

Critical Limits in a Bump Attractor Network of Spiking Neurons

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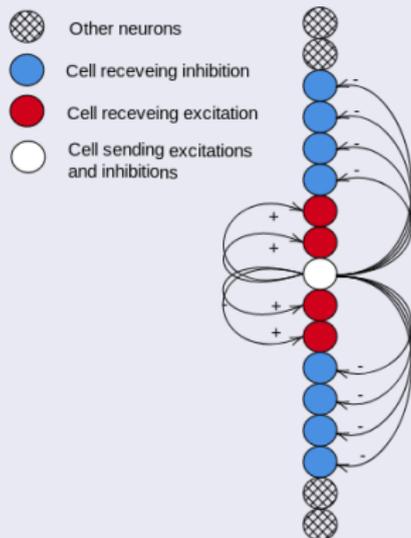
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- 2 The Bump Attractor Network
 - Structure and Function
- 3 Simulations
 - The neural model
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 - Activation Patterns
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The (stationary) Bump Attractor Network

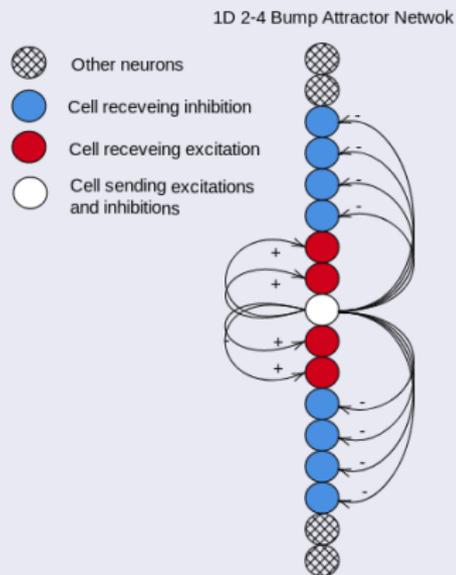
The proposed structure

1D 2-4 Bump Attractor Network

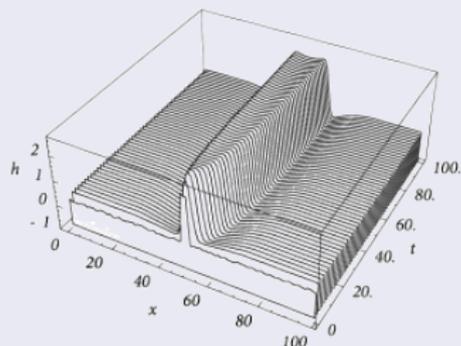


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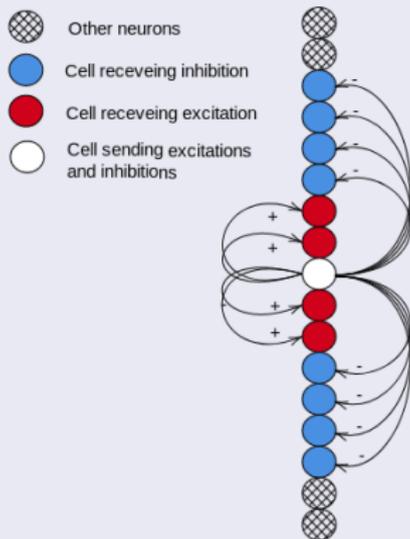
Localized bump of activation



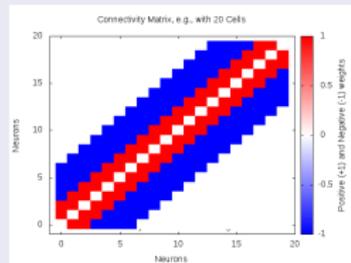
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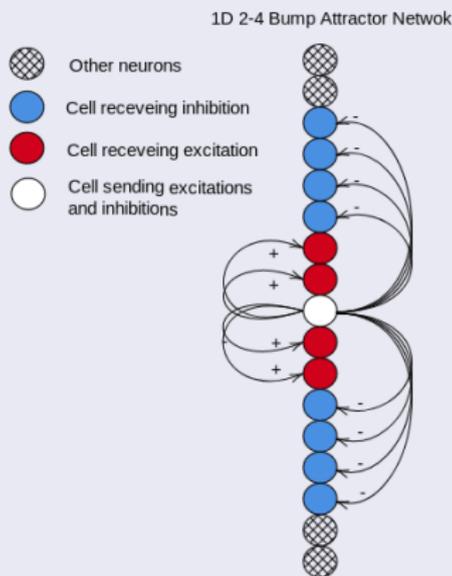


