DFT Summer School: Lecture 2

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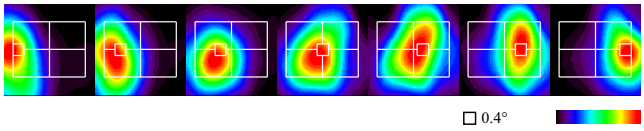
Metric spaces

- Single dynamical node can 'represent' the present/absence of input, but can't tell you what that input is (features) or where it is (space)
- For that, we need metric spaces…
  - Green hue value
  - 20 deg to the right of midline
  - The dog is similar to the cat

How do we represent metrics neurally?

- Simplest example: topographic representation in visual cortex…



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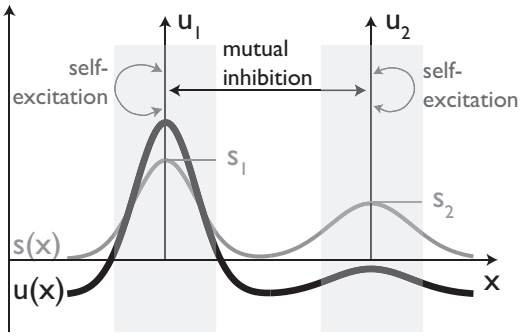
From nodes to fields



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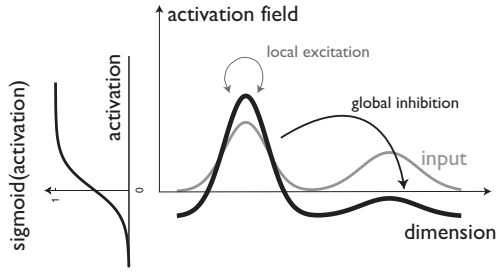
Dynamic fields

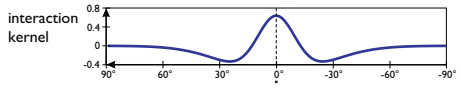
$$\tau \dot{u}(x,t) = -u(x,t) + h + s(x,t) + \int k(x-x')g(u(x',t))dx' + q\xi(x,t)$$

$$g(u) = \frac{1}{1+\exp(-\beta u)}.$$



$$k(x-x') = \frac{c_{\text{exc}}}{\sqrt{2\pi}\sigma_{\text{exc}}}\exp\left[-\frac{(x-x')^2}{2\sigma_{\text{exc}}^2}\right] - \frac{c_{\text{inh}}}{\sqrt{2\pi}\sigma_{\text{inh}}}\exp\left[-\frac{(x-x')^2}{2\sigma_{\text{inh}}^2}\right] - c_{\text{glob}}.$$

$$s(x,t) = \sum_i a_i \exp\left[-\frac{(x-p_i)^2}{2w_i^2}\right].$$



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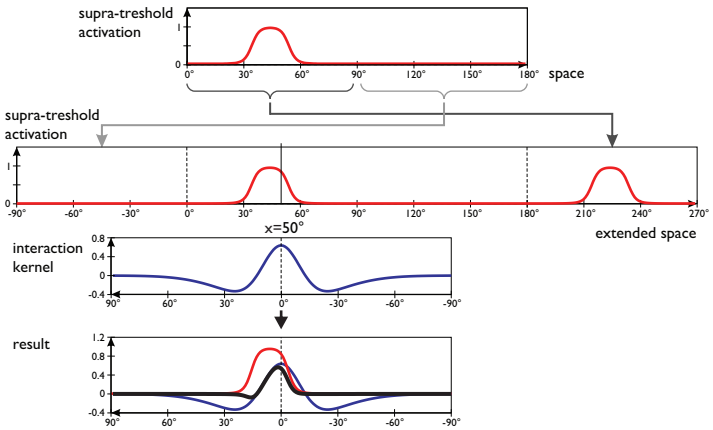
Convolution



