

STRONG ORDER 1 CONVERGENCE OF THE EULER-MARUYAMA METHOD FOR RANDOM ORDINARY DIFFERENTIAL EQUATIONS

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ABSTRACT. It is well known that the Euler-Maruyama method of approximating a random ordinary differential equation $dX_t/dt = f(t, X_t, Y_t)$ driven by a stochastic process $\{Y_t\}_t$ with θ -Hölder sample paths is estimated to be of strong order θ with respect to the time step, provided $f = f(t, x, y)$ is sufficiently regular. Here, we show that, in common situations, it is possible to exploit further conditions on the noise and prove that the strong convergence is actually of order 1, regardless of the Hölder regularity of the sample paths. This applies to Itô process noises (such as Wiener, Ornstein-Uhlenbeck, and Geometric Brownian process), which have Hölder continuous sample paths; to point-process noises (such as Poisson point processes and Hawkes self-exciting processes), which are not even continuous and have jump-type discontinuities, and to transport-type processes. The order 1 convergence is based on two main ideas: First of all, we do not estimate directly the local error and, instead, add up the local steps and work directly with an accumulated global error. Secondly, we assume either a control of the total variation of the sample paths of the noise or that the noise is an Itô process, in which case we exploit the Iso isometry on the global error term.

1. INTRODUCTION

Consider the following initial value problem for a **random ordinary differential equation (RODE)**:

$$\begin{cases} \frac{dX_t}{dt} = f(t, X_t, Y_t), & 0 \leq t \leq T, \\ X_t|_{t=0} = X_0, \end{cases} \quad (1.1)$$

on a time interval $I = [0, T]$, with $T > 0$, and where the noise $\{Y_t\}_{t \in I}$ is a given stochastic process. The sample space is denoted by Ω .

The Euler-Maruyama method for solving this initial value problem consists in approximating the solution on a uniform time mesh $t_j = j\Delta t_N$, $j = 0, \dots, N$, with fixed time step $\Delta t_N = T/N$, for a given $N \in \mathbb{N}$. In such a mesh, the Euler-Maruyama

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scheme takes the form

$$X_{t_j}^N = X_{t_{j-1}}^N + \Delta t_N f(t_{j-1}, X_{t_{j-1}}^N, Y_{t_{j-1}}), \quad j = 1, \dots, N, \quad (1.2)$$

with the initial condition

$$X_0^N = X_0. \quad (1.3)$$

Notice $t_j = j\Delta t_N = jT/N$ also depends on N , but we do not make this dependency explicit, for the sake of notational simplicity.

When the noise $\{Y_t\}_{t \in I}$ has θ -Hölder continuous sample paths, it can be show [3], under further suitable conditions, that the Euler-Maruyama scheme converges strongly with order θ with respect to the time step, i.e. there exists a constant $C \geq 0$ such that

$$\max_{j=0, \dots, N} \mathbb{E} \left[\left| X_{t_j} - X_{t_j}^N \right| \right] \leq C \Delta t_N^\theta, \quad \forall N \in \mathbb{N}, \quad (1.4)$$

where $\mathbb{E}[\cdot]$ indicates the expectation of a random variable on Ω .

Our aim is to show that, in many classical examples, it is possible to exploit further conditions that yield in fact a strong order 1 convergence, with the sample paths still being Hölder continuous or even discontinuous. This is the case, for instance, when the noise is an Itô noise, or a point process or a transport process.

The first main of the proof is to not estimate the local error and, instead, work with an explicit formula for the global error, namely (see [Lemma 3.1](#))

$$\begin{aligned} X_{t_j} - X_{t_j}^N &= X_0 - X_0^N \\ &+ \int_0^{t_j} (f(s, X_s, Y_s) - f(s, X_{\tau^N(s)}, Y_s)) \, ds \\ &+ \int_0^{t_j} (f(s, X_{\tau^N(s)}, Y_s) - f(s, X_{\tau^N(s)}^N, Y_s)) \, ds \\ &+ \int_0^{t_j} (f(s, X_{\tau^N(s)}^N, Y_s) - f(\tau^N(s), X_{\tau^N(s)}^N, Y_{\tau^N(s)})) \, ds, \end{aligned} \quad (1.5)$$

for $j = 1, \dots, N$, where τ^N is a piecewise constant function with jumps at the mesh points t_j . The first term vanishes due to the initial condition $X_0^N = X_0$. The second term only depends on the solution and can be easily estimated with natural regularity conditions on the term $f = f(t, x, y)$. The third term is handled solely with the typical required condition on $f = f(t, x, y)$ of being uniformly globally Lipschitz continuity with respect to x . With those, we obtain the following basic bound for the global error (see [Lemma 4.1](#))

$$\begin{aligned} |X_{t_j} - X_{t_j}^N| &\leq \left(|X_0 - X_0^N| + L_X \int_0^{t_j} |X_s - X_{\tau^N(s)}| \, ds \right. \\ &\quad \left. \left| \int_0^{t_j} (f(s, X_{\tau^N(s)}^N, Y_s) - f(\tau^N(s), X_{\tau^N(s)}^N, Y_{\tau^N(s)})) \, ds \right| \right) e^{L_X t_j}. \end{aligned} \quad (1.6)$$

The only problematic term is the last one. The classical analysis is to use an assumed θ -Hôlder regularity of noise and estimate the local error as

$$|f(s, X_{\tau^N(s)}^N, Y_s) - f(\tau^N(s), X_{\tau^N(s)}^N, Y_{\tau^N(s)})| \leq C\Delta t^\theta.$$

Instead, we keep the global error formula and assume the steps of $F_t = f(t, X_{\tau^N(t)}^N, Y_t)$ are somehow integrable. In order to give the main idea, let us assume for the moment that the sample paths of $\{F_t\}_{t \in I}$ satisfy

$$F_s - F_\tau = \int_\tau^s dF_\xi,$$

either in the sense of a Riemann-Stieltjes integral or of an Itô integral. The first sense fits the case of noises with bounded total variation. The second one fits the case of an Itô noise. In any case, we bound the global error term using integration by parts,

$$\begin{aligned} \int_0^{t_j} \left(f(s, X_{\tau^N(s)}^N, Y_s) - f(\tau^N(s), X_{\tau^N(s)}^N, Y_{\tau^N(s)}) \right) ds &= \int_0^{t_j} \int_{\tau^N(s)}^s dF_\xi ds \\ &= \int_0^{t_j} \int_\xi^{\tau^N(\xi) + \Delta t_N} ds dF_\xi. \end{aligned}$$

Then, we find that

$$\begin{aligned} \mathbb{E} \left[\left| \int_0^{t_j} \left(f(s, X_{\tau^N(s)}^N, Y_s) - f(\tau^N(s), X_{\tau^N(s)}^N, Y_{\tau^N(s)}) \right) ds \right| \right] \\ \leq \Delta t_N \mathbb{E} \left[\int_0^{t_j} dF_\xi \right], \end{aligned}$$

which yields the strong order 1 convergence provided the remaining expectation is finite.

In the case of an Itô integral, this is exactly what we assume, because the Itô integral is not order preserving. The bound on the remaining expectation is obtained via Itô isometry. In the case of bounded variation, however, we can relax the above condition and work not with $\{F_t\}_{t \in I}$ itself but with a bound on the step of the form

$$|f(s, X_{\tau^N(s)}^N, Y_s) - f(\tau^N(s), X_{\tau^N(s)}^N, Y_{\tau^N(s)})| \leq \bar{F}_s - \bar{F}_{\tau^N(s)}.$$

Only this bounding process $\{\bar{F}_t\}_{t \in I}$ is required to have sample paths of bounded variation, which is usually easier to check. These two cases are treated in [Section 5](#) (see [Lemma 5.1](#) and [Theorem 5.1](#)) and [Section 6](#) (see [Lemma 6.1](#) and [Theorem 6.1](#)).

The conditions in [Theorem 5.1](#) and [Theorem 6.1](#) are not readily verifiable, but [Theorem 5.2](#) and [Theorem 6.2](#) give more explicit conditions for each of the two cases. Essentially, $f = f(t, x, y)$ is required to have minimal regularity in the sense of differentiability and growth conditions and the noise $\{Y_t\}_{t \in I}$ is either required to have sample paths of bounded variation or to be an Itô noise.

