

## Consistency of the Cramér-von Mises Test

By  
Kang Sup Lee

*Seoul National University, Seoul, Korea*

### 1. Introduction and summary

It is valuable to study the properties of a test for goodness of fit. The oldest and widely known goodness of fit test is chi-square test for goodness of fit which was introduced by Pearson. In this paper we shall study the properties of the Cramér-von Mises test.

Let  $X_1, X_2, \dots, X_n$  be a random sample of  $n$  observations from some unknown distribution function  $F(x)$ . Let  $X_{(1)} < X_{(2)} < \dots < X_{(n)}$  are the ordered observations. And define the empirical distribution function as following.

$$\begin{aligned} F_n(x) &= 0 && \text{if } x < X_{(1)} \\ &= \frac{k}{n} && \text{if } X_{(k)} \leq x < X_{(k+1)} \\ &= 1 && \text{if } x \geq X_{(n)} \end{aligned}$$

In other word,  $nF_n(x)$  is equal to the number of observations in the sample that are smaller than or equal to  $x$ . If  $F_0(x)$  is a completely specified continuous distribution function, we may reject the null hypothesis that  $F_0 \equiv F$  for large value of

$$d_1 = \frac{1}{12n} + \sum_{k=1}^n \left[ F_0(x_{(k)}) - \frac{2k-1}{2n} \right]^2$$

i. e. rejects the null hypothesis at the level of significance  $\alpha$  if the  $d_1$  exceeds the  $1-\alpha$  quantile  $w_{1-\alpha}$  as given by Anderson and Darling [1]. We say that  $d_1$  is one sample Cramér-von Mises test statistic. Let  $F_n(x)$  be the empirical distribution function based on the random sample  $X_1, X_2, \dots, X_n$  with unknown distribution function  $F(x)$  and let  $G_m(x)$  be the empirical distribution function based on the other random sample  $Y_1, \dots, Y_m$  with unknown distribution function  $G(x)$ . We say that  $d_2$  is two sample Cramér-von Mises statistic

$$d_2 = \frac{\dots}{(m+n)^2} \sum_{\substack{x=x_i \\ x=x_j}} [F_n(x) - G_m(x)]^2 \quad [2]$$

Reject the null hypothesis  $F(x) \equiv G(x)$  at the approximate level  $\alpha$  if  $d_2$  exceeds the  $1-\alpha$  quantile  $w_{1-\alpha}$  as given by Anderson. and Darling, [1].

Thompson, R. [4] showed that the one sample Cramér-von Mises test is biased.

The objects of this paper are as follows;

In Theorem 2-1, we show that the one sample Cramér-von Mises test is consistent.

In Theorem 2-2, We show that the two sample Cramér-von Mises test is consistent.

## 2. Consistency

**Definition.** A test is said to be consistent against a class of alternatives if with increasing sample size probability that it rejects the hypothesis being tested tends 1 whenever one of the alternatives in the class is true.

The following lemmas are discussed in [3].

**Lemma 1.** Let  $F_n(x)$  be the empirical distribution of a sample size  $n$  from  $F(x)$ , then

$$P\left[F_n(x) = \frac{k}{n}\right] = \binom{n}{k} [F(x)]^k [1-F(x)]^{n-k}, \quad k=0, 1, 2, \dots, n$$

According to lemma 1,

**Lemma 2.** Let  $E[F_n(x)]$ ,  $\text{var}[F_n(x)]$  denote the mean and variance of  $F_n(x)$ , respectively; then

$$E[F_n(x)] = F(x)$$

$$\text{var}[F_n(x)] = \frac{1}{n} F(x) [1-F(x)]$$

Lemma 2 show that for fixed  $x$ ,  $F_n(x)$  is an unbiased and mean-squared-error consistent estimator of  $F(x)$ . And by the following Glivenko-Cantelli theorem.

$$P\left[\sup_x |F_n(x) - F(x)| \rightarrow 0\right] = 1 \quad \text{as } n \rightarrow \infty$$

the estimating function  $F_n(x)$  of the  $F(x)$  converges to  $F(x)$  uniformly for all  $x$  with probability one. Thus the  $F_n(x)$  is a consistent estimator of  $F(x)$ .