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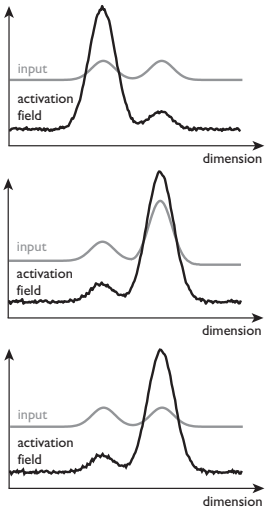
Different interactions = different behaviors



- Global inhibition → winner-take-all

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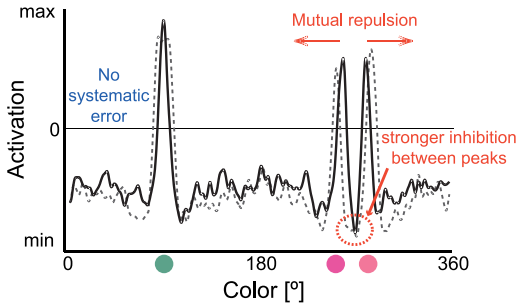
Different interactions = different behaviors

- Local-excitation / surround inhibition → multi-peak [simulator]

(a)



- Weak interactions = self-stabilized peaks
- Strong interactions = self-sustaining peaks

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Summary: Dynamic Fields

- Neuronal dynamics distributed over a metric space = dynamic field
- Fields combine...
  - Sigmoidal non-linearity
  - Neural interaction function (convolution kernel)
  - inputs
- Different neural interactions yield different behaviors
  - Self-stabilized (input-driven 'encoding')
  - Self-sustaining (working memory 'consolidation')
  - Winner-take-all (decision-making)
  - Multi-peak (multi-item working memory)

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Dynamic fields are not a neural analogy

- Evidence suggests that the brain actually work this way
- Neural population dynamics captured by DFT are observable in cortex (e.g., surround inhibition)

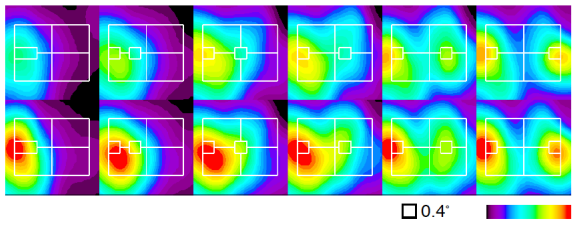

Figure 6. The measured two-dimensional DPAs (*top*) of composite stimuli (from *left* to *right*, 0.4–2.4° separation) were compared to the superpositions of the representations of their component elementary stimuli (*bottom*). The DPAs were based on spike activity of 178 cells averaged over the time interval from 30 to 80 msec after stimulus onset. Same conventions as in Figure 2*B*, the color scale was normalized to peak activation separately for each column. For small stimulus separation, note the remarkably reduced level of activation for the measured as compared to the superimposed responses. The bimodal distribution recorded for the largest stimulus separation comes close to match the superposition. However, inhibitory interaction can still be observed.

Jancke et al. (1999)

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Neural dynamics over multiple timescales

- Thus far, we've covered local decisions (peaks) within neural populations
- In some cases, these decisions are short-lived → detect a stimulus and then relax back to resting state
- In other cases, these decisions can remain for up to 30 or more seconds → self-sustaining peaks (working memory)
- But what about neural dynamics that extend over the timescales of learning and development?

