



UNIVERSITY OF CORDOBA
INSTITUTE OF POSTGRADUATE STUDIES



UNIVERSITY MASTER'S DEGREE

**PHYSICAL TECHNOLOGY:
RESEARCH AND APPLICATIONS**

MASTER'S THESIS

**Exploring the relationship between Hawkes processes
and self-organized criticality in living systems**

Antonio Rivas Blanco

Tutor(s): Jorge Hidalgo Aguilera and Serena di Santo

Line of research: Modelling of complex systems and their interdisciplinary applications

Córdoba, 07/2024

Autorización de defensa del Trabajo Fin de Máster

Tutor 1: Jorge Hidalgo Aguilera

Tutor 2: Serena di Santo

INFORMAN: Que el presente trabajo titulado *Exploring the relationship between Hawkes processes and self-organized criticality in living systems* que constituye la memoria del Trabajo Fin de Máster ha sido realizado por Antonio Rivas Blanco y AUTORIZA/N su presentación para que pueda ser defendido en la convocatoria 1^a con fecha 23/07/2024.

Firmado en Córdoba a X de julio de 2024

Tutor 1: Jorge Hidalgo Aguilera

Tutor 2: Serena di Santo

Declaración de autoría

Nombre y apellidos: Antonio Rivas Blanco
DNI: 49832223D

DECLARA

1. Que el trabajo que presenta es totalmente original y que se hace responsable de todo su contenido.
2. Que no ha sido publicado no total ni parcialmente.
3. Que todos los aportes de otros autores/as han sido debidamente referenciados.
4. Que no ha incurrido en fraude científico, plagio o vicios de autoría.
5. Que, en caso de no cumplir los requerimientos anteriores, aceptará las medidas disciplinarias sancionadoras que correspondan.

Firmado en Córdoba a, X de julio de 2024

Contents

Contents	III
List of Figures	IV
List of Tables	V
Abstract. Keywords	1
1 Introduction	2
1.1 Criticality and its presence in living systems	2
1.2 Point processes	2
1.2.1 Poisson processes	3
1.2.2 Hawkes processes	4
2 Objectives	9
3 Methodology	10
3.1 Time series factory	10
3.2 When physics and cooking merge	13
4 Results	17
4.1 Results from the original paper	17
4.2 Results for $n=2$	19
4.3 Inhibitory and excitatory neurons coupled	21
5 Conclusions	22
A Python scripts	24

List of Figures

1.1	Representation of a point process. The intensity function $\lambda(t)$ is a time-dependent function.	3
1.2	Left: event number in time for different rates. Right: Probability of having a certain number of events for different rates.	4
1.3	On the left, a temporal series of $K = 150$ events of a Hawkes process with $\mu = 0.01$, on the right, a raster plot of the same process.	5
1.4	On the left, a temporal series of $K = 150$ events of a Hawkes process with $\mu = 0.01$, on the right, a raster plot of the same process.	5
1.5	First, a temporal series of $K = 10^5$ events of a Hawkes process with $\mu = 0.01$, on the right, the event distribution.	6
1.6	First, a temporal series of $K = 10^5$ events of a Hawkes process with $\mu = 10$, on the right, the event distribution.	6
1.7	On the left, a temporal series of $K = 10^5$ events of a Hawkes process with $\mu \in \{10^{-2}, 10^2\}$ and $n = 2$, on the right, the λ distribution versus the event number. . . .	7
1.8	Raster plots of Hawkes processes with $n = 2$. In both cases, the number of events is $K = 10^3$, they also have the same structure, the first event, on average, happens in $\mu^{-1}a.u.$ of time; then, an avalanche of events takes place.	7
1.9	Scheme of the interaction between the excitatory and inhibitory populations. As illustrated, the excitatory population can excite itself and the inhibitory population, while the inhibitory population can only inhibit the excitatory population, because on most cases the auto-inhibition is negligible [9].	8
3.1	Diagram to calculate the cumulative probability of the inter-event time.	11
3.2	Five a temporal series of $K = 10^5$ events of Hawkes processes with $\mu = 10^{-4}$ on the left side and $\mu = 10^2$ on the right one.	15
3.3	Diagram for $\mu \ll 1$. Red lines represent the events, clusters are coloured. As we can see, we have two regimes, one when Δ is of the order of the average cluster size and another when is of the order of the inter-event time where the system percolates. . . .	16
3.4	Diagram for $\mu \gg 1$. Red lines represent the events, clusters are coloured. In this situation, events occur more regularly, resulting in a unique transition corresponding the case of Δ is similar to the inter-event time producing the system percolation. . . .	16
4.1	Percolation phase diagrams for different event number K taking average values of $R = 1000$ realizations.	17
4.2	Avalanche statistics for a self-exciting Hawkes process with $n = 1$ for $K = 10^5$ events averaged over $R = 1000$ realizations.	18
4.3	Time series for $n = 1$ and $n = 2$	19
4.4	Percolation phase diagrams for a Hawkes process with $n = 2$	19
4.5	Avalanche statistics for a self-exciting Hawkes process with $n = 2$ for $K = 10^5$ events averaged over $R = 1000$ realizations.	20

List of Tables

3.1 Configuration of the parameters for the simulations of [5]. 14

List of Algorithms

1	Slow method to generate Hawkes processes.	10
2	Algorithm to generate K Hawkes events.	13
3	Algorithm to generate K Hawkes events for two coupled processes.	14

Abstract

Chapter 1

Introduction

ESTRUCTURA:

The following Master's thesis is divided into 5 chapters. In the first chapter, we will introduce the concept of criticality in complex systems, both in living and non-living systems. We will also make a brief summary of stochastic and their relation with point processes and Hawkes processes, which are the main focus of this work. After that, we will present the objectives of this work. In the third chapter, we will present the methodology used in this work, including the simulation of Hawkes processes, the phase diagram of the process, and the avalanche analysis. In the penultimate chapter, we will present the results of the simulations, including the phase diagram of the process, the susceptibility analysis, and the avalanche analysis and we will discuss them. Finally, in the fifth chapter, we will present the conclusions of this work and the future lines of research.

1.1 Criticality and its presence in living systems

For the first simulations, we will fix $n = 1$, making our self-excitation critical.

The concept of criticality is a central idea in the study of complex systems. It is a state of the system where the dynamics of the system are scale-invariant, which means that the dynamics of the system are the same at different scales. This means that the system is at the edge of chaos, where the system is neither ordered nor disordered. This state is characterized by the presence of avalanches of activity that follow a power-law distribution. This means that the probability of having an avalanche of size s is proportional to $s^{-\tau}$, where τ is the exponent of the power-law distribution. This state is present in many systems such as earthquakes, forest fires, or the brain. In the brain, it is believed that the critical state is the optimal state for information processing, as it allows the system to respond quickly to stimuli and to have a high capacity for information storage. This state is also associated with the presence of avalanches of activity that follow a power-law distribution. This means that the probability of having an avalanche of size s is proportional to $s^{-\tau}$, where τ is the exponent of the power-law distribution. This state is present in many systems such as earthquakes, forest fires, or the brain. In the brain, it is believed that the critical state is the optimal state for information processing, as it allows the system to respond quickly to stimuli and to have a high capacity for information storage.

1.2 Point processes

Within the large framework of complex systems, stochastic processes lend us a hand to decypher properties of living systems, bridging randomness with structured behaviour. This processes are used

to model the dynamics of systems which evolve randomly in time. This is why they are ideal for describing natural phenomena such as the spread of diseases [1], social networks [2] or ecological systems [3]. Mathematically, a stochastic process is a collection of random variables [4], generally ordered in time $\{X_t\}_{t \in T}$, where t is the time and X_t is the system state at time t . T is the time index set, which can be discrete or continuous, in this work we will focus on the discrete case because we are interested in the study of point (Hawkes) processes for modeling neurons.

Point processes are a type of stochastic process that describe the occurrence of events in time or space. We will be interested in time point processes because we are going to model the spiking activity of neurons. For our purposes, they will be characterized by two parameters, the time of occurrence of the events t_k and the intensity or rate of occurrence of these events λ . This rate tell us how likely is that an event occurs at time t given the history of the process (probability density function, PDF) as pictured in Figure 1.1.

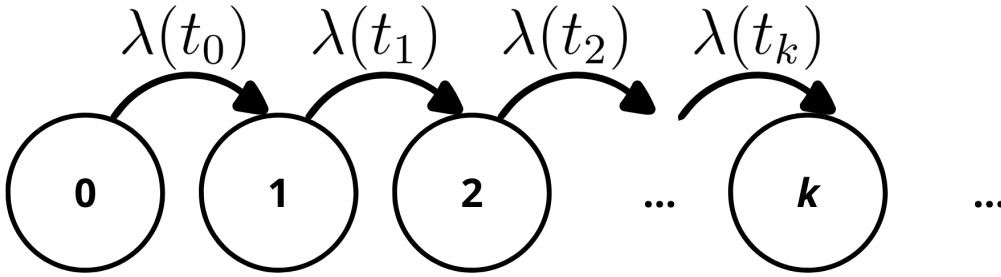


Figure 1.1. Representation of a point process. The intensity function $\lambda(t)$ is a time-dependent function.

1.2.1 Poisson processes

In general, the rate is a function of the history of the process, which makes the process non-Markovian, but in our case, it will be a Markovian process, which means that the rate depends only on the last event that occurred as we will see. An example of a Markovian point process is the Poisson process, which is a simple and one of the most studied point processes because they are present in many everyday situations such as the arrival of customers at a store, occurrence of defects on a Production line. They are also present in some physics phenomena, for instance, the decay of radioactive particles or the arrival of photons at a detector. These processes are characterized by a rate of occurrence of events λ . The dynamics of these processes are described by the Poisson distribution which is the probability distribution of a random variable N such that the probability that $N = n$ is:

$$P(N = n) = \frac{\lambda^n}{n!} e^{-\lambda}. \quad (1.1)$$

Furthermore, the mean value and the variance of the distribution are also equal to λ . Poisson processes can be homogeneous or inhomogeneous, depending on whether the rate is constant or time-dependent. In Figure 1.2 we can see an example of a homogeneous Poisson process.

