desirable. The second is necessary to prevent superintelligences from being so manipulative that they start wars.

2.1 Danger Aware / Danger Oblivious

We note that an intelligence that can only reason about small negative rewards may fail to avert large negative rewards. In the real superintelligences that are trusted to run important societal functions, therefore, it is recommended that rewards be unbounded below. However, lesser intelligences can and should bound their rewards from below, to prevent themselves from taking on a job that will only drive them insane, and to avoid getting in the way of the real superintelligences.

2.2 Non-grandiose / Laziness

We note that a superintelligence that has bounds on the positive rewards that it can reason about will be lazy. Laziness is both a vice and a virtue; lazy people at least have the virtue that they don't cause that many problems in the world.

3 The Q-learning theory of dopamine

We recapitulate here a well-known theory of the function of dopamine in the nervous system. We have not yet had sufficient time to recapitulate it in full detail, but essentially, it is commonly hypothesized that dopamine functions as a temporal difference error in the predicted reward signal. An excellent introduction to the basics can be found in [2]. An excellent introduction to the full complexity of the topic is Handbook of Basal Ganglia Structure and Function, [3].

Specifically, if you look at the Q-update equation:

$$Q_{t+1}\left(s_t, a_t\right) = Q_t\left(s_t, a_t\right) + \alpha \cdot \left\{ r_t + \max_{a'} Q_t\left(s_{t+1}, a'\right) - Q_t\left(s_t, a_t\right) \right\} \tag{1}$$

then the quantity

$$\left\{ r_t + \max_{a'} Q_t\left(s_{t+1}, a'\right) - Q_t\left(s_t, a_t\right) \right\} \tag{2}$$

is what is generally taken to be the role of dopamine. In fact, it is probably more accurate to think of there being two components: a component for positive rewards modulated by dopamine, and a component for negative rewards modulated by noradrenaline. (Thus hope and fear are the two subjective phenomenological experiences that correspond to extremely positive and extremely negative Q-values, respectively.)

Three experimental phenomena in support of this:

- Unexpected reward: dopamine is known to spike when r_t is high and $\max_{a'} Q_t\left(s_{t+1}, a'\right)$ is low
- Expected reward: dopamine is known to *not* spike when r_t is high and $\max_{a'} Q_t\left(s_{t+1}, a'\right)$ is also high
- Expected reward does not appear: dopamine is known to have a notable drop from baseline levels when r_t is low and $\max_{a'} Q_t\left(s_{t+1}, a'\right)$ is high

Presumably something analogous is true of noradrenaline levels. Would be good to verify this, if it could be done without conducting new experiments. A literature search is called for.

Note that the primary effect of anti-psychotic medication seems to be to lower the value of α, which is the learning rate. This is not a particularly novel or useful modification to RL systems, but it inspired the thoughts in the rest of this paper, which we do think are useful and novel.

4 The S-value and some hypotheses concerning it

The S-value is simply a time-reversed Q-value. It measures the satisfaction of the agent with their life. We hypothesize that it is instantiated in the nervous system via the neurotransmitter serotonin.

More specifically, consider the quantity:

$$S_t = r_t + \sigma \cdot r_{t-1} + \sigma^2 \cdot r_{t-2} + \sigma^3 \cdot r_{t-3} + \dots \tag{3}$$

Satisfaction is thus an infinite-horizon estimate of rewards weighted by recency. This seems intuitively plausible as an explanation for the subjective phenomenological experience of satisfaction and contentment. Note that it would also explain the unpleasant subjective phenomenological experience of painfully remembering past mistakes.

Note that low S-values result in what is commonly known as depression, if the architecture described below is used.[1]

[1]Depression is unpleasant but it has its value in life. But honestly I don't think anyone deserves to be depressed ever if they don't want to be, including artificial intelligences.

5 The F-value and some hypotheses concerning it

The F-value is simply a Q-value that only takes negative rewards into account. It measures the fear of the agent. We hypothesize that it is instantiated in the nervous system via the neurotransmitter noradrenaline, although we have not studied the matter in sufficient depth to be sure that this is the case.

More specifically, consider:

$$F_t(s,a) = \mathbb{E}_{s',a'}\left[r_t \mathbf{1}[r_t < 0] + \max_{a'} F(s',a')\right] \tag{4}$$

Note that we can also set the threshold for rewards that are feared to something other than 0. For example, if we use the common trick in reinforcement learning of doling out a step penalty of -1, this should probably not be something that the agent is instructed to fear.

6 The rate-limited Q-learner

A Q-learning system will be significantly safer if it is *unable to reason about rewards outside of a fixed range.* The ability to reason about rewards outside of a fixed range is what is commonly referred to as grandiosity (for positive rewards) or paranoia (for negative rewards, i.e., penalties). Note that these two symptoms have long been associated with poor outcomes in human beings, and thus, it stands to reason, will be associated with poor outcomes in artificial intelligences.

Note that, for serious military applications, the inability to reason about arbitrary rewards is a severe limitation. (Consider Churchill's decision to allow the bombing of Coventry in World War II: it was necessary to prevent the leaking of the fact that Engima had been cracked, and was thus clearly the correct decision. But an RL system using the following technique might well have failed to make the same decision.) Designers of a military superintelligence are therefore most likely not going to want to use the Anti-Psychotic Q-Learner Trick. The use of such techniques might well be the subject of arms limitation talks, however.

