Sobolev penalty:univariate

Given a function h, the Sobolev penalty for h is

$$P(h) = \int (h^{(r)}(x))^2 dx$$

Suppose $\sup_{q} ||g||_{\infty} \leq G$.

We shall suppose for simplicity that the domain is [0, 1].

Suppose we have the function class (so no additional ridge penalty)

$$\hat{\mathcal{G}}(T) = \left\{ \hat{g}(\cdot|\lambda) = \arg\min_{g \in \mathcal{G}} \frac{1}{2} \|y - g\|_T^2 + \lambda P(g) : \lambda \in \Lambda \right\}$$

Using the logic in Example 9.3.2 in Vandegeer, we can express any function in \mathcal{G} as

$$f+g$$

where

$$g = \sum_{k=1}^{r} \alpha_k \psi_k, f = \int_0^1 \beta_u \tilde{\phi}_u$$

where $\langle \psi_k, \tilde{\phi}_u \rangle_T = 0$ and $P(\psi_k) = 0$.

Suppose the observations were drawn from $y = f^*(x) + g^*(x) + \epsilon$ where ϵ are independent subgaussian random variables.

Now we have the function class

$$\hat{\mathcal{G}}(T) = \left\{ \hat{g}(\cdot|\lambda), \hat{f}(\cdot|\lambda) = \arg\min_{g \in \mathcal{G}} \frac{1}{2} \|y - (f+g)\|_T^2 + \lambda P(f) : \lambda \in \Lambda, g = \sum_{k=1}^r \alpha_k \psi_k, f = \int_0^1 \beta_u \tilde{\phi}_u \right\}$$

We will show that

$$\left\| \left(\hat{g}(\cdot|\lambda^{(1)}) + \hat{f}(\cdot|\lambda^{(1)}) \right) - \left(\hat{g}(\cdot|\lambda^{(2)}) + \hat{f}(\cdot|\lambda^{(2)}) \right) \right\|_{\infty} \leq |\lambda^{(1)} - \lambda^{(2)}|n^{\tau_{min}} \sqrt{\frac{n^{\tau_{min}}}{2} \|\epsilon\|_T^2 + P(f^*)} G^{-\frac{1}{2}} \|\hat{g}(\cdot|\lambda^{(1)}) - \hat{g}(\cdot|\lambda^{(2)}) + \hat{f}(\cdot|\lambda^{(2)}) + \hat{f}(\cdot|\lambda^{(2)}) \|_{\infty}$$

Proof

First by Vandegeer Example 9.3.2, we know that

$$\hat{g}(\cdot|\lambda) = \arg\min_{g = \sum \alpha_k \psi_k} -2\langle \epsilon, g - g^* \rangle_T + \|g - g^*\|_T^2$$

$$\hat{f}(\cdot|\lambda) = \arg\min_{f = \int_0^1 \beta_u \tilde{\phi}_u} -2\langle \epsilon, f - f^* \rangle_T + \|f - f^*\|_T^2 + \lambda P(f)$$

So $\hat{g}(\cdot|\lambda)$ is actually independent of λ and is therefore constant. We will just denote it \hat{g} from now on.

Now consider

$$h = c\left(\hat{f}(\cdot|\lambda^{(1)}) - \hat{f}(\cdot|\lambda^{(2)})\right)$$

where c is some constant s.t. P(h) = 1.

We can assume that $P(h) \neq 0$. Otherwise, if

$$P\left(\hat{f}(\cdot|\lambda^{(1)}) - \hat{f}(\cdot|\lambda^{(2)})\right) = 0$$

then we know that

$$\hat{f}(\cdot|\lambda^{(1)}) - \hat{f}(\cdot|\lambda^{(2)}) \in span\{\psi_k\}_{k=1}^r$$

This is true if and only if $\hat{f}(\cdot|\lambda^{(1)}) \equiv \hat{f}(\cdot|\lambda^{(2)})$ (by the fact that the function spaces are orthogonal). Consider the optimization problem

$$\hat{m}_h(\lambda) = \arg\min_{m} \frac{1}{2} \|y - (\hat{g} + \hat{f}(\cdot|\lambda^{(1)}) + mh)\|_T^2 + \lambda P\left(\hat{f}(\cdot|\lambda^{(1)}) + mh\right)$$

