

# Metastability of a system of interacting neurons

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workshop Metastability, mean-field particle systems and non linear processes, Saint-Étienne

Joint work with Eva Löcherbach



# The model

- $N$  neurons, potential  $u \geq 0$ .
- Jump rate (spikes)  $\lambda$  :

$$\mathbb{P}(\text{emits a spike during } [0, t]) = \lambda(u) t + o_{t \rightarrow 0}(t).$$

At the jump time, reset to its resting value ( $u = 0$ ).

- Mean-field and excitative network : when neuron  $j$  spikes,

$$u_i \leftarrow u_i + \frac{h}{N} \quad i \neq j, h > 0.$$

- Between spikes :

$$\dot{u} = -\alpha u, \quad \alpha > 0$$

- Parameters :  $h, \alpha, \lambda$ .

## A first interesting result

Introduced by Galves, Löcherbach (2013), studied by De Masi, Galves, Löcherbach, Presutti (2015) Fournier, Löcherbach (2016), Robert, Touboul (2016), Duarte, Ost (2016).

### Assumption on $\lambda$ (for the whole talk)

$\lambda : \mathbb{R}_+ \rightarrow \mathbb{R}_+$  is continuous bounded non-decreasing and  $\lambda(0) = 0$ .

### Theorem (Duarte Ost 2016)

If  $\lambda$  is differentiable at 0 then, for all  $N, \alpha, h$ , almost surely, there is only a finite number of spikes (i.e. there exists a random finite time after which there is no spike and the system relaxes towards 0).

## Analogy with a population model

Consider the following model : population  $n_t \in \mathbb{N}$ ,

- Death rate :  $\mu > 0$ .
- Birth rate :  $(1 - n_t/N)\nu$

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- Almost sure extinction : over all time intervals  $[n, n + 1]$ ,

$$\mathbb{P}(\text{apocalypse}) \geq q_n = e^{-N\mu}(1 - e^{-\nu})^N > 0.$$

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- Law of large number : if  $n_0$  is of order  $N \rightarrow +\infty$ , then

$$\partial_t n_t \simeq -\mu n_t + (1 - n_t/N)\nu n_t.$$

On  $[0, T]$ ,  $n_t/N$  converges to the solution of  $\dot{x} = ((1 - x)\nu - \mu)x$ .

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- If  $\nu > \mu$ ,  $x$  admits a unique fixed point  $x_* > 0$ , globally attractive.
- We expect  $n_t/N \simeq x_*$  for all  $1 \ll t \ll e^{\kappa N}$  for some  $\kappa > 0$ , and an abrupt (unpredictable) extinction : **metastability**.



# The Markov process

The process  $U^N(t) = U(t) = (U_i(t))_{i \in \llbracket 1, N \rrbracket}$ , with  $U_i(t)$  the membrane potential of neuron  $i$  at time  $t$ , is a Markov process on  $\mathbb{R}_+^N$  with generator  $A$  given by

$$A\varphi(u) = -\alpha u \cdot \nabla \varphi(u) + \sum_{i=1}^N \lambda(u_i) (\varphi(u + \Delta_i(u)) - \varphi(u))$$

with

$$(\Delta_i(u))_j = \begin{cases} \frac{h}{N} & j \neq i \\ -u_i & j = i \end{cases},$$

Let  $L^N$  be the last spiking time (which is not a stopping time).

# The non-linear limit process

Propagation of chaos phenomenon :

$$\frac{h}{N} \#\{\text{spike of a neuron } j \text{ during } [0, t], j \neq i\} \underset{N \rightarrow +\infty}{\simeq} h \int_0^t \mathbb{E}(\lambda(U_i(s))) ds.$$

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Limit process  $\bar{U}$  (non-linear/time inhomogeneous) with generator

$$\bar{A}_t \varphi(u) = \left( -\alpha u + h \int_0^{+\infty} \lambda(w) \eta_t(dw) \right) \partial_u \varphi + \lambda(u) (\varphi(0) - \varphi(u))$$

with  $\eta_t = \mathcal{L}aw(\bar{U}(t))$ , which solves

$$\begin{aligned} \partial_t \eta_t &= \partial_u \left[ \left( \alpha u + h \int_0^{+\infty} \lambda(w) \eta_t(dw) \right) \eta_t \right] - \lambda \eta_t \\ \eta_t(0) &= \int_0^{+\infty} \lambda(w) \eta_t(dw). \end{aligned}$$

The interaction, a jump mechanism, gives in the limit a non-linear deterministic drift.