2. PATHWISE SOLUTION

For the notion and main results on pathwise solution for RODEs, we refer the reader to [4, Section 2.1]. We consider two sets of hypotheses, namely **Hypothesis 2.1** and **Hypothesis 2.2**, each suitable to one of the two main cases we consider, namely the case in which the steps are bounded by processes with monotonic expected values and the case with Itô type noises.

We start with the following hypotheses, which imply the existence and uniqueness of pathwise solutions of the RODE (1.1) in the sense of Carathéodory.

Hypothesis 2.1. *We consider a function $f = f(t, x, y)$ defined on $I \times \mathbb{R} \times \mathbb{R}$ and a real-valued stochastic process $\{Y_t\}_{t \in I}$, where $I = [0, T]$, $T > 0$. We make the following standing hypotheses.*

- (i) *f is globally Lipschitz continuous on x , uniformly in t and y , i.e. there exists a constant $L_X \geq 0$ such that*

$$|f(t, x_1, y) - f(t, x_2, y)| \leq L_X |x_1 - x_2|, \quad \forall t \in I, \forall x_1, x_2, y \in \mathbb{R}. \quad (2.1)$$

- (ii) *We also assume that $(t, x) \mapsto f(t, x, Y_t)$ satisfies the Carathéodory conditions:*
 - (a) *The mapping $x \mapsto f(t, x, y)$ is continuous on $x \in \mathbb{R}$, for almost every $(t, y) \in I \times \mathbb{R}$;*
 - (b) *The mapping $t \mapsto f(t, x, Y_t)$ is Lebesgue measurable in $t \in I$, for each $x \in \mathbb{R}$ and each sample path $t \mapsto Y_t(\omega)$;*
 - (c) *The bound $|f(t, x, Y_t)| \leq M_t + L_X |x|$ holds for all $t \in I$ and all $x \in \mathbb{R}$, where $\{M_t\}_{t \in I}$ is a real stochastic process with Lebesgue integrable sample paths $t \mapsto M_t(\omega)$ on $t \in I$.*

Under these assumptions, for each sample value $\omega \in \Omega$, the integral equation

$$X_t = X_0 + \int_0^t f(s, X_s, Y_s) \, ds \quad (2.2)$$

has a unique solution, in the Lebesgue sense, for the realization $X_0 = X_0(\omega)$ of the initial condition and the sample path $t \mapsto Y_t(\omega)$ of the noise process (see [2, Theorem 1.1]). Moreover, the mapping $(t, \omega) \mapsto X_t(\omega)$ is measurable (see [4, Section 2.1.2]) and, hence, give rise to a well-defined stochastic process $\{X_t\}_{t \in I}$.

Each sample path solution $t \mapsto X_t(\omega)$ is bounded by

$$|X_t| \leq \left(|X_0| + \int_0^t M_s \, ds \right) e^{L_X t}, \quad \forall t \in I. \quad (2.3)$$

For the strong convergence of the Euler-Maruyama approximation, we also need to control the expectation of the solution above, among other things. With that in mind, we have the following useful result.

Lemma 2.1. *Under **Hypothesis 2.1**, suppose further that*

$$\mathbb{E}[|X_0|] < \infty \quad (2.4)$$

and

$$\int_0^T \mathbb{E}[|M_s|] \, ds < \infty \quad (2.5)$$

Then,

$$\mathbb{E}[|X_t|] \leq \left(\mathbb{E}[|X_0|] + \int_0^t \mathbb{E}[|M_s|] \, ds \right) e^{L_X t}, \quad t \in I. \quad (2.6)$$

Proof. Thanks to (2.3), the result is straightforward \square

In special *dissipative* cases, depending on the structure of the equation, we might not need the second condition and only require $\mathbb{E}[|X_0|] < \infty$, but we do not exploit this case here.

When $f = f(t, x, y)$ is continuous on all three variables, as well as uniformly globally Lipschitz continuous in x , and the sample paths of $\{Y_t\}_{t \geq 0}$ are continuous, then the integrand in (2.2) is continuous in t and the integral becomes a Riemann integral. In this case, the integral form (2.2) of the pathwise solutions of (1.1) holds in the Riemann sense.

This setting is assumed in the analysis of the case of Itô noise. With that in mind, we define, more precisely, a second set of hypotheses, on top of the first one above.

Hypothesis 2.2. *We consider a function $f = f(t, x, y)$ defined on $I \times \mathbb{R} \times \mathbb{R}$ and a real-valued stochastic process $\{Y_t\}_{t \in I}$, where $I = [0, T]$, $T > 0$. Besides *Hypothesis 2.1*, we also assume*

- (i) $f = f(t, x, y)$ is continuous on $I \times \mathbb{R} \times \mathbb{R}$.
- (ii) For each $x \in \mathbb{R}$, the map $(t, y) \mapsto f(t, x, y)$ is twice continuously differentiable on $I \times \mathbb{R}$.
- (iii) The sample paths $t \mapsto Y_t(\omega)$ of the noise process are continuous on I .
- (iv) The noise process $\{Y_t\}_{t \in I}$ is an Itô noise in the sense of satisfying

$$dY_t = A_t \, dt + B_t \, dW_t, \quad (2.7)$$

where $\{W_t\}_{t \geq 0}$ is a standard Wiener process and $\{A_t\}_{t \in I}$ and $\{B_t\}_{t \in I}$ are stochastic processes adapted to $\{W_t\}_{t \geq 0}$.

3. INTEGRAL FORMULA FOR THE GLOBAL PATHWISE ERROR

In this section, we derive the following integral formula for the global error:

Lemma 3.1. *Under *Hypothesis 2.1*, the Euler-Maruyama approximation (1.2) for any pathwise solution of the random ordinary differential equation (1.1) satisfies the*

global error formula

$$\begin{aligned}
X_{t_j} - X_{t_j}^N &= X_0 - X_0^N \\
&+ \int_0^{t_j} (f(s, X_s, Y_s) - f(s, X_{\tau^N(s)}, Y_s)) \, ds \\
&+ \int_0^{t_j} (f(s, X_{\tau^N(s)}, Y_s) - f(s, X_{\tau^N(s)}^N, Y_s)) \, ds \\
&+ \int_0^{t_j} (f(s, X_{\tau^N(s)}^N, Y_s) - f(\tau^N(s), X_{\tau^N(s)}^N, Y_{\tau^N(s)})) \, ds,
\end{aligned} \tag{3.1}$$

for $j = 1, \dots, N$, where τ^N is the piecewise constant jump function along the time mesh:

$$\tau^N(t) = \max_j \{j\Delta t_N; j\Delta t_N \leq t\} = \left\lfloor \frac{t}{\Delta t_N} \right\rfloor \Delta t_N = \left\lfloor \frac{tN}{T} \right\rfloor \frac{T}{N}. \tag{3.2}$$

Proof. Under **Hypothesis 2.1**, the solutions of (1.1) are pathwise solutions in the Lebesgue sense of (2.2). With that in mind, we first obtain an expression for a single time step, from time t_{j-1} to $t_j = t_{j-1} + \Delta t_N$.

For notational simplicity, we momentarily write $t = t_{j-1}$ and $\tau = \Delta t_N$, so that $t_j = t + \tau$. The exact pathwise solution satisfies

$$X_{t+\tau} = X_t + \int_t^{t+\tau} f(s, X_s, Y_s) \, ds.$$

The Euler-Maruyama step is given by

$$X_{t+\tau}^N = X_t^N + \tau f(t, X_t^N, Y_t).$$

Subtracting, we obtain

$$X_{t+\tau} - X_{t+\tau}^N = X_t - X_t^N + \int_t^{t+\tau} (f(s, X_s, Y_s) - f(t, X_t^N, Y_t)) \, ds.$$

We arrange the integrand as

$$\begin{aligned}
f(s, X_s, Y_s) - f(t, X_t^N, Y_t) &= f(s, X_s, Y_s) - f(s, X_t, Y_s) \\
&+ f(s, X_t, Y_s) - f(s, X_t^N, Y_s) \\
&+ f(s, X_t^N, Y_s) - f(t, X_t^N, Y_t).
\end{aligned}$$

