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43. On the Normal Stationary Process with no Hysteresis.

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§ 1. Let (Ω, P) be a probability field and \mathfrak{M} a system of real valued random variables. \mathfrak{M} is called to be normal or of the Gaussian type, if, for any $x_i(\omega) \in \mathfrak{M}$, i=1,2,...,n, the random variable $(x_1(\omega), x_2(\omega), ..., x_n(\omega))$ is subjected to an n-dimensional (sometimes perhaps degenerated) Gaussian distribution. This condition is equivalent to the property that, for any $x_i(\omega) \in \mathfrak{M}$, and for any real a_i , $\sum_{i=1}^n a_i x_i(\omega)$ is normally distributed. Let $x_i(\omega)$, i=1,2,...,m, $y_j(\omega)$, j=1,2,...,n, be elements in a normal system \mathfrak{M} . Then the non-correlatedness of $x_i(\omega)$ and $y_j(\omega)$ for any, i,j, $1 \leq i \leq m$, $1 \leq j \leq n$, implies the independence of $(x_1(\omega), x_2(\omega), ..., x_m(\omega))$ and $(y_1(\omega), y_2(\omega), ..., y_n(\omega))$.

Let $x(t, \omega)$, $-\infty < t < \infty$, be a stochastic process. If the system of $x(t, \omega)$, $-\infty < t < \infty$, is normal, then the process will be said to be *normal*. If the (conditional) probability law of $x(t, \omega)$ under the condition that $x(t_1, \omega)$, $x(t_2, \omega)$, ..., $x(t_n, \omega)$ should be given depends only on the value $x(t_n, \omega)$ for any $t_1 < t_2 < \cdots < t_n < t$, we say that $x(t, \omega)$ has no hysteresis or is a simple Markoff process. This terminology is applied to the case of a stochastic sequence $x(k, \omega)$, $k=0, \pm 1, \pm 2, \ldots$

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§ 2. The form of the correlation function.

Theorem 1. Let $x(k, \omega)$ be a normal stationary (in the sense of A. Khintchine) sequence. A necessary and sufficient condition that $x(k, \omega)$ should have no hysteresis is that its correlation function $\rho(k)$ is of the form α^k , $-1 \le \alpha \le 1$.

Proof. In order to avoid trivial complications we assume $E_{\omega}(x(k,\omega))=0$, and $E_{\omega}(x(k,\omega)^2)=1$. If we define $(f(\omega),g(\omega))$ by $E_{\omega}(f(\omega)g(\omega))$, the closed linear subspace determined by the set $x(k,\omega)$, $k=0,\pm 1,\pm 2,\ldots$, is considered as a Hilbert space, where *orthogonality implies* (stochastic) independence (Cf. § 1).

Sufficiency. For the proof it is sufficient to show that the conditional probability law of $x(k,\omega)$ under the condition that $x(k-i,\omega)$ = ξ_i , i=1,2,...,n, depends only on ξ_1 .

We put $y(k, \omega) = x(k, \omega) - \alpha x(k-1, \omega)$. Then we have $E_{\omega}(y(k, \omega)x(k-i, \omega)) = \alpha^i - \alpha \alpha^{i-1} = 0$, $i=1, 2, \ldots$. Since the sequence is normal, $y(k, \omega)$ is independent of $(x(k-1, \omega), x(k-2, \omega), \ldots, x(k-n, \omega))$. Therefore the probability law of $y(k, \omega)$ is invariant even if we add the condition: $x(k-i, \omega) = \xi_i$, $i=1, 2, \ldots, n$. Therefore the probability