By implicit differentiation of the KKT conditions, we get

$$\left. \frac{\partial}{\partial \lambda} \hat{m}_h(\lambda) \right|_{\lambda = \lambda} = -\left(\|h\|_T^2 + \lambda \frac{\partial^2}{\partial m^2} P\left(\hat{f}(\cdot | \lambda^{(1)}) + mh \right) \right)^{-1} \frac{\partial}{\partial m} P\left(\hat{f}(\cdot | \lambda^{(1)}) + mh \right) \right|_{m = \hat{m}_h(\lambda)}$$

Then the first multiplicand is bounded by

$$\left| \|h\|_T^2 + \lambda \frac{\partial^2}{\partial m^2} P\left(\hat{f}(\cdot|\lambda^{(1)}) + mh\right) \right|^{-1} \leq n^{\tau_{min}} \frac{\partial^2}{\partial m^2} P\left(\hat{f}(\cdot|\lambda^{(1)}) + mh\right)^{-1}$$
$$= \frac{n^{\tau_{min}}}{2P(h)}$$

The equality follows from the Lemma Sobolev Facts (see below). From the Lemma Sobolev Facts and by the fact that P(h) = 1, we have

$$\left| \frac{\partial}{\partial \lambda} \hat{m}_h(\lambda) \right|_{\lambda = \lambda} \leq \frac{n^{\tau_{min}}}{P(h)} \sqrt{P\left(\hat{f}(\cdot|\lambda^{(1)}) + \hat{m}_h(\lambda)h\right) P(h)}$$
$$= n^{\tau_{min}} \sqrt{P\left(\hat{f}(\cdot|\lambda^{(1)}) + \hat{m}_h(\lambda)h\right)}$$

By the definition of $\hat{m}_h(\lambda)$ and $\hat{f}(\cdot|\lambda^{(1)})$, we have that

$$\lambda P\left(\hat{f}(\cdot|\lambda^{(1)}) + \hat{m}_{h}(\lambda)h\right) \leq \frac{1}{2}\|y - (\hat{g} + \hat{f}(\cdot|\lambda^{(1)}))\|_{T}^{2} + \lambda P\left(\hat{f}(\cdot|\lambda^{(1)})\right) \\
= \frac{1}{2}\|y - (\hat{g} + \hat{f}(\cdot|\lambda^{(1)}))\|_{T}^{2} + \lambda^{(1)}P\left(\hat{f}(\cdot|\lambda^{(1)})\right) + \left(\lambda - \lambda^{(1)}\right)P\left(\hat{f}(\cdot|\lambda^{(1)})\right) \\
\leq \frac{1}{2}\|y - (g^{*} + f^{*})\|_{T}^{2} + \lambda^{(1)}P\left(f^{*}\right) + \left(\lambda - \lambda^{(1)}\right)P\left(\hat{f}(\cdot|\lambda^{(1)})\right)$$

In addition, by definition of $\hat{f}(\cdot|\lambda^{(1)})$, we have

$$P\left(\hat{f}(\cdot|\lambda^{(1)})\right) \le \frac{1}{2\lambda^{(1)}} \|y - (g^* + f^*)\|_T^2 + P(f^*)$$

Combining the two inequalities above, we have

$$\lambda P\left(\hat{f}(\cdot|\lambda^{(1)}) + \hat{m}_{h}(\lambda)h\right) \leq \frac{1}{2} \|\epsilon\|_{T}^{2} + \lambda^{(1)} P\left(f^{*}\right) + \left(\lambda - \lambda^{(1)}\right) \left(\frac{1}{2\lambda^{(1)}} \|\epsilon\|_{T}^{2} + P\left(f^{*}\right)\right)$$

$$\leq \frac{\lambda}{2\lambda^{(1)}} \|\epsilon\|_{T}^{2} + \lambda P\left(f^{*}\right)$$

Therefore

$$P\left(\hat{f}(\cdot|\lambda^{(1)}) + \hat{m}_h(\lambda)h\right) \le \frac{n^{\tau_{min}}}{2} \|\epsilon\|_T^2 + P(f^*)$$