Connectivity, e.g., 20 cells

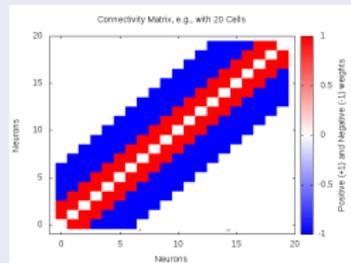


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Functions

- Brain Features Selection
- *Winner Takes All (WTA)*
- Concept representation

The neural model

Leaky Integrate and Fire formalism with fixed threshold

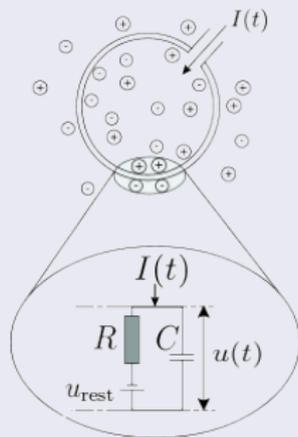
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Electric circuit

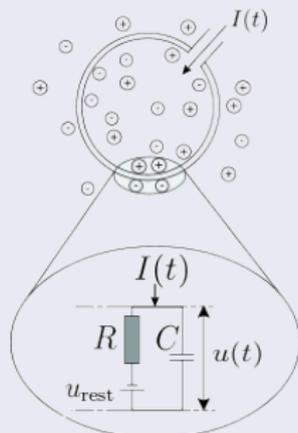


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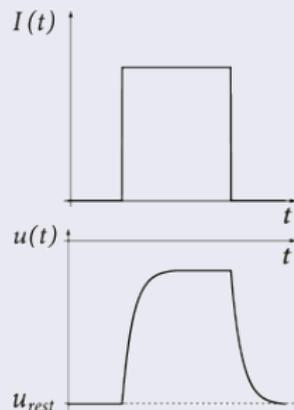
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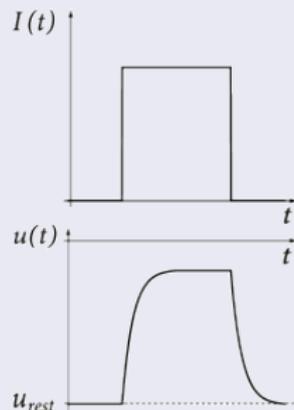
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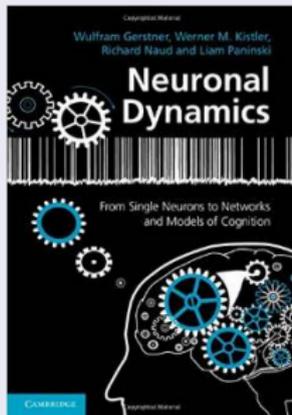
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Gerstner et al 2014



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- the computational **run-time** used is 300ms;
- the simulation are computed with the **neuromorphic hardware** (SpiNNaker 4-Chips board system - Petrut's seminar Feb 21st)

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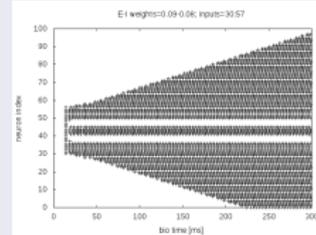
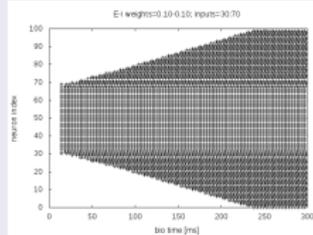
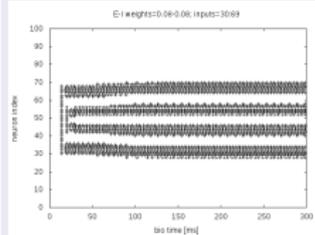
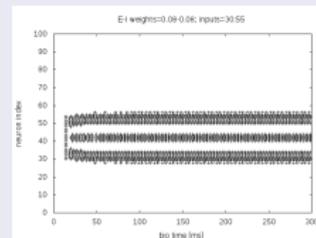
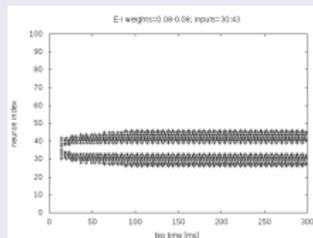
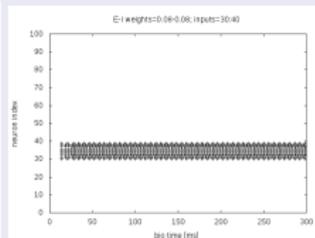
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- the **questions** that are investigated are
 - 1) if the network *ignites* and
 - 2) if it does, do the spike trains have either a stable *persistence*, a *splitting* shape or a *divergent* pattern?
 - \implies What are the patterns the network emerges?

