A Confidence sets with high probability

In this appendix we will build up to a proof of Proposition 5, that the confidence sets defined by β^* in equation 7 hold with high probability. We begin with some elementary results from martingale theory.

Lemma 4 (Exponential Martingale)**.**
Let $Z_i \in L^1$ be real-calued random variables adapted to $\mathcal{H}_i$. We define the conditional mean $\mu_i = \mathbb{E}[Z_i|\mathcal{H}_{i-1}]$ and conditional cumulant generating function $\psi_i(\lambda) = \log \mathbb{E}[\exp(\lambda(Z_i - \mu_i))|\mathcal{H}_{i-1}]$, then

$$M_n(\lambda) = \exp\left(\sum_1^n \lambda(Z_i - \mu_i) - \psi_i(\lambda)\right)$$

is a martingale with $\mathbb{E}[M_n(\lambda)] = 1$.

Lemma 5 (Concentration Guarantee)**.**
For Z_i adapted real L^1 random variables adapted to $\mathcal{H}_i$. We define the conditional mean $\mu_i = \mathbb{E}[Z_i|\mathcal{H}_{i-1}]$ and conditional cumulant generating function $\psi_i(\lambda) = \log \mathbb{E}[\exp(\lambda(Z_i - \mu_i))|\mathcal{H}_{i-1}]$.

$$\mathbb{P}\left(\bigcup_{n=1}^{\infty}\{\sum_1^n \lambda(Z_i - \mu_i) - \psi_i(\lambda) \geq x\}\right) \leq e^{-x}$$

Both of these lemmas are available in earlier discussion for real-valued variables [14]. We now specialize our discussion to the vector space $\mathcal{Y} \subseteq \mathbb{R}^d$ where the inner product $< y, y >= \|y\|_2^2$. To simplify notation we will write $f_t^* := f^*(x_t)$ and $f_t = f(x_t)$ for arbitrary $f \in \mathcal{F}$. We now define

$$\begin{aligned} Z_t &= \|f_t^* - y_t\|_2 - \|f_t - y_t\|_2 \\ &= < f_t^* - y_t, f_t^* - y_t > - < f_t - y_t, f_t - y_t, f_t - y_t > \\ &= - < f_t - f_t^*, f_t - f_t^* > +2 < f_t - f_t^*, y_t - f_t^* > \\ &= -\|f_t - f_t^*\|_2 + 2 < f_t - f_t^*, \epsilon_t > \end{aligned}$$

so that clearly $\mu_t = -\|f_t - f_t^*\|_2$. Now since we have said that the noise is σ-sub-Gaussian, $\mathbb{E}[\exp(<\phi, \epsilon>)] \leq \exp\left(\frac{\|\phi\|_2^2\sigma^2}{2}\right)$ $\forall \phi \in \mathcal{Y}$. From here we can deduce that:

$$\begin{aligned} \psi_t(\lambda) &= \log \mathbb{E}[\exp(\lambda(Z_t - \mu_t))|\mathcal{H}_{t-1}] \\ &= \log \mathbb{E}[\exp(2\lambda < f_t - f_t^*, \epsilon_t >)] \\ &\leq \frac{\|2\lambda(f_t - f_t^*)\|_2^2\sigma^2}{2}. \end{aligned}$$

We now write $\sum_{i=1}^{t-1} Z_i = L_{2,t}(f^*) - L_{2,t}(f)$ according to our earlier definition of $L_{2,t}$. We can apply Lemma 5 with $\lambda = 1/4\sigma^2$, $x = log(1/\delta)$ to obtain:

$$\mathbb{P}\{\left(L_{2,t}(f) \geq L_{2,t}(f^*) + \frac{1}{2}\|f - f^*\|_{2,E_t} - 4\sigma^2 \log(1/\delta)\right) \ \forall t\} \geq 1 - \delta$$

substituting $f = \hat{f}$ to be the least squares solution which minimizes $L_{2,t}(f)$ we can remove $L_{2,t}(\hat{f}) - L_{2,t}(f^*) \leq 0$. From here we use an α-cover discretization argument to complete the proof of Proposition 5.