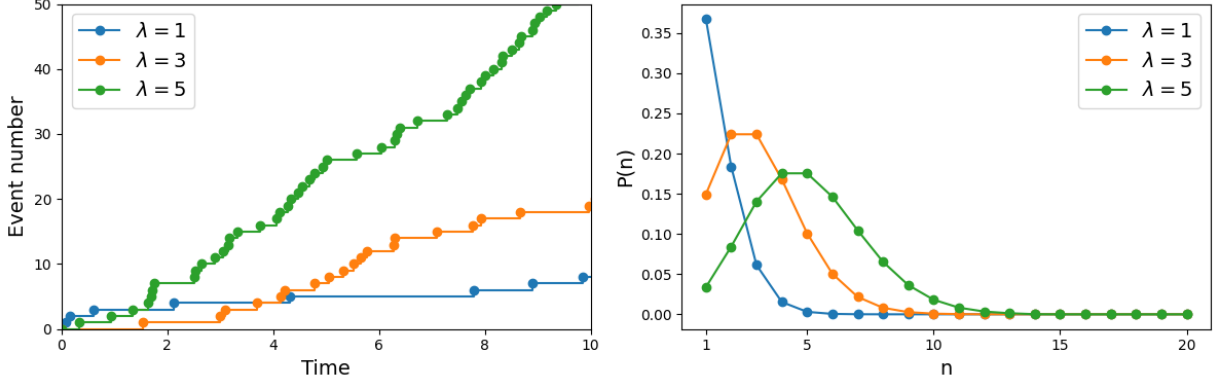


Figure 1.2. Left: event number in time for different rates. Right: Probability of having a certain number of events for different rates.

1.2.2 Hawkes processes

On the other hand if we consider a non-homogeneous Poisson process, the rate is a function of time, $\lambda(t)$, which is the case of the Hawkes process. The rate can be written in several ways [5, 6, 7, 8]. We will use the expression from [5]:

$$\lambda(t|t_1, \dots, t_k) = \mu + n \sum_{i=1}^k \phi(t - t_i), \quad (1.2)$$

where μ is the background rate of a homogeneous Poisson process, n is a parameter that controls the strength the self-excitation, and $\phi(t)$ is the kernel function that describes the influence of the past events on the rate of occurrence of the events. The kernel function is a non-negative and monotonically non-increasing function that integrates to 1. Typical choices for the kernel function are the exponential or the power-law functions. In this work we will focus on the exponential kernel. From Eq 1.2 we can see that the rate depends on the history of the process, making it non-Markovian in general, but with an exponential kernel, the process becomes Markovian. The kernel function can be written as: $\phi(t) = \sum_{t_i < t} \alpha e^{-\beta(t-t_i)}$ so the rate becomes:

$$\begin{aligned} \lambda(t) &= \mu + \sum_{t_i < t} \alpha e^{-\beta(t-t_i)} \\ &= \mu + \sum_{\substack{t_i < t_k \\ t_k: \text{last event}}} \alpha e^{-\beta(t-t_k+t_k-t_i)} \\ &= \mu + e^{-\beta(t-t_k)} \underbrace{\sum_{t_i < t_k} \alpha e^{-\beta(t_k-t_i)}}_{\lambda(t_k)} \\ &= \mu + e^{-\beta(t-t_k)} (\lambda(t_k) - \mu + \alpha). \end{aligned} \quad (1.3)$$

Where we have used the following expression for the rate of the Hawkes process at time t_k :

$$\lambda(t_k) = \mu + \sum_{t_i < t_k} \alpha e^{-\beta(t_k - t_i)} \Rightarrow \sum_{t_i < t_k} \alpha e^{-\beta(t_k - t_i)} = \lambda(t_k) - \mu + \alpha \quad (1.4)$$

Despite being a Markovian process, it is still an inhomogeneous Poisson process because the rate is not constant. In addition, it is a self-exciting process, which means that the occurrence of an event increases the probability of the occurrence of another event. This is why it is used to model the spiking activity of neurons, where the occurrence of a spike increases the probability of the occurrence of another spike. This self-excitation will enable the appearance of bursts of activity that we will measure. The parameters chosen for the kernel function will be $\alpha = \beta = 1$ and we will vary the background rate μ from values much smaller than 1 to values greater than 1. In Figures 1.3 and 1.4 we can see typical diagrams of Hawkes processes with these parameters.

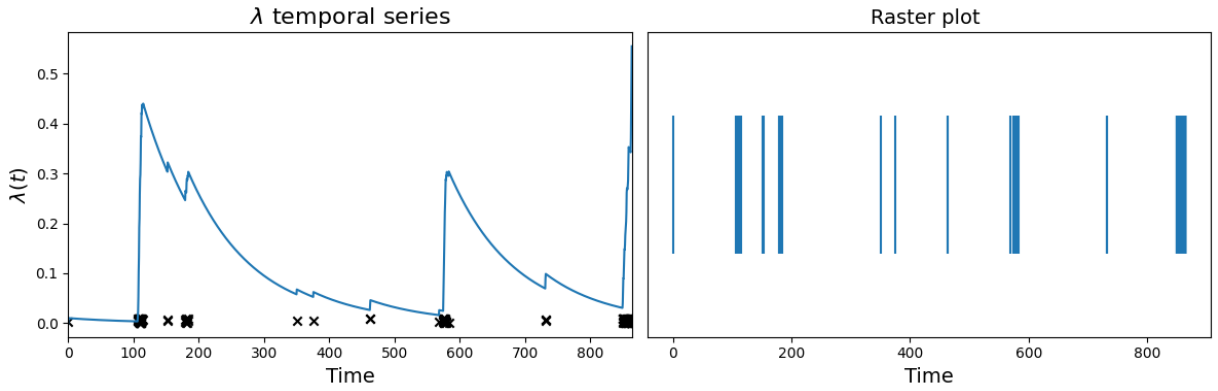


Figure 1.3. On the left, a temporal series of $K = 150$ events of a Hawkes process with $\mu = 0.01$, on the right, a raster plot of the same process.

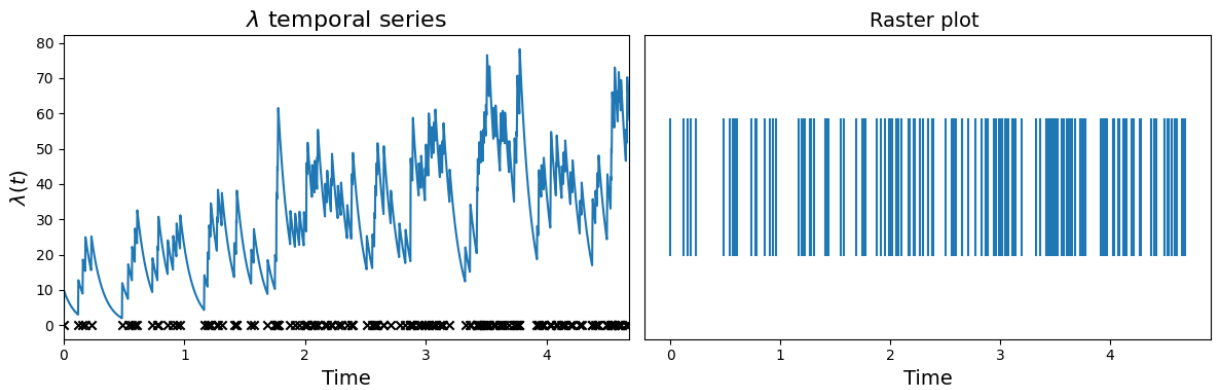


Figure 1.4. On the left, a temporal series of $K = 150$ events of a Hawkes process with $\mu = 0.01$, on the right, a raster plot of the same process.

As shown in Figure 1.3, when the background rate is smaller than 1, events are less likely to occur, but when they do, they tend to form avalanches of activity thanks to the self-excitation. On the other

hand, when the background rate is greater than 1, events occur more frequently, forming avalanches of activity more frequently and longer, as shown in Figure 1.4. If we ignore the time of occurrence of the events and we focus only on the structure of λ and therefore of the events, we can see that the process with $\mu = 0.01$ has a bursty structure, while the process with $\mu = 10$ has a more regular structure. This phenomenon is exposed in Figures 1.5 and 1.6.

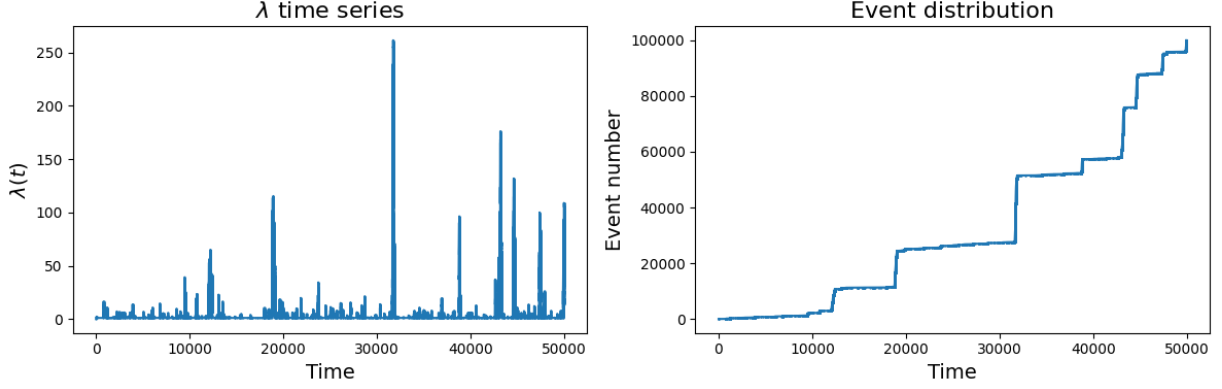


Figure 1.5. First, a temporal series of $K = 10^5$ events of a Hawkes process with $\mu = 0.01$, on the right, the event distribution.

