

On a Monte-Carlo Semi-Lagrangian scheme: variance estimate and simulations

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CEMRACS 2013

The Monte-Carlo method

Problem: approximation of the solution of PDEs like

$$\frac{\partial u(t, x)}{\partial t} = \frac{1}{2} \Delta u(t, x) + c(x) \cdot \nabla u(t, x), \quad 0 < t \leq T, x \in \mathbb{R}^d,$$
$$u(0, x) = u_0(x), \text{ for any } x \in \mathbb{R}^d.$$

Probabilistic representation:

$$u(t, x) = \mathbb{E} u_0(X_t^x)$$
$$dX_t^x = c(X_t^x) dt + dB_t, \quad X_0^x = x.$$

Monte-Carlo method:

$$\mathbb{E} \left| \frac{1}{N} \sum_{m=1}^N u_0(X_t^{x, (m)}) - u(t, x) \right|^2 \leq \frac{C(t, x)}{N}.$$

Problems:

- ▶ Realizations of X_t^x ? Need of a numerical scheme.
- ▶ Computations at points in a grid: $u(n\delta t, j\delta x)$. Dependence of $C(t, x)$ with respect to δt and δx ?

Semi-lagrangian scheme

Recursive construction of u_j^n approximating $u(n\delta t, j\delta x)$.

1. Representation formula between $n\delta t$ and $(n+1)\delta t$:

$$u((n+1)\delta t, j\delta x) = \mathbb{E}u(n\delta t, X_{\delta t}^{j\delta x});$$

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$$\mathbb{E}u(n\delta t, j\delta x + \delta tc(j\delta x) + \sqrt{\delta t}\mathcal{N});$$

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3. Use of an interpolation operator \mathcal{J} :

$$v_j^{n+1} := \mathbb{E}(\mathcal{J}(u^n)(j\delta x + \delta tc(j\delta x) + \sqrt{\delta t}\mathcal{N}));$$

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4. Monte-Carlo approximation:

$$u_j^{n+1} := \frac{1}{N} \sum_{m=1}^N (\mathcal{J}(u^n)(j\delta x + \delta tc(j\delta x) + \sqrt{\delta t}\mathcal{N}^{n,m,j})).$$

Structure of the noise

Independence of the $\mathcal{N}^{n,m,j} \sim \mathcal{N}(0, I)$, with respect to:

- ▶ m : Monte-Carlo approximation.
Consequence: variance of size $\mathcal{C}(\delta t, \delta x)/N$;
- ▶ n : independent increments/Markov property;

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- ▶ n : independent increments/Markov property;
- ▶ j : spatial independence.

Consequences:

Improved estimate for the l^2 -norm:

$$\|u\|_{l^2}^2 := \delta x \sum_j u_j^2;$$

but irregular functions in the h^1 semi-norm:

$$|u|_{h^1}^2 := \delta x \sum_j \frac{(u_{j+1} - u_j)^2}{\delta x^2}.$$

Simplified setting for a convergence estimate

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In dimension $d = 1$.

No drift: $c(x) = 0$.

Boundary conditions: periodic.

Interpolation: linear.

Initial condition: u_0 is of class \mathcal{C}^2 .

First convergence result

Theorem

For any final time $T > 0$, there exists a constant $C > 0$, such that for any $\delta t > 0$, $\delta x > 0$ and $N \in \mathbb{N}^*$ we have

$$\sup_{j \in \mathbb{N}; 0 \leq j \delta x < 1} |u(n\delta t, x_j) - v_j^n| \leq C \frac{\delta x^2}{\delta t} \sup_{x \in [0,1]} |u_0''(x)|$$

and for any $n \in \mathbb{N}$ with $n\delta t \leq T$

$$\mathbb{E} \|u^n - v^n\|_{l^2}^2 = \delta x \sum_{j; 0 \leq j \delta x < 1} \mathbb{E} |u_j^n - v_j^n|^2$$

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and for any $n \in \mathbb{N}$ with $n\delta t \leq T$

$$\mathbb{E} \|u^n - v^n\|_{\ell^2}^2 \leq 2C |u^0|_{h^1}^2 \left(1 + \frac{\delta x^2}{\delta t}\right) \frac{\delta t}{N}$$

whenever N is sufficiently large:

$$\frac{C}{N} \mathcal{A}(\delta t, \delta x) \leq \frac{1}{2}.$$

with $\mathcal{A}(\delta t, \delta x) = 1 + \frac{\delta x}{\delta t} + \frac{\delta x^2}{\delta t^2} (1 + |\log(\delta t)|)$.

