

## STAT 222: Bayesian Nonparametric Methods (Spring 2020)

Homework set on Dirichlet processes: prior properties and simulation  
(due Wednesday April 22)

1. Assume that random vector  $(Y_1, \dots, Y_k)$  follows a Dirichlet( $k; a_1, \dots, a_k$ ) distribution, such that  $(Y_1, \dots, Y_{k-1})$  has density

$$\frac{\Gamma(a_1 + \dots + a_k)}{\Gamma(a_1) \times \dots \times \Gamma(a_k)} y_1^{a_1-1} \times \dots \times y_{k-1}^{a_{k-1}-1} \times (1 - y_1 - \dots - y_{k-1})^{a_k-1}$$

where  $y_i > 0$ , for  $i = 1, \dots, k-1$ , and  $\sum_{i=1}^{k-1} y_i < 1$ . Consider a partition  $I_1, \dots, I_M$  of  $\{1, \dots, k\}$  (so that the  $I_j$ ,  $j = 1, \dots, M$ , are pairwise disjoint, and their union is  $\{1, \dots, k\}$ ), and let  $U_j = \sum_{i \in I_j} Y_i$ , for  $j = 1, \dots, M$ . Show that:

- (1)  $(U_1, \dots, U_M)$  follows a Dirichlet( $M; b_1, \dots, b_M$ ) distribution, where  $b_j = \sum_{i \in I_j} a_i$ , for  $j = 1, \dots, M$ .
- (2)  $(Y_i/U_j : i \in I_j) \stackrel{ind.}{\sim} \text{Dirichlet}(M_j; a_i, i \in I_j)$ , for  $j = 1, \dots, M$ , where  $M_j$  is the size of  $I_j$ .
- (3)  $(U_1, \dots, U_M)$  and  $(Y_i/U_j : i \in I_j)$ ,  $j = 1, \dots, M$ , are independent.

(**Hint.** Use the definition of the Dirichlet distribution in terms of independent gamma random variables: the Dirichlet( $k; a_1, \dots, a_k$ ) distributed random vector  $(Y_1, \dots, Y_k)$  can be constructed as  $(Y_1, \dots, Y_k) = (Z_1/Z, \dots, Z_k/Z)$ , where  $Z_i \stackrel{ind.}{\sim} \text{gamma}(a_i, 1)$ , for  $i = 1, \dots, k$ , and  $Z = \sum_{i=1}^k Z_i$ . Moreover,  $(Z_1/Z, \dots, Z_k/Z)$  is independent of  $Z$ .)

For problems 2 and 3, consider a Dirichlet process (DP) prior,  $\text{DP}(\alpha, P_0)$ , for distributions (probability measures)  $P$  on sample space  $\mathcal{X}$ , where  $\alpha > 0$  is the total mass (precision) parameter, and  $P_0$  is a specified distribution on  $\mathcal{X}$ .

2. Show that for any (measurable) disjoint subsets  $B_1$  and  $B_2$  of  $\mathcal{X}$ ,  $\text{Corr}(P(B_1), P(B_2))$  is negative. Is the negative correlation for random probabilities induced by the DP prior a restriction? Discuss.

3. Let  $B$  be a specific (measurable) subset of  $\mathcal{X}$  such that  $P_0(B) > 0$ , and denote by  $P_B$  the corresponding conditional distribution, that is,  $P_B(A) = P(A | B) = P(A \cap B)/P(B)$ .

- (a) Prove that if  $P \sim \text{DP}(\alpha, P_0)$ , then  $P_B \sim \text{DP}(\alpha P_0(B), P_0(A | B))$ , that is, a DP with precision parameter  $\alpha P_0(B)$  and centering distribution  $P_0(A | B) = P_0(A \cap B)/P_0(B)$ .
- (b) Consider finite measurable partitions  $A_1, \dots, A_r$  and  $C_1, \dots, C_s$  of  $B$  and  $B^c$ , respectively. Show that  $P(B)$ ,  $P(B^c)$ ,  $\{P_B(A_1), \dots, P_B(A_r)\}$  and  $\{P_{B^c}(C_1), \dots, P_{B^c}(C_s)\}$  are independent.

(**Hint.** Use problem 1. Note that, given the definition of the conditional distribution  $P_B$ , it suffices to consider partitions of  $B$  in order to verify the DP definition for part (a).)

#### 4. Simulation of Dirichlet process prior realizations

Consider a  $\text{DP}(\alpha, G_0)$  prior over the space of distributions (equivalently c.d.f.s)  $G$  on  $\mathbb{R}$ , with  $G_0 = \text{N}(0, 1)$ .

- (a) Use both Ferguson's original definition and Sethuraman's constructive definition to generate (multiple) prior c.d.f. realizations from the  $\text{DP}(\alpha, \text{N}(0, 1))$ , for different values of  $\alpha$  ranging from *small* to *large*.
- (b) In addition to prior c.d.f. realizations, obtain, for each value of  $\alpha$ , the corresponding prior distribution for the mean functional  $\mu(G) = \int t \, dG(t)$  and for the variance functional  $\sigma^2(G) = \int t^2 \, dG(t) - \{\int t \, dG(t)\}^2$ . (Note that, because  $G_0$  has finite first and second moments, both of the random variables  $\mu(G)$  and  $\sigma^2(G)$  take finite values almost surely.)
- (c) Consider also simulation under a mixture of DPs (MDP) prior, which extends the DP above by adding a prior for  $\alpha$ . Therefore, the MDP prior for  $G$  is defined such that,  $G \mid \alpha \sim \text{DP}(\alpha, \text{N}(0, 1))$ , with a prior assigned to precision parameter  $\alpha$ . To simulate from the MDP, you can use either of the DP definitions given draws for  $\alpha$  from its prior. You can work with a gamma prior for  $\alpha$  and 2-3 different choices for the gamma prior parameters.