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A WEAK LAW OF LARGE NUMBERS FOR THE SAMPLE COVARIANCE MATRIX

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Abstract

In this article we consider the sample covariance matrix formed from a sequence of independent and identically distributed random vectors from the generalized domain of attraction of the multivariate normal law. We show that this sample covariance matrix, appropriately normalized by a nonrandom sequence of linear operators, converges in probability to the identity matrix.

1. Introduction:

Let $X, X_1, X_2 \cdots$ be iid R^d valued random vectors with $\mathcal{L}(X)$ full. The condition of fullness is the multivariate analogue of nondegeneracy and will be in force throughout this article. It means that $\mathcal{L}(X)$ is not concentrated on any $d-1$ dimensional hyperplane. Equivalently, $\langle X, \theta\rangle$ is nondegenerate for every θ. Here $\langle\ ,\ \rangle$ denotes the inner product.

Throughout this article all vectors in R^d are assumed to be column vectors. For any matrix, A, A^t denotes its transpose. Let $\bar{X}_n = \frac{1}{n}\sum_{i=1}^n X_i$. We denote and define the sample covariance matrix by $C_n = \frac{1}{n}\sum_{i=1}^n (X_i - \bar{X}_n)(X_i - \bar{X}_n)^t$. That C_n has a unique nonnegative symmetric square root, denoted above by $C_n^{1/2}$, follows from the fact that $\langle C_n\theta, \theta\rangle = \sum_{i=1}^n \langle X_i - \bar{X}_n, \theta\rangle^2 \geq 0$, so that C_n is nonnegative. Also, C_n is clearly symmetric. However, there is no guarantee that C_n is invertible with probability one.

In [3] we describe two ways to circumvent the problem of lack of invertibility of C_n. One such approach is to define

$$B_n = \begin{cases} C_n & \text{if } C_n \text{ is invertible} \\ I & \text{otherwise} \end{cases} \tag{1.3}$$

The success of this approach relies on the fact that if $\mathcal{L}(X)$ is in the Generalized Domain of Attraction of the Normal Law (see (1.6) below for the definition), then $P(C_n = B_n) \to 1$. (See

[3], Lemma 5.) In light of this, we will assume without loss of generality that C_n is invertible. $\mathcal{L}(X)$ is said to be in the Generalized Domain of Attraction (GDOA) of the Normal Law if there exist matrices A_n and vectors v_n such that

$$A_n \sum_{i=1}^{n} X_i - v_n \Rightarrow N(0, I). \tag{1.6}$$

One construction of A_n is such that A_n is invertible, symmetric and diagonalizable. See Hahn and Klass [2].

The main result is Theorem 1 below. This result was shown in Sepanski [5]. However, there the proof was based on a highly technical comparison of the eigenvalues and eigenvectors of C_n and A_n. There the proof was essentially real valued. The purpose of this note is to give a more efficient proof that is operator theoretic and multivariate in nature. For more details, we refer the interested reader to the original article. In particular, Sepanski [5] contains a more complete list of references.

2. Results

Theorem 1: *If the law of X is in the generalized domain of attraction of the multivariate normal law, then*

$$\sqrt{n} A_n C_n^{1/2} \to I \quad \textit{in pr.}$$

Proof: Let $P_n(\omega)$ denote the empirical measure. That is, $P_n(\omega)(A) = \frac{1}{n}\sum_{i=1}^{n} I[X_i(\omega) \in A]$. Here I is the indicator function. For each $\omega \in \Omega$ let $X_1^*, \cdots X_n^*$ be iid with law $P_n(\omega)$.
Sepanski [4], Theorem 2, shows that under the hypothesis of GDOA,

$$A_n \sum_{j=1}^{n} X_j^* - n\mu \Rightarrow N(0, I) \quad \textit{in pr.}$$

Sepanski [3], Theorem 1, shows that under the hypothesis of GDOA,

$$(nC_n)^{-1/2} \sum_{j=1}^{n} X_j^* - n\mu \Rightarrow N(0, I) \quad \textit{in pr.}$$

