## SLMath Exercise Sheet 2

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This is a long list of exercises, of very different flavors. I encourage you to attempt all or most of them, but only complete those that speak to you.

1. We proved the bound  $\mathbb{E}\sup_{\nu\in\mathcal{P}(B_1)}|S_{\varepsilon}(\mu_n,\nu)-S_{\varepsilon}(\mu,\nu)|\lesssim_{s,d}\varepsilon^{-s+1}n^{-1/2}$  for any s>d/2 when  $\mu\in\mathcal{P}(B_1)$  and  $\varepsilon<1$ . Show that when  $\varepsilon>1$ ,

$$\mathbb{E} \sup_{\nu \in \mathcal{P}(B_1)} |S_{\varepsilon}(\mu_n, \nu) - S_{\varepsilon}(\mu, \nu)| \lesssim_{s, d} n^{-1/2}, \tag{1}$$

with no dependence on  $\varepsilon$ . (Hint: it suffices to show that  $||D^{\alpha}\varphi||_{\infty} \lesssim_{\alpha} 1$  when  $\varepsilon > 1$ .)

2. Prove the Faà di Bruno formula

$$D^{\alpha} \log j(x) = \sum_{v=1}^{|\alpha|} \frac{(-1)^{v-1}}{v} \sum_{\beta_1 + \dots + \beta_v = \alpha} \prod_{\ell=1}^{v} \frac{D^{\beta_{\ell}} j(x)}{j(x)}.$$
 (2)

in two ways:

- (a) By induction on  $\alpha$
- (b) By examination of the power series  $\log(j(x) + y) = \log j(x) + \sum_{v=1}^{\infty} \frac{(-1)^{v-1} y^v}{v j(x)^v}$  and  $j(x+z) = \sum_{\beta>0} \frac{D^{\beta} j(x) z^{\beta}}{\beta!}$ .
- 3. In the lecture, we claimed that the bound  $\int (1+\|\xi\|^2)^s |\bar{\Phi}(\xi)|^2 d\xi \lesssim_s \varepsilon^{-2s+2}$  for all  $s \geq 1$  follows from the bound where s is a positive integer by "interpolation." This exercise justifies this claim.
  - (a) Let  $t \in (0,1)$  and let  $p,q \in (1,\infty)$ . Via Hölder's inequality, show the  $L_p$  interpolation inequality

$$||h||_{L_r} \le ||h||_{L_p}^t ||h||_{L_q}^{1-t}$$

where  $\frac{1}{r} = \frac{t}{p} + \frac{1-t}{q}$ .

(b) Arguing as in part (a), show that for any integer k and  $\delta \in (0,1)$ ,

$$\int (1 + \|\xi\|^2)^{k+\delta} |\bar{\Phi}(\xi)|^2 d\xi \le \left( \int (1 + \|\xi\|^2)^k |\bar{\Phi}(\xi)|^2 d\xi \right)^{1-\delta} \left( \int (1 + \|\xi\|^2)^{k+1} |\bar{\Phi}(\xi)|^2 d\xi \right)^{\delta}.$$
 (3)

Conclude that the bound claimed in lecture holds.

- 4. This exercise establishes some important facts about Reproducing Kernel Hilbert Spaces (RKHS). A Hilbert space  $\mathcal{H}$  of functions from a set  $\mathcal{X}$  to  $\mathbb{R}$  is an RKHS if, for each  $x \in \mathcal{X}$ , the evaluation functional  $\delta_x : \mathcal{H} \to \mathbb{R}$  given by  $f \mapsto f(x)$  is continuous.
  - (a) Using the calculation given in the lecture, verify that the Sobolev space  $H^s(\mathbb{R}^d)$  is an RKHS when s > d/2.
  - (b) For each  $x \in \mathcal{X}$ , show the existence of a  $k_x \in \mathcal{H}$  such that  $f(x) = \langle k_x, f \rangle_{\mathcal{H}}$  for all  $f \in \mathcal{H}$ . (Hint: Riesz representation theorem.)