This yields

$$\begin{aligned}
X_{t+\tau} - X_{t+\tau}^N &= X_t - X_t^N \\
&= \int_t^{t+\tau} (f(s, X_s, Y_s) - f(s, X_t, Y_s)) \, ds \\
&\quad + \int_t^{t+\tau} (f(s, X_t, Y_s) - f(s, X_t^N, Y_s)) \, ds \\
&\quad + \int_t^{t+\tau} (f(s, X_t^N, Y_s) - f(t, X_t^N, Y_t)) \, ds.
\end{aligned}$$

Going back to the notation $t = t_{j-1}$ and $t + \tau = t_j$, the above identity reads

$$\begin{aligned}
X_{t_j} - X_{t_j}^N &= X_{t_{j-1}} - X_{t_{j-1}}^N \\
&= \int_{t_{j-1}}^{t_j} (f(s, X_s, Y_s) - f(s, X_{t_{j-1}}, Y_s)) \, ds \\
&\quad + \int_{t_{j-1}}^{t_j} (f(s, X_{t_{j-1}}, Y_s) - f(s, X_{t_{j-1}}^N, Y_s)) \, ds \\
&\quad + \int_{t_{j-1}}^{t_j} (f(s, X_{t_{j-1}}^N, Y_s) - f(t_{j-1}, X_{t_{j-1}}^N, Y_{t_{j-1}})) \, ds.
\end{aligned} \tag{3.3}$$

Now we iterate the time steps (3.3) to find that

$$\begin{aligned}
X_{t_j} - X_{t_j}^N &= X_0 - X_0^N \\
&\quad + \sum_{i=1}^j \left(\int_{t_{i-1}}^{t_i} (f(s, X_s, Y_s) - f(s, X_{t_i}, Y_s)) \, ds \right. \\
&\quad + \int_{t_{i-1}}^{t_i} (f(s, X_{t_{i-1}}, Y_s) - f(s, X_{t_{i-1}}^N, Y_s)) \, ds \\
&\quad \left. + \int_{t_{i-1}}^{t_i} (f(s, X_{t_{i-1}}^N, Y_s) - f(t_{i-1}, X_{t_{i-1}}^N, Y_{t_{i-1}})) \, ds \right).
\end{aligned}$$

Using the jump function τ^N , we may rewrite the above expression as in (3.1). \square

Remark 3.1. Strictly speaking, we only need condition (ii) from Hypothesis 2.1 in order to deduce (4.1), but since we need (i) for the strong convergence anyways, it is simpler to state the result as in Lemma 4.1.

4. BASIC ESTIMATE FOR THE GLOBAL PATHWISE ERROR

Here we derive an estimate, under minimal hypotheses, that will be the basis for the estimates in specific cases.

Lemma 4.1. *Under [Hypothesis 2.1](#), the global error [\(3.1\)](#) is estimated as*

$$|X_{t_j} - X_{t_j}^N| \leq \left(|X_0 - X_0^N| + L_X \int_0^{t_j} |X_s - X_{\tau^N(s)}| \, ds \right. \\ \left. \left| \int_0^{t_j} \left(f(s, X_{\tau^N(s)}^N, Y_s) - f(\tau^N(s), X_{\tau^N(s)}^N, Y_{\tau^N(s)}) \right) \, ds \right| \right) e^{L_X t_j}. \quad (4.1)$$

for $j = 1, \dots, N$, where τ^N is given by [\(3.2\)](#).

Proof. We estimate the first two integrals in [\(3.1\)](#). For the first one, we use [\(2.1\)](#), so that

$$|f(s, X_s, Y_s) - f(s, X_t, Y_s)| \leq L_X |X_s - X_t|,$$

for $t, s \in I$, and, in particular, for $t = \tau^N(s)$. Hence,

$$\left| \int_0^{t_j} \left(f(s, X_s, Y_s) - f(s, X_{\tau^N(s)}, Y_s) \right) \, ds \right| \leq L_X \int_0^{t_j} |X_s - X_{\tau^N(s)}| \, ds.$$

For the second term, we use again [\(2.1\)](#), so that

$$|f(s, X_t, Y_s) - f(s, X_t^N, Y_s)| \leq L_X |X_t - X_t^N|,$$

again for any $t, s \in I$, and, in particular, for $t = \tau^N(s)$. Hence,

$$\left| \int_0^{t_j} \left(f(s, X_{\tau^N(s)}, Y_s) - f(s, X_{\tau^N(s)}^N, Y_s) \right) \, ds \right| \leq L_X \int_0^{t_j} |X_{\tau^N(s)} - X_{\tau^N(s)}^N| \, ds \\ \leq L_X \sum_{i=0}^{j-1} |X_{t_i} - X_{t_i}^N| \Delta t_N.$$

With these two estimates, we bound [\(3.1\)](#) as

$$|X_{t_j} - X_{t_j}^N| \leq |X_0 - X_0^N| \\ + L_X \int_0^{t_j} |X_s - X_{\tau^N(s)}| \, ds \\ + L_X \sum_{i=0}^{j-1} |X_{t_i} - X_{t_i}^N| \Delta t_N \\ + \left| \int_0^{t_j} \left(f(s, X_{\tau^N(s)}^N, Y_s) - f(\tau^N(s), X_{\tau^N(s)}^N, Y_{\tau^N(s)}) \right) \, ds \right|.$$

Using the discrete version of the Gronwall Lemma, we prove [\(4.1\)](#). \square

The first term in the right hand side of [\(4.1\)](#) usually vanishes since in general we take $X_0^N = X_0$, but it suffices to assume that X_0^N approximates X_0 to order Δt_N , which is useful for lower order approximations or for the discretization of (random) partial differential equations.

The third term in (4.1) is the more delicate one that will be handled differently in the next sections.

As for the second term, which only concerns the solution itself, not the approximation, we use the following simple but useful general result.

Lemma 4.2. *Under Hypothesis 2.1, it follows that*

$$\int_0^{t_j} |X_s - X_{\tau^N(s)}| \, ds \leq \Delta t_N \int_0^{t_j} (M_s + L_X |X_s|) \, ds. \quad (4.2)$$

Proof. By assumption, we have $|f(t, X_t, Y_t)| \leq M_t + L_X |X_t|$, for all $t \in I$ and all sample paths. Thus,

$$|X_s - X_{\tau^N(s)}| = \left| \int_{\tau^N(s)}^s f(\xi, X_\xi, Y_\xi) \, d\xi \right| \leq \int_{\tau^N(s)}^s (M_\xi + L_X |X_\xi|) \, d\xi.$$

Integrating over $[0, t_j]$ and using integration by parts,

$$\begin{aligned} \int_0^{t_j} |X_s - X_{\tau^N(s)}| \, ds &\leq \int_0^{t_j} \int_{\tau^N(s)}^s (M_\xi + L_X |X_\xi|) \, d\xi \, ds \\ &= \int_0^{t_j} \int_{\xi}^{\tau^N(\xi) + \Delta t_N} (M_\xi + L_X |X_\xi|) \, ds \, d\xi \\ &= \int_0^{t_j} (\tau^N(\xi) + \Delta t_N - \xi) (M_\xi + L_X |X_\xi|) \, d\xi. \end{aligned}$$

Using that $\tau^N(\xi) \leq \xi$ and that the remaining terms are non-negative, we have $\tau^N(\xi) + \Delta t_N - \xi \leq \Delta t_N$ and we obtain exactly (4.2). \square

Combining the two previous results we obtain

Proposition 4.1. *Under Hypothesis 2.1, suppose further that (2.4) and (2.5) hold and that, for some constant $C_0 \geq 0$,*

$$\mathbb{E}[|X_0 - X_0^N|] \leq C_0 \Delta t_N, \quad N \in \mathbb{N}. \quad (4.3)$$

Then, for every $j = 0, \dots, N$,

$$\begin{aligned} &\mathbb{E} \left[|X_{t_j} - X_{t_j}^N| \right] \\ &\leq \left(C_0 \Delta t_N + \Delta t_N L_X \left(\mathbb{E}[|X_0|] + \int_0^{t_j} \mathbb{E}[M_\xi] \, d\xi \right) e^{L_X t_j} \right. \\ &\quad \left. \mathbb{E} \left[\left| \int_0^{t_j} \left(f(s, X_{\tau^N(s)}^N, Y_s) - f(\tau^N(s), X_{\tau^N(s)}^N, Y_{\tau^N(s)}) \right) \, ds \right| \right] \right) e^{L_X t_j}. \end{aligned} \quad (4.4)$$

