

# Stochastic travelling waves and computation

Gabriel Lord

Heriot Watt University, Maxwell Institute, Edinburgh

[g.j.lord@hw.ac.uk](mailto:g.j.lord@hw.ac.uk), <http://www.macs.hw.ac.uk/~gabriel>

Joint with : V.Thümmler, E. Tzitzili.

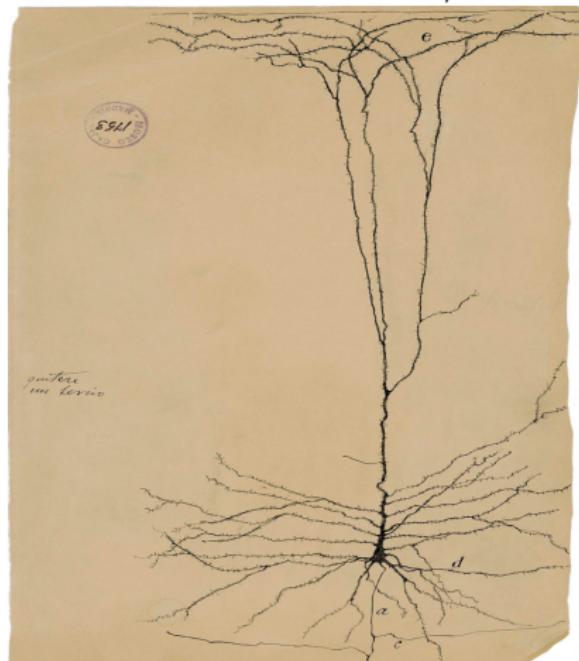
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Ramon y Cajal (1888)

## Nagumo equation

Reduced model for voltage wave propagation in neural axon

$$u_t = u_{xx} + u(1-u)(u-\alpha) \quad u(x, t) \in \mathbb{R}, \quad x \in \mathbb{R}, \quad t > 0$$

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... interested in travelling wave propagation

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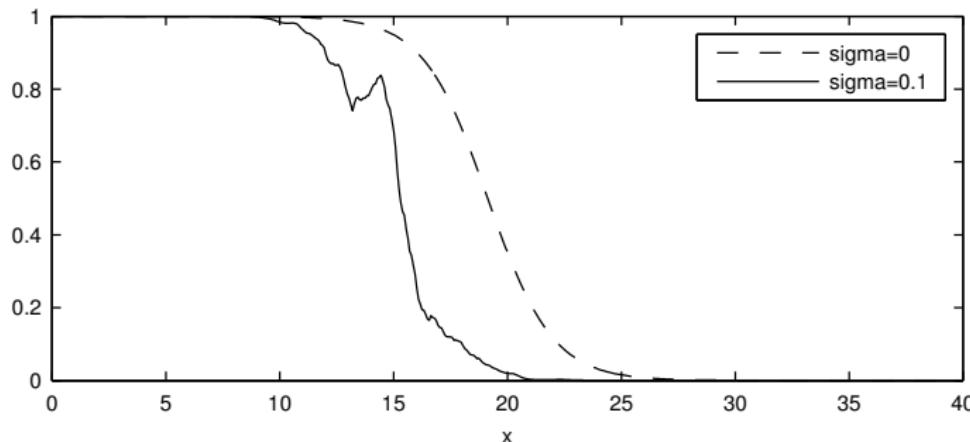
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## (Stochastic) FitzHugh–Nagumo equation

