# ON THE ESTIMATION IN A CLASS OF DIFFUSION-TYPE PROCESSES. APPLICATION FOR DIFFUSION BRANCHING PROCESSES

- M. Molina Fernández<sup>(1)</sup> and A. Hermoso Carazo<sup>(2)</sup>
- (1) Departamento de Matematicas. Universidad de Extremadura.
- (2) Departamento de Estadística e I.O.. Universidad de Granada.

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#### Introduction

In this work a stochastic differential equations family whose  $sol\underline{u}$  tions are multidimensional diffusion-type (non necessarily markovians) processes is considered, and the estimation of a parametric vector  $\theta$  which relations the coefficients is studied. The conditions for the existence of the likelihood function are proved and observing continuously the process, the estimator is obtained. An application for Diffusion Branching Processes is given. This problem has been studied in some special cases by Brown and Hewitt (1975), Liptser and Shiryayev (1978) and Sorensen (1983).

## The basic model

Let  $(\Omega,F,P)$  be our basic complete probability space, and let a sequence of  $\sigma$ -algebras  $(F_t, 0 \le t \le T < \infty)$  such that  $s \le t \implies F_s \subseteq F_t \subseteq F$ . We shall consider the stochastic differential equations family :

$$dX(t) = A(t,X)\theta dt + A^{1/2}(t,X)dW(t)$$

$$X(0) = Y \qquad 0 \le t \le T \qquad (1)$$

where  $(W(t), \ 0 \le t \le T)$  is a n-dimensional Wiener process with independent components, A(t,X) is a nonanticipating functional, Y is a random vector  $F_0$ -measurable such that  $P(\sum |Y_i| < \infty) = 1$ , and  $\theta$  is a parameter with values in an open set  $\theta \in \mathbb{R}^n$ . Let us consider the case when the matrix A(t,X) is know and non degenerate. Let  $C_T$  be the set of continuous functions  $f\colon [0,T] \longrightarrow \mathbb{R}^n$ , and let  $\beta_T = \sigma(x\colon x(s),\ 0 \le s \le T)$ . We shall denote by  $\mu_\theta$  the measure induced in  $(C_T,\beta_T)$  by the solution of (1) when  $\theta$  is the true parameter.

#### Theorem

If for each t $\epsilon$ [0,T] and x,y $\epsilon$ C<sub>T</sub> the components A<sub>ij</sub>(t,X), for i,j=1,...,n, of A(t,X) satisfy the conditions:

i). 
$$A_{ij}^2(t,x) \le k_1 \int_0^t (1 + \sum x_i^2(s)) dK(s) + k_2(1 + \sum x_i^2(t))$$

ii). 
$$|A_{i,j}(t,x)-A_{i,j}(t,y)|^2 \le k_1 \sum_{j=0}^{t} (x_j(s)-y_j(s))^2 dK(s) + k_2 \sum_{j=0}^{t} (x_j(t)-y_j(t))^2 dK(s) + k_2 \sum_{j=0}^{t} (x_j(t)-x_j(t))^2 dK(s) + k_2 \sum_{j=0}^{t} (x_j(t)-x_j(t)^2 dK($$

where  $k_1$  and  $k_2$  are constants, and K(.) is a nondecreasing right-continuous function,  $0 \le K(s) \le 1$ . Then for all  $\theta \in \Theta$ ,  $\mu_{\theta} \sim \mu_{\theta_0}$ , where  $\theta_0$  denote a fixed value of the parameter, and the corresponding Radon-Nikodym derivative is :

$$\frac{d\mu_{\theta}}{d\mu_{\theta}}(X) = \exp\{(\theta - \theta_{0})^{\bullet}(X(T) - Y) - (1/2)(\theta - \theta_{0})^{\bullet}(\int_{0}^{T} A(t, X)dt)(\theta + \theta_{0})\}$$
or (of

It is enough prove (Liptser and Shiryayev (1977) :

I). For i=1,...,n, the equation  $A^{1/2}(t,X)B_{i}(t,X) = A_{i}(t,X)$  has solution with respect to  $B_{i}(t,X) = \mu_{\theta_{0}}$ , where  $A_{i}(t,X) = (A_{1i}(t,X),...,A_{N}(t,X))^{1}$ 