Second convergence result

Theorem

For any $p \in \mathbb{N}$ and any final time $T > 0$, there exists a constant $C_p > 0$, such that for any $\delta t > 0$, $\delta x > 0$ and $N \in \mathbb{N}^*$ we have

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Remark

Explicit method, with no CFL.

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$$\mathbb{E} \|u^n - v^n\|_{l^2}^2 \leq C_p |u^0|_{h^1}^2 \left(1 + \frac{\delta x^2}{\delta t}\right) \mathcal{A}(\delta t, \delta x)^p \left(\frac{\delta t}{N} + \frac{1}{N^{p+1}}\right)$$

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Interpretation: *anti-CFL condition* and *variance of size $\frac{\delta t}{N}$* .

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Numerical illustration

Periodic case:

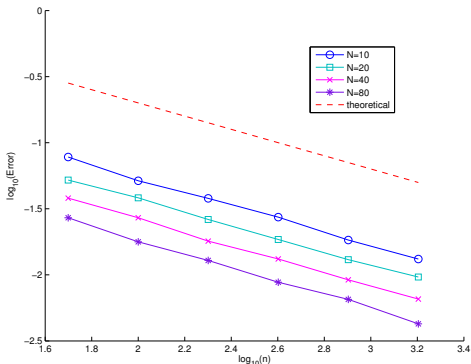


Figure: Error for periodic boundary conditions when $\delta t = \delta x = 1/n$, in logarithmic scales.

Dirichlet case:

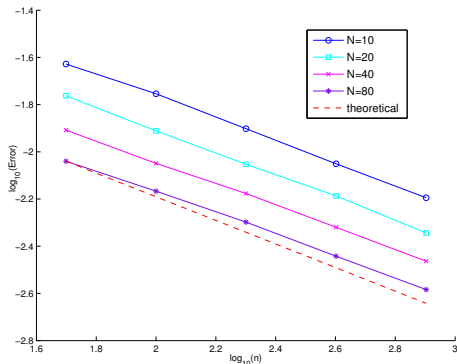


Figure: Error for Dirichlet boundary conditions when $\delta t = \delta x = 1/n$, in logarithmic scales.

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Possible extensions

In higher dimension $d \geq 2$: no change in principle for the implementation; but for the analysis?

Addition of a drift $c(x)$: discretization of a SDE via the Euler scheme.
Analysis: need to change the norm?

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Dirichlet (resp. Neumann) boundary conditions: killed (resp. reflected) diffusion processes.

Non-linear equations: more involved schemes.

Dirichlet boundary conditions

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Still in the simplified setting ($d = 1$, $c(x) = 0$).

Dirichlet boundary conditions

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Equation:

$$\begin{aligned}\partial_t u &= \frac{1}{2} \partial_{xx}^2 u; \\ u(t, b) &= u(t, a) = 0 \text{ for any } t \geq 0, \\ u(0, x) &= u_0(x) \text{ for any } x \in [a, b].\end{aligned}$$

The probabilistic representation formula:

$$u(t, x) = \mathbb{E}[u_0(X_t^x) \mathbf{1}_{t < \tau^x}],$$

with

$$\tau^x = \inf \{s > 0; x + B_s \notin (a, b)\}.$$

Algorithm for the Dirichlet boundary conditions

Difficulty: evaluation of (the law of) the exit time τ^x .

Solution (cf Gobet): Law $(B_{n\delta t+t})_{0 \leq t \leq \delta t}$ conditionally to $B_{n\delta t} = x$ and $B_{(n+1)\delta t} = y$ is the law of the process

$$(\tilde{B}_t^{x,y,\delta t} := \frac{t}{\delta t}y + \frac{\delta t - t}{\delta t}x + W_t - \frac{t}{\delta t}W_{\delta t})_{0 \leq t \leq \delta t},$$

a Brownian Bridge.

Application: a more performant test for the exit.

Requires a refined time-step (and a larger Monte-Carlo parameter).

Solution: decomposition of the domain into two zones.

An non-linear example: 2D-Burgers equations

$$\frac{\partial u}{\partial t} + (u \cdot \nabla)u = \nu \Delta u + f.$$

Domain $(-1, 1)^2$, with homogeneous Dirichlet B.C.

A semi-implicit scheme: for $n\delta t \leq t \leq (n+1)\delta t$ and $x \in D$

$$\frac{\partial v^{n+1}}{\partial t} + (u^n \cdot \nabla)v^{n+1} = \nu \Delta v^{n+1} + f^n,$$

with initial condition is $v^{n+1}(n\delta t, \cdot) = u^n = v^n(n\delta t, \cdot)$.

Approximation $u^n = v^n(n\delta t, \cdot)$.

