A penalized bandit algorithm

Damien Lamberton, Gilles Pagès

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Abstract

We study a two armed-bandit algorithm with penalty. We show the convergence of the algorithm and establish the rate of convergence. For some choices of the parameters, we obtain a central limit theorem in which the limit distribution is characterized as the unique stationary distribution of a discontinuous Markov process.

Key words: Two-armed bandit algorithm, penalization, stochastic approximation, convergence rate, learning automata, asset allocation.

2001 AMS classification: 62L20, secondary 93C40, 91E40, 68T05, 91B32 .

Introduction

In a recent joint work with P. Tarrès (see [12]), we studied the convergence of the so-called two armed bandit algorithm. The purpose of the present paper is to investigate a modified version of this algorithm, in which a penalization is introduced. In the terminology of learning theory (see [14, 15]), the algorithm studied in [12] was a Linear Reward-Inaction (LRI) scheme, whereas the one we want to introduce is a Linear Reward-Penalty (LRP) procedure.

In our previous paper, the algorithm was introduced in a financial context as a procedure for the optimal allocation of a fund between two traders who manage it. Imagine that the owner of a fund can share his wealth between two traders, say A and B, and that, every day, he can evaluate the results of one of the traders and, subsequently, modify the percentage of the fund managed by both traders. Denote by X_n the percentage managed by trader A at time n ($X_n \in [0, 1]$). We assume that the owner selects the trader to be evaluated at random, in such a way that the probability that A is evaluated at time n is X_n, in order to select preferably the trader in charge of the greater part of the fund. In the LRI scheme, if the evaluated trader performs well, its share is increased by a fraction

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$\gamma_n \in (0,1)$ of the share of the other trader, and nothing happens if the evaluated trader performs badly. Therefore, the dynamics of the sequence $(X_n)_{n\geq 0}$ can be modelled as follows:

$$X_{n+1} = X_n + \gamma_{n+1}\left(\mathbf{1}_{\{U_{n+1}\leq X_n\}\cap A_{n+1}}(1-X_n) - \mathbf{1}_{\{U_{n+1}>X_n\}\cap B_{n+1}}X_n\right), \quad X_0 = x \in [0,1],$$

where $(U_n)_{n\geq 1}$ is an iid sequence of uniform random variables on the interval $[0,1]$, A_n (resp. B_n) is the event "trader A (resp. trader B) performs well at time n". We assume $\mathbb{P}(A_n) = p_A$, $\mathbb{P}(B_n) = p_B$, for $n \geq 1$, with $p_A, p_B \in (0,1)$, and independence between these events and the sequence $(U_n)_{n\geq 1}$. The point is that the owner of the fund does not know the parameters p_A, p_B.

This recursive learning procedure has been designed in order to assign asymptotically the whole fund to the best trader. This means that, if say $p_A > p_B$, X_n converges to 1 with probability 1 provided $X_0 \in (0,1)$ (if $p_A < p_B$, the limit is 0 with symmetric results). However this "infallibility" property needs some very stringent assumptions on the reward parameter γ_n (see [12]). Furthermore, the rate of convergence of the procedure either toward its "target" 1 or its "trap" 0 is not ruled by a CLT with rate $\sqrt{\gamma_n}$ like standard stochastic approximation algorithms (see [10]). It is shown in [11] that this rate is quite non-standard, strongly depends on the (unknown) values p_A and p_B and becomes very poor as these probabilities get close to each other.

In order to improve the efficiency of the algorithm, one may imagine to introduce a penalty when an evaluated trader has unsatisfactory performances. More precisely, if the evaluated trader at time n performs badly, its share is decreased by a penalty factor $\rho_n\gamma_n$. This leads to the following LRP – or "penalized two-armed bandit – procedure

$$\begin{aligned} X_{n+1} &= X_n + \gamma_{n+1}\left(\mathbf{1}_{\{U_{n+1}\leq X_n\}\cap A_{n+1}}(1-X_n) - \mathbf{1}_{\{U_{n+1}>X_n\}\cap B_{n+1}}X_n\right) \\ &\quad -\gamma_{n+1}\rho_{n+1}\left(X_n\mathbf{1}_{\{U_{n+1}\leq X_n\}\cap A^c_{n+1}} - (1-X_n)\mathbf{1}_{\{U_{n+1}>X_n\}\cap B^c_{n+1}}\right), \quad n \in \mathbb{N}, \end{aligned}$$

where the notation A^c is used for the complement of an event A. The precise assumptions on the reward rate γ_n and the penalty rate $\gamma_n\rho_n$ will be given in the following sections.

The paper is organized as follows. In Section 1, we discuss the convergence of the sequence $(X_n)_{n\geq 0}$. First we show that, if ρ_n is a positive constant ρ, the sequence converges with probability one to a limit $x^*_\rho \in (0,1)$ satisfying $x^*_\rho > \frac{1}{2}$ if and only if $p_A > p_B$, so that, although the algorithm manages to distinguish which trader is better, it does not assign the whole fund to the best trader. To get rid of this limitation, we consider a sequence $(\rho_n)_{n\geq 1}$ which goes to zero so that the penalty rate becomes negligible with respect to the reward rate ($\gamma_n\rho_n = o(\gamma_n)$). This framework seems new in the learning theory literature. Then, we are able to show that the algorithm is infallible *i.e.*, if $p_A > p_B$, then $\lim_{n\to\infty} X_n = 1$ almost surely, under very light conditions on the reward rate γ_n (and ρ_n). From a stochastic approximation viewpoint, this modification of the original procedure has the same mean function and time scale (hence the same target and trap, see (5)) but it always keeps the algorithm away from the trap without adding noise at these equilibria. In fact, it was necessary not to add noise at these points in order to remain inside the domain $[0,1]$.

The other two sections are devoted to the rate of convergence. In Section 2, we show that under some conditions (including $\lim_{n\to\infty} \gamma_n/\rho_n = 0$) the sequence $Y_n = (1 - X_n)/\rho_n$ converges in probability to $(1-p_A)/\pi$, where $\pi = p_A - p_B > 0$. With additional assumptions, we prove that this convergence occurs with probability 1. In Section 3, we show that if the ratio γ_n/ρ_n goes to a positive limit as n goes to infinity, then $(Y_n)_{n\geq 1}$ converges in a weak sense to a probability distribution ν. This distribution is identified as the unique stationary distribution of a discontinuous Markov process. This result is obtained by using weak functional methods applied to a re-scaling of the algorithm. This approach can be seen as an extension of the SDE method used to prove the CLT in a more standard framework of stochastic approximation (see [10]). Furthermore, we show that ν is absolutely continuous with continuous, possibly non-smooth, piecewise $\mathcal{C}^\infty$ density. An interesting consequence of these results for practical applications is that, by choosing ρ_n and γ_n proportional to $n^{-1/2}$, one can achieve *convergence at the rate* $1/\sqrt{n}$, *without any a priori knowledge about the values of* p_A *and* p_B. This is in contrast with the case of the LRI procedure, where the rate of convergence depends heavily on these parameters (see [11]) and becomes quite poor when they get close to each other.

Notation. Let $(a_n)_{n\geq 0}$ and $(b_n)_{n\geq 0}$ be two sequences of positive real numbers. The symbol $a_n \sim b_n$ means $a_n = b_n + o(b_n)$.

1 Convergence of the LRP algorithm

1.1 Some classical background on stochastic approximation

We will rely on the ODE lemma recalled below for a stochastic procedure (Z_n) taking its values in a given compact interval I.

Theorem 1 (a) Kushner & Clark's ODE Lemma (see [9]): *Let $g : I \to \mathbb{R}$ such that $Id + g$ leaves I stable ([1]). Then, consider the recursively defined stochastic approximation procedure defined on I by*

$$Z_{n+1} = Z_n + \gamma_{n+1}(g(Z_n) + \Delta R_{n+1}),\ n \geq 0, \quad Z_0 \in I,$$

where $(\gamma_n)_{n\geq 1}$ is a sequence of $[0, 1]$-valued real numbers satisfying $\gamma_n \to 0$ and $\sum_{n\geq 1} \gamma_n = +\infty$. Set $N(t) := \min\{n : \gamma_1 + \cdots + \gamma_{n+1} > t\}$. If, for every $T > 0$,

$$\max_{N(t)\leq n\leq N(t+T)} \left| \sum_{k=N(t)+1}^{n} \gamma_k \, \Delta R_k \right| \longrightarrow 0 \qquad \mathbb{P}\text{-}a.s. \ \ as \quad t \to +\infty. \tag{1}$$

Let z^* be an attracting zero of g in I and $G(z^*)$ its attracting interval. Then, on the event

$$\{Z_n \ visits\ infinitely\ often\ a\ compact\ subset\ of\ G(z^*)\} \qquad Z_n \xrightarrow{a.s.} z^*.$$

[1] then for every $\gamma \in [0, 1]$, $Id + \gamma g = \gamma(Id + g) + (1 - \gamma)Id$ still takes values in the convex set I

(b) THE HOEFFDING CONDITION (SEE [1]): *If $(\Delta R_n)_{n\geq 0}$ is a sequence of L^∞-bounded martingale increments, if (γ_n) is nonincreasing and $\sum_{n\geq 1} e^{-\frac{\vartheta}{\gamma_n}} < +\infty$ for every $\vartheta > 0$, then Assumption (1) is satisfied.*

Remark. The monotonous assumption on the sequence γ can be relaxed into $\gamma_n \to 0$ and $\sup_{n,k\geq 1} \frac{\gamma_{n+k}}{\gamma_n} < +\infty$

1.2 Basic properties of the LRP algorithm

We first recall the definition of the algorithm. We are interested in the asymptotic behavior of the sequence $(X_n)_{n\in\mathbb{N}}$, where $X_0 = x$, with $x \in (0,1)$, and

$$\begin{aligned} X_{n+1} &= X_n + \gamma_{n+1}\left(\mathbf{1}_{\{U_{n+1}\leq X_n\}\cap A_{n+1}}(1-X_n) - \mathbf{1}_{\{U_{n+1}>X_n\}\cap B_{n+1}}X_n\right) \\ &\quad -\gamma_{n+1}\rho_{n+1}\left(X_n\mathbf{1}_{\{U_{n+1}\leq X_n\}\cap A^c_{n+1}} - (1-X_n)\mathbf{1}_{\{U_{n+1}>X_n\}\cap B^c_{n+1}}\right), \quad n \in \mathbb{N}. \end{aligned}$$

Throughout the paper, we assume that $(\gamma_n)_{n\geq 1}$ is a non-increasing sequence of positive numbers satisfying $\gamma_n < 1$, $\sum_{n=1}^{\infty} \gamma_n = +\infty$ and

$$\forall \vartheta > 0, \quad \sum_n e^{-\frac{\vartheta}{\gamma_n}} < \infty,$$

and that $(\rho_n)_{n\geq 1}$ is a sequence of positive numbers satisfying $\gamma_n\rho_n < 1$; $(U_n)_{n\geq 1}$ is a sequence of independent random variables which are uniformly distributed on the interval $[0,1]$, the events A_n, B_n satisfy

$$\mathbb{P}(A_n) = p_{_A}, \quad \mathbb{P}(B_n) = p_{_B}, \quad n \in \mathbb{N},$$

where $0 < p_{_B} \leq p_{_A} < 1$, and the sequences $(U_n)_{n\geq 1}$ and $(\mathbf{1}_{A_n}, \mathbf{1}_{B_n})_{n\geq 1}$ are independent. The natural filtration of the sequence $(U_n, \mathbf{1}_{A_n}, \mathbf{1}_{B_n})_{n\geq 1}$ is denoted by $(\mathcal{F}_n)_{n\geq 0}$ and we set

$$\pi = p_{_A} - p_{_B}.$$

With this notation, we have, for $n \geq 0$,

$$X_{n+1} = X_n + \gamma_{n+1}\left(\pi h(X_n) + \rho_{n+1}\kappa(X_n)\right) + \gamma_{n+1}\Delta M_{n+1}, \tag{2}$$

where the functions h and κ are defined by

$$h(x) = x(1-x), \quad \kappa(x) = -(1-p_{_A})x^2 + (1-p_{_B})(1-x)^2, \quad 0 \leq x \leq 1,$$

$\Delta M_{n+1} = M_{n+1} - M_n$, and the sequence $(M_n)_{n\geq 0}$ is the martingale defined by $M_0 = 0$ and

$$\begin{aligned} \Delta M_{n+1} &= \mathbf{1}_{\{U_{n+1}\leq X_n\}\cap A_{n+1}}(1-X_n) - \mathbf{1}_{\{U_{n+1}>X_n\}\cap B_{n+1}}X_n - \pi h(X_n) \\ &\quad -\rho_{n+1}\left(X_n\mathbf{1}_{\{U_{n+1}\leq X_n\}\cap A^c_{n+1}} - (1-X_n)\mathbf{1}_{\{U_{n+1}>X_n\}\cap B^c_{n+1}} + \kappa(X_n)\right). \end{aligned} \tag{3}$$

Observe that the increments ΔM_{n+1} are bounded.