# A phase transition

## Theorem

- 1 If  $h\lambda'(0) > \alpha$ , the non-linear system admits at least one non-zero stationary solution  $(\eta_t = \mathcal{L}aw(\bar{U}(t)) = \eta_0$  for all  $t \geq 0$  with  $\eta_0 \neq \delta_0$ ) and there exists  $c > 0$  such that for all initial condition  $\nu_0 \neq \delta_0$ ,  $\int_0^{+\infty} \lambda(w)\nu_t(dw) \geq c$  for  $t$  large enough. The non-zero stationary solutions have a density of the form

$$g(x) = \frac{p}{hp - \alpha x} \exp\left(-\int_0^x \frac{\lambda(y)}{hp - \alpha y} dy\right) \mathbf{1}_{\{0 \leq x < hp/\alpha\}}$$

with  $p = \int_0^{+\infty} \lambda(w)g(x)dx$ .

- 2 If  $h\lambda'(0) < \alpha$  and if  $\lambda$  is concave, the only stationary solution of the non-linear equation is  $\delta_0$ , globally attractive in Wasserstein distance :

$$\mathbb{E}\left(\bar{U}(t)\right) \leq e^{-(\alpha - h\lambda'(0))t} \mathbb{E}\left(\bar{U}(0)\right).$$

# Exponentially long survival

For simplicity, in the rest of the talk :

## Hypothèse

$\lambda(u) = (ku) \wedge \lambda_*$  for some  $k, \lambda_* > 0$ . We write  $a = \alpha/(kh)$  and  $b = \lambda_*/(kh)$ .

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## Theorem

Assume that  $a + b < 1$  and that for all  $\varepsilon > 0$ , there exists  $x_0 > 0$  such that  $\mathbb{P}(\sum_{i=1}^N \lambda(U_i^N(0)) \geq Nx_0) \geq 1 - \varepsilon$  for all  $N$  large enough (ok if the  $U_i(0)$  are i.i.d. non a.s. zero). Then, for all  $\delta > 0$ ,

$$\lim_{N \rightarrow +\infty} \mathbb{P}\left(L^N \geq e^{(W_0 - \delta)N}\right) = 1, \quad \text{with}$$

$$W_0 = \frac{\lambda_*}{kh} \left( \frac{kh - \lambda_*}{r} - 1 - \ln \left( \frac{kh - \lambda_*}{r} \right) - \frac{1}{2} \ln^2 \left( \frac{kh - \lambda_*}{r} \right) \right) > 0.$$

# Propagation of chaos

## Theorem

Let  $U^N = (U_1^N, \dots, U_N^N)$  be a system of interacting neurons with i.i.d. initial conditions and  $\bar{U}^N = (\bar{U}_1^N, \dots, \bar{U}_N^N)$  be independent non-linear processes with  $\bar{U}^N(0) = U^N(0)$ , so that the jump times of both processes are defined with the same Poisson measures (synchronous coupling). Then for all  $t \geq 0$  and  $\varepsilon > 0$ ,

$$\mathbb{E} \left( \sum_{i=1}^N |\bar{U}_i^N(t) - U_i^N(t)| \right) \leq h \left( \sqrt{\lambda_* t} + 2t\lambda_* \right) e^{(\alpha + hk + \lambda_*)t} \sqrt{N}$$

$$\mathbb{P} \left( \sup_{s \in [0, t]} \sum_{i=1}^N |U_i^N(s) - \bar{U}_i^N(s)| \geq \varepsilon \right) \leq \frac{C_t \sqrt{N}}{\varepsilon},$$

with  $C_t = 4h(1 + \sqrt{\lambda_* t} + t\lambda_*)^2 e^{(2\alpha + hk + \lambda_*)t}$ .