These two results, together with the multivariate Convergence of Types theorem of Billingsley [1], imply that

$$(nC_n)^{-1/2} = B_n R_n A_n, \tag{1}$$

where $B_n \to I$ *in pr.*, and R_n are (random) orthogonal. The proof of Theorem 1 is thereby reduced to showing that $R_n \to I$ *in pr.* However, convergence in probability is equivalent to every subsequence having a further subsequence which converges almost surely. This reduces the proof to a pointwise result about the behavior of the linear operators.
Write $A_n = Q_n D_n Q_n^t$ where Q_n is orthogonal and D_n is diagonal with nonincreasing diagonal entries. Let $P_n = Q_n R_n Q_n^t$ and $K_n = Q_n B_n Q_n^t$.

$$\|K_n - I\| = \|Q_n^t B_n Q_n - Q_n^t Q_n\| \leq \|B_n - I\| \to 0$$

By the same token, $R_n \to I$ if and only if $P_n \to I$. Also, $(nC_n)^{-1/2}$ is positive and symmetric and therefore so are $B_n R_n A_n$ and $K_n P_n D_n$. The proof of Theorem 1 is reduced to the following lemma.

Lemma 2: Let P_n be orthogonal. Let $D_n = \mathrm{diag}(\lambda_{n1}, \cdots, \lambda_{nd})$ be diagonal such that $\lambda_{n1} \geq \lambda_{n2} \geq \cdots \geq \lambda_{nd} > 0$. Suppose $K_n \to I$. If $K_n P_n D_n$ is positive and symmetric for every n, then $P_n \to I$.

Proof: Given a subsequence of P_n we show that there is a further subsequence along which $P_n \to I$. Let $E_n = \lambda_{n1}^{-1} D_n$. This is a diagonal matrix of all positive entries that are bounded above by 1. Therefore, given any subsequence, there is a further subsequence along which $K_n \to I$, $P_n \to P$, and $E_n \to E$. Necessarily, P is orthogonal and E is diagonal with entries in $[0, 1]$. Furthermore, E has at least one diagonal entry that is 1 and its entries are nonincreasing. Since $K_n P_n E_n$ is symmetric, nonnegative and $K_n \to I$, we have that $PE = EP^t$, and PE is nonnegative. Now, $(PE)^2 = (PE)^t PE = EP^{-1} PE = E^2$. Hence, since PE and E are both nonnegative, $PE = E$. If E is invertible, then $P = I$ and we are done. Suppose E is not invertible. Write $E = \begin{pmatrix} E_{(1)} & 0 \\ 0 & 0 \end{pmatrix}$ where $E_{(1)}$ is an $m \times m$ invertible diagonal matrix with $m < d$. Next, write $P = \begin{pmatrix} P_{(1)} & P_{(2)} \\ P_{(3)} & P_{(4)} \end{pmatrix}$ where $P_{(1)}$ is an $m \times m$ matrix. Since $PE = E$, we have

$$\begin{pmatrix} P_{(1)} E_{(1)} & 0 \\ P_{(3)} E_{(1)} & 0 \end{pmatrix} = \begin{pmatrix} E_{(1)} & 0 \\ 0 & 0 \end{pmatrix}.$$

From $P_{(1)} E_{(1)} = E_{(1)}$ and the invertibility of $E_{(1)}$, we have that $P_{(1)} = I_m$. Similarly, from $P_{(3)} E_{(1)} = 0$ we have that $P_{(3)} = 0$. Therefore, $P = \begin{pmatrix} I_m & P_{(2)} \\ 0 & P_{(4)} \end{pmatrix}$. Next, multiplying PP^t, and $P^t P$, and equating the $(1,1)$ entries we have that $I_m + P_{(2)} P_{(2)}^t = I_m$. From this we conclude that $P_{(2)} P_{(2)}^t = 0$, and therefore also, $P_{(2)} = 0$. We have that,

$$P = \begin{pmatrix} I & 0 \\ 0 & P_{(4)} \end{pmatrix}.$$

The proof continues inductively. Let $K_{(n4)}, P_{(n4)}, E_{(n4)}$ be the (2,2) block of K_n, P_n, E_n respectively. $P_{(n4)}$ may not be orthogonal, but $P_{(4)}$ is. Apply the previous argument to $\left(K_{(n4)} P_{(n4)} P_{(4)}^t\right) P_{(4)} E_{(n4)}$. Note that $K_{(n4)} P_{(n4)} P_{(4)}^t \to I P_{(4)} P_{(4)}^t = I$, so that we may apply the argument with $K_{(n4)} P_{(n4)} P_{(4)}^t$ as the new K_n in the induction step. Since the matrices are all finite dimensional, the argument will eventually terminate.

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