# Microsimulation and population dynamics in longevity, credit, HFT modelling

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### Padoue, Fevrier 2016

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#### 1 Motivation to model global population

- 2 The demographic transition in a nutshell
- 3 Individual based centered dynamic model
- 4 Random set point of view and Thinning of Poisson population
- 5 Hawkes processes

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#### Population dynamics and Longevity

- First motivation, longevity risk
- ▶ To take into account the complexity of the gobal population
- General Model for population dynamics in Ecology

#### Marked Point Process: Renew of interest

Useful tool, under different denominations, for other domains:

- Credit risk Modelling
- Hawkes processes in Hight Frequency Trading
- Brain study
- Data Mining

#### Probability Theory and Simulation

- ▶ Based on useful in probability theory, Poisson Point measure,
- Birth and Death process
- Particular Method for Monte Carlo Simulation

#### Data and Calibration

- Completely different situations for different domains
- Hard to calibrate
- Hard to simulate

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# Demographic Transition in a nutshell

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### Mortality Transition, Canning (2011)

+30 years for Life Expectancy (LE) in the last century The demographic observation

- Substantial decline in mortality rate, in particular in small ages
- followed by reduction in fertility rate
- Heath transition (physical and cognitive development) and compression of morbidity

#### Economics aspects

- Economic growth, (income by head) and
- increase in social and political policy (education, democratie..)
- Growth in world population, citer Cohen

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### Health Determinants of mortality improvement

Health point of view from Cutler, Deaton, alii (2006)

- Decline in infectious disease (60% of deaths in1848, < 5% in 1971 in UK)
- Nutritional improvement (debate on the importance)
- Progress in medecine, vaccins, …

#### Public policies

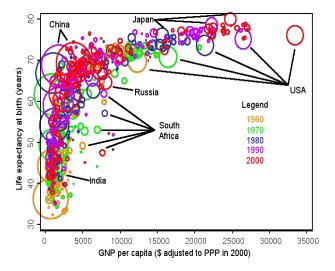
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- ► Macro public health: big public work projects (water purifica- tion explain half of mortality reduction in US (1900 ~ 1930)
- Reduction in alcoholism, in smoking
- public and private health,...also contribute with complex impacts,
- ► large heterogenity with differences by age, type of sub-population, countries, with reverse or delayed effects.

### Economic and Wealth Point of view

- Strong evidence on the links, but only 20% as impact
- Relation non-linear and concave
- Unexplained recent slower pace for LifeExp in US /Europa

### Wealth and longevity: complex dependency



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# Evolutionary theory for aging

#### Example of Biological views

- Aging is characterized by the decline of physiological capacity
- Explain heterogeneity and randomness in individual patterns
- Nevertheless a robust observation in evolution theory, Gompertz (1825): The log mortality rate between 35-80y is linear in age.
- After 80y, large debate on the rectangularization of the survival curve, the question of "limited human life span"?

Example of data: EU15, 2011, Age-specific mortality rates per 100.000

- **1** [0, 1*y*], 486(382)
- [1y, 10y], 19(15)| [11y, 20y, 41(19)| [21y, 30y], 93(32)
- **B** [31y, 40y], 133(63)| [41y, 50y], 313(163)| [51y, 60y], 750(385)
- 4 [61*y*, 70*y*], 1869(953) | [71*y* -

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### Aggregate mortality indicators

### Life exptectancy at birth

- Lifetime of an individual: au
- Life expectancy at birth:  $\mathbb{E}[\tau]$ , at ten  $\mathbb{E}[\tau 10/\tau > 10]$

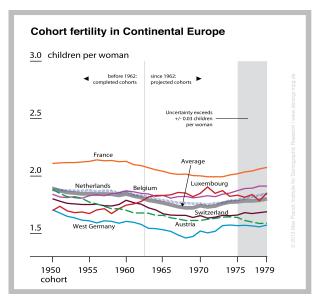
### Death rate

- Death rate d(a) such that  $\mathbb{P}(\tau > a) = e^{-\int_0^a d(s)ds}$
- ▶ In practice annual death probability reduction  $q(a) = \mathbb{P}(\tau < a + 1 \mid \tau \ge a)$
- Mortality plateau (old ages)