Deterministic voltage wave propagation in neural axon

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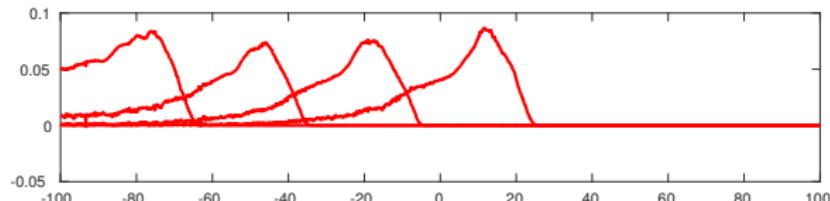
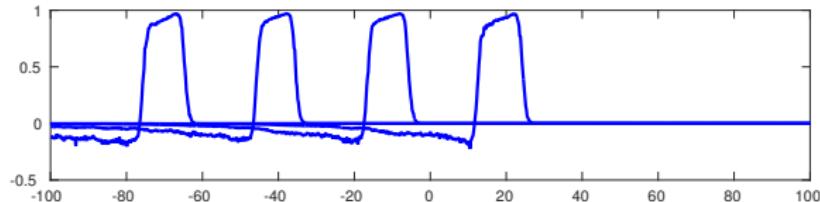
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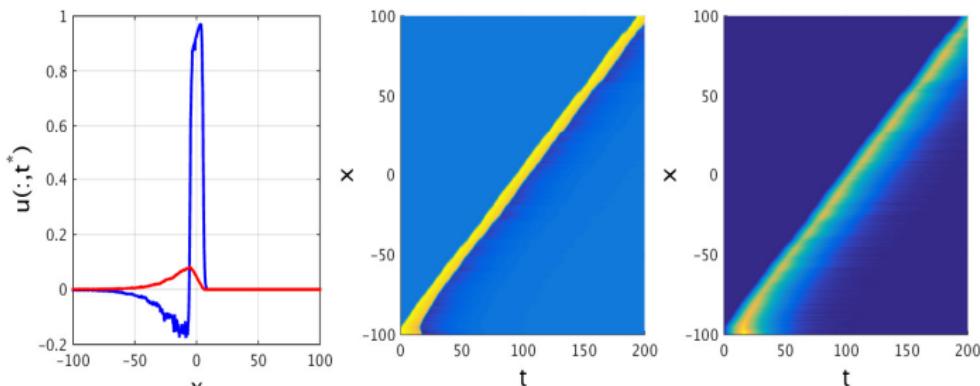
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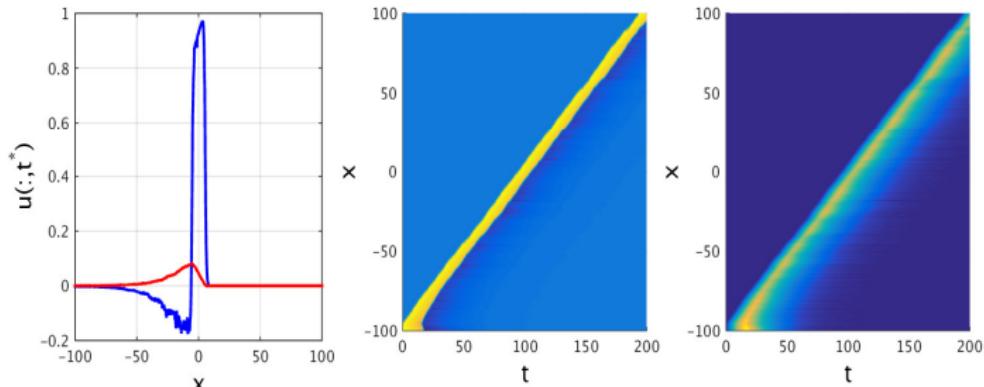
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► Numerical Scheme for Simulation of Stratonovich System...

## Stratonovich exponential integrator

Stratonovich SDE (1D)

$$du = [Au + f(u)]dt + g(u) \circ d\beta$$

has mild solution

$$u(t) = e^{tA}u(0) + \int_0^t e^{(t-s)A}f(u(s))ds + \int_0^t e^{(t-s)A}g(u(s)) \circ d\beta(s).$$

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Let's use mild solution for numerics,

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From deterministic integral

$$u(\Delta t) = e^{\Delta t A} u(0) + A^{-1}(e^{\Delta t A} - 1)f(u(0)) + \int_0^{\Delta t} e^{(\Delta t - s)A} g(u(s)) \circ d\beta(s).$$

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using Taylor's Theorem

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► Scheme ( $\Delta b^{n+1} = b(t_{n+1}) - b(t_n)$ )

$$u^{n+1} = e^{\Delta t A} u^n + \phi_1(A) f(u^n) + \frac{1}{2} e^{(\frac{\Delta t}{2}) A} (g(u^n) + g(u^{n+1})) \Delta b^{n+1}.$$

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Need to estimate  $u^{n+1}$  for  $g(u^{n+1})$ .

## Stratonovich exponential integrator

In practice predict  $g(u^{n+1})$  by an Euler–Maruyama type step

- Semi-implicit EM predictor

$$\tilde{u}^{n+1} = u^n + [Au^{n+1} + f(u^n)] \Delta t + g(u^n) \Delta b^{n+1}.$$

$$u^{n+1} = e^{\Delta t A} u^n + \phi_1(A) f(u^n) + \frac{1}{2} e^{(\frac{\Delta t}{2})A} (g(u^n) + g(\tilde{u}^{n+1})) \Delta b^{n+1}.$$

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- ▶ Exponential predictor

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Developed in one-dimension - similar for  $u \in \mathbb{R}^d$  - or  $u(x, t) \in H$ .

- ▶ Ito SPDE case:

Parabolic : [L.& Rougemont, Jentzen et al, L. & Tambue, Larsson et al.]

Wave equation : [Cohen & Quer-Sardanyons]

## Strong Convergence [L. & Efthalia Tzitzili]

$$du = [Au + f(u)] dt + G(u) \circ dW$$

### Assumptions

- ▶  $W(t) = [\beta_1(t), \dots, \beta_m(t)].$

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Then

$$(E [\|u(t_n) - u_n\|^2])^{1/2} \leq C \Delta t^{1/2}.$$

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- ▶ Milstein version :

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Finite Element approximation in space

$$du_h = [A_h u_h + f(u_h)] dt + G(u_h) \circ dW_h$$

Assumptions

- ▶  $W(x, t) = \sum_{n \in \mathbb{Z}} \sqrt{q_n} \phi_n(x) \beta_n(t)$ ,  $\beta_n$  iid Brownian motions.