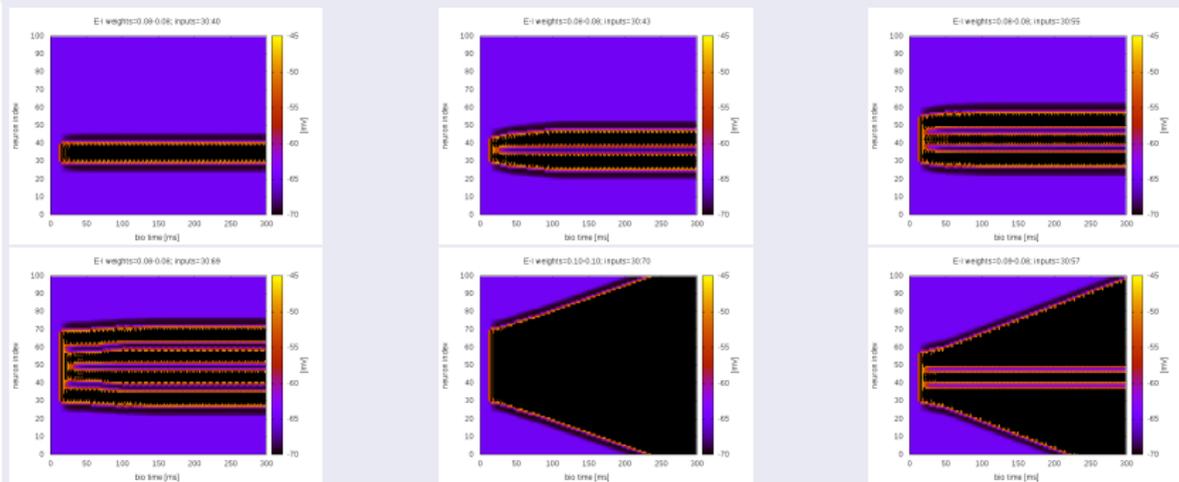
Activation patterns found

spikes



Activation patterns found

voltage



Towards critical limits ...

Example of limits

- Set
 - Ex Weights = 0.08
 - In Weights = 0.08
- Increase inputs
 - from 1 to 40

splitting patterns

1st critical limit: Minimal sources to ignite the bump attractor network

E-I Weights	0.05	0.06	0.07	0.08	0.09	0.1
0.05	4	4	4	4	5	/
0.06	2	2	2	2	2	2
0.07	2	2	2	2	2	2
0.08	2	2	2	2	2	2
0.09	2	2	2	2	2	2
0.1	1	1	1	1	1	1

2nd critical limit: Minimal sources to split the network dynamics in 2 streams

E-I Weights	0.05	0.06	0.07	0.08	0.09	0.1
0.05	13	13	12	/	/	/
0.06	15	13	13	12	11	11
0.07	D	15	14	13	13	12
0.08	D	17(+D)	15(+D)	13	13	13
0.09	D	D	D	15(+D)	15(+D)	15
0.1	D	D	D	D	D	D

3rd critical limit:

Minimal sources to split the network dynamics in 3/4 streams

E-I Weights	3S	4S
0.06-0.05	25	37
0.07-0.06	26	39
0.08-0.06	26 (+D)	na
0.08-0.07	23 (+D)	na
0.08-0.08	25	39
0.09-0.08	27 (+D)	na
0.09-0.09	25 (+D)	na

e.g., 0.09-0.08

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- The **splitting behaviour** with two streams is related to similar weights or with **greater negative weights** than positive ones (*ihinbition matters*).

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Propositions about the starting firing

- **Ignition** can be achieved by a few inputs.
- It is not enough to ignite the network with only one spike source, except when the excitatory weight has high values, as 0.10.

Propositions about 2S splitting and diverging

- The **splitting behaviour** with two streams is related to similar weights or with **greater negative weights** than positive ones (*inhibition matters*).
- To the contrary, **the diverging behaviour** is related to **greater positive weights** than negative ones (*excitation matters*).

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⇒ *The more inputs ignite the bump network, the more (could be) the streams within the splitting behaviour*
- The weights that determine the **streaming with divergence** are at the **boundary** between the weight condition underlying the splitting and the divergent patterns.

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- The spike train patterns with **multiple streams** (3 and 4) seem related with the **size of the input window**.
⇒ *The more inputs ignite the bump network, the more (could be) the streams within the splitting behaviour*
- The weights that determine the **streaming with divergence** are at the **boundary** between the weight condition underlying the splitting and the divergent patterns.
⇒ *It's an intermediate situation close to both the pattern possibilities.*

Future works

Next directions

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 - \implies *Description vs Explanation*

Cheers

Thank you for the attention!

Reference for other details



Vergani and Huyck 2020

Critical Limits in a Bump Attractor Network of Spiking Neurons

[Preprint on Researchgate](#)

Useful links

- [Images of simulation results](#)
- [Playlist video on Youtube](#)