.,  $A_{ni}(t,X)$ )'
II). For i=1,...,n and  $\theta \in \Theta$   $\mu_{\theta}(\int_{0}^{T} B_{1}^{!}(t,X)B_{1}(t,X)dt < \infty)=1$ 

But since  $A^{1/2}(t,X)$  is a non-singular matrix and  $B_i^1(t,X)B_i^2(t,X) = A_i^1(t,X)A_i^{-1}(t,X)A_i^{-1}(t,X) = A_{ij}^1(t,X)$ , I) and II) are hold.

### Maximum Likelihood Estimation.

Suppose we observe a process X , which we know solves one of the equations (1) continuously in the time interval [0,T] and that we want to infer which one it is. For this purpose let us consider the likelihood function  $L_T(\theta) = (d\mu_\theta/d\mu_\theta)(X)$ . From (2) we find that :

$$1_{\mathsf{T}}^{\bullet}(\theta) = (\mathsf{X}(\mathsf{T})-\mathsf{Y}) - (\int_{0}^{\mathsf{T}} \mathsf{A}(\mathsf{t},\mathsf{X})d\mathsf{t})\theta \qquad \text{and} \qquad 1_{\mathsf{T}}^{\bullet}(\theta) = -\int_{0}^{\mathsf{T}} \mathsf{A}(\mathsf{t},\mathsf{X})d\mathsf{t}$$
(3)

where  $l_T(\theta) = ln(L_T(\theta))$  and "." denote derivative with respect to  $\theta$ . The solution of the likelihood equation  $l_T^{\bullet}(\theta) = 0$  is :

$$\hat{\theta}_{T} = (X(T)-Y)(\int_{0}^{T} A(t,X)dt)^{-1}$$

If  $\hat{\theta}_T \in \Theta$  , from (3) it is the unique maximum likelihood estimate.

The observed Fisher information is  $\int_0^T A(t,X)dt$ , and the statistic (X(T)-Y,  $\int_0^T A(t,X)dt)$  is sufficient for  $\theta$ .

# Application for Diffusion Branching Processes.

A Diffusion Branching Process (DBP), is a non negative diffusion process with X(0) = a > 0, drift coefficient  $\theta x$ , and diffusion coeffi-

cient  $\alpha x$ ,  $(\alpha > 0)$ , where a ,  $\theta$ , and  $\alpha$  are constants. The DBP serve in their own right as models for various physical and biological phenomena, but are probably viewed most often as approximations to Galton Watson processes. Inference on a DBP will be inference on the two parameters  $\theta$  and  $\alpha$ . However, provided we observed X in continuous time, we can use a version of the Lévy result for the quadratic variation of Brownian Motion to give us  $\alpha$ , (Basawa and Prakasa-Rao (1980), pp:212). Therefore without loss of generality, take  $\alpha$ =1. The estimation of  $\theta$ , has been considered using a sequential procedure by Brown and Hewitt (1975). But the DBP with drift coefficient  $\theta x$ , ( $\theta \in R$ ), diffusion coefficient x, and initial value X(0)=a, are solutions of the stochastic differential equations family:

$$dX(t) = \theta X(t)dt + \sqrt{X(t)}dW(t)$$

$$X(0) = a \qquad 0 \le t \le T$$
(4)

But (4) is the particular case of (1) when n=1, A(t,X)=X(t), Y=a. Therefore from (2) the Radon-Nikodym derivative is :

$$\frac{d\mu_{\theta}}{d\mu_{\theta}}(X) = \exp\{(\theta - \theta_{0})(X(T)-a) - (1/2)(\theta^{2} - \theta_{0}^{2})\} \int_{0}^{T} X(t)dt \}$$

and the estimator of  $\theta$  is  $\hat{\theta}_T = (X(T)-a)/(\int_0^T X(t)dt)$ . A sufficient sta-

tistic for 
$$\theta$$
 is  $(X(T), \int_0^T X(t)dt)$ , and  $\int_0^T X(t)dt$  is the observed  $F_{\underline{i}}$ 

sher information.

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