Manual of Testing for Equal Distributions Based on E-statistics

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1 Statement of problem

Let X and Y be random vectors in \mathbb{R}^d with distributions F_1 and F_2 respectively, $d \geq 1$. Let $\mathcal{A}_1 = \{X_1, \ldots, X_{n_1}\}, \ \mathcal{A}_2 = \{Y_1, \ldots, Y_{n_2}\}$ be finite sample sets containing random samples $X_i, Y_j \in \mathbb{R}^d$ of X and Y, $i = 1, 2, \ldots, n_1, j = 1, 2, \ldots, n_2$. Need to test $H_0: F_1 = F_2$ against $H_1: F_1 \neq F_2$ at significance level α .

2 Test statistic

The test statistic, namely E-statistic, is given by

$$\varepsilon_{n_1,n_2} = \frac{n_1 n_2}{n_1 + n_2} \left(\frac{2}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{m=1}^{n_2} ||X_i - Y_m|| - \frac{1}{n_1^2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_1} ||X_i - X_j|| - \frac{1}{n_2^2} \sum_{l=1}^{n_2} \sum_{m=1}^{n_2} ||Y_l - Y_m|| \right)$$

$$(1)$$

where $\|\mathbf{a}\|$ denotes the Euclidean norm of some vector \mathbf{a} . The proposed test statistic is based on the V-statistic

$$V_{n_1,n_2} = \frac{1}{n_1^2 n_2^2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_1} \sum_{l=1}^{n_2} \sum_{m=1}^{n_2} h(x_i, x_j; y_l, y_m)$$

associated with the symmetric kernel function

$$h(x_i, x_i; y_l, y_m) = ||x_i - y_l|| + ||x_i - y_m|| - ||x_i - x_i|| - ||y_l - y_m||$$

Under H_0 , we have $E[h(x_i, x_j; y_l, y_m)] = 0$. And since $g(x, y) = E[h(x, X_1; y, Y_1)] = 0$ for almost all (x, y), V_{n_1, n_2} is a degenerate kernel V-statistic. In this case, it can be proved that with necessary moment conditions (on h), degenerate kernel V-statistic V_n satisfies

$$nV_n \xrightarrow{D} \sum_{i=1}^{\infty} \lambda_i Z_i^2$$

where Z_i^2 s are independent $\chi^2(1)$ random variables and λ_i s are constants dependent on distribution F. Since computation shows that

$$\varepsilon_{n_1,n_2} = \frac{n_1 n_2}{n_1 + n_2} V_{n_1,n_2}$$

the test statistic is an asymptotic weighted sum of χ^2 variables. H_0 should be rejected if ε_{n_1,n_2} is too large.

3Test procedure

Concerning the data of us, the total sample size $n = n_1 + n_2$ is large. As a result, the approximate permutation test, instead of the exact permutation test would be more feasible. Procedure:

- 1. Acquire 2 sample sets A_1 , A_2 with cardinalities n_1 , n_2 respectively.
- Acquire pooled samples {W₁,..., W_n} = A₁ ∪ A₂, n = n₁ + n₂.
 Calculate the observed value of test statistic ε^{obs}_n based on A₁, A₂.
- 4. Define $m_j := \sum_{i=1}^{j} n_i$, $j = 1, 2, m_0 = 0$. Determine positive integer B such that $(B+1)\alpha$ is an integer.
- 5. Monte Carlo sampling (without replacement): for $b = 1, 2, \dots, B$, do:

- (a). Acquire {W₁^(b),..., W_n^(b)}, a random permutation of {W₁,..., W_n}.
 (b). Let A_i^(b) = {W_{mi-1+1},..., W_{mi}^(b)}, i = 1, 2.
 (c). Calculate ε_n^(b) based on A₁^(b), A₂^(b).
 6. Define edf of ε_n: F_n(t) = P_n(ε_n ≤ t) := ½ ∑_{b=1}^B I_{ε_n^(b)≤t}. Reject H₀ if ε_n^{obs}
- exceeds $100(1-\alpha)$ percent of the replicates $\varepsilon_n^{(b)}$. OR 7. Estimate p-value: $\hat{p} = \frac{1}{B} \sum_{b=1}^{B} I_{\{\varepsilon_n^{(b)} \geqslant \varepsilon_n^{obs}\}}$. Reject H_0 if $\hat{p} \leqslant \alpha$.

Note that Gandy, A. (2009) Sequential Implementation of Monte Carlo Tests with Uniformly Bounded Resampling Risk provides a good alternative in estimating p-value and bounding power loss of Monte Carlo tests compared with corresponding theoretical tests, which may be used for reference.