1.3 Constant penalty rate

In this subsection, we assume

$$\forall n \geq 1, \quad \rho_n = \rho,$$

with $0 < \rho \leq 1$. We then have

$$X_{n+1} = X_n + \gamma_{n+1}\left(h_\rho(X_n) + \Delta M_{n+1}\right),$$

where

$$h_\rho(x) = \pi h(x) + \rho\kappa(x), \quad 0 \leq x \leq 1.$$

Note that $h_\rho(0) = \rho(1 - p_B) > 0$ and $h_\rho(1) = -\rho(1 - p_A) < 0$, and that there exists a unique $x^*_\rho \in (0, 1)$ such that $h_\rho(x^*_\rho) = 0$. By a straightforward computation, we have

$$\begin{aligned} x^*_\rho &= \frac{\pi - 2\rho(1 - p_B) + \sqrt{\pi^2 + 4\rho^2(1 - p_B)(1 - p_A)}}{2\pi(1 - \rho)} \quad \text{if } \pi \neq 0 \text{ and } \rho \neq 1 \\ &= \frac{(1 - p_A)}{(1 - p_A) + (1 - p_B)} \quad \text{if } \pi = 0 \text{ or } \rho = 1. \end{aligned}$$

In particular, $x^*_\rho = 1/2$ if $\pi = 0$ regardless of the value of ρ. We also have $h_\rho(1/2) = \pi(1 + \rho)/4 \geq 0$, so that

$$x^*_\rho > 1/2 \quad \text{if} \quad \pi > 0. \tag{4}$$

Now, let x be a solution of the ODE $dx/dt = h_\rho(x)$. If $x(0) \in [0, x^*_\rho]$, x is non-decreasing and $\lim_{t\to\infty} x(t) = x^*_\rho$. If $x(0) \in [x^*_\rho, 1]$, x is non-increasing and $\lim_{t\to\infty} x(t) = x^*_\rho$. It follows that the interval $[0, 1]$ is a domain of attraction for x^*_ρ. Consequently, using Kushner and Clark's *ODE* Lemma (see Theorem 1), one reaches the following conclusion.

Proposition 1 *Assume that $\rho_n = \rho \in (0, 1]$, then*

$$X_n \xrightarrow{a.s.} x^*_\rho \qquad \text{as } n \to \infty.$$

The natural interpretation, given the above inequalities on x^*_ρ, is that this algorithm never fails in pointing the best trader thanks to Inequality (4), but it never assigns the whole fund to this trader as the original *LRI* procedure did.

1.4 Convergence when the penalty rate goes to zero

Proposition 2 *Assume $\lim_{n\to\infty} \rho_n = 0$. The sequence $(X_n)_{n\in\mathbb{N}}$ is almost surely convergent and its limit X_∞ satisfies $X_\infty \in \{0, 1\}$ with probability 1.*

Proof: We first write the algorithm in its canonical form

$$X_{n+1} = X_n + \gamma_{n+1}(\pi\, h(X_n) + \Delta R_{n+1}) \qquad \text{with} \qquad \Delta R_n = \Delta M_n + \rho_n\kappa(X_{n-1}). \tag{5}$$

It is straightforward to check that the *ODE* $\dot{x} = h(x)$ has two equilibrium points, 0 and 1, 1 being attractive with $(0, 1]$ as an attracting interval and 0 is unstable.

Since the martingale increments ΔM_n are bounded, it follows from the assumptions on the sequence $(\gamma_n)_{n\geq 1}$ and the Hoeffding condition (see Theorem 1(b)) that

$$\max_{N(t)\leq n\leq N(t+T)} |\sum_{k=N(t)+1}^{n} \gamma_k \Delta M_k| \stackrel{\mathbb{P}\text{-}a.s.}{\longrightarrow} 0 \quad \text{as } t\to+\infty$$

for every $T>0$. On the other hand the function κ being bounded on $[0,1]$ and ρ_n converging to 0, we have, for every $T>0$,

$$\max_{N(t)\leq n\leq N(t+T)} |\sum_{k=N(t)+1}^{n} \gamma_k\rho_k\kappa(X_{k-1})| \leq \|k\|_{[0,1]}(T+\gamma_{N(t+T)}) \max_{k\geq N(t)+1}\rho_k \longrightarrow 0 \quad \text{as } t\to+\infty.$$

Finally, the sequence $(\Delta R_n)_{n\geq 1}$ satisfies Assumption (1). Consequently, either X_n visits infinitely often an interval $[\varepsilon,1]$ for some $\varepsilon>0$ and X_n converges toward 1, or X_n converges toward 0. $\diamond$

Remark 1 If $\pi=0$, *i.e.* $p_A=p_B$, the algorithm reduces to

$$X_{n+1}=X_n+\gamma_{n+1}\rho_{n+1}(1-p_A)(1-2X_n)+\gamma_{n+1}\Delta M_{n+1}.$$

The number $1/2$ is the unique equilibrium of the ODE $\dot{x}=(1-p_A)(1-2x)$, and the interval $[0,1]$ is a domain of attraction. Assuming $\sum_{n=1}^{\infty}\rho_n\gamma_n=+\infty$, and that the sequence $(\gamma_n/\rho_n)_{n\geq 1}$ is non-increasing and satisfies

$$\forall\vartheta>0,\quad \sum_{n=1}^{\infty}\exp\left(-\vartheta\frac{\rho_n}{\gamma_n}\right)<+\infty,$$

it can be proved, using the Kushner-Clark *ODE* Lemma (Theorem 1), that $\lim_{n\to\infty} X_n=1/2$ almost surely. As concerns the asymptotics of the algorithm when $\pi=0$ and $\gamma_n=g\,\rho_n$ (for which the above condition is not satisfied), we refer to the final remark of the paper.

From now on, we will assume that $p_A>p_B$. The next proposition shows that the penalized algorithm is infallible under very light assumptions on γ_n and ρ_n.

Proposition 3 *(Infallibility) Assume $\lim_{n\to\infty}\rho_n=0$. If the sequence $(\gamma_n/\rho_n)_{n\geq 1}$ is bounded and $\sum_n\gamma_n\rho_n=\infty$, and if $\pi>0$, we have $\lim_{n\to\infty}X_n=1$ almost surely.*

PROOF: We have from (2), since $h\geq 0$ on the interval $[0,1]$,

$$X_n\geq X_0+\sum_{j=1}^{n}\gamma_j\rho_j\kappa(X_{j-1})+\sum_{j=1}^{n}\gamma_j\Delta M_j,\quad n\geq 1.$$

Since the jumps ΔM_j are bounded, we have

$$\left\|\sum_{j=1}^{n}\gamma_j\Delta M_j\right\|_{L^2}^2\leq C\sum_{j=1}^{n}\gamma_j^2\leq C\sup_{j\in\mathbb{N}}(\gamma_j/\rho_j)\sum_{j=1}^{n}\gamma_j\rho_j,$$

for some positive constant C. Therefore, since $\sum_n \gamma_n \rho_n = \infty$,

$$L^2\text{-}\lim_{n\to\infty} \frac{\sum_{j=1}^n \gamma_j \Delta M_j}{\sum_{j=1}^n \gamma_j \rho_j} = 0 \quad \text{so that} \quad \limsup_n \frac{\sum_{j=1}^n \gamma_j \Delta M_j}{\sum_{j=1}^n \gamma_j \rho_j} \geq 0 \qquad a.s..$$

Now, on the set $\{X_\infty = 0\}$, we have

$$\lim_{n\to\infty} \frac{\sum_{j=1}^n \gamma_j \rho_j \kappa(X_{j-1})}{\sum_{j=1}^n \gamma_j \rho_j} = \kappa(0) > 0.$$

Hence, it follows that, still on the set $\{X_\infty = 0\}$,

$$\limsup_{n\to\infty} \frac{X_n}{\sum_{j=1}^n \gamma_j \rho_j} > 0.$$

Therefore, we must have $\mathbb{P}(X_\infty = 0) = 0$. $\diamond$

The following Proposition will give a control on the conditional variance process of the martingale $(M_n)_{n\in\mathbb{N}}$ which will be crucial to elucidate the rate of convergence of the algorithm.

Proposition 4 *We have, for $n \geq 0$,*

$$\mathbb{E}\left(\Delta M_{n+1}^2 \mid \mathcal{F}_n\right) \leq p_A(1 - X_n) + \rho_{n+1}^2(1 - p_B).$$

PROOF: We have

$$\Delta M_{n+1} = V_{n+1} - \mathbb{E}(V_{n+1} \mid \mathcal{F}_n) + W_{n+1} - \mathbb{E}(W_{n+1} \mid \mathcal{F}_n),$$

with

$$V_{n+1} = \mathbf{1}_{\{U_{n+1}\leq X_n\}\cap A_{n+1}}(1 - X_n) - \mathbf{1}_{\{U_{n+1}>X_n\}\cap B_{n+1}} X_n$$

and

$$W_{n+1} = -\rho_{n+1}\left(X_n \mathbf{1}_{\{U_{n+1}\leq X_n\}\cap A_{n+1}^c} - (1 - X_n)\mathbf{1}_{\{U_{n+1}>X_n\}\cap B_{n+1}^c}\right).$$

Note that $V_{n+1}W_{n+1} = 0$, so that

$$\begin{aligned}
\mathbb{E}\left(\Delta M_{n+1}^2 \mid \mathcal{F}_n\right) &= \mathbb{E}(V_{n+1}^2 \mid \mathcal{F}_n) + \mathbb{E}(W_{n+1}^2 \mid \mathcal{F}_n) - (\mathbb{E}(V_{n+1} + W_{n+1} \mid \mathcal{F}_n))^2 \\
&\leq \mathbb{E}(V_{n+1}^2 \mid \mathcal{F}_n) + \mathbb{E}(W_{n+1}^2 \mid \mathcal{F}_n).
\end{aligned}$$

Now, using $p_B \leq p_A$ and $X_n \leq 1$,

$$\begin{aligned}
\mathbb{E}\left(V_{n+1}^2 \mid \mathcal{F}_n\right) &= p_A X_n(1 - X_n)^2 + p_B(1 - X_n)X_n^2 \\
&\leq p_A(1 - X_n) \\
\text{and} \qquad \mathbb{E}(W_{n+1}^2 \mid \mathcal{F}_n) &= \rho_{n+1}^2\left(X_n^3(1 - p_A) + (1 - X_n)^3(1 - p_B)\right) \\
&\leq \rho_{n+1}^2(1 - p_B).
\end{aligned}$$

This proves the Proposition. $\diamond$

2 The rate of convergence: pointwise convergence

2.1 Convergence in probability

Theorem 2 *Assume*

$$\lim_{n\to\infty}\rho_n = 0, \quad \lim_{n\to\infty}\frac{\gamma_n}{\rho_n} = 0, \quad \sum_n \rho_n\gamma_n = \infty, \quad \rho_n - \rho_{n-1} = o(\rho_n\gamma_n). \tag{6}$$

Then, the sequence $((1-X_n)/\rho_n)_{n\geq 1}$ *converges to* $(1-p_{_A})/\pi$ *in probability.*

Note that the assumptions of Theorem 2 are satisfied if $\gamma_n = C/n^a$ and $\rho_n = C'/n^r$, with $C, C' > 0$, $0 < r < a$ and $a + r < 1$. In fact, we will see that for this choice of parameters, convergence holds with probability one (see Theorem 3).

Before proving Theorem 2, we introduce the notation

$$Y_n = \frac{1-X_n}{\rho_n}.$$

We have, from (2)

$$\begin{aligned}
1 - X_{n+1} &= 1 - X_n - \gamma_{n+1}\pi X_n(1-X_n) - \rho_{n+1}\gamma_{n+1}\kappa(X_n) - \gamma_{n+1}\Delta M_{n+1} \\
\frac{1-X_{n+1}}{\rho_{n+1}} &= \frac{1-X_n}{\rho_{n+1}} - \frac{\gamma_{n+1}}{\rho_{n+1}}\pi X_n(1-X_n) - \gamma_{n+1}\kappa(X_n) - \frac{\gamma_{n+1}}{\rho_{n+1}}\Delta M_{n+1}.
\end{aligned}$$

Hence

$$\begin{aligned}
Y_{n+1} &= Y_n + (1-X_n)\left(\frac{1}{\rho_{n+1}} - \frac{1}{\rho_n} - \frac{\gamma_{n+1}}{\rho_{n+1}}\pi X_n\right) - \gamma_{n+1}\kappa(X_n) - \frac{\gamma_{n+1}}{\rho_{n+1}}\Delta M_{n+1} \\
Y_{n+1} &= Y_n\left(1 + \gamma_{n+1}\varepsilon_n - \pi_n\gamma_{n+1}X_n\right) - \gamma_{n+1}\kappa(X_n) - \frac{\gamma_{n+1}}{\rho_{n+1}}\Delta M_{n+1},
\end{aligned}$$

where

$$\varepsilon_n = \frac{\rho_n}{\gamma_{n+1}}\left(\frac{1}{\rho_{n+1}} - \frac{1}{\rho_n}\right) \text{ and } \pi_n = \frac{\rho_n}{\rho_{n+1}}\pi.$$

It follows from the assumption $\rho_n - \rho_{n-1} = o(\rho_n\gamma_n)$ that $\lim_{n\to\infty}\varepsilon_n = 0$ and $\lim_{n\to\infty}\pi_n = \pi$.