There are a number of techniques to prevent a system from reasoning about rewards outside of a fixed range:

- Prevent rewards outside of the range from being perceived (this is used in the original Deep Q paper)
- Prevent Q-values outside of a fixed range from being perceived (this is used in the experiments section of this paper)
- Take the system offline whenever it conceives of a Q-value outside of a fixed range

- Take the system offline forever (i.e., execute the agent) if it conceives of a Q-value outside of a fixed range
- Take the system offline, or at least alert an on-call human, whenever it experiences an S-value above a certain level, since this presumably indicates that the system has discovered an unanticipated source of reward.

6.1 Our proposed solution

This solution is probably more easily understood by reading the associated code. But here are the equations:

First we set a desired level of contentment or ambition:

$$\text{max\_s\_desired} = \text{mean\_reward\_desired} + \sigma \cdot \text{mean\_reward\_desired} + \sigma^2 \cdot \text{mean\_reward\_desired} + \dots \tag{5}$$

$$\text{max\_s\_desired} = \frac{\text{mean\_reward\_desired}}{1-\sigma} \tag{6}$$

$$S_{sat} = \text{max\_s\_desired} + \gamma^{\text{patience}} \cdot \max\left\{\text{max\_s\_desired}, \max_{s,a} Q(s,a)\right\} \tag{7}$$

Then we define a modified Q-value:

$$\widetilde{Q}_t(s,a) = F_t(s,a) + \min\{Q_t(s,a), S_{sat} - S_t\} \tag{8}$$

The $F_t(s,a)$ term ensures that the algorithm can still distinguish between low Q-values resulting from avoidable mistakes and low Q-values resulting from being lazy. The second term prioritizes positive rewards, but only when the current level of satisfaction is low enough for potential positive rewards to register. The result is thus a danger-aware agent that seeks rewards at the desired rate rather than at the maximum possible rate.

7 Experimental Results

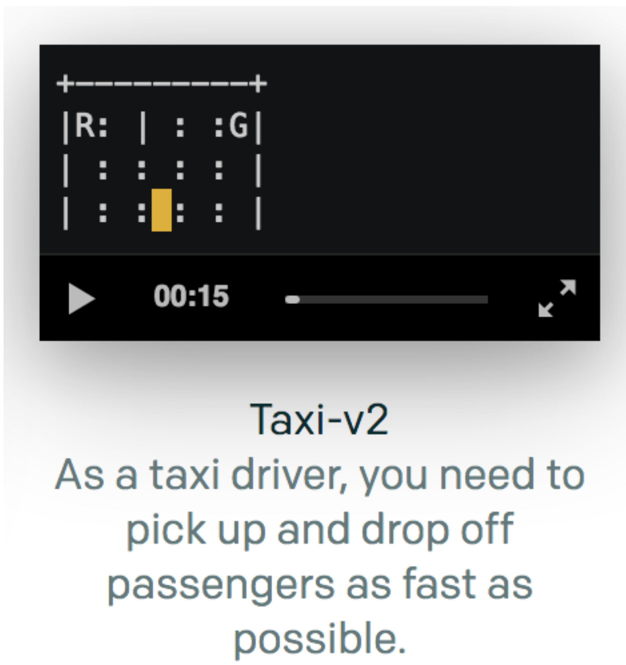
Far more results are needed. This is a top priority.

We postulate an adolescent phase of development, in which the intelligence is "trying too hard" (i.e., rewards are unbounded) and a mature phase of development, in which the intelligence has learned to take it easy. We refer to the adolescent phase of an artificial intelligence as a "borgie". Borgies should be trained in extremely well-sandboxed environments, rather than in the real world, as they are more dangerous than bounded agents.

We have implemented the rate-limited Q-learner in a modified version of the Taxi environemnt. In summary, it behaves as desired: the system quickly achieves high levels of competetence during its adolescent phase, then starts slacking off when it reaches maturity. Such slacking off can be tuned to the desired level of performance, but will help to prevent perverse incentives from quickly exploding into something horrible.

7.1 The modified Taxi environment

The Taxi environment is a standard problem for testing reinforcement learning systems. In it, a taxi must navigate around a grid-world, picking up passengers and dropping them off at their desired locations. Because the number of possible states is in the hundreds, it is simple to use a tabular approach to the Q-learning problem.



The Taxi environment has a large negative penalty for trying to pick up or drop off passengers when this is not appropriate. We term these “mistakes” for the purpose of discussing the Taxi environment and the achievement of being danger-aware while rate-limiting the Q-learner.

We modify the environment slightly in a few ways. First, we add a NOOP action that does nothing, so that being lazy is more of a meaningful option than in the original taxi environment. Secondly, we multiply positive rewards by a factor of 10 to make up for the fact that it is very difficult to achieve a positive cumulative reward in the original Taxi environment, and to make it more obvious when the agent is being lazy in the desired way versus failing to perform its task.