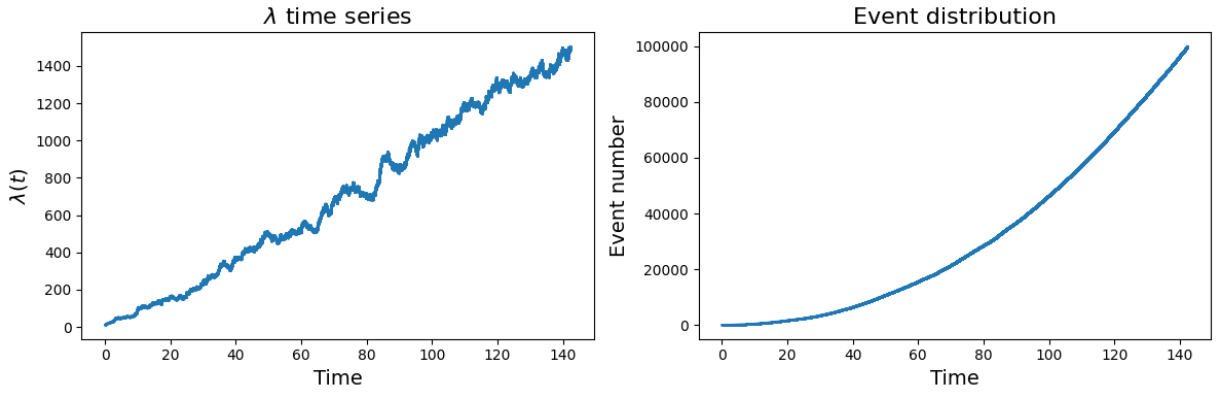


Figure 1.6. First, a temporal series of $K = 10^5$ events of a Hawkes process with $\mu = 10$, on the right, the event distribution.

In most cases, the motivation of study of point processes is counting the events, but in our case we also are interested in the time of occurrence of the events which will let us define bursts or avalanches of activity that we will use to describe the dynamics of the system. As we have said previously $\alpha = 1$, $\beta = 1$, making n the parameter that controls the weight of the self-excitation. Essentially, n and α play the same role, so we will use them indistinctly. The previous figures showed the dynamics for $n = 1$, making the system critical as a critical branching process PONER ALGO AQUÍ EN REFERENCIA A LA SECCIÓN ANTERIOR [5]. , but we will also study the dynamics for $n = 2$ and two coupled Hawkes processes.

Hawkes processes with $n = 2$

In this case, the self-excitation does not lead to a critical dynamic, but to a supercritical dynamic. In this situation, the time until the first event occur is given in mean by μ^{-1} , after it occurs, an avalanche of activity starts as shown in Figure 1.7.

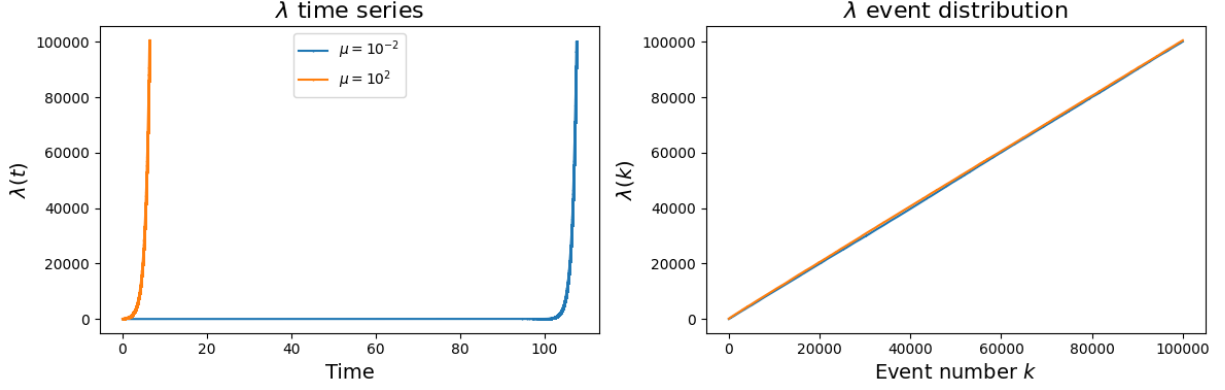


Figure 1.7. On the left, a temporal series of $K = 10^5$ events of a Hawkes process with $\mu \in \{10^{-2}, 10^2\}$ and $n = 2$, on the right, the λ distribution versus the event number.

As expected, after the first event, we have an exponential increase in time and a linear increase in the number of events for the rate. This behaviour will change also the structure of the raster plots, which are where we will get the dynamics information. In Figures 1.8(a) and 1.8(b) two raster plots are shown for the two different background intensities.

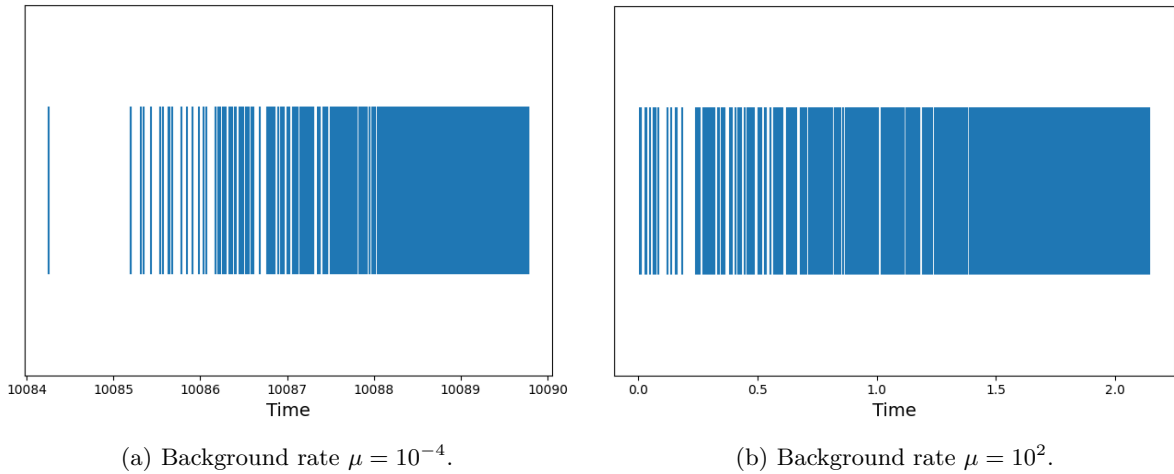


Figure 1.8. Raster plots of Hawkes processes with $n = 2$. In both cases, the number of events is $K = 10^3$, they also have the same structure, the first event, on average, happens in $\mu^{-1} a.u.$ of time; then, an avalanche of events takes place.

Coupled Hawkes processes

With the previous knowledge, we can model an isolated neuron working in different regimes, but as we know, the brain is composed of an enormous amount of neurons connected to each other forming a network. Moreover, neurons can be classified into two kinds, excitatory and inhibitory neurons. To get closer to modelling the brain, we will also generate two coupled Hawkes processes, one corresponding to an excitatory population and the other to an inhibitory population or just an excitatory and inhibitory neuron. Both populations (neuron) will have a background rate μ_E and μ_I , and they will be able to interact with each other and with themselves, the “strength” of the interactions will be controlled by the parameters n_{EE} , n_{EI} , n_{IE} and n_{II} . In most cases, the auto-inhibition can be considered negligible. These interactions are illustrated in Figure 1.9.

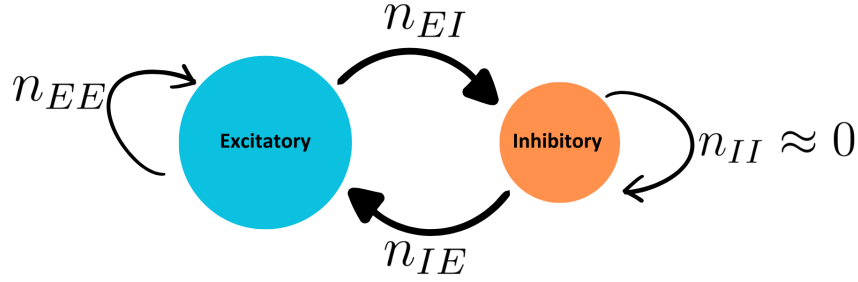


Figure 1.9. Scheme of the interaction between the excitatory and inhibitory populations. As illustrated, the excitatory population can excite itself and the inhibitory population, while the inhibitory population can only inhibit the excitatory population, because on most cases the auto-inhibition is negligible [9].

In a similar way to the previous cases, the background rates will only change time until the first event occurs, but signals will only rely on the “strength” $N_{i,j}$ of the interactions. Studying this parameter space, the different phases and the respective avalanche statistics could be a Master’s thesis in itself. That is why we will only look at a few parameter configurations.

Chapter 2

Objectives

Ordenar los objetivos una vez escrito el trabajo para que coincidan con como se presenta.

The main objectives of this Master's thesis are:

- To understand what Hawkes processes are, where we can find them, how to generate them computationally and relate them with neuroscience.
- To understand the importance of time binning and reproduce the results of the original paper [5] and compare them with the results obtained in this work.
- ¿Criticality?
- To study the behaviour of a self-exciting process with $n = 2$ and compare it with the case $n = 1$.
- To study the behaviour of an inhibitory and excitatory neuron coupled.

Chapter 3

Methodology

In the following sections, the methodology for data generation, management and analysis will be presented. To address these issues, we will use Python [10, 11] due to its versatility and the wide range of libraries available. The two used will be NumPy [12] and Matplotlib [13] for the visualization.

3.1 Time series factory

The first step is the generation of time series, there are two ways to do this: the slow one and the fast one. The first one is discretizing the time and calculating the rate at each time step according with Eq 1.2, then accept or reject the event if $p < \lambda \cdot dt$ for a random number $p \in \mathcal{U}[0, 1]$. This method works for small time series, but for large ones is not efficient because the summation of the kernel function has to be done at each time step. The pseudo-code for this method is presented in Algorithm 1.

