## Recursive estimation of one-dimensional parameter of Compound Poisson process\*

Nanuli Lazrieva<sup>a,b</sup>, Temur Toronjadze<sup>a,b</sup>

<sup>a</sup>Business School, Georgian–American University, 8 M. Aleksidze Str., Tbilisi 0160, Georgia <sup>b</sup>A. Razmadze Mathematical Institute of I. Javakhishvili Tbilisi State University, 6 Tamarashvili Str., Tbilisi 0177, Georgia

## Abstract

Recursive estimation procedure of a one-dimensional parameter of Levy measure of Compound Poisson process is introduced and their asymptotic properties are investigated.

The object of our investigation is a parameter filtered statistical model

$$\mathcal{E} = (\Omega, \mathcal{F}, \mathbb{F} = (\mathcal{F}_t)_{t>0}, (P_\theta, \theta \in R))$$
(1)

associated with one-dimensional  $\mathbb{F}$ -adapted RCLL process  $X = (X_t)_{t\geq 0}$  in the following way: for each  $\theta \in R$ ,  $P_{\theta}$  is assumed to be the unique measure on  $(\Omega, \mathcal{F})$  such that under  $P_{\theta}$ ,  $X = (X_t)_{t\geq 0}$  is a semimartingale the triplet of predictable characteristics  $(B_{\theta}, 0, \nu_{\theta})$ , where  $B_{\theta}(t) = \lambda_t \int_R x I_{(|x|\leq 1)} \nu(\theta, dx), \ \nu_{\theta}(dt, dx) = \lambda dt \nu(\theta; dx)$ , where  $\lambda > 0, \ \nu(\theta, \cdot)$  is probability measure with  $\int_R x^2 \nu(\theta, dx) < \infty$ .

It is obvious that under  $P_{\theta}$ ,  $X = (X_t)_{t \ge 0}$  is a Compound Poisson process that can be written in the following form:

$$X_t = \sum_{i=1}^{N_t} \xi_i,$$

where  $N = (N_t)_{t\geq 0}$  is a Standard Poisson process with intensity  $\lambda > 0$ , and  $\xi = (\xi_n)_{n\geq 1}$  is the sequence of i.i.d. random variables with the probability distribution  $\nu(\theta, \cdot)$  (see, e.g., [1]).

Our aim is to construct recursive estimation procedure for unknown parameter  $\theta \in R$ .

Suppose that for each pair  $(\theta, \theta')$  the measures  $\nu(\theta, \cdot)$  and  $\nu(\theta', \cdot)$  are equivalent. Fix some  $\tilde{\theta} \in R$  and denote  $P_{\tilde{\theta}} := P$ ,  $\nu_{\tilde{\theta}} := \nu$ ,  $\nu(\tilde{\theta}; x) = \nu(\cdot)$ . Then

$$P_{\theta} \stackrel{loc}{\sim} P, \quad \theta \in R,$$

and the local density process  $\rho_t(\theta) = \frac{dP_{\theta,t}}{dP_t}$  can be represented as the Dolean esponential

$$\rho_t(\theta) = \mathcal{E}_t(M(\theta)),$$

where  $M(\theta) = (Y(\theta) - 1) * (\mu - \nu)$ , where  $Y(\theta, x) = \frac{d\nu(\theta, x)}{d\nu(x)}$ .

<sup>\*</sup> Email addresses: lazrieva@gmail.com (Nanuli Lazrieva), toronj333@yahoo.com (Temur Toronjadze)

Further, assume that the density  $Y(\theta, x)$  is continuously differentiable in  $\theta$  for each  $x \in R$ , and differentiability under integral signs is possible. Note that under assumptions listed above the model (1) is regular in the sense given in [2].