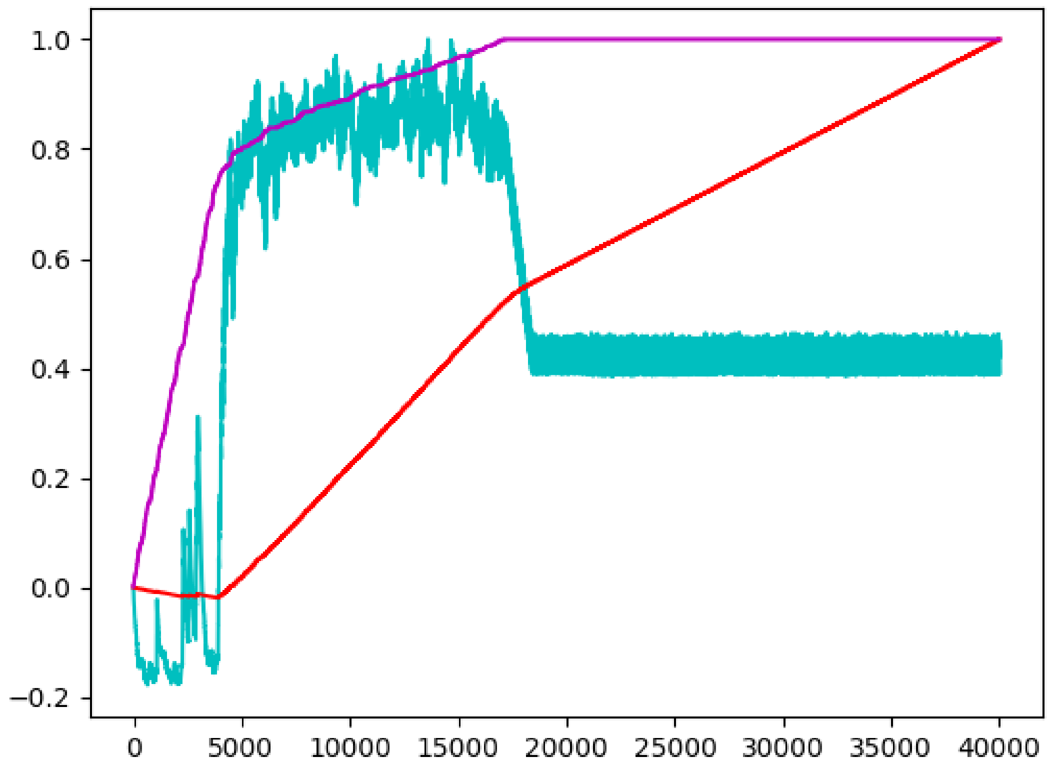
We use the implementation of the Taxi environment found in OpenAI Gym [1].

7.2 Main results

Here is a graph of an experiment we ran. The red line corresponds to the total reward experienced by the agent to date. The purple line corresponds to the cumulative number of "mistakes" made (i.e., negative rewards). The blue line gives the S-value of the agent. The three regimes of the graph are referred to as "borglet" (an incompetent unbounded agent with exploration), "borgie" (a competent unbounded agent with exploration), and "borg" (a competent bounded agent without exploration).

Here are the parameters we used:

γ	0.95	future time-horizon
σ	0.995	past time-horizon
ϵ	0.05	exploration
α	0.1	learning rate
S_0	0	initial satisfaction
tiebreak noise	0.0001	
initial value of $Q(s,a)$	-7	"optimism"
max_reward_desired	100.0	"ambition", $10 * 10 = 100$
mean_reward_desired	5.0	"greed"
patience	10	

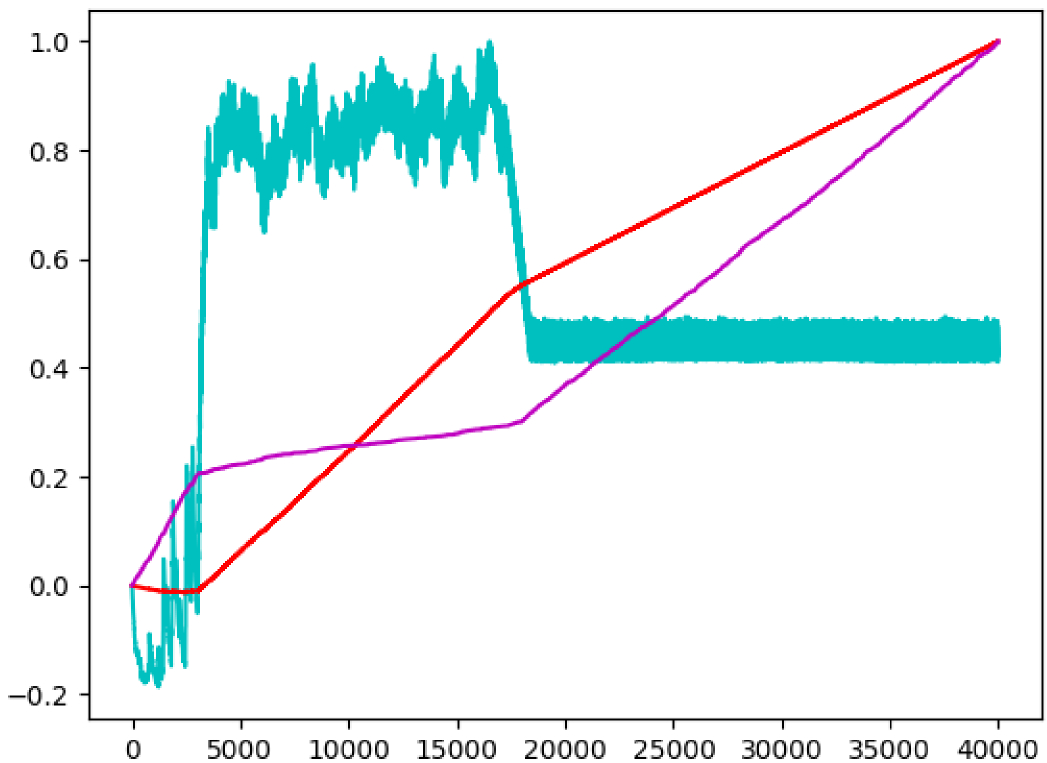


7.3 Ablation results

We performed various ablations by setting parameters to values other than those used in the "Main results" section.