Algorithm 1 Slow method to generate Hawkes processes.

Require: t_{max} , $n_{intervals}$, $\lambda(t_0) = \mu$, p

$$dt \leftarrow \frac{t_{max}}{n_{intervals}}$$

for $i = 0$ to $n_{intervals}$ **do**

$$\lambda(t_k) \leftarrow \mu + n \sum_{t_i < t_k} \phi(t_k - t_i)$$

$$\triangleright t_i = i \cdot dt$$

if $\lambda(t_k) \cdot dt > p$ **then**

$$t_{event} \leftarrow t_k$$

end if

end for

The fast method takes advantage of Monte Carlo methods [14] to generate the time series. The idea of this procedure consists in computing the inter-event time instead of the time of the event. To get to the algorithm, we start from the following expression:

$$PDF(\text{inter-event time} = \Delta t) = \lambda(t + \Delta t) e^{-\int_t^{t+\Delta t} \lambda(t') dt'} \quad (3.1)$$

To demonstrate this, we have to take a look at the Figure 3.1 and recall that λ is a probability per unit of time.

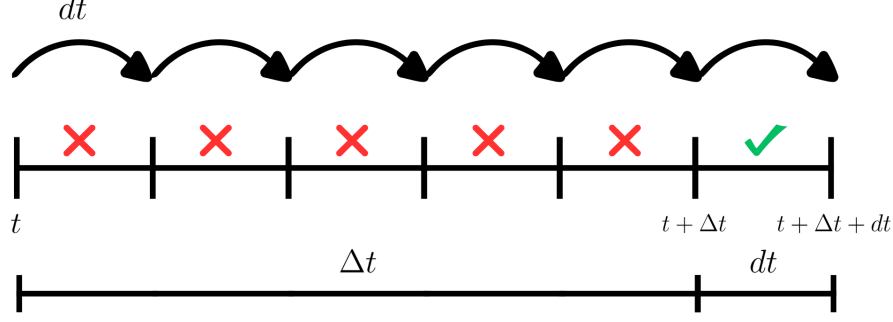


Figure 3.1. Diagram to calculate the cumulative probability of the inter-event time.

The probability per unit of time of having an event in the interval $[t + \Delta t, t + \Delta t + dt]$ is the probability of no events in the interval $[t, t + \Delta t]$ times the probability of happening in the interval $[t + \Delta t, t + \Delta t + dt]$. Putting words into mathematics, we have that the probability of not having an event in the interval $[t, t + \Delta t]$ is:

$$\begin{aligned}
 P(\text{event} \in [t + \Delta t + dt]) &= (1 - \lambda(0) \cdot dt) (1 - \lambda(dt) \cdot dt) (1 - \lambda(2dt) \cdot dt) \dots \\
 &= \prod_{k=0}^{\infty} \underbrace{(1 - \lambda(kdt) \cdot dt)}_{e^{\ln(1 - \lambda(kdt)dt)}} = e^{\sum_{k=0}^{\infty} \ln(1 - \lambda(kdt)dt)} = \dots \quad \text{Using } \ln(1 - \varepsilon) \approx -\varepsilon \\
 &= e^{-\sum_{k=0}^{\infty} \lambda(kdt)dt} \underset{dt \rightarrow 0}{=} e^{-\int_t^{t+\Delta t} \lambda(t')dt'}.
 \end{aligned} \tag{3.2}$$

Knowing that the probability of having an event in the interval $[t + \Delta t, t + \Delta t + dt]$ is $\lambda(t + \Delta t)dt$, we have:

$$P(\text{event} \in [t + \Delta t, t + \Delta t + dt])d\mathcal{t} = \lambda(t + \Delta t)dt \cdot e^{-\int_t^{t+\Delta t} \lambda(t')dt'} \times PDF(\text{inter-event time} = \Delta t)d\mathcal{t}. \tag{3.3}$$

Having that we can calculate the inter-event time following the next steps.

$$PDF(\text{inter-event time} = \Delta, t) = \lambda(t + \Delta t) \times \underbrace{e^{\int_t^{t+\Delta t} \lambda(t')dt'}}_{\text{No events during } (t, t+\Delta t)}$$

In order to generate Δt , we will use the inverse transform method [15], therefore we have to calculate the cumulative probability of the inter-event time:

$$\begin{aligned}
 \text{accum}(\Delta t) &= \int_0^{\Delta t} PDF(\Delta t') d\Delta t' = u \in \mathcal{U}[0, 1] \\
 &= \int_0^{\Delta t} \underbrace{\lambda(t + \Delta t') e^{\int_t^{t+\Delta t'} \lambda(t')dt'}}_{-\frac{d}{d\Delta t'} \left[e^{-\int_t^{t+\Delta t} \lambda(t')dt'} \right]} d\Delta t' = u \quad \text{Using Barrow rule} \\
 &= e^{-\int_t^{t+\Delta t} \lambda(t')dt'} \Big|_0^{\Delta t} = 1 - e^{-\int_t^{t+\Delta t} \lambda(t')dt'} = u \quad \text{Taking logarithms} \\
 &\int_t^{t+\Delta t} \lambda(t')dt' = -\ln(1 - u) = \ln(\bar{u})
 \end{aligned} \tag{3.4}$$

To compute the inter-event time, we have to generate $\bar{u} \sim$ and solve the equation. Having in mind this relation and using Eq 1.4 we have: EN EL LA ECUACIÓN REFERENCIADA Y LA SEGUNDA EXPONENCIAL SE PUEDE PONER $\lambda(t_k^-)$ en lugar de $\lambda(t_k)$? .

$$\begin{aligned}
u &= 1 - e^{-\mu(t-t_k)} e^{-\underbrace{(\lambda(t_k)+\alpha-\mu) \cdot \int_{t_k}^t e^{-\beta(t'-t_k)} dt'}_{-\frac{1}{\beta} [e^{-\beta(t-t_k)}-1]}} \\
u &= 1 - \underbrace{e^{-\mu(t-t_k)}}_{P(t_{k+1}^{(1)} > t)} \underbrace{e^{-[(\lambda(t_k)+\alpha-\mu)\beta^{-1}(1-e^{-\beta(t-t_k)})]}}_{P(t_{k+1}^{(2)} > t)}
\end{aligned} \tag{3.5}$$

Then we apply the composition method [7]. If we take $t_{k+1} = \min(t_{k+1}^{(1)}, t_{k+1}^{(2)})$; then $t_{k+1} \sim P(t_{k+1} > t)$, hence:

$$\begin{aligned}
\text{Prob}(t_{k+1} = \min(t_{k+1}^{(1)}, t_{k+1}^{(2)}) \leq t) &= 1 - \text{Prob}\left(\min(t_{k+1}^{(1)}, t_{k+1}^{(2)}) > t\right) \\
&= 1 - \text{Prob}(t_{k+1}^{(1)} > t) \cdot \text{Prob}(t_{k+1}^{(2)} > t)
\end{aligned} \tag{3.6}$$

where we have used that the probability that the smaller is greater than t is that each separately is greater than t because both have to be greater than t . As we can see the expressions in Eqs 3.5 and 3.6 are the same, so we can use the composition method to generate the inter-event time. Then, the algorithm to generate the inter-event time is:

1. Generate $t_{k+1}^{(1)} \sim P(t_{k+1}^{(1)} > t) = e^{-\mu(t-t_k)}$ using

$$P(t_{k+1}^{(1)} \leq t) = 1 - \underbrace{e^{-\mu(t-t_k)}}_{\substack{\bar{u}_1 \in \mathcal{U}[0,1] \\ 1-\bar{u}_1=u_1}} = u_1 \in \mathcal{U}[0,1]$$

This is done by generating $u_1 \in \mathcal{U}[0,1]$ and solving the equation.

$$\begin{aligned}
u_1 &= 1 - e^{-\mu(t_{k+1}^{(1)}-t_k)} \\
\ln(u_1) &= -\mu(t_{k+1}^{(1)}-t_k) \Rightarrow t_{k+1}^{(1)} = t_k - \frac{\ln(u_1)}{\mu}
\end{aligned} \tag{3.7}$$

2. Generate $t_{k+1}^{(2)} \sim P(t_{k+1}^{(2)} > t) = e^{-\left((\lambda(t_k)+\alpha-\mu)\beta^{-1}\left(1-e^{-\beta(t_{k+1}^{(2)}-t_k)}\right)\right)}$ in a similar way as before:

$$\begin{aligned}
u_2 &= 1 - e^{-\left((\lambda(t_k)+\alpha-\mu)\beta^{-1}\left(1-e^{-\beta(t_{k+1}^{(2)}-t_k)}\right)\right)} \\
-\ln(u_2) &= \left((\lambda(t_k)+\alpha-\mu)\beta^{-1}\left(1-e^{-\beta(t_{k+1}^{(2)}-t_k)}\right)\right) \\
1 + \frac{\beta \ln u_2}{\lambda(t_k) + \alpha - \mu} &= e^{-\beta(t_{k+1}^{(2)}-t_k)} \\
t_{k+1}^{(2)} &= t_k - \beta^{-1} \ln \underbrace{\left(1 + \frac{\beta \ln u_2}{\lambda(t_k) + \alpha - \mu}\right)}_{\text{This number must be positive}}
\end{aligned} \tag{3.8}$$

3. Choose $t_{k+1} = \min \left(t_{k+1}^{(1)}, t_{k+1}^{(2)} \right)$
4. Calculate the rate at t_{k+1} using Eq 1.3 and go back to step 1.

With this method, we can generate time series efficiently. The pseudo-code for this method is presented in Algorithm 2.

Algorithm 2 Algorithm to generate K Hawkes events.