Proof. Under Hypothesis 2.1, Lemma 4.2 applies and estimate (4.2) holds. Using (2.4) and (2.5), that estimate yields

$$\int_0^{t_j} \mathbb{E}[|X_s - X_{\tau^N(s)}|] \, ds \leq \Delta t_N \int_0^{t_j} (\mathbb{E}[M_s] + L_X \mathbb{E}[|X_s|]) \, ds.$$

Using now (2.3), we obtain

$$\begin{aligned}
& \int_0^{t_j} \mathbb{E}[|X_s - X_{\tau^N(s)}|] \, ds \\
& \leq \Delta t_N \int_0^{t_j} \left(\mathbb{E}[M_s] + L_X \left(\mathbb{E}[|X_0|] + \int_0^s \mathbb{E}[M_\xi] \, d\xi \right) e^{L_X s} \right) \, ds \\
& \leq \Delta t_N \left(\int_0^{t_j} \mathbb{E}[M_s] \, ds + L_X \int_0^{t_j} \left(\mathbb{E}[|X_0|] + \int_0^s \mathbb{E}[M_\xi] \, d\xi \right) e^{L_X s} \, ds \right) \\
& = \Delta t_N \left(\int_0^{t_j} \mathbb{E}[M_s] \, ds + \left(\mathbb{E}[|X_0|] + \int_0^{t_j} \mathbb{E}[M_\xi] \, d\xi \right) (e^{L_X t_j} - 1) \right).
\end{aligned}$$

Thus,

$$\int_0^{t_j} \mathbb{E}[|X_s - X_{\tau^N(s)}|] \, ds \leq \Delta t_N \left(\mathbb{E}[|X_0|] + \int_0^{t_j} \mathbb{E}[M_\xi] \, d\xi \right) e^{L_X t_j}. \quad (4.5)$$

Now we turn our attention to Lemma 4.1. Taking the expectation of the global error formula (4.1) gives

$$\begin{aligned}
\mathbb{E} \left[|X_{t_j} - X_{t_j}^N| \right] & \leq \left(\mathbb{E} [|X_0 - X_0^N|] + L_X \int_0^{t_j} \mathbb{E} [|X_s - X_{\tau^N(s)}|] \, ds \right. \\
& \quad \left. \mathbb{E} \left[\left| \int_0^{t_j} \left(f(s, X_{\tau^N(s)}^N, Y_s) - f(\tau^N(s), X_{\tau^N(s)}^N, Y_{\tau^N(s)}) \right) \, ds \right| \right] \right) e^{L_X t_j}.
\end{aligned}$$

Using now estimate (4.5) and condition (4.3), we find (4.4), which completes the proof. \square

5. THE CASE OF MONOTONIC SAMPLE PATH BOUNDS

Here, the noise $\{Y_t\}_{t \in I}$ is *not* assumed to be an Itô noise and f is not assumed to be differentiable, but, instead, that the steps can be controlled by monotonic nondecreasing processes with finite expected growth. This fits well with the typical case of point processes, such as renewal-reward processes, Hawkes process, and such.

More precisely, we have the following result:

Lemma 5.1. *Besides Hypothesis 2.1, suppose that, for all $0 \leq s \leq T$,*

$$|f(s, X_{\tau^N(s)}^N, Y_s) - f(\tau^N(s), X_{\tau^N(s)}^N, Y_{\tau^N(s)})| \leq \bar{F}_s - \bar{F}_{\tau^N(s)}, \quad (5.1)$$

where $\{\bar{F}_t\}$ is a real stochastic process satisfying

$$\mathbb{E}[\bar{F}_t] \text{ is monotonic nondecreasing and bounded in } t \in I. \quad (5.2)$$

Then,

$$\mathbb{E} \left[\left| \int_0^t \left(f(s, X_{\tau^N(s)}^N, Y_s) - f(\tau^N(s), X_{\tau^N(s)}^N, Y_{\tau^N(s)}) \right) \, ds \right| \right] \leq (\mathbb{E}[\bar{F}_t] - \mathbb{E}[\bar{F}_0]) \Delta t_N, \quad (5.3)$$

for all $0 \leq t \leq T$ and every $N \in \mathbb{R}$.

Proof. Let $N \in \mathbb{R}$. From the assumption (5.1) we have

$$\mathbb{E} \left[|f(s, X_{\tau^N(s)}^N, Y_s) - f(\tau^N(s), X_{\tau^N(s)}^N, Y_{\tau^N(s)})| \right] \leq \mathbb{E}[\bar{F}_s] - \mathbb{E}[\bar{F}_{\tau^N(s)}],$$

for every $0 \leq s \leq T$. Thus, upon integration,

$$\begin{aligned} \mathbb{E} \left[\left| \int_0^t \left(f(s, X_{\tau^N(s)}^N, Y_s) - f(\tau^N(s), X_{\tau^N(s)}^N, Y_{\tau^N(s)}) \right) ds \right| \right] \\ \leq \int_0^t \mathbb{E} \left[|f(s, X_{\tau^N(s)}^N, Y_s) - f(\tau^N(s), X_{\tau^N(s)}^N, Y_{\tau^N(s)})| \right] ds \\ \leq \int_0^t (\mathbb{E}[\bar{F}_s] - \mathbb{E}[\bar{F}_{\tau^N(s)}]) ds. \end{aligned}$$

Now we need to bound the right hand side. When $0 \leq t \leq t_1 = \Delta t_N$, we have $\tau^N(s) = 0$ for all $0 \leq s < t_1$, so that,

$$\int_0^t (\mathbb{E}[\bar{F}_s] - \mathbb{E}[\bar{F}_{\tau^N(s)}]) ds = \int_0^t (\mathbb{E}[\bar{F}_s] - \mathbb{E}[\bar{F}_0]) ds.$$

Using the monotonicity and the condition that $t \leq \Delta t_N$,

$$\begin{aligned} \int_0^t (\mathbb{E}[\bar{F}_s] - \mathbb{E}[\bar{F}_{\tau^N(s)}]) ds &\leq \int_0^t (\mathbb{E}[\bar{F}_t] - \mathbb{E}[\bar{F}_0]) ds \\ &= (\mathbb{E}[\bar{F}_t] - \mathbb{E}[\bar{F}_0])t \leq (\mathbb{E}[\bar{F}_t] - \mathbb{E}[\bar{F}_0])\Delta t_N. \end{aligned}$$

When $\Delta t_N \leq t \leq T$, we split the integration of the second term at time $s = t_1 = \Delta t_N$ and write

$$\int_0^t (\mathbb{E}[\bar{F}_s] - \mathbb{E}[\bar{F}_{\tau^N(s)}]) ds = \int_0^t \mathbb{E}[\bar{F}_s] ds - \int_0^{t_1} \mathbb{E}[\bar{F}_{\tau^N(s)}] ds - \int_{t_1}^t \mathbb{E}[\bar{F}_{\tau^N(s)}] ds$$

Using the monotonicity together with the fact that $s - \Delta t_N \leq \tau^N(s) \leq s$ for all $\Delta t_N \leq s \leq T$,

$$\begin{aligned} \int_0^t (\mathbb{E}[\bar{F}_s] - \mathbb{E}[\bar{F}_{\tau^N(s)}]) ds &\leq \int_0^t \mathbb{E}[\bar{F}_s] ds - \int_0^{\Delta t_N} \mathbb{E}[\bar{F}_0] ds - \int_{\Delta t_N}^t \mathbb{E}[\bar{F}_{s-\Delta t_N}] ds \\ &= \int_0^t \mathbb{E}[\bar{F}_s] ds - \int_0^{\Delta t_N} \mathbb{E}[\bar{F}_0] ds - \int_0^{T-\Delta t_N} \mathbb{E}[\bar{F}_s] ds \\ &= \int_{t-\Delta t_N}^t \mathbb{E}[\bar{F}_s] ds - \mathbb{E}[\bar{F}_0]\Delta t_N. \end{aligned}$$

Using again the monotonicity yields

$$\int_0^t (\mathbb{E}[\bar{F}_s] - \mathbb{E}[\bar{F}_{\tau^N(s)}]) ds \leq \int_{t-\Delta t_N}^t \mathbb{E}[\bar{F}_t] ds - \mathbb{E}[\bar{F}_0]\Delta t_N = (\mathbb{E}[\bar{F}_t] - \mathbb{E}[\bar{F}_0])\Delta t_N.$$

Putting the estimates together proves (5.3). \square

Theorem 5.1. Under *Hypothesis 2.1*, suppose also that (2.4), (2.5), (4.3), (5.1), and (5.2) hold. Then, the Euler-Maruyama scheme (1.2)-(1.3) is of strong order 1, i.e.

$$\max_{j=0,\dots,N} \mathbb{E} \left[\left| X_{t_j} - X_{t_j}^N \right| \right] \leq C \Delta t_N, \quad \forall N \in \mathbb{N}, \quad (5.4)$$

for a constant C given by

$$C = \left(C_0 + L_X \left(\mathbb{E}[|X_0|] + \int_0^T \mathbb{E}[M_\xi] \, d\xi \right) e^{L_X T} + (\mathbb{E}[\bar{F}_T] - \mathbb{E}[\bar{F}_0]) \right) e^{L_X T} \quad (5.5)$$

Proof. Under *Hypothesis 2.1*, the *Lemma 4.1* applies and the global error estimate (4.1) holds.

