

Testing independence of simulation subruns: a note on the power of the Von Neumann test

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Received 9 April 1981

In simulation experiments confidence intervals may be based on subruns. To test whether subruns are independent the Von Neumann statistic is often used. This note shows that the power of this statistic may be very small. The practical recommendation is to apply the statistic only if at least 100 subruns are available.

The simulation literature shows a continuing interest in the use of subruns for the derivation of confidence intervals; see [2,4,5,6]. In such an approach the total run is divided into, say, n subruns, and the subrun-averages are tested for independence. A popular statistic to test for independence is the Von Neumann ratio; see [7]. The purpose of the present note is to emphasize that the power (complement of β -error) of this test statistic is small for less than, say, 100 observations, i.e., if $n < 100$, then there is a sizable chance that the experimenter erroneously accepts the independence hypothesis. Note that this power issue is indirectly addressed in [4, pp. 518–519].

The Von Neumann statistic is defined as

$$Q = \frac{\sum_{i=1}^{n-1} (x_{i+1} - x_i)^2}{\sum_{i=1}^n (x_i - \bar{x})^2}. \quad (1)$$

If H_0 denotes the hypothesis of independent x , then

$$E(Q|H_0) = 2. \quad (2)$$

If moreover x is normally distributed, then

$$\sigma^2(Q|H_0) = 4(n-2)/(n-1)(n+1). \quad (3)$$

Hence while the expected value remains 2 for any n the standard deviation is quite large for small n , for instance, 0.57 for $n = 10$ and 0.20 for $n = 100$. For $n > 20$ the distribution of Q may be approximated by a normal distribution.

We wish to concentrate on the power of the above test as a function of the sample size n . Therefore we assume that x is indeed normal. We characterize the dependence among the x through the first-order autocorrelation coefficient ρ_1 . We quantify the power of the test in two ways, namely analytically introducing some additional assumptions, and empirically using Monte Carlo simulation.

Analytically it is well known that

$$E(Q) = 2 - \frac{2}{n} - 2E(\hat{\rho}_1). \quad (4)$$

If we further assume that under the alternative hypothesis H_1 , the statistic Q remains normally distributed with the variance, say σ^2 , shown in (3), then (5) results:

$$E\{Q|H_1\} = E\{Q|H_0\} - 1.96\sigma - D_\beta\sigma \quad (5)$$

where D_β stands for the distance between the mean and the $\beta\%$ point of the H_1 distribution. Substituting (3) and (4) into (5) enables us to compute the relation between ρ_1 and β for different n values (provided we neglect the bias of $\hat{\rho}_1$; see below). This results in Table 1; see also fig. 1. This table means that, e.g., a correlation between successive observations of 0.92 results in acceptance of H_0 in 5% of the applications in which 10 subruns are available.

The analytical derivation can be checked through a Monte Carlo simulation. This simulation generates normally distributed variables x with prescribed ρ_1 ; see [3, p. 234]. The experiment is replicated 100 times for each n value; ρ_1 varies between 0.001 and 0.5. This experiment yields the dashed curves in Fig. 1. The simulation confirms the analytical result except in the situation of $n = 10$ subruns. This deviation is probably explained by the bias of $\hat{\rho}_1$ for instance $E\{\hat{\rho}_1|H_0\} \approx -1/n$. The exact bias under H_1 is complicated

Table 1
 ρ_1 as a function of number of subruns n and β -error ($\alpha=0.05$)

Sample size	β (in%)							
	5	10	15	25	50	75	90	97.5
10	0.92	0.82	0.75	0.65	0.46	0.26	0.09	0
50	0.48	0.43	0.40	0.35	0.25	0.16	0.07	0
100	0.35	0.31	0.29	0.25	0.18	0.12	0.06	0

and depends on the structure of the x -process; see [1].

In conclusion, it may be good practice to compute confidence intervals in simulation from only

10 to 20 subruns; see [6]. However, first it must be decided whether the batches are independent. The Von Neumann test yields reliable results only if, say, 100 subruns are available!

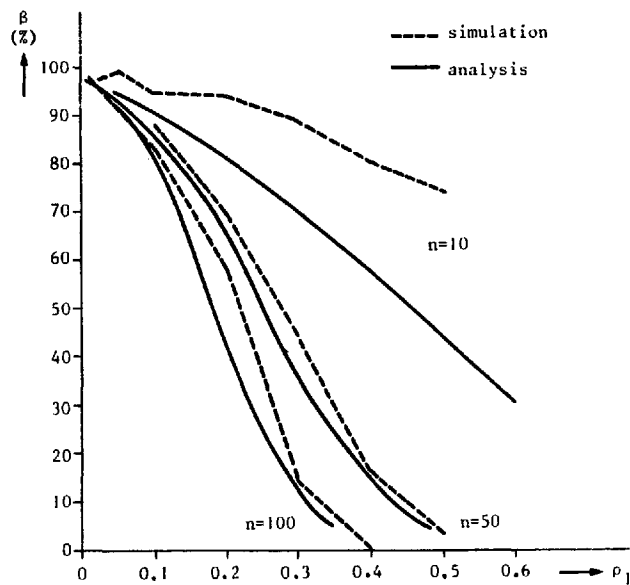


Fig. 1. Relationship between β error, sample size n and correlation ρ_1 .

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