Require: $\alpha, \beta, \lambda(t_0) = \mu, K$
for $k = 0$ to K **do**
 $u_1, u_2 \leftarrow \mathcal{U}[0, 1]$
 $t_{k+1}^{(1)} \leftarrow \frac{\ln(u_1)}{\mu}$
 $t_{k+1}^{(2)} \leftarrow \beta^{-1} \ln \left(1 + \frac{\beta \ln u_2}{\lambda(t_k) + \alpha - \mu} \right)$
 $t_{k+1} \leftarrow \min \left(t_{k+1}^{(1)}, t_{k+1}^{(2)} \right)$
 $\lambda(t_{k+1}) \leftarrow \mu + e^{-\beta(t_{k+1}-t_k)} (\lambda(t_k) - \mu + n)$
end for

To conclude generation of time series section, we can generalise the algorithm in order to generate M Hawkes processes coupled [7, 8]. The essence of the algorithm is the same as the one presented. First, we generate the inter-event time for the excitatory population and the inhibitory population, after that, we choose the minimum of both and update the rates of both populations according to the event that has just occurred. Mathematically it is expressed as follows:

1. Generate $\Delta_{k+1} = \min \left\{ \Delta_{k+1}^{(1)}, \Delta_{k+1}^{(2)} \right\}$ with $\Delta_{k+1}^{(j)} = t_{k+1}^{(j)} - t_k^{(j)}$ generated as in Eqs 3.7 and 3.8.

$$\Delta_{k+1}^{(j)} = \min \left\{ -\frac{\ln(u_1^{(j)})}{\mu_j}, -\beta_j^{-1} \ln \left(1 + \frac{\beta_j \ln u_2^{(j)}}{\underbrace{\lambda_j(t_k^{(j)}) + \alpha_j - \mu_j}_{g_j}} \right) \right\} \quad (3.9)$$

Note that g_j must be positive, otherwise, take the other term.

2. Once we have the process (l), we update the time for the following event as $t_{k+1} = t_k + \Delta_{k+1}^{(l)}$.
3. Update the rates for the excitatory and inhibitory populations as follows:

$$\lambda_j(t_{k+1}) = \mu_j + e^{-\beta_j(t_{k+1}-t_k)} (\lambda_j(t_k) - \mu_j + \alpha_{l \rightarrow j}) \quad \text{with } j = 1, 2 \quad (3.10)$$

The pseudo-code for this method is presented in Algorithm 3.

3.2 When physics and cooking merge

Once we have a method to generate time series, we can start analyzing them. We should establish a control parameter to distinguish between different regimes of the process. In this case, we will define

Algorithm 3 Algorithm to generate K Hawkes events for two coupled processes.

Require: $\alpha_{11}, \alpha_{12}, \beta_1, \mu_1, \alpha_{22}, \alpha_{21}, \beta_2, \mu_2, K$

for $k = 0$ to K **do**

$u_1^{(1)}, u_2^{(1)}, u_1^{(2)}, u_2^{(2)} \leftarrow \mathcal{U}[0, 1]$

$\Delta_{k+1}^{(1)} \leftarrow \min \left(-\frac{\ln(u_1^{(1)})}{\mu_1}, -\beta_1^{-1} \ln \left(1 + \frac{\beta_1 \ln u_2^{(1)}}{\lambda_1(t_k) + \alpha_{11} - \mu_1} \right) \right)$

$\Delta_{k+1}^{(2)} \leftarrow \min \left(-\frac{\ln(u_1^{(2)})}{\mu_2}, -\beta_2^{-1} \ln \left(1 + \frac{\beta_2 \ln u_2^{(2)}}{\lambda_2(t_k) + \alpha_{22} - \mu_2} \right) \right)$

$l \leftarrow \arg \min (\Delta_{k+1}^{(1)}, \Delta_{k+1}^{(2)})$

$t_{k+1} \leftarrow t_k + \Delta_{k+1}^{(l)}$

$\lambda_1(t_{k+1}) \leftarrow \mu_1 + e^{-\beta_1(t_{k+1}-t_k)} (\lambda_1(t_k) - \mu_1 + \alpha_{l \rightarrow 1})$

$\lambda_2(t_{k+1}) \leftarrow \mu_2 + e^{-\beta_2(t_{k+1}-t_k)} (\lambda_2(t_k) - \mu_2 + \alpha_{l \rightarrow 2})$

end for

resolution parameter $\Delta > 0$ as a time interval which will help us to identify clusters of activities. Our time series will have K events that occur in times $\{t_1, \dots, t_K\}$. Considering this, a cluster of events starts at time t_i and ends at time t_j if $t_j - t_i \leq \Delta$. The number of events in the cluster (cluster size) is the number of events in the interval $[t_i, t_j]$ and its duration is $t_j - t_i$. The extreme cases are when Δ is smaller than the minimum inter-event time, in this case, each event is a cluster of size 1 and duration 0. On the other hand when Δ is greater than the largest inter-event time, all the events are in the same cluster of size K and duration $t_K - t_1$. Between these two extremes, we will have different regimes of the process and we should be careful with the choice of Δ because it will determine the characteristics of the clusters and their statistics. To identify these regimes, we need a phase diagram, in our case, it will be a percolation diagram where we will plot the percolation strength P_∞ as a function of the resolution parameter Δ . The percolation strength is defined as the fraction of events that are in the largest cluster over the total number of events. Three different set of parameters will be used to generate the time series in order to compare them. The parameters α and β will be fixed to 1 in all cases, the other parameters are shown in Table 3.1.

Table 3.1. Configuration of the parameters for the simulations of [5].

Configuration	μ	n
First	1	0
Second	10^{-4}	1
Third	10^2	1

The percolation diagram will be generated by generating 1000 time series for each configuration and calculating the percolation strength for each one because in general they are not stationary processes as we can observe in Figure 3.2.

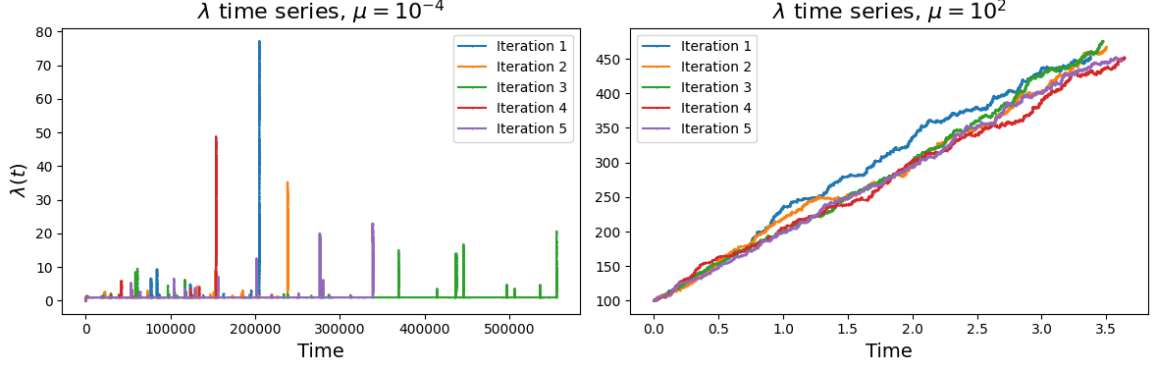


Figure 3.2. Five a temporal series of $K = 10^5$ events of Hawkes processes with $\mu = 10^{-4}$ on the left side and $\mu = 10^2$ on the right one.

Beginning with the first configuration, we have an homogeneous Poisson process which we know that its interevent time will be distributed randomly with a probability of having an inter-event time x_i given by $P(x_i) = \mu e^{-\mu x_i}$. Consequently, two consecutive events will be a part of a cluster fixing the resolution parameter to Δ with a probability of

$$P(x_i \leq \Delta) = 1 - e^{-\mu \Delta} \quad \forall i. \quad (3.11)$$

This represents the probability in a homogeneous 1D percolation model [16], where we can identify a non percolant phase and a percolant phase separated by the critical point Δ^* . We can calculate this parameter if we know the maximum inter-event time of the time series. Let us assume that our time series has K events, therefore, it will percolate if the condition we have just established is satisfied. We can calculate this threshold as the average of the maximum inter-event time in K samples from the inter-event time distribution solving the following equation:

$$\begin{aligned} K \int_{\Delta^*}^{\infty} P(x) dx &= 1 \\ K \int_{\Delta^*}^{\infty} \mu e^{-\mu x} dx &= 1 \\ -K [e^{-\mu x}]_{\Delta^*}^{\infty} &= K \left[e^{-\mu \Delta^*} - \cancel{e^{-\mu \infty}} \right] \overset{0}{=} 1 \\ K e^{-\mu \Delta^*} &= 1 \\ \Delta^*(K) &= -\frac{\ln(K)}{\mu} \end{aligned} \quad (3.12)$$

For the other two configurations, on both we have a self-exciting process with $n = 0$, which means that we have a critical dynamical regime as we shall see later but with different background rates, one much smaller than 1 and the other much greater than 1. This fact will be reflected in the percolation diagram. We will not approach this cases from a theoretical point of view but from a graphic one. With the second configuration, as we have seen in Figure 1.5 if the condition $\mu \ll 1$ is satisfied, we will have a bursty structure in the time series. Due to the low background rate, the events are less likely to occur, but when they do, they tend to form avalanches of activity thanks to the self-excitation. This will be reflected in the percolation diagram as a first phase transition at a critical point Δ_1^* when Δ is of the order of the average cluster size. Then, a second phase transition will occur at a critical point Δ_2^* when Δ is greater than the greatest inter-event time. This phenomena is illustrated in Figure 3.3.