- (c) Using the functionals constructed in part (b), define the kernel  $k: \mathcal{X} \times \mathcal{X} \to \mathbb{R}$  by  $k(x,y) := \langle k_x, k_y \rangle_{\mathcal{H}}$ . Show that k is symmetric (i.e., k(x,y) = k(y,x)) and positive (i.e.,  $\sum_{i,j=1}^n a_i a_j k(x_i,x_j) \geq 0$  for all  $a_1,\ldots,a_n \in \mathbb{R}$  and  $x_1,\ldots,x_n \in \mathcal{X}$ ).
- (d) Prove the representer property: for each  $x \in X$ , the function  $k(\cdot, x) \in \mathcal{H}$  and  $\langle k(\cdot, x), f \rangle_{\mathcal{H}} = f(x)$ .
- (e) Show that if  $\sup_{x \in \mathcal{X}} k(x, x) < \infty$ , then all the functions in  $\mathcal{H}$  are bounded. (Hint:  $k(x, x) = \|k_x\|_{\mathcal{H}}^2$ .)
- (f) Show that  $\mathcal{H} = \overline{\operatorname{span}(k(\cdot,x): x \in \mathcal{X})}$ . (Hint: it suffices to show that if  $f \perp k(\cdot,x)$  for all  $x \in \mathcal{X}$ , then f = 0.) This shows that the kernel k completely determines H. In fact, for every symmetric, positive  $k: \mathcal{X} \times \mathcal{X} \to \mathbb{R}$  there exists a unique (up to isomorphism) RKHS with k as its kernel.
- (g) Let  $(\mathcal{Y}, \nu)$  be a measure space, and fix a function  $\phi : \mathcal{X} \times \mathcal{Y} \to \mathbb{R}$ . Assume that for each  $x \in \mathcal{X}$  the function  $y \mapsto \phi(x, y)$  lies in  $L_2(Y, \nu)$ . Show that the space

$$\mathcal{H} := \left\{ \int_{\mathcal{V}} \phi(x, y) g(y) \, \mathrm{d}\nu(y) : g \in L_2(\mathcal{Y}, \nu) \right\}$$
 (4)

equipped with the norm  $||f||_{\mathcal{H}} := \inf\{||g||_{L_2} : f = \int_{\mathcal{Y}} \phi(\cdot, y)g(y) \,\mathrm{d}\nu(y)\}$  is an RKHS. Show that this generalizes the example of the Sobolev space considered in part (a).

- 5. (Statistical Optimal Transport, Section 2.8.2) This exercise establishes some statistical properties of RKHS's. We have already seen that  $\sup_{\varphi:\|\varphi\|_{H^s}\leq 1}\int \varphi\,\mathrm{d}(\mu_n-\mu)\lesssim n^{-1/2}$ . We will now show that this phenomenon is more general.
  - (a) Let  $\mathcal{H}$  be an RKHS with kernel k which satisfies  $\sup_{x \in \mathcal{X}} k(x, x) < \infty$ . Show that for any  $\mu \in \mathcal{P}(\mathcal{X})$ , the function  $f_{\mu}$  defined by

$$f_{\mu}(x) = \int k(x, x') \,\mathrm{d}\mu(x') \tag{5}$$

defines an element of  $\mathcal{H}$ , which satisfies  $\langle f_{\mu}, g \rangle_{\mathcal{H}} = \int g \, d\mu$  for any  $g \in \mathcal{H}$ . The function  $f_{\mu}$  is sometimes called the "kernel mean embedding" of  $\mu$ .

(b) Show that for any probability measures  $\mu$  and  $\nu$ ,

$$\sup_{g \in \mathcal{H}: \|g\|_{\mathcal{H}} \le 1} \int g \, \mathrm{d}(\mu - \nu) = \|f_{\mu} - f_{\nu}\|_{\mathcal{H}},$$
 (6)

where  $f_{\mu}$  and  $f_{\nu}$  are the kernel mean embeddings of  $\mu$  and  $\nu$ .