**Theorem 2-1.** One sample Cramér-von Mises test is consistent.

**Proof.** Let the null hypothesis be  $F_0(x) = F(x)$  and the alternative hypothesis be  $F_1(x)$ , where  $F_1(x) \neq F_0(x)$ . Let  $\Delta = F_0(x_{(k)}) - F_1(x_{(k)})$ , that is,  $F_0(x_{(k)}) = F_1(x_{(k)}) + \Delta$ . Then  $\Delta$  is a number which is concerned with sample size  $n$  such that  $0 < |\Delta| \leq 1$ . However, we choose then sufficiently large,  $\Delta$  doesn't converge to 0 since  $F_0$  is different from  $F_1$ . Let

$$d_1 = \frac{1}{12n} + \sum_{k=1}^n \left[ F_0(x_{(k)}) - \frac{2k-1}{2n} \right]^2$$

$$d_1' = \frac{1}{12n} + \sum_{k=1}^n \left[ F_1(x_{(k)}) - \frac{2k-1}{2n} \right]^2$$

Then the probability of rejecting the null hypothesis  $P\{d_1 > w_{1-\alpha}\}$  when a alternative hypothesis is true is

$$P\{d_1 > w_{1-\alpha}\} = 1 - P\{d_1 \leq w_{1-\alpha}\}$$

$$= 1 - P\left\{ \frac{1}{12n} + \sum_{k=1}^n \left[ F_0(x_{(k)}) - \frac{2k-1}{2n} \right]^2 \leq w_{1-\alpha} \right\}$$

$$= 1 - P\left\{ \frac{1}{12n} + \sum_{k=1}^n \left[ F_1(x_{(k)}) + \Delta - \frac{2k-1}{2n} \right]^2 \leq w_{1-\alpha} \right\}$$

$$= 1 - P\left\{ d_1' + 2\Delta \sum_{k=1}^n F_1(x_{(k)}) - 4n + 4^2 n \leq w_{1-\alpha} \right\}$$

Here, we have

$$\sum_{k=1}^n F_1(x_{(k)}) \rightarrow \frac{n+1}{2} \quad \text{with probability one. Thus the equation (1) tends}$$

$$1 - P\{d_1' + 4^2 n \leq w_{1-\alpha}\}$$

$$\begin{aligned}
&= 1 - P\left\{-\frac{\delta}{\sqrt{n}} \leq \Delta \leq \frac{\delta}{\sqrt{n}}\right\}, \text{ where } \delta^2 = \max(0, w_{1-\alpha} - \Delta - d_1') \\
&= 1 - P\left\{-\frac{\delta}{\sqrt{n}} \leq F_0(x_{(k)}) - F(x_{(k)}) \leq \frac{\delta}{\sqrt{n}}\right\} \\
&= 1 - P\left\{\frac{\kappa - \delta}{\eta} \leq \frac{k}{\eta} \leq \frac{\kappa + \delta}{\eta}\right\} \\
&= 1 - \int_{\lambda_1}^{\lambda_2} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt \quad \text{by } F_1(x) = F(x) \text{ and lemma 2.}
\end{aligned}$$

where  $\kappa = [F_n(x_{(k)}) - F_0(x_{(k)})] \sqrt{n}$ ,  $\eta = \sqrt{F_1(x_{(k)}) [1 - F_1(x_{(k)})]}$ ,

$$\lambda_1 = \frac{\kappa - \delta}{\eta} \quad \text{and} \quad \lambda_2 = \frac{\kappa + \delta}{\eta}$$

For sufficiently large  $n$ , both  $\kappa - \delta$  and  $\kappa + \delta$  have the same sign. Thus the probability that it rejects the hypothesis when a alternative is true tends to 1. Q.E.D.

