# Graph Testing: Notes for the Week of 12/11 - 12/18

#### Alden Green

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# 1 Setup

**Data model.** We are given two distributions, P and Q, defined over compact set  $\mathcal{X} \subset \mathbb{R}^d$ , with the ability to sample from either one. Our goal is to test the hypothesis  $H_0: P = Q$  vs. the alternative  $H_a: P \neq Q$ .

Under the **binomial data model**, our sampling procedure is to draw i.i.d Rademacher labels  $L_i \in \{1, -1\}$  for  $i \in \{1, ..., N\}$ , and then sample  $Z_i \sim P$  if  $L_i = 1$  and  $Z_i \sim Q$  otherwise. Define  $1_X$  to be the length-N indicator vector for  $L_i = 1$ 

$$1_X[i] = \begin{cases} 1, L_i = 1\\ 0 \text{ otherwise} \end{cases}$$

and similarly for  $1_Y$ 

$$1_Y[j] = \begin{cases} 1, L_i = -1\\ 0 \text{ otherwise} \end{cases}$$

and define  $a = \frac{1_X}{N/2} - \frac{1_Y}{N/2}$ .

Under the **fixed label data model** we use the same data generating process as above, except fix  $\mathcal{L}_X = \{1, \dots, N/2\}$  and  $\mathcal{L}_Y = \{N/2, \dots, N\}$ . Say that  $L_i = 1$  for  $i \in \mathcal{L}_X$  and  $L_i = -1$  for  $i \in \mathcal{L}_Y$ , and call  $\{X_1, \dots, X_{|\mathcal{L}_X|}\} = \{Z_i : i \in \mathcal{L}_X\}$  and likewise for Y.

**Graph.** Form an  $N \times N$  Gram matrix A, where  $A_{ij} = K(Z_i, Z_j)$  for **kernel function** K. Let G = (V, E) with  $V = \{Z_1, \ldots, Z_n\}$  and  $E = \{A_{ij} : 1 \le i < j \le n\}$ . Take L = D - A to be the (unnormalized) **Laplacian matrix** of A (where D is the diagonal degree matrix with  $D_{ii} = \sum_{j \in [n+m]} A_{ij}$ ). Let M be the number of non-zero entries of A. Denote by B the  $M \times N$  incidence matrix of A, where we denote the ith row of B as  $B_i$  and set  $B_i$  to have entry  $A_{ij}$  in position i,  $-A_{ij}$  in position j, and 0 everywhere else.

Test statistics. We define our laplacian smooth test statistic.

$$T_2 = \left(\max_{\theta: \|B\theta\|_2 \le 1} a^T \theta\right)^2 = a^T L^{\dagger} a.$$

Distances between probability measures. An integral probability metric (IPM) with respect to a function class  $\mathcal{F}$  is defined

$$\sup_{f \in \mathcal{F}} \mathbb{E}\left[f(X)\right] - \mathbb{E}\left[f(Y)\right]$$

for  $X \sim P$ ,  $Y \sim Q$ .

Hereafter, we will assume P and Q are absolutely continuous with respect to Lebesgue measure, with density functions p and q, respectively. Denote the **mixture density** by  $\mu = \frac{p+q}{2}$ .

Denote the **gradient** of a function f by  $\nabla_x$ . Then we can define the **Sobolev semi-norm** and **dot product**,  $||f||_{W_0^{1,2}(\mathcal{X},\mu^2)}$  and  $\langle f,g\rangle_{W_0^{1,2}(\mathcal{X},\mu^2)}$ , by

$$\langle f, g \rangle_{W_0^{1,2}(\mathcal{X}, \mu)} = \int_{\mathcal{X}} \langle \nabla_x f(x), \nabla_x g(x) \rangle_{\mathbb{R}^d} \mu^2(x), \quad \|f\|_{W_0^{1,2}(\mathcal{X}, \mu)} = \sqrt{\int_{\mathcal{X}} \|\nabla_x f(x)\|^2 \mu^2(x) dx}$$

Let the **Sobolev space**,  $W^{1,2}(\mathcal{X}, \mu^2)$ , be

$$W^{1,2}(\mathcal{X}, \mu^2) = \left\{ f : \mathcal{X} \to \mathbb{R}, \int_{\mathcal{X}} \|\nabla_x f(x)\|^2 \, \mu^2(x) dx < \infty \right\}.$$

and denote by  $W_0^{1,2}(\mathcal{X},\mu^2)$  the restriction of  $W^{1,2}(\mathcal{X},\mu^2)$  to functions which vanish at the boundary of  $\mathcal{X}$ . Note that  $\|f\|_{W_0^{1,2}(\mathcal{X},\mu^2)}$  defines a semi-norm over  $W_0^{1,2}(\mathcal{X},\mu^2)$ . Finally, let  $B_W(\mathcal{X},\mu^2)$  be the **unit ball** of  $W_0^{1,2}(\mathcal{X},\mu^2)$ , meaning

$$B_W(\mathcal{X},\mu^2) = \left\{ f \in W_0^{1,2}(\mathcal{X},\mu^2) : \|f\|_{W_0^{1,2}(\mathcal{X},\mu^2)} \le 1 \right\}$$

Now we can define the **Sobolev IPM**,  $S_{\mu^2}(P,Q)$  It is simply an IPM where the function class is the Sobolev unit ball with respect to  $\mu^2$ .

$$\mathcal{S}_{\mu^2}(P,Q) \stackrel{\mathrm{def}}{=} \sup_{f \in B_W} \left\{ \mathbb{E}\left[f(X)\right] - \mathbb{E}\left[f(Y)\right] \right\}$$

We will show that the Laplacian constraint  $||B\theta||_2 \leq 1$  is very similar to the constraint  $f_{\theta} \in B_W(X, \mu^2)$  for the right choice of K, over all Holder functions.