(c) Show that if  $\mu_n$  is an empirical measure, then  $\mathbb{E}||f_{\mu} - f_{\mu_n}|| \lesssim n^{-1/2}$ . Conclude that for any RKHS whose kernel is bounded,

$$\mathbb{E} \sup_{g \in \mathcal{H}: \|g\|_{\mathcal{H}} \le 1} \int g \, \mathrm{d}(\mu_n - \mu) \lesssim n^{-1/2} \,. \tag{7}$$

6. This exercise verifies some basic facts about dual solutions to the entropic optimal transport problem. Let  $(f_n, g_n)$  be optimal solutions to the dual entropic OT problem

$$\sup_{f,g} \int f \, \mathrm{d}\mu_n + \int g \, \mathrm{d}\nu - \varepsilon \int e^{\frac{f(x) + g(y) - \frac{1}{2} \|x - y\|^2}{\varepsilon}} \, \mathrm{d}\mu_n(x) \, \mathrm{d}\nu(y) \,, \tag{8}$$

where as usual  $\mu, \nu \in \mathcal{P}(B_1)$  and  $\mu_n$  is an empirical measure. Write  $\varphi_n(x) = \frac{1}{2} ||x||^2 - f_n(x)$ .

- (a) Show that if  $(f_n, g_n)$  are optimal solutions, then so are  $(f_n + c, g_n c)$  for any constant c, so there is no uniqueness in the solution to the dual problem.
- (b) Show that the normalization  $\int f_n d\mu = 0$  is enough to ensure that  $(f_n, g_n)$  are unique.
- (c) Show that if the solutions are normalized such that  $\int f_n d\mu = 0$ , then  $\sup_{x \in B_2} \varphi_n(x) \leq 3$ .

- 7. This exercise gives practice with "big-Oh in probability" notation. Recall that we say that  $X_n = o_p(a_n)$  for some positive sequence  $a_n$  if  $a_n^{-1}X_n \stackrel{p}{\to} 0$ , and  $X_n = O_p(a_n)$  if for any  $\varepsilon > 0$  there exists a positive R such that  $\mathbb{P}\{|X_n| \leq a_n R\} \leq \varepsilon$  for all n.
  - (a) Show that if  $X_n = o_p(a_n)$  and  $Y_n = O_p(b_n)$ , then  $X_n Y_n = o_p(a_n b_n)$ .
  - (b) Conclude that the quantity  $\Delta_n$  as defined in the lecture is  $o_p(n^{-1/2})$ , as claimed.
- 8. This exercise completes the proof of the limit theorem for the Wasserstein distances on finite metric spaces.
  - (a) Prove the continuous mapping theorem, if you don't know it already: if  $Z_n \stackrel{d}{\to} Z$  and g is continuous, then  $g(Z_n) \stackrel{d}{\to} g(Z)$ . (Hint: recall that  $Z_n \stackrel{d}{\to} Z$  means that  $\mathbb{E}h(Z_n) \to \mathbb{E}h(Z)$  for all continuous, bounded h.)
  - (b) Use this to show that

$$\sqrt{n} \sup_{f^* \in \mathcal{D}^*} \langle f^*, \mu_n - \mu \rangle \xrightarrow{d} \sup_{f^* \in \mathcal{D}^*} \langle f^*, G \rangle, \tag{9}$$

where  $G \sim \mathcal{N}(0, \Sigma)$ , with  $\Sigma_{ii} = \mu_i(1 - \mu_i)$ .

- 9. Since  $\sqrt{n}W_p^p(\mu_n,\nu) \geq 0$ , the same property must hold for its distributional limit. Use the expression developed in lecture to verify that this is the case.
  - (a) Show that, when  $\mu = \nu$ , the set  $\mathcal{D}^*$  satisfies

$$\mathcal{D}^* = \{ f \in \mathbb{R}^k : f(x) - f(x') \le d^p(x, x') \}$$
 (10)

- (b) Conclude that, in this case,  $\sup_{f^* \in \mathcal{D}^*} \langle f^*, G \rangle \geq 0$ , and that it is almost surely positive if  $\mu$  is supported on at least 2 points.
- 10. Mimic the analysis of the entropic optimal transport problem to show that if  $f_n \in \mathcal{D}_n$  is a sequence of optimal dual solutions for  $(\mu_n, \nu)$  and if  $f_{\infty}$  is any limit point, then  $f_{\infty} \in \mathcal{D}^*$  almost surely.
- 11. Let  $\nu \in \mathcal{P}_2(\mathbb{R}^d)$  be an absolutely continuous probability measure such that  $\nu$  has positive density on int supp  $\nu$  and such that supp  $\nu$  is convex, and let  $\mu \in \mathcal{P}_2(\mathbb{R}^d)$  be arbitrary. Show that the optimal solution to the dual problem

$$\sup_{\psi} \int ||x||^2 - 2\psi^*(x) \,\mathrm{d}\mu + \int ||y||^2 - 2\psi(y) \,\mathrm{d}\nu \tag{11}$$

is unique up to a constant shift. Defining  $\phi$  to be the convex conjugate of the optimal  $\psi$  yields a canonical pair of optimal potentials, up to constant shift. (Hint: Brenier's theorem implies that  $\nabla \psi$  is well defined and unique almost everywhere on int supp  $\nu$ .)