### Fertility rate

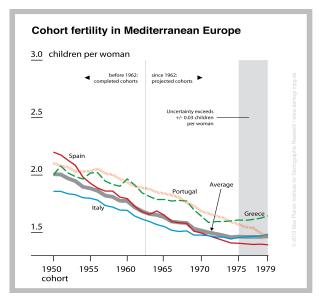
- Complex notion
- ▶ With large political connotation (Fertility, Immigration)

### Fertility rate in Continental Europa/1950-80



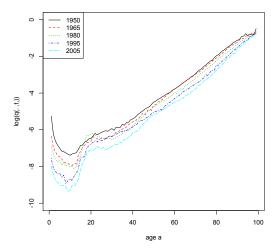
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### Fertility rate in Mediterranean Europa

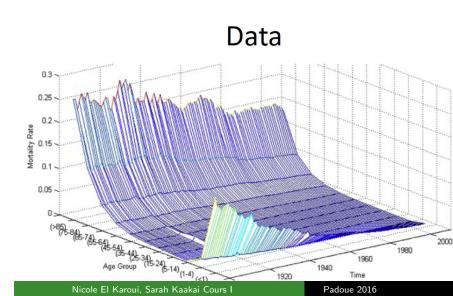


# National mortality: $\log q(a,t)$

- Looking at  $\log q(a, t)$  age a in [0,100]
- ▶ for different years *t* (1950,1965,1980,1995,2005)

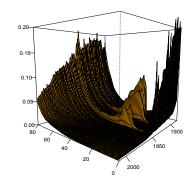


# National mortality Surface



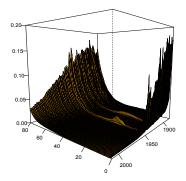
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### National mortality by gender (France)



probabilités de décès (hommes, FR)

probabilités de décès (femmes, FR)







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# New economic and social challenge

Aging populations: new phenomenon, without past historical reference

- viability of shared collective systems, in particular (state or private) pension systems
- new generational equilibrium
- role and place of aging population in the society

#### Complex phenomenon, multi-causes

- Difficult to model.
- The role of age
- The heterogenity

#### **Complex Estimation**

- Coherence of the data
- Age, cohort, period

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### Individual based centered dynamic model

#### Aims of microscopic models

- Provide population evolution at the scale of individual
- allows to understand paterns of aggregate indicators

#### Two examples in these lessons

- Impact of aging
- How individual birth patterns in heterogeneous population can create artificial mortality changes ("Cohort effect")

# Microscopic models in different fields:

#### Individual-Based models in Public Economy:

- ► Agent-based models in economics (Orcutt, 1957)
- Microsimulation models of government bodies (Ex : INSEE, model "DESTINIE")
- Individual-Based models in ecology (mathematical framework):

#### Individual-Based models in ecology:

- Modelling a population with birth, death, and mutation at birth
- Population structured by traits (*i.e.* individual characteristics) (Fournier-Méléard 2004) (Champagnat-Ferrière-Méléard 2006), with age (Tran 2006, Ferrière-Tran 2009)

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### Microsimulation exercise

First step Define clear specification of the objectives, for determining methods, assumptions and scenarios, in view of constitution of *Data base* storing the information on all individuals on study

- State space: state of variables to be projected, as traits, attributes of individuals, (as age, sex, residence, level of schooling, wealth)
- ▶ *support variables* (marital statuts, children..) used to predict events.
- Covariates Y or factors of type demographic or environmental.

At the macrolevel, the state space is the set of all combinations of individual state variables.

#### Dynamic simulation over the time

- to predict the future state, be careful on the causality of the events, since demographic events influences population,
- ► and intensity of demographic events are themselves influenced by the composition of the population.