It is not hard to observe that

$$L_t(\theta) := \frac{\partial}{\partial \theta} \ln \rho_t(\theta) = \frac{\dot{Y}(\theta)}{Y(\theta)} * (\mu - \nu_\theta) = \Phi(\theta) * (\mu - \nu_\theta) \quad \left(\Phi(\theta) = \frac{\dot{Y}(\theta)}{Y(\theta)}\right).$$
(2)

Hence, the maximum likelihood equation is

$$L_t(\theta) = \Phi(\theta) * (\mu - \nu_\theta)_t = 0.$$
(3)

**Remark 1.** The problem of solvability of Eq. (3) in more general setting is studied in [3].

Eq. (3) can be rewritten in the equivalent form

$$\sum_{n=1}^{N_t} \frac{\dot{Y}(\theta, \xi_n)}{Y(\theta, \xi_n)} = 0 \implies \widehat{\theta}_t - \text{MLE}.$$
(3')

So, for each t > 0, we need to solve Eq. (3) or (3') which is not easy task (in general).

Instead in [2] we proposed the recursive procedure to obtain the process  $\theta = (\theta_t)_{t\geq 0}$  (recursive estimate) with the same asymptotic properties as MLE  $\hat{\theta}_t$ , as  $t \to \infty$ ,  $P_{\theta}$ -a.s.

To develop this procedure first of all assume that

$$I(\theta) := \int_{R} \Phi^{2}(x,\theta)\nu(\theta,dx) < \infty.$$

Then  $L(\theta) = (L_t(\theta), t \ge 0) \in M^2_{loc}(P_{\theta})$  and the Fisher information process is

$$I_t(\theta) = \langle L(\theta), L(\theta) \rangle_t = \lambda t I(\theta).$$

Denote  $\gamma_t(\theta) = I_t^{-1}(\theta)$ . The recursive estimation procedure, SDE (3.4) of [4] in the case under consideration is of the following form:

$$\theta_t = \theta_0 + \int_0^t \int_R \gamma_s(\theta_{s-}) \Phi(\theta_{s-}, x) \left( 1 - \frac{Y(\theta_{s-}, x)}{Y(\theta, x)} \right) \nu(ds, dx) + \int_0^t \int_R \gamma_s(\theta_{s-}) \Phi(\theta_{s-}, x) (\mu - \nu_\theta) (ds, dx).$$
(4)

**Remark 2.** Although Eq. (4) is equivalent to the following equation

$$\theta_t = \theta_0 + \sum_{n=1}^{N_t} \frac{\Phi(\theta_{n-1}, \xi_n)}{nI(\theta)}, \qquad (4')$$

we prefer the form of Eq. (4) to investigate asymptotic properties of  $\theta_t$ , as  $t \to \infty$ ,  $P_{\theta}$ -a.s., based on results concerning asymptotic behaviour of solutions of Robbins–Monro (RM) type SDE. The Robbins–Monro type SDE

$$z_t = z_0 + \int_0^t H_s(z_{s-}) dK_s + \int_0^t M(ds, z_{s-}),$$
(5)

where  $H_s(0) = 0$ ,  $H_s(u)u < 0$ ,  $u \neq 0$ , was introduced in [5]. In [5], [6], the asymptotic behaviour of  $z = (z_t)_{t\geq 0}$ , as  $t \to \infty$ ,  $P_{\theta}$ -a.s. was investigated.

Assume that for each  $x \in R$  the function  $Y(\theta, x)$  is strongly monotone in  $\theta$ . Denote  $z_t = \theta_t - \theta$ , then Eq. (4) becomes

$$z_{t} = z_{0} + \int_{0}^{t} \int_{R} \gamma_{s}(\theta + z_{s-}) \Phi(\theta + z_{s-}, x) \left(1 - \frac{Y(\theta + z_{s-}, x)}{Y(\theta, x)}\right) \nu_{\theta}(ds, dx)$$
$$+ \int_{0}^{t} \int_{R} \gamma_{s}(\theta + z_{s-}) \Phi(\theta + z_{s-}, x) (\mu - \nu_{\theta})(ds, dx)$$
(5')

and is of the form (5) with  $K_t = \lambda t$ ,

4

$$H_t(u) = \int_R \gamma_t(\theta + u) \Phi(\theta + u, x) \left( 1 - \frac{Y(\theta + u, x)}{Y(\theta, x)} \right) \nu(\theta, dx), \tag{6}$$

$$M(u) = [M_t(u), t \ge 0] = \left[\int_0^t \int_R \gamma_s(\theta + u)\Phi(\theta + u, x)(\mu - \nu_\theta)(ds, dx), \ t \ge 0\right].$$
(7)