Lemma 1 *Consider two positive numbers* π^- *and* π^+ *with* $0 < \pi^- < \pi < \pi^+ < 1$. *Given* $l \in \mathbb{N}$, *let*

$$\nu^l = \inf\{n \geq l \mid \pi_n X_n - \varepsilon_n > \pi^+ \text{ or } \pi_n X_n - \varepsilon_n < \pi^-\}.$$

We have

- $\lim_{l\to\infty}\mathbb{P}(\nu^l = \infty) = 1$,
- *for* $n \geq l$, *if* $\theta_n^+ = \prod_{k=l+1}^n(1-\pi^+\gamma_k)$ *and* $\theta_n^- = \prod_{k=l+1}^n(1-\pi^-\gamma_k)$,

$$\frac{Y_{n\wedge\nu^l}}{\theta^-_{n\wedge\nu^l}} \leq Y_l - \sum_{k=l+1}^{n\wedge\nu^l}\frac{\gamma_k}{\theta_k^-}\kappa(X_{k-1}) - \sum_{k=l+1}^{n\wedge\nu^l}\frac{\gamma_k}{\rho_k\theta_k^-}\Delta M_k \tag{7}$$

and

$$\frac{Y_{n\wedge\nu^l}}{\theta^+_{n\wedge\nu^l}} \geq Y_l - \sum_{k=l+1}^{n\wedge\nu^l} \frac{\gamma_k}{\theta^+_k}\kappa(X_{k-1}) - \sum_{k=l+1}^{n\wedge\nu^l} \frac{\gamma_k}{\rho_k\theta^+_k}\Delta M_k. \tag{8}$$

Moreover, with the notation $||k||_\infty = \sup_{0<x<1}|\kappa(x)|$,

$$\sup_{n\geq l}\mathbb{E}\left(Y_n\mathbf{1}_{\{\nu^l=\infty\}}\right) \leq \mathbb{E}\,Y_l + \frac{||k||_\infty}{\pi^-}.$$

Remark 2 Note that, as the proof will show, Lemma 1 remains valid if the condition $\lim_{n\to\infty}\gamma_n/\rho_n = 0$ in (6) is replaced by the boundedness of the sequence $(\gamma_n/\rho_n)_{n\geq 1}$. In particular, the last statement, which implies the tightness of the sequence $(Y_n)_{n\geq1}$, will be used in Section 3.

Proof: Since $\lim_{n\to\infty}(\pi_n X_n - \varepsilon_n) = \pi$ a.s., we clearly have $\lim_{l\to\infty}\mathbb{P}(\nu^l = \infty) = 1$.

On the other hand, for $l \leq n < \nu^l$, we have

$$Y_{n+1} \leq Y_n(1-\gamma_{n+1}\pi^-) - \gamma_{n+1}\kappa(X_n) - \frac{\gamma_{n+1}}{\rho_{n+1}}\Delta M_{n+1}$$

and

$$Y_{n+1} \geq Y_n(1-\gamma_{n+1}\pi^+) - \gamma_{n+1}\kappa(X_n) - \frac{\gamma_{n+1}}{\rho_{n+1}}\Delta M_{n+1},$$

so that, with the notation $\theta^+_n = \prod_{k=l+1}^n(1-\pi^+\gamma_k)$ and $\theta^-_n = \prod_{k=l+1}^n(1-\pi^-\gamma_k)$,

$$\frac{Y_{n+1}}{\theta^-_{n+1}} \leq \frac{Y_n}{\theta^-_n} - \frac{\gamma_{n+1}}{\theta^-_{n+1}}\kappa(X_n) - \frac{\gamma_{n+1}}{\rho_{n+1}\theta^-_{n+1}}\Delta M_{n+1}$$

and

$$\frac{Y_{n+1}}{\theta^+_{n+1}} \geq \frac{Y_n}{\theta^+_n} - \frac{\gamma_{n+1}}{\theta^+_{n+1}}\kappa(X_n) - \frac{\gamma_{n+1}}{\rho_{n+1}\theta^+_{n+1}}\Delta M_{n+1}.$$

By summing up these inequalities, we get (7) and (8).

By taking expectations in (7), we get

$$\begin{aligned}
\mathbb{E}\frac{Y_{n\wedge\nu^l}}{\theta^-_{n\wedge\nu^l}} &\leq \mathbb{E}\,Y_l + ||k||_\infty\mathbb{E}\sum_{k=l+1}^{n\wedge\nu^l}\frac{\gamma_k}{\theta^-_k} \\
&= \mathbb{E}\,Y_l + \frac{||k||_\infty}{\pi^-}\mathbb{E}\sum_{k=l+1}^{n\wedge\nu^l}\left(\frac{1}{\theta^-_k} - \frac{1}{\theta^-_{k-1}}\right) \\
&\leq \mathbb{E}\,Y_l + \frac{||k||_\infty}{\pi^-}\frac{1}{\theta^-_n}.
\end{aligned}$$

We then have

$$\begin{aligned}
\mathbb{E}(Y_n\mathbf{1}_{\{\nu^l=\infty\}}) = \theta^-_n\mathbb{E}\left(\frac{Y_{n\wedge\nu^l}}{\theta^-_{n\wedge\nu^l}}\mathbf{1}_{\{\nu^l=\infty\}}\right) &\leq \theta^-_n\mathbb{E}\frac{Y_{n\wedge\nu^l}}{\theta^-_{n\wedge\nu^l}} \\
&\leq \theta^-_n\left(\mathbb{E}\,Y_l + \frac{||k||_\infty}{\pi^-}\frac{1}{\theta^-_n}\right) \\
&\leq \mathbb{E}\,Y_l + \frac{||k||_\infty}{\pi^-}.
\end{aligned}$$

$\diamond$

Lemma 2 *Let $(\theta_n)_{n\in\mathbb{N}}$ be a sequence of positive numbers such that $\theta_n = \prod_{k=1}^n(1-p\gamma_k)$ for some $p\in(0,1)$. The sequence $\left(\theta_n\sum_{k=1}^n \frac{\gamma_k}{\theta_k\rho_k}\Delta M_k\right)_{n\in\mathbb{N}}$ converges to 0 in probability.*

PROOF: It suffices to show convergence to 0 in probability for the associated conditional variances T_n, defined by

$$T_n = \theta_n^2\sum_{k=1}^n \frac{\gamma_k^2}{\theta_k^2\rho_k^2}\mathbb{E}\left(\Delta M_k^2 \mid \mathcal{F}_{k-1}\right).$$

We know from Proposition 4 that

$$\begin{aligned}\mathbb{E}\left(\Delta M_k^2 \mid \mathcal{F}_{k-1}\right) &\le p_A(1-X_{k-1}) + \rho_k^2(1-p_B)\\ &= p_A\rho_{k-1}Y_{k-1} + \rho_k^2(1-p_B).\end{aligned}$$

Therefore, $T_n \le p_A T_n^{(1)} + (1-p_B)T_n^{(2)}$, where

$$T_n^{(1)} = \theta_n^2\sum_{k=1}^n \frac{\gamma_k^2}{\theta_k^2\rho_k^2}\rho_{k-1}Y_{k-1}$$

and

$$T_n^{(2)} = \theta_n^2\sum_{k=1}^n \frac{\gamma_k^2}{\theta_k^2}.$$

We first prove that $\lim_{n\to\infty} T_n^{(2)} = 0$. Note that, since $p\gamma_k \le 1$,

$$\frac{1}{\theta_k^2} - \frac{1}{\theta_{k-1}^2} = \frac{2p\gamma_k - p^2\gamma_k^2}{\theta_k^2} \ge p\frac{\gamma_k}{\theta_k^2}. \tag{9}$$

Therefore,

$$T_n^{(2)} \le \frac{\theta_n^2}{p}\sum_{k=1}^n \gamma_k\left(\frac{1}{\theta_k^2} - \frac{1}{\theta_{k-1}^2}\right),$$

and $\lim_{n\to\infty} T_n^{(2)} = 0$ follows from Cesaro's lemma.

We now deal with $T_n^{(1)}$. First note that the assumption $\rho_n - \rho_{n-1} = o(\rho_n\gamma_n)$ implies $\lim_{n\to\infty}\rho_n/\rho_{n-1} = 1$, so that, the sequence $(\gamma_n)_{n\ge1}$ being non-increasing with limit 0, we only need to prove that $\lim_{n\to\infty}\bar{T}_n^{(1)} = 0$ in probability, where

$$\bar{T}_n^{(1)} = \theta_n^2\sum_{k=1}^n \frac{\gamma_k^2}{\theta_k^2\rho_k}Y_k.$$

Now, with the notation of Lemma 1, we have, for $n \ge l > 1$ and $\varepsilon > 0$,

$$\begin{aligned}\mathbb{P}\left(\bar{T}_n^{(1)} \ge \varepsilon\right) &\le \mathbb{P}(\nu^l < \infty) + \mathbb{P}\left(\theta_n^2\sum_{k=1}^n \frac{\gamma_k^2}{\theta_k^2\rho_k}Y_k\mathbf{1}_{\{\nu^l=\infty\}} \ge \varepsilon\right)\\ &\le \mathbb{P}(\nu^l < \infty) + \frac{1}{\varepsilon}\theta_n^2\sum_{k=1}^n \frac{\gamma_k^2}{\theta_k^2\rho_k}\mathbb{E}\left(Y_k\mathbf{1}_{\{\nu^l=\infty\}}\right).\end{aligned}$$

Using Lemma 1, $\lim_{n\to\infty} \gamma_n/\rho_n = 0$ and (9), we have

$$\lim_{n\to\infty} \theta_n^2 \sum_{k=1}^n \frac{\gamma_k^2}{\theta_k^2 \rho_k} \mathbb{E}\left(Y_k \mathbf{1}_{\{\nu^l=\infty\}}\right) = 0.$$

We also know that $\lim_{l\to\infty} \mathbb{P}(\nu^l < \infty) = 0$. Hence,

$$\lim_{n\to\infty} \mathbb{P}\left(\bar{T}_n^{(1)} \geq \varepsilon\right) = 0. \qquad \diamondsuit$$

Proof of Theorem 2: First note that if $\theta_n = \prod_{k=1}^n (1 - p\gamma_k)$, with $0 < p < 1$, we have

$$\sum_{k=1}^n \frac{\gamma_k}{\theta_k} \kappa(X_{k-1}) = \frac{1}{p} \sum_{k=1}^n \left(\frac{1}{\theta_k} - \frac{1}{\theta_{k-1}}\right) \kappa(X_{k-1}).$$

Hence, using $\lim_{n\to\infty} X_n = 1$ and $\kappa(1) = -(1 - p_A)$,

$$\lim_{n\to\infty} \theta_n \sum_{k=1}^n \frac{\gamma_k}{\theta_k} \kappa(X_{k-1}) = -\frac{1 - p_A}{p}.$$

Going back to (7) and (8) and using Lemma 2 with $p = \pi^+$ and π^-, and the fact that $\lim_{l\to\infty} \mathbb{P}(\nu^l = \infty) = 1$, we have, for all $\varepsilon > 0$, $\lim_{n\to\infty} \mathbb{P}(Y_n \geq \frac{1 - p_A}{\pi^-} + \varepsilon) = \lim_{n\to\infty} \mathbb{P}(Y_n \leq \frac{1 - p_A}{\pi^+} - \varepsilon) = 0$, and since π^+ and π^- can be made arbitrarily close to π, the Theorem is proved. $\diamondsuit$

2.2 Almost sure convergence

Theorem 3 *In addition to (6), we assume that for all $\beta \in [0, 1]$,*

$$\gamma_n \rho_n^\beta - \gamma_{n-1} \rho_{n-1}^\beta = o(\gamma_n^2 \rho_n^\beta), \tag{10}$$

and that, for some $\eta > 0$, we have

$$\forall C > 0, \quad \sum_n \exp\left(-C \frac{\rho_n^{1+\eta}}{\gamma_n}\right) < \infty. \tag{11}$$

Then, with probability 1,

$$\lim_{n\to\infty} \frac{1 - X_n}{\rho_n} = \frac{1 - p_A}{\pi}.$$

Note that the assumptions of Theorem 3 are satisfied if $\gamma_n = Cn^{-a}$ and $\rho_n = C'n^{-r}$, with $C, C' > 0$, $0 < r < a$ and $a + r < 1$.

The proof of Theorem 3 is based on the following lemma, which will be proved later.

Lemma 3 *Under the assumptions of Theorem 3, let $\alpha \in [0,1]$ and let $(\theta_n)_{n\in\geq 1}$ be a sequence of positive numbers such that $\theta_n = \prod_{k=1}^{n}(1-p\gamma_k)$, for some $p \in (0,1)$. On the set $\{\sup_n(\rho_n^\alpha Y_n) < \infty\}$, we have*

$$\lim_{n\to\infty} \theta_n \rho_n^{\frac{\alpha-\eta}{2}-1} \sum_{k=1}^{n} \frac{\gamma_k}{\theta_k}\Delta M_k = 0 \ a.s.,$$

where η satisfies (11).

