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# Spectral theory of large deviations in birth-death systems 

Baruch Meerson

Hebrew University of Jerusalem, Israel
with Michael Assaf

Assaf and Meerson, PRL 97, 200602 (2006)
Assaf and Meerson, PRE 74, 041115 (2006)
Assaf and Meerson, PRE 75, 154703 (2007)

## Introduction

Birth-death processes: Markov processes involving transitions, with known rules, within an ensemble of microscopic states

Numerous examples in physics, chemistry and astrochemistry, population biology, epidemiology, cell biochemistry etc...


Atomic processes and quantum optics


Chemical reactions recombination, dissociation, desorption...


Population dynamics birth, death, emigration/immigration, competition etc.

## Extinction and meta-stability

Example: a branching-annihilation process
(chemical reactions $2 A \longrightarrow B, A+C \longrightarrow 2 A+D$; population dynamics...)
$2 A \rightarrow 0$

a two-step birthdeath process


What does the rate equation predict?

$$
\dot{n}=-\mu n^{2}+\lambda n
$$

attracting fixed point $\quad n_{s}=\frac{\lambda}{\mu} \equiv \Omega \gg 1$
a natural large parameter
$\Longrightarrow$ System stays at $n=\Omega$ forever

In the master equation formulation this result breaks down at long times

- existence of absorbing state at $n=0$
- Particle discreteness brings fluctuations, ultimately driving the system to absorbing state Fluctuations work against deterministic effect $\Rightarrow$ extinction time exponentially large the stable (attracting) fixed point of the rate equation becomes meta-stable


Interesting to calculate:

- quasi-stationary distribution
- extinction time statistics
time


## Master equation

$$
\{\begin{array}{l}
\dot{P}_{n}=\frac{\mu}{2}\left[(n+2)(n+1) P_{n+2}-n(n-1) P_{n}\right] \\
\dot{P}_{0}=\mu P_{2}
\end{array} \underbrace{\lambda\left[(n-1) P_{n-1}-n P_{n}\right]}_{\text {annihilation }} \quad \begin{array}{c}
\begin{array}{c}
2 A \xrightarrow{\mu} 0 \\
\text { branching }
\end{array} \\
A \xrightarrow{\lambda} 2 A
\end{array}
$$

A particular case of a general gain-loss master equation

$$
\frac{d P_{n}(t)}{d t}=\sum_{m \neq n} W_{m n} P_{m}(t)-W_{n m} P_{n}(t) \quad W_{n m} \text { - transition matrix }
$$

Master equations are rarely soluble analytically

## Existing methods of dealing with single- and multi-step birth-death systems

- Fokker-Planck (FP) approximation - good for "typical behavior", fails for extreme statistics (Gaveau, Moreau, and Toth 1996, Doering, Sargsyan, and Sander 2005)
- Eikonal approximations: in the master equation (Dykman et.al. 1994), or in the PDE for the generating function (Elgart and Kamenev 2004) - significantly improve over FP, give new insight (optimal paths), but miss pre-exponents

Recent work by Kessler and Shnerb (2007) on branching-annihilation: WKB approximation etc. to quasi-stationary master equation

No general and self-contained analytical method to accurately calculate complete (incl. time-dependent) statistics, even for univariate problems

Can one go beyond the optimal path approximation?
Here comes the spectral method

## Step 1: employing the generating function

Define $\quad G(x, t)=\sum_{m=0}^{\infty} x^{m} P_{m}(t)$
The probabilities are recovered from $\quad P_{n}(t)=\left.\frac{1}{n!} \frac{\partial^{n} G(x, t)}{\partial x^{n}}\right|_{x=0}=\frac{1}{2 \pi i} \oint \frac{G(x, t)}{x^{n+1}} d x$
Master equation collapses into a single PDE $\quad \frac{\partial G(x, t)}{\partial t}=\hat{L}(x) G(x, t)$

| $0 \rightarrow j A$ |
| :--- |
| $A \rightarrow k A$ |
| $2 A \rightarrow m A$ | $\quad$| $P_{n}(t)$ |
| :--- |
| $n P_{n}(t)$ |
| $(1 / 2) n(n-1) P_{n}(t)$ |$\quad \sim$| $G(x, t)$ |
| :--- |
| $\partial_{x} G(x, t)$ |
| $\partial_{x}^{2} G(x, t)$ |