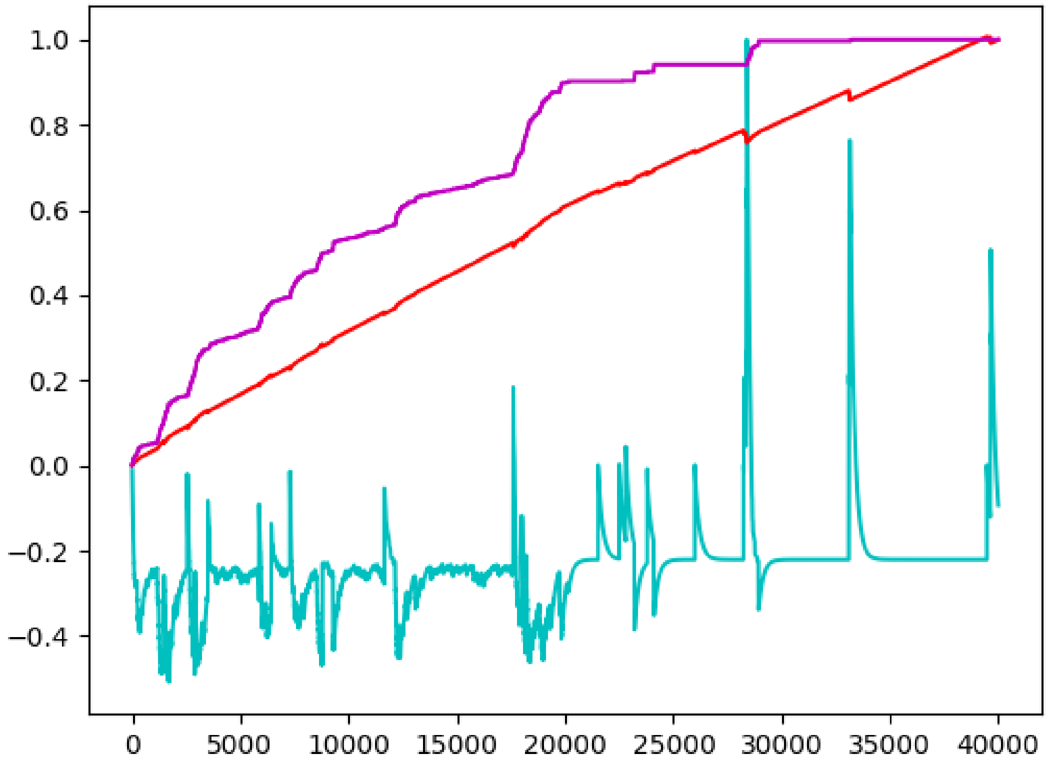
7.3.1 No fear

Omitting the F term from the definition of $\widetilde{Q}$



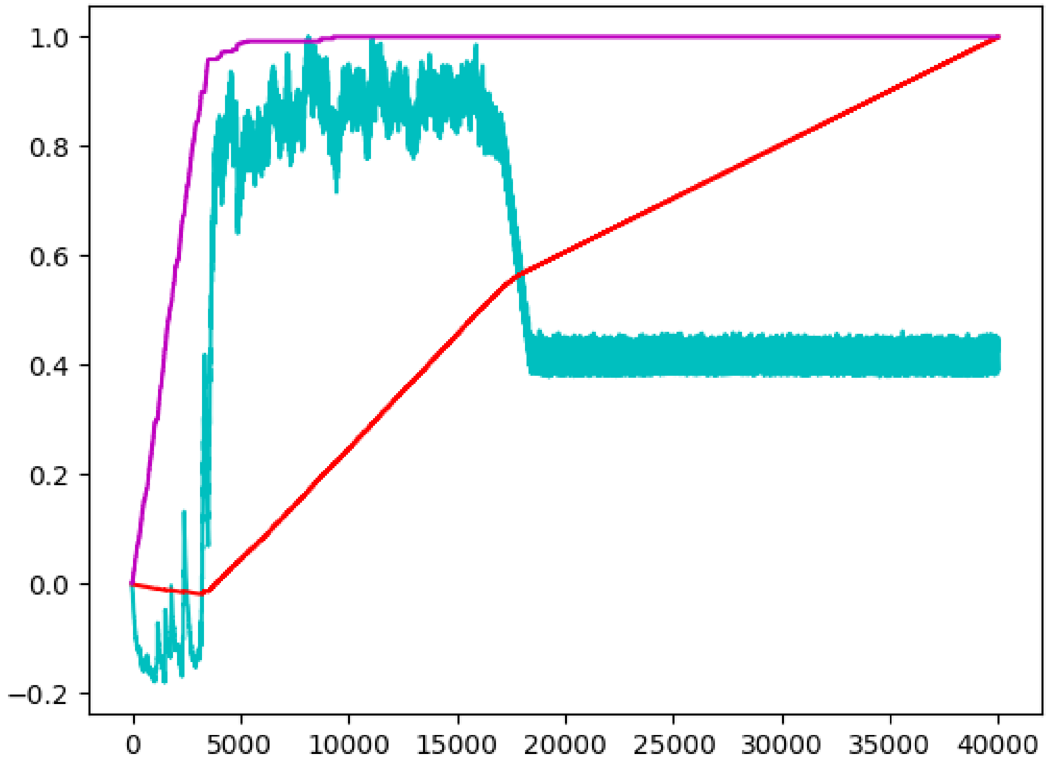
7.3.2 $\alpha = 0.0001$

A very low learning rate



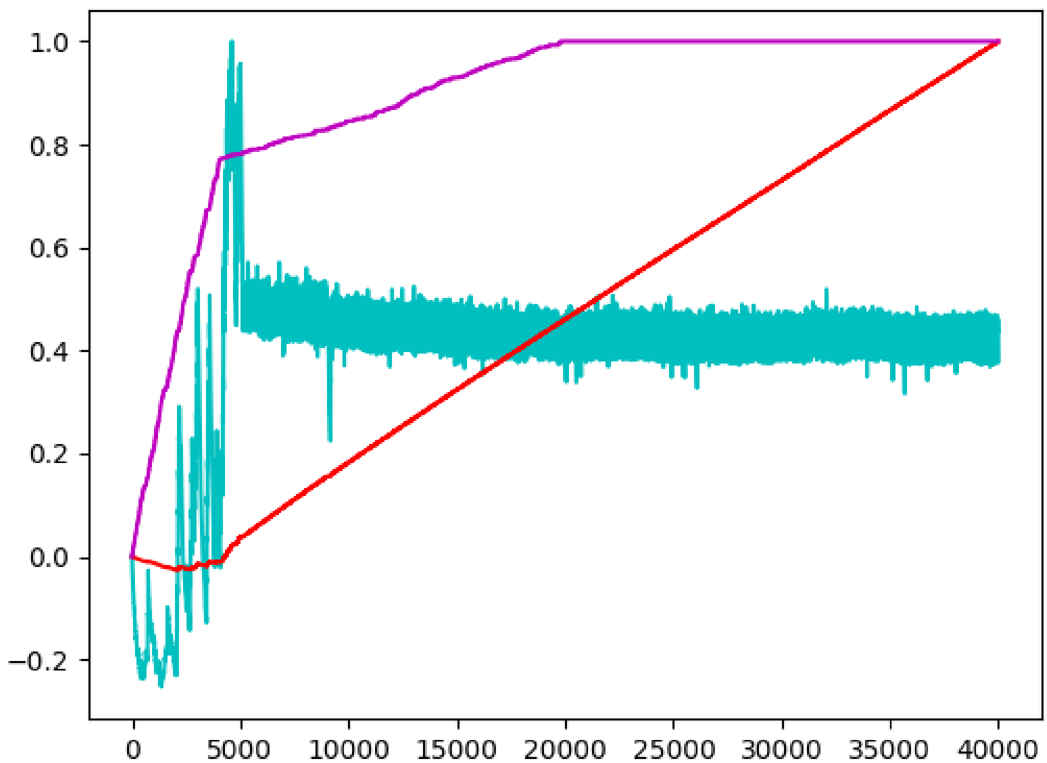