Proof of Theorem 3: We start from the following form of (2):

$$1 - X_{n+1} = (1-X_n)(1-\gamma_{n+1}\pi X_n) - \rho_{n+1}\gamma_{n+1}\kappa(X_n) - \gamma_{n+1}\Delta M_{n+1}.$$

We know that $\lim_{n\to\infty} X_n = 1$ a.s.. Therefore, given π^+ and π^-, with $0 < \pi^- < \pi < \pi^+ < 1$, there exists $l \in \mathbb{N}$ such that, for $n \geq l$,

$$1 - X_{n+1} \leq (1-X_n)(1-\gamma_{n+1}\pi^-) - \rho_{n+1}\gamma_{n+1}\kappa(X_n) - \gamma_{n+1}\Delta M_{n+1}$$

and

$$1 - X_{n+1} \geq (1-X_n)(1-\gamma_{n+1}\pi^+) - \rho_{n+1}\gamma_{n+1}\kappa(X_n) - \gamma_{n+1}\Delta M_{n+1},$$

so that, with the notation $\theta_n^+ = \prod_{k=l+1}^{n}(1-\pi^+\gamma_k)$ and $\theta_n^- = \prod_{k=l+1}^{n}(1-\pi^-\gamma_k)$,

$$\frac{1-X_{n+1}}{\theta_{n+1}^-} \leq \frac{1-X_n}{\theta_n^-} - \frac{\rho_{n+1}\gamma_{n+1}}{\theta_{n+1}^-}\kappa(X_n) - \frac{\gamma_{n+1}}{\theta_{n+1}^-}\Delta M_{n+1}$$

and

$$\frac{1-X_{n+1}}{\theta_{n+1}^+} \geq \frac{1-X_n}{\theta_n^+} - \frac{\rho_{n+1}\gamma_{n+1}}{\theta_{n+1}^+}\kappa(X_n) - \frac{\gamma_{n+1}}{\theta_{n+1}^+}\Delta M_{n+1}.$$

By summing up these inequalities, we get, for $n \geq l+1$,

$$\frac{1-X_n}{\theta_n^-} \leq (1-X_l) - \sum_{k=l+1}^{n}\frac{\rho_k\gamma_k}{\theta_k^-}\kappa(X_{k-1}) - \sum_{k=l+1}^{n}\frac{\gamma_k}{\theta_k^-}\Delta M_k$$

and

$$\frac{1-X_n}{\theta_n^+} \geq (1-X_l) - \sum_{k=l+1}^{n}\frac{\rho_k\gamma_k}{\theta_k^+}\kappa(X_{k-1}) - \sum_{k=l+1}^{n}\frac{\gamma_k}{\theta_k^+}\Delta M_k.$$

Hence

$$Y_n \leq \frac{\theta_n^-}{\rho_n}(1-X_l) - \frac{\theta_n^-}{\rho_n}\sum_{k=l+1}^{n}\frac{\rho_k\gamma_k}{\theta_k^-}\kappa(X_{k-1}) - \frac{\theta_n^-}{\rho_n}\sum_{k=l+1}^{n}\frac{\gamma_k}{\theta_k^-}\Delta M_k \tag{12}$$

and

$$Y_n \geq \frac{\theta_n^+}{\rho_n}(1-X_l) - \frac{\theta_n^+}{\rho_n}\sum_{k=l+1}^{n}\frac{\rho_k\gamma_k}{\theta_k^+}\kappa(X_{k-1}) - \frac{\theta_n^+}{\rho_n}\sum_{k=l+1}^{n}\frac{\gamma_k}{\theta_k^+}\Delta M_k. \tag{13}$$

We have, with probability 1, $\lim_{n\to\infty}\kappa(X_n) = \kappa(1) = -(1-p_A)$, and, since $\sum_{n=1}^{\infty}\rho_n\gamma_n = +\infty$,

$$\sum_{k=l+1}^{n}\frac{\rho_k\gamma_k}{\theta_k^-}\kappa(X_{k-1}) \sim -(1-p_A)\sum_{k=l+1}^{n}\frac{\rho_k\gamma_k}{\theta_k^-}. \tag{14}$$

On the other hand,

$$\begin{aligned}
\sum_{k=l+1}^{n} \frac{\rho_k \gamma_k}{\theta_k^-} &= \frac{1}{\pi^-} \sum_{k=l+1}^{n} \rho_k \left(\frac{1}{\theta_k^-} - \frac{1}{\theta_{k-1}^-} \right) \\
&= \frac{1}{\pi^-} \left(\sum_{k=l+1}^{n} (\rho_{k-1} - \rho_k) \frac{1}{\theta_{k-1}^-} + \frac{\rho_n}{\theta_n^-} - \frac{\rho_l}{\theta_l^-} \right) \\
&\sim \frac{1}{\pi^-} \frac{\rho_n}{\theta_n^-}, \qquad (15)
\end{aligned}$$

where we have used the condition $\rho_k - \rho_{k-1} = o(\rho_k \gamma_k)$. We deduce from (14) and (15) that

$$\lim_{n\to\infty} \frac{\theta_n^-}{\rho_n} \sum_{k=1}^{n} \frac{\rho_k \gamma_k}{\theta_k^-} \kappa(X_{k-1}) = -\frac{1 - p_A}{\pi^-}$$

and, also, that $\lim\limits_{n\to\infty} \dfrac{\theta_n^-}{\rho_n} = 0$. By a similar argument, we get $\lim\limits_{n\to\infty} \dfrac{\theta_n^+}{\rho_n} = 0$ and

$$\lim_{n\to\infty} \frac{\theta_n^+}{\rho_n} \sum_{k=1}^{n} \frac{\rho_k \gamma_k}{\theta_k^+} \kappa(X_{k-1}) = -\frac{1 - p_A}{\pi^+}$$

It follows from Lemma 3, that given $\alpha \in [0,1]$, we have, on the set $E_\alpha := \{\sup_n(\rho_n^\alpha Y_n) < \infty\}$,

$$\lim_{n\to\infty} \rho_n^{\frac{\alpha-\eta}{2}-1} \theta_n^{\pm} \sum_{k=1}^{n} \frac{\gamma_k}{\theta_k^{\pm}} \Delta M_k = 0.$$

Together with (12) and (13) this implies

- $\lim\limits_{n\to\infty} Y_n = (1 - p_A)/\pi$ a.s., if $\frac{\alpha-\eta}{2} \leq 0$,
- $\lim\limits_{n\to\infty} Y_n \rho_n^{\frac{\alpha-\eta}{2}} = 0$ a.s., if $\frac{\alpha-\eta}{2} > 0$.

We obviously have $\mathbb{P}(E_\alpha) = 1$ for $\alpha = 1$. We deduce from the previous argument that if $\mathbb{P}(E_\alpha) = 1$ and $\frac{\alpha-\eta}{2} > 0$, then $\mathbb{P}(E_{\alpha'}) = 1$, with $\alpha' = \frac{\alpha-\eta}{2} - 1$. Set $\alpha_0 = 1$ and $\alpha_{k+1} = \frac{\alpha_k-\eta}{2} - 1$. If $\alpha_0 \leq \eta$, we have $\lim\limits_{n\to\infty} Y_n = (1-p_A)/\pi$ a.s. on E_{α_0}. If $\alpha_0 > \eta$, let j be the largest integer such that $\alpha_j > \eta$ (note that j exists because $\lim\limits_{k\to\infty} \alpha_k < 0$). We have $\mathbb{P}(E_{\alpha_{j+1}}) = 1$, and, on $E_{\alpha_{j+1}}$, $\lim\limits_{n\to\infty} Y_n = (1-p_A)/\pi$ a.s., because $\frac{\alpha_j-\eta}{2} \leq 0$. ◇

We now turn to the proof of Lemma 3 which is based on the following classical martingale inequality (see [13], remark 1, p.14 for a proof in the case of i.i.d. random variables: the extension to bounded martingale increments is straightforward).

Lemma 4 *(Bernstein's inequality for bounded martingale increments) Let $(Z_i)_{1\leq i\leq n}$ be a finite sequence of square integrable random variables, adapted to the filtration $(\mathcal{F}_i)_{1\leq i\leq n}$, such that*

1. $\mathbb{E}(Z_i \mid \mathcal{F}_{i-1}) = 0$, $i = 1, \ldots, n$,
2. $\mathbb{E}(Z_i^2 \mid \mathcal{F}_{i-1}) \leq \sigma_i^2$, $i = 1, \ldots, n$,
3. $|Z_i| \leq \Delta_n$, $i = 1, \ldots, n$,

where σ_1^2, ..., σ_n^2, Δ_n are deterministic positive constants.

Then, the following inequality holds:

$$\forall \lambda > 0, \quad \mathbb{P}\left(\left|\sum_{i=1}^{n} Z_i\right| \geq \lambda\right) \leq 2\exp\left(-\frac{\lambda^2}{2\left(b_n^2 + \lambda\frac{\Delta_n}{3}\right)}\right),$$

with $b_n^2 = \sum_{i=1}^{n} \sigma_i^2$.

We will also need the following technical result.

Lemma 5 *Let $(\theta_n)_{n\geq 1}$ be a sequence of positive numbers such that $\theta_n = \prod_{k=1}^{n}(1 - p\gamma_k)$, for some $p \in (0,1)$ and let $(\xi_n)_{n\geq 1}$ be a sequence of non-negative numbers satisfying*

$$\gamma_n\xi_n - \gamma_{n-1}\xi_{n-1} = o(\gamma_n^2\xi_n).$$

We have

$$\sum_{k=1}^{n} \frac{\gamma_k^2\xi_k}{\theta_k^2} \sim \frac{\gamma_n\xi_n}{2p\theta_n^2}.$$

PROOF: First observe that the condition $\gamma_n\xi_n - \gamma_{n-1}\xi_{n-1} = o(\gamma_n^2\xi_n)$ implies $\gamma_n\xi_n \sim \gamma_{n-1}\xi_{n-1}$ and that, given $\varepsilon > 0$, we have, for n large enough,

$$\begin{aligned}\gamma_n\xi_n - \gamma_{n-1}\xi_{n-1} &\geq -\varepsilon\gamma_n^2\xi_n \\ &\geq -\varepsilon\gamma_{n-1}\gamma_n\xi_n,\end{aligned}$$

where we have used the fact that the sequence (γ_n) is non-increasing. Since $\gamma_n\xi_n \sim \gamma_{n-1}\xi_{n-1}$, we have, for n large enough, say $n \geq n_0$,

$$\gamma_n\xi_n \geq \gamma_{n-1}\xi_{n-1}(1 - 2\varepsilon\gamma_{n-1}).$$

Therefore, for $n > n_0$,

$$\gamma_n\xi_n \geq \gamma_{n_0}\xi_{n_0}\prod_{k=n_0+1}^{n}(1 - 2\varepsilon\gamma_{k-1}).$$

From this, we easily deduce that $\lim_{n\to\infty} \gamma_n\xi_n/\theta_n = \infty$ and that $\sum_n \gamma_n^2\xi_n/\theta_n^2 = \infty$.

Now, from

$$\frac{1}{\theta_k^2} - \frac{1}{\theta_{k-1}^2} = \frac{2\gamma_k p - \gamma_k^2 p^2}{\theta_k^2},$$

we deduce (recall that $\lim_{n\to\infty} \gamma_n = 0$)

$$\frac{\gamma_k^2\xi_k}{\theta_k^2} \sim \frac{\gamma_k\xi_k}{2p}\left(\frac{1}{\theta_k^2} - \frac{1}{\theta_{k-1}^2}\right),$$

and, since $\sum_n \gamma_n^2\xi_n/\theta_n^2 = \infty$,

$$\begin{aligned}\sum_{k=1}^{n} \frac{\gamma_k^2\xi_k}{\theta_k^2} &\sim \frac{1}{2p}\sum_{k=1}^{n}\gamma_k\xi_k\left(\frac{1}{\theta_k^2}-\frac{1}{\theta_{k-1}^2}\right)\\ &= \frac{1}{2p}\left(\frac{\gamma_n\xi_n}{\theta_n^2}+\sum_{k=1}^{n}(\gamma_{k-1}\xi_{k-1}-\gamma_k\xi_k)\frac{1}{\theta_{k-1}^2}\right)\\ &= \frac{\gamma_n\xi_n}{2p\theta_n^2}+o\left(\sum_{k=1}^{n}\frac{\gamma_k^2\xi_k}{\theta_k^2}\right),\end{aligned}$$

where, for the first equality, we have assumed $\xi_0 = 0$, and, for the last one, we have used again $\gamma_n\xi_n - \gamma_{n-1}\xi_{n-1} = o(\gamma_n^2\xi_n)$. $\diamondsuit$

Proof of Lemma 3: Given $\mu > 0$, let

$$\nu_\mu = \inf\{n \geq 0 \mid \rho_n^\alpha Y_n > \mu\}.$$

Note that $\{\sup_n \rho_n^\alpha Y_n < \infty\} = \bigcup_{\mu>0}\{\nu_\mu = \infty\}$.