One boundary condition is universal

$$
G(x=1, t)=\left.\sum_{m=0}^{\infty} x^{m} P_{m}(t)\right|_{x=1}=\sum_{m=0}^{\infty} P_{m}(t)=1
$$

The mean extinction time

$$
<\tau_{\text {ext }}>\frac{\int_{0}^{\infty} t \dot{P}_{0}(t) d t}{\int_{0}^{\infty} \dot{P}_{0}(t) d t}=\frac{\int_{0}^{\infty} t t \frac{\partial G(0, t)}{\partial t} d t}{G(0, \infty)-G(0,0)}
$$

$\frac{\partial G(x, t)}{\partial t}=\frac{\mu}{2}\left(1-x^{2}\right) \frac{\partial^{2} G(x, t)}{\partial x^{2}}+\lambda x(x-1) \frac{\partial G(x, t)}{\partial x}$
$n_{0}$ particles at $t=0: \quad G(x, 0)=x^{n_{0}}$

First boundary condition $G(x=1, t)=1 \quad \begin{aligned} & \text { or we should rather say that the PDE is }\end{aligned}$ degenerate at $x=1$, so no $B C$ is needed

Second boundary condition follows from demand that all probabilities be non-negative and normalizable to unity

In this example it emerges at the singular point $x=-1$ of the corresponding $O D E$, see later.

$$
G(x=-1, t)=\sum_{m=0}^{\infty} P_{2 m}(t)-\sum_{m=0}^{\infty} P_{2 m+1}(t)<\infty
$$

## Step 2: steady state

$$
\text { Extinction, so we expect } \quad \lim _{t \rightarrow \infty} P_{0}(t)=1 \quad \Longleftrightarrow G_{s t}(x)=1
$$

Steady state equation

$$
0=\frac{\mu}{2}\left(1-x^{2}\right) G_{s t}^{\prime \prime}(x)+\lambda x(x-1) G_{s t}^{\prime}(x)
$$

$G$ bounded at $x=-1$

$$
\longmapsto \frac{d}{d x} G_{s t}(x=-1)=0
$$

$$
\Longleftrightarrow \quad G_{s t}(x)=1
$$

## Step 3: expanding in eigenfunctions

$$
g(x, t)=G(x, t)-G_{s t}(x)=G(x, t)-1=\sum_{k=1}^{\infty} a_{k} e^{-\gamma_{k} t} \varphi_{k}(x)
$$

$$
\left(1-x^{2}\right) \varphi_{k}^{\prime \prime}(x)-2 \Omega x(1-x) \varphi_{k}{ }^{\prime}(x)+2 E_{k} \varphi_{k}(x)=0 \quad E_{k}=\frac{2 \gamma_{k}}{\mu}
$$

$$
\text { boundedness of } \varphi_{k} \text { at } x=-1 \Longrightarrow\left\{\begin{array}{l}
\varphi_{k}(1)=0 \\
2 \Omega \varphi_{k}^{\prime}(-1)+E_{k} \varphi_{k}(-1)=0
\end{array}\right.
$$

self-adjoint form $\left\{\begin{array}{l}\frac{d}{d x}\left[e^{-2 \Omega x}(1+x)^{2 \Omega} \frac{d \varphi_{k}(x)}{d x}\right]+E_{k} w(x) \varphi_{k}(x)=0 \\ w(x)=2 e^{-2 \Omega x}(1+x)^{2 \Omega}\left(1-x^{2}\right)^{-1}\end{array}\right.$

Solving the whole set of self-adjoint ODEs with the homogenous BCs yields a complete orthogonal set $\left\{\varphi_{k}(x), E_{k}\right\}_{k=0}^{\infty}$ by virtue of Sturm-Liouville theory