Then by the MVT, we have

$$\begin{split} \|\hat{f}(\cdot|\lambda^{(1)}) - \hat{f}(\cdot|\lambda^{(2)})\|_{\infty} &= \|\left(m_{h}(\lambda^{(2)}) - m_{h}(\lambda^{(1)})\right)h\|_{\infty} \\ &= \|h\|_{\infty} \left|\lambda^{(2)} - \lambda^{(1)}\right| \left.\frac{\partial}{\partial \lambda} \hat{m}_{h}(\lambda)\right|_{\lambda \in [\lambda^{(1)}, \lambda^{(2)}]} \\ &\leq G\left|\lambda^{(1)} - \lambda^{(2)}\right| \left(\sup_{\lambda \in [\lambda^{(1)}, \lambda^{(2)}]} \left|\frac{\partial}{\partial \lambda} \hat{m}_{h}(\lambda)\right|_{\lambda = \lambda}\right) \\ &\leq \left|\lambda^{(1)} - \lambda^{(2)}\right| Gn^{\tau_{min}} \sqrt{\frac{n^{\tau_{min}}}{2}} \|\epsilon\|_{T}^{2} + P(f^{*}) \end{split}$$

Sobolev penalty: multivariate

The function class of interest

$$\hat{\mathcal{G}}(T) = \left\{ \left\{ \hat{g}_j(\cdot|\lambda), \hat{f}_j(\cdot|\lambda) \right\} = \arg\min_{g \in \mathcal{G}} \frac{1}{2} \|y - \sum_{j=1}^J g_j(x_j)\|_T^2 + \sum_{j=1}^J \lambda_j P(g_j) : \lambda \in \Lambda \right\}$$

We can show that

$$\|\hat{f}_{\ell}(\cdot|\lambda^{(1)}) - \hat{f}_{\ell}(\cdot|\lambda^{(2)})\|_{\infty} \leq G \|\lambda^{(1)} - \lambda^{(2)}\| \frac{n^{\tau_{min}}}{2} \sqrt{\frac{n^{\tau_{min}} + Jn^{\tau_{max} + 2\tau_{min}}}{2} \|\epsilon\|_{T}^{2} + n^{\tau_{max} + 2\tau_{min}} \sum_{j=1}^{J} P\left(f_{j}^{*}\right)}$$

A second approach gives a different bound:

$$\|\hat{f}_{\ell}(\cdot|\lambda^{(1)}) - \hat{f}_{\ell}(\cdot|\lambda^{(2)})\|_{\infty} \le \|\lambda^{(1)} - \lambda^{(2)}\| \frac{G^2(2G + \|\epsilon\|_T)n^{3\tau_{min}}}{4}$$

Proof

First by Vandegeer Example 9.3.2, we know that

$$\{\hat{g}_j(\cdot|\lambda)\}_{j=1}^J = \arg\min_{g_j = \sum \alpha_k \psi_k} -2\langle \epsilon, \sum_{j=1}^J g_j - g_j^* \rangle_T + \|\sum_{j=1}^J g_j - g_j^*\|_T^2$$

$$\left\{\hat{f}_{j}(\cdot|\lambda)\right\}_{j=1}^{J} = \arg\min_{f_{j} = \int_{0}^{1} \beta_{u}\tilde{\phi}_{u}} -2\langle \epsilon, \sum_{j=1}^{J} f_{j} - f_{j}^{*} \rangle_{T} + \|\sum_{j=1}^{J} f_{j} - f_{j}^{*}\|_{T}^{2} + \sum_{j=1}^{J} \lambda_{j} P(f_{j})$$

For every j = 1: J, we again notice that $\hat{g}_j(\cdot|\lambda)$ is independent of λ . We will just denote it \hat{g}_j from now on.

For every j = 1 : J, define functions

$$h_j = c \left(\hat{f}_j(\cdot | \lambda^{(1)}) - \hat{f}_j(\cdot | \lambda^{(2)}) \right)$$

where c is some constant s.t. $P(h_j) = 1$.