Thanks to (2.4), (2.5), and (4.3), the *Proposition 4.1* applies and the global error is bounded according to (4.4).

With assumptions (5.1) and (5.2), *Lemma 5.1* applies and the last term in (4.4) is bounded according to (5.3). Using (5.3) in (4.4) yields

$$\begin{aligned} \mathbb{E} \left[|X_{t_j} - X_{t_j}^N| \right] &\leq \left(C_0 \Delta t_N + \Delta t_N L_X \left(\mathbb{E}[|X_0|] + \int_0^{t_j} \mathbb{E}[M_\xi] \, d\xi \right) e^{L_X t_j} \right. \\ &\quad \left. + (\mathbb{E}[\bar{F}_{t_j}] - \mathbb{E}[\bar{F}_0]) \Delta t_N \right) e^{L_X t_j}. \end{aligned}$$

Since this holds for every $j = 0, \dots, N$, we obtain the desired (5.4). \square

The conditions of *Theorem 5.1*, especially (5.1)-(5.2), are not readily verified, but the following result gives more explicit conditions.

Theorem 5.2. Suppose that $f = f(t, x, y)$ is uniformly globally Lipschitz continuous in x and is continuously differentiable in (t, y) , with partial derivatives $\partial_t f$ and $\partial_y f$ with at most linear growth in x and y , i.e.

$$|\partial_t f(t, x, y)| \leq C_1 + C_2|x| + C_3|y|, \quad |\partial_y f(t, x, y)| \leq C_4 + C_5|x| + C_6|y|, \quad (5.6)$$

in $(t, x, y) \in I \times \mathbb{R} \times \mathbb{R}$, for suitable constants $C_1, C_2, C_3, C_4 \geq 0$. Assume, further, that the sample paths of $\{Y_t\}_{t \in I}$ are of bounded variation $V(\{Y_t\}_{t \in I}; I)$, on I , with finite quadratic mean,

$$\mathbb{E}[V(\{Y_t\}_{t \in I}; I)^2] < \infty, \quad (5.7)$$

and with

$$\mathbb{E}[|X_0|^2] < \infty. \quad (5.8)$$

Then, the Euler-Maruyama scheme is of strong order 1, i.e.

$$\max_{j=0,\dots,N} \mathbb{E} \left[\left| X_{t_j} - X_{t_j}^N \right| \right] \leq C \Delta t_N, \quad \forall N \in \mathbb{N}, \quad (5.9)$$

for a suitable constant $C \geq 0$.

Proof. Notice that

$$\begin{aligned} |f(t, x, y)| &\leq |f(t, x, y) - f(t, 0, y)| + |f(t, 0, y) - f(0, 0, y)| + |f(0, 0, y) - f(0, 0, 0)| \\ &\leq L_X|x| + C_1 + C_3|y| + C_4 + C_6|y|. \end{aligned}$$

Thus,

$$|f(t, x, Y_t)| \leq M_t + L_X|x|,$$

where

$$M_t = C_1 + C_4 + (C_3 + C_6)|Y_t|.$$

Since the sample paths of $\{Y_t\}_{t \in I}$ are of bounded variation, the process $\{M_t\}_{t \in I}$ has integrable sample paths. This means that we are under the **Hypothesis 2.1**. Moreover, thanks to (5.7), we see that

$$\mathbb{E}[|Y_t|] \leq \mathbb{E}[|Y_t|^2] \leq \mathbb{E}[V(\{Y_t\}_{t \in I}; I)^2] < \infty.$$

Then, thanks to the Lyapunov inequality $\mathbb{E}[|Y_t|] \leq \mathbb{E}[|Y_t|^2]^{1/2}$, we see that $\{M_t\}_{t \in I}$ satisfies (2.5). By assumption, (2.4) also holds, so that, from (2.3), we have

$$K_X = \sup_{t \in I} \mathbb{E}[|X_t|^2] < \infty.$$

Now, in order to apply **Theorem 5.1**, it remains to verify (5.1)-(5.2). We have

$$\begin{aligned} |f(s, X_\tau, Y_s) - f(\tau, X_\tau, Y_\tau)| &= \left| \int_\tau^s \partial_t f(\xi, X_\tau, Y_\xi) d\xi + \int_\tau^s \partial_y f(\xi, X_\tau, Y_\xi) dY_\xi \right| \\ &\leq C_1(s - \tau) + C_2(s - \tau)|X_\tau| + (C_3 + C_4|X_\tau|)V(\{Y_t\}_{t \in I}; \tau, s). \end{aligned}$$

Thus, (5.1) holds with

$$\bar{F}_t = (C_1 + C_2|X_{\tau^N(t)}|)t + (C_3 + C_4|X_{\tau^N(t)}|)V(\{Y_t\}_{t \in I}; 0, t).$$

It is clear that, not only the expectation, but all the sample paths of $\{F_t\}_{t \in I}$ are monotonic non-decreasing in $t \in I$, with $\bar{F}_0 = 0$. Moreover, thanks to (5.7), and using the Cauchy-Schwarz inequality in the last term, we have

$$\mathbb{E}[\bar{F}_T] \leq (C_1 + C_2K_1)T + (C_3 + C_4K_1)\mathbb{E}[V(\{Y_t\}_{t \in I}; 0, T)^2] < \infty.$$

Thus, **Theorem 5.1** and we deduce the strong order 1 convergence of the Euler-Maruyama method. \square

Remark 5.1. The conditions (5.7) and (5.8) on the finite mean square of the total variation of the noise and of the initial condition can be relaxed provided we have a better control on the growth of the $\partial_y f(t, x, y)$ with respect to x . More precisely, if

$$|\partial_y f(t, x, y)| \leq C_4 + C_5|x|^{p-1} + C_6|y|,$$

and

$$\mathbb{E}[V(\{Y_t\}_{t \in I}; T, 0)^p] < \infty,$$

along with

$$\mathbb{E}[|X_0|^p] < \infty,$$

with $1 \leq p < \infty$, then the process $\{\bar{F}_t\}_{t \in I}$ becomes

$$\bar{F}_t = (C_1 + C_2|X_{\tau^N(t)}|)t + (C_3 + C_4|X_{\tau^N(t)}|^{p-1})V(\{Y_t\}_{t \in I}; 0, t).$$

Applying the Hölder inequality yields

$$\bar{F}_t \leq (C_1 + C_2|X_{\tau^N(t)}|)t + C_3V(\{Y_t\}_{t \in I}; 0, t) + C_4\frac{p-1}{p}|X_{\tau^N(t)}|^p + \frac{C_4}{p}V(\{Y_t\}_{t \in I}; 0, t)^p.$$

With that, the required conditions on $\{\bar{F}_t\}_{t \in I}$ are met and we are allowed to apply [Theorem 5.1](#) and deduce the strong order 1 convergence of the Euler-Maruyama method.

Remark 5.2. One particular example that fits the conditions of [Theorem 5.2](#) is when $f = f(t, x, y)$ is semi-separable, i.e.

$$f(t, x, y) = a(t, y)h(x) + b(t, y), \quad (5.10)$$

where $a = a(t, y)$ and $b = b(t, y)$ are continuously differentiable on $I \times \mathbb{R}$ with uniformly bounded first derivatives, $a = a(t, y)$ itself is uniformly bounded, and $h = h(x)$ is globally Lipschitz continuous on \mathbb{R} .

