

# Notes for Week 8/7/19 - 8/15/19

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Suppose we observe samples  $X = (x_1, \dots, x_n) \in \mathcal{X} \subseteq \mathbb{R}^d$ . For a given  $r > 0$ , the  $r$ -neighborhood graph  $G = (V, E)$  over  $X$  is defined to be the undirected graph with vertex set  $V = [n]$ , and edge set  $E = \{(i, j) : \|i - j\|_2 \leq r\}$ . Let  $A = (A_{ij})_{i,j=1}^n$  be the adjacency matrix of  $G$ , with entries  $A_{ij}$  equal to 1 if  $(i, j) \in E$  and 0 otherwise. Let  $D$  be the edge incidence matrix of  $G$ , with  $\ell$ th row  $D_\ell = (0, \dots, -1, \dots, 1, \dots)$  with a  $-1$  in the  $i$ th entry, and 1 in the  $j$ th entry, and 0 elsewhere, provided that the  $\ell$ th edge  $e_\ell = (i, j)$  and  $i < j$ . Let  $L = D^T D$  be the graph Laplacian matrix of  $G$ .

Let  $\mathbb{Z}_+^d$  denote the set of all ordered  $d$ -tuples of nonnegative integers. For  $\alpha \in \mathbb{Z}_+^d$ ,  $\alpha = (\alpha_1, \dots, \alpha_d)$ , denote  $|\alpha| = \sum_{i=1}^d \alpha_i$ , and by  $\mathcal{D}^\alpha f$  the partial derivative

$$\mathcal{D}^\alpha f = \frac{\partial^{|\alpha|} f}{\partial x_1^{\alpha_1} \dots \partial x_d^{\alpha_d}}.$$

The Sobolev space  $W^{s,p}(\mathcal{X})$  consists of all functions  $f$  such that for each multiindex  $\alpha$  with  $|\alpha| \leq k$ ,  $\mathcal{D}^\alpha f$  exists in the weak sense and belongs to  $L^p(\mathcal{X})$ . For  $f \in W^{s,p}(\mathcal{X})$ , we define the Sobolev norm of  $f$  to be

$$\|f\|_{W^{s,p}(\mathcal{X})} = \left( \sum_{|\alpha| \leq s} \int_{\mathcal{X}} |\mathcal{D}^\alpha f(x)|^p \right)^{1/p}. \quad (1)$$

We will focus our attentions on  $W^{s,2}(\mathcal{X})$ .

For a function  $f : \mathcal{X} \rightarrow \mathbb{R}$ , we can define a notion of smoothness of  $f$  over  $G$ . Letting  $\tilde{f} = (f(x_1), \dots, f(x_n)) \in \mathbb{R}^n$ , introduce the smoothness functional

$$S(f) := \tilde{f}^T L^s \tilde{f} \quad (2)$$

Our objective is to establish a relation between (1) and (2). In particular, suppose the samples  $x_i$  are sampled i.i.d from a probability measure  $P$  over  $\mathcal{X}$ . Our goal is to establish that, for an appropriate scaling  $C_n$ , with high probability

$$S(f) \leq C_n \|f\|_{W^{s,2}(\mathcal{X})} \quad (3)$$

## 1 Expectation of $S(f)$ .

For  $y \in \mathcal{X}$ , define the partial difference operator  $D_y$  by  $D_y f(x) = (f(y) - f(x))\eta(x, y)$ , where  $\eta(x, y) = \mathbf{1}(\|x - y\| \leq r)$ . For  $\alpha = (\alpha_1, \dots, \alpha_q) \in [n]^q$ , define the iterated difference operator  $D_\alpha$  to be

$$D_\alpha f(x) = D_{x_{\alpha_1}}(D_{x_{\alpha_2}}(\dots D_{x_{\alpha_q}} f))(x) \quad (4)$$

We begin by re-expressing the smoothness functional  $S(f)$  in terms of sums of the iterated difference operator, similarly to [Sadhanala et al., 2017].