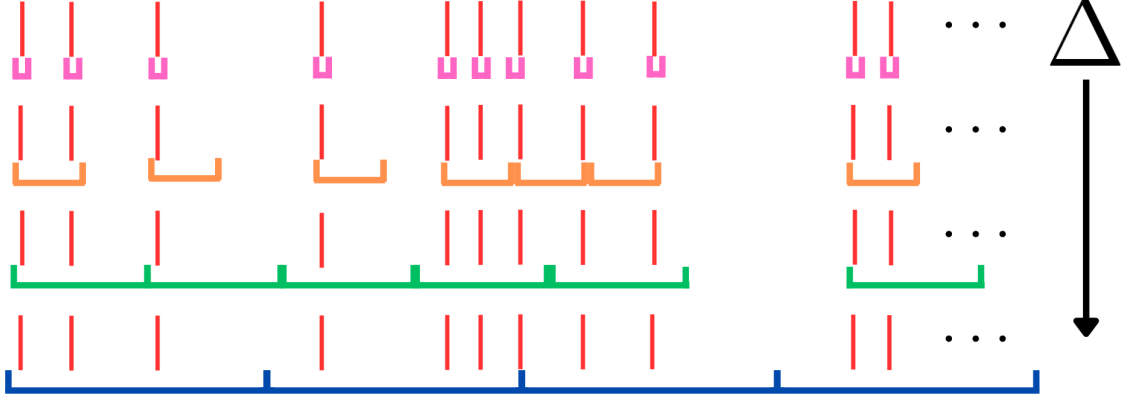


Figure 3.3. Diagram for $\mu \ll 1$. Red lines represent the events, clusters are coloured. As we can see, we have two regimes, one when Δ is of the order of the average cluster size and another when is of the order of the inter-event time where the system percolates.

On the other hand, when $\mu \gg 1$ events occur more frequently, without making the bursty structure of Figure 1.5, but making a more regular structure as illustrated in Figure 1.6. This will be reflected in the phase diagram as a single phase transition at a critical point Δ^* when Δ is of the order of the average cluster size. This phenomena is illustrated in Figure 3.4. Note the absence of a time scale in both diagram, they are diagrams for the explanation of the phase diagram.

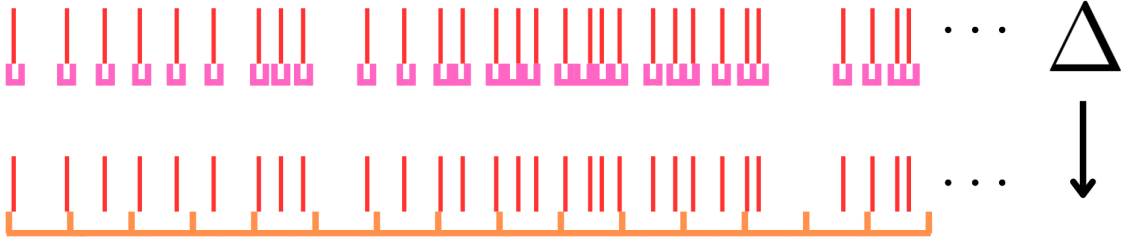


Figure 3.4. Diagram for $\mu \gg 1$. Red lines represent the events, clusters are coloured. In this situation, events occur more regularly, resulting in a unique transition corresponding the case of Δ is similar to the inter-event time producing the system percolation.

Chapter 4

Results

This section provides the main results of the investigation. First, the results reproduced from the original paper [5] are presented. Then, the results of the analysis with $n = 2$ are shown. Finally, we have studied the behaviour of an inhibitory and excitatory neuron coupled.

4.1 Results from the original paper

The first result is the percolation phase diagram is shown in Figure 4.1. It displays the percolation strength P_∞ versus the resolution parameter Δ .

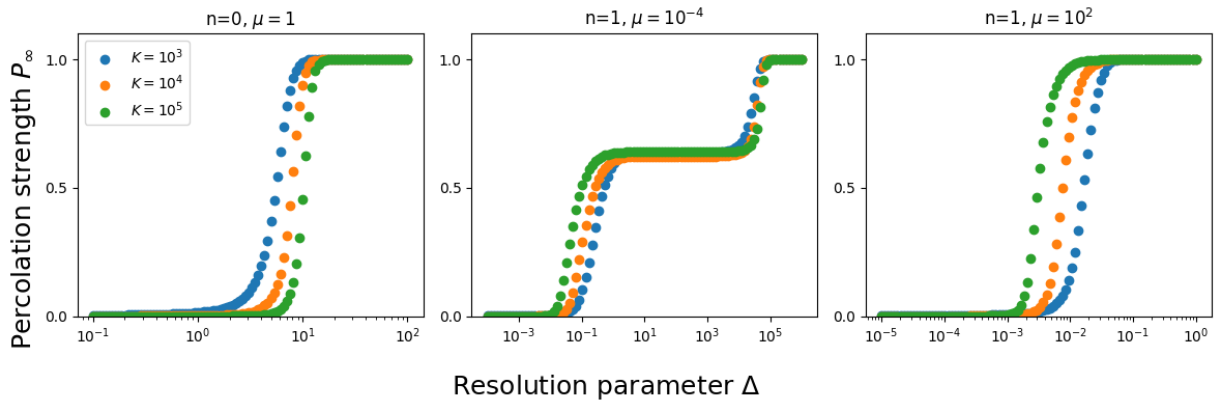


Figure 4.1. Percolation phase diagrams for different event number K taking average values of $R = 1000$ realizations.

The first plot configuration is a Markovian ($n = 0$) Poisson process with rate μ . This is the simplest case, where the inter-event time $x = t_i - t_{i-1}$ follows an exponential distribution $P(x_i) = \mu e^{-\mu x_i}$. The other two plots are Hawkes processes for $\mu \ll 1$ and $\mu \gg 1$ that are also Markovian as we have chosen an exponential kernel (REFERENCIAR AQUÍ A LA PARTE EN LA QUE SE EXPLICA EN METODOLOGÍA.) . In one hand, a double transition is observed when $\mu = 10^{-4}$, in the other hand, a single transition occurs when $\mu = 10^2$.

Once we have the phase diagram, we can study avalanche statistics. Given a resolution parameter Δ , we can spot clusters or avalanches of activity. A cluster starts when a neuron fires and ends if

the neuron does not fire for a time greater than Δ . We define the size of a cluster as the number of spikes it contains and the duration as the time between the first and last spike. We have studied the avalanches for $K = 10^5$ events and $R = 1000$ realizations to obtain the average values since the process is highly not stationary. We will study the size and duration of the avalanches for the three different regions of the phase diagram for $\mu = 10^{-4}$ and the two regions of the phase diagram for $\mu = 10^2$. These regions are separated by two thresholds, a pseudocritical threshold Δ_1^* and the threshold of the second transition at Δ_2^* . We can compute these with the following formulas [5]:

$$\Delta_1^* \simeq \frac{\log(K)}{\langle \lambda \rangle} = \frac{\log(K)}{\mu + \sqrt{2\mu K}} \quad (4.1)$$

$$\Delta_2^* = \frac{\log(K)}{\mu} \quad (4.2)$$

Once we have the thresholds, we can study the avalanches for the different regions of the diagram. The results are shown in Figure 4.2.

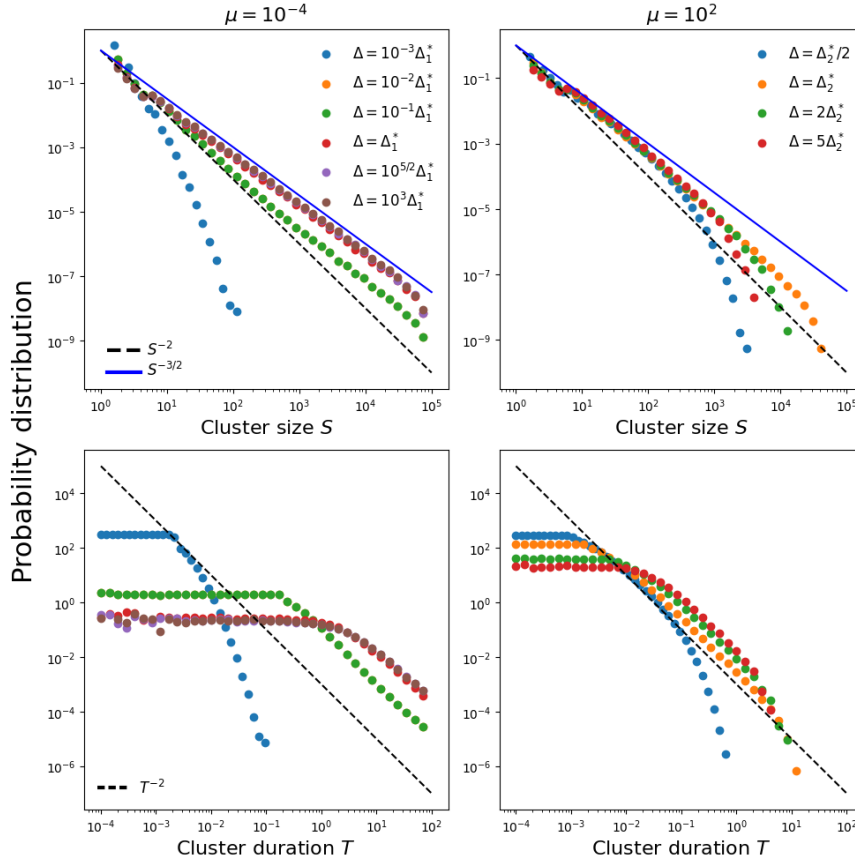


Figure 4.2. Avalanche statistics for a self-exciting Hawkes process with $n = 1$ for $K = 10^5$ events averaged over $R = 1000$ realizations.

For $\mu = 10^{-4}$, the results show a power-law distribution for the size and duration of the avalanches. In the case of duration, the exponent is $\tau = 2$ and for the size, we can notice a transition of the exponent from $\alpha = 2$ to $\alpha = 3/2$ as we increase the resolution parameter Δ . The first exponent corresponds to the universality class of 1D percolation, whereas the second is compatible with the universality class of mean-field branching process. However, if $\Delta \ll \Delta_1^*$, the behaviour is subcritical for the size and duration of the avalanches.