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Let  $u_h^n \approx u(t_n)$  by Stochastic Exponential Integrator

Then, for  $\epsilon > 0$

$$(E [\|u(t_n) - u_h^n\|^2])^{1/2} \leq C \Delta t^{1/2-\epsilon}.$$

(Hiding space dependence)

## Elements of the Proofs

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- ▶ Consider continuous version of scheme
- ▶ Compare mild form of solutions.
- ▶ Add in interpolants and estimate each term...

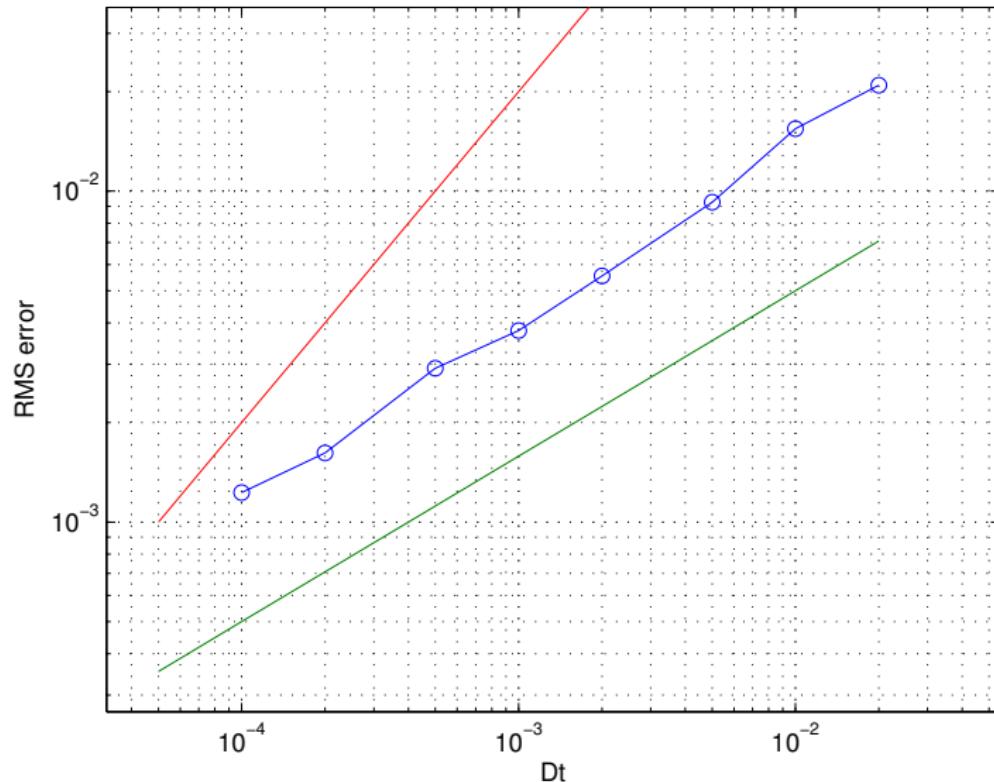
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- ▶ For diagonal noise

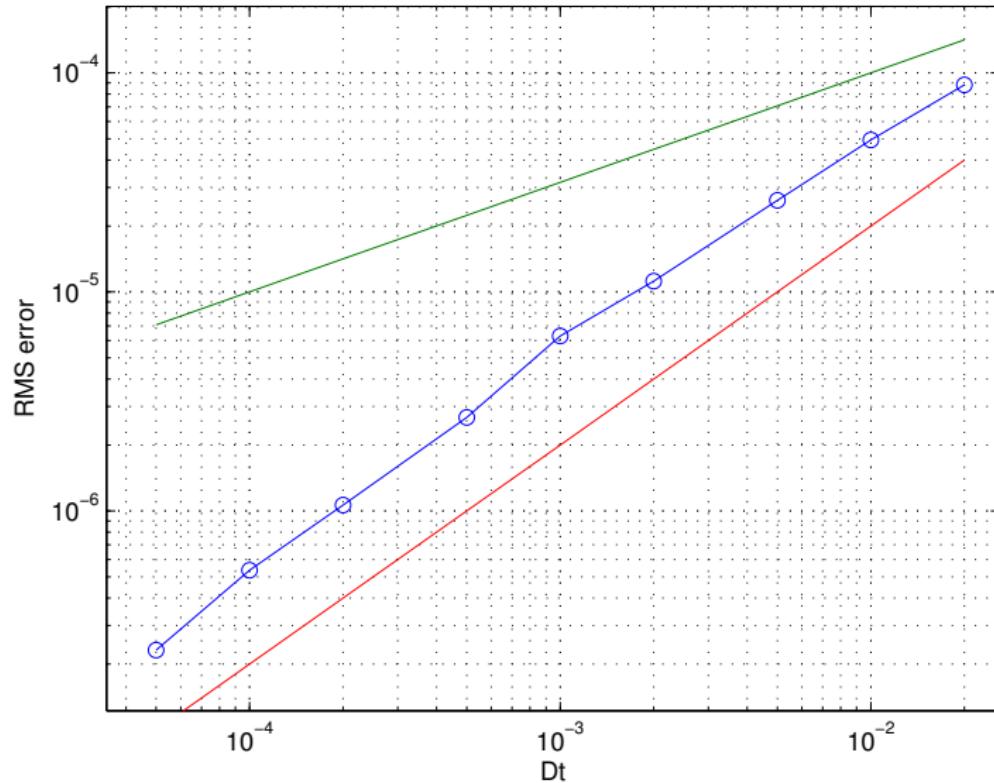
$$(E [\|u(t_n) - u_n\|^2])^{1/2} \leq C\Delta t^{1-\epsilon}.$$