We can assume that $P(h_j) \neq 0$. Otherwise, if

$$P\left(\hat{f}_j(\cdot|\lambda^{(1)}) - \hat{f}_j(\cdot|\lambda^{(2)})\right) = 0$$

then we know that

$$\hat{f}_j(\cdot|\lambda^{(1)}) - \hat{f}_j(\cdot|\lambda^{(2)}) \in span\left\{\psi_k\right\}_{k=1}^r$$

This is true if and only if $\hat{f}_j(\cdot|\lambda^{(1)}) \equiv \hat{f}_j(\cdot|\lambda^{(2)})$ (by the fact that the function spaces are orthogonal). Now consider the optimization problem

$$\{\hat{m}_j(\lambda, h)\}_{j=1}^J = \arg\min_{m_j} \frac{1}{2} \|y - \sum_{j=1}^J (\hat{g}_j + \hat{f}_j(\cdot | \lambda^{(1)}) + m_j h_j)\|_T^2 + \sum_{j=1}^J \lambda_j P\left(\hat{f}_j(\cdot | \lambda^{(1)}) + m_j h_j\right)$$

(If $h_j \equiv 0$, then set $m_j = 0$ as a constant.) For simplicity, we will assume $h_j \neq 0$. The KKT conditions give us for all $\ell = 1: J$

$$\left\langle h_{\ell}, y - \left(\sum_{j=1}^{J} \hat{g}_{j}(\cdot | \lambda^{(1)}) + \hat{f}_{j}(\cdot | \lambda^{(1)}) + \hat{m}_{j}(\lambda, h) h_{j} \right) \right\rangle_{T} + \lambda_{\ell} \frac{\partial}{\partial m_{\ell}} P\left(\hat{f}_{\ell}(\cdot | \lambda^{(1)}) + m_{\ell} h \right) \bigg|_{m_{\ell} = \hat{m}_{\ell}(\lambda, h)} = 0$$

For all k = 1: J, by implicit differentiation of the KKT conditions with respect to λ_k , we get

$$\left\langle h_{\ell}, y - \sum_{j=1}^{J} h_{j} \frac{\partial}{\partial \lambda_{k}} \hat{m}_{j}(\lambda, h) \right\rangle_{T} + \lambda_{\ell} \frac{\partial^{2}}{\partial m_{\ell}^{2}} P\left(\hat{f}_{\ell}(\cdot | \lambda^{(1)}) + m_{\ell} h\right) \frac{\partial}{\partial \lambda_{k}} \hat{m}_{\ell}(\lambda, h)$$

$$+1[\ell = k] \frac{\partial}{\partial m_{\ell}} P\left(\hat{f}_{\ell}(\cdot | \lambda^{(1)}) + m_{\ell} h\right) = 0$$

Define the following matrices

$$S: S_{ij} = \langle h_j, h_\ell \rangle_T$$

$$D_1 = diag \left(\lambda_\ell \frac{\partial^2}{\partial m_\ell^2} P\left(\hat{f}_\ell(\cdot | \lambda^{(1)}) + \hat{m}_\ell(\lambda) h_\ell \right) \right)$$

$$D_3 = diag \left(\frac{\partial}{\partial m_\ell} P\left(\hat{f}_\ell(\cdot | \lambda^{(1)}) + \hat{m}_\ell(\lambda) h_\ell \right) \right)$$

$$M = \left(\begin{array}{cc} \frac{\partial \hat{m}_1(\lambda)}{\partial \lambda} & \frac{\partial \hat{m}_2(\lambda)}{\partial \lambda} & \dots & \frac{\partial \hat{m}_J(\lambda)}{\partial \lambda} \end{array} \right)$$

From the implicit differentiation equations, we have the following system of equations:

$$M = D_3 \left(S + D_1 \right)^{-1}$$

We know that S is a PSD matrix (since it can be written as $S = HH^T$ where $H_j = h_j$ evaluated at covariates T).