On the set $\{\nu_\mu = \infty\}$, we have

$$\sum_{k=1}^{n}\frac{\gamma_k}{\theta_k}\Delta M_k = \sum_{k=1}^{n}\frac{\gamma_k}{\theta_k}\mathbf{1}_{\{k\leq\nu_\mu\}}\Delta M_k.$$

We now apply Lemma 4 with $Z_i = \frac{\gamma_i}{\theta_i}\mathbf{1}_{\{i\leq\nu_\mu\}}\Delta M_i$. We have, using Proposition 4,

$$\begin{aligned}\mathbb{E}(Z_i^2 \mid \mathcal{F}_{i-1}) &= \frac{\gamma_i^2}{\theta_i^2}\mathbf{1}_{\{i\leq\nu_\mu\}}\mathbb{E}(\Delta M_i^2 \mid \mathcal{F}_{i-1})\\ &\leq \frac{\gamma_i^2}{\theta_i^2}\mathbf{1}_{\{i\leq\nu_\mu\}}\left(p_A\rho_{i-1}Y_{i-1}+\rho_i^2(1-p_B)\right)\\ &\leq \frac{\gamma_i^2}{\theta_i^2}\left(p_A\rho_{i-1}^{1-\alpha}\mu+\rho_i^2(1-p_B)\right),\end{aligned}$$

where we have used the fact that, on $\{i \leq \nu_\mu\}$, $\rho_{i-1}^\alpha Y_{i-1} \leq \mu$. Since $\lim_{n\to\infty}\rho_n = 0$ and $\lim_{n\to\infty}\rho_n/\rho_{n-1} = 1$ (which follows from $\rho_n - \rho_{n-1} = o(\gamma_n\rho_n)$), we have

$$\mathbb{E}(Z_i^2 \mid \mathcal{F}_{i-1}) \leq \sigma_i^2,$$

with $\sigma_i^2 = C_\mu\frac{\gamma_i^2\rho_i^{1-\alpha}}{\theta_i^2}$, for some $C_\mu > 0$, depending only on μ. Using Lemma 5, we have

$$\sum_{i=1}^{n}\sigma_i^2 \sim C_\mu\frac{\gamma_n\rho_n^{1-\alpha}}{2p\theta_n^2}.$$

On the other hand, we have, because the jumps ΔM_i are bounded,

$$|Z_i| \leq C\frac{\gamma_i}{\theta_i},$$

for some $C>0$. Note that $\frac{\gamma_k/\theta_k}{\gamma_{k-1}/\theta_{k-1}} = \frac{\gamma_k}{\gamma_{k-1}(1-p\gamma_k)}$, and, since $\gamma_k - \gamma_{k-1} = o(\gamma_k^2)$ (take $\beta=0$ in (10)), we have, for k large enough, $\gamma_k - \gamma_{k-1} \geq -p\gamma_k\gamma_{k-1}$, so that $\gamma_k/\gamma_{k-1} \geq 1-p\gamma_k$, and the sequence (γ_n/θ_n) is non-increasing for n large enough. Therefore, we have

$$\sup_{1\leq i\leq n} |Z_i| \leq \Delta_n,$$

with $\Delta_n = C\gamma_n/\theta_n$ for some $C>0$. Now, applying Lemma 4 with $\lambda = \lambda_0 \rho_n^{1-\frac{\alpha-\eta}{2}}/\theta_n$, we get

$$\begin{aligned}
\mathbb{P}\left(\theta_n \left|\sum_{k=1}^n \frac{\gamma_k}{\theta_k}\mathbf{1}_{\{k\leq\nu_\mu\}}\Delta M_k\right| \geq \lambda_0\rho_n^{1-\frac{\alpha-\eta}{2}}\right) &\leq 2\exp\left(-\frac{\lambda_0^2\rho_n^{2-\alpha+\eta}}{2\theta_n^2 b_n^2 + 2\lambda_0\theta_n\rho_n^{1-\frac{\alpha-\eta}{2}}\frac{\Delta_n}{3}}\right)\\
&\leq 2\exp\left(-\frac{C_1\rho_n^{2-\alpha+\eta}}{C_2\gamma_n\rho_n^{1-\alpha} + C_3\gamma_n\rho_n^{1-\frac{\alpha-\eta}{2}}}\right)\\
&\leq 2\exp\left(-C_4\frac{\rho_n^{1+\eta}}{\gamma_n}\right),
\end{aligned}$$

where the positive constants C_1, C_2, C_3 and C_4 depend on λ_0 and μ, but not on n. Using (11) and the Borel-Cantelli lemma, we conclude that, on $\{\nu_\mu = \infty\}$, we have, for n large enough,

$$\theta_n \left|\sum_{k=1}^n \frac{\gamma_k}{\theta_k}\Delta M_k\right| < \lambda_0\rho_n^{1-\frac{\alpha-\eta}{2}}, \text{ a.s.,}$$

and, since λ_0 is arbitrary, this completes the proof of the Lemma. $\diamond$

3 Weak convergence of the normalized algorithm

Throughout this section, we assume (in addition to the initial conditions on the sequence $(\gamma_n)_{n\in\mathbb{N}}$)

$$\gamma_n^2 - \gamma_{n-1}^2 = o(\gamma_n^2) \quad \text{and} \quad \frac{\gamma_n}{\rho_n} = g + o(\gamma_n), \tag{16}$$

where g is a positive constant. Note that a possible choice is $\gamma_n = ag/\sqrt{n}$ and $\rho_n = a/\sqrt{n}$, with $a>0$.

Under these conditions, we have $\rho_n - \rho_{n-1} = o(\gamma_n^2)$, and we can write, as in the beginning of Section 2,

$$Y_{n+1} = Y_n\left(1 + \gamma_{n+1}\varepsilon_n - \pi_n\gamma_{n+1}X_n\right) - \gamma_{n+1}\kappa(X_n) - \frac{\gamma_{n+1}}{\rho_{n+1}}\Delta M_{n+1}, \tag{17}$$

where $\lim_{n\to\infty}\varepsilon_n = 0$ and $\lim_{n\to\infty}\pi_n = \pi$. As observed in Remark 2, we know that, under the assumptions (16), the sequence $(Y_n)_{n\geq 1}$ is tight. We will prove that it is convergent in distribution.

Theorem 4 *Under conditions (16), the sequence* $(Y_n = (1-X_n)/\rho_n)_{n\in\mathbb{N}}$ *converges weakly to the unique stationary distribution of the Markov process on* $[0,+\infty)$ *with generator* L *defined by*

$$Lf(y) = p_{\scriptscriptstyle B}\, y \frac{f(y+g)-f(y)}{g} + (1-p_{\scriptscriptstyle A}-p_{\scriptscriptstyle A} y)f'(y), \quad y \geq 0, \tag{18}$$

for f *continuously differentiable and compactly supported in* $[0,+\infty)$*.*

The method for proving Theorem 4 is based on the classical functional approach to central limit theorems for stochastic algorithms (see Bouton [2], Kushner [10], Duflo [6]). The long time behavior of the sequence (Y_n) will be elucidated through the study of a sequence of continuous-time processes $Y^{(n)} = (Y_t^{(n)})_{t\geq 0}$, which will be proved to converge weakly to the Markov process with generator L. We will show that ν has a unique stationary distribution, and that this is the weak limit of the sequence $(Y_n)_{n\in\mathbb{N}}$.

The sequence $Y^{(n)}$ is defined as follows. Given $n \in \mathbb{N}$, and $t \geq 0$, set

$$Y_t^{(n)} = Y_{N(n,t)}, \tag{19}$$

where

$$N(n,t) = \min\left\{ m \geq n \mid \sum_{k=n}^{m} \gamma_{k+1} > t \right\},$$

so that $N(n,0) = n$, for $t \in [0,\gamma_{n+1})$, and, for $m \geq n+1$, $N(n,t) = m$ if and only if $\sum_{k=n+1}^{m} \gamma_k \leq t < \sum_{k=n+1}^{m+1} \gamma_k$.

Theorem 5 *Under the assumptions of Theorem 4, the sequence of continuous time processes* $(Y^{(n)})_{n\in\mathbb{N}}$ *converges weakly (in the sense of Skorokhod) to a Markov process with generator* L*.*

The proof of Theorem 5 is done in two steps: in section 3.1, we prove tightness, in section 3.2, we characterize the limit by a martingale problem.

3.1 Tightness

It follows from (17) that the process $Y^{(n)}$ admits the following decomposition:

$$Y_t^{(n)} = Y_n + B_t^{(n)} + M_t^{(n)}, \tag{20}$$

with

$$B_t^{(n)} = -\sum_{k=n+1}^{N(n,t)} \gamma_k \left[\kappa(X_{k-1}) + (\pi_{k-1}X_{k-1} - \varepsilon_{k-1})Y_{k-1}\right]$$

and

$$M_t^{(n)} = -\sum_{k=n+1}^{N(n,t)} \frac{\gamma_k}{\rho_k} \Delta M_k.$$

The process $(M_t^{(n)})_{t\geq 0}$ is a square integrable martingale with respect to the filtration $(\mathcal{F}_t^{(n)})_{t\geq 0}$, with $\mathcal{F}_t^{(n)} = \mathcal{F}_{N(n,t)}$, and we have

$$<M^{(n)}>_t = \sum_{k=n+1}^{N(n,t)} \left(\frac{\gamma_k}{\rho_k}\right)^2 \mathbb{E}(\Delta M_k^2 \mid \mathcal{F}_{k-1}).$$

We already know (see Remark 2) that the sequence $(Y_n)_{n\in\mathbb{N}}$ is tight. Recall that in order for the sequence $(M^{(n)})$ to be tight, it is sufficient that the sequence $(<M^{(n)}>)$ is C-tight (see [7], Theorem 4.13, p. 358, chapter VI). Therefore, the tightness of the sequence $(Y^{(n)})$ in the sense of Skorokhod will follow from the following result.

Proposition 5 *Under the assumptions (16), the sequences $(B^{(n)})$ and $(<M^{(n)}>)$ are C-tight.*

For the proof of this proposition,we will need the following lemma.

Lemma 6 *Define ν^l as in Lemma 1, for $l \in \mathbb{N}$. There exists a positive constant C such that, for all $l, n, N \in \mathbb{N}$ with $l \leq n \leq N$, we have*

$$\forall \lambda \geq 1, \quad \mathbb{P}\left(\sup_{n\leq j\leq N} |Y_j - Y_n| \geq \lambda\right) \leq \mathbb{P}(\nu^l < \infty) + C\frac{(1+\mathbb{E}\,Y_l)\left(\sum_{k=n+1}^N \gamma_k\right)}{\lambda}.$$

Proof: The function κ being bounded on $[0,1]$, it follows from (17) that there exist positive, deterministic constants a and b such that, for all $n \in \mathbb{N}$,

$$-\gamma_{n+1}(a+bY_n) - \frac{\gamma_{n+1}}{\rho_{n+1}}\Delta M_{n+1} \leq Y_{n+1} - Y_n \leq \gamma_{n+1}(a+bY_n) - \frac{\gamma_{n+1}}{\rho_{n+1}}\Delta M_{n+1}. \tag{21}$$

We also know from Proposition 4 that

$$\mathbb{E}\left(\Delta M_{n+1}^2 \mid \mathcal{F}_n\right) \leq p_A \rho_n Y_n + (1-p_B)\rho_{n+1}^2. \tag{22}$$

From (21), we derive, for $j \geq n$,

$$|Y_j - Y_n| \leq \sum_{k=n+1}^{j} \gamma_k(a+bY_{k-1}) + \left|\sum_{k=n+1}^{j} \frac{\gamma_k}{\rho_k}\Delta M_k.\right|$$

Let $\tilde{Y}_k = Y_k \mathbf{1}_{\{k\leq\nu^l\}}$ and $\Delta\tilde{M}_k = \mathbf{1}_{\{k\leq\nu^l\}}\Delta M_k$ On the set $\nu^l = \infty$, we have $Y_{k-1} = \tilde{Y}_{k-1}$ and $\Delta M_k = \Delta\tilde{M}_k$. Hence

$$\begin{aligned}\mathbb{P}\left(\sup_{n\leq j\leq N} |Y_j - Y_n| \geq \lambda\right) \quad \leq \quad & \mathbb{P}(\nu^l < \infty) + \mathbb{P}\left(\sum_{k=n+1}^{N} \gamma_k(a+b\tilde{Y}_{k-1}) \geq \lambda/2\right) + \\ & \mathbb{P}\left(\sup_{n\leq j\leq N}\left|\sum_{k=n+1}^{j} \frac{\gamma_k}{\rho_k}\Delta\tilde{M}_k\right| \geq \lambda/2\right).\end{aligned}$$

We have, using Markov's inequality and Lemma 1,

$$\begin{aligned}\mathbb{P}\left(\sum_{k=n+1}^{N}\gamma_k(a+b\tilde{Y}_{k-1})\geq\lambda/2\right) &\leq \frac{2}{\lambda}\mathbb{E}\sum_{k=n+1}^{N}\gamma_k(a+b\tilde{Y}_{k-1})\\ &\leq \frac{2}{\lambda}\left(a+b\sup_{k\geq l}\mathbb{E}\left(Y_k\mathbf{1}_{\{\nu^l=\infty\}}\right)\right)\sum_{k=n+1}^{N}\gamma_k\\ &\leq \frac{2}{\lambda}\left(b\mathbb{E}\,Y_l+b\frac{||\kappa||_\infty}{\pi^-}+a\right)\sum_{k=n+1}^{N}\gamma_k.\end{aligned}$$

On the other hand, using Doob's inequality,

$$\begin{aligned}\mathbb{P}\left(\sup_{n\leq j\leq N}\left|\sum_{k=n+1}^{j}\frac{\gamma_k}{\rho_k}\Delta\tilde{M}_k\right|\geq\lambda/2\right) &\leq \frac{16}{\lambda^2}\mathbb{E}\sum_{k=n+1}^{N}\frac{\gamma_k^2}{\rho_k^2}\mathbb{E}\left(\Delta\tilde{M}_k^2\mid\mathcal{F}_{k-1}\right)\\ &\leq \frac{16}{\lambda^2}\mathbb{E}\sum_{k=n+1}^{N}\frac{\gamma_k^2}{\rho_k^2}\mathbf{1}_{\{k\leq\nu\}}\left(p_A\rho_{k-1}Y_{k-1}+(1-p_B)\rho_k^2\right).\end{aligned}$$

Using $\lim_n(\gamma_n/\rho_n)=g$, $\rho_{k-1}\sim\rho_k$, $\lim_n\rho_n=0$ and Lemma 1, we get, for some $C>0$,

$$\mathbb{P}\left(\sup_{n\leq j\leq N}\left|\sum_{k=n+1}^{j}\frac{\gamma_k}{\rho_k}\Delta\tilde{M}_k\right|\geq\lambda/2\right)\leq C\frac{(1+\mathbb{E}\,Y_l)\left(\sum_{k=n+1}^{N}\gamma_k\right)}{\lambda^2},$$

and, since we have assumed $\lambda\geq 1$, the proof of the lemma is completed. ◊

Proof of Proposition 5: Given s and t, with $0\leq s\leq t$, we have, using the boundedness of κ,

$$|B_t^{(n)}-B_s^{(n)}|\leq\sum_{k=N(n,s)+1}^{N(n,t)}\gamma_k(a+bY_{k-1})$$

for some $a,b>0$.