# Convergence to equilibrium for the non-linear process

For  $\nu, \mu \in \mathcal{P}(\mathbb{R}_+)$ , we consider the Wasserstein distance

$$W_1(\nu, \mu) = \inf\{\mathbb{E}(|X - Y|), X \sim \nu, Y \sim \mu\}.$$

## Theorem

For  $a$  and  $b$  small enough (explicit condition), there exists  $\kappa \in (0, 1)$  such that : for all  $\gamma > 0$ , there exists  $C_\gamma > 0$  so that for all initial conditions  $\mu_0^1, \mu_0^2$  with  $\int_0^\infty \lambda(w) \mu_0^i(w) dw \geq \gamma$ , the corresponding solutions of the non-linear equation satisfy, for all  $t \geq 0$ ,

$$W_1(\mu_t^1, \mu_t^2) \leq C_\gamma \kappa^t W_1(\mu_0^1, \mu_0^2).$$

In particular there is a unique globally attractive equilibrium (if  $\mu_0 \neq \delta_0$ ).



# Asymptotic exponentiality

## Theorem

Suppose that  $a$  and  $b$  are small enough (explicit condition), write  $\bar{\lambda}(u) = N^{-1} \sum_{i=1}^N \lambda(u_i)$  and  $\tau = \inf\{t \geq 0, U^N \notin \mathcal{D}\}$  with either :

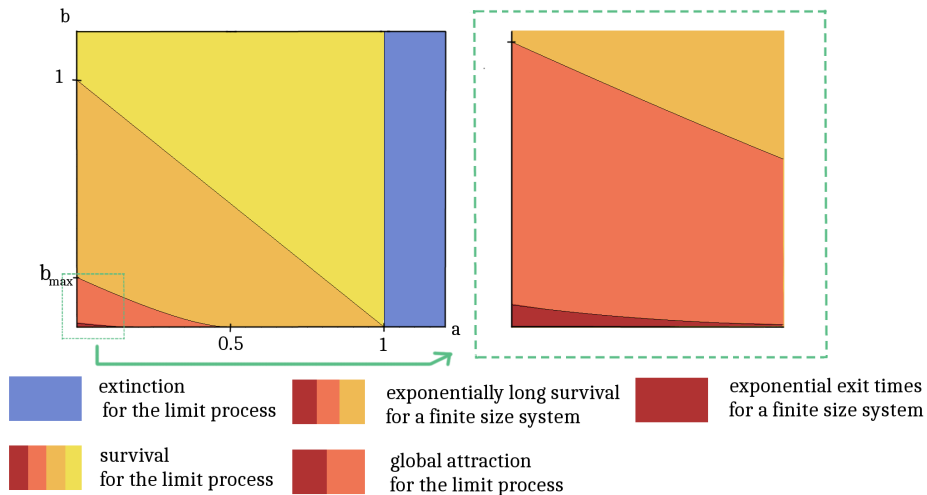
- 1  $\mathcal{D} = \{\bar{\lambda} \geq \gamma\}$  for  $\gamma > 0$  small enough (explicit condition).
- 2  $\mathcal{D}$  measurable  $\mathbb{R}_+^N$  such that, for some  $\delta > 0$ ,  $\{p_* - \delta \leq \bar{\lambda} \leq p_* + \delta\} \subset \mathcal{D} \subset \{\bar{\lambda} \geq \delta\}$ , with  $p_* = \int_0^{+\infty} \lambda(w)g(dw)$  where  $g$  is the unique non-linear equilibrium.

In the case (1) set  $\mathcal{K} = \{\bar{\lambda} \geq \delta\}$  for some  $\delta > \gamma$  and in the case (2),  $\mathcal{K} = \{p_* - \gamma \leq \bar{\lambda} \leq p_* + \gamma\}$  for some  $\gamma \in (0, \delta)$ . Then, in both cases, there exist  $C, \theta, N_0$  such that  $N \geq N_0$ ,

$$\sup_{u, v \in \mathcal{K}} \left| \frac{\mathbb{E}_u(\tau)}{\mathbb{E}_v(\tau)} - 1 \right| + \sup_{t \geq 0} \sup_{u \in \mathcal{K}} |\mathbb{P}_u(\tau \geq t \mathbb{E}_u(\tau)) - e^{-t}| \leq \varepsilon(N)$$

with  $\varepsilon(N) = Ce^{-\theta N}$  in the case (1) and  $C \ln N / N^{1/4}$  in the case (2).