Let $\mathcal{F}^\alpha \subset \mathcal{F}$ be an α-2 cover of $\mathcal{F}$ such that $\forall f \in \mathcal{F}$ there is some $\|f^\alpha - f\|_2 \leq \alpha$. We can use a union bound on $\mathcal{F}^\alpha$ so that $\forall f \in \mathcal{F}$:

$$L_{2,t}(f) - L_{2,t}(f^*) \geq \frac{1}{2}\|f - f^*\|_{2,E_t} - 4\sigma^2 \log(N(\mathcal{F}, \alpha, \|\cdot\|_2)/\delta) + DE(\alpha) \tag{17}$$

$$\text{For } DE(\alpha) = \min_{f^\alpha \in \mathcal{F}^\alpha} \left\{\frac{1}{2}\|f^\alpha - f^*\|_{2,E_t}^2 - \frac{1}{2}\|f - f^*\|_{2,E_t}^2 + L_{2,t}(f) - L_{2,t}(f^\alpha)\right\}$$

We will now seek to bound this discretization error with high probability.

Lemma 6 (Bounding discretization error)**.**
If $\|f^\alpha(x) - f(x)\|_2 \leq \alpha$ for all $x \in \mathcal{X}$ then with probability at least $1 - \delta$:

$$DE(\alpha) \leq \alpha t \left[8C + \sqrt{8\sigma^2 \log(4t^2/\delta)}\right]$$

Proof. For non-trivial bounds we will consider the case of $\alpha \leq C$ and note that via Cauchy-Schwarz:

$$\|f^\alpha(x)\|_2^2 - \|f(x)\|_2^2 \leq \max_{\|y\|_2 \leq \alpha} \|f(x)+y\|_2^2 - \|f\|_2^2 \leq 2C\alpha + \alpha^2.$$

From here we can say that

$$\|f^\alpha(x) - f^*(x)\|_2^2 - \|f(x) - f^*(x)\|_2^2 = \|f^\alpha(x)\|_2^2 - \|f(x)\|_2^2 + 2 < f^*(x), f(x) - f^\alpha(x) > \leq 4C\alpha$$
$$\|y - f(x)\|_2^2 - \|y - f^\alpha(x)\|_2^2 = 2 < y, f^\alpha(x) - f(x) > + \|f(x)\|_2^2 - \|f^\alpha(x)\|_2^2 \leq 2\alpha|y| + 2C\alpha + \alpha^2$$

Summing these expressions over time $i = 1, .., t-1$ and using sub-gaussian high probability bounds on $|y|$ gives our desired result. $\square$

Finally we apply Lemma 6 to equation 17 and use the fact that $\hat{f}_t^{LS}$ is the $L_{2,t}$ minimizer to obtain the result that with probability at least $1 - 2\delta$:

$$\|\hat{f}_t^{LS} - f^*\|_{2,E_t} \leq \sqrt{\beta_t^*(\mathcal{F}, \alpha, \delta)}$$

Which is our desired result.

B Bounding the number of large widths

Lemma 1 (Bounding the number of large widths)**.**
If $\{\beta_t > 0 \big| t \in \mathbb{N}\}$ is a nondecreasing sequence with $\mathcal{F}_t = \mathcal{F}_t(\beta_t)$ then

$$\sum_{k=1}^{m} \sum_{i=1}^{\tau} \mathbb{1}\{w_{\mathcal{F}_{t_k}}(x_{t_k+i}) > \epsilon\} \leq \left(\frac{4\beta_T}{\epsilon^2} + \tau\right) \dim_E(\mathcal{F}, \epsilon)$$

Proof. We first imagine that $w_{\mathcal{F}_t}(x_t) > \epsilon$ and is ϵ-dependent on K disjoint subsequences of $x_1, .., x_{t-1}$. If x_t is ϵ-dependent on K disjoint subsequences then there exist $\|\overline{f} - \underline{f}\|_{2,E_t} > K\epsilon^2$. By the triangle inequality $\|\overline{f} - \underline{f}\|_{2,E_t} \leq 2\sqrt{\beta_t} \leq 2\sqrt{\beta_T}$ so that $K < 4\beta_T/\epsilon^2$.

In the case without episodic delay, Russo went on to show that in any sequence of length l there is some element which is ϵ-dependent on at least $\frac{l}{\dim_E(\mathcal{F},\epsilon)} - 1$ disjoint subsequences [14]. Our analysis follows similarly, but we may lose up to $\tau - 1$ proper subsequences due to the delay in updating the episode. This means that we can only say that $K \geq \frac{l}{\dim_E(\mathcal{F},\epsilon)} - \tau$. Considering the subsequence $w_{\mathcal{F}_{t_k}}(x_{t_k+i}) > \epsilon$ we see that $l \leq \left(\frac{4\beta_T}{\epsilon^2} + \tau\right) \dim_E(\mathcal{F}, \epsilon)$ as required. $\square$

C Eluder dimension for specific function classes

In this section of the appendix we will provide bounds upon the eluder dimension for some canonical function classes. Recalling Definition 3, $\dim_E(\mathcal{F}, \epsilon)$ is the length d of the longest sequence $x_1, .., x_d$ such that for some $\epsilon' \geq \epsilon$:

$$w_k = \sup\left\{ \|(\overline{f} - \underline{f})(x_k)\|_2 \;\middle|\; \|\overline{f} - \underline{f}\|_{2,E_t} \leq \epsilon' \right\} > \epsilon' \tag{18}$$

for each $k \leq d$.