We are interested in bounding $\nabla_{\lambda}\hat{m}_{\ell}(\lambda, h)$, which is the ℓ -th column of M has norm. By Lemma PSD_Matrix_Inverse (see additive_models.pdf), we know that

$$\begin{split} \|\nabla_{\lambda}\hat{m}_{\ell}(\lambda,h)\| &= \|Me_{\ell}\| \\ &= \|D_{3}(S+D_{1})^{-1}e_{\ell}\| \\ &\leq \|D_{3}D_{1}^{-1}e_{\ell}\| \\ &= \left|\frac{\partial}{\partial m_{\ell}}P\left(\hat{f}_{\ell}(\cdot|\lambda^{(1)}) + \hat{m}_{\ell}(\lambda)h_{\ell}\right)\right| \left|\lambda_{\ell}\frac{\partial^{2}}{\partial m_{\ell}^{2}}P\left(\hat{f}_{\ell}(\cdot|\lambda^{(1)}) + \hat{m}_{\ell}(\lambda)h_{\ell}\right)\right|^{-1} \end{split}$$

By Lemma Sobolev Facts (below), we have

$$\frac{\partial^2}{\partial m_\ell^2} P\left(\hat{f}_\ell(\cdot|\lambda^{(1)}) + \hat{m}_\ell(\lambda)h_\ell\right) = 2P(h_\ell) = 2$$

Also by Lemma Sobolev Facts (below), we note that

$$\left| \frac{\partial}{\partial m_{\ell}} P\left(\hat{f}_{\ell}(\cdot | \lambda^{(1)}) + \hat{m}_{\ell}(\lambda) h_{\ell} \right) \right| \leq 2\sqrt{P\left(\hat{f}_{\ell}(\cdot | \lambda^{(1)}) + \hat{m}_{\ell}(\lambda) h_{\ell} \right) P(h_{\ell})}$$

$$= 2\sqrt{P\left(\hat{f}_{\ell}(\cdot | \lambda^{(1)}) + \hat{m}_{\ell}(\lambda) h_{\ell} \right)}$$

By the definition of $\hat{m}_{\ell}(\lambda)$ and $\hat{f}(\cdot|\lambda^{(1)})$, we have

$$\lambda_{\ell} P\left(\hat{f}_{\ell}(\cdot|\lambda^{(1)}) + \hat{m}_{\ell}(\lambda)h_{\ell}\right) \leq \frac{1}{2} \|y - (\hat{g} + \hat{f}(\cdot|\lambda^{(1)}))\|_{T}^{2} + \sum_{j=1}^{J} \lambda_{j} P\left(\hat{f}_{j}(\cdot|\lambda^{(1)})\right)$$

$$= \frac{1}{2} \|y - (g^{*} + f^{*})\|_{T}^{2} + \sum_{j=1}^{J} \lambda_{j}^{(1)} P\left(f_{j}^{*}\right) + \sum_{j=1}^{J} \left(\lambda_{j} - \lambda_{j}^{(1)}\right) P\left(\hat{f}_{j}(\cdot|\lambda^{(1)})\right)$$

$$\leq \frac{1}{2} \|\epsilon\|_{T}^{2} + \lambda_{max} \sum_{j=1}^{J} P\left(f_{j}^{*}\right) + J\lambda_{max} \left[\max_{j=1:J} P\left(\hat{f}_{j}(\cdot|\lambda^{(1)})\right)\right]$$

By definition of $\hat{f}_j(\cdot|\lambda^{(1)})$, we know

$$\max_{j=1:J} P\left(\hat{f}_{j}(\cdot|\lambda^{(1)})\right) \leq \frac{1}{\lambda_{min}} \left(\frac{1}{2} \|\epsilon\|_{T}^{2} + \sum_{j=1}^{J} \lambda_{j}^{(1)} P\left(f_{j}^{*}\right)\right)$$

So

$$P\left(\hat{f}_{\ell}(\cdot|\lambda^{(1)}) + m_{\ell}h_{\ell}\right) \leq \frac{n^{\tau_{min}} + Jn^{\tau_{max} + 2\tau_{min}}}{2} \|\epsilon\|_{T}^{2} + n^{\tau_{max} + 2\tau_{min}} \sum_{i=1}^{J} P\left(f_{i}^{*}\right)$$