# Summary of the results (except propagation of chaos)



## 1 Model and results

## 2 Some ideas of the proofs

- Coupling with an auxiliary process
- Exponentiality of exit times
- Convergence for the non-linear system

## Synchronous coupling

Given a process  $(Y_t)_{t \geq 0}$  with jump rate  $y \mapsto \lambda(y)$ , the jumps of  $Y$  can be realized as the jumps of

$$\int_{[0,t] \times \mathbb{R}_+} \mathbf{1}_{z \leq \lambda(Y_{s-})} \pi(ds, dz)$$

with  $\pi$  a standard Poisson measure over  $\mathbb{R}_+ \times \mathbb{R}_+$ .

Most our results are based on synchronous couplings : we define two different processes  $Y$  and  $Z$  with the same Poisson measure. In other words, the processes are forced to jump together as much as possible. Asynchronous jumps occur at rate  $|\lambda(Y_t) - \lambda(Z_t)|$ .

## An auxiliary process

To prove that the last spiking time is exponentially large with  $N$ , we would like to study

$$\Lambda_N(t) = \frac{1}{N} \sum_{i=1}^N \lambda(U_i(t))$$

(this is just a real number, containing the useful information concerning the jump times). However it is not Markov (there is no closed equation for its evolution).

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The idea : design a process  $Z_N$  on  $\mathbb{R}_+$  with the following properties :

- $Z_N$  Markov (simple explicit evolution)
- $Z_N(t) \leq \Lambda_N(t)$  for all  $t \geq 0$ .
- All jumps of  $Z_N$  are jumps of  $U^N$ .

Then we bound the last jump time of  $U^N$  by the one of  $Z_N$ , that we compare to  $\inf\{t \geq 0, Z_N \leq z\}$  for some small  $z > 0$ , which is then studied with classical Large Deviations results.

## Evolution of $\Lambda_N$

- Between jump times,  $\dot{U}_i = -\alpha U_i(t)$ , where

$$\dot{\Lambda}_N \geq -\alpha \Lambda_N$$

- At a spiking time  $t$  of the neuron  $i$ ,  $\lambda(U_i)$  decreases at most by  $\lambda_*$ , and for all  $j \neq i$  with  $U_j \leq \lambda_*/k - h/N$ ,  $\lambda(U_j)$  increases by  $kh/N$ . Besides, since  $\lambda$  is non-decreasing,

$$\# \left\{ j \in \llbracket 1, N \rrbracket, U_j(t-) \leq \frac{\lambda_*}{k} - \frac{h}{N} \right\} \geq N \left( 1 - \frac{\Lambda_N(t-)}{\lambda_*(1 - kh/N)} \right),$$

and thus

$$\Lambda_N(t) - \Lambda_N(t-) \geq -\frac{\lambda_*}{N} + \frac{kh}{N} \left( 1 - \frac{\Lambda_N(t-)}{\lambda_*(1 - kh/N)} \right).$$

In particular, if  $\lambda_* < kh$  (i.e.  $b < 1$ ), below some positive threshold, a jump can only increase  $\Lambda_N$ .

- Jumps occur at a rate  $N\Lambda_N$ .

## Construction of $Z_N$

$Z_N$  designed by taking the worst cases in the evolution of  $\Lambda_N$  :

- Between jumps,  $\dot{Z}_N = -\alpha Z_N$ .
- At a jump time,

$$Z_N(t) = -\frac{\lambda_*}{N} + \frac{kh}{N} \left( 1 - \frac{Z_N(t-)}{\lambda_*(1 - kh/N)} \right)_+$$

(with a slight modification close to  $z_* := \lambda_*(1 - \lambda_*/kh)$ , above which the jump of  $\Lambda_N$  can be negative : we have to avoid the situation where  $\Lambda_N > z_* > Z_N$  and  $\Lambda_N$  jumps alone and pass below  $Z_N$ ).

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The synchronous coupling of  $U^N$  and  $Z_N$  (with  $Z_N(0) = \max(z_*, \Lambda_N(0))$ ) ensures that  $\Lambda_N(t) \geq Z_N(t)$  for all  $t \geq 0$  (and in particular any jump  $Z_N$  is a jump of  $U^N$ ).

# Asymptotic of $Z_N$

For  $N \rightarrow +\infty$ , on any time interval  $[0, t]$ ,  $Z_N$  converges to the solution of

$$\dot{z} = -\alpha z + \left( kh \left( 1 - \frac{z}{\lambda_*} \right) - \lambda_* \right) \max(z, z_*),$$

which, under the condition  $\lambda_* + \alpha < kh$  (i.e.  $a + b < 1$ ) has a unique positive equilibrium.

