Supplementary Material

Theorem 1. Given any constants $\delta > 0$ and $M < \infty$, there exist a time instant $t_0 < \infty$ and a resolution parameter $n_0 < \infty$ such that $\forall t > t_0$ and $\forall n > n_0$:

$$\Pr\{G_i(t) > M\} > 1 - \delta, i \in N_r.$$

Proof: Theorem 1 is equivalent to

$$\Pr\left\{G_i\left(t\right) \le M\right\} \le \delta, i \in N_r. \tag{1}$$

The events $\{G_i(t) = k\}$ and $\{G_i(t) = j\}$ are mutually exclusive when $j \neq k$. So (1) is equivalent to

$$\sum_{k=1}^{M} \Pr\left\{G_i\left(t\right) = k\right\} \le \delta \tag{2}$$

where

$$\Pr\left\{G_i\left(t\right) = k\right\} = C\left(t, k\right) \left(\Pr\left\{a_i \text{ is chosen}\right\}\right)^k$$

$$\left(\Pr\left\{a_i \text{ is not chosen}\right\}\right)^{t-k}.$$
(3)

A threshold of resolution parameter n(i) is given for each a_i , by which $p_i(t) > 0$ if $t \le t(i)$. t(i) is a threshold of time. $r(t) = |\{a_i|p_i(t) \ne 0\}|$, where $|\cdot|$ denotes the cardinality of a set. When LA has not converged, $r(t) \ge 2$.

First, for any iteration of DEP_{RI} ,

$$\Pr\left\{a_i \text{ is chosen}\right\} \le 1. \tag{4}$$

Then, for action a_i , $t \le t(i)$. If n = n(i) and a_i is punished until t(i), $p_i(t(i)) = \left(p_i(0) - \sum_{j=1}^{t(i)} \frac{1}{r(t)n(i)}\right)$. Therefore, for all n > n(i) and t < t(i),

$$p_{i}(t) \geq \left(p_{i}(0) - \sum_{j=1}^{t(i)} \frac{1}{r(t) n(i)}\right)$$

$$= \left(p_{i}(0) - \frac{t(i)}{r(t) n(i)}\right)$$

$$\geq \left(p_{i}(0) - \frac{t(i)}{2n(i)}\right), i \in N_{r}.$$

$$(5)$$

The second line of (5) is equal to the first line's right part because $\sum_{j=1}^{t(i)} \frac{1}{r(t)n(i)} = \frac{t(i)}{r(t)n(i)}$. It is greater than the item in the third line because $r(t) \geq 2$ when LA has not converged.

To make $p_i(0) - \frac{t(i)}{2n(i)} > 0$, n(i) can be set as

$$n(i) = r \cdot t(i). \tag{6}$$

Then, at time $t \leq t(i)$, we have

$$\Pr\{a_i \text{ is not chosen}\} \le 1 - \frac{1}{2r} < 1. \tag{7}$$

Then, according to (3),(4) and (7), we have

$$\Pr \{G_{i}(t) < M\} = \sum_{k=1}^{M} \Pr \{G_{i}(t) = k\}$$

$$\leq \sum_{k=1}^{M} C(t, k) (1)^{k} \left(1 - p_{i}(0) + \frac{t(i)}{2n(i)}\right)^{t-k}$$

$$\leq \sum_{k=1}^{M} C(t, k) (1)^{k} (1 - \frac{1}{2r})^{t-k}.$$
(8)

To prove the sum of M terms less than δ , we just need to make each element less than δ/M . It suffices to prove that M times the k'th term is less than δ . It can be observed that $C(t,k') \leq t^{k'}$. Let $\psi = 1 - \frac{1}{2r}$. So we have to prove that:

$$\Pr\left\{G_i(t) < M\right\} \le M t^{k'} \psi^{t-k'} \le \delta. \tag{9}$$

By using l'Hopital's rule k' times, we obtain:

$$\lim_{t \to \infty} M t^{k'} \psi^{t-k'} = M \lim_{t \to \infty} \frac{t^{k'}}{(1/\psi)^{t-k'}}$$

$$= M \lim_{t \to \infty} \frac{k'!}{(\ln(1/\psi))^{k'} (1/\psi)^{t-k'}}$$

$$= 0.$$
(10)