C.1 Finite domain $\mathcal{X}$

Any $x \in \mathcal{X}$ is ϵ-dependent upon itself for all $\epsilon > 0$. Therefore for all $\epsilon > 0$ the eluder dimension of $\mathcal{F}$ is bounded by $|\mathcal{X}|$.

C.2 Linear functions $f(x) = \theta\phi(x)$

Let $\mathcal{F} = \{f \mid f(x) = \theta\phi(x) \text{ for } \theta \in \mathbb{R}^{n \times p}, \phi \in \mathbb{R}^p, \|\theta\|_2 \leq C_\theta, \|\phi\|_2 \leq C_\phi\}$. To simplify our notation we will write $\phi_k = \phi(x_k)$ and $\theta = \theta_1 - \theta_2$. From here, we may manipulate the expression

$$\|\theta\phi\|_2^2 = \phi_k^T\theta^T\theta\phi_k = Tr(\phi_k^T\theta^T\theta\phi_k) = Tr(\theta\phi_k\phi_k^T\theta)$$

$$\implies w_k = \sup_\theta\{\|\theta\phi_k\|_2 \;\big|Tr(\theta\Phi_k\theta^T) \leq \epsilon^2\} \text{ where } \Phi_k := \sum_{i=1}^{k-1} \phi_i\phi_i^T$$

We next require a lemma which gives an upper bound for trace constrained optimizations.

Lemma 7 (Bounding norms under trace constraints)**.**
Let $\theta \in \mathbb{R}^{n\times p}, \phi \in \mathbb{R}^p$ and $V \in \mathbb{R}^{p\times p}_{++}$, the set of positive definite $p \times p$ matrices, then:

$$W^2 = \max_{\theta} \|\theta\phi\|_2^2 \text{ subject to } Tr(\theta V \theta^T) \leq \epsilon^2$$

is bounded above by $W^2 \leq (2n-1)\epsilon^2 \|\phi\|^2_{V^{-1}}$ where $\|\phi\|_A^2 := \phi^T A \phi$.

Proof. We first note that $\|\theta\phi\|_2^2 = Tr(\theta\phi\phi^T\theta^T) = \sum_1^n (\theta\phi)_i^2 \leq \left(\sum_1^n (\theta\phi)_i\right)^2$ by Jensen's inequality. We define $\tilde{\Phi} \in \mathbb{R}^{n\times p}$ such that each row of $\tilde{\Phi} = \phi^T$. Then this inequality can be expressed as:

$$W^2 = Tr(\theta\phi\phi^T\theta^T) \leq Sum(\theta \otimes \tilde{\Phi})^2$$

Where $A \otimes B = C$ for $C_{ij} = A_{ij}B_{ij}$ and $Sum(C) := \sum_{i,j} C_{ij}$ We can now obtain an upper bound for our original problem through this convex relaxation:

$$\max_{\theta} Sum(\theta \otimes \tilde{\Phi}) \text{ subject to } Tr(\theta V \theta^T) \leq \epsilon^2$$

We can now form the lagrangian $\mathcal{L}(\theta,\lambda) = -Sum(\theta\otimes\tilde{\Phi}) + \lambda(Tr(\theta V\theta^T) - \epsilon^2)$. Solving for first order optimality $\nabla_\theta \mathcal{L} = 0 \implies \theta^* = \frac{1}{2\lambda}\tilde{\Phi}V^{-1}$. From here we form the dual objective

$$g(\lambda) = -Sum(\frac{1}{2\lambda}\tilde{\Phi}V^{-1}\otimes\tilde{\Phi}) + Tr(\frac{1}{4\lambda}\tilde{\Phi}V^{-1}\tilde{\Phi}^T) - \lambda\epsilon^2$$