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Memory traces

- Operates like a linear system at each field site (activation in field moves attractor to 1; absence of activation moves attractor to 0)
- Accumulate a trace as long as above-threshold activity
- Can have a convolution kernel that smears memory trace effects out over metric space
- Can also have a separate decay rate

$$\tau_{\text{mem}}\dot{u}_{\text{mem}}(x,t) = -u_{\text{mem}}(x,t) + g(u(x,t)) \quad (2.4)$$

$$\tau\,\dot{u}(x.t) = -u(x,t) + h + s(x,t) + c_{\text{mem}}u_{\text{mem}}(x,t) + \int k(x-x')g\big(u(x',t)\big)dx' \quad (2.5)$$

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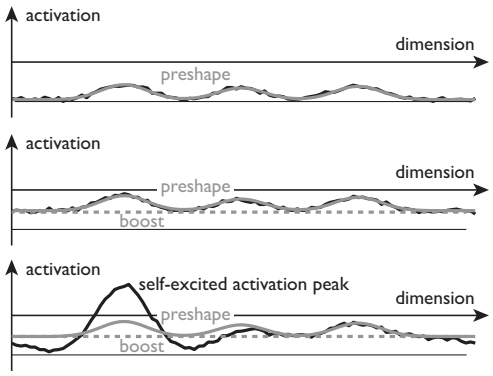
Building peaks from memory traces

- Memory trace + h boost



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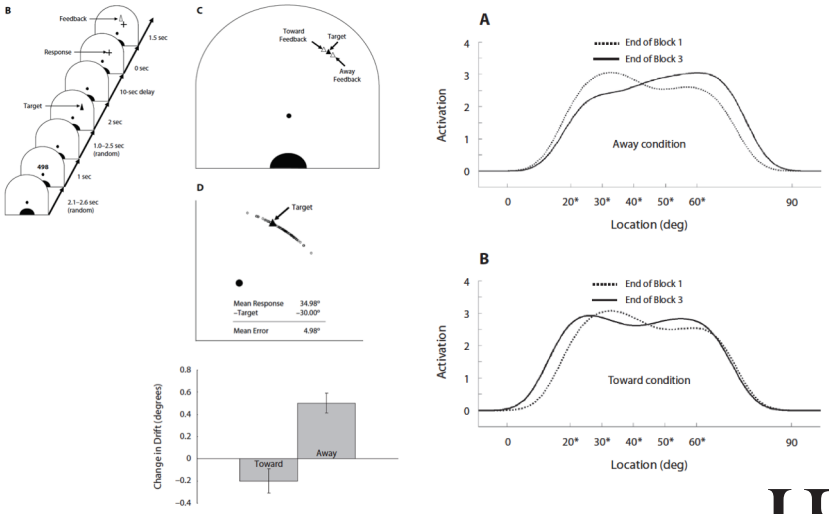
Evidence for memory traces



Lipinksi, Samuelson, Spencer (2010)

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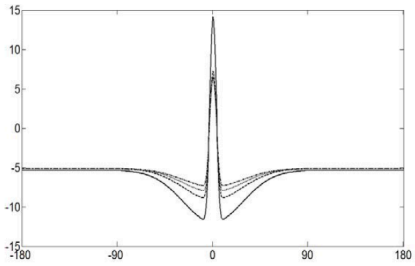
What about development?

- Spatial precision hypothesis: excitatory and inhibitory neural interactions become stronger over development (via a self-organizing or locally Hebbian process)
- This has multiple consequences…
  - Peaks build faster (faster RTs)
  - Peaks become narrower (enhance discrimination)
  - Peaks become stronger and more self-sustaining (more robust WM and higher capacity)



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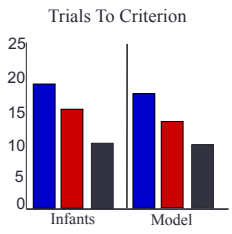
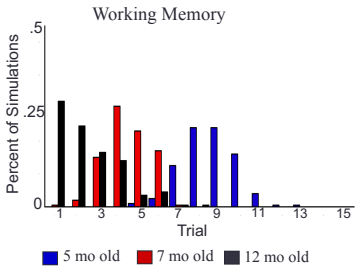
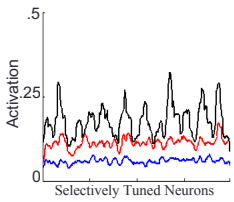
