

Estimating Variance

Andreas Maurer

The purpose of this note is to give an upper bound on the variance of a bounded vector- or real valued random variable in terms of an iid sample. Let X, X', X_1, \dots, X_n be iid random variables with values in a ball B of diameter 1 in some Hilbert space (which could be \mathbb{R}). We write

$$V = \frac{1}{2} \mathbb{E} \|X - X'\|^2 \quad \text{and} \quad \hat{V} = \frac{1}{2n(n-1)} \sum_{i,j} \|X_i - X_j\|^2.$$

Theorem 1 $\Pr \{V - \hat{V} > t\} \leq \exp(-nt^2/4V)$.

The proof relies on the following concentration inequality (Theorem 13, 2nd conclusion in [4], similar results from [2] or [3] could also be used):

Theorem 2 *Let $\mathbf{X} = (X_1, \dots, X_n)$ be a vector of independent random variables with values in some set Ω . For $1 \leq k \leq n$ and $y \in \Omega$, we use $\mathbf{X}_{y,k}$ to denote the vector obtained from \mathbf{X} by replacing X_k by y . Suppose that $a > 1$ and that $Z = Z(\mathbf{X})$ satisfies the inequalities*

$$Z(\mathbf{X}) - \inf_{y \in \Omega} Z(\mathbf{X}_{y,k}) \leq 1, \forall k \quad (1)$$

$$\sum_{k=1}^n \left(Z(\mathbf{X}) - \inf_{y \in \Omega} Z(\mathbf{X}_{y,k}) \right)^2 \leq aZ(\mathbf{X}) \quad (2)$$

almost surely. Then, for $t > 0$,

$$\Pr \{\mathbb{E}Z - Z > t\} \leq \exp\left(\frac{-t^2}{2a\mathbb{E}Z}\right).$$

Proof of Theorem 1. Write $Z = n\hat{V}$. Fix some k and choose any $y \in B$. Then

$$Z(\mathbf{X}) - Z(\mathbf{X}_{y,k}) = \frac{1}{n-1} \sum_j \left(\|X_k - X_j\|^2 - \|y - X_j\|^2 \right) \leq \frac{1}{n-1} \sum_j \|X_k - X_j\|^2.$$

It follows that $Z(\mathbf{X}) - \inf_{y \in \Omega} Z(\mathbf{X}_{y,k}) \leq 1$. We also get

$$\begin{aligned} \sum_k \left(Z(\mathbf{X}) - \inf_{y \in \Omega} Z(\mathbf{X}_{y,k}) \right)^2 &\leq \sum_k \left(\frac{1}{n-1} \sum_j \|X_k - X_j\|^2 \right)^2 \\ &\leq \frac{1}{n-1} \sum_k \sum_j \|X_k - X_j\|^2 = 2Z(\mathbf{X}), \end{aligned}$$

so that Z satisfies (1) and (2) with $a = 2$. Since $\mathbb{E}Z = n\mathbb{E}\hat{V} = nV$, Theorem 2 gives the conclusion. ■

In the real valued case the exponent can be improved. This also furnishes an opportunity to show the advantages of Theorem 2 over the results in [2] and [3]. We need a technical lemma.

Lemma 3 *Let X, Y be iid random variables with values in an interval $[a, a + 1]$. Then*

$$\mathbb{E}_X \left[\mathbb{E}_Y (X - Y)^2 \right]^2 \leq (1/2) \mathbb{E} (X - Y)^2.$$

Proof. The right side above is of course the variance $\mathbb{E} [X^2 - XY]$. One computes

$$\begin{aligned} \mathbb{E}_X \left[\mathbb{E}_Y (X - Y)^2 \right]^2 &= \mathbb{E} (X^2 - 2X\mathbb{E}(Y) + \mathbb{E}(Y^2))^2 \\ &= \mathbb{E} (X^4) + 3\mathbb{E} (X^2)^2 - 4\mathbb{E} (X^3) \mathbb{E} (X) \\ &= \mathbb{E} [X^4 + 3X^2Y^2 - 4X^3Y] \end{aligned}$$

