## Report

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## 1 Entropy Regularized POMDP Model

Assume when  $\alpha=1$ , namely using standard Gumbel distribution, the related functions and parameters are  $U_{\tau}^{(1)}, V_{t}^{(1)}, Q^{(1)}, r^{(1)}, \pi^{(1)}, \theta^{(1)}$ . Then for any  $\alpha \neq 1$ , then we have the following equations

•  $U_{\tau}^{\alpha} = \alpha \cdot U_{\tau}^{(1)}$ 

 $\bullet \ \pi^{\alpha} = \pi^{(1)}$ 

•  $V_t^{\alpha} = \alpha \cdot V_t^{(1)}$ 

•  $\sigma^{\alpha} = \sigma^{(1)}$ 

 $\bullet \ Q_t^{\alpha} = \alpha \cdot Q_t^{(1)}$ 

•  $\lambda^{\alpha} = \lambda^{(1)}$ 

•  $r^{\alpha} = \alpha \cdot r^{(1)}$ •  $\theta_1^{\alpha} = \alpha \cdot \theta_1^{(1)}$ 

 $\bullet \ \theta_2^{\alpha} = \theta_2^{(1)}$ 

Parameter	α	$  \theta_{3,0,0}  $	$\theta_{3,0,1}$	$\theta_{3,0,2}$	$\theta_{3,1,0}$	$\theta_{3,1,1}$	$\theta_{3,1,2}$	$\theta_{2,0}$	$\theta_{2,1}$	$\theta_{1,0}$	$\theta_{1,1}$	RC
Good State	1	0.020	0.222	0.500				0.040		0.219	.	9.257
	0.1	0.039	0.333	0.590	*	*	*	0.949	*	0.022	*	
	0.01									0.002		0.926
	1									0.002		0.320
Bad State	1	*	*	*	0.181	0.759	0.061	*	0.988	*	1.165	
Bad State	0.1	"		-1-	0.101	0.100	0.001		0.000		0.116	0.093
	0.01											
	"""										0.012	
log-Likelihood		-3819										
<u> </u>												

TABLE 1. PARAMETER ESTIMATES AND LOG-LIKELIHOOD PROVIDED BY THE POMDP MODEL ON GROUP 4 DATA SET

## 2 Appendix: Reasons

$$U_{\tau,\theta}(h_{\tau}) = \sup_{\pi \in \Pi} \mathbb{E} \left[ \sum_{t \geq \tau} \beta^{t-\tau} [r_{\theta_1}(z_t, s_t, a_t) + \alpha \mathcal{H}(\pi(\cdot|h_t))] \right]$$
$$= \sup_{\pi \in \Pi} \mathbb{E} \left[ r_{\theta_1}(z_\tau, s_\tau, a_\tau) + \alpha \mathcal{H}(\pi(\cdot|h_\tau)) + \beta \sum_{t \geq \tau+1} \beta^{t-(\tau+1)} [r_{\theta_1}(z_t, s_t, a_t) + \alpha \mathcal{H}(\pi(\cdot|h_t))] \right]$$

$$U_{t,\theta}(h_t) = \max_{\pi(\cdot|h_t)} \left\{ \sum_{a_t} \sum_{s_t} r_{\theta_1}(z_t, s_t, a_t) x_{t,\theta_2}(s_t) \pi(a_t|h_t) + \frac{\alpha \mathcal{H}(\pi(\cdot|h_t))}{2} + \beta \sum_{z_{t+1}} \sum_{a_t} \mathbb{P}_{\theta_2}(z_{t+1}|h_t, a_t) \pi(a_t|h_t) U_{t+1,\theta}(h_{t+1}) \right\}.$$
(2.1)

$$\sigma_{\theta_2}(z_{t+1}, z_t, x_{t,\theta_2}, a_t) \triangleq \sum_{s'} \sum_{s} x_{t,\theta_2}(s) \mathbb{P}_{\theta_2}(z_{t+1}, s' | z_t, s, a_t),$$

$$\lambda_{\theta_2}(z_{t+1}, z_t, x_{t,\theta_2}, a_t) \triangleq \frac{x_{t,\theta_2}^{\top} P_{\theta_2}(z_{t+1}, z_t, a_t)}{\sigma_{\theta_2}(z_{t+1}, z_t, x_{t,\theta_2}, a_t)}, \tag{2.2}$$

assuming  $\sigma_{\theta_2}(z_{t+1}, z_t, x_{t,\theta_2}, a_t) \neq 0$ , where we denote the (s, s') element of the matrix  $[P_{\theta_2}(z_{t+1}, z_t, a_t)]_{s,s'} \triangleq \mathbb{P}_{\theta_2}(z_{t+1}, s' | z_t, s, a_t), s, s' \in S, x_{t,\theta_2}^{\top}$  is the transpose of  $x_{t,\theta_2}$ , and

$$\begin{split} [x_{t,\theta_2}^\top P_{\theta_2}(z_{t+1}, z_t, a_t)]_{s_{t+1}} \\ &\triangleq \sum_s x_{t,\theta_2}(s) \mathbb{P}_{\theta_2}(z_{t+1}, s_{t+1} | z_t, s, a_t). \end{split}$$

$$r_{\theta_1}(z_t, x_{t,\theta_2}, a_t) \triangleq \sum_s r_{\theta_1}(z_t, s, a_t) x_{t,\theta_2}(s).$$

## Proposition 1.

$$V_{t,\theta}(z,x) = \max_{\pi(\cdot|z,x)} \left\{ \sum_{a} r_{\theta_1}(z,x,a) \pi(a|z,x) + \alpha \mathcal{H}(\pi(\cdot|z,x)) + \beta \sum_{a} \sum_{z'} \sigma_{\theta_2}(z',z,x,a) V_{t+1,\theta}(z',x'(a)) \pi(a|z,x) \right\}$$

$$[\mathcal{B}_{\theta}Q](z,x,a) = r_{\theta_1}(z,x,a) + \beta \sum_{z'} \sigma_{\theta_2}(z',z,x,a) V(z',x'), \tag{2.3}$$

where  $x' = \lambda_{\theta_2}(z', z, x, a)$  and

$$\frac{1}{\alpha}V(z,x) \triangleq \max_{\hat{\pi}(\cdot|z,x)} \Big[ \sum_{a} \frac{1}{\alpha} Q(z,x,a) \hat{\pi}(a|z,x) + \mathcal{H}(\hat{\pi}(\cdot|z,x)) \Big].$$

**Theorem 1.** (a)  $V(z,x) = \alpha \log \sum_a \exp(\frac{1}{\alpha}Q(z,x,a))$  for all  $Q \in \mathcal{Q}$ . (b)  $\mathcal{B}_{\theta} : \mathcal{Q} \to \mathcal{Q}$  is a contraction mapping with modulus  $\beta \in (0,1)$  and (c) the optimal policy is of the form:

$$\pi_{\theta}(a|z,x) = \frac{\exp\frac{1}{\alpha}Q_{\theta}(z,x,a)}{\sum_{a'\in A}\exp\frac{1}{\alpha}Q_{\theta}(z,x,a')},\tag{2.4}$$

where  $Q_{\theta}$  is the unique fixed point of  $\mathcal{B}_{\theta}$  (i.e.  $Q_{\theta} = \mathcal{B}_{\theta}Q_{\theta}$ ).