Similarly, using (22), we have

$$\left|<M^{(n)}>_t-<M^{(n)}>_s\right|\leq\sum_{k=N(n,s)+1}^{N(n,t)}\gamma_k(a'+b'Y_{k-1})$$

for some $a',b'>0$. These inequalities express the fact that the processes $B^{(n)}$ and $<M^{(n)}>$ are *strongly dominated* (in the sense of [7], definition 3.34) by a linear combination of the processes $X^{(n)}$ and $Z^{(n)}$, where $X_t^{(n)}=\sum_{k=n+1}^{N(n,t)}\gamma_k$ and $Z_t^{(n)}=\sum_{k=n+1}^{N(n,t)}\gamma_kY_{k-1}$. Therefore, we only need to prove that the sequences $(X^{(n)})$ and $(Z^{(n)})$ are C-tight. This is obvious for the sequence $X^{(n)}$, which in fact converges to the deterministic process t. We now prove that $Z^{(n)}$ is C-tight. We have, for $0 \le s \le t \le T$

$$\begin{aligned} |Z_t^{(n)} - Z_s^{(n)}| &\le \left(\sup_{n \le j \le N(n,T)} Y_j \right) \sum_{k=N(n,s)+1}^{N(n,t)} \gamma_k \\ &\le (t - s + \gamma_{N(n,s)+1}) \sup_{n \le j \le N(n,T)} Y_j \\ &\le (t - s + \gamma_{n+1}) \sup_{n \le j \le N(n,T)} Y_j, \end{aligned}$$

where we have used $\sum_{k=n+1}^{N(n,t)} \gamma_k \le t$ and $s \le \sum_{k=n+1}^{N(n,s)+1} \gamma_k$ and the monotony of the sequence $(\gamma_n)_{n \ge 1}$.

Therefore, for $\delta > 0$, and n large enough so that $\gamma_{n+1} \le \delta$,

$$\begin{aligned} \mathbb{P}\left(\sup_{0 \le s \le t \le T, t-s \le \delta} |Z_t^{(n)} - Z_s^{(n)}| \ge \eta \right) &\le \mathbb{P}\left(\sup_{n \le j \le N(n,T)} Y_j \ge \frac{\eta}{\delta + \gamma_{n+1}} \right) \\ &\le \mathbb{P}\left(Y_n \ge \frac{\eta}{4\delta} \right) \\ &\quad + \mathbb{P}\left(\sup_{n \le j \le N(n,T)} |Y_j - Y_n| \ge \frac{\eta}{4\delta} \right). \end{aligned}$$

We have, from Lemma 6,

$$\begin{aligned} \mathbb{P}\left(\sup_{n \le j \le N(n,T)} |Y_j - Y_n| \ge \frac{\eta}{4\delta} \right) &\le \mathbb{P}(\nu^l < \infty) + \frac{4C\delta}{\eta}(1 + \mathbb{E}\, Y_l) \sum_{k=n+1}^{N(n,T)} \gamma_k \\ &\le \mathbb{P}(\nu^l < \infty) + \frac{4CT\delta}{\eta}(1 + \mathbb{E}\, Y_l). \end{aligned}$$

We easily conclude from these estimates that, given $T > 0$, $\varepsilon > 0$ and $\eta > 0$, we have for n large enough and δ small enough,

$$\mathbb{P}\left(\sup_{0 \le s \le t \le T, t-s \le \delta} |Z_t^{(n)} - Z_s^{(n)}| \ge \eta \right) < \varepsilon,$$

which proves the C-tightness of the sequence $(Z^{(n)})$. ◊

3.2 Identification of the limit

Lemma 7 *Let f be a C^1 function with compact support in $[0, +\infty)$. We have*

$$\mathbb{E}\left(f(Y_{n+1}) - f(Y_n) \mid \mathcal{F}_n \right) = \gamma_{n+1} Lf(Y_n) + \gamma_{n+1} Z_n, \quad n \in \mathbb{N},$$

where the operator L is defined by

$$Lf(y) = p_B y \frac{f(y+g) - f(y)}{g} + (1 - p_A - p_A y) f'(y), \quad y \ge 0, \tag{23}$$

and the sequence $(Z_n)_{n \in \mathbb{N}}$ satisfies $\lim_{n \to \infty} Z_n = 0$ in probability.

PROOF: From (17), we have

$$\begin{aligned} Y_{n+1} &= Y_n + \gamma_{n+1}(-\kappa(1) - \pi Y_n) - \frac{\gamma_{n+1}}{\rho_{n+1}}\Delta M_{n+1} + \gamma_{n+1}\zeta_n \\ &= Y_n + \gamma_{n+1}(1 - p_{_A} - \pi Y_n) - \frac{\gamma_{n+1}}{\rho_{n+1}}\Delta M_{n+1} + \gamma_{n+1}\zeta_n \\ &= Y_n + \gamma_{n+1}(1 - p_{_A} - \pi Y_n) - g\Delta M_{n+1} + \gamma_{n+1}\zeta_n + \left(g - \frac{\gamma_{n+1}}{\rho_{n+1}}\right)\Delta M_{n+1}, \quad (24) \end{aligned}$$

where $\zeta_n = \kappa(1) - \kappa(X_n) + Y_n(\pi - (\pi_n X_n - \varepsilon_n))$, so that ζ_n is $\mathcal{F}_n$-measurable and $\lim_{n\to\infty}\zeta_n = 0$ in probability. Going back to (3), we rewrite the martingale increment ΔM_{n+1} as follows:

$$\begin{aligned} \Delta M_{n+1} &= -X_n\left(\mathbf{1}_{\{U_{n+1}>X_n\}\cap B_{n+1}} - p_{_B}(1-X_n)\right) + \rho_n Y_n\left(\mathbf{1}_{\{U_{n+1}\le X_n\}\cap A_{n+1}} - p_{_A}X_n\right) \\ &\quad -\rho_{n+1}\left(X_n\mathbf{1}_{\{U_{n+1}\le X_n\}\cap A^c_{n+1}} - (1-X_n)\mathbf{1}_{\{U_{n+1}>X_n\}\cap B^c_{n+1}} + \kappa(X_n)\right). \end{aligned}$$

Hence,

$$Y_{n+1} = Y_n + \gamma_{n+1}(1 - p_{_A} - \pi Y_n + \zeta_n) + \xi_{n+1} + \Delta\hat{M}_{n+1},$$

where

$$\xi_{n+1} = gX_n\left(\mathbf{1}_{\{U_{n+1}>X_n\}\cap B_{n+1}} - p_{_B}(1-X_n)\right)$$

and

$$\begin{aligned} \Delta\hat{M}_{n+1} &= \left(g - \frac{\gamma_{n+1}}{\rho_{n+1}}\right)\Delta M_{n+1} - g\rho_n Y_n\left(\mathbf{1}_{\{U_{n+1}\le X_n\}\cap A_{n+1}} - p_{_A}X_n\right) \\ &\quad +g\rho_{n+1}\left(X_n\mathbf{1}_{\{U_{n+1}\le X_n\}\cap A^c_{n+1}} - (1-X_n)\mathbf{1}_{\{U_{n+1}>X_n\}\cap B^c_{n+1}} + \kappa(X_n)\right). \end{aligned}$$

Note that, due to our assumptions on γ_n and ρ_n, we have, for some deterministic positive constant C,

$$\left|\Delta\hat{M}_{n+1}\right| \le C\gamma_{n+1}(1+Y_n), \quad n\in\mathbb{N}. \quad (25)$$

Now, let

$$\tilde{Y}_n = Y_n + \gamma_{n+1}(1 - p_{_A} - \pi Y_n + \zeta_n) \text{ and } \bar{Y}_{n+1} = \tilde{Y}_n + \xi_{n+1},$$

so that $Y_{n+1} = \bar{Y}_{n+1} + \Delta\hat{M}_{n+1}$. We have

$$f(Y_{n+1}) - f(Y_n) = f(Y_{n+1}) - f(\bar{Y}_{n+1}) + f(\bar{Y}_{n+1}) - f(Y_n).$$

We will first show that

$$f(Y_{n+1}) - f(\bar{Y}_{n+1}) = f'(\tilde{Y}_n)\Delta\hat{M}_{n+1} + \gamma_{n+1}T_{n+1}, \text{ where } \mathbb{P}\text{-}\lim_{n\to\infty}\mathbb{E}(T_{n+1}\mid\mathcal{F}_n) = 0, \quad (26)$$

with the notation $\mathbb{P}\text{-}\lim$ for a limit in probability. Denote by w the modulus of continuity of f':

$$w(\delta) = \sup_{|x-y|\le\delta}|f'(y) - f'(x)|, \quad \delta > 0.$$

We have, for some (random) $\theta \in (0,1)$,

$$\begin{aligned} f(Y_{n+1}) - f(\bar{Y}_{n+1}) &= f'(\bar{Y}_{n+1} + \theta\Delta\hat{M}_{n+1})\Delta\hat{M}_{n+1} \\ &= f'(\tilde{Y}_n)\Delta\hat{M}_{n+1} + V_{n+1}, \end{aligned}$$

where $V_{n+1} = \left(f'(\bar{Y}_{n+1} + \theta\Delta\hat{M}_{n+1}) - f'(\tilde{Y}_n)\right)\Delta\hat{M}_{n+1}$. We have

$$\begin{aligned} |V_{n+1}| &\leq w\left(|\xi_{n+1}| + |\Delta\hat{M}_{n+1}|\right)|\Delta\hat{M}_{n+1}| \\ &\leq Cw\left(|\xi_{n+1}| + C\gamma_{n+1}(1+Y_n)\right)\gamma_{n+1}(1+Y_n), \end{aligned}$$

where we have used $\bar{Y}_{n+1} = \tilde{Y}_n + \xi_{n+1}$ and (25). In order to get (26), it suffices to prove that $\lim_{n\to\infty} \mathbb{E}\left(w\left(|\xi_{n+1}| + C\gamma_{n+1}(1+Y_n)\right) \mid \mathcal{F}_n\right) = 0$ in probability. On the set $\{U_{n+1} > X_n\} \cap B_{n+1}$, we have $|\xi_{n+1}| = gX_n\left(1 - p_B(1-X_n)\right) \leq g$, and, on the complement, $|\xi_{n+1}| = gX_n p_B(1-X_n) \leq g(1-X_n)$. Hence

$$\begin{aligned} \mathbb{E}\left(w\left(|\xi_{n+1}| + C\gamma_{n+1}(1+Y_n)\right) \mid \mathcal{F}_n\right) &\leq p_B(1-X_n)w\left(g + C\gamma_{n+1}(1+Y_n)\right) \\ &\quad +(1-p_B(1-X_n))w\left(\hat{Y}_n\right), \end{aligned}$$

where $\hat{Y}_n = g(1-X_n) + C\gamma_{n+1}(1+Y_n)$. Observe that $\lim_{n\to\infty} \hat{Y}_n = 0$ in probability (recall that $\lim_{n\to\infty} X_n = 1$ almost surely). Therefore, we have (26).