**Lemma 1.** For  $s$  even, letting  $q = s/2$ , we have

$$S(f) = \sum_{i=1}^n \left( \sum_{\alpha \in [n]^q} D_\alpha f(x_i) \right)^2 \quad (5)$$

For  $s$  odd, letting  $q = (s-1)/2$ , we have

$$S(f) = \frac{1}{2} \sum_{i,j=1}^n \left( \sum_{\alpha \in [n]^q} D_{x_i} D_\alpha f(x_j) \right)^2 \quad (6)$$

*Proof.* Note that for any function  $g : V \rightarrow \mathbb{R}$ ,  $(-Lg)(x_i) = \sum_{j=1}^n D_{x_j} g(x_i)$ . To see this, note that  $Dg$  is a length  $m$  vector with  $\ell$ th entry  $(Dg)_\ell = g_i - g_j$  provided that  $e_\ell = (i, j)$  and  $i < j$ . Therefore, as  $Lg = \sum_{\ell=1}^m D_\ell (Dg)_\ell$ , we have that  $Lg = \sum_{j>i} (g_i - g_j) \mathbf{1}((i, j) \in E) - \sum_{j<i} (g_j - g_i) \mathbf{1}((j, i) \in E) = \sum_{j=1}^n (g_i - g_j) \eta_r(x_i, x_j) = \sum_{j=1}^n D_{x_j} g(x_i)$ . The statement follows since  $-D_x f(y) = D_y f(x)$ .

Therefore, when  $s$  is even, letting  $q = s/2$ , we have

$$\begin{aligned} f^T L^s f &= \sum_{i=1}^n ((-L)^q f(x_i))^2 \\ &= \sum_{i=1}^n \left( \sum_{j_1=1}^n D_{x_{j_1}} L^{q-1} f(x_i) \right)^2. \end{aligned}$$

If  $q = 1$ , this suffices. Otherwise, if  $q \geq 2$ , as  $D_y$  is a linear operator, we obtain

$$\begin{aligned} \sum_{i=1}^n \left( \sum_{j_1=1}^n D_{x_{j_1}} L^{q-1} f(x_i) \right)^2 &= \sum_{i=1}^n \left( \sum_{j_1=1}^n D_{x_{j_1}} \sum_{j_2=1}^n D_{x_{j_2}} L^{q-2} f(x_i) \right)^2 \\ &= \sum_{i=1}^n \left( \sum_{j_1, j_2=1}^n D_{x_{j_1}} D_{x_{j_2}} L^{q-2} f(x_i) \right)^2 \end{aligned}$$

and recursively, we arrive at the desired result.

When  $s$  is odd, letting  $q = (s-1)/2$  we have that

$$\begin{aligned} f^T L^s f &= \sum_{i < j} ((L^q f(x_i) - L^q f(x_j))^2 \mathbf{1}((x_i, x_j) \in E)) \\ &= \frac{1}{2} \sum_{i,j=1}^n ((-L)^q f(x_i) - (-L)^q f(x_j))^2 \eta(x_i, x_j). \end{aligned}$$

By similar reasoning to above, we obtain

$$f^T L^s f = \frac{1}{2} \sum_{i,j=1}^n \left( \sum_{\alpha \in [n]^q} D_\alpha f(x_i) - D_\alpha f(x_j) \right)^2 \eta(x_i, x_j)$$

Then, since  $\eta = \eta^2$ , we can replace  $\eta(x_i, x_j)$  with  $\eta^2(x_i, x_j)$  in the previous display, and obtain

$$\begin{aligned} f^T L^s f &= \frac{1}{2} \sum_{i,j=1}^n \left( \sum_{\alpha \in [n]^q} D_\alpha f(x_i) - D_\alpha f(x_j) \right)^2 \eta^2(x_i, x_j) \\ &= \frac{1}{2} \sum_{i,j=1}^n \left( \sum_{\alpha \in [n]^q} (D_\alpha f(x_i) - D_\alpha f(x_j)) \eta(x_i, x_j) \right)^2 \end{aligned}$$

and (6) follows.  $\square$

### 1.1 Expectation when $s = 2$ .

Let  $P$  be absolutely continuous with density function  $p$  over  $\mathbb{R}^d$ .