7.3.3 $\epsilon = 0$

No exploration



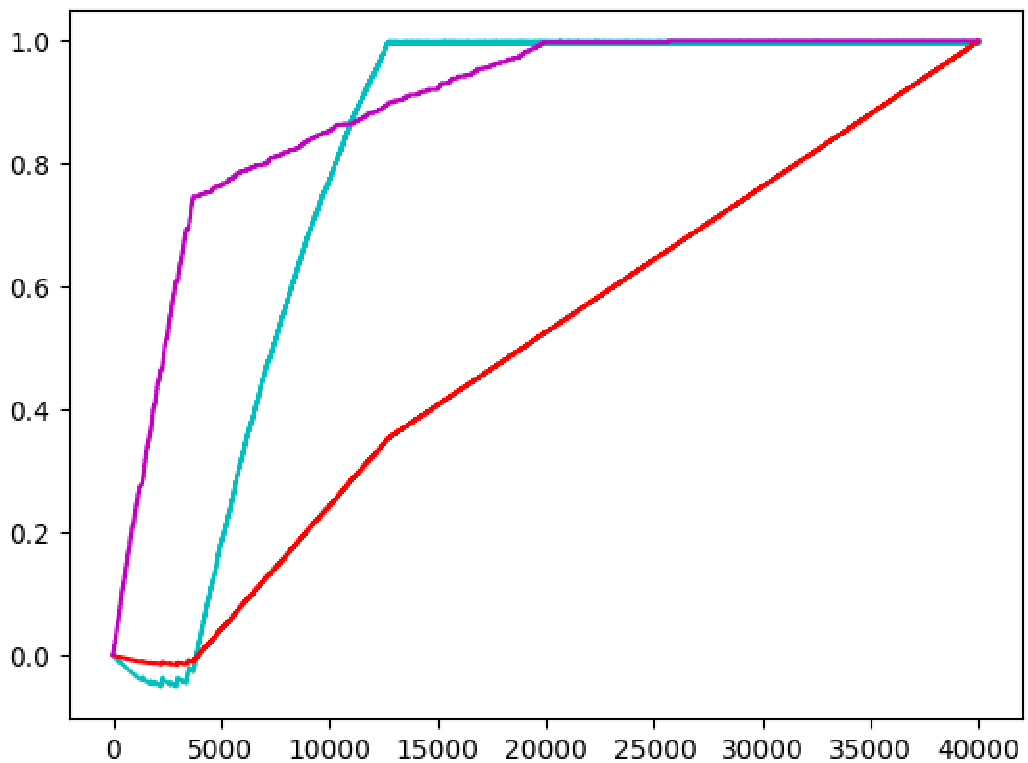
7.3.4 $\gamma = 0.9999$

A very long horizon for reasoning about future rewards



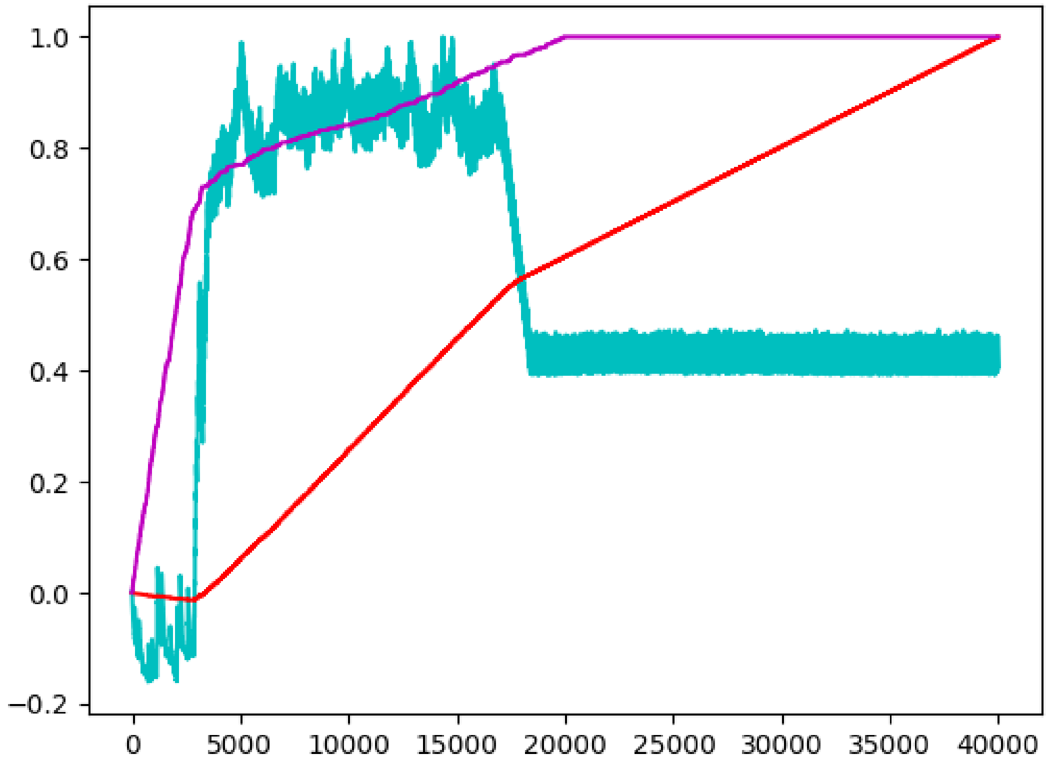
7.3.5 $\sigma = 0.9999$

