Summary

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Five things needed to generate behavior

- sensors
- motors
- linked by a nervous system
- linked physically by a body
- an appropriately structured environment
Emergent behavior: this is a dynamics

- feedforward nervous system
- + closed loop through environment
- => (behavioral) dynamics
Internal loops generate neural dynamics

- that generate cognition: internal decisions...
- bifurcations => different cognitive regimes
neural state variable activation

- linked to membrane potential of neurons in some accounts
- linked to spiking rate in our account
- through: population activation... (later)
Activation

- activation as a real number, abstracting from biophysical details

- low levels of activation: not transmitted to other systems (e.g., to motor systems)

- high levels of activation: transmitted to other systems

- as described by sigmoidal threshold function

- zero activation defined as threshold of that function
Activation dynamics

- Activation evolves in continuous time

- No evidence for a discretization of time, for spike timing to matter for behavior
Neural dynamics

- stationary state = fixed point = constant solution
- stable fixed point: nearby solutions converge to the fixed point = attractor

\[
\frac{du(t)}{dt} = \dot{u}(t) = -u(t) + h \quad (h < 0)
\]
Neuronal dynamics with self-excitation

\[ \tau \dot{u}(t) = -u(t) + h + S(t) + c\sigma(u(t)) \]
Neuronal dynamics with self-excitation

\[ \tau \dot{u}(t) = -u(t) + h + S(t) + c \sigma(u(t)) \]
Neuronal dynamics with competition

\[ \tau \dot{u}_1(t) = -u_1(t) + h - \sigma(u_2(t)) + S_1 \]
\[ \tau \dot{u}_2(t) = -u_2(t) + h - \sigma(u_1(t)) + S_2 \]
Neuronal dynamics with competition

=> biased competition

before input is presented

after input is presented
Distribution of population activation

\[ \text{Distribution of population activation} = \sum_{\text{neurons}} \text{tuning curve} \times \text{current firing rate} \]

[After Bastian, Riehle, Schöner, submitted]
Dynamical Field Theory: space

- fields: continuous activation variables defined over continuous spaces

Information, probability, certainty

Activation field

Dimension

Metric contents

e.g., retinal space, movement parameters, feature dimensions, viewing parameters, ...
the dynamics such activation fields is structured so that localized peaks emerge as attractor solutions.
mathematical formalization

Amari equation

\[ \tau \dot{u}(x, t) = -u(x, t) + h + S(x, t) + \int w(x - x')\sigma(u(x', t)) \, dx' \]

where

- time scale is \( \tau \)
- resting level is \( h < 0 \)
- input is \( S(x, t) \)
- interaction kernel is
  \[ w(x - x') = w_i + w_e \exp \left[ -\frac{(x - x')^2}{2\sigma_i^2} \right] \]
- sigmoidal nonlinearity is
  \[ \sigma(u) = \frac{1}{1 + \exp[-\beta(u - u_0)]} \]
Relationship to the dynamics of discrete activation variables

\[ s(x) \]
\[ u(x) \]

self-excitation

mutual inhibition

self-excitation

s_1

u_1

x

u_2

s_2
How does a field come to stand for “its” dimension?

=> by its input/output connectivity…
Detection instability

input dimension

0

0

h

h

sub-threshold hill

self-excited peak

sub-threshold hill

self-excited peak

sub-threshold hill

self-excited peak

self-excited peak
selection
instability

input
activation field

input
activation field

input
activation field

dimension
Stabilizing selection decisions

[Wilimzig, Schöner, 2006]
activation leaves a trace that may influence the activation dynamics later...

a simplest form of learning

relevant in DFT because the detection instability may amplify the slightly inhomogeneous activation patterns induced by the memory trace into peaks of activation
mov **

an act fiel

A loct

B locat

move mame

[Thelen, et al., BBS (2001)]

[Diueva, Schöner, Dev. Science 2007]
DFT of infant perseverative reaching

that is because reaches to B on A trials leave memory trace at B

[Dinveva, Schöner, Dev. Science 2007]
From neural to behavioral dynamics

\[ x_{\text{peak}} = \frac{\int dx \ x \ \sigma(u(x, t))}{\int dx \ \sigma(u(x, t))} \]

\[ \dot{x} = -\left[\int dx \ \sigma(u(x, t))\right] (x - x_{\text{peak}}) \]

\[ \Rightarrow \dot{x} = -\left[\int dx \ \sigma(u(x, t))\right] x + \left[\int dx \ x \ \sigma(u(x, t))\right] \]
New functions from higher-dimensional fields

- visual search: combine ridge input with 2D input..

[Slides adapted from Sebastian Schneegans, see Schneegans, Lins, Spencer, Chapter 5 of Dynamic Field Theory-A Primer, OUP, 2015]
New functions from higher-dimensional fields

- peaks at intersections of ridges: bind two dimensions

[Slides adapted from Sebastian Schneegans, see Schneegans, Lins, Spencer, Chapter 5 of Dynamic Field Theory-A Primer, OUP, 2015]
New functions from higher-dimensional fields: coordinate transforms

[Slides adapted from Sebastian Schneegans, see Schneegans, Chapter 7 of Dynamic Field Theory-A Primer, OUP, 2015]
Toward higher cognition: Grounding spatial concepts

- bring objects into foreground
- make coordinate transformation
- apply comparison operators

[Lipinski et al: JEP:LMC (2011)]