Here we solve for the dual-optimal λ^* $\nabla_\lambda g = 0 \implies \frac{1}{2\lambda^*}^2 Sum(\frac{1}{2\lambda}\tilde{\Phi}V^{-1}\otimes\tilde{\Phi}) - \frac{1}{4\lambda^*}^2 Tr(\frac{1}{4\lambda}\tilde{\Phi}V^{-1}\tilde{\Phi}^T) = \epsilon^2$. From the definition of $\tilde{\Phi}$, $Sum(\tilde{\Phi}V^{-1}\otimes\tilde{\Phi}) = n\phi^T V^{-1}\phi$ and $Tr(\tilde{\Phi}V^{-1}\tilde{\Phi}^T) = \phi^T V^{-1}\phi$. From this we can simplify our expression to conclude:

$$\begin{aligned}
\frac{n}{2\lambda^{*2}}\phi^T V^{-1}\phi - \frac{1}{4\lambda^{*2}}\phi^T V^{-1}\phi = \epsilon^2 &\implies \lambda^* = \sqrt{\frac{(n-1/2)}{2\epsilon^2}}\|\phi\|_{V^{-1}} \\
&\implies g(\lambda^*) = -\frac{n}{2\lambda^*}\|\phi\|^2_{V^{-1}} + \frac{1}{4\lambda^*}\|\phi\|^2_{V^{-1}} - \lambda^*\epsilon \\
\text{strong duality } &\implies f(\theta^*) = g(\lambda^*) = \sqrt{2n-1}\epsilon\|\phi\|_{V^{-1}}
\end{aligned}$$

From here we conclude that the optimal value of $W^2 \leq f(\theta^*)^2 \leq (2n-1)\epsilon^2\|\phi\|^2_{V^{-1}}$. ☐

Using this lemma, we will be able to address the eluder dimension for linear functions. Using the definition of w_k from equation 18 together with Φ_k we may rewrite:

$$w_k = \max_{\theta}\{\sqrt{Tr(\theta\phi_k\phi_k^T\theta)} \;\big|\; Tr(\theta\Phi_k\theta^T) \leq \epsilon^2\}.$$

Let $V_k := \Phi_k + \left(\frac{\epsilon}{2C_\theta}\right)^2 I$ so that $Tr(\theta\Phi_k\theta^T) \leq \epsilon^2 \implies Tr(\theta V_k\theta^T) \leq 2\epsilon^2$ through a triangle inequality. Now applying Lemma 7 we can say that $w_k \leq \epsilon\sqrt{4n-2}\|\phi_k\|_{V_k^{-1}}$. This means that if $w_k \geq \epsilon$ then $\|\phi_k\|^2_{V_k^{-1}} > \frac{1}{4n-2} > 0$.

We now imagine that $w_i \geq \epsilon$ for each $i < k$. Then since $V_k = V_{k-1} + \phi_k\phi_k^T$ we can use the Matrix Determinant together with the above observation to say that:

$$det(V_k) = det(V_{k-1})(1 + \phi_k^T V_K^{-1}\phi_k) \geq det(V_{k-1})\left(1 + \frac{1}{4n-2}\right) \geq .. \geq \lambda^p\left(1+\frac{1}{4n-2}\right)^{k-1} \quad (19)$$

for $\lambda := \left(\frac{\epsilon}{2C_\theta}\right)^2$. To get an upper bound on the determinant we note that $det(V_k)$ is maximized when all eigenvalues are equal or equivalently:

$$det(V_k) \leq \left(\frac{Tr(V_k)}{p}\right)^p \leq \left(\frac{C_\phi^2(k-1)}{p} + \lambda\right)^p \quad (20)$$

Now using equations 19 and 20 together we see that k must satistfy the inequality $\left(1+\frac{1}{4n-2}\right)^{(k-1)/p} \leq \frac{C_\phi^2(k-1)}{\lambda p} + 1$. We now write $\zeta_0 = \frac{1}{4n-2}$ and $\alpha_0 = \frac{C_\phi^2}{\lambda} = \left(\frac{2C_\phi C_\theta}{\epsilon}\right)^2$ so that we can epress this as:

$$(1+\zeta_0)^{\frac{k-1}{p}} \leq \alpha_0\frac{k-1}{p} + 1$$

We now use the result that $B(x, \alpha) = \max\{B \mid (1+x)^B \leq \alpha B + 1\} \leq \frac{1+x}{x} \frac{e}{e-1} \{\log(1+\alpha) + \log(\frac{1+x}{x})\}$. We complete our proof of Proposition 2 through computing this upper bound at (ζ_0, α_0),

$$\dim_E(\mathcal{F}, \epsilon) \leq p(4n-1)\frac{e}{e-1}\log\left[\left(1 + \left(\frac{2C_\phi C_\theta}{\epsilon}\right)^2\right)(4n-1)\right] + 1 = \tilde{O}(np).$$