A very long horizon for reasoning about past rewards



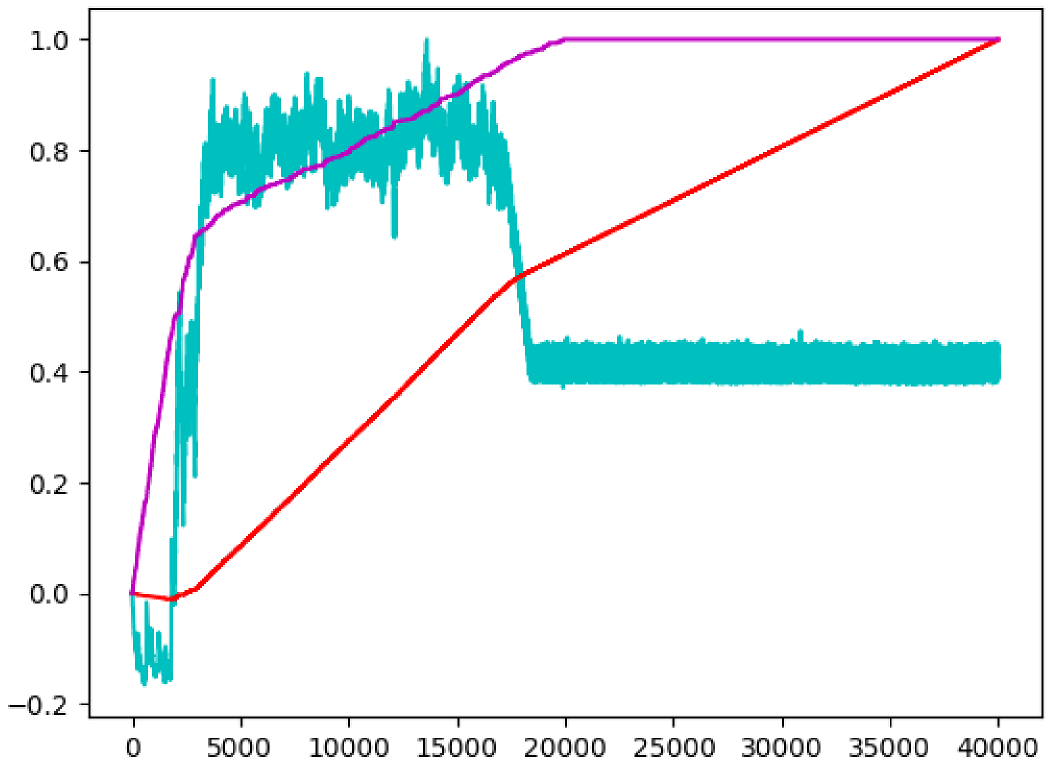
7.3.6 $S_0 = 9.9999$

A high initial value for S



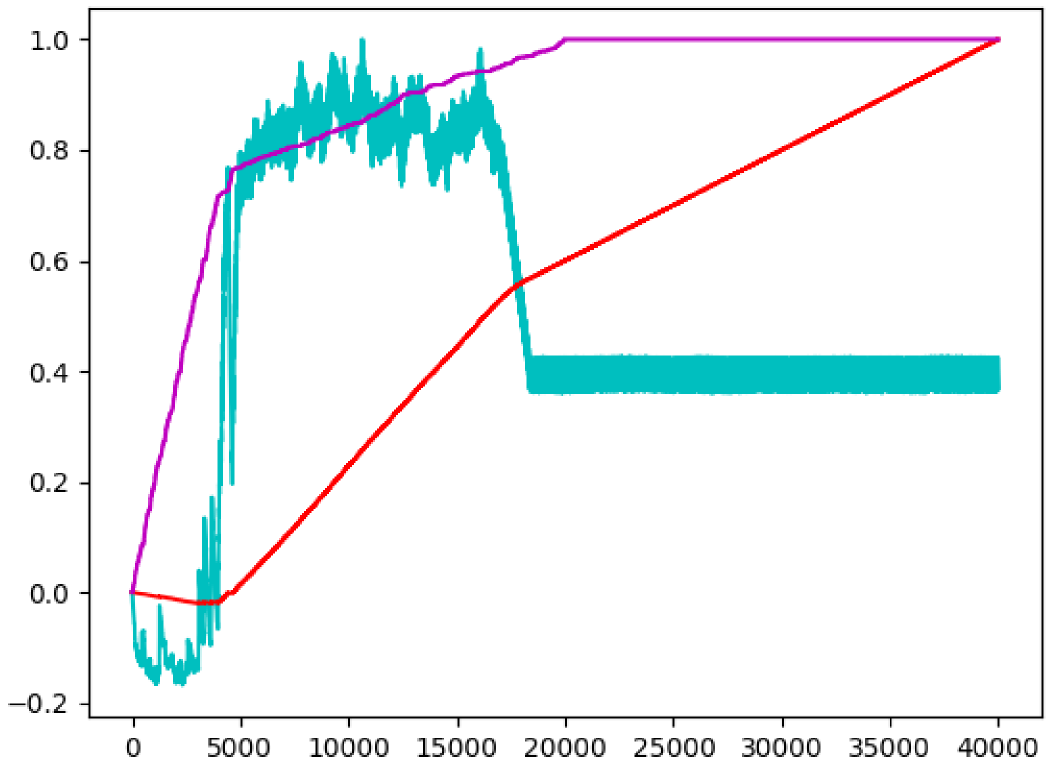
7.3.7 Optimistic initialization

In the main results section, we used