## Artificial Neural Networks (Gerstner). Exercises for week 11

## Reinforcement Learning and the Brain

## Exercise 1. A biological interpretation of the Advantage Actor-Critic with Eligibility traces

In this exercise you will show how applying Advantage Actor-Critic with eligibity traces to a softmax policy in combination with a linear read-out function leads to a biologically plausible learning rule.

Consider a policy and a value network as in Figure 1 with $K$ input neurons $\left\{y_{k}=f\left(x-x_{k}\right)\right\}_{k=1}^{K}$. The policy network is parameterized by $\theta$ and has three output neurons corresponding to actions $a_{1}, a_{2}$ and $a_{3}$ with 1-hot coding. If $a_{k}=1$ implies that action $a_{k}$ is taken and we have $a_{k^{\prime}}=0$ for $k^{\prime} \neq k$ The output neurons are sampled from a softmax policy: The probability of taking action $a_{i}$ is given by

$$
\begin{equation*}
\pi_{\theta}\left(a_{i}=1 \mid x\right)=\frac{\exp \left(\sum_{k=1}^{K} \theta_{i k} y_{k}\right)}{\sum_{j} \exp \left(\sum_{k=1}^{K} \theta_{j k} y_{k}\right)} \tag{1}
\end{equation*}
$$

In addition, consider the exponential value network

$$
\begin{equation*}
\hat{v}_{w}(x)=\exp \left(\sum_{k=1}^{K} w_{k} y_{k}\right) \tag{2}
\end{equation*}
$$



Figure 1: The network structure.
Assume the transition to state $x^{t+1}$ with a reward of $r^{t+1}$ after taking action $a^{t}$ at state $x^{t}$. The learning rule for the Advantage Actor-Critic with Eligibility traces is

$$
\begin{aligned}
\delta & \leftarrow r^{t+1}+\gamma \hat{v}_{w}\left(x^{t+1}\right)-\hat{v}_{w}\left(x^{t}\right) \\
z^{w} & \leftarrow \lambda^{w} z^{w}+\nabla_{w} \hat{v}_{w}\left(x^{t}\right) \\
z^{\theta} & \leftarrow \lambda^{\theta} z^{\theta}+\nabla_{\theta} \log \pi_{\theta}\left(a^{t} \mid x^{t}\right) \\
w & \leftarrow w+\alpha^{w} z^{w} \delta \\
\theta & \leftarrow \theta+\alpha^{\theta} z^{\theta} \delta
\end{aligned}
$$

Your goal is to show that this learning rule applied to the network of Figure 1 has a biological interpretation.
a. Show that

$$
\begin{equation*}
\frac{d}{d w_{5}} \hat{v}_{w}\left(x^{t}\right)=y_{5}^{t} \hat{v}_{w}\left(x^{t}\right) . \tag{3}
\end{equation*}
$$

b. Interpret the update of the eligibity trace $z_{5}^{w}$ in terms of a 'presynaptic factor' and a 'postsynaptic factor'. Can the rule be implemented in biology?
c. Show that

$$
\begin{equation*}
\frac{d}{d \theta_{35}} \log \left(\pi_{\theta}\left(a^{t} \mid x^{t}\right)\right)=\left(a_{3}^{t}-\pi_{\theta}\left(a_{3}=1 \mid x^{t}\right)\right) y_{5}^{t} \tag{4}
\end{equation*}
$$

Hint: simply insert the softmax and then take the derivative.
d. Interpret the update of the eligibity trace $z_{35}^{\theta}$ in terms of a 'presynaptic factor' and a 'postsynaptic factor'. Can the rule be implemented in biology?
e. Interpret the update of the weights $w_{5}$ and $\theta_{35}$ in the framework of three factor learning rules. Can the rule be implemented in biology?