Thus, for any given constants $\delta > 0$ and $M < \infty$, there exists a threshold t(i) such that for all t > t(i) and $n > n(i) = r \cdot t(i)$, (9) is satisfied. Since, we can repeat this argument for all the actions. t_0 and n_0 are defined as follows:

$$t_0 = \max_{i \in N_-} \{ t(i) \}, \tag{11}$$

$$n_0 = \max_{i \in N_r} \{ n(i) \} = \max_{i \in N_r} \{ r \cdot t(i) \}.$$
 (12)

Therefore, for all i, it is true that for all $t > t_0$ and $n > n_0$, $\Pr\{G_i(t) > M\} > 1 - \delta$, which completes the proof.

Theorem 2. Given any $\delta \in (0,1)$, there exists $t_0 < \infty$, such that $\Pr \left\{ \overline{C} \left(t_0 \right) \right\} = 1$, where $\overline{C} \left(t_0 \right)$

is defined as follows:

$$q_{j}(t) = \Pr\left\{ \left| \widetilde{d}_{j}(t) - d_{j} \right| < \frac{w}{2} \right\}, \tag{13}$$

$$q(t) = \Pr\left\{ \left| \tilde{d}_{j}(t) - d_{j} \right| < \frac{w}{2}, \ \forall j \in N_{r} \right\} = \prod_{j \in N_{r}} q_{j}(t), \tag{14}$$

$$C(t) = \{q(t) > 1 - \delta\}, \ \delta \in (0, 1),$$
 (15)

$$\overline{C}(t_0) = \left\{ \bigcap_{t > t_0} \left\{ q(t) > 1 - \delta \right\} \right\}, \ \delta \in (0, 1)$$
(16)

where w is the minimum difference between the reward probabilities of any two actions.

Proof: Theorem 2 is equivalent to

$$\Pr\left\{ \left| \widetilde{d}_i\left(t\right) - d_i \right| < \frac{w}{2}, \forall i \in N_r, \forall t > t_0 \right\} > 1 - \delta.$$
(17)

By the weak law of large numbers, for a given $\delta > 0$, $\exists M_i < \infty$, such that if a_i is chosen at least M_i times:

$$\Pr\left\{ \left| \widetilde{d}_i\left(t\right) - d_i \right| < \frac{w}{2}, \forall t > t_0 \right\} > 1 - \delta.$$
(18)

Let $M = \max_{1 \le i \le r} \{M_i\}$. According to Theorem 1, there exist a time instant $t_0 < \infty$ and a resolution parameter $n_0 < \infty$ such that $\forall t > t_0$ and $\forall n > n_0$:

$$\Pr\left\{G_{i}\left(t\right)>M\right\}>1-\delta,i\in N_{r}.$$

Thus, if all actions are chosen at least M times, then each of the $\widetilde{d}_i(t)$ will be in an w/2 neighborhood of d_i with a probability greater than $1 - \delta$, which completes the proof.

Theorem 3. $p_m(t)_{t>t_0} = \sum_{i \in \widetilde{X}(t)} p_i(t)$ is submartingale under DEP_{RI}.

Proof: First,

$$E\left[p_m\left(t\right)\right] \le 1 < \infty. \tag{19}$$

Then, according to the updating rule of DEP_{RI} , we have:

$$E\left[p_{m}(t+1) | Q(t)\right]$$

$$\geq \sum_{j \in N_{r}} p_{j}(t) \left(d_{j}\left(s\left(t\right)\left(p_{m}\left(t\right) + c_{t}\Delta\right)\right) + o\left(t\right)\left(p_{m}\left(t\right) + f_{t}\Delta\right) + \left(1 - s\left(t\right) - o\left(t\right)\right)\left(p_{m}\left(t\right) + \frac{c_{t}}{\widehat{r}}\left(\widehat{r} - e_{t}\right)\Delta - e_{t}\Delta\right)\right) + \left(1 - d_{j}\right)p_{m}\left(t\right)\right)$$