# Analysis of the "artificial" database

### The classical point of view in population dynamics

- As a family of individual biographies influenced by the others, or by covariates
- Valid only in the linear case
- Essential assumption in demographic practice

#### Cross-sectional point of view

- The population is described every date by the characteristics of its individuals
- well- adapted to interacting individuals
- ▶ very similar description as for interacting particules system in physics

The "macro point of view" is cross-sectional (similar to continuous time Markov chain

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### Sources of randomness

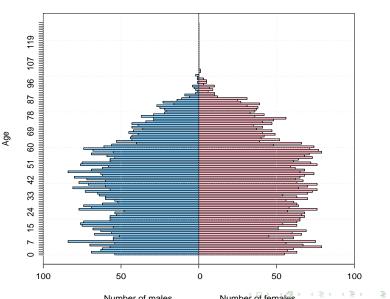
#### From Vanimhoff 1998

- inherent randomness due to Monte Carlo Methods, reduced by increase the number of runs, or the size of the database or variance reduction. Not equivalent in general
- starting-population randomness: in general a subsample of the population; be careful that any deviation of the sample distribution impact future projections
- Specification randomness Choice of the number of state variables: more variables increase the MC randomness, calibrations errors, implied correlation due to calibration.
- Reduced by *sorting methods*, or alignment methods to respect of some macro properties

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### Initial population for $N=10\ 000$ in 2008





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# Classical example: Poisson population

- A marked population χ is a finite set of individuals, points, particles, characterized by quantitative attributes with values in E
- Uncertainty concerns card(ξ)=nb of individuals, and the "vector" of attributes (X<sub>1</sub>,...X<sub>n</sub>...)

#### Poisson population:

- Let (X<sub>1</sub>,...X<sub>n</sub>..) be an iid sample of μ(dx) on E, stopped randomly at ν, an independent ~ Pois(λ).
- The marked population ξ = {X<sub>1</sub>,...X<sub>ν</sub>} is a Poisson population, with mean η(dx) = λμ(dx), iff N<sup>ξ</sup>(B) = card(ξ ∩ B) = ∑<sup>ν</sup><sub>k</sub> 1<sub>X<sub>n</sub>∈B</sub> is a Poisson variable Pois(λμ(B)).

#### Restricted or thinned Poisson population:

► The population  $\xi^B = \{X_1, ..., X_\nu\} \cap B$  restricted to B is still a Poisson population with Poisson parameter  $\lambda^B = \lambda \mu(B)$  and spatial distribution  $\mu^B(dx) = \mu(dx | B) = \mathbf{1}_B(x)\mu(dx)/\mu(B)$ .

### Classical example: Poisson population II

► All standard properties of finite Poisson measure are satisfied:

- $N(B) = \sum_{n=1}^{\nu} \mathbf{1}_B(X_n) = \text{card} \sim \text{Pois}(\eta(B))$
- $(N(B_i))$  are independent if  $B_i \cap B_j) = \emptyset$
- Assume η is only σ-finite, and finite on an increasing sequence of (finite measure) windows K<sub>k</sub>, with reunion E.
  - By assumption, the Poisson set restricted to K<sub>k</sub> is a finite Poisson population ξ<sup>k</sup>.
  - The "countable " reunion of these sets ξ<sup>k</sup> is now countable. The decomposition is not unique.

#### Random marked population

- A marked population χ is an at most countable set of individual with patterns in E. The space of outcomes is the so-called population (configuration) space Γ(E)
- To study the spatial distribution of  $\xi$ , we introduce
  - $N(B)(\xi)$  the number of individuals of  $\xi$  in B, that is  $N(B)(\xi) = \operatorname{card}(\xi \cap B)$  (additive properties)
  - V(B)(ξ) the vacancy indicator and the vacancy set
    V(B) = {ξ : N(B)(ξ) = 0} = {ξ : no points in B}

• 
$$N_{R\cup Y}(B) = N_R(B) + N_Y(B)$$
 if  $\xi_R \cap \xi_Y = \emptyset$  and  
 $V_{R\cup Y}(B) = V_R(B)V_Y(B)$ 

- ► The first moment, called *mean measure*, η(B) = ℝ(N(B)) is often viewed as the main information on the population
- ► The remarkable property of V(B) is that this "minimal" operator characterizes the distribution of the marked population.