- 1 From a Large Deviation result on  $Z_N$  we deduce that the extinction of  $U^N$  is exponentially large.
- 2 Combining this with propagation of chaos (in finite time), we get that a solution of the non-linear equation satisfies  $\mathbb{E}(\lambda(\bar{U}(t))) \geq z(t)$  with  $z$  a solution of the ODE (hence the instability of  $\delta_0$ ; this is also an ingredient involved in the global convergence toward equilibrium).

## 1 Model and results

## 2 Some ideas of the proofs

- Coupling with an auxiliary process
- Exponentiality of exit times
- Convergence for the non-linear system

## A general framework

Let  $(X_t)_{t \geq 0}$  be a Markov process on a polish space  $E$ ,  $\mathcal{D}, \mathcal{K} \subset E$  measurables with  $\emptyset \neq \mathcal{K} \subset \mathcal{D}$ , and we write  $\tau_A = \inf\{t \geq 0, X_t \in A\}$  for  $A \subset E$ . Let  $\varepsilon_1, \varepsilon_2, \varepsilon_3 \in [0, 1]$  and  $s_1 \geq s_2 > 0$  such that :

- 1 Exit from  $\mathcal{D}$  from the stable zone  $\mathcal{K}$  unlikely in a time  $s_1$  :

$$\varepsilon_1 \geq \sup_{x \in \mathcal{K}} \mathbb{P}_x (\tau_{\mathcal{D}^c} \leq s_1) .$$

- 2 From a point of  $\mathcal{D}$ , if we haven't exited before time  $s_2$ , we are probably in the stable zone  $\mathcal{K}$  :

$$\varepsilon_2 \geq \sup_{x \in \mathcal{D}} \mathbb{P}_x (\tau_{\mathcal{D}^c} \wedge \tau_{\mathcal{K}} > s_2) .$$

- 3 Loss of memory in  $\mathcal{K}$  in time  $s_1$  : for all  $x, y \in \mathcal{K}$  there exists a coupling  $(X_t, Y_t)_{t \geq 0}$  of two processes initially at  $x$  and  $y$  with

$$\mathbb{P}(X_t = Y_t \forall t \geq s_1) \geq 1 - \varepsilon_3 .$$

## A general result

Adapting a result of Brassesco, Olivieri, Vares (1998) for low-temperature diffusions :

### Theorem

Suppose that  $\varepsilon_1 + \varepsilon_2 + \varepsilon_3 \leq 1/2$  and  $\tau := \tau_{\mathcal{D}^c}$  is  $\mathbb{P}_{x_0}$ -a.s. for some  $x_0 \in \mathcal{K}$ . Then there exist  $\beta > 0$  such that  $\mathbb{P}_{x_0}(\tau > \beta) \in [1/4, 3/4]$ . Suppose that there exist  $C, \delta, M \geq 0$  such that

$$\frac{s_2}{\beta} \vee (\varepsilon_2 + \varepsilon_3) \leq Ce^{-\delta M}.$$

then there exist  $K, M_0 > 0$  (depending only on  $C, \delta$ , not on  $M$ ) such that, if  $M \geq M_0$ , then  $\sup_{x \in \mathcal{D}} \mathbb{E}_x(\tau) < +\infty$  and for all  $x, y \in \mathcal{K}$ ,

$$\left| \frac{\mathbb{E}_x(\tau)}{\mathbb{E}_y(\tau)} - 1 \right| + \sup_{t \geq 0} |\mathbb{P}_x(\tau \geq t\mathbb{E}_x(\tau)) - e^{-t}| \leq K'M^3 e^{-\min(\delta/3, 1/2)M}$$

## For the neuron model

- The return time to  $\mathcal{K}$  and the exit time from  $\mathcal{D}$  from  $\mathcal{K}$  are easily obtained by comparison with the auxiliary process  $Z_N$  or with the limit process  $\bar{U}$ .
- For the coupling from  $\mathcal{K}$ , we start by proving that

$$\mathbb{E} \left( \sum_{i=1}^N |\lambda(U_i^N(t)) - \lambda(\tilde{U}_i^N(t))| \right) \leq C \left( \kappa^t N + e^{-\theta N} \right)$$

following the strategy used for the convergence of the non-linear system.