Non-diagonal noise :  $(E [\|u(t_n) - u_n\|^2])^{1/2} \leq C\Delta t^{1/2-\epsilon}.$



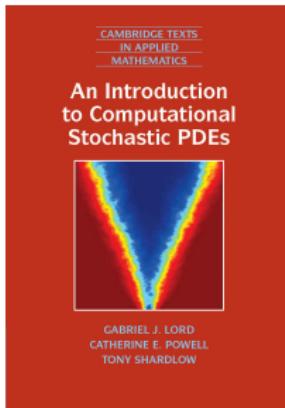
Reference lines have slope  $1/2$  (green) and  $1$  (red)

Diagonal noise:  $(E [\|u(t_n) - u_n\|^2])^{1/2} \leq C\Delta t^{1-\epsilon}.$



Reference line slope  $1/2$  (green) and  $1$  (red)

## Advert Break



► Stochastic Travelling Wave

## Deterministic travelling waves $u_t = u_{xx} + f(u)$

► TW with wave speed  $\lambda$

Into co-moving frame  $u(x, t) = u(x - \lambda t, t)$

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of which the travelling wave  $u$  is a stationary solution ( $u_t = 0$ ) .

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Co-moving frame : unknown position of wave  $\gamma(t) = \int_0^t \lambda(s)ds$ .

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- Add advection term to freeze wave

Have an extra variable  $\lambda(t)$ . To fix this we add a phase condition

Given a reference function  $\hat{u}$ ,

$$\min_y \|u(x - y, t) - \hat{u}(x, t)\|_2^2.$$

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$$u_t = u_{xx} + \lambda u_x + f(u), \quad x \in \mathbb{R}, \quad t \geq 0$$

of which the travelling wave  $u$  is a stationary solution ( $u_t = 0$ ) .

- What if we do not know wavespeed or if wavespeed a func. of  $t$ ?

Co-moving frame : unknown position of wave  $\gamma(t) = \int_0^t \lambda(s)ds$ .

$$u(x, t) = u(x - \gamma(t), t)$$

$$u_t = u_{\xi\xi} + \lambda(t)u_\xi + f(u)$$

- Add advection term to freeze wave

Have an extra variable  $\lambda(t)$ . To fix this we add a phase condition

Given a reference function  $\hat{u}$ ,

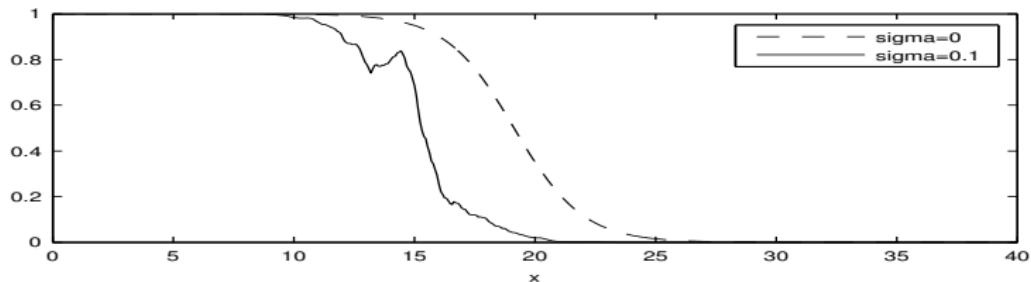
$$\min_y \|u(x - y, t) - \hat{u}(x, t)\|_2^2.$$