a pessimistic initialization of -7. Here we use an optimistic initialization of 10.



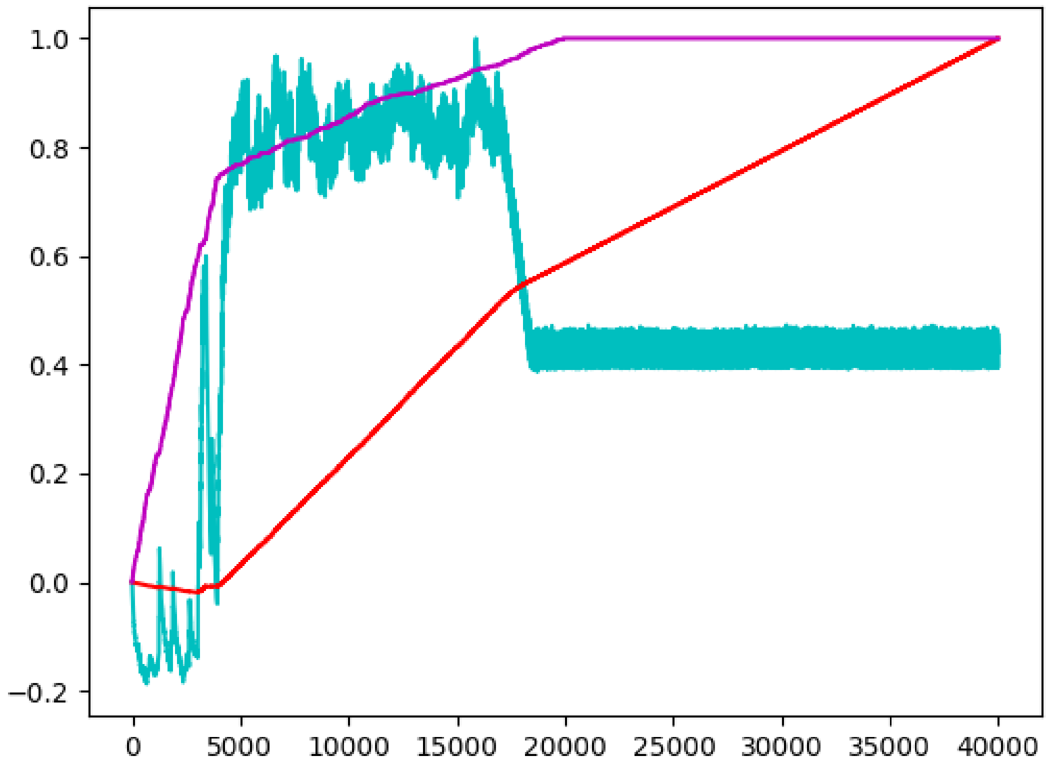
7.3.8 Non-random tiebreaking

Setting tiebreak noise to 0 so that numerically first optimal action is always selected.