### Dynamic Poisson population

On-line Poisson process = Poisson population on  $\mathbb{R}^+$  with mean measure proportional to Lebesgue  $\eta(dt) = \lambda \text{Leb}(dt)$ 

- ▶ Restricted to a window [0, T],  $N_T = N(]0, T]) \sim Poi(\lambda T)$
- Conditionally to N<sub>T</sub> = n, the temporal characteristics (θ<sup>T</sup><sub>i</sub>) are uniformly distributed on [0, T]
- ► Process representation as non decreasing function in T, with jumps times  $T_j$  and waiting times  $\tau_j = T_j T_{j-1}$  exponential with parameter  $\Lambda$

Dynamic Poisson population = marks added at the temporal component

- ► Finite total mass *m*. Simple extension of the static construction with iid sample  $(X_n)$  of m(dx)/m(E),  $\xi_t = \{X_1, \dots, X_{N_t}\}$
- Extension to  $\sigma$  finite case, without difficulty

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## General population with stochastic intensity

Notation  $z \mapsto \langle m, f_z \rangle = \int_{x \in E} \int_{y \in F} f(x, y, z)m(dx, dy) =$  function General filtration and Martingale point of view

- ► Stochastic intensity  $\mu(t, dx)dt$ :  $N_t(B) \int_0^t \mu(s, B)ds$  is a  $\mathcal{F}_t$  martingale
- ►  $\mathcal{F}_t$ -Poisson process: martingale property for  $(N_t(B) \mu(B)t)$  is equality to the independence of  $(N_{t+h} N_t)$  to  $\mathcal{F}_t$
- Extension to  $\mathcal{P} \otimes \mathcal{B}(E)$  integrable predictable processes  $f_t$ :  $(\langle N_t, f \rangle - \int_0^t \langle \mu, f_s \rangle ds)$  is a martingale

First projection point of view, with digital predictable intensity

- Assume that  $\mathbf{1}_D(\omega, t, x)$  is  $\mathcal{P} \otimes \mathcal{B}(E)$  mesurable, with  $\int_0^t \int_E \mathbf{1}_D(\omega, s, x) ds\mu(dx) < \infty$ ,  $\eta(dt, dx) = dt\mu(dx)$
- ► The marked population  $N^D(dt, dx) = \mathbf{1}_D(\omega, t, x) \cdot N(dt, dx)$  has the intensity:  $\eta^D(dt, dx) = \mathbf{1}_D(t, x) \cdot \eta(dt, dx) = \mu_t^D(dx) dt$

# Density assumption and thinning procedure

- Let us consider a predictable measure, η<sup>λ</sup>(ω, dt, dx) = λ(ω, t, x)η(dt, dx), where η is a deterministic product measure on ℝ<sup>+</sup> × E. (Density assumption)
- ► How the construct a dynamic random population with intensity  $\eta^{\lambda}(dt, dx)$  from the Poisson measure Q(dt, dx) with intensity  $\eta(dt, dx)$ ?

#### Thinning of extended Poisson measure

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- Introduce a thinning parameter θ erasing all the points (t, x) such that λ(t, x) < θ. Put D(ω, t, x, θ) = {θ ≤ λ(ω, t, , x)}</p>
- On  $E \times \mathbb{R}^+ \times \mathbb{R}_+$ , with current point  $(t, x, \theta)$  and product measure  $q(dt, dx, d\theta) = dt m(dx) d\theta$ , and Poisson measure  $Q(dt, dx, d\theta)$ ,
- Restricted  $Q(dt, dx, d\theta)$ , to  $Q^D(dt, dx, d\theta)$
- Projected  $Q^D(dt, dx, d\theta)$  on  $E \times \mathbb{R}^+$  into N(dt, dx)

#### Birth Dates in on-line Poisson process

- ► From a set point of view, put \$\xi\_t = {T<sub>1</sub>, T<sub>Nt</sub>}, where T<sub>k</sub> is the date of birth (of entry time) of the k individual in the population. Obviously, (\$\xi\_t\$) is not a Poisson population.

#### Cohort Market Dynamic population

- ▶ With marks, the random set becomes  $\xi_t = \{(T_1, X_1), (T_{N_t}, X_{N_t})\}$  with intensity measure  $\Delta(dt, du)m(dx)$ .
- The population is said to be structured by cohort, with a natural order of enumeration of individuals in the population.