- Get a PDE with algebraic constraint : PDAE

$$u_t = [u_{xx} + \lambda(t)u_x + f(u)] \quad u(0) = u^0$$

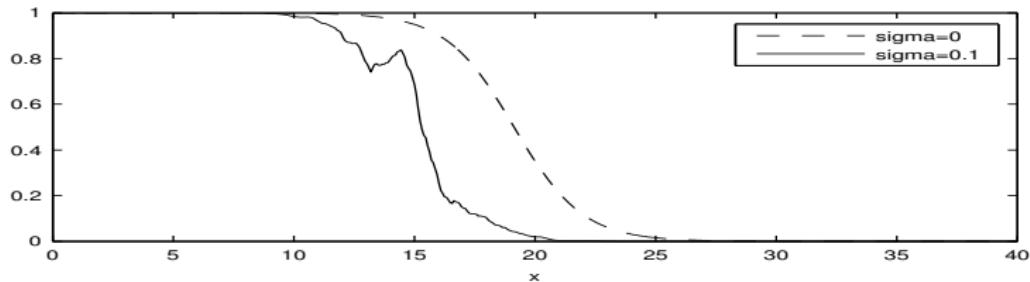
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## Stochastic Travelling wave



- ▶ Small noise, mean profiles eg Mikhailov, Schimansky–Geier & Ebeling '83 Reviews in Garcia-Ojalvo & Sancho or Panja.

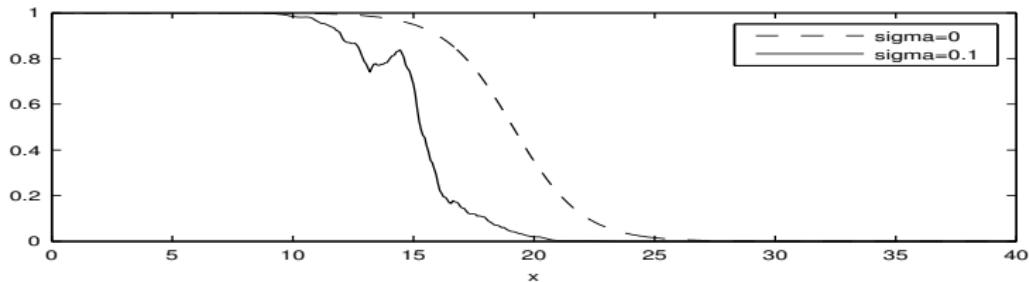
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- ▶ Evolution of a level set: eg sFKPP Tribe, Elworthy& Zhao, Mueller & Sowers & Doering  
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- ▶ Stannat : equation for motion of the wave front

## Freezing a Stochastic Travelling wave

$$du = \left[ u_{xx} + f(u) \right] dt + g(u) \circ dW(t)$$

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s.t.  $\|u - \hat{u}\|$  is minimized and  $v$  satisfies **SPDAE**

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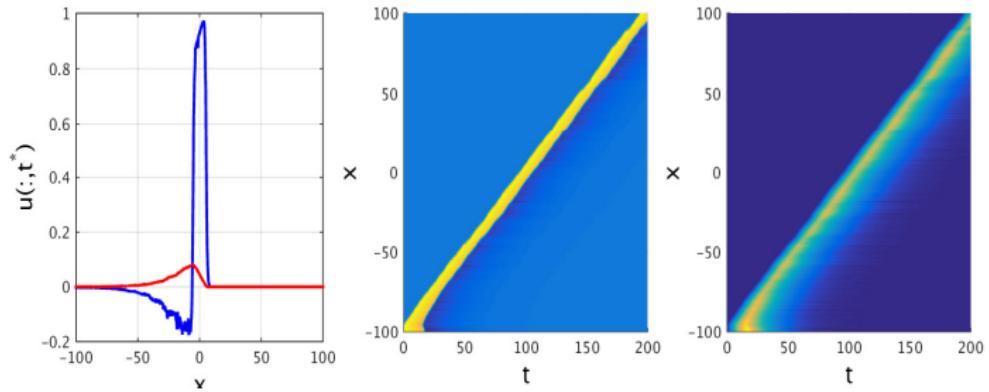
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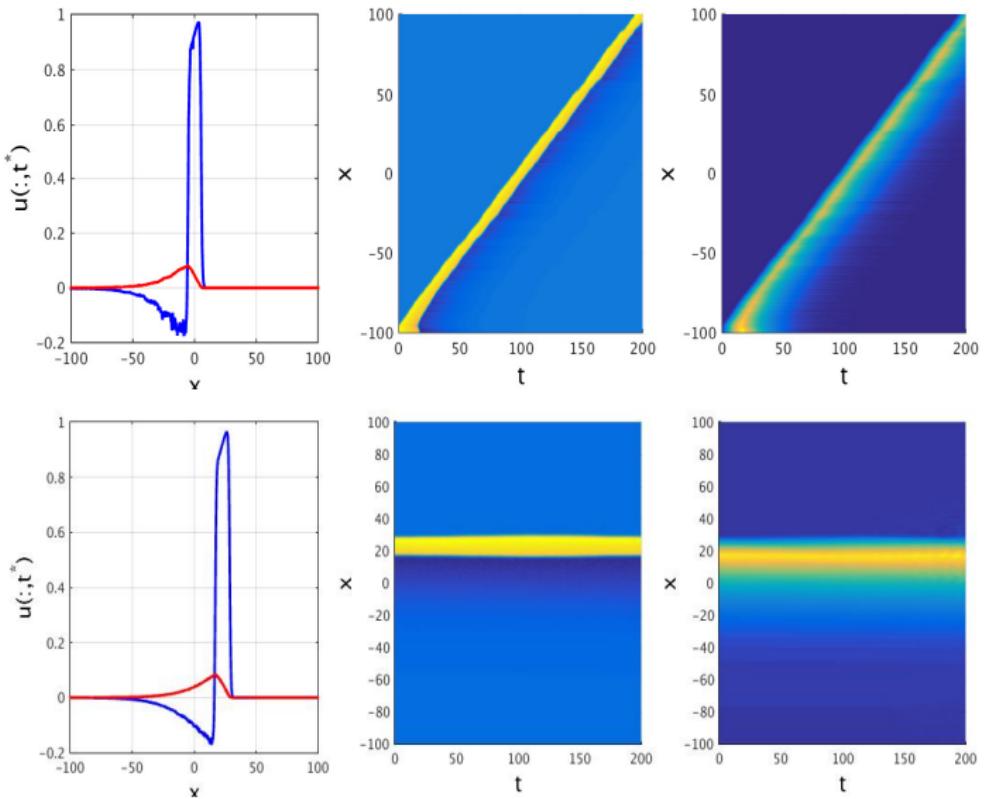
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►  $\lambda(t)$  “instantaneous” wave speed  
► **Wavespeed** :  $\Lambda(t) = \frac{1}{t} \int_0^t \lambda(s) ds$