Denote

$$h_t(u) = \frac{d\langle M(u), M(u) \rangle_t}{dK_t} = \gamma_t^2(\theta + u) \int_R \Phi^2(\theta + u, x)\nu(\theta, dx) = \gamma_t^2(\theta + u)I(\theta + u).$$

Hence, (5') is the special case of the RM type SDE (5) with objects  $H(u) = (H_t(u))_{t\geq 0}$  and  $M(u) = (M(t, u))_{t\geq 0}$  specified by Eqs. (6) and (7), respectively.

Therefore one can use the results about asymptotic behaviour of solution  $z = (z_t)_{t\geq 0}$  of general SDE (5) to establish asymptotic behaviour of solution of SDE (5'), as  $t \to \infty$ .

Namely, one can use Theorem 3.1 of [5] to derive sufficient conditions for the convergence:  $z_t \to 0$ , as  $t \to \infty$ ,  $P_{\theta}$ -a.s., for all  $\theta \in R$  (recall that from now  $z = (z_t)_{t\geq 0}$  is the solution of SDE (5')). Further, sufficient conditions for the convergence: for all  $\delta$ ,  $0 < \delta < \frac{1}{2}$ ,  $I_t^{\delta} z_t \to 0$  (rate of convergence), as  $t \to \infty$ ,  $P_{\theta}$ -a.s., can be obtained from Theorem 2.1 of [6] and, finally, to establish the asymptotic distribution of  $I_t^{1/2}(\theta)z_t$ , as  $t \to \infty$  (under measure  $P_{\theta}$ ), one can use Theorem 3.1 of [6].

As an illustration, in the present work we restrict ourselves by results concerning the convergence:  $z_t \to 0$ , as  $t \to \infty$ ,  $P_{\theta}$ -a.s., rate of convergence, to avoid complex notation needed to state conditions for the validity of asymptotic expansion of  $I_t^{1/2} z_t$  (see Eq. (3.1) from [?], with  $R_t \xrightarrow{P_{\theta}} 0$ , as  $t \to \infty$ .

Note that this convergence is equivalent to the strong consistency of recursive estimate  $(\theta_t)_{t\geq 0}$  given by (4) or (4'), that is  $\theta_t \to \theta$ , as  $t \to \infty$ ,  $P_{\theta}$ -a.s.

**Theorem 1.** Let the following conditions be satisfied: for all  $\theta \in R$ 

- (i)  $I^{-1}(\theta + u) < c(\theta)(1 + u^2), c(\theta) > 0;$
- (ii) for each  $\varepsilon$ ,  $\varepsilon > 0$ ,

$$\inf_{\varepsilon \le |u| \le \frac{1}{\varepsilon}} \left| uI^{-1}(\theta+u) \int_{R} \Phi(\theta+u,x) \left( 1 - \frac{Y(\theta+u,x)}{Y(\theta,x)} \right) \nu(\theta,dx) \right| > 0.$$

Then  $z_t \to 0$ , as  $t \to \infty$ ,  $P_{\theta}$ -a.s.

*Proof.* Condition (A) of Theorem 3.1 from [5] follows from the strong monotonicity of  $Y(\theta, x)$  w.r.t.  $\theta$ , for all  $x \in R$ .