- Then we couple  $U^N(t) = \tilde{U}^N(t)$  in a time  $t = N^\alpha$ ,  $\alpha \in (0, 1]$  :
  - ▶ At half the time,  $N^\alpha/2$ , the rates are close. There is probably no asynchronous jump in the interval  $[N^\alpha/2, N^\alpha]$ .
  - ▶ Moreover, on this interval, each pair  $(U_i^N, \tilde{U}_i^N)$  probably has a (synchronous) spike, from which  $U_i^N(s) = \tilde{U}_i^N(s)$  (up to the first asynchronous jump in the system).

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## Synchronous coupling

Consider a non-linear process solving (writing  $\bar{\lambda}_t = \mathbb{E}(\lambda(\bar{U}(t)))$ )

$$d\bar{U}(t) = -\alpha\bar{U}(t)dt + h\bar{\lambda}_t dt - \bar{U}(t-) \int_{\mathbb{R}_+} \mathbf{1}_{\{z \leq \lambda(\bar{U}(t-))\}} \pi(dt, dz),$$

and a similar  $\hat{U}$  (same  $\pi$ ) but with a different initial law. We want

$$\mathbb{E} \left( |\bar{U}(t) - \hat{U}(t)| \right) \leq C\kappa^t, \quad \kappa \in (0, 1).$$

We first prove

$$\mathbb{E} \left( \left| \lambda(\bar{U}(t)) - \lambda(\hat{U}(t)) \right| \right) \leq C\kappa^t, \quad \kappa \in (0, 1),$$

The first point is then proven similarly and by using this first information.



## Synchronous coupling

- Saturation : for  $u \geq u_* = \lambda_*/k$ ,  $\lambda(u) = \lambda_*$ . for  $a$  and  $b$  small enough and  $\bar{\lambda}_0$  large enough (which we can assume), the solution of

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starting from 0 upcrosses the threshold  $u_*$  (and stays above).

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- Without any spike, the two processes  $\bar{U}$  and  $\hat{U}$  upcrosses the threshold and then  $\lambda(\bar{U}(s)) = \lambda(\hat{U}(s))$  up to the next jump (which will thus be synchronous).

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- Without any spike, the two processes  $\bar{U}$  and  $\hat{U}$  upcrosses the threshold and then  $\lambda(\bar{U}(s)) = \lambda(\hat{U}(s))$  up to the next jump (which will thus be synchronous).
- Problem : at this synchronous jump, the derivatives being different, the (rates of the) processes immediatly split. Then there can be asynchronous jumps.
- Solution : if  $a$  and  $b$  are small enough, not only (1) upcrosses the threshold  $u_*$ , but it upcrosses it *fast*, which means the time window for asynchronous jumps is short.

# Truncated Gronwall

Considering the different cases (no jump, only synchronous jumps, at least one asynchronous jump), we get that  $f(t) := \mathbb{E} \left( |\lambda(\bar{U}(t)) - \lambda(\hat{U}(t))| \right)$  satisfies

$$f(t) \leq \theta \int_{(t-t_*)_+}^t f(s) ds + \left( kf \int_0^t f(s) ds + f(0) \right) \mathbf{1}_{t \in [0, t_*]}$$

with  $\theta = kh\lambda_* t_* + \lambda_*$  and  $t_*$  (roughly) the hitting time of  $u_*$  by (1). Iterating Gronwall's lemma, for  $n \in \mathbb{N}$  and  $t \in [nt_*, (n+1)t_*]$ ,

$$f(t) \leq (\theta t_* e^{\theta t_*})^n e^{(\theta+kh)t_*} f(0).$$

Finally, for  $a, b$  small enough,  $\theta t_*$  is smaller than the solution  $x$  of  $xe^x = 1$ , which concludes.

# Conclusion

- Can we get the asymptotic exponentiality of  $L^N$ ?
- Could the (quantitative) bounds proven to establish the asymptotic exponentiality be used to get the convergence of the process conditioned to have stayed in  $\mathcal{D}$  toward its quasi-stationary distribution (with a rate independent from  $N$ , or at least polynomial in  $N$ )?

# Conclusion

- Can we get the asymptotic exponentiality of  $L^N$ ?
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Thanks for your attention !