Since $a = a(t, x)$ is uniformly bounded and $h = h(x)$ is globally Lipschitz continuous, it follows that $f = f(t, x, y)$ is uniformly globally Lipschitz continuous in x . Moreover, it is continuously differentiable in (t, y) , with partial derivatives $\partial_t f$ and $\partial_y f$ given by

$$\partial_t f = \partial_t a(t, y)h(x) + \partial_t b(t, y), \quad \partial_y f = \partial_y a(t, y)h(x) + \partial_t b(t, y)$$

Since the partial derivatives of $a = a(t, y)$ and $b = b(t, y)$ are uniformly bounded and h is Lipschitz, it follows that the partial derivatives $\partial_t f$ and $\partial_y f$ have at most linear growth. Thus, [\(5.6\)](#) is satisfied.

6. THE CASE OF AN ITÔ NOISE

In [Lemma 5.1](#), we assumed a control of the steps of $s \mapsto f(s, X_{\tau^N(s), Y_s})$ by the steps of a process $\{\bar{F}_s^N\}_s$ with non-decreasing expectation. A particular case, presented in [Theorem 5.2](#), is when the steps are controlled by the steps of a process with bounded variation. In this case, we find that

$$|f(s, X_{\tau^N(s), Y_s}) - f(\tau, X_{\tau^N(\tau), Y_\tau})| \leq \int_\tau^s d\bar{F}_\xi^N.$$

An alternative condition considered in this section is to assume that $s \mapsto f(s, X_{\tau^N(s), Y_s})$ itself is an Itô process and, as such,

$$f(s, X_{\tau^N(s), Y_s}) - f(\tau, X_{\tau^N(\tau), Y_\tau}) = \int_\tau^s A_\xi d\xi + \int_\tau^s B_\xi dW_\xi,$$

for suitable $\{A_t\}_{t \in I}$ and $\{B_t\}_{t \in I}$.

In practice, we may assume $f = f(t, x, y)$ is twice continuously differentiable in (t, y) and the noise $\{Y_t\}_{t \in I}$ itself is an Itô noise, so that, by the Itô formula, the steps above are themselves Itô noises.

With that in mind, we first have the following result.

Lemma 6.1. *Besides [Hypothesis 2.1](#), suppose that $F_t^N = f(t, X_{\tau^N(t)}, Y_t)$ is an Itô noise, satisfying*

$$dF_t^N = A_t dt + B_t dW_t, \quad (6.1)$$

for a Wiener process $\{W_t\}_{t \in 0}$ and stochastic processes $\{A_t\}_{t \in I}$, $\{B_t\}_{t \in I}$ adapted to $\{W_t\}_{t \geq 0}$ and such that

$$\int_0^T \mathbb{E}[|A_t|] dt < \infty, \quad \int_0^T \mathbb{E}[|B_t|^2] dt < \infty. \quad (6.2)$$

Then,

$$\begin{aligned} \mathbb{E} \left[\left| \int_0^t \left(f(s, X_{\tau^N(s)}^N, Y_s) - f(\tau^N(s), X_{\tau^N(s)}, Y_{\tau^N(s)}) \right) ds \right| \right] \\ \leq \Delta t_N \left(\int_0^t \mathbb{E}[|A_\xi|] d\xi + \left(\int_0^t \mathbb{E}[|B_\xi|^2] d\xi \right)^{1/2} \right), \end{aligned} \quad (6.3)$$

for all $0 \leq t \leq T$ and every $N \in \mathbb{R}$.

Proof. We write

$$f(s, X_{\tau^N(s)}^N, Y_s) - f(\tau^N(s), X_{\tau^N(s)}, Y_{\tau^N(s)}) = \int_{\tau^N(s)}^s A_\xi d\xi + \int_{\tau^N(s)}^s B_\xi dW_\xi.$$

Upon integration,

$$\begin{aligned} \int_0^t \left(f(s, X_{\tau^N(s)}^N, Y_s) - f(\tau^N(s), X_{\tau^N(s)}, Y_{\tau^N(s)}) \right) ds \\ = \int_0^t \left(\int_{\tau^N(s)}^s A_\xi d\xi + \int_{\tau^N(s)}^s B_\xi dW_\xi \right) ds \end{aligned}$$

Using integration by parts,

$$\begin{aligned} \int_0^t \left(f(s, X_{\tau^N(s)}^N, Y_s) - f(\tau^N(s), X_{\tau^N(s)}, Y_{\tau^N(s)}) \right) ds \\ = \int_0^t \int_{\xi}^{\tau^N(\xi) + \Delta t_N} A_\xi ds d\xi + \int_0^t \int_{\xi}^{\tau^N(\xi) + \Delta t_N} B_\xi ds dW_\xi \\ = \int_0^t (\tau^N(\xi) + \Delta t_N - \xi) A_\xi d\xi + \int_0^t (\tau^N(\xi) + \Delta t_N - \xi) B_\xi dW_\xi. \end{aligned}$$

Taking the absolute mean and using the Itô isometry on the second term yields

$$\begin{aligned} & \mathbb{E} \left[\left| \int_0^t \left(f(s, X_{\tau^N(s)}^N, Y_s) - f(\tau^N(s), X_{\tau^N(s)}, Y_{\tau^N(s)}) \right) ds \right| \right] \\ & \leq \int_0^t |\tau^N(\xi) + \Delta t_N - \xi| \mathbb{E}[|A_\xi|] d\xi + \left(\int_0^t (\tau^N(\xi) + \Delta t_N - \xi)^2 \mathbb{E}[|B_\xi|^2] d\xi \right)^{1/2}. \end{aligned}$$

Since $|\tau^N(\xi) + \Delta t_N - \xi| \leq \Delta t_N$, we find

$$\begin{aligned} & \mathbb{E} \left[\left| \int_0^t \left(f(s, X_{\tau^N(s)}^N, Y_s) - f(\tau^N(s), X_{\tau^N(s)}, Y_{\tau^N(s)}) \right) ds \right| \right] \\ & \leq \Delta t_N \left(\int_0^t \mathbb{E}[|A_\xi|] d\xi + \left(\int_0^t \mathbb{E}[|B_\xi|^2] d\xi \right)^{1/2} \right), \end{aligned}$$

which completes the proof. \square

Theorem 6.1. *Under [Hypothesis 2.1](#), suppose also that [\(2.4\)](#), [\(2.5\)](#), [\(4.3\)](#), [\(6.1\)](#), and [\(6.2\)](#) hold. Then, the Euler-Maruyama scheme [\(1.2\)](#)-[\(1.3\)](#) is of strong order 1, i.e.*

$$\max_{j=0,\dots,N} \mathbb{E} \left[|X_{t_j} - X_{t_j}^N| \right] \leq C \Delta t_N, \quad \forall N \in \mathbb{N}, \quad (6.4)$$

for a constant C given by

$$\begin{aligned} C = & \left(C_0 + L_X \left(\mathbb{E}[|X_0|] + \int_0^T \mathbb{E}[M_\xi] d\xi \right) e^{L_X T} \right. \\ & \left. + \left(\int_0^T \mathbb{E}[|A_\xi|] d\xi + \left(\int_0^T \mathbb{E}[|B_\xi|^2] d\xi \right)^{1/2} \right) e^{L_X T} \right) \quad (6.5) \end{aligned}$$

Proof. Under [Hypothesis 2.1](#), the [Lemma 4.1](#) applies and the global error estimate [\(4.1\)](#) holds.

Thanks to [\(2.4\)](#), [\(2.5\)](#), and [\(4.3\)](#), the [Proposition 4.1](#) applies and the global error is bounded according to [\(4.4\)](#).