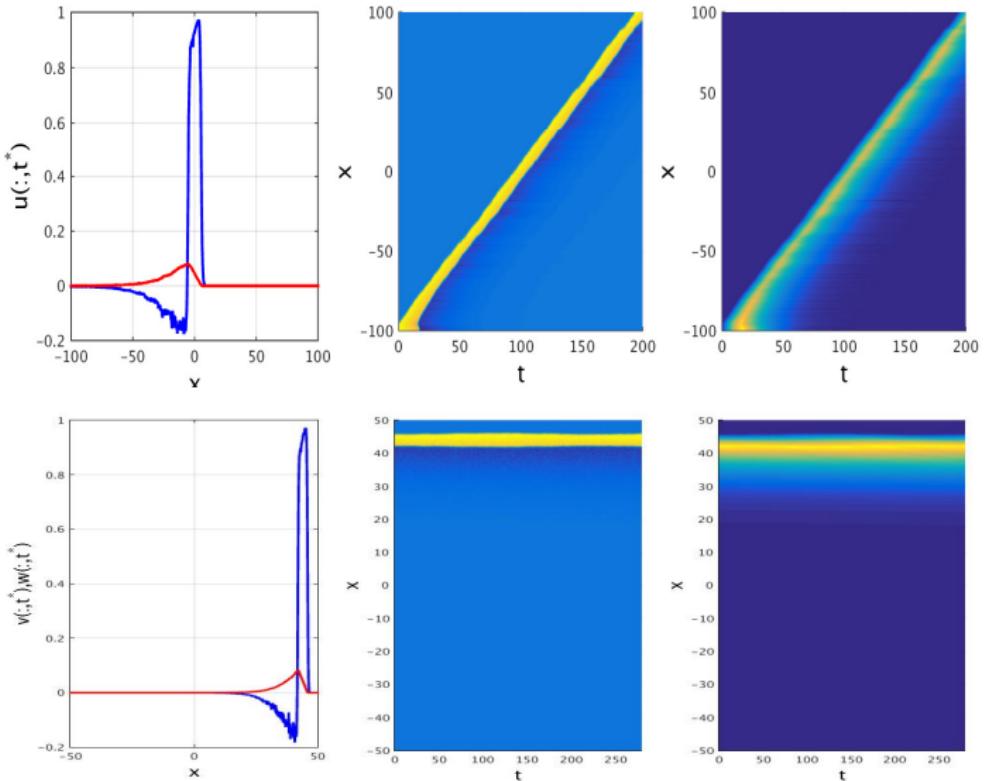
# Single realisation: SPDE /SPDAE



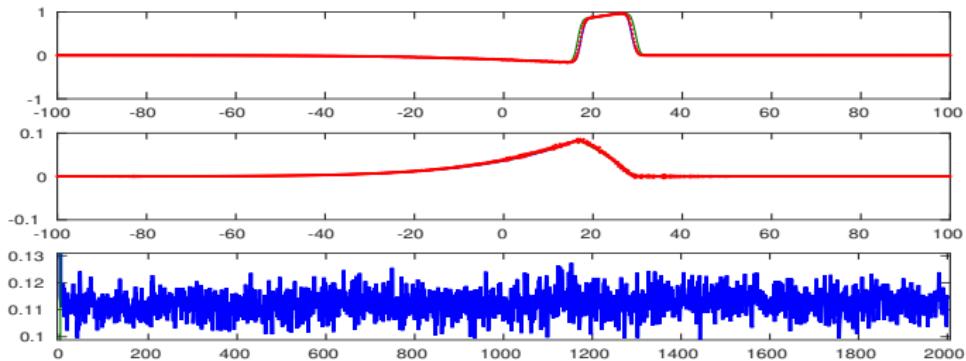
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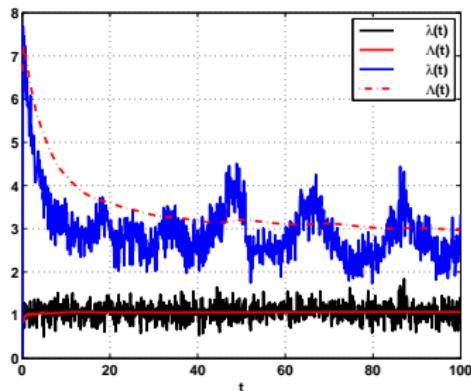
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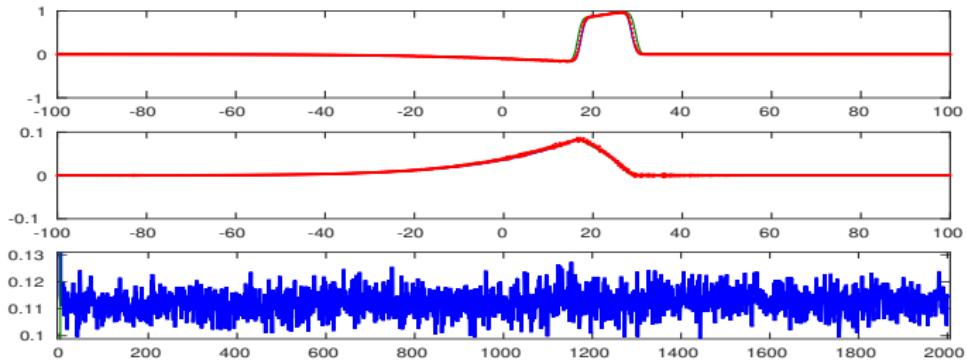
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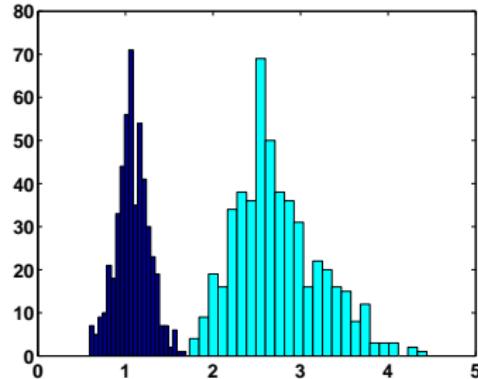
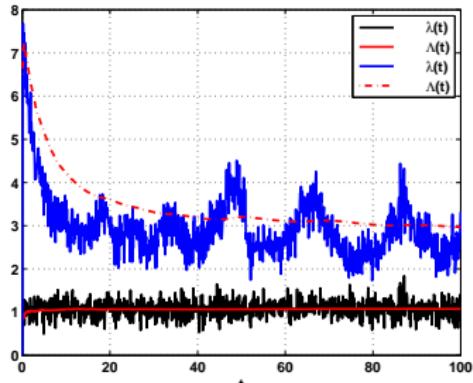
Wave speeds vs time



# Single realisation: SPDE /SPDAE



Wave speeds vs time