## Step 4: projecting the initial condition and reconstructing $\mathbf{G}(x, t)$

$a_{k}$ determined by the initial condition

$$
\begin{aligned}
& G(x, 0)=\sum_{m=0}^{\infty} x^{m} P_{m}(t=0)=x^{n_{0}} \\
& a_{k}=\frac{\int_{-1}^{1}\left(x^{n_{0}}-1\right) \varphi_{k}(x) w(x) d x}{\int_{-1}^{1} \varphi_{k}^{2}(x) w(x) d x}, \text { where } \int_{-1}^{1} \varphi_{k}(x) \varphi_{l}(x) w(x) d x \propto \delta_{k l} \\
& G(x, t)=1+\sum_{k=1}^{\infty} a_{k} \varphi_{k}(x) e^{-\mu E_{k} t}
\end{aligned}
$$

$G(x, t)$ encodes the complete statistics, including large deviations. For example,

$$
<\tau_{e x t}>=-\frac{1}{\mu} \sum_{k=1}^{\infty} \frac{a_{k} \varphi_{k}(0)}{E_{k}}
$$

We obtained an exact mapping between solving the original, time-dependent master equation and finding the eigenvalues and eigenfunctions of a linear differential operator

## Solving for the eigenvalues and eigenfunctions

$$
\left(1-x^{2}\right) \varphi_{k}^{\prime \prime}(x)-2 \Omega x(1-x) \varphi_{k}^{\prime}(x)+2 E_{k} \varphi_{k}(x)=0
$$

This eqn. can be transformed into a zero-energy Schrödinger eqn.

$$
\begin{gathered}
\left\{-\frac{1}{2} \frac{d^{2}}{d x^{2}}+V\left(x, E_{k}\right)\right\} \psi_{k}(x)=0 \quad\left\{\begin{array}{l}
\psi_{k}(x)=(1+x)^{\Omega} e^{-\Omega x} \varphi_{k}(x) \\
V(x)=\frac{\Omega^{2} x^{2}-\Omega}{2(1+x)^{2}}-\frac{E_{k}}{1-x^{2}}
\end{array}\right. \\
E_{2}, E_{3}, \ldots \sim O(\Omega)
\end{gathered}
$$

$E_{1}$ exponentially small in $\Omega$

$$
G(x, t) \cong 1+a_{1} \varphi_{1}(x) e^{-\mu E_{1} t} \quad \text { for } \quad \mu t \gg \Omega^{-1}
$$

Highly lying states can be accurately calculated via WKB approx. (Assaf and Meerson 2006)

## Ground state calculation: a matched asymptotic expansion

Ground state problem

$$
\left(1-x^{2}\right) \varphi_{1}{ }^{\prime \prime}(x)-2 \Omega x(1-x) \varphi_{1}{ }^{\prime}(x)+2 E_{1} \varphi_{1}(x)=0
$$

with homogenous $\mathrm{BCs} \quad\left\{\begin{array}{l}\varphi_{1}(1)=0 \\ \varphi_{1}{ }^{\prime}(-1) \cong 0\end{array}\right.$
We solve the ODE separately in two different regions

$$
\begin{aligned}
& \varphi_{\text {bulk }}(x)=1+\delta \varphi(x) \quad \delta \varphi \ll 1 \\
& \delta \varphi^{\prime}(x)-\frac{2 \Omega x}{1+x} \delta \varphi^{\prime}(x) \cong-\frac{2 E_{1}}{1-x^{2}}
\end{aligned}
$$

$$
\varphi_{b u l k}(x)=1-E_{1} \delta \widetilde{\varphi}(x)
$$

$$
\varphi_{b l}{ }^{\prime \prime}(x)-\frac{2 \Omega x}{1+x} \varphi_{b l}{ }^{\prime}(x) \cong 0
$$

$$
\varphi_{b l}(x)=C\left[1-\frac{2^{2 \Omega}}{e^{2 \Omega}} \frac{e^{2 \Omega x}}{(1+x)^{2 \Omega}}\right]
$$