$$\geq \sum_{j \in N_{r}} p_{j}(t) \left(d_{j}\left(s\left(t\right)\left(p_{m}\left(t\right) + c_{t}\Delta\right)\right) + \left(1 - s\left(t\right)\right)\left(p_{m}\left(t\right) + \min\{f_{t}, \frac{c_{t}\widehat{r} - c_{t}e_{t} - \widehat{r}e_{t}}{\widehat{r}}\}\Delta\right) + \left(1 - d_{j}\right)p_{m}\left(t\right)\right)$$

$$= p_{m}\left(t\right) + \sum_{j \in N_{r}} p_{j}(t)d_{j}$$

$$\left(s\left(t\right)\left(c_{t} - \min\{f_{t}, \frac{c_{t}\widehat{r} - c_{t}e_{t} - \widehat{r}e_{t}}{\widehat{r}}\}\Delta\right) + \min\{f_{t}, \frac{c_{t}\widehat{r} - c_{t}e_{t} - \widehat{r}e_{t}}{\widehat{r}}\}\Delta\right)$$

$$\left(20\right)$$

where $c_t = 1, 2, ..., r - \widehat{r}$, $f_t \in [-\frac{\widehat{r}-1}{\widehat{r}^2\Delta}, \frac{\widehat{r}-1}{\widehat{r}^2\Delta}]$ and $e_t = 1, 2, ..., \widehat{r}$. s(t) is the probability that all actions in \widehat{A} are in the currently estimated arbitrary action subset $\widetilde{A}(t)$ at time t and we can see that:

$$s(t) = \Pr\{a_i \in \widetilde{A}(t), \forall a_i \in \widehat{A}\}$$

$$\geq \prod_{j \in \widetilde{X}(t)} q_j(t)$$
(21)

and o(t) is the probability that actions in $\widetilde{A}(t)$ have changed after being updated at time t and $\exists a_i \in \widehat{A}$ is not in $\widetilde{A}(t)$ after the change.

We denote $g_t = \frac{c_t \widehat{r} - c_t e_t - \widehat{r} e_t}{\widehat{r}}$. Then, we have

$$E[p_{m}(t+1)|Q(t)] - p_{m}(t)$$

$$\geq \sum_{j \in N_{r}} p_{j}(t)d_{j}(s(t)(c_{t} - \min\{f_{t}, g_{t}\})\Delta + \min\{f_{t}, g_{t}\}\Delta).$$
(22)

Given that $p_j(t) > 0$ and $d_j > 0$, we denote

$$Z_t = \frac{\min\{f_t, g_t\}}{\min\{f_t, g_t\} - c_t}$$

and

$$\max \{Z_t\} = \left\{ \begin{array}{l} \frac{\hat{r}}{\hat{r}+1}, \Delta \leq \frac{\hat{r}-1}{\hat{r}^3} \\ \frac{\hat{r}}{\hat{r}^2} - 1, \Delta > \frac{\hat{r}-1}{\hat{r}^3} \end{array} \right..$$

Let $1-\delta = \max\{Z_t\}$. According to Theorem 2, there exists t_0 such that $\forall t > t_0$, $\prod_{j \in \widetilde{X}(t)} q_j(t) \ge \max\{Z_t\}$. Thus,

$$E[p_m(t+1)|Q(t)] - p_m(t) > 0. (23)$$

 $p_m(t)_{t>t_0}$ is a submartingale, which completes the proof.

Based on the Martingale convergence theory and Theorem 3, we have Corollary 1.

Corollary 1. Under DEP_{RI} ,

$$p_m(\infty) = 0$$
 or 1.

Theorem 4. In all stationary environments, DEP_{RI} is ϵ -optimal, i.e., given any $1 - \delta \ge \max\{Z_t\}$, there exists $t_0 < \infty$ and $n_0 < \infty$, such that $\forall t > t_0$ and $\forall n > n_0$, $\text{Pr}\{p_m(\infty) = 1\} \to 1$.