**Lemma 2.** *Suppose  $f \in W^{2,2}(\mathcal{X})$ ,  $p \in C^1(\mathcal{X})$ , and  $\partial X \in C^2$ . Then there exists a constant  $c$  which does not depend on  $n$  or  $f$  such that*

$$\mathbb{E}(f^T L^2 f) \leq c \left( n^2 r^{d+2} \sum_{|\alpha|=1} \|\mathcal{D}^\alpha f\|_2^2 + n^3 r^{2d+4} \sum_{|\alpha| \leq 2} \|\mathcal{D}^\alpha f\|_2^2 \right)$$

*Proof.* Using Lemma 1, we may rewrite

$$\begin{aligned} f^T L^2 f &= \sum_{i=1}^n \left( \sum_{j=1}^n D_{x_j} f(x_i) \right)^2 \\ &= \sum_{i=1}^n \sum_{j=1}^n \sum_{k=1}^n D_{x_j} f(x_i) D_{x_k} f(x_i) \\ &= \sum_{i \neq j}^n (D_{x_j} f(x_i))^2 + \sum_{i \neq j \neq k}^n D_{x_j} f(x_i) D_{x_k} f(x_i) \end{aligned}$$

so that the expectation  $\mathbb{E}(f^T L^2 f)$  becomes

$$\mathbb{E}(f^T L^2 f) = n(n-1) \mathbb{E}(D_{X_1} f(X_2))^2 + n(n-1)(n-2) \mathbb{E}(D_{X_2} f(X_1) D_{X_3} f(X_2)).$$

The statement then follows from Lemmas 3 and 4.  $\square$

## 2 Additional Theory

**Lemma 3.** *For any function  $f \in W^{2,2}(\mathcal{X})$ , if  $\partial X \in C^2$  and  $p \in C^1(\mathcal{X}, L)$  then there exists a constant  $c$  which does not depend on  $f$  such that*

$$\mathbb{E}(D(X_2) f(X_1) D_{X_3} f(X_1)) \leq c r^{2d+4} \sum_{|\alpha| \leq 2} \|\mathcal{D}^\alpha f\|_{L^2}^2 \quad (7)$$

*Proof.* We rewrite the expectation on the right hand side of (7) as an integral:

$$\begin{aligned}
\mathbb{E}(D(X_2)f(X_1)D_{X_3}f(X_1)) &= \int_{\mathcal{X}} \int_{\mathcal{X}} \int_{\mathcal{X}} D_y f(x) D_z f(x) dP(z) dP(y) dP(x) \\
&= \int_{\mathcal{X}} \left\{ \int_{\mathcal{X}} D_y f(x) dP(y) \right\}^2 dP(x) \\
&\leq 2 \int_{\mathcal{X}} \left\{ \int_{\mathcal{X}} D_y f(x) p(x) dy \right\}^2 + \left\{ \int_{\mathcal{X}} D_y f(x) (p(y) - p(x)) dy \right\}^2 dP(x) \\
&\leq 2 \int_{\mathbb{R}^d} \left\{ \int_{\mathcal{X}} D_y g(x) p(x) dy \right\}^2 + \left\{ \int_{\mathbb{R}^d} D_y g(x) (p(y) - p(x)) dy \right\}^2 dP(x)
\end{aligned}$$

where  $g$  is an extension of  $f$  which is equal to  $f$  almost everywhere on  $\mathcal{X}$ , and satisfies  $\|g\|_{W^{2,2}(\mathbb{R}^d)} \leq c\|f\|_{W^{2,2}(\mathbb{R}^d)}$  for some  $c$  which does not depend on  $f$ . We will handle each term inside the integral separately. Assume without loss of generality that  $g \in C^2$ ; otherwise, we can take  $g_m \in C^2$  such that  $\|g_m - g\|_{W^{2,2}(\mathbb{R}^d)} \rightarrow 0$ . For the first term, we use Lemma 5 to obtain

$$\left\{ \int_{\mathcal{X}} D_y g(x) p(x) dy \right\}^2 dP(x) \leq \lambda_{\max}^3 \frac{d^2 r^{4+2d}}{\nu_d} \sum_{|\alpha|=2} \int_{B(0,1)} \int_0^1 (1-t)^2 (\mathcal{D}^\alpha g(x+trz))^2 dt dz,$$