- 12. This exercise justifies the variance bounds presented in Lecture 4.
  - (a) Prove the Efron–Stein inequality, if you don't know it already: let  $X_1, \ldots, X_n$  be i.i.d. random variables, let  $Z = f(X_1, \ldots, X_n)$  for some function f, and write  $Z_i = f(X_1, \ldots, X_i', \ldots, X_n)$  for a version of Z where  $X_i$  is replaced by an independent copy  $X_i'$ . Then

$$\operatorname{Var}(Z) \le \sum_{i=1}^{n} \mathbb{E}(Z - Z_i)_{+}^{2}. \tag{12}$$

(Hint: Let  $\Delta_i = \mathbb{E}[Z \mid X_1, \dots, X_i] - \mathbb{E}[Z \mid X_1, \dots, X_{i-1}]$ . Show that  $\operatorname{Var}(Z) = \sum_{i=1}^n \mathbb{E}\Delta_i^2$ . Then, show that  $\mathbb{E}\Delta_i^2 \leq \mathbb{E}(Z - \mathbb{E}[Z \mid \{X_j : j \neq i\}])^2$ . Finally, use the identity  $\operatorname{Var}(W) = (W - W')_+^2$ , whenever W' is an i.i.d. copy of W.)

- (b) Let  $(\mathcal{X}, d)$  be any compact metric space, and let  $\mu, \nu \in \mathcal{P}(\mathcal{X})$  be arbitrary. Use the Efron-Stein inequality to prove that  $Var(W_2^2(\mu_n, \nu)) \lesssim n^{-1}$ . (Hint: view  $W_2^2(\mu_n, \nu)$  as a function of n i.i.d. samples from  $\mu$ .)
- (c) Let  $\nu$  satisfy the assumptions of the previous problem, so that there exist unique dual solutions for the 2-Wasserstein distance  $\nu$  and any element of  $\mathcal{P}_2(\mathbb{R}^d)$ . Assume that  $\mu$  and  $\nu$  are compactly supported. Let  $\mu_n$  be the empirical measure corresponding to  $(X_1, \ldots, X_n)$  and let  $\mu'_n$  correspond to  $(X'_1, X_2, \ldots, X_n)$ . We aim to show that  $\operatorname{Var}\left(W_2^2(\mu_n, \nu) - \int (\|\cdot\|^2 - 2\varphi^*) \,\mathrm{d}\mu_n\right) = o(n^{-1})$ , where  $\varphi^*$  is the (unique) optimal dual solution for  $(\mu, \nu)$ 
  - i. Let  $\varphi_n$  be the unique optimal dual solution for  $(\mu_n, \nu)$ . Show that, up to a constant shift,  $\varphi_n \to \varphi^*$  uniformly on the support of  $\mu$  almost surely.
  - ii. Using the Efron–Stein inequality, argue that it suffices to prove that  $n^2\mathbb{E}(R_n-R_n')_+^2\to 0$ ,
  - where  $R_n = W_2(\mu_n, \nu) \int (\|\cdot\|^2 2\varphi^*) d\mu_n$  and  $R'_n = W_2(\mu'_n, \nu) \int (\|\cdot\|^2 2\varphi^*) d\mu'_n$ . iii. Show that  $R_n R'_n \leq \frac{2}{n}((\varphi^*(X_1) \varphi_n(X_1)) (\varphi^*(X_1') \varphi_n(X_1')))$ . Conclude that  $n^2(R_n R'_n)^2_+ \lesssim \|\varphi^* \varphi_n\|^2_{L_{\infty}(\mu)}$ .
  - iv. Argue that  $\mathbb{E}\|\varphi^* \varphi_n\|_{L_{\infty}(\mu)}^2 \to 0$ .