Forcing: $f^n(t, x) = f(n\delta t, x, u^n(x))$.

On $[n\delta t, (n+1)\delta t]$:

$$v^{n+1}(t, x) = \mathbb{E}[v^{n+1}(n\delta t, X_t^x) \mathbb{1}_{t < \tau^x} + \int_{n\delta t}^{t \wedge \tau^x} f^n(X_s^x) ds],$$

with

$$dX_t^x = -u^n(X_t^x)dt + \sqrt{2\nu}dB_t, X_{n\delta t}^x = x.$$

and the associated stopping time τ^x .

Simulations: $u_0(x) = 0$,

$$f(t, x) = (-\sin(\pi t) \sin(\pi x) \sin(\pi y)^2, -\sin(\pi t) \sin(\pi x)^2 \sin(\pi y)),$$

$$\nu = 0.001.$$

$$\delta t = 0.02, \delta x = 0.04, N = 10.$$

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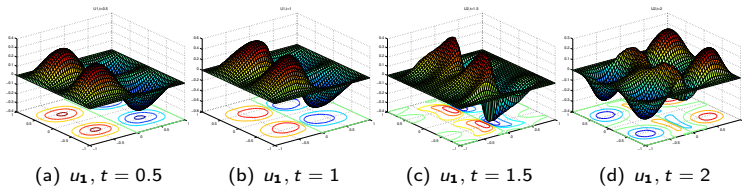
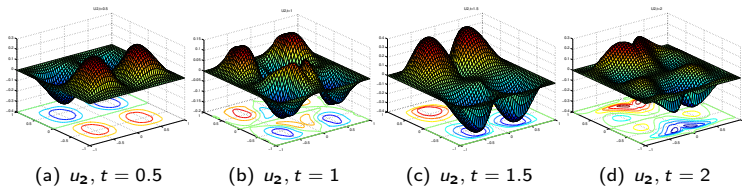


Figure: Solution of the 2D Burgers equation at different times



Idea of the proof (1)

$$P_{j,k}^{(n,m)} := \phi_k(j\delta x + \delta tc(j\delta x) + \sqrt{\delta t}\mathcal{N}^{n,m,j}),$$
$$Q_{j,k} = \mathbb{E}P_{j,k}^{(n,m)}.$$

Matrix formulation:

$$u^{n+1} = \left(\frac{1}{N} \sum_{m=1}^N P^{(n,m)} \right) u^n = P^{(n)} u^n,$$
$$v^{n+1} = Q v^n.$$

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Property

$P^{(n,m)}$ is a stochastic matrix, with *independent rows*.

Q is symmetric.

$\mathbb{E} \|P^{(n,m)} u\|_{l^2}^2 \leq \|u\|^2$. But $\mathbb{E} \|P^{(n,m)} u\|_{h^1}^2$?

Idea of the proof (2)

One-step variance:

$$\mathbb{E} \|(P^{(n)} - Q)u\|_{l^2}^2 \leq C \frac{\delta t + \delta x^2}{N} |u|_{h^1}^2.$$

Idea of the proof (2)

One-step variance:

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Decomposition of the error:

$$\mathbb{E}\|u^n - v^n\|_{l^2}^2 = \sum_{k=0}^{n-1} \mathbb{E}\|Q^{n-1-k}(P^{(k)} - Q)P^{(k-1)} \dots P^{(0)}u^0\|_{l^2}^2.$$

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Decomposition of the error:

$$\mathbb{E}\|u^n - v^n\|_{l^2}^2 = \sum_{k=0}^{n-1} \left(Q^{2(n-1-k)} \right)_{1,1} \mathbb{E}\|(P^{(k)} - Q)P^{(k-1)} \dots P^{(0)}u^0\|_{l^2}^2.$$

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One-step variance:

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$$\begin{aligned} \mathbb{E}\|u^n - v^n\|_{l^2}^2 &= \sum_{k=0}^{n-1} \left(Q^{2(n-1-k)}\right)_{1,1} \mathbb{E}\|(P^{(k)} - Q)Q^k u^0\|_{l^2}^2 \\ &+ \sum_{k=0}^{n-1} \left(Q^{2(n-1-k)}\right)_{1,1} \mathbb{E}\|(P^{(k)} - Q)(P^{(k-1)} \dots P^{(0)} - Q^k)u^0\|_{l^2}^2. \end{aligned}$$

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Blue part: improved bound.

Red part: recursion, with p .

Conclusion

- ▶ A numerical scheme combining Semi-Lagrangian and Monte-Carlo techniques.
- ▶ Simple and can be widely generalized (dimension, domains, boundary conditions).
- ▶ Example of applications: fluids, kinetic equations.