Distributions instantaneous wave speeds  $\lambda$

## Expected values

Compare :

- ▶ SPDAE :  $\Lambda^{\text{fix}}$
- ▶ SPDE : Reference  $\Lambda_{\text{fit}}$
- ▶ SPDE : Level set  $\Lambda_c$

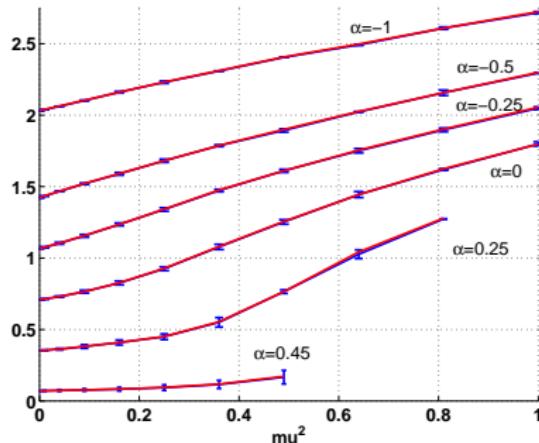
	$\Lambda$ or $\Lambda^{\text{fix}}$	$\Lambda_c$
SPDE	$1.08588 \pm 0.19680$	$1.08381 \pm 2.81\text{e-}03$
SPDAE	$1.08951 \pm 0.19512$	$-4.0\text{e-}05 \pm 2.0\text{e-}5$

Based on 100 realizations

# Correlation length $\xi = 0.1$

Different nonlinearities  $\alpha$ .