For $\mu = 10^2$, the result shows another power-law distribution for both size and duration of the avalanches unless $\Delta \ll \Delta_2^*$, where the behaviour is subcritical. In this case, the exponents are $\alpha = \tau = 2$ corresponding to the universality class of 1D percolation.

HABLAR AQUÍ DE LA INFLUENCIA DEL MENOR NÚMERO DE EVENTOS, SE SIGUE PRODUCIENDO LA TRANSICIÓN, PERO PARA OTROS VALORES DE DELTA

4.2 Results for $n=2$

In the article, the authors have studied a process which is critical itself because the parameter n is fixed to $n = 1$. We have studied the case $n = 2$ to see if the process is still critical. In the Figure 4.3 two time series for $n = 1$ and $n = 2$ are shown.

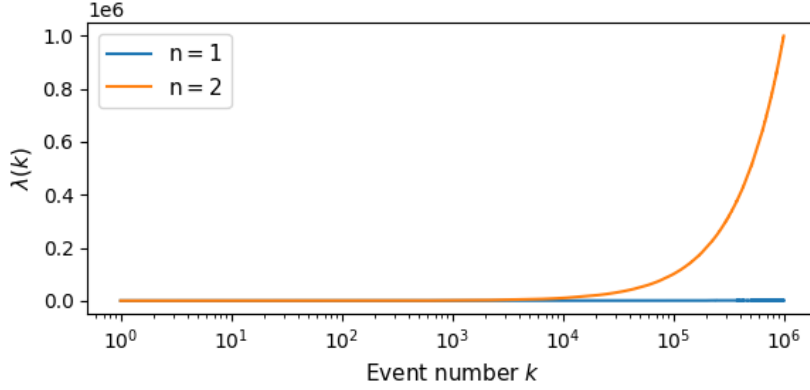


Figure 4.3. Time series for $n = 1$ and $n = 2$.

Similarly to the previous section, first we obtain the phase diagram in order to observe the transitions. In this case, Eqs 4.1-4.2 are not valid. Therefore, we will obtain this parameter graphically from the phase diagrams shown in Figure 4.4.

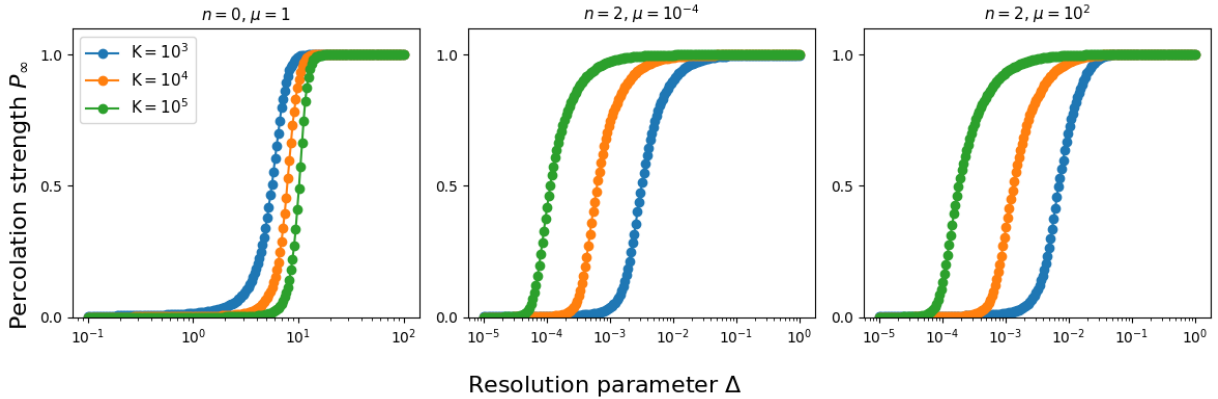


Figure 4.4. Percolation phase diagrams for a Hawkes process with $n = 2$.

As we can see, now we have a single transition for $\mu = 10^{-4}$ and $\mu = 10^2$ corresponding to 1D percolation, consequently, the exponents for the size and duration should be $\alpha = \tau = 2$. In a similar way, we have studied the avalanches for $K = 10^5$ events and $R = 1000$ realizations to obtain the

average values. The statistics of the avalanches are shown in Figure 4.5.

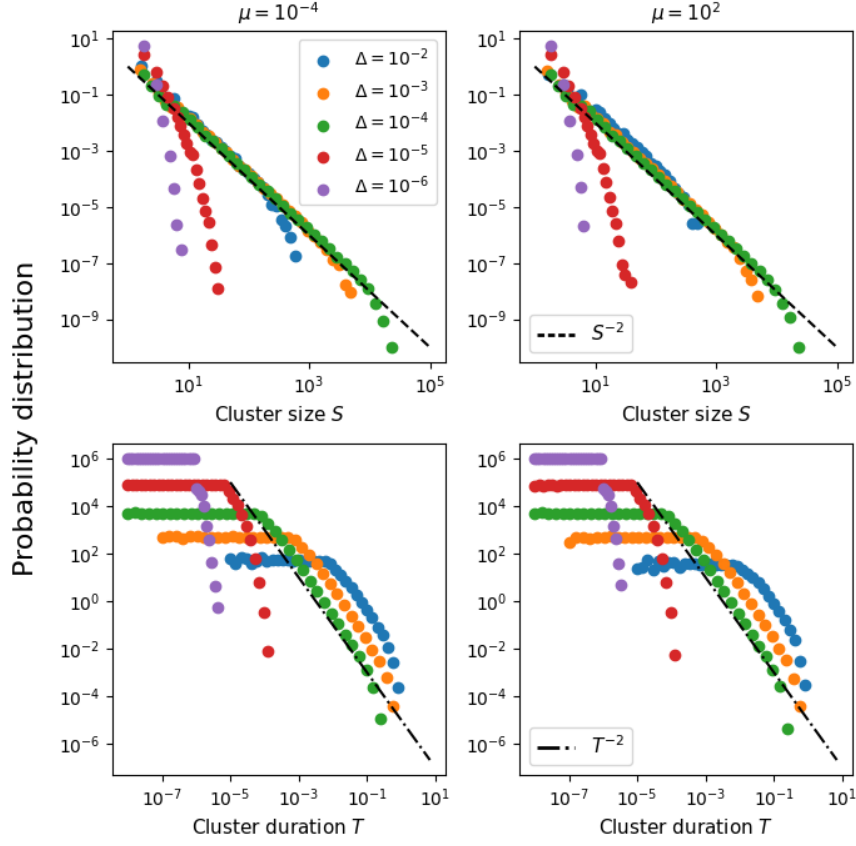


Figure 4.5. Avalanche statistics for a self-exciting Hawkes process with $n = 2$ for $K = 10^5$ events averaged over $R = 1000$ realizations.

4.3 Inhibitory and excitatory neurons coupled

Chapter 5

Conclusions

Bibliography

- [1] Gerardo Chowell et al. “Mathematical models to characterize early epidemic growth: A review”. In: *Physics of life reviews* 18 (2016), pp. 66–97.
- [2] Claudio Castellano, Santo Fortunato, and Vittorio Loreto. “Statistical physics of social dynamics”. In: *Reviews of modern physics* 81.2 (2009), p. 591.
- [3] Sandro Azaele et al. “Statistical mechanics of ecological systems: Neutral theory and beyond”. In: *Reviews of Modern Physics* 88.3 (2016), p. 035003.
- [4] Alan J McKane. *Stochastic Processes*. 2009.
- [5] Daniele Notarmuzi et al. “Percolation theory of self-exciting temporal processes”. In: *Physical Review E* 103.2 (2021), p. L020302.
- [6] Kiyoshi Kanazawa and Didier Sornette. “Ubiquitous power law scaling in nonlinear self-excited Hawkes processes”. In: *Physical review letters* 127.18 (2021), p. 188301.
- [7] Angelos Dassios and Hongbiao Zhao. “Exact simulation of Hawkes process with exponentially decaying intensity”. In: (2013).
- [8] Patrick J Laub, Young Lee, and Thomas Taimre. *The elements of Hawkes processes*. Springer, 2021.
- [9] Felipe Yaroslav Kalle Kossio et al. “Growing critical: self-organized criticality in a developing neural system”. In: *Physical review letters* 121.5 (2018), p. 058301.
- [10] Wes McKinney. *Python for data analysis: Data wrangling with Pandas, NumPy, and IPython*. “” O’Reilly Media, Inc.”, 2012.
- [11] Jake VanderPlas. *Python data science handbook: Essential tools for working with data*. ” O’Reilly Media, Inc.”, 2016.
- [12] Travis Oliphant et al. *NumPy*. <https://numpy.org/>. Accessed: 2024-06-21. 2024.
- [13] John D. Hunter et al. *Matplotlib*. <https://matplotlib.org/>. Accessed: 2024-06-21. 2024.
- [14] Adrian Barbu, Song-Chun Zhu, et al. *Monte Carlo Methods*. Vol. 35. Springer, 2020.
- [15] Raúl Toral and Pere Colet. *Stochastic numerical methods: an introduction for students and scientists*. John Wiley & Sons, 2014.
- [16] Dietrich Stauffer and Ammon Aharony. *Introduction to percolation theory*. Taylor & Francis, 2018.

Appendix A

Python scripts

REVISAR LOS CÓDIGOS PARA QUE ESTÉN ACTUALIZADOS

CAMBIAR FUNCIONES.PY PARA QUITAR LA GENERATE_SERIES_PERC

Here are the main functions used in the main functions of the project. The first one is the algorithm used to simulate the inter-event time of a Hawkes process with exponential kernel. The second one is the function for the generation of time series of these Hawkes processes. The third one is the function associated to the calculation of the percolation strength, P_∞ , for the phase diagrams. The fourth one is the function to identify the clusters size and duration distribution. The fifth one is the function to generate the inter-event time of a bivariate Hawkes process with exponential kernel. The last one is the function to generate the time series of the bivariate Hawkes process.