Then by the MVT, we have for some $\alpha \in (0,1)$

$$\begin{split} \|\hat{f}_{\ell}(\cdot|\lambda^{(1)}) - \hat{f}_{\ell}(\cdot|\lambda^{(2)})\|_{\infty} &= \|\left(\hat{m}_{\ell}(\lambda^{(2)}, h) - \hat{m}_{\ell}(\lambda^{(1)}, h)\right) h_{\ell}\|_{\infty} \\ &= \|h_{\ell}\|_{\infty} \langle \lambda^{(1)} - \lambda^{(2)}, \nabla_{\lambda} \hat{m}_{\ell}(\lambda, h) \rangle_{\lambda = \alpha \lambda^{(1)} + (1 - \alpha)\lambda^{(2)}} \\ &\leq G \|\lambda^{(1)} - \lambda^{(2)}\| \|\nabla_{\lambda} \hat{m}_{\ell}(\lambda, h)\| \\ &\leq G \|\lambda^{(1)} - \lambda^{(2)}\| \frac{n^{\tau_{min}}}{2} \sqrt{\frac{n^{\tau_{min}} + Jn^{\tau_{max} + 2\tau_{min}}}{2} \|\epsilon\|_{T}^{2} + n^{\tau_{max} + 2\tau_{min}} \sum_{j=1}^{J} P\left(f_{j}^{*}\right)} \end{split}$$

A second approach:

By the KKT conditions, we also know that

$$\left| \frac{\partial}{\partial m_{\ell}} P\left(\hat{f}_{\ell}(\cdot|\lambda^{(1)}) + \hat{m}_{\ell}(\lambda)h_{\ell}\right) \right| = \frac{1}{\lambda_{\ell}} \left| \left\langle h_{\ell}, y - \left(\sum_{j=1}^{J} \hat{g}_{j}(\cdot|\lambda^{(1)}) + \hat{f}_{j}(\cdot|\lambda^{(1)}) + \hat{m}_{j}(\lambda,h)h_{j} \right) \right\rangle_{T} \right|$$

$$\leq \frac{1}{\lambda_{min}} \|h_{\ell}\|_{T} \left\| y - \left(\sum_{j=1}^{J} \hat{g}_{j}(\cdot|\lambda^{(1)}) + \hat{f}_{j}(\cdot|\lambda^{(1)}) + \hat{m}_{j}(\lambda,h)h_{j} \right) \right\|_{T}$$

$$\leq G(2G + \|\epsilon\|_{T})n^{\tau_{min}}$$

Hence

$$\|\nabla_{\lambda}\hat{m}_{\ell}(\lambda, h)\| \le G(2G + \|\epsilon\|_T)n^{2\tau_{min}} \frac{1}{2}$$

Then by the MVT, we have for some $\alpha \in (0,1)$

$$\begin{split} \|\hat{f}_{\ell}(\cdot|\lambda^{(1)}) - \hat{f}_{\ell}(\cdot|\lambda^{(2)})\|_{\infty} &= \|\left(\hat{m}_{\ell}(\lambda^{(2)}, h) - \hat{m}_{\ell}(\lambda^{(1)}, h)\right) h_{\ell}\|_{\infty} \\ &= \|h_{\ell}\|_{\infty} \langle \lambda^{(1)} - \lambda^{(2)}, \nabla_{\lambda} \hat{m}_{\ell}(\lambda, h) \rangle_{\lambda = \alpha \lambda^{(1)} + (1 - \alpha) \lambda^{(2)}} \\ &\leq G \|\lambda^{(1)} - \lambda^{(2)}\| \|\nabla_{\lambda} \hat{m}_{\ell}(\lambda, h)\| \\ &\leq \|\lambda^{(1)} - \lambda^{(2)}\| G^{2}(2G + \|\epsilon\|_{T}) n^{3\tau_{min}} \frac{1}{4} \end{split}$$

Lemma: Sobolev Facts

For any function h, we have

$$\left| \frac{\partial}{\partial m} P(g + mh) \right| = \left| 2 \int (g^{(r)}(x) + mh^{(r)}(x)) h^{(r)}(x) dx \right|$$

$$\leq 2 \sqrt{P(g + mh)P(h)}$$

and

$$\frac{\partial^2}{\partial m^2}P(g+mh)=2\int (h^{(r)}(x))^2dx=2P(h)$$