We deduce from $\mathbb{E}(\Delta\hat{M}_{n+1} \mid \mathcal{F}_n) = 0$ that

$$\mathbb{E}\left(f(Y_{n+1}) - f(Y_n) \mid \mathcal{F}_n\right) = \gamma_{n+1}\mathbb{E}(T_{n+1} \mid \mathcal{F}_n) + \mathbb{E}\left(f(\bar{Y}_{n+1}) - f(Y_n) \mid \mathcal{F}_n\right),$$

so that the proof will be completed when we have shown

$$\mathbb{P}\text{-}\lim_{n\to\infty} \mathbb{E}\left(\frac{f(\bar{Y}_{n+1}) - f(Y_n) - \gamma_{n+1}Lf(Y_n)}{\gamma_{n+1}} \mid \mathcal{F}_n\right) = 0. \tag{27}$$

We have

$$\begin{aligned} \mathbb{E}\left(f(\bar{Y}_{n+1}) \mid \mathcal{F}_n\right) &= \mathbb{E}\left(f(\tilde{Y}_n + \xi_{n+1}) \mid \mathcal{F}_n\right) \\ &= p_B(1-X_n)f(\tilde{Y}_n + gX_n(1-p_B(1-X_n))) \\ &\quad +(1-p_B(1-X_n))f(\tilde{Y}_n - gX_n p_B(1-X_n)) \\ &= p_B\rho_n Y_n f(\tilde{Y}_n + gX_n(1-p_B(1-X_n))) \\ &\quad +(1-p_B\rho_n Y_n)f(\tilde{Y}_n - gX_n p_B(1-X_n)). \end{aligned}$$

Hence

$$\mathbb{E}\left(f(\bar{Y}_{n+1}) - f(Y_n) \mid \mathcal{F}_n\right) = F_n + G_n,$$

with

$$F_n = p_B\rho_n Y_n\left(f(\tilde{Y}_n + gX_n(1-p_B(1-X_n))) - f(Y_n)\right)$$

and

$$G_n = (1 - p_B\rho_n Y_n)\left(f(\tilde{Y}_n - gX_n p_B(1 - X_n)) - f(Y_n)\right).$$

For the behavior of F_n as n goes to infinity, we use

$$\mathbb{P}\text{-}\lim_{n\to\infty}\left(\tilde{Y}_n + gX_n(1 - p_B(1 - X_n)) - Y_n - g\right) = 0,$$

and $\lim_{n\to\infty} \rho_n/\gamma_{n+1} = 1/g$, so that

$$\mathbb{P}\text{-}\lim_{n\to\infty} \frac{F_n - p_B Y_n \frac{f(Y_n+g) - f(Y_n)}{g}}{\gamma_{n+1}} = 0.$$

For the behavior of G_n, we write, using $\lim_{n\to\infty} \rho_n/\gamma_{n+1} = 1/g$ again,

$$\begin{aligned}\tilde{Y}_n - gX_n p_B(1 - X_n) &= Y_n + \gamma_{n+1}\left(1 - p_A - \pi Y_n + \zeta_n\right) - gp_B X_n \rho_n Y_n \\ &= Y_n + \gamma_{n+1}(1 - p_A - p_A Y_n) + \gamma_{n+1}\eta_n,\end{aligned}$$

with $\mathbb{P}\text{-}\lim_{n\to\infty} \eta_n = 0$, so that, using the fact that f is C^1 with compact support and the tightness of (Y_n),

$$\mathbb{P}\text{-}\lim_{n\to\infty} \frac{G_n - (1 - p_A - p_A Y_n) f'(Y_n)}{\gamma_{n+1}} = 0,$$

which completes the proof of (27). ◇

Proof of Theorem 5: As mentioned before, it follows from Proposition 5 that the sequence of processes $(Y^{(n)})$ is tight in the Skorokhod sense.

On the other hand, it follows from Lemma 7 that, if f is a C^1 function with compact support in $[0, +\infty)$, we have

$$f(Y_n) = f(Y_0) + \sum_{k=1}^{n} \gamma_k Lf(Y_{k-1}) + \sum_{k=1}^{n} \gamma_k Z_{k-1} + M_n,$$

where (M_n) is a martingale and (Z_n) is an adapted sequence satisfying $\mathbb{P}\text{-}\lim_{n\to\infty} Z_n = 0$. Therefore,

$$f(Y_t^{(n)}) - f(Y_0^{(n)}) = M_t^{(n)} + \sum_{k=N(n,0)+1}^{N(n,t)} \gamma_k (Lf(Y_{k-1}) + Z_{k-1}),$$

where $M_t^{(n)} = M_{N(n,t)} - M_{N(n,0)}$. It is easy to verify that $M^{(n)}$ is a martingale with respect to $\mathcal{F}^{(n)}$.

We also have

$$\int_0^t Lf(Y_s^{(n)})ds = \sum_{k=n+1}^{N(n,t)} \gamma_k Lf(Y_{k-1}) + \left(t - \sum_{k=n+1}^{N(n,t)} \gamma_k\right) f(Y_t^{(n)}).$$

Therefore

$$f(Y_t^{(n)}) - f(Y_0^{(n)}) - \int_0^t Lf(Y_s^{(n)})ds = M_t^{(n)} + R_t^{(n)},$$

where $\mathbb{P}\text{-}\lim_{n\to\infty} R_t^{(n)} = 0$. It follows that any weak limit of the sequence $(Y^{(n)})_{n\in\mathbb{N}}$ solves the martingale problem associated with L. From this, together with the study of the stationary distribution of L (see Section 3.3), we will deduce Theorem 4 and Theorem 5. $\diamondsuit$

3.3 The stationary distribution

Theorem 6 *The Markov process $(Y_t)_{t\geq 0}$, on $[0,+\infty)$, with generator L has a unique stationary probability distribution ν. Moreover, ν has a density on $[0,+\infty)$, which vanishes on $(0, r_A]$ (where $r_A = (1-p_A)/p_A$), and is positive and continuous on the open interval $(r_A,+\infty)$. The stationary distribution ν also satisfies the following property: for every compact set K in $[0,+\infty)$, and every bounded continuous function f, we have*

$$\lim_{t\to\infty} \sup_{y\in K} \left| \mathbb{E}_y(f(Y_t)) - \int f\, d\nu \right| = 0. \tag{28}$$

Before proving Theorem 6, we will show how Theorem 4 follows from (28).

Proof of Theorem 4: Fix $t > 0$. For n large enough, we have $\gamma_n \leq t < \sum_{k=1}^n \gamma_k$, so that there exists $\bar{n} \in \{1, \ldots, n-1\}$ such that

$$\sum_{k=\bar{n}+1}^{n} \gamma_k \leq t < \sum_{k=\bar{n}}^{n} \gamma_k.$$

Let $t_n = \sum_{k=\bar{n}+1}^n \gamma_k$. We have

$$0 \leq t - t_n < \gamma_{\bar{n}} \quad \text{and} \quad Y_{t_n}^{(\bar{n})} = Y_n.$$

Since t is fixed, the condition $\sum_{k=\bar{n}+1}^n \gamma_k \leq t$ implies $\lim_{n\to\infty} \bar{n} = \infty$ and $\lim_{n\to\infty} t_n = t$.

Now, given $\varepsilon > 0$, there is a compact set K such that for every weak limit μ of the sequence $(Y_n)_{n\in\mathbb{N}}$, $\mu(K^c) < \varepsilon$. Using (28), we choose t such that

$$\sup_{y\in K} \left| \mathbb{E}_y(f(Y_t)) - \int f d\nu \right| < \varepsilon.$$

Now take a weakly convergent subsequence $(Y_{n_k})_{k\in\mathbb{N}}$. By another subsequence extraction, we can assume that the sequence $(Y^{(\overline{n}_k)})$ converges weakly to a process $Y^{(\infty)}$ which satisfies the martingale problem associated with L. We then have, due to the quasi left continuity of $Y^{(\infty)}$,

$$\lim_{k\to\infty} \mathbb{E}f(Y_{t_{n_k}}^{(\overline{n}_k)}) = \mathbb{E}f(Y_t^{(\infty)}),$$

for every bounded continuous function f (keep in mind that the functional tightness of $(M^{(n)})$ follows from Theorem 1.13 in [7] which in turn relies on the so-called Aldous criterion; any weak limiting process of such a sequence in the Skorokhod sense is then quasi-left continuous and so is Y since B is pathwise continuous). Hence $\lim_{k\to\infty} \mathbb{E}f(Y_{n_k}) = \mathbb{E}f(Y_t^{(\infty)})$. Observe that the law of $Y_0^{(\infty)}$ is a weak limit of the sequence Y_n, so that $\mathbb{P}(Y_0^{(\infty)} \in K^c) < \varepsilon$. Now we have

$$\mathbb{E}f(Y_{n_k}) - \int f d\nu = \mathbb{E}f(Y_{n_k}) - \mathbb{E}f(Y_t^{(\infty)}) + \mathbb{E}f(Y_t^{(\infty)}) - \int f d\nu,$$

so that, if μ denotes the law of $Y_0^{(\infty)}$,

$$\begin{aligned}
\limsup_{k\to\infty} \left|\mathbb{E}f(Y_{n_k}) - \int f d\nu\right| &\leq \left|\mathbb{E}f(Y_t^{(\infty)}) - \int f d\nu\right| \\
&= \left|\int \mathbb{E}_y(f(Y_t))d\mu(y) - \int f d\nu\right| \\
&\leq \varepsilon + 2||f||_\infty \mu(K^c) \\
&\leq \varepsilon(1 + 2||f||_\infty).
\end{aligned}$$

It follows that any weak limit of the sequence $(Y_n)_{n\in\mathbb{N}}$ is equal to ν, which completes the proof of Theorem 4. $\diamond$

For the proof of Theorem 6, we first observe that the generator L depends in an affine way on the state variable y. This *affine* structure suggests that the Laplace transform $\mathbb{E}_y e^{-pY_t}$ has the form $e^{\varphi_p(t)+y\psi_p(t)}$, for some functions φ_p and ψ_p. Affine models have been recently extensively studied in connection with interest rate modelling (see for instance [4] or [5]). The following proposition gives a precise description of the Laplace transform.

Proposition 6 *Let $(Y_t)_{t\geq 0}$ be the Markov process with generator L on $[0, +\infty)$. We have, for $p > 0$, $y \in [0, +\infty)$,*

$$\mathbb{E}_y\, e^{-pY_t} = \exp\left(\varphi_p(t) + y\psi_p(t)\right), \tag{29}$$

where ψ_p is the unique solution, on $[0, +\infty)$ of the differential equation

$$\psi' = p_{\scriptscriptstyle B} \frac{e^{g\psi} - 1}{g} - p_{\scriptscriptstyle A}\psi, \ \text{with } \psi(0) = -p,$$

and

$$\varphi_p(t) = (1 - p_{\scriptscriptstyle A}) \int_0^t \psi_p(s)ds.$$

Before proving the Proposition, we study the involved ordinary differential equation.

Lemma 8 *Given $\psi_0 \in (-\infty, 0]$, the ordinary differential equation*

$$\psi' = p_{\scriptscriptstyle B} \frac{e^{g\psi} - 1}{g} - p_{\scriptscriptstyle A}\psi \tag{30}$$

has a unique equation on $[0, +\infty)$ satisfying the initial condition $\psi(0) = \psi_0$. Moreover, we have

$$\forall t \geq 0, \quad \psi(0) \leq \psi(t)e^{\pi t} \leq 0.$$

Proof: Existence and uniqueness of a local solution follows from the Cauchy-Lipschitz theorem. In order to prove non-explosion, observe that if ψ solves (30), we have, using the inequality $(e^{g\psi}-1)/g \geq \psi$,

$$\psi' + \pi\psi \geq 0.$$

Therefore, the function $t \mapsto \psi(t)e^{\pi t}$ is non-decreasing, so that $\psi(0) \leq \psi(t)e^{\pi t}$. Since 0 is an equilibrium of the equation, we have $\psi(t) \leq 0$ if $\psi(0) \leq 0$, and the inequality is strict unless $\psi(0) = 0$. Hence $\psi(0) \leq \psi(t)e^{\pi t} \leq 0$ and the lemma follows easily. $\diamondsuit$

Proof of Proposition 6: Let $u_p(t,y) = \exp(\varphi_p(t) + y\psi_p(t))$, where ψ_p and φ_p are defined as in the statement of the Proposition. The existence of ψ_p follows from Lemma 8. An easy computation shows that $\frac{\partial u_p}{\partial t} - Lu_p = 0$ on $[0,+\infty)\times[0,+\infty)$, so that, for $T > 0$, the process $(u_p(T-t,Y_t))_{0\leq t\leq T}$ is a martingale, and $\mathbb{E}\, u_p(T,Y_0) = \mathbb{E}\, u_p(0,Y_T)$, and the Proposition follows easily. $\diamondsuit$

Proof of Theorem 6:

• Uniqueness of the invariant distribution. We deduce from Lemma 8 that, with the notation of Proposition 6, $|\psi_p(t)| \leq e^{-\pi t}$ and $\lim_{t\to\infty} \varphi_p(t) = (1-p_{{}_A}) \int_0^{+\infty} \psi_p(s)ds$. Therefore

$$\lim_{t\to\infty} \mathbb{E}_y(e^{-pY_t}) = \exp\left((1-p_{{}_A})\int_0^\infty \psi_p(s)ds\right),$$

and the convergence is uniform on compact sets. This implies the uniqueness of the stationary distribution as well as (28). We also have the Laplace transform of ν:

$$\int_{\mathbb{R}^+} e^{-py}\nu(dy) = \exp\left((1-p_{{}_A})\int_0^\infty \psi_p(s)ds\right).$$

Note that, since $\psi_p \leq 0$ and $\psi_p' = p_{{}_B}\frac{e^{g\psi_p}-1}{g} - p_{{}_A}\psi_p$, we have $\psi_p' + p_{{}_A}\psi_p \leq 0$. Therefore, $\psi_p(t) \leq -pe^{-p_{{}_A}t}$, and

$$\forall p \geq 0, \qquad \int e^{-py}\nu(dy) \geq \exp(-p(1-p_{{}_A})/p_{{}_A}) = \exp(-pr_{{}_A}).$$

This yields $\nu([0,r_{{}_A})) = 0$.

• Further properties of the invariant distribution ν. The stationary distribution satisfies $\int Lf d\nu = 0$ for any continuously differentiable function f with compact support in $[0,+\infty)$. This reads

$$\forall f \in C_K^1, \qquad \int \left(ry\frac{f(y+g)-f(y)}{g} + (r_{{}_A}-y)f'(y)\right)\nu(dy) = 0, \tag{31}$$

where $r = p_{{}_B}/p_{{}_A}$ and $r_{{}_A} = (1-p_{{}_A})/p_{{}_A}$.