and therefore,

$$\begin{aligned}
\int_{\mathbb{R}^d} \left\{ \int_{\mathcal{X}} D_y g(x) p(x) dy \right\}^2 &\leq \lambda_{\max}^3 \frac{d^2 r^{4+2d}}{\nu_d} \sum_{|\alpha|=2} \int_{\mathbb{R}^d} \int_{B(0,1)} \int_0^1 (1-t)^2 (\mathcal{D}^\alpha g(x+trz))^2 dt dz dx \\
&= \lambda_{\max}^3 \frac{d^2 r^{4+2d}}{\nu_d} \sum_{|\alpha|=2} \int_{B(0,1)} \int_0^1 (1-t)^2 \int_{\mathbb{R}^d} (\mathcal{D}^\alpha g(x+trz))^2 dx dt dz \\
&= \frac{\lambda_{\max}^3 d^2 r^{4+2d}}{3} \sum_{|\alpha|=2} \|\mathcal{D}^\alpha g\|_{L^2}^2.
\end{aligned}$$

For the second summand, since  $p(x) \in C^2(\mathcal{X}; L)$ , using reasoning similar to the proof of Lemma we have

$$\begin{aligned}
\int_{\mathbb{R}^d} \left\{ \int_{\mathbb{R}^d} D_y g(x) (p(y) - p(x)) dy \right\}^2 dP(x) &\leq \lambda_{\max} \int_{\mathbb{R}^d} \left( \int_{\mathbb{R}^d} (D_y g(x))^2 dy \right) \left( \int_{B(x,r)} (p(y) - p(x))^2 dy \right) dx \\
&\leq \lambda_{\max} \int_{\mathbb{R}^d} \left( \int_{\mathbb{R}^d} (D_y g(x))^2 dy \right) \left( \int_{B(x,r)} L^2 \|x - y\|^2 dy \right) dx \\
&\leq \lambda_{\max} \nu_d r^{d+2} \int_{\mathbb{R}^d} \int_{\mathbb{R}^d} (D_y g(x))^2 dy dx \\
&\leq c \nu_d \lambda_{\max} \nu_d r^{2d+4} \sum_{|\alpha|=1} \|\mathcal{D}^\alpha f\|_2^2.
\end{aligned}$$

□

**Lemma 4.** For any function  $f \in W^{1,2}(\mathcal{X})$ , if  $\partial\mathcal{X} \in C^1$ , then there exists a constant  $c$  which does not depend on  $f$  such that

$$\mathbb{E}(D_{X_1} f(X_2))^2 \leq c r^{d+2} \sum_{|\alpha|=1} \|\mathcal{D}^\alpha f\|_2^2$$

*Proof.* We write  $\mathbb{E}(D_{X_1}f(X_2))^2$  as an integral,

$$\mathbb{E}(D_{X_1}f(X_2))^2 = \int_{\mathcal{X}} \int_{\mathcal{X}} (f(x) - f(y))^2 \eta(y, x) dP(y) dP(x) \leq \lambda_{\max}^2 \int_{\mathcal{X}} \int_{\mathcal{X}} (f(x) - f(y))^2 \eta(y, x) dy dx$$

Now, as  $\partial\mathcal{X} \in C^1$ , there exists a function  $g : \mathbb{R}^d \rightarrow \mathbb{R}$  such that  $g(x) = f(x)$ , almost everywhere in  $\mathcal{X}$ , and  $\|g\|_{W^{1,2}(\mathbb{R}^d)} \leq c\|f\|_{W^{1,2}(\mathcal{X})}$ . Since  $g = f$  almost everywhere in  $\mathcal{X}$ , we have

$$\int_{\mathcal{X}} \int_{\mathcal{X}} (f(x) - f(y))^2 dy dx \leq \int_{\mathbb{R}^d} \int_{\mathbb{R}^d} (g(x) - g(y))^2 \eta(y, x) dy dx. \quad (8)$$

We may assume without loss of generality that  $g \in C^\infty$  (otherwise take approximations  $g_m \in C^\infty(\mathbb{R}^d)$ ,  $g_m \rightarrow g \in W^{s,2}(\mathbb{R}^d)$ .) We expand

$$\begin{aligned} \int_{\mathbb{R}^d} (g(x) - g(y))^2 dy &= \int_{\mathbb{R}^d} \left( \int_0^1 \frac{d}{dt} g(x + t(y - x)) dt \right)^2 dy \\ &= \int_{\mathbb{R}^d} \left( \int_0^1 \nabla g(x + t(y - x)) \cdot (y - x) dt \right)^2 dy \\ &\leq \int_{\mathbb{R}^d} \int_0^1 \|\nabla g(x + t(y - x))\|^2 \|y - x\|^2 dt dy \end{aligned}$$