The unknowns $E_{1}$ and $C$ are found by asymptote matching in the common region

$$
\varphi_{1}(x)=\left\{\begin{array}{cc}
1-2 E_{1} \int_{0}^{x} \frac{e^{2 \Omega s}}{(1+s)^{2 \Omega}} d s \int_{-1}^{s} \frac{e^{-2 \Omega r}(1+r)^{2 \Omega}}{1-r^{2}} d r, & 1-x \gg \frac{1}{\Omega} \\
1-e^{2 \Omega(1-\ln 2)} \frac{e^{2 \Omega x}}{(1+x)^{2 \Omega}}, & 1-x \ll 1 \\
E_{1}=\frac{\Omega^{3 / 2} e^{-2 \Omega(1-\ln 2)}}{2 \sqrt{\pi}}
\end{array}\right.
$$

$$
G(x, t) \cong 1-\varphi_{1}(x) e^{-\mu E_{1} t}
$$

Indeed, for $n_{0} \gg 1$

$$
a_{1}=\frac{\int_{-1}^{1} \varphi_{1}(x)\left(x^{n_{0}}-1\right) 2 e^{-2 \Omega x}(1+x)^{2 \Omega}\left(1-x^{2}\right)^{-1} d x}{\int_{-1}^{1} \varphi_{1}^{2}(x) 2 e^{-2 \Omega x}(1+x)^{2 \Omega}\left(1-x^{2}\right)^{-1} d x} \cong-1
$$

## Average and variance of distribution

$$
\begin{cases}\bar{n}(t)=\sum_{n=0}^{\infty} n P_{n}(t)=\partial_{x} G(x=1, t) & \bar{n}(t)=\Omega e^{-\mu E_{1} t} \\ \sigma^{2}=\sum_{n=0}^{\infty} n^{2} P_{n}(t)-\left(\sum_{n=0}^{\infty} n P_{n}(t)\right)^{2}=\partial_{x}^{2} G(x=1, t)+\partial_{x} G(x=1, t)-\left[\partial_{x} G(x=1, t)\right]^{2} & \sigma^{2}=\left[\frac{3}{2} \Omega+\Omega^{2}\left(1-e^{-\mu E_{1} t}\right)\right] e^{-\mu E_{1} t}\end{cases}
$$



## Complete probability distribution

$$
P_{n}(t)=\left.\frac{1}{n!} \frac{\partial^{n} G(x, t)}{\partial x^{n}}\right|_{x=0}=\delta_{0 n}-\frac{1}{n!} \frac{d^{n} \varphi(x=0)}{d x^{n}} e^{-\mu E_{1} t}
$$

$$
\left\{P_{0}(t) \approx 1-e^{-\mu E_{1} t} \mu t \gg \Omega^{-1}\right.
$$

$$
P_{n>0}(t)=\frac{2 E_{1}(2 \Omega)^{n-1} e^{2 \Omega} \Gamma(2 \Omega)}{n \Gamma(2 \Omega+n)}{ }_{1} F_{1}(\underbrace{(2 \Omega, n+2 \Omega,-2 \Omega) e^{-\mu E_{1} t}}
$$

Kummer confluent hypergeometric function.
(Actually, one must use the $\Omega \gg 1$ asymptote
of this result, see Assaf and Meerson 2007)

For $\quad|n-\Omega| \ll \Omega$

$$
P_{n}^{C}(t) \cong \frac{1}{\sqrt{3 \pi \Omega}} e^{-\frac{(n-\Omega)^{2}}{3 \Omega}-\mu E_{1} t}
$$

A Gaussian with mean $\Omega$ and variance $3 \Omega / 2$
$<\tau_{\text {ext }}>=\int_{0}^{\infty} t \frac{d P_{0}(t)}{d t} d t \approx\left(\mu E_{1}\right)^{-1}=\frac{2 \sqrt{\pi}}{\mu \Omega^{3 / 2}} e^{2 \Omega(1-\ln 2)} \quad \begin{aligned} & \text { agrees with Turner and Malek-Mansour (1978); } \\ & \text { exponent agrees with Elgart and Kamenev (2004) }\end{aligned}$

