## Supplementary meterial

# A Bayesian nonparametric procedure for comparing algorithms

#### 1. Proof of Theorem 1

A probability measure sampled from the posterior DP (9) has the following form:

$$P = w_0 P_0 + \sum_{j=1}^n w_j \delta_{\mathbf{X}_j},$$

with  $P_0 \sim Dp(s, \alpha^*)$ . Let us consider  $E[R(X_m)]$  w.r.t. P, we have that

$$E[R(X_i)] = w_0 R_{m0} + \sum_{j=1}^n w_j R_{mj} = w_0 R_{m0} + \mathbf{R}_m^T \mathbf{w},$$

where  $R_{m0} = \int \sum_{k=1}^{m-1} I_{\{X_m > X_k\}}(\mathbf{X}) dP_0(\mathbf{X}), \ R_{mj} = \sum_{k=1}^{m-1} I_{\{X_{mj} > X_{kj}\}} + 1$  and  $\mathbf{R}_m^T = [R_{m1}, \dots, R_{mn}].$  Assuming  $P_0 = \alpha^* = \delta_{\mathbf{x}}$ , we have that  $R_{m0} = \int \sum_{k=1}^{m-1} I_{\{X_m > X_k\}}(\mathbf{X}) d\alpha^*(\mathbf{X})$ . By defining the vector  $\mathbf{R}_0 = [R_{1l}, \dots, R_{m0}]^T$  and the matrix  $\mathbf{R}$  whose rows are the vectors  $\mathbf{R}_m^T$ , we obtain (15).

Since the weights are Dirichlet distributed  $(w_0, \mathbf{w}^T) \sim Dir(s, 1, 1, \dots, 1)$ , it follows that

$$\mathcal{E}\left[E[R(X_1),\ldots,R(X_m)]^T\right] = E_{Dir}[w_0\mathbf{R}_0 + \mathbf{R}\mathbf{w}]$$

where the r.h.s. expected value is taken w.r.t. the Dirichlet distribution above. From  $E_{Dir}[w_0] = s/(s+n)$  and  $E_{Dir}[w_i] = 1/(s+n)$  for i>0, we obtain the mean vector  $\boldsymbol{\mu}$  in (16). The covariance matrix can be obtained in a similar way by computing  $E_{Dir}[w_0^2]$ ,  $E_{Dir}[\mathbf{w}^T w_0]$ ,  $E_{Dir}[\mathbf{w}\mathbf{w}^T]$  etc..

#### 2. Proof of Theorem 2

From (13) we can write

$$\mathcal{P}\left[P(X_{2} > X_{1}) + \frac{1}{2}P(X_{2} = X_{1}) > \frac{1}{2}\right]$$

$$= P_{Dir}\left[w_{0}\left(P_{0}(X_{2} > X_{1}) + \frac{1}{2}P_{0}(X_{2} = X_{1})\right) + \sum_{i=1}^{n} w_{i}H(X_{2i} - X_{1i}) > \frac{1}{2}\right]$$

$$= P_{Dir}\left[\frac{w_{0}}{2} + \sum_{i=1}^{n} w_{i}H(X_{2i} - X_{1i}) > \frac{1}{2}\right],$$
(1)

where we have used the fact that  $\alpha^* = \delta_{X_1 = X_2}$  and thus  $P_0(X_2 = X_1) = 1$ . By denoting with  $\theta_t = w_0 + w_0$ 

 $\sum_{i=1}^n w_i I_{\{X_{2i}=X_{1i}\}}, \ \theta_g = \sum_{i=1}^n w_i I_{\{X_{2i}>X_{1i}\}} \ \text{and} \ \theta_l = 1-\theta_t-\theta_g, \ \text{and considering a partition of the space} \ \mathbb{X} \ \text{of the form} \ B_0 = \{(X_2,X_1): X_2=X_1\}, \ B_g = \{(X_2,X_1): X_2>X_1\} \ \text{and} \ B_l = \{(X_2,X_1): X_2< X_1\} \ \text{it can easily be verified that} \ \boldsymbol{\theta} = (\theta_t,\theta_g,\theta_l) \ \text{has a Dirichlet distribution} \ \text{with parameters} \ (s+n_t,n_g,n-n_t-n_g). \ \text{Then we have}$ 

$$P_{Dir} \left[ \frac{w_0}{2} + \sum_{i=1}^{n} w_i H(X_{2i} - X_{1i}) > \frac{1}{2} \right]$$

$$= P_{Dir} \left[ \frac{1}{2} \left( w_0 + \sum_{i=1}^{n} w_i I_{\{X_{2i} = X_{1i}\}} \right) + \sum_{i=1}^{n} w_i I_{\{X_{2i} > X_{1i}\}} > \frac{1}{2} \right]$$

$$= \int I_{\{0.5\theta_t + \theta_g > 0.5\}}(\boldsymbol{\theta})$$

$$Dir(\boldsymbol{\theta}; s + n_t, n_g, n - n_t - n_g) d\theta_t d\theta_g$$

$$= K_1 \int_{0}^{1} d\theta_t \int_{0.5(1-\theta_t)}^{1} \theta_t^{s+n_t-1} \theta_g^{n_g-1}$$

$$(1 - \theta_t - \theta_g)^{n-n_t-n_g-1} d\theta_g,$$
(2)

where  $K_1 = \frac{\Gamma(n+s)}{\Gamma(s+n_t)\Gamma(n_g)\Gamma(n-n_t-n_g)}$ . By the change of variables  $\theta_g' = \frac{\theta_g}{1-\theta_t}$  we obtain

$$P_{Dir} \left[ \frac{w_0}{2} + \sum_{i=1}^{n} w_i H(X_{2i} - X_{1i}) > \frac{1}{2} \right]$$

$$= K_1 \int_{0}^{1} \theta_t^{s+n_t-1} (1 - \theta_t)^{n-n_t-1} d\theta_t$$

$$\int_{0.5}^{1} (\theta_g')^{n_g-1} (1 - \theta_g')^{n-n_t-n_g-1} d\theta_g'$$

$$= K_1 K_2 K_3 \int_{0.5}^{1} Beta(\theta; n_g, n - n_t - n_g) d\theta,$$
(3)

where  $K_2=rac{\Gamma(n-n_t)\Gamma(s+n_t)}{\Gamma(s+n)}$  and  $K_3=rac{\Gamma(n_g)\Gamma(n-n_t-n_g)}{\Gamma(n)}$ . This proves the theorem, since  $K_1K_2K_3=1$ .

### 3. Matrix of the ranks of Example 1

Table 1 gives the ranks in n=30 datasets of the four algorithms in Example 1.

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10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32																																
33 34 35																		ns in														
36 37	$\frac{X_1}{X_2}$	3	4 3 2	3 2	3 2	3 2	3 4 2	3 4 2	3 4 2	3 4 2	3 4 2	2 3	2 3	2 3	2 3	2 3	3 2 4	3 2 4	3 2 4	3 2 4	3 2 4	3 4	3 4	2 4 3	2 4 3	3	4 3 1	3 4 1	3 4 1	4 2 1	3 2 1	-
8 9 .0	$X_3$ $X_4$	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	3	4	-
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