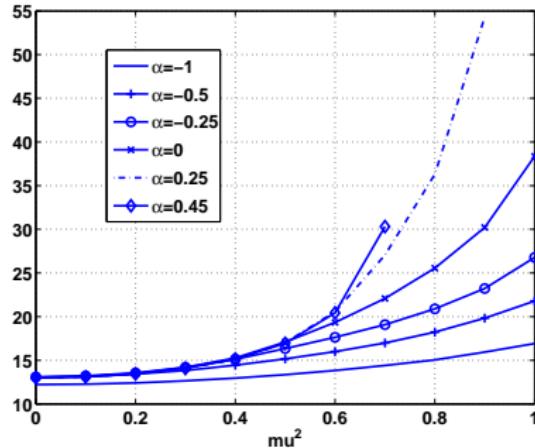
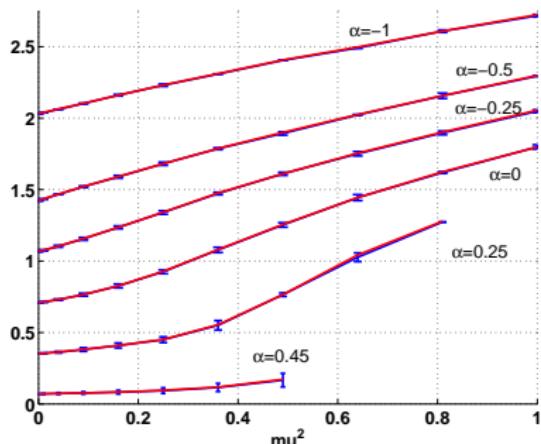
Wave speeds as noise intensity increases



# Correlation length $\xi = 0.1$

Different nonlinearities  $\alpha$ .

Wave speeds as noise intensity increases



Width of wave

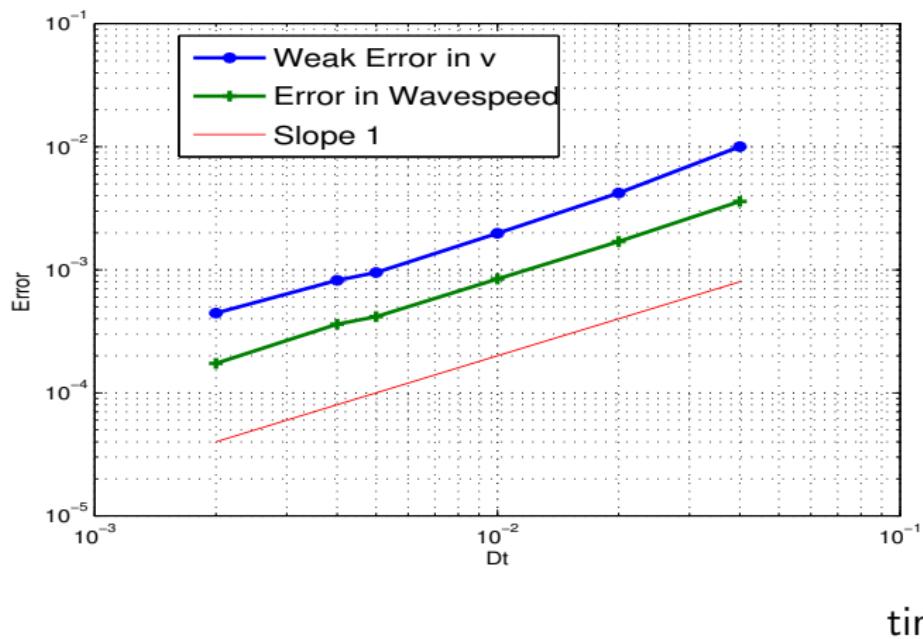
## Strong Errors for SPDAEs?

No analysis ...

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No analysis ...

Estimate numerically :



## Summary:

New exponential integrator for Stratonovich SDEs

► Stochastic Differential Algebraic Equations ?

Stochastic travelling wrt reference function  $\hat{u}$ .

Some advantages of freezing method

- ▶ Efficient : smaller domain
- ▶ Does not rely on deterministic wave/ small noise
- ▶ Faster convergence than via level set  $c$ .
- ▶ But - large advection terms: numerically challenging.

Thank You

## Refs

- [1] GJL and Vera Thümmler. SISC 2012.
- [2] Emma Coutts and GJL. J. Compt. Neuroscience. 2013.
- [3] Iyabo Adamu and GJL. J. Comp. Math. 2012
- [4] GJL and Efthalia Tzitzili. In prep.