With assumptions [\(6.1\)](#) and [\(6.2\)](#), [Lemma 6.1](#) applies and the last term in [\(4.4\)](#) is bounded according to [\(6.3\)](#). Using [\(6.3\)](#) in [\(4.4\)](#) yields

$$\begin{aligned} \mathbb{E} \left[|X_{t_j} - X_{t_j}^N| \right] & \leq \left(C_0 \Delta t_N + \Delta t_N L_X \left(\mathbb{E}[|X_0|] + \int_0^{t_j} \mathbb{E}[M_\xi] d\xi \right) e^{L_X t_j} \right. \\ & \quad \left. + \Delta t_N \left(\int_0^{t_j} \mathbb{E}[|A_\xi|] d\xi + \left(\int_0^{t_j} \mathbb{E}[|B_\xi|^2] d\xi \right)^{1/2} \right) e^{L_X t_j} \right). \end{aligned}$$

Since this holds for every $j = 0, \dots, N$, we obtain the desired [\(6.4\)](#). \square

Theorem 6.2. *Let $f = f(t, x, y)$ be twice continuously differentiable with uniformly bounded derivatives. Suppose that the noise $\{Y_t\}_{t \in I}$ is an Itô noise,*

$$dY_t = a(t, Y_t) dt + b(t, Y_t) dW_t, \quad (6.6)$$

with $a = a(t, y)$ and $b = b(t, y)$ continuous and satisfying

$$|a(t, y)| \leq A_M + A_Y|y|, \quad |b(t, y)| \leq B_M + B_Y|y|. \quad (6.7)$$

Assume the bounds (2.4), (4.3), and

$$\mathbb{E}[|Y_0|] < \infty \quad (6.8)$$

Then, the Euler-Maruyama scheme is of strong order 1, i.e.

$$\max_{j=0, \dots, N} \mathbb{E} \left[\left| X_{t_j} - X_{t_j}^N \right| \right] \leq C \Delta t_N, \quad \forall N \in \mathbb{N}, \quad (6.9)$$

for a suitable constant $C \geq 0$.

Proof. Let us start by showing that **Hypothesis 2.1** is valid. Since $f = f(t, x, y)$ is (twice) continuously differentiable with, in particular, bounded derivative in x , then it is uniformly globally Lipschitz in x . Since $a = a(t, y)$ and $b = b(t, y)$ are continuous, the noise has continuous sample paths. Thus, the remaining condition in **Hypothesis 2.1** to be verified is (iic).

From (6.6) and (6.7), we have

$$Y_t = \int_0^t a(s, Y_s) ds + \int_0^t b(s, Y_s) dW_s.$$

Using the Itô formula, we have

$$dY_t^2 = (2a(t, Y_t)Y_t + b(t, Y_t)^2) dt + 2b(t, Y_t)Y_t dW_t.$$

Thus

$$Y_t^2 = Y_0^2 + \int_0^t (2a(s, Y_s)Y_s + b(s, Y_s)^2) ds + \int_0^t 2b(s, Y_s)Y_s dW_s.$$

Taking the expectation,

$$\mathbb{E}[|Y_t|^2] = \mathbb{E}[|Y_0|^2] + \int_0^t (2\mathbb{E}[a(s, Y_s)Y_s] + \mathbb{E}[b(s, Y_s)^2]) ds.$$

Using (6.7), this yields

$$\begin{aligned} \mathbb{E}[|Y_t|^2] &\leq \mathbb{E}[|Y_0|^2] + \int_0^t (2\mathbb{E}[(A_M + A_Y|Y_s|)|Y_s|] + \mathbb{E}[(B_M + B_Y|Y_s|)^2]) ds \\ &\leq \mathbb{E}[|Y_0|^2] + \int_0^t (4(A_M^2 + (1 + A_Y)\mathbb{E}[|Y_s|^2]) + 2(B_M^2 + B_Y^2\mathbb{E}[|Y_s|^2])) ds \end{aligned}$$

By the Gronwall Lemma,

$$\mathbb{E}[|Y_t|^2] \leq (\mathbb{E}[|Y_0|^2] + (4A_M^2 + 2B_M^2)t) e^{(4(1+A_Y)+2B_Y^2)t}.$$

Thus,

$$\sup_{t \in I} \mathbb{E}[|Y_t|^2] \leq (\mathbb{E}[|Y_0|^2] + (4A_M^2 + 2B_M^2)T) e^{(4(1+A_Y)+2B_Y^2)T}. \quad (6.10)$$

Since $f = f(t, x, y)$ is Lipschitz in x and twice continuously differentiable in (t, y) with uniformly bounded first order derivatives, we have the bound

$$|f(t, x, y)| \leq |f(0, 0, 0)| + L_X|x| + L_T|t| + L_Y|y|.$$

Thus,

$$|f(t, x, Y_t)| \leq M_t + L_X|x|$$

with

$$M_t = |f(0, 0, 0)| + L_T|t| + L_Y|y|.$$

Thanks to (6.10), we see that

$$\int_0^T M_t \, dt < \infty.$$

Therefore, we are under the condition of (2.1).

Now, in view of Theorem 6.1, it remains to prove that $F_t^N = f(t, X_{\tau^N(t)}, Y_t)$ is an Itô noise (6.1), with the bounds (6.2). The fact that it is an Itô noise follows from the Itô formula and the fact the smoothness of $f = f(t, x, y)$. Indeed, since $(t, y) \mapsto f(t, x, y)$ is twice continuously differentiable, for each fixed x , the Itô formula is applicable and yields

$$\begin{aligned} df(t, x, Y_t) = & \left(\partial_t f(t, x, Y_t) + a(t, Y_t) \partial_y f(t, x, Y_t) + \frac{b(t, Y_t)^2}{2} \partial_{yy} f(t, x, Y_t) \right) dt \\ & + b(t, Y_t) \partial_y f(t, x, Y_t) dW_t, \end{aligned} \quad (6.11)$$

for every fixed $x \in \mathbb{R}$. This means (6.1) holds with

$$A_t = \partial_t f(t, x, Y_t) + a(t, Y_t) \partial_y f(t, x, Y_t) + \frac{b(t, Y_t)^2}{2} \partial_{yy} f(t, x, Y_t)$$

and

$$B_t = b(t, Y_t) \partial_y f(t, x, Y_t).$$

It remains to show that $\{A_t\}_{t \in I}$ is mean integrable and that $\{B_t\}_{t \in I}$ is square mean integrable. Since $f = f(t, x, y)$ has uniformly bounded derivatives, we have

$$|A_t| \leq L_T + L_Y(A_M + A_Y|Y_t|) + 2L_{YY}(B_M^2 + B_Y^2|Y_t|^2),$$

and

$$|B_t| \leq L_Y(B_M + B_Y|Y_t|),$$

for a suitable constants $L_{YY} \geq 0$. Now, thanks to (6.10), we see that (6.2) is satisfied.

Therefore, all the conditions of Theorem 6.1 are met and we deduce the strong order 1 convergence of the Euler-Maruyama method. \square

7. APPLICATIONS

In this section, we describe a few explicit examples that fall into one of the cases considered above and, hence, the Euler-Maruyama method exhibits a strong order one convergence.

7.1. Earthquake and other impulse driven models. See Neckel and Rupp pg 582 as a starting point of a model driven by a transport process as the source of ground motion excitation (both Kanai-Tajima and Bogdanoff, check out also the Clough-Penzien).

7.2. RODE with Itô noise. Here, we consider a class of RODEs treated in [1, Chapter 3], namely the (1.1) with a noise $\{Y_t\}_{t \in I}$ satisfying

$$dY_t = a(Y_t) dt + b(Y_t) dW_t \quad (7.1)$$

with the assumptions that

$$\text{the functions } a = a(y), b = b(y), \text{ and } f = f(t, x, y) \text{ are twice continuously differentiable with all partial derivatives uniformly bounded.} \quad (7.2)$$

In the case that the diffusion term $b = b(y)$ is actually independent of y , then the noise is an additive noise and the Euler-Maruyama scheme is of strong order 1, otherwise, it is thought to be of order 1/2 (CITATION...). Here, however, we deduce that, even if $b = b(y)$ depends on y , the strong convergence of the Euler-Maruyama scheme is of order 1, under the assumptions (7.2).

7.3. Population dynamics.

$$\frac{dX_t}{dt} = \mu X_t(r - X_t) \cos(Y_t), \quad (7.3)$$

where $\mu, r > 0$ are constant and $\{Y_t\}_{t \geq 0}$ is an Itô noise process satisfying (6.6), which includes a Wiener process, an Orstein-Uhlenbeck process or a geometric Brownian motion process.

Define

$$f(t, x, y) = x(r - x) \cos(y).$$

We have

$$f(t, x, y)x = x^2(r - x) \cos(y)$$

and notice that $f(t, x, y)x \geq 0$, for $x \geq 0$ and $y \geq 0$, and $f(t, x, y)x \leq 0$, for $x \geq r$ and $y \geq 0$. Hence the interval $[0, R]$ in x is positively invariant and the pathwise solutions of (7.4) are almost surely bounded as well, with

$$0 \leq X_t \leq R,$$

for all $t \geq 0$.

7.4. Population dynamics. Our first example is a population dynamics model modified from [4, Section 15.2],

$$\frac{dX_t}{dt} = Z_t X_t (r - X_t) \quad (7.4)$$

where $r > 0$ is constant and $\{Z_t\}_{t \geq 0}$ is a stochastic process playing the role of a random growth parameter and given by

$$Z_t = \lambda(1 + \varepsilon \sin(Y_t)),$$

where $0 < \varepsilon < 1$ and $\{Y_t\}_{t \geq 0}$ is an Itô noise process satisfying (6.6). We assume Y_t has an analytic formula so we do not need to approximate the coupled stochastic differential equation system for (X_t, Y_t) . This setting includes a Wiener process, an Ornstein-Uhlenbeck process and a geometric Brownian motion process.

We suppose the initial condition is non-negative and bounded almost surely:

$$0 \leq X_0 \leq R,$$

for some $R > r$.

The noise process $\{Z_t\}_{t \geq 0}$ itself satisfies

$$0 < \lambda - \varepsilon \leq Z_t \leq \lambda + \varepsilon < 2\lambda, \quad \forall t \geq 0.$$

Define

$$f(t, x, z) = zx(r - x)$$

and notice that $f(t, x, z)x \geq 0$, for $x \geq 0$ and $z \geq 0$, and $f(t, x, z)x \leq 0$, for $x \geq r$ and $z \geq 0$. Hence the interval $[0, R]$ in x is positively invariant and the pathwise solutions of (7.4) are almost surely bounded as well, with

$$0 \leq X_t \leq R,$$

for all $t \geq 0$.

The function $f = f(t, x, z)$ is continuously differentiable infinitely many times and with

$$\left| \frac{\partial f}{\partial x}(t, x, y) \right| = |y(r - 2x)| \leq 2\lambda(2R - r),$$

for $|x| \leq R$ and $0 \leq z \leq 2\lambda$. In turn, the function $z = z(y) = \lambda(1 + \varepsilon \sin(y))$ is also continuously differentiable infinitely many times and is uniformly bounded along with all its derivatives.

The right hand side of (7.4) is not globally Lipschitz, but, for the sake of analysis, since X_t and Y_t are bounded, the right hand side can be modified to a twice continuously differentiable, uniformly globally Lipschitz function $\tilde{f}(t, x, y)$ that coincides with $f(t, x, y)$ for $(t, x, y) \in \mathbb{R} \times [0, R] \times [0, 2\lambda]$ and satisfies (2.1) with

$$L_X = 2\lambda(2R - r).$$

Thus, the RODE (7.4) with $0 \leq X_0 \leq R$ almost surely, for some $R > r$, is equivalent to the RODE

$$\frac{dX_t}{dt} = \tilde{f}(t, X_t, Y_t). \quad (7.5)$$

With $\tilde{f} = \tilde{f}(t, x, y)$, the Hypothesis 2.2 hold. Moreover, it follows from (2.3) (notice $M_t = 0$ here) that

$$|X_t| \leq |X_0|e^{2\lambda(2R-r)t} \leq Re^{2\lambda(2R-r)T}, \quad 0 \leq t \leq T.$$

almost surely.

OLD Condition on $\{F_t\}$ SHOULD BE FIXED is satisfied with

$$F_t \text{?!?!?!}$$

CAREFULL, WE CHANGED THE NOTATION, MUST FIX FROM HERE ON AND CHECK EVERYTHING.

The Itô formula applied to $Y_t = g(O_t)$, where $g(\eta) = \lambda(1 + \varepsilon \sin(\eta))$ implies $\{Y_t\}_{t \geq 0}$ is an Itô process with

$$dY_t = \left((\theta_1 - \theta_2 O_t)g'(O_t) + \frac{\theta_3^2}{2}g''(O_t) \right) dt + \theta_3 g'(O_t) dW_t.$$

We have

$$g'(\eta) = \lambda \varepsilon \cos(\eta), \quad g''(\eta) = -\lambda \varepsilon \sin(\eta)$$

hence both are uniformly bounded. Therefore, all the conditions of Theorem 6.2 hold and the Euler-Maruyama method is of strong order 1.

7.5. **Drug delivery.**

7.6. **Earthquake model.**

7.7. **Point-process noise.**

APPENDIX A. DISCRETE GROWNWALL LEMMA

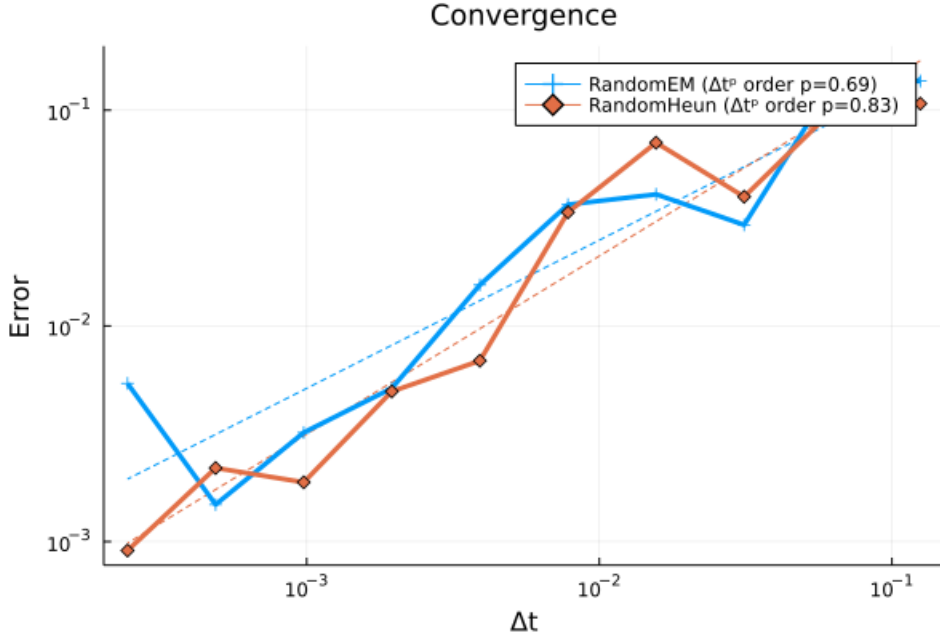
We end this section by abstracting away the Gronwall type inequality we use (this is probably written somewhere, and I need to find the source):

Lemma A.1. *Let $(e_j)_j$ be a (finite or infinite) sequence of positive numbers satisfying*

$$e_j \leq a \sum_{i=0}^{j-1} e_i + b, \quad (A.1)$$

with $e_0 = 0$, where $a, b > 0$. Then,

$$e_j \leq be^{aj}, \quad \forall j. \quad (A.2)$$



Proof. The result is trivially true for $j = 0$. Suppose, by induction, that the result is true up to $j - 1$. Then,

$$e_j \leq a \sum_{i=0}^{j-1} b e^{a i} + b = b \left(a \sum_{i=0}^{j-1} e^{a i} + 1 \right).$$

Using that $1 + a \leq e^a$, we have $a \leq e^a - 1$, hence

$$e_j \leq b \left((e^a - 1) \sum_{i=0}^{j-1} e^{i a} + 1 \right).$$

Using that $\sum_{i=0}^{j-1} \theta^i = (\theta^j - 1)(\theta - 1)$, with $\theta = e^a$, we see that

$$(e^a - 1) \sum_{i=0}^{j-1} e^{i a} \leq e^{j a} - 1,$$

so that

$$e_j \leq b e^{j a},$$

which completes the induction. \square

APPENDIX B. NUMERICAL EXAMPLES

B.1. Lower-order converge. For a lower order convergence, below order 1, we take the noise $\{Y_t\}_t$ to be the transport process defined by

$$Y_t = \sin(t/Z)^{1/3},$$

where Z is a beta random variable $Z \sim B(\alpha, \beta)$. Notice Z takes values strictly within $(0, 1)$ and, hence, $\sin(t/Z)$ can have arbitrarily high frequencies and, hence, go through the critic value $y = 0$ extremely often.

(Need to remove the Heun method and do more tests).

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