## Comparison with Fokker-Planck approximation

Assume $n \gg 1$ and expand in Taylor series up to the second order in $1 / \Omega$
$\dot{P}_{n}=\frac{\mu}{2}\left[(n+2)(n+1) P_{n+2}-n(n-1) P_{n}\right]+\lambda\left[(n-1) P_{n-1}-n P_{n}\right]$

$$
\begin{aligned}
& P(n-1, t) \cong P(n, t)-\frac{\partial P(n, t)}{\partial n}+\frac{1}{2} \frac{\partial^{2} P(n, t)}{\partial n^{2}} \\
& P(n+2, t) \cong P(n, t)+2 \frac{\partial P(n, t)}{\partial n}+2 \frac{\partial^{2} P(n, t)}{\partial n^{2}}
\end{aligned}
$$

$$
\text { Kramers - Moyal expansion } \quad n \rightarrow \Omega x \quad \frac{\partial}{\partial n} \rightarrow \frac{1}{\Omega} \frac{\partial}{\partial x}
$$

$$
\frac{\partial P(n, t)}{\partial t}=\frac{\mu}{2} \frac{\partial}{\partial n}\left\{-2 n(\Omega-n) P(n, t)+\frac{1}{2} \frac{\partial}{\partial n}[2 n(2 n+\Omega) P(n, t)]\right\}
$$

(Zero flux) steady state probability distribution

$$
P^{F P}(n, t) \cong \frac{1}{\sqrt{3 \pi \Omega}} e^{\Omega-n+\frac{3}{2} \Omega \ln \frac{2 n+\Omega}{3 \Omega}}
$$

For $|n-\Omega| \ll \Omega$

$$
\begin{aligned}
& \left.P^{F P}(n, t)=\frac{1}{\sqrt{3 \pi \Omega}} e^{-\frac{( }{2}}(n+1, t) \right\rvert\, \cong 1-e^{-1} \nmid<1
\end{aligned}
$$

$$
\left|1-\frac{P^{F P}(n+1, t)}{P^{F P}(n, t)}\right| \cong 1-e^{-\frac{1}{3 \Omega}} \ll 1
$$

For $\mathrm{n} \gg \Omega \quad\left|1-\frac{P^{F P}(n+1, t)}{P^{F P}(n, t)}\right| \cong 1-e^{-1} \nless 1$
FP fails in tails
For $\mathrm{n} \sim 1 \mathrm{FP}$ is inapplicable too.



Extinction time (spectral method) ~ Exp[ $\Omega(2-2 \ln 2)]$
Extinction time (Fokker-Planck) ~ $\operatorname{Exp}\{\Omega[(3 / 2) \ln 3-1]\}$ includes an exponentially large error

## Different definitions related to quasi-stationarity/metastability

1. Quasi-stationary distribution = amplitude $P_{n}{ }^{(0)}$ of long-time asymptote of the timedependent pdf

$$
P_{n>0}(t)=P_{n}{ }^{(0)} e^{-\mu E_{1} t}=-\frac{1}{n!} \frac{d^{n} \varphi(x=0)}{d x^{n}} e^{-\mu E_{1} t}
$$

2. Stationary distribution obtained by assuming zero flux to $n=0$

## Definitions 1 and 2 are different

In the branching-annihilation example def. 2 gives the same result as def. 1 in the leading order in $1 / \Omega$. Sub-leading terms might be different. In the SIS problem def. 2 gives a different result already in the leading order, Nåsell 2001. It might be meaningless to pursue to a high accuracy while using def. 2.

## Is spectral method generalizable to two and more species?

Generating function for two species

$$
G\left(x_{1}, x_{2}, t\right)=\sum_{m, n=0}^{\infty} x_{1}^{m} x_{2}^{n} P_{m n}(t)
$$

The master equation transforms to $\frac{\partial G(\mathbf{x}, t)}{\partial t}=\hat{L}(\mathbf{x}) G(\mathbf{x}, t), \quad \mathbf{x}=\left(x_{1}, x_{2}\right)$

This parabolic PDE demands, in addition to the initial condition, a boundary condition on a closed curve (finite or infinite) in the plane ( $x_{1}, x_{2}$ ). This BC must follow from the boundedness and nonnegativeness of the probabilities, and is yet unknown.

The eikonal approaches circumvent the need for the explicit $B C$.

## Conclusions

- We developed a simple spectral approach for univariate birth-death processes that employs the generating function technique in conjunction with Sturm-Liouville theory
- The spectral approach yields accurate rare-event statistics for singlestep and multiple-step processes, where other methods in general fail