**Holder functions** For mapping  $f : \mathbb{R}^d \to \mathbb{R}$  and  $\beta$  a positive integer, we say f is a  $\beta$ -Holder function if there exists C > 0 such that for all  $x, y \in \mathcal{X}$ 

$$\left| f^{(\beta-1)}(x) - f^{(\beta-1)}(y) \right| \le K \|x - y\|$$

Roughly speaking, this means the functions have bounded  $\beta$  partial derivatives.

### 2 DESIRED RESULTS

**Theorem 1.** For bandwidth parameter h > 0 and decreasing function  $k(\cdot, \cdot)$ , write

$$K(Z_i, Z_j) = \frac{1}{h^m} k(\|Z_i - Z_j\|^2 / h^2).$$

For Sobolev IPM  $S_{\mu^2}(P,Q)$  as defined above,

$$\sqrt{T_2} \stackrel{p}{\to} \mathcal{S}_{\mu^2}(P,Q)$$

Proof attempt of Proposition 1. Recall that, for incidence matrix B,

$$\sqrt{T_2} = \left(\max_{\theta:\|B\theta\|_2 \le 1} a^T \theta\right).$$

We expand  $|\sqrt{T_2} - \mathcal{S}_{\mu^2}(P,Q)|$ ,

$$\left| \sqrt{T_2} - \mathcal{S}_{\mu^2}(P, Q) \right| \leq \left| \max_{\theta: \|B\theta\|_2 \leq 1} \left\{ a^T \theta \right\} - \sup_{f \in B_W(\mathcal{X}, \mu^2)} \left\{ \mathbb{P}_n(f) - \mathbb{Q}_n(f) \right\} \right|$$

$$+ \left| \sup_{f \in B_W(\mathcal{X}, \mu^2)} \left\{ \mathbb{P}_n(f) - \mathbb{Q}_n(f) \right\} - \sup_{f \in B_W(\mathcal{X}, \mu^2)} \left\{ \mathbb{P}(f) - \mathbb{Q}(f) \right\} \right|$$

$$\tag{1}$$

(The following statement would hold only if Proposition 1 held over  $B_W(\mathcal{X}, \mu^2)$ , rather than over  $B_W([0,1], \lambda)$  for  $\lambda$  Lebesgue measure.)

By Proposition 1, the second term in the summand on the right hand side of (1) is  $o_P(1)$ .

(The following statement would hold only if Proposition 2 were uniform over  $B_W(\mathcal{X}, \mu^2)$  rather than over the class of  $\alpha$ -Holder functions  $\mathcal{F}_{\alpha}$ )

Then, Proposition 2 implies that for any  $\epsilon > 0$ , there exists N such that for  $n \geq N$ ,

$$\sup_{f \in B_W(\mathcal{X}, \mu^2)} \left\{ \mathbb{P}_n(f) - \mathbb{Q}_n(f) \right\} - \max_{\theta : \|B\theta\|_2 \le 1} \left\{ a^T \theta \right\} \le \epsilon$$

with high probability.

To complete the proof, we will have to show that for any  $\epsilon > 0$ , there exists N such that for  $n \geq N$ ,

$$\max_{\theta:\|B\theta\|_2 \le 1} \left\{ a^T \theta \right\} - \sup_{f \in B_W(\mathcal{X}, \mu^2)} \left\{ \mathbb{P}_n(f) - \mathbb{Q}_n(f) \right\} \le \epsilon$$

with high probability.

# 3 SUPPLEMENTAL RESULTS

**Empirical process over Sobolev classes.** The following theorem is a standin; it handles only functions with domain on the unit interval, and is stated specifically with respect to Lebesgue measure.

**Proposition 1.** Let  $\mathcal{F}$  be the set of all absolutely continuous functions  $f:[0,1]\to\mathbb{R}$  such that  $\|f\|_{\infty}\leq 1$  such that  $\int (f'(x))^2dx\leq 1$ . Then, there exists a constant K such that for every  $\epsilon>0$ ,

$$\log N_{[]}(\epsilon, \mathcal{F}, \|\cdot\|_{\infty}) \le K\left(\frac{1}{\epsilon}\right).$$

Thus, the class  $\mathcal{F}$  is P-Donsker (and P-Glivenko-Cantelli) for all P.

#### Regularization functional.

**Proposition 2.** Let  $\mathcal{F}_{\alpha}$  be a unit ball in the space of  $\alpha$ -Holder functions, and define  $k(\cdot, \cdot)$  as in Theorem 1. For function  $f \in \mathcal{F}_{\alpha}$ , denote f evaluated on the data,  $\mathbf{f} = (f(Z_1), \ldots, f(Z_N))$ . Then, there exists a constant c depending only on k such that for  $\alpha \geq 3$  and a sequence  $(h_n) \to 0$  such that

$$\sup_{f \in \mathcal{F}_{\alpha}} \left| \|B\mathbf{f}_{2}\| - \|f\|_{W_{0}^{1,2}(\mathcal{X},\mu^{2})} \right| \xrightarrow{p} 0$$

### 4 PROOFS