Condition (B) of Theorem 3.1 of [5] is also satisfied, since

$$h_t(u) = \gamma_t^2(\theta + u)I(\theta + u) = \frac{1}{\lambda^2 t^2 I^2(\theta + u)}I(\theta + u) = I^{-1}(\theta + u)\frac{1}{\lambda^2 t^2}.$$

Therefore

$$h_t(u) \le B_t(1+u^2),$$

with  $B_t = \frac{c(\theta)}{\lambda^2} \frac{1}{t^2}$  and  $\int_0^\infty B_s \, ds = \infty$ . Condition (I) of Theorem 3.1 from [5] is satisfied, since

$$\int_{0}^{\infty} \inf_{\varepsilon \le |u| \le \frac{1}{\varepsilon}} |uH_t(u)| \, dK_t = \int_{0}^{\infty} \inf \left| u\gamma_t(\theta+u) \int_R \Phi(\theta+u,x) \left( 1 - \frac{Y(\theta+u,x)}{Y(\theta)} \right) \nu(\theta,dx) \right| \lambda \, dt$$
$$= \inf_{\varepsilon \le |u| \le \frac{1}{\varepsilon}} \left| uI^{-1}(\theta+u) \int_R \Phi(\theta+u,x) \left( 1 - \frac{Y(\theta+u,x)}{Y(\theta)} \right) \nu(\theta,dx) \right| \int_{0}^{\infty} \frac{dt}{t} = \infty. \qquad \Box$$

Below we assume that  $z_t \to 0$ , as  $t \to \infty$ ,  $P_{\theta}$ -a.s. Denote

$$\beta_t = -\lim_{u \to 0} \frac{H_t(u)}{u}, \quad \beta(u) = \begin{cases} -\frac{H_t(u)}{u}, & u \neq 0, \\ \beta_t, & u = 0. \end{cases}$$

**Theorem 2.** Suppose that for each  $\delta$ ,  $0 < \delta < 1$ , the following conditions are satisfied:

(i) 
$$\int_{0}^{\infty} [\delta_t - 2\beta_t(u)]^+ dt < \infty;$$
  
(ii) 
$$\int_{0}^{\infty} I_t^{\delta}(\theta) h_t(z_{t-}, z_{t-}) dt < \infty \quad P_{\theta}\text{-a.s., where } h_t(u, v) = \frac{d\langle M(u), M(v) \rangle_t}{dK_t}.$$

Then  $I_t^{\delta}(\theta) z_t^2 \to 0$ , as  $t \to \infty$ ,  $P_{\theta}$ -a.s.

*Proof.* It is enough to note that in Theorem 2.1 of [6] we must take  $\gamma_t = t$  and  $r_t^{\delta} = \frac{\delta}{t}$ .

## References

- J. Jacod and A. N. Shiryaev, *Limit theorems for stochastic processes*. Grundlehren der Mathematischen Wissenschaften [Fundamental Principles of Mathematical Sciences], 288. Springer-Verlag, Berlin, 1987.
- [2] N. Lazrieva, T. Sharia and T. Toronjadze, Semimartingale stochastic approximation procedure and recursive estimation. Martingale theory and its application. J. Math. Sci. (N. Y.) 153 (2008), no. 3, 211–261.
- [3] N. Lazrieva and T. Toronjadze, Asymptotic theory of *M*-estimates in general statistical models. Parts I and II. *Centrum Voor Wiskunde en Information*, Reports BS-R9019-20 (1990).
- [4] N. Lazrieva and T. Toronjadze, Recursive estimation procedures for one-dimensional parameter of statistical models associated with semimartingales. *Trans. A. Razmadze Math. Inst.* 171 (2017), no. 1, 57–75.
- [5] N. Lazrieva, T. Sharia and T. Toronjadze, The Robbins-Monro type stochastic differential equations. I. Convergence of solutions. *Stochastics Stochastics Rep.* **61** (1997), no. 1-2, 67–87.
- [6] N. Lazrieva, T. Sharia and T. Toronjadze, T. The Robbins-Monro type stochastic differential equations. II. Asymptotic behaviour of solutions. *Stochastics Stochastics Rep.* 75 (2003), no. 3, 153–180.