Proof: We need to prove that

$$\Gamma_m(P) = \Pr\{p_m(\infty) = 1 | P(0) = P\} \to 1.$$
 (24)

Define $\Phi_m(P) = e^{-x_m p_m}$, where x_m is a positive constant. An operator U is defined as

$$U(\Phi_m(P)) = E[\Phi_m(P(t+1))|P(t) = P]. \tag{25}$$

Therefore,

$$U(\Phi_{m}(P)) - \Phi_{m}(P)$$

$$= E[\Phi_{m}(P(t+1))|P(t) = P] - \Phi_{m}(P)$$

$$\leq \sum_{j \in N_{r}} p_{j}(t) \left(d_{j}\left(s(t) e^{-x_{m}(p_{m}(t)+c_{t}\Delta)}\right) + o(t) e^{-x_{m}(p_{m}(t)+f_{t}\Delta)} + (1-s(t)-o(t)) e^{-x_{m}(p_{m}(t)+g_{t}\Delta)}\right) + (1-d_{j}) e^{-x_{m}p_{m}(t)} - \sum_{j \in N_{r}} p_{j}(t) e^{-x_{m}p_{m}(t)}$$

$$= \sum_{j \in N_{r}} p_{j}(t) d_{j}e^{-x_{m}p_{m}(t)} \left(s(t) \left(e^{-x_{m}c_{t}\Delta} - e^{-x_{m}g_{t}\Delta}\right) + o(t) \left(e^{-x_{m}f_{t}\Delta} - e^{-x_{m}g_{t}\Delta}\right) + \left(e^{-x_{m}g_{t}\Delta} - 1\right)\right). \tag{26}$$

 $U(\Phi_m(P)) - \Phi_m(P) \leq 0$ is equivalent to the following formula:

$$s(t)\left(e^{-x_m c_t \Delta} - e^{-x_m g_t \Delta}\right) + o(t)\left(e^{-x_m f_t \Delta} - e^{-x_m g_t \Delta}\right) + \left(e^{-x_m g_t \Delta} - 1\right) \le 0.$$

$$(27)$$

If b>0 and $x\to 0$, $b^x\doteq 1+(\ln b)\,x+\frac{(\ln b)^2}{2}x^2$. So let $b=e^{-x_m}$, as $\Delta\to 0$, we have

$$s(t) \left((\ln b) (c_t - g_t) \Delta + \frac{(\ln b)^2}{2} (c_t^2 - g_t^2) \Delta^2 \right)$$

$$+ o(t) \left((\ln b) (f_t - g_t) \Delta + \frac{(\ln b)^2}{2} (f_t^2 - g_t^2) \Delta^2 \right)$$

$$+ (\ln b) g_t \Delta + \frac{(\ln b)^2}{2} g_t^2 \Delta^2 \le 0.$$
(28)

Replacing b with e^{-x_m} , then

$$x_m(x_m - \frac{2(s(t)(c_t - g_t) + o(t)(f_t - g_t) + g(t))}{\Delta(s(t)(c_t^2 - g_t^2) + o(t)(f_t^2 - g_t^2) + g_t^2)}) \le 0.$$
(29)

Thus,

$$0 < x_m \le \frac{2(s(t)(c_t - g_t) + o(t)(f_t - g_t) + g(t))}{\Delta(s(t)(c_t^2 - g_t^2) + o(t)(f_t^2 - g_t^2) + g_t^2)}.$$
(30)

Denote $x_{m_0} = \frac{2(s(t)(c_t-g_t)+o(t)(f_t-g_t)+g(t))}{\Delta(s(t)(c_t^2-g_t^2)+o(t)(f_t^2-g_t^2)+g_t^2)}$, when $\Delta \to 0$, $x_{m_0} \to \infty$ as $s(t) > \max\{Z_t\}$. Thus, $\Phi_m(P)$ is superregular.

Denote $\phi_m(P) = \frac{1-e^{-x_m P_m(t)}}{1-e^{-x_m}}$. Obviously, $0 \le \phi_m(P) \le 1$. According to (30), $\phi_m(P)$ is a subregular.

Therefore,

$$\Gamma_m(P) \ge \phi_m(P) = \frac{1 - e^{-x_m p_m(t)}}{1 - e^{-x_m}}.$$
(31)

As $x_{m_0} \to \infty$, $\Gamma_m(P) \to 1$, implying that DEP_{RI} is ϵ -optimality.