# Dynamic population structured by age

- The new population becomes  $\tilde{\xi}_t = \{(t T_1, X_1), (t T_{N_t}, X_{N_t})\}.$
- The mark is now depending on the point of time t by  $r_t(a) = (t a)^+$ ,
- $\tilde{N}_t^a(A \times B) = N_t(r_t(A) \times B)$  is no more a measure in t, although if its expectation  $\int_0^t \mathbf{1}_A(t-s)dsm(B) = \int_0^t \mathbf{1}_A(s)ds$

#### Deterministic formula for counting measure with age

- ► For differentiable f in age, coupled with integration by parts (formula for the online process)  $z_t(f) = f(0)z_t(1) + \int_0^t z_v(f')dv.$
- $z_t(f)$  is of finite variation
- Application to Hawkes process

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# Thinning equations for Birth processes

The thinning construction can be used to define a wide variety of processes as solution to stochastic equations.

#### Intensity for linear Birth Process

- Generalisation of Poisson process, but pure jump Markov process on  $\mathbb{N}$ ,  $(N_t)$  non decreasing in time with jump 1 and intensity  $\lambda n$
- The time between two jumps is exponential of parameter  $\lambda n$ , and independent

#### Representation as solution of SDE

- Stochastic intensity  $\lambda_t N_{t-}$
- Equation  $dN_t = \int_{\mathbb{R}_+} \mathbf{1}_{\{\theta \leq \lambda_t N_{t-}\}} Q(dt, d\theta), N_0 = x$
- ► Solution by recursive method starting with the process  $dX_t^1 = \int_{\mathbb{R}_+} \mathbf{1}_{\{\theta \le \lambda_t x\}} Q(dt, d\theta),$   $dX_t^2 = \int_{\mathbb{R}_+} \mathbf{1}_{\{X_{t-}^1 > x\}} \mathbf{1}_{\{\theta \le \lambda_t X_{t-}^1\}} Q(dt, d\theta) \text{ and so on....}$

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### Linear self-exciting processes

A point process N with jump times (T<sub>n</sub>) and path-dependent intensity λ<sub>t</sub>, (N<sub>t</sub> = N<sub>0</sub> + ∫<sub>(0,t]</sub> λ<sub>s</sub>dt + F-martingale)

Hawkes (1971): Linear self-excitation

$$\lambda_t = \bar{\mu} + \int_{(0,t)} \phi(t-s) N_s = \bar{\mu} + \sum_{T_n < t} \phi(t-T_n),$$

•  $\phi$ =fertility function

- ► Simple Hawkes example: Autoregressive point process,  $\phi(t) = \alpha e^{-\beta t} \quad \lambda_t = \bar{\mu} + \alpha \int_{(0,t)} e^{-\beta(t-s)} N_s$
- Credit: (Gieseke, Dufie,....) (i)  $\lambda_t = \overline{\mu} + \int_{(0,t)} \psi(s) N_s = \overline{\mu} + \sum_{T_n < t} \psi(T_n)$ , (ii)  $\lambda_t$  is differentiable in time,
- No true in general for Hawkes intensity

# Self-exciting models for applications

### Physics and Biology

- seismology (AfterShoks), epidemiology
- ecology
- neuroscience, DNA modelling

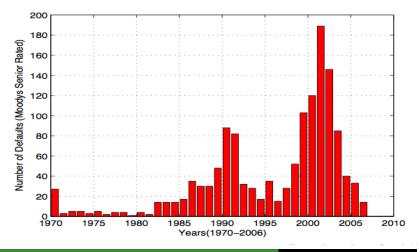
### Social Sciences

- epidemics in Socio-Economic networks
- ▶ finance: credit risk, contagion, mortgage prepayments
- ▶ insurance: risk processes, ruin theory, surrender lapse
- High Frequency trading and market microstructure

# Default Clusters, US compagnies Senior rates

#### from Gieseke,1970-2006

# **Defaults cluster**



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# Financial applications

### "Low frequency"

- Credit risk (e.g. Gieseke, Errais et al. 2010)
- ▶ Daily financial data (e.g. Embrechts et al. 2011)
- ▶ Financial contagion (e.g. At-Sahalia et al. 2010)