Script A.1. Script with the main functions.

```
1 import numpy as np
2
3 def algorithm(rate, mu, n):
4     """
5     Algorithm that computes interevent times and Hawkes intensity for a self-exciting
6     process
7
8     ## Inputs:
9     rate: Previous rate
10    mu: Background intensity
11    n: Weight of the Hawkes process
12
13    ## Outputs: rate x_k, x_k
14    x_k: Inter-event time
15    rate_tk: Intensity at time tk
16    """
17    # 1st step
18    u1 = np.random.uniform()
19    if mu == 0:
20        F1 = np.inf
21    else:
22        F1 = -np.log(u1) / mu
23
24    # 2nd step
25    u2 = np.random.uniform()
26    if (rate - mu) == 0:
27        G2 = 0
28    else:
29        G2 = 1 + np.log(u2) / (rate - mu)
```

```

29
30
31 # 3rd step
32 if G2 <= 0:
33     F2 = np.inf
34 else:
35     F2 = -np.log(G2)
36
37 # 4th step
38 xk = min(F1, F2)
39
40 # 5th step
41 rate_tk = (rate - mu) * np.exp(-xk) + n + mu
42 return rate_tk, xk
43
44 def generate_series(K, n, mu):
45     """
46     Generates temporal series for K Hawkes processes
47
48     ##Inputs:
49     K: Number of events
50     n: Strength of the Hawkes process
51     mu: Background intensity
52
53     ##Output:
54     times_between_events: time series the inter-event times
55     times: time series the events
56     rate: time series for the intensity
57     """
58     times_between_events = [0]
59     rate = [mu]
60     for _ in range(K):
61         rate_tk, xk = algorithm(rate[-1], mu, n)
62         rate.append(rate_tk)
63         times_between_events.append(xk)
64     times = np.cumsum(times_between_events)
65     return times_between_events, times, rate
66
67 def calculate_percolation_strength(times_between_events, deltas):
68     """
69     Calculate the percolation strength for a given set of deltas (resolution parameters)
70
71     ## Inputs:
72     times_between_events: time series of interevent times
73     deltas: list of resolution parameters
74
75     ## Output:
76     percolation_strengths: list of percolation strengths
77     """
78
79     percolation_strengths = []
80
81     for delta in deltas:
82         cluster_sizes = []
83         current_cluster_size = 1 # The first event is always a cluster
84
85         for time in times_between_events:
86             if time < delta:
87                 current_cluster_size += 1
88             else:
89                 if current_cluster_size > 1: # Only consider clusters with more than one
event

```



```

90         cluster_sizes.append(current_cluster_size)
91         current_cluster_size = 1 # The next event is always a cluster
92
93         if current_cluster_size > 1: # Consider the last cluster if it ends at the last
event
94             cluster_sizes.append(current_cluster_size)
95
96         if len(cluster_sizes) != 0: # Check if cluster_sizes is not empty to avoid
errors
97             max_cluster_size = max(cluster_sizes)
98         else:
99             max_cluster_size = 0
100
101         percolation_strengths.append(max_cluster_size / len(times_between_events))
102
103     return percolation_strengths
104
105 def identify_clusters(times, delta):
106     """
107     Identifies clusters in a temporal series given a resolution parameter delta
108
109     ## Inputs:
110     times: temporal series
111     delta: resolution parameter
112
113     ## Output:
114     clusters: list of clusters
115     """
116     clusters = []
117     current_cluster = []
118     for i in range(len(times) - 1):
119         if times[i + 1] - times[i] <= delta:
120             if not current_cluster:
121                 current_cluster.append(times[i])
122                 current_cluster.append(times[i + 1])
123             else:
124                 if current_cluster:
125                     clusters.append(current_cluster)
126                     current_cluster = []
127     return clusters
128
129 def model(n_max, mu_E, mu_I, tau, n_EE, n_IE, n_EI, n_II, dt):
130     """
131     Solve the equations of the mena field model for a given number of iterations n_max
132
133     Inputs:
134     n_max: number of iterations
135     mu_E: Poisson rate of excitatory neurons
136     mu_I: Poisson rate of inhibitory neurons
137     tau: characteristic time of the system
138     n_EE: influence of excitatory neurons on excitatory neurons
139     n_IE: influence of excitatory neurons on inhibitory neurons
140     n_EI: influence of inhibitory neurons on excitatory neurons
141     n_II: influence of inhibitory neurons on inhibitory neurons
142     dt: time step
143
144     Outputs:
145     time: time series
146     t_events_E: times of events of excitatory neurons
147     t_events_I: times of events of inhibitory neurons
148     rates_E: rates of excitatory neurons
149     rates_I: rates of inhibitory neurons

```

```

150 """
151 n_E = n_I = n = 0
152 t_events_E = [0]
153 t_events_I = [0]
154 rates_E = [mu_E]
155 rates_I = [mu_I]
156 time = [0]
157 while n <= n_max:
158     # Excitation neurons
159     l_Enew = rates_E[-1] + dt * (mu_E - rates_E[-1])/tau
160     if np.random.uniform() < rates_E[-1]*dt:
161         l_Enew += n_EE
162         t_events_E.append(time[-1]+dt*np.random.uniform())
163         n_E += 1
164     if np.random.uniform() < rates_I[-1]*dt:
165         l_Enew -= n_IE
166         t_events_E.append(time[-1]+dt*np.random.uniform())
167         n_E += 1
168
169     # Inhibition neurons
170     l_Inew = rates_I[-1] + dt * (mu_I - rates_I[-1])/tau
171     if np.random.uniform() < rates_E[-1]*dt:
172         l_Inew += n_EI
173         t_events_I.append(time[-1]+dt*np.random.uniform())
174         n_I += 1
175     if np.random.uniform() < rates_I[-1]*dt:
176         l_Inew -= n_II
177         t_events_I.append(time[-1]+dt*np.random.uniform())
178         n_I += 1
179     rates_E.append(l_Enew)
180     rates_I.append(l_Inew)
181     time.append(time[-1]+dt)
182
183     n = n_E + n_I
184 return time, t_events_E, t_events_I, rates_E, rates_I
185
186 def identify_clusters_model(times, delta):
187     """
188     Identifies clusters in a temporal series given a resolution parameter delta
189     Computes the size and duration of clusters
190
191     ## Inputs:
192     times: temporal series
193     delta: resolution parameter
194
195     ## Output:
196     clusters: list of clusters
197     clusters_sizes: list of sizes of clusters
198     clusters_times: list of durations of clusters
199     """
200     clusters = []
201     current_cluster = []
202     for i in range(len(times) - 1):
203         if times[i + 1] - times[i] <= delta:
204             if not current_cluster:
205                 current_cluster.append(times[i])
206                 current_cluster.append(times[i + 1])
207             else:
208                 if current_cluster:
209                     clusters.append(current_cluster)
210                     current_cluster = []

```

```

212     clusters_sizes = [len(cluster) for cluster in clusters]
213     clusters_times = [cluster[-1] - cluster[0] for cluster in clusters]
214     return clusters, clusters_sizes, clusters_times
215
216 def bivariate_algorithm(rate1, rate2, muE, muI, nEE, nII, nEI, nIE):
217     """
218     Algorithm that computes interevent times and Hawkes intensity for a bivariate Hawkes
219     process
220
221     #Inputs:
222     rate1: Previous excitation rate
223     rate2: Previous inhibition rate
224     nEE: "Strength" of the autoexcitation process
225     nII: "Strength" of the autoinhibition process
226     nEI: "Strength" of the excitation to the inhibition
227     nIE: "Strength" of the inhibition to the excitation
228     muE: Background intensity of the excitation
229     muI: Background intensity of the inhibition
230
231     #Output: ratex_k, x_k, reaction (0 for excitatory events and 1 for inhibitory events)
232     """
233     _, xk1 = algorithm(rate1, muE, nEE)
234     _, xk2 = algorithm(rate2, muI, nII)
235
236     xks = [xk1, xk2]
237
238     reaction = np.argmin(xks)
239
240     rate1_tk = 0.
241     rate2_tk = 0.
242
243     if reaction == 0:
244         rate1_tk = (rate1 - muE) * np.exp(-xk1) + nEE + muE
245         rate2_tk = (rate2 - muI) * np.exp(-xk1) + nEI + muI
246     else:
247         rate1_tk = (rate1 - muE) * np.exp(-xk2) + nIE + muE
248         rate2_tk = (rate2 - muI) * np.exp(-xk2) + nII + muI
249
250
251     if rate1_tk <= muE:
252         rate1_tk = muE
253     if rate2_tk <= muI:
254         rate2_tk = muI
255
256     xk = xks[reaction]
257
258     return rate1_tk, rate2_tk, xk, reaction
259
260 def generate_series_bivariate(K, nEE, nII, nEI, nIE, muE, muI):
261     """
262     Generates temporal series for K bivariate Hawkes processes
263
264     ##Inputs:
265     K: Number of events
266     nEE: "Strength" of the autoexcitation process
267     nII: "Strength" of the autoinhibition process
268     nEI: "Strength" of the excitation to the inhibition
269     nIE: "Strength" of the inhibition to the excitation
270     muE: Background intensity of the excitation
271     muI: Background intensity of the inhibition
272

```

```

273  """Output:
274  times_between_events: time series the interevent times
275  times: time series the events
276  rate1: time series for the intensity of process 1 (Excitation)
277  rate2: time series for the intensity of process 2 (Inhibition)
278  reactions: list the event type (0 for excitation. 1 for inhibition)
279  """
280  times_between_events = [0]
281  rate1 = [muE]
282  rate2 = [muI]
283  reactions= []
284  for _ in range(K):
285      rate1_tk, rate2_tk, xk, reaction = bivariate_algorithm(rate1[-1], rate2[-1], muE,
286      muI, nEE, nII, nEI, nIE)
287      rate1.append(rate1_tk)
288      rate2.append(rate2_tk)
289      reactions.append(reaction)
290      times_between_events.append(xk)
291  times = np.cumsum(times_between_events)
292  return times_between_events, times, rate1, rate2, reactions

```