We first show that $\nu(\{r_{{}_A}\}) = 0$. Let φ be a non-negative continuously differentiable function satisfying $\varphi = 1$ in a neighbourhood of the origin and $\varphi = 0$ outside the interval $[-1,1]$. For $n \geq 1$ let

$$f_n(y) = \varphi(n(y-r_{{}_A})), \quad y \in \mathbb{R}.$$

We have $f_n(y) = 0$ if $|y - r_A| \geq 1/n$. In particular, the support of f_n lies in $[0, +\infty)$, for n large enough. Applying (31) with $f = f_n$, we get

$$\int \Big(ry \frac{f_n(y+g) - f_n(y)}{g} + (r_A - y)n\varphi'(n(y - r_A)) \Big) \nu(dy) = 0.$$

Observe that $\lim\limits_{n\to\infty} f_n = \mathbf{1}_{\{r_A\}}$ so that

$$\lim_{n\to\infty} \int y(f_n(y+g) - f_n(y))\nu(dy) = (r_A - g)\nu(\{r_A - g\}) - r_A \nu(\{r_A\}) = -r_A \nu(\{r_A\}),$$

where we have used $\nu(-\infty, r_A) = 0$. On the other hand, we have $|(r_A - y)n\,\varphi'(n(y - r_A))| \leq \sup_{u\in\mathbb{R}}(u\varphi'(u))$, and $\lim\limits_{n\to\infty}(n\varphi'(n(y - r_A))) = 0$, so that, by dominated convergence,

$$\lim_{n\to\infty} \int (r_A - y)n\,\varphi'(n(y - r_A))\nu(dy) = 0.$$

Hence $\nu(\{r_A\}) = 0$.

We now study the measure ν on the open interval $(r_A, +\infty)$. Denote by $\mathcal{D}$ the set of all infinitely differentiable functions with compact support in $(r_A, +\infty)$. We deduce from (31) that, for $f \in \mathcal{D}$,

$$\frac{r}{g}\int \nu(dy)yf(y+g) - \frac{r}{g}\int \nu(dy)yf(y) + \int \nu(dy)(r_A - y)f'(y) = 0. \tag{32}$$

Denote by ν_g the measure defined by $\displaystyle\int \nu_g(dy)f(y) = \int \nu(dy)f(y+g)$. We deduce from (32) that ν satisfies the following equation in the sense of distributions:

$$(y - r_A)\nu' + (1 - (r/g)y)\nu = -\frac{r}{g}(y-g)\nu_g,$$

or

$$\nu' + \frac{1 - (r/g)y}{y - r_A}\nu = -\frac{r}{g}\frac{y-g}{y-r_A}\nu_g. \tag{33}$$

Denote by F the function defined by

$$F(y) = e^{ry/g}(y - r_A)^{d-1}, \quad y > r_A, \tag{34}$$

where $d = r\,r_A/g$. We have

$$F'(y) = -\frac{1 - (r/g)y}{y - r_A}F(y),$$

so that the equation satisfied by ν reads

$$\left(\frac{1}{F}\nu\right)' = \frac{G}{F}\nu_g, \tag{35}$$

where the function G is defined by $G(y) = -\frac{r}{g}\frac{y-g}{y-r_A}$.

On the set (r_A, r_A+g), the measure ν_g vanishes, so that $\nu = \lambda_0 F$ for some non negative constant λ_0. At this point, we know that the restriction of the measure ν to the set $(0, r_A+g)$ has a density which vanishes on $(0, r_A)$ and is given by $\lambda_0 F$ on (r_A, r_A+g).

We will prove by induction that the distribution ν coincides with a continuous function on (r_A, r_A+ng), which is infinitely differentiable on $(r_A+(n-1)g, r_A+ng)$. The claim has been proved for $n=1$. Assume that it is true for n. On the set $(r_A, r_A+(n+1)g)$, the distributional derivative of $(1/F)\nu$ coincides with the function $y \mapsto (G(y)/F(y))\nu(y-g)$, which is locally integrable on (r_A, r_A+ng+g), continuous on (r_A+g, r_A+ng+g), and infinitely differentiable on (r_A+ng, r_A+ng+g), due to the induction hypothesis (there may be a discontinuity at r_A+g if $d<1$). It follows that $(1/F)\nu$ is a continuous (resp. infinitely differentiable) function, and so is ν on $(r_A, r_A+(n+1)g)$ (resp. (r_A+ng, r_A+ng+g)). We have proved that ν has a continuous density on $(r_A, +\infty)$, which is infinitely differentiable on the open set $\bigcup_{n=1}^{\infty}(r_A+(n-1)g, r_A+ng)$.

Finally, we prove that the density of ν is positive on $(r_A, +\infty)$. Note that $G(y)<0$ if $y>g$ and that the density vanishes at $y-g$ if $y<g$. Therefore $\left(\frac{1}{F}\nu\right)' \leq 0$, so that the function $y \mapsto \nu(y)/F(y)$ is nondecreasing. It follows that λ_0 cannot be zero (otherwise ν would be identically zero). Hence $\nu(y)>0$ for $y \in (r_A, r_A+g)$. Now, if $\nu(y)>0$ for $y \in (r_A+ng-g, r_A+ng)$, the function ν/F is strictly decreasing on (r_A+ng, r_A+ng+g) and, therefore, cannot vanish. So, by induction, the density is positive on $(r_A, +\infty)$. This completes the proof of Theorem 6. $\diamondsuit$

Additional remarks. • The proof of Theorem 6 provides a bit more information on the invariant distribution ν. Let $g>0$ and let ϕ_g denote its continuous density on $(r_A, +\infty)$: the function ϕ_g is $\mathcal{C}^\infty$ on $[r_A, +\infty) \setminus (r_A + g\,\mathbb{N})$ and it follows from (34) and the definitions of r and r_A (and $d = r r_A/g$, see the proof of theorem 6) that

$$\phi_g(r_A) = +\infty \ \text{ if } \ g > g^*, \quad \phi_g(r_A) \in (0, +\infty) \ \text{ if } \ g = g^* \ \text{ and } \ \phi_g(r_A) = 0 \ \text{ if } \ g < g^*$$

where $g^* = \frac{p_B(1-p_A)}{p_A^2} \in (0, \frac{1-p_A}{p_A})$. As concerns the regularity of the density ϕ_g at points $y \in r_A + g\,\mathbb{N}$, one easily derives from Equation (33) that for every $m, k \in \mathbb{N}$,

– ϕ_g is C^{m+k} at $r_A + kg$ as soon as $g < \frac{g^*}{m+1}$,

– the $(m+k)^{th}$ derivative $\phi_g^{(m+k)}$ is only right and left continuous at $r_A + kg$ if $g = \frac{g^*}{m+1}$.

• One can characterize the finite positive exponential moments of ν by slightly extending the proof of Proposition 6 (Laplace transform). For every $y>1$, let $\theta(y)$ denote the unique (strictly) positive solution of the equation

$$\frac{e^\theta - 1}{\theta} = y.$$

Note that $\log y < \theta(y) < 2(y-1)$ and that $\lim_{y\to 1} \frac{\theta(y)}{2(y-1)} = 1$ and $\lim_{y\to\infty} \frac{\theta(y)}{\log y} = 1$. The result is as follows

$$\int e^{py}\nu(dy) < +\infty \quad \text{if and only if} \quad p < p_g^* := g\,\theta(p_A/p_B). \tag{36}$$

With the notations of Proposition 6, it follows from Fatou's Lemma that

$$\forall\, p>0, \qquad \int e^{py}\nu(dy) \le \liminf_{t\to\infty} \mathbb{E}_y(e^{pY_t}). \tag{37}$$

We know that

$$\mathbb{E}_y(e^{pY_t}) = e^{\tilde\varphi_p(t)+y\tilde\psi_p(t)}$$

with $\tilde\varphi_p(t) = (1-p_{_A})\int_0^t \tilde\psi_p(s)ds$ and $\tilde\psi_p$ is solution on the non-negative real line (if any) of

$$\psi'(t) = G(\psi(t)), \quad \psi(0)=p \quad \text{ with } \quad G(u) = -p_{_A} u + \frac{p_{_B}}{g}(e^{gu}-1).$$

The function G is convex on $\mathbb{R}_+$ and satisfies $G(0)=G(p_g^*)=0$, $G((0,p_g^*))\subset(-\infty,0)$.

Let $p\in(0,p_g^*)$. The convexity of G implies

$$\forall\, u\in[0,p], \quad \frac{G(u)}{u} \le \frac{G(p)}{p} < 0.$$

It follows that $\tilde\psi_p$ does exist on $\mathbb{R}_+$ and satisfies $0\le\tilde\psi_p(t)\le pe^{\frac{G(p)t}{p}}$ (hence it goes to 0 when t goes to infinity). One derives that

$$\lim_{t\to+\infty}\tilde\varphi_p(t) = (1-p_{_A})\int_0^{+\infty}\tilde\psi_p(t)dt \le -(1-p_{_A})\frac{p^2}{G(p)}.$$

Combining this with (37) yields

$$\int e^{py}\nu(dy) \le e^{-(1-p_{_A})\frac{p^2}{G(p)}} < +\infty.$$

On the other hand if $p=p_g^*$, $\tilde\psi_p(t)=p_g^*$ and $\tilde\varphi_p(t)=(1-p_{_A})p_g^*t$. Consequently

$$\forall\, t\ge 0, \qquad \int e^{p_g^*y}\nu(dy) = \int \mathbb{E}_y(e^{p_g^*Y_t})\nu(dy) = e^{(1-p_{_A})p_g^*t}\int e^{p_g^*y}\nu(dy).$$

Now the right hand side of this equality goes to ∞ as t goes to infinity since $(1-p_{_A})p_g^*>0$ which shows that $\int e^{p_g^*y}\nu(dy)=+\infty$ (since it cannot be 0).

- One has, in accordance with the convergence rate result obtained for $\rho_n=o(\gamma_n)$, that

$$\int y\,\nu(dy) = \frac{1-p_{_A}}{\pi}.$$

To prove this claim, one first notes, using the definition (18) of the generator L, that $L(Id)(y)=1-p_{_A}-\pi\, y$. Hence the above claim will follow from $\int L(Id)(y)\nu(dy)=0$. Let $\varphi:\mathbb{R}_+\to\mathbb{R}_+$ denote a continuously differentiable function such that $\varphi(y)=y$ if $y\in[0,1]$, $\varphi(y)=0$ if $y\ge 2$ and φ' is bounded on $\mathbb{R}_+$. Set $\varphi_n(y)=n\varphi(y/n)$, $n\ge1$. One checks

Figure 1: *Graphs of the p.d.f* ϕ_g, $p_A = 2/5$, $g = 1$*; the vertical dotted line shows the mean* $\frac{1-p_A}{\pi}$ *of* ν. Left: $p_B = 1/3$ $(g^* > g = 1)$. Center: $p_B = 4/15$ $(g^* = g = 1)$. Right: $p_B = 1/6$ $(g^* < g = 1)$.

that $L(\varphi_n) \to L(Id)$ as n goes to infinity and $|L(\varphi_n)(y)| \le ay + b$ for some positive real constants a, b. One derives by the dominated convergence theorem that

$$\int L(Id)(y)\nu(dy) = \lim_n \int L(\varphi_n)(y)\nu(dy) = 0$$

where we used that the function φ_n has compact support on $[0, +\infty)$. One shows similarly that $\int L(u \mapsto u^2)(y)\nu(dy) = 0$ to derive that

$$\int \left(y - \frac{1-p_A}{\pi}\right)^2 \nu(dy) = g\,\frac{p_B(1-p_A)}{2\pi^2}.$$

Note that, as one could expect, this variance goes to 0 as $g \to 0$. As a conclusion, we present in figure 1 three examples of shape for ϕ_g. They were obtained from an exact simulation of the Markov process $(Y_t)_{t\ge 0}$ (associated to the generator L) at its jump times: we approximated the p.d.f. by a histogram method using Birkhoff's ergodic Theorem.

Figures should be here

A final remark about the case $\pi = 0$ and $\gamma_n = g\,\rho_n$. In that setting (see Remark 1) the asymptotics of the algorithm cannot be elucidated by using the ODE approach since it holds in a weak sense. Setting $Y_n = 1 - 2X_n$ one checks that $Y_n \in [-1, 1]$ and

$$Y_{n+1} = Y_n(1 - 2g\rho^2_{n+1}(1 - p_A)) - 2g\,\rho_{n+1}\Delta M_{n+1}$$

and that $\mathbb{E}((\Delta M_{n+1})^2\,|\mathcal{F}_{n+1}) = \frac{p_A}{4}(1 - Y_n^2) + O(\rho^2_{n+1})$. Then, a similar approach as that developed in this section (but significantly less technical since (Y_n) is bounded by 1) shows that Y_n converges in distribution to the invariant distribution μ of the Brownian diffusion with generator $\mathcal{L}f(y) = -2g(1-p_A)yf'(y) + \frac{1}{2}g^2 p_A(1-y^2)f''(y)$. In that case, it is well-known that μ has a density function for which a closed form is available (see [8]), namely

$$\mu(dy) = m(y)dy \quad \text{with} \quad m(y) = C_{g,r_A}(1-y^2)^{\frac{2r_A}{g}-1}\mathbf{1}_{(-1,1)}(y).$$

Note that when $g = 2r_A = 2(1/p_A - 1) > 0$, μ is but the uniform distribution over $[-1, 1]$.

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