

#### 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

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

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#### Autorización de defensa del Trabajo Fin de Máster

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"Va por los días en los que quiero un abrazo y acabo encerrado solo en en cuarto". —Piezas

# Cambiar encabezado y pie de página en .sty

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### Abstract

## Introduction

# Objectives

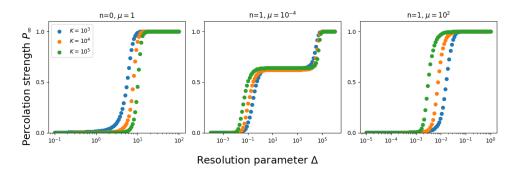
# Methodology

### Results

This section provides the main results of the investigation. First, the results reproduced from the original paper [1] 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  $P_{\infty}$  versus the resolution parameter  $\Delta$ .



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

### Conclusions

### Anexo

# REVISAR LOS CÓDIGOS PARA QUE ESTÉN ACTUALIZADOS

#### Script 5.1. Script Python con todas las funciones.

```
1 import numpy as np
  import matplotlib.pyplot as plt
  def algorithm (rate, mu, n):
       Algorithm that computes interevent times and Hawkes intensity
      #Output: rate x_k, x_k
9
      # Paso 1
10
       u1 = np.random.uniform()
11
       if mu = 0:
12
           F1 = np.inf
13
14
           F1 = -np.\log(u1) / mu
15
16
      # Paso 2
17
       u2 = np.random.uniform()
       if (rate - mu) = 0:
19
           G2 = 0
20
       else:
21
           G2 = 1 + np.log(u2) / (rate - mu)
22
23
24
      # Paso 3
25
       if G2 <= 0:
26
          F2 = np.inf
       else:
          F2 = -np \cdot log(G2)
30
      # Paso 4
31
      xk = \min(F1, F2)
32
33
      # Paso 5
34
       rate_tk = (rate - mu) * np.exp(-xk) + n + mu
35
       return rate_tk, xk
36
37
  def generate_series(K, n, mu):
39
       Generates temporal series for K Hawkes processes
40
41
      ##Inputs:
```

```
K: Number of events
43
       n: Strength of the Hawkes process
44
       mu: Background intensity
45
       ##Output:
47
       times: time series the events
48
        rate: time series for the intensity
49
50
       times\_between\_events = [0]
51
       rate = [mu]
        for \underline{\phantom{a}} in range(K):
53
            rate_t , xk = algorithm(rate[-1], mu, n)
54
            rate.append(rate_tk)
55
56
            times_between_events.append(xk)
        times = np.cumsum(times_between_events)
57
58
        return times, rate
59
   def identify_clusters(times, delta):
60
61
        Identifies clusters in a temporal series given a resolution parameter delta
62
63
       ## Inputs:
64
       times: temporal series
65
        delta: resolution parameter
66
67
       ## Output:
        clusters: list of clusters
69
70
71
        clusters = []
        current_cluster = []
72
        for i in range (len(times) - 1):
73
            if times[i + 1] - times[i] \le delta:
74
75
                 if not current_cluster:
                     current_cluster.append(times[i])
76
                current_cluster.append(times[i + 1])
77
78
79
                 if current_cluster:
                     clusters.append(current_cluster)
80
                     current_cluster = []
81
        return clusters
82
83
   def generate_series_perc(K, n, mu):
84
85
        Generates temporal series for K Hawkes processes
86
87
       ##Inputs:
       K: Number of events
       n: Strength of the Hawkes process
90
       mu: Background intensity
91
92
       ##Output:
93
       times_between_events: time series the interevent times
94
       times: time series the events
95
        rate: time series for the intensity
96
97
       times\_between\_events = [0]
98
        rate = [mu]
        for \underline{\phantom{}} in range (K):
            rate_tk, xk = algorithm(rate[-1], mu, n)
101
            rate.append(rate_tk)
            times_between_events.append(xk)
103
        times = np.cumsum(times_between_events)
104
```

```
return times_between_events, times, rate
106
   def calculate_percolation_strength(times_between_events, deltas):
       percolation\_strengths = []
108
109
       for delta in deltas:
           cluster\_sizes = []
111
           # Initialize the size of the current cluster
           current\_cluster\_size = 1 \# The first event is always a cluster
113
114
           for i in range(len(times_between_events)):
                if times_between_events[i] <= delta:</pre>
116
                    current_cluster_size += 1
117
                else:
118
119
                    if current_cluster_size > 1: # Only consider clusters with more than one
       event
                        cluster_sizes.append(current_cluster_size)
                    # Reset the size of the current cluster
121
                    current_cluster_size = 1 # The next event is always a cluster
123
           # Add the size of the last cluster
           if current_cluster_size > 1: # Only consider clusters with more than one event
                cluster_sizes.append(current_cluster_size)
126
127
           max_cluster_size = max(cluster_sizes)
129
           percolation_strengths.append(max_cluster_size / len(times_between_events))
130
131
       return percolation_strengths
       model(n_max, mu_E, mu_I, tau, n_EE, n_IE, n_EI, n_II, dt):
133
134
       Solve the equations of the mena field model for a given number of iterations n_max
136
       Inputs:
137
       n_max: number of iterations
138
       mu_E: Poisson rate of excitatory neurons
       mu_I: Poisson rate of inhibitory neurons
       tau: characteristic time of the system
       n_EE: influence of excitatory neurons on excitatory neurons
142
       n_IE: influence of excitatory neurons on inhibitory neurons
143
       n_EI: influence of inhibitory neurons on excitatory neurons
144
       n_II: influence of inhibitory neurons on inhibitory neurons
145
       dt: time step
146
147
       Outputs:
148
       time: time series
149
       t_events_E: times of events of excitatory neurons
       t_events_I: times of events of inhibitory neurons
151
       rates_E: rates of excitatory neurons
       rates_I: rates of inhibitory neurons
153
154
       n_E = n_I = n = 0
155
       t_{events} = [0]
156
       t_{events}I = [0]
157
       rates_E = [mu_E]
158
       rates_I = [mu_I]
159
       time = [0]
       while n \le n_max:
           # Excitation neurons
162
           l\_Enew = rates\_E[-1] + dt * (mu\_E- rates\_E[-1])/tau
163
           if np.random.uniform() < rates_E[-1]*dt:
164
                l_Enew += n_EE
165
```

```
t\_events\_E.append(time[-1]+dt*np.random.uniform())
166
                 n_E += 1
167
             if \ np.random.uniform() < rates\_I[-1]*dt:
168
169
                 l\_Enew -= n\_IE
                 t_{events} . append (time[-1]+dt*np.random.uniform())
170
                 n\_E \ +\!= \ 1
171
172
            \# Inhibition neurons
173
             l\_Inew \, = \, rates\_I \, [-1] \, + \, dt \, * \, (mu\_I \!\! - \, rates\_I \, [-1]) / tau
174
             if np.random.uniform() < rates_E[-1]*dt:
175
                 l\_Inew += n\_EI
176
                 t_{events}I.append(time[-1]+dt*np.random.uniform())
177
                 n_I += 1
178
179
             if np.random.uniform() < rates_I[-1]*dt:
180
                 l\_Inew -= n\_II
                 t\_events\_I.append(time[-1]+dt*np.random.uniform())
                 n\_I \ +\!= \ 1
             rates\_E.append(l\_Enew)
183
             rates_I.append(l_Inew)
184
             time.append(time[-1]+dt)
185
186
             n = n\_E + n\_I
187
        return time, t_events_E, t_events_I, rates_E, rates_I
188
```