A Neural Based Feature-Binding Model

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Outline

1. Introduction
2. Bumps in spiking networks
3. Neural Feature-Binding Model
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- Understanding brain functions via computational methods
- Linking behavioral experiments and findings from neurobiology
- With the means of dynamical systems
- On both analytical and simulative levels.
- Therefore simplifying of the behavioral and the biological level
- To identify critical aspects
- And extract them to make predictions or proposals for further experiments.
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- Modeling processes in the brain as dynamical systems
  - Single neurons
  - Whole Networks of neurons
  - phenomenological aspects
- Taking into account experimental results
- Reproducing effects found in psychological or biological experiments
- Finding their causes (at least in the model)
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Neural Coding
Introduction

How does the brain store or process information?

- Particular neurons have individual functions
- Columnar structure of the cortex
- Location of collective activity of nearby neurons is important

Therefore we have to know first
  - why activation does not spread
  - why activation does not die out

- but forms localized regions of activation.
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Summary: Computational Neuroscience

- Use *experimental data* to model the physical processes in the brain
  - as realistic as possible
  - as simple as possible.
- There is always a tradeoff between biological meaning and computational hardness.
- On the level of connectivity and distribution of tasks in the brain, not much is known. Models provide a hypothesis to be tested.
Use *experimental data* to model the physical processes in the brain
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A Neural Based Feature-Binding Model
Bumps in spiking networks

**Single Unit Model**
Neural Breathers

\[
\frac{1}{\gamma} \frac{dv}{dt} = v_\infty - v + r_m I_e
\]

- Leaky Integrate’n’Fire Neurons:
  - resting potential \(v_\infty\)
  - threshold potential \(v_{th}\)
  - refraction potential \(v_{reset}\)
Network structure

- **delta coupling**
  - spatial organization in a chain
  - equal synaptic weights $\epsilon$ only to the two nearest neighbours, all excitatory

- synaptic delay $\tau$
  - network size arbitrary, only localized activations are of interest
  - no synaptic changes, i.e. no learning
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\[
\begin{align*}
\dot{v}_i &= \epsilon (v_{i-2} + v_{i-1} - 2v_i + v_{i+1} + v_{i+2}) \\
\text{synaptic delay } \tau \\
\text{network size arbitrary, only localized activations are of interest} \\
\text{no synaptic changes, i.e. no learning}
\end{align*}
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Network structure

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\[
\begin{align*}
\epsilon & \quad \epsilon \\
V_{i-2} & \quad V_{i-1} & \quad V_i & \quad V_{i+1} & \quad V_{i+2}
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$$v_{i-2} \xrightarrow{\epsilon} v_{i-1} \xrightarrow{\epsilon} v_{i} \xrightarrow{\epsilon} v_{i+1} \xrightarrow{} v_{i+2}$$

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$$v_i - 2 \quad v_i - 1 \quad v_i \quad v_i + 1 \quad v_i + 2$$

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Simplest persistent bump

\[ \tau > \ln \left(1 + \sqrt{\frac{v_{\text{reset}} - v_{\text{th}}}{v_{\infty} - v_{\text{th}}}}\right) \]
Feature Binding

exemplary setting in the visual pathway:

- Features of objects in the view are decomposed
  - Shape
  - Color
- This information has to be recombined
  - Flexible
  - Persistent for some time
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Feature Binding Model

- 3 chains of leaky integrate and fire neurons
- More complex intern neighborhood for
  - strong localization
  - global inhibition
- Inter-layer connections are
  - All to all
  - equally excitatory
- between
  - PFC ↔ V4
  - PFC ↔ IT
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Neural Feature-Binding Model

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Results of the feature-binding model

Bump Initiation

IT

PFC

V4

time vs. neuron index

external input
Results of the feature-binding model
Multiple Objects

IT

PFC

V4
Results of the feature-binding model
Killing Memory

- IT
- PFC
- V4
Results of the feature-binding model
Searching for a Lost Feature
Results of the feature-binding model
Changing a Feature
Bumps in spiking networks provide the flexibility to model feature binding in the visual system.

- Only a proof of concept yet
- Several effects match the real situation:
  - Ability for short term memory
  - Limited memory capacity
  - Wrong binding with a certain probability
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Outlook

- Extension of the chains to a structure that allows for more interesting behavior
  - two dimensional grid
  - random connectivity network

- Tuning to greater robustness

- Compare to Experiments
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