Therefore,

$$\begin{aligned} \int_{\mathbb{R}^d} (g(x) - g(y))^2 \eta(y, x) dy dx &\leq \int_{\mathbb{R}^d} \int_{\mathbb{R}^d} \int_0^1 \|\nabla g(x + t(y - x))\|^2 \|y - x\|^2 dt \eta(y, x) dy dx \\ &\leq r^2 \int_{\mathbb{R}^d} \int_{\mathbb{R}^d} \int_0^1 \|\nabla g(x + t(y - x))\|^2 dt \eta(y, x) dy dx \\ &= r^{2+d} \int_{\mathbb{R}^d} \int_{B(0,1)} \int_0^1 \|\nabla g(x + trz)\|^2 dt dz dx \quad (z = (y - x)/r) \\ &= r^{2+d} \int_{B(0,1)} \int_0^1 \int_{\mathbb{R}^d} \|\nabla g(x + trz)\|^2 dx dt dz \\ &= \nu_d r^{2+d} \sum_{|\alpha|=1} \|\mathcal{D}^\alpha g\|_{L^2}^2 \end{aligned}$$

□

**Lemma 5.** For any function  $g \in C^2(\mathbb{R}^d)$ , and any  $x \in \mathbb{R}^d$

$$\left( \int_{B(x,r)} g(y) - g(x) dy \right)^2 \leq \frac{d^2 r^{4+2d}}{\nu_d} \sum_{|\alpha|=2} \int_{B(0,1)} \int_0^1 (1-t)^2 (\mathcal{D}^\alpha f(x + trz))^2 dt dz.$$

*Proof.* As  $g \in C^2(\mathbb{R}^d)$ , taking a Taylor expansion of  $g$  around  $x$ , we obtain

$$g(y) = g(x) + \sum_{|\alpha|=1} \mathcal{D}^\alpha g(x) (y - x)^\alpha + \sum_{|\alpha|=2} (y - x)^\alpha \int_0^1 (1-t) \mathcal{D}^\alpha g(x + t(y - x)) dt.$$

We note that, by standard facts of the uniform distribution

$$\int_{B(x,r)} (x - y)^\alpha = 0, \quad \text{for all } |\alpha| = 1$$

and we therefore have

$$\begin{aligned}
\left( \int_{B(x,r)} g(y) - g(x) dy \right)^2 &= \left( \int_{B(x,r)} \sum_{|\alpha|=2} (y-x)^\alpha \int_0^1 (1-t) \mathcal{D}^\alpha g(x+t(y-x)) dt \right)^2 \\
&\leq \left( \int_{B(x,r)} \left( \sum_{|\alpha|=2} (y-x)^{2\alpha} \right)^{1/2} \left( \sum_{|\alpha|=2} \left\{ \int_0^1 (1-t) \mathcal{D}^\alpha g(x+t(y-x)) dt \right\}^2 \right)^{1/2} dy \right)^2 \\
&\leq d^2 r^4 \left( \int_{B(x,r)} \left( \sum_{|\alpha|=2} \int_0^1 (1-t)^2 [\mathcal{D}^\alpha g(x+t(y-x))]^2 dt \right)^{1/2} dy \right)^2 \\
&= d^2 r^{4+2d} \left( \int_{B(0,1)} \left( \sum_{|\alpha|=2} \int_0^1 (1-t)^2 [\mathcal{D}^\alpha g(x+trz)]^2 dt \right)^{1/2} dz \right)^2 \\
&\leq \frac{d^2 r^{4+2d}}{\nu_d} \int_{B(0,1)} \sum_{|\alpha|=2} \int_0^1 (1-t)^2 [\mathcal{D}^\alpha g(x+trz)]^2 dt dz
\end{aligned}$$

□

## REFERENCES

Veeranjaneyulu Sadhanala, Yu-Xiang Wang, James L Sharpnack, and Ryan J Tibshirani. Higher-order total variation classes on grids: Minimax theory and trend filtering methods. In *Advances in Neural Information Processing Systems*, pages 5800–5810, 2017.