

## ON COVERAGE PROBABILITY OF THE PREDICTION INTERVAL FOR NORMAL VARIABLE

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### ABSTRACT

This paper presents a coverage probability of a one-step-ahead prediction interval for a normal variable. This coverage probability is proved to be functionally independent of  $(\mu, \sigma^2)$ . Because of this functional independence, Monte Carlo simulation will include some variance reduction by setting  $(\mu, \sigma^2) = (0, 1)$ . This result will then valid for all possible values of  $(\mu, \sigma^2)$ . This leads to a great reduction in computation effort.

**KEYWORDS:** Coverage probability, prediction interval.

### 1. INTRODUCTION

Suppose  $X = (X_1, X_2, \dots, X_n)$  be independent and identically distributed random variables and  $X_i \sim N(\mu, \sigma^2)$ ,  $i = 1, 2, 3, \dots, n$ . A one-step-ahead prediction interval for  $X_{n+1}$ , where  $X_{n+1}$  is also a normally distributed with mean  $\mu$  and variance  $\sigma^2$  and is independent of  $X$ , is well-known see e.g., Bikel and Doksum [1]. This one-step-ahead prediction interval for  $X_{n+1}$  is very important in many applications, see e.g., Walpole et al. [4, pp. 241-243] and Bikel and Doksum [1, pp. 252-254].

As in Niwitpong [3], I have also derived a coverage probability of this prediction interval which is proved to be functionally independent of  $(\mu, \sigma^2)$ . This important result allows us to set  $\mu$  equals zero and  $\sigma^2$  equals one in Monte Carlo simulation and is valid for all possible parameter values of  $(\mu, \sigma^2)$ . This leads to a great reduction in computational effort. Section 2 reviews the method to construct prediction intervals for  $X_{n+1}$ . Section 3 gives the method to compute the coverage probability of a prediction interval for  $X_{n+1}$ . Section 4 presents Monte Carlo simulation results of the coverage probabilities of a prediction interval. The conclusion is in Section 5.

### 2. PREDICTION INTERVAL FOR A NORMAL VARIABLE

Bikel and Doksum [1] show that a  $(1 - \alpha)100\%$  prediction interval for  $X_{n+1}$  is

$$PI = \left[ \bar{X} - t_{1-\frac{\alpha}{2}, n-1} s \sqrt{1+n^{-1}}, \bar{X} + t_{1-\frac{\alpha}{2}, n-1} s \sqrt{1+n^{-1}} \right] \quad (1)$$

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where  $t_{1-\frac{\alpha}{2}}$  is a  $(1-\frac{\alpha}{2})$ th quantile of the t distribution,

$$\bar{X} = n^{-1} \sum_{i=1}^n X_i \text{ and } s^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2.$$

In the next section, we prove that the coverage probability of a prediction interval for  $X_{n+1}$  is not depend on  $(\mu, \sigma^2)$ .

### 3. THE COVERAGE PROBABILITY OF PREDICTION INTERVAL

The unconditional coverage probability of  $PI$  for  $X_{n+1}$  in (1) is

$$\begin{aligned} \Pr(X_{n+1} \in PI) &= \Pr\left[\bar{X} - t_{1-\frac{\alpha}{2}, (n-1)} s\sqrt{1+n^{-1}} \leq X_{n+1} \leq \bar{X} + t_{1-\frac{\alpha}{2}, (n-1)} s\sqrt{1+n^{-1}}\right] \\ &= \Pr\left[(\bar{X} - \mu) - t_{1-\frac{\alpha}{2}, (n-1)} s\sqrt{1+n^{-1}} \leq X_{n+1} - \mu \leq (\bar{X} - \mu) + t_{1-\frac{\alpha}{2}, (n-1)} s\sqrt{1+n^{-1}}\right] \\ &= \Pr\left[\frac{(\bar{X} - \mu)}{\sigma} - t_{1-\frac{\alpha}{2}, (n-1)} \frac{s}{\sigma} \sqrt{1+n^{-1}} \leq \frac{X_{n+1} - \mu}{\sigma} \leq \frac{(\bar{X} - \mu)}{\sigma} + t_{1-\frac{\alpha}{2}, (n-1)} \frac{s}{\sigma} \sqrt{1+n^{-1}}\right] \\ &= \Pr\left[\bar{Z} - t_{1-\frac{\alpha}{2}, (n-1)} s_Z \sqrt{1+n^{-1}} \leq Z_{n+1} \leq \bar{Z} + t_{1-\frac{\alpha}{2}, (n-1)} s_Z \sqrt{1+n^{-1}}\right] \\ &= \Phi\left[\bar{Z} + t_{1-\frac{\alpha}{2}, (n-1)} s_Z \sqrt{1+n^{-1}}\right] - \Phi\left[\bar{Z} - t_{1-\frac{\alpha}{2}, (n-1)} s_Z \sqrt{1+n^{-1}}\right] \end{aligned} \quad (2)$$

$$\text{where } \frac{\bar{X} - \mu}{\sigma} = \frac{n^{-1} \sum_{i=1}^n X_i - \mu}{\sigma} = \frac{n^{-1} \left[ \sum_{i=1}^n X_i - n\mu \right]}{\sigma} = \frac{\sum_{i=1}^n [(X_i - \mu)\sigma^{-1}]}{n} = \frac{\sum_{i=1}^n Z_i}{n} = \bar{Z},$$

$$s_Z^2 = \frac{1}{\sigma^2(n-1)} \sum_{i=1}^n [X_i - \bar{X}]^2 = \frac{1}{(n-1)} \sum_{i=1}^n [\sigma^{-1}(X_i - \mu) - \sigma^{-1}(\bar{X} - \mu)]^2 = \frac{1}{(n-1)} \sum_{i=1}^n [Z_i - \bar{Z}]^2,$$

and  $\Phi(\cdot)$  is a cumulative standard normal distribution.