### "High frequency "

- Midquote and transaction prices, market impact (e.g. Bacry & Muzy, 2013)
- Limit order book (e.g. Large, 2007)
- Scaling limits (e.g. Jaisson & Rosenbaum, 2013)

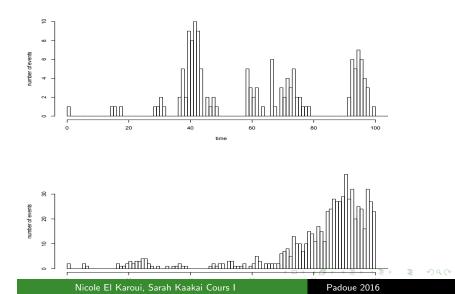
[Review from Jaisson & Rosenbaum (2013)]

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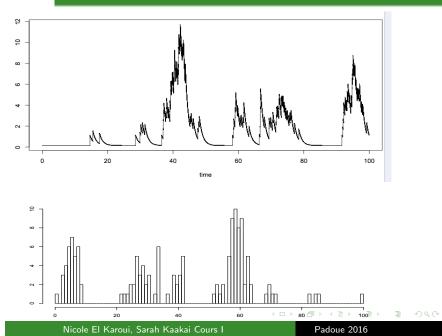
### History for two Populations

Human population:  $\phi^2(a) = \mu + k \exp -c(t - t_f)^{+,2}$ 

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## Intensity and Age Pyramid for Hawkes



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# Population point of view

#### Birth process with immigration

- Each individual has an age a
- Immigrants arrive according to a Poisson  $(\bar{\mu})$
- Any individual aged a gives birth with rate  $\phi(a)$

Same definition as in Hawkes process

### Age pyramid at time *t*:

Fix t.  $Z_t([\alpha, \beta))$  is the number of events with age in  $[\alpha, \beta)$ .

$$\blacktriangleright N_t = Z_t(\mathbb{R}^+) = \langle Z_t, \mathbf{1} \rangle$$

- $\blacktriangleright \langle Z_t, f \rangle = \int_{\mathbb{R}_+} f(a) Z_t(da) = \sum_n \mathbf{1}_{[0,T_n]}(t) f(t-T_n) = \int_0^t f(t-s) dN_s$
- Intensity process:  $\lambda_t = \bar{\mu} + \langle Z_{t-}, \phi \rangle$

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### **Dynamics**

### Differential property

- What is the dynamics of the age pyramid  $Z_t(da)$  over time ?
- Recall that  $N_t = \langle Z_t, \mathbf{1} \rangle$

### Key (!) lemma

For each differentiable 
$$f_{,\langle Z_t, f \rangle} = f(0)dN_t + \underbrace{\langle Z_t, f' \rangle}_{\text{ageing}} dt.$$

Proof Use that  $f(t-s) - f(0) = \int_{s}^{t} f(t-u) du$  and make an integration by parts.

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# Hawkes process as strong solution of SDE

Define the Hawkes process as the solution to the stochastic equation

$$N_t = \int_{(0,t)} \int_{\mathbb{R}_+} \mathbf{1}_{[0,\bar{\mu}+\int_{(0,s)}\phi(s-u)dN_u]}(\theta)Q(ds,d\theta),$$

- Existence easy if φ is bounded by K, by using 1<sub>[0,K]</sub>.dθ = dθ<sup>K</sup> and the sequence (S<sub>n</sub>, Θ<sub>n</sub>) associated with dt ⊗ dθ<sup>K</sup>.
- By Picard iteration, starting with  $N_t^0 = N_0$  and

$$N_t^{K} = N_0 + \int_{(0,t)} \int_{\mathbb{R}_+} \mathbf{1}_{[0,\bar{\mu} + \int_{(0,s)} \phi(s-u) d N_u^{K-1}]}(\theta) Q(d, d\theta),$$

#### Avantage of the SDE representation

- Strong solution even in the non linear case
- Allows comparison theorem since same noise
- Study the sensitivity to the initial condition