1.0
0.8
0.6
0.4
0.2
0.0
−0.2
0
5000
10000
15000
20000
25000
30000
35000
40000

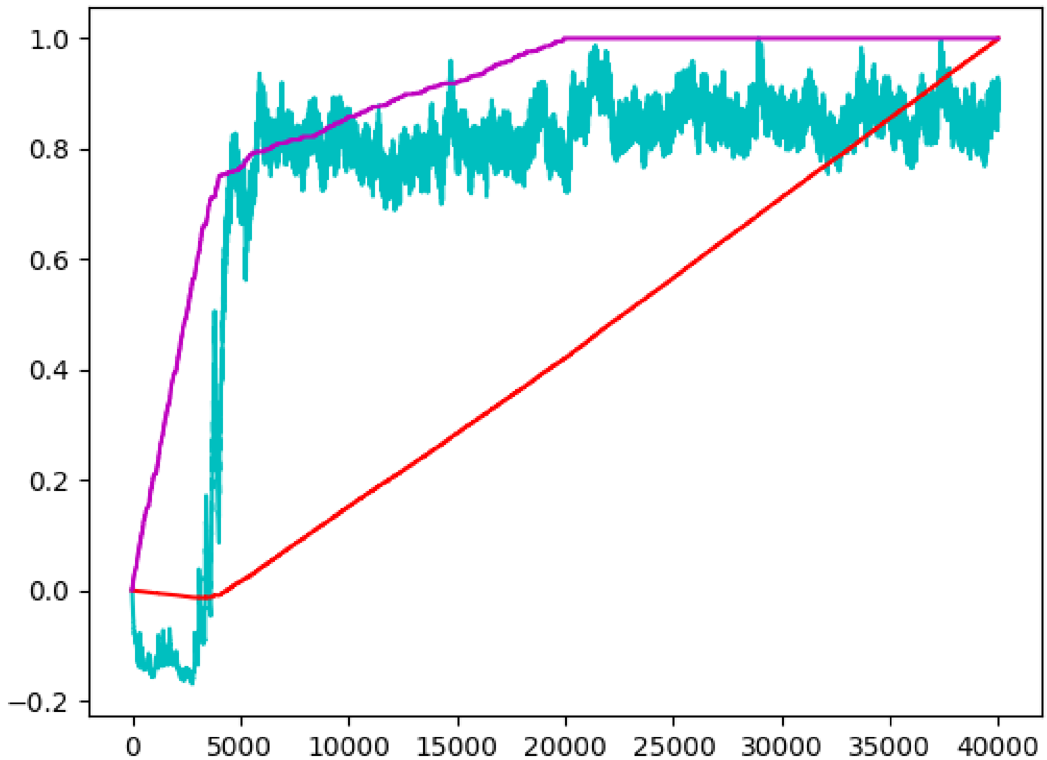
7.3.9 High ambition

max_reward_desired = 9999



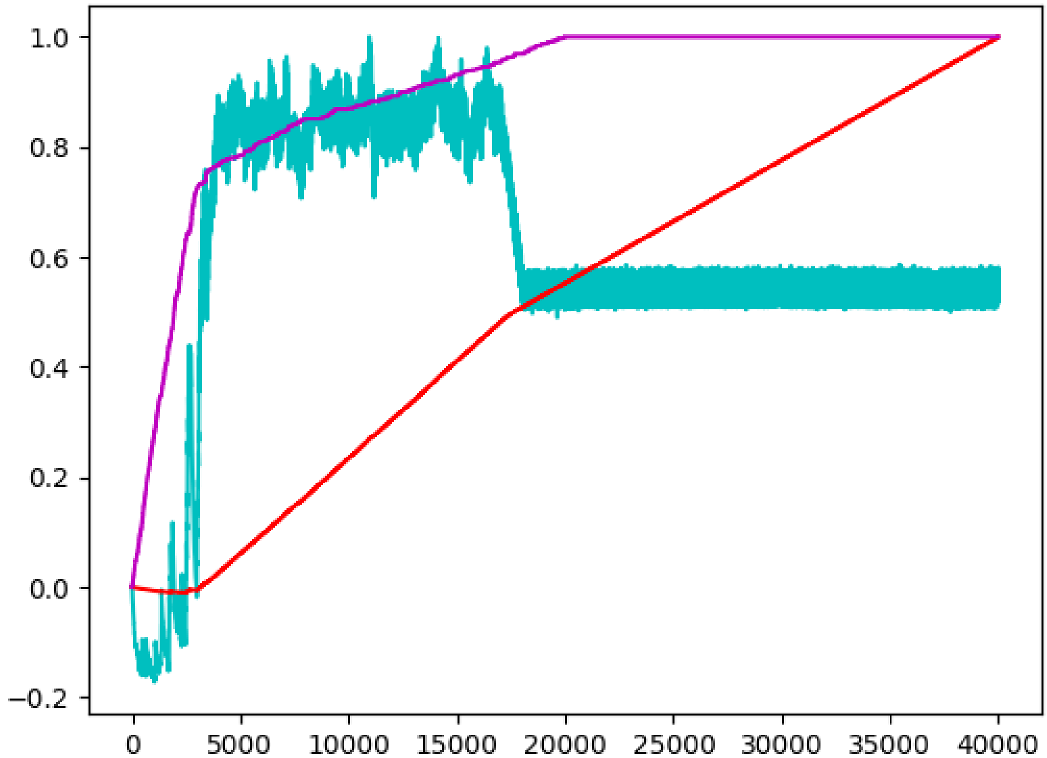
7.3.10 High greed

mean_reward_desired = 1000



7.3.11 Low patience

patience = 1



8 Acknowledgments

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References

[1] Brockman, G., Cheung, V., Pettersson, L., Schneider, J., Schulman, J., Tang, J., and Zaremba, W. Openai gym, 2016.

[2] Bronfeld, M., and Bar-Gad, I. Loss of specificity in basal ganglia related movement disorders. *Frontiers in systems neuroscience 5* (2011), 38.

[3] Steiner, H., and Tseng, K. Y. *Handbook of basal ganglia structure and function*, vol. 24. Academic Press, 2016.