The coverage probability of  $PI$  is therefore independent of  $(\mu, \sigma^2)$ . These important results allow us to set  $(\mu, \sigma^2) = (0, 1)$  in Monte Carlo simulation. This leads to a great reduction in computation of the coverage probability of prediction interval  $PI$ .

### 4. MONTE CARLO SIMULATION

In this section, the coverage probabilities of  $PI$  is computed using Monte Carlo simulation. Now, we set the indicator  $I_{PI}(X_{n+1})$  defined by  $I_{PI}(X_{n+1}) = 1$  if  $X_{n+1} \in PI$  and 0 otherwise. Therefore, from (2), we have (see, Klimov [2, p. 30]).

$$\begin{aligned} \Pr(X_{n+1} \in PI) &= E(I_{PI}(X_{n+1})), \\ &= E\left[\Phi\left[\bar{Z} + t_{1-\frac{\alpha}{2}, (n-1)} s_Z \sqrt{1+n^{-1}}\right] - \Phi\left[\bar{Z} - t_{1-\frac{\alpha}{2}, (n-1)} s_Z \sqrt{1+n^{-1}}\right]\right]. \end{aligned} \quad (3)$$



Now  $P(X_{n+1} \in PI)$  can be estimated using Monte Carlo simulation. We set  $\{W_i\}$  ( $i = 1, 2, \dots, M$ ) to be independent and identically distributed random variables having the same distribution of (2). We estimate  $P(X_{n+1} \in PI)$  in (3) by

$$\frac{\sum_{i=1}^M W_i}{M}.$$

All simulations were performed using programs written in **R** with  $M = 10000$  and  $\alpha = 0.05$ ,  $n = 30, 50, 100, 250$ ,  $\mu = \{0, 5, 10, 50, -5, -10, -50\}$  and  $\sigma^2 = \{1, 5, 10, 50\}$ .

The estimated coverage probabilities of a prediction interval  $PI$  are reported in Table 1. From Table 1, the estimated coverage probabilities are very closed to a nominal value of 0.95 for all sample sizes and parameter values of  $(\mu, \sigma^2)$  considered here. Therefore, we can set only  $\mu = 0$  and  $\sigma^2 = 1$  in Monte Carlo simulation. This result is valid for the parameter values of  $(\mu, \sigma^2)$ . This leads to a great reduction in computation effort.

## 5. CONCLUSION

The coverage probability of a one-step-ahead prediction interval for a normal variable is proved to be functionally independent of  $(\mu, \sigma^2)$ . A high speed computer simulation can be carried out by setting only  $\mu = 0$  and  $\sigma^2 = 1$ .

**Table1.** The estimated coverage probabilities of a prediction interval  $PI$  for  $M = 10000$  and  $\alpha = 0.05$ .

n	$\mu$	$\sigma^2$	Coverage Probability
30	0	1	0.9506
50			0.9505
100			0.9499
250			0.9500
30	5	5	0.9504
50			0.9499
100			0.9501
250			0.9500
30	10	10	0.9502
50			0.9493
100			0.9507
250			0.9497
30	50	50	0.9509
50			0.9498
100			0.9500
250			0.9499
30	-5	5	0.9500
50			0.9497
100			0.9505
250			0.9499
30	-10	10	0.9503
50			0.9497
100			0.9497
250			0.9501
30	-50	50	0.9499
50			0.9503
100			0.9498
250			0.9502



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### Program R for computing the coverage probability and the expected length of a one-step-ahead prediction interval for Normal variable

```
pi.cov <- function(mu, sigma, n, M)
{
  # Written by Sa-aat Niwitpong in November, 2005.
  # This function computes a coverage probability of a prediction interval for Y[n+1]
  # where Y[n+1] is a one-step-ahead predictor of Y[i] ~ N(mu, sigma^2), i = 1, 2, ..., n.
  # The expected length of this prediction interval is also included.
  # cov and ex denote the coverage probability and its expected length of this prediction # interval
  cov <- rep(0, M)
  ex <- rep(0, M)
  for(i in 1:M) {
    y <- rnorm(n, mu, sigma)
    z <- (y - mu)/sigma
    z.mean <- mean((y - mu)/sigma)
    s.z <- var(z)

    # .....
    # Coverage probability for a PI and its expected length using a standard method.
    # .....
    cov[i] <- pnorm(z.mean + qt(0.975, (n - 1)) * sqrt(1/n + 1) * sqrt(s.z)) - pnorm(z.mean
+ qt(0.025, (n - 1)) * sqrt(1/n + 1) * sqrt(s.z))
    ex[i] <- 2 * qt(0.975, n - 1) * sqrt(1/n + 1) * sqrt(s.z) #
  }
  cov.mean <- mean(cov)
  ex.mean <- mean(ex)
  out <- cbind(cov.mean, ex.mean)
  out
}
```