We therefore have to show that $\mathbb{E}[g(X, Y)] \geq 0$ where

$$g(X, Y) = X^2 - XY - X^4 - 3X^2Y^2 + 4X^3Y$$

A rather tedious computation gives

$$\begin{aligned} g(X, Y) + g(Y, X) &= X^2 - XY - X^4 - 3X^2Y^2 + 4X^3Y \\ &\quad + Y^2 - XY - Y^4 - 3X^2Y^2 + 4Y^3X \\ &= (X - Y + 1)(Y - X + 1)(Y - X)^2. \end{aligned}$$

The latter expression is clearly nonnegative, so

$$2[\mathbb{E}g(X, Y)] = \mathbb{E}[g(X, Y) + g(Y, X)] \geq 0,$$

which completes the proof. ■

Theorem 4 *If $B = [0, 1]$ then $\Pr \left\{ V - \hat{V} > t \right\} \leq \exp \left(-(n - 1) t^2 / 2V \right)$.*

Proof. We apply Lemma 3 to the empirical measure uniform on (X_1, \dots, X_n) , multiply with n^3 and divide by $(n - 1)^2$ to obtain obtain

$$\sum_k \left(\frac{1}{n-1} \sum_j (X_k - X_j)^2 \right)^2 \leq \frac{n}{2(n-1)^2} \sum_{kj} (X_k - X_j)^2 = \frac{n}{n-1} \hat{V}.$$

The conditions of Theorem 1 are therefore satisfied with $a = n / (n - 1)$. Proceed as above. ■

Corollary 5 (i) For $\delta > 0$ we have with probability at least δ that

$$V \leq \hat{V} + \sqrt{\frac{4\hat{V} \ln 1/\delta}{n}} + \frac{4 \ln 1/\delta}{n}.$$

(ii) If $B = [0, 1]$ we have with probability at least δ that

$$V \leq \hat{V} + \sqrt{\frac{2\hat{V} \ln 1/\delta}{n-1}} + \frac{2 \ln 1/\delta}{n-1}.$$

(iii) If $B = [0, 1]$ and $\hat{X} = (1/n) \sum X_i$ then, for $\delta > 0$, we have with probability at least δ that

$$\mathbb{E}X \leq \hat{X} + \sqrt{\frac{2\hat{V} \ln 2/\delta}{n}} + \frac{7 \ln 2/\delta}{3(n-1)}.$$

Proof. Equating the right side of the bound in Theorem 1 to δ and solving for t gives, with probability at least δ ,

$$\begin{aligned} V &\leq \hat{V} + \sqrt{\frac{4V \ln 1/\delta}{n}} \implies \\ \sqrt{V} &\leq \sqrt{\hat{V} + \frac{\ln 1/\delta}{n}} + \sqrt{\frac{\ln 1/\delta}{n}}. \end{aligned}$$

Squaring and the estimate $\sqrt{a+b} \leq \sqrt{a} + \sqrt{b}$ then give conclusion (i). For (ii) we use Theorem 4 in an analogous way to obtain

$$\sqrt{V} \leq \sqrt{\hat{V} + \frac{\ln 1/\delta}{2(n-1)}} + \sqrt{\frac{\ln 1/\delta}{2(n-1)}} \quad (3)$$

and the conclusion. Finally recall that Bernstein's inequality [5] implies

$$\mathbb{E}X \leq \hat{X} + \sqrt{V} \sqrt{\frac{2 \ln 1/\delta}{n}} + \frac{\ln 1/\delta}{3n},$$

so that the last conclusion follows from combining this with (3) in a union bound and some simple estimates. ■

Part (iii) above is a version of an *empirical Bernstein bound* (see Audibert et al [1]). In [1] the result is obtained in a triple application of Bernstein's inequality, resulting in a slightly larger constant in the last term.

References

- [1] J. Y. Audibert, R. Munos, C. Szepesvári. Exploration-exploitation trade-off using variance estimates in multi-armed bandits, Preprint.

- [2] S. Boucheron, G. Lugosi, P. Massart, *A sharp concentration inequality with applications in random combinatorics and learning*, Random Structures and Algorithms, (2000) 16:277-292.
- [3] S. Boucheron, G. Lugosi, P. Massart, *Concentration inequalities using the entropy method*, Annals of Probability (2003) 31:1583-1614.
- [4] Maurer, A. (2006). Concentration inequalities for functions of independent variables. *Random Structures Algorithms* 29 121–138.
- [5] C. McDiarmid, *Concentration*, in *Probabilistic Methods of Algorithmic Discrete Mathematics*, (1998) 195-248. Springer, Berlin