**Lemma 3.**  $\text{var}[F_n(x) - G_n(y)] = \frac{1}{n} [F(x) - G(y)] [1 - F(x) + G(y)]$

**Theorem 2-2.** Two sample Cramér-von Mises test is consistent.

**Proof.** Two sample Cramér-von Mises test statistic  $d_2$  is defined as

$$d_2 = \frac{mn}{(m+n)^2} \sum_{\substack{x=x_i \\ y=y_j}} [F_n(x) - G_m(x)]^2$$

Then,

$$d_2 = \frac{mn}{(m+n)^2} \left\{ \sum_{i=1}^n [F_n(x_i) - G_m(x_i)]^2 + \sum_{j=1}^m [F_n(y_j) - G_m(y_j)]^2 \right\}$$

According to the Glivenko-Cantelli theorem, we have

$$\begin{aligned}
d_2 &= \frac{mn}{(m+n)^2} \left\{ \sum_{i=1}^n [F_n(x_i) - F_0(x_i)]^2 + \sum_{j=1}^m [F_n(y_j) - F_0(y_j)]^2 \right\} \\
&= \frac{mn}{(m+n)^2} \left\{ \sum_{i=1}^n \left[ F_0(x_i) - \frac{i}{n} \right]^2 + \sum_{j=1}^m \left[ F_0(y_j) - \frac{j}{n} \right]^2 \right\}
\end{aligned}$$

Let  $\Delta = F_0(x_i) - F_1(x_i)$ , then the above equation approaches

$$d_2' + \frac{mn\Delta^2}{m+n} + \frac{m+1}{2} \left(1 - \frac{m}{n}\right) \text{ where}$$

$$d_2' = \frac{mn}{(m+n)^2} \left\{ \sum_{i=1}^n \left[ F_1(x_i) - \frac{i}{n} \right]^2 + \sum_{j=1}^m \left[ F_1(y_j) - \frac{j}{n} \right]^2 \right\}. \text{ Thus}$$

$$P\{d_2 > w_{1-\alpha}\} = 1 - P\{d_2 \leq w_{1-\alpha}\}$$

$$\begin{aligned}
&= 1 - P\left\{d_2' + \frac{mn}{m+n} \Delta^2 + \frac{m+1}{2} \left(1 - \frac{m}{n}\right) \leq w_{1-\alpha}\right\} \\
&= 1 - P\left\{-\eta \leq \Delta \leq \eta\right\}, \text{ where } \eta^2 = \frac{\max\left(0, w_{1-\alpha} - d_2' - \frac{m+1}{2} \left(1 - \frac{m}{n}\right)\right)}{\frac{mn}{m+n}} \\
&= 1 - P\left\{\frac{\kappa - \eta}{\sigma} \leq \frac{F_n(x_i) - G_m(y_j) - [F_1(x_i) - G(y_j)]}{\sigma} \leq \frac{\kappa + \eta}{\sigma}\right\} \\
&= 1 - \int_{\lambda_1}^{\lambda_2} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt
\end{aligned}$$

where  $\kappa = F_n(x_i) - G_m(y_j) - [F_0(x_i) - G(y_j)]$ ,

$$\sigma = \sqrt{\frac{m+n}{mn}} \sqrt{[F(x) - G(y)][1 - F(x) + G(y)]},$$

$$\lambda_1 = \frac{\kappa - \eta}{\sigma} \quad \text{and} \quad \lambda_2 = \frac{\kappa + \eta}{\sigma}$$

Since  $\lambda_1$  and  $\lambda_2$  are same sign as  $m, n \rightarrow \infty$ ,  $\int_{\lambda_1}^{\lambda_2} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt$   
tendsto 0 with probability 1. Q.E.D.

### References

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