C.3 Quadratic functions $f(x) = \phi^T(x)\theta\phi(x)$

Let $\mathcal{F} = \{f \mid f(x) = \phi(x)^T\theta\phi(x) \text{ for } \theta \in \mathbb{R}^{p\times p}, \phi \in \mathbb{R}^p, \|\theta\|_2 \leq C_\theta, \|\phi\|_2 \leq C_\phi\}$ then for any $\mathcal{X}$ we can say that:

$$\dim_E(\mathcal{F}, \epsilon) \leq p(4p-1)\frac{e}{e-1}\log\left[\left(1 + \left(\frac{2pC_\phi^2 C_\theta}{\epsilon}\right)^2\right)(4p-1)\right] + 1 = \tilde{O}(p^2).$$

Where we have simply applied the linear result with $\tilde{\epsilon} = \frac{\epsilon}{pC_\mathcal{P}}$. This is valid since if we can identify the linear function $g(x) = \theta\phi(x)$ to within this tolerance then we will certainly know $f(x)$ as well.

C.4 Generalized linear models

Let $g(\cdot)$ be a component-wise independent function on $\mathbb{R}^n$ with derivative in each component bounded $\in [\underline{h}, \overline{h}]$ with $\underline{h} > 0$. Define $r = \frac{\overline{h}}{\underline{h}} > 1$ to be the condition number. If $\mathcal{F} = \{f \mid f(x) = g(\theta\phi(x)) \text{ for } \theta \in \mathbb{R}^{n\times p}, \phi \in \mathbb{R}^p, \|\theta\|_2 \leq C_\theta, \|\phi\|_2 \leq C_\phi\}$ then for any $\mathcal{X}$:

$$\dim_E(\mathcal{F}, \epsilon) \leq p\left(r^2(4n-2)+1\right)\frac{e}{e-1}\left(\log\left[\left(r^2(4n-2)+1\right)\left(1 + \left(\frac{2C_\theta C_\phi}{\epsilon}\right)^2\right)\right]\right) + 1 = \tilde{O}(r^2 np)$$

This proof follows exactly as per the linear case, but first using a simple reduction on the form of equation (18).

$$\begin{aligned}
w_k &= \sup\left\{\|(\overline{f} - \underline{f})(x_k)\|_2 \;\middle|\; \|\overline{f} - \underline{f}\|_{2,E_t} \leq \epsilon'\right\} \\
&\leq \max_{\theta_1,\theta_2}\left\{\|g(\theta_1\phi_k) - g(\theta_2\phi_k)\|_2 \;\Big|\; \sum_{i=1}^{k-1}\|g(\theta_1\phi_i) - g(\theta_2\phi_i)\|_2^2 \leq \epsilon^2\right\} \\
&\leq \max_{\theta}\left\{\overline{h}\|\theta\phi_k\|_2 \;\Big|\; \sum_{i=1}^{k-1}\underline{h}^2\|\theta\phi_i\|_2^2 \leq \epsilon^2\right\}
\end{aligned}$$

To which we can now apply Lemma 7 with the ϵ rescaled by r. Following the same arguments as for linear functions now completes our proof.

D UCRL-Eluder

For completeness, we explicitly outline an optimistic algorithm which uses the confidence sets in our analysis of PSRL to guarantee similar regret bounds with high probability over all MDP M^*. The algorithm follows the style of UCRL2 [7] so that at the start of the kth episode the algorithm form $\mathcal{M}_k = \{M | P^M \in \mathcal{P}_k, R^M \in \mathcal{R}_k\}$ and then solves for the optimistic policy that attains the highest reward over any M in $\mathcal{M}_k$.

Algorithm 2
UCRL-Eluder

Input: Confidence parameter $\delta > 0$, t=1
for episodes $k = 1, 2, ..$ **do**
  form confidence sets $\mathcal{R}_k(\beta^*(\mathcal{R}, \delta, 1/k^2))$ and $\mathcal{P}_k(\beta^*(\mathcal{P}, \delta, 1/k^2))$
  compute μ_k optimistic policy over $\mathcal{M}_k = \{M | P^M \in \mathcal{P}_k, R^M \in \mathcal{R}_k\}$
  for timesteps $j = 1, .., \tau$ **do**
    apply $a_t \sim \mu_k(s_t, j)$
    observe r_t and s_{t+1}
    advance $t = t + 1$
  end for
end for

Generally, step 4 of this algorithm with not be computationally tractable even when solving for μ^M is possible for a given M.