## Classical Exponential fertility function

 $\langle Z_t, f \rangle = f(0)N_t + \int_0^t \langle Z_s, f' \rangle ds.$ 

• If  $\phi(a) = \alpha e^{\beta a}$ ,  $\phi' = \beta \phi$  and

$$\langle \mathsf{Z}_t,\phi\rangle=\langle \mathsf{Z}_u,\phi\rangle+\alpha\int_u^t\int_{\mathbb{R}_+}\mathbf{1}_{[0,\bar{\mu}+\langle \mathsf{Z}_{s-},\phi\rangle]}(\theta)\mathsf{Q}(ds,d\theta)+\beta\int_u^t\langle \mathsf{Z}_s,\phi\rangle ds.$$

• EDS in  $\langle Z_t, \phi \rangle$  only, and  $\lambda_t = \overline{\mu} + \langle Z_{t-}, \phi \rangle$  is a Markov process

Distribution properties for  $\phi(a) = \alpha e^{-\beta a}$ 

- Errais, Gieseken et al. (2010)
- At-Sahalia et al. (2010)
- ▶ DASSIOS, (2011)
- Da Fonseca and Zaatour (2014)

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# Fertility function: setting

The map  $a \in \mathbb{R}_+ \mapsto \phi(a)$  is of class  $C^n(\mathbb{R}_+)$  and is solution to the equation  $\phi^{(n)} = c_{-1} + \sum_{k=0}^{n-1} c_k \phi^{(k)},$ 

with initial conditions  $\phi^{(k)}(0) = m_k$ , for  $0 \le k \le n-1$ . For instance exponential functions multiplied by a polynome

Fertility function: examples

 Approximation of a power law kernel (~ <sup>1</sup>/<sub>t<sup>1+e</sup></sub>) with cut-off (Hardiman-Bercot-Bouchaud, 2013)

$$\phi(t) = \frac{n}{Z} \left( \sum_{i=0}^{M-1} \frac{e^{-t/(\tau_0 m^i)}}{(\tau_0 m^i)^{1+\epsilon}} - S e^{-t/(\tau_0 m^i)} \right)$$

- Z is such that  $\int_0^\infty \phi = n$  and S such that  $\phi(0) = 0$ .
- Used to allow tractable likelihood

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# **Dynamics**

$$\phi^{(n)} = c_{-1} + \sum_{k=0}^{n-1} c_k \phi^{(k)}, \ \phi^{(k)}(0) = m_k$$

A system differential linear

$$N_{t} = \int_{0}^{t} \int_{\mathbb{R}_{+}} frm[o] - -_{[0,\bar{\mu}+\langle Z_{s-},\phi\rangle]}(\theta)Q(ds,\theta)$$
$$\langle Z_{t},\phi\rangle = m_{0}N_{t} + \int_{0}^{t} \langle Z_{s},\phi'\rangle ds$$
$$\vdots$$
$$\langle Z_{t},\phi^{(k)}\rangle = m_{k}N_{t} + \int_{0}^{t} \langle Z_{s},\phi^{(k+1)}\rangle ds$$
$$\vdots$$
$$\langle Z_{t},\phi^{(n-1)}\rangle = m_{n-1}N_{t} + \int_{0}^{t} \langle Z_{s},\phi^{(n)}\rangle ds$$

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### **Dynamics**

### A linear system of affine type

▶ The (n + 1)-dimensional process  $X_t := (\langle Z_t, 1 \rangle, \langle Z_t, \phi \rangle, ..., \langle Z_t, \phi^{(n-1)} \rangle)$  is solution of the affine differential sytem

$$X_t = N_t \hat{m} + \int_0^t C X_s ds, \quad N_t - \int_0^t X_s^1 ds =$$
martingale

• The Laplace transform has a closed form  $\mathbb{E}\left[\exp\left(v.X_{T}\right)\right] = \exp\left(-\bar{\mu}\int_{0}^{T}(1-e^{A_{s}.\hat{m}})ds\right),$ 

- Martingale = exp  $(\alpha_t N_t \int_0^t \alpha'_s N_s ds \int_0^t (e^{\alpha_s} 1)(\bar{\mu} + \lambda_s) ds)$
- The matrix A is solution of the deterministic equation

$$^{t}CA_{t} + A'_{t} + (e^{A_{t} \cdot \hat{m}} - 1)\mathbf{1}_{i=2} = 0, \quad A_{T} = v$$