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- ▶ A numerical scheme combining Semi-Lagrangian and Monte-Carlo techniques.
- ▶ Simple and can be widely generalized (dimension, domains, boundary conditions).
- ▶ Example of applications: fluids, kinetic equations.
- ▶ The variance estimate: interesting but only for a simple case...
- ▶ A lot to be done!

An additional example

Incompressible Navier-Stokes equations:

$$\begin{aligned}\frac{\partial u}{\partial t} + (u \cdot \nabla)u - \nu \Delta u + \nabla p &= f \\ \operatorname{div}(u) &= 0, \\ u(0, \cdot) &= u_0, \\ &+ \text{boundary conditions.}\end{aligned}$$

Use of a projection method:

$$\frac{\partial v^{n+1}}{\partial t} + (u^n \cdot \nabla)v^{n+1} - \nu \Delta v^{n+1} = f(n\delta t, \cdot), \quad (1)$$

and $u^{n+1} = v^{n+1} - \nabla p^{n+1}$ with

$$\Delta p^{n+1} = \operatorname{div}(v^{n+1}). \quad (2)$$

Example: driven cavity, with different Reynolds numbers.

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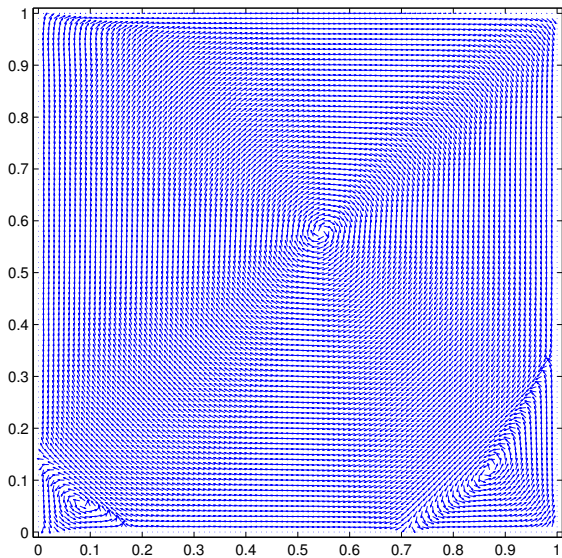


Figure: The driven cavity flow for $Re = 1000$.

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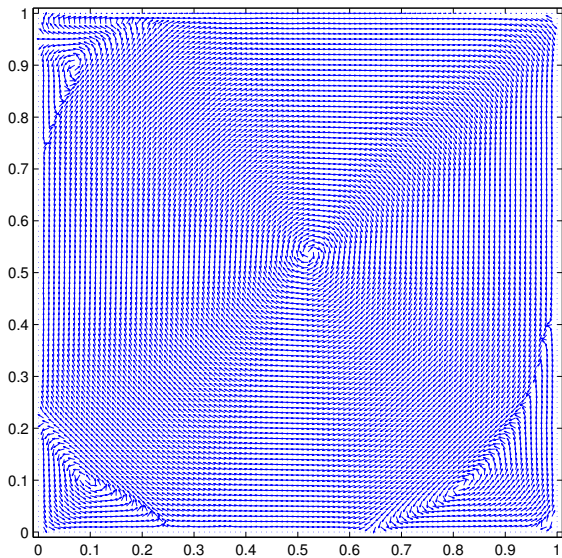


Figure: The driven cavity flow for $Re = 5000$.

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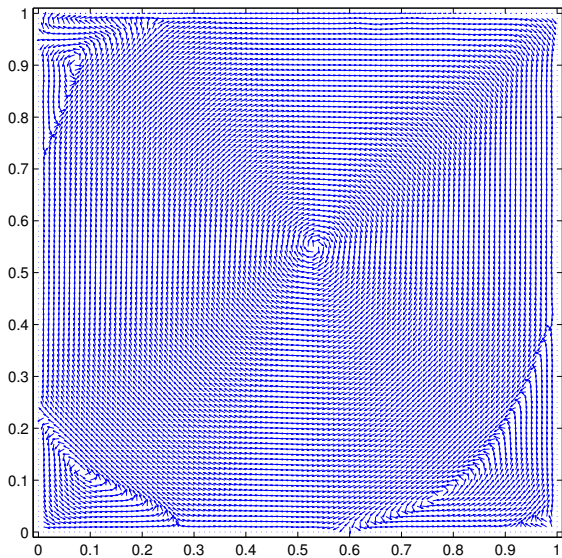


Figure: The driven cavity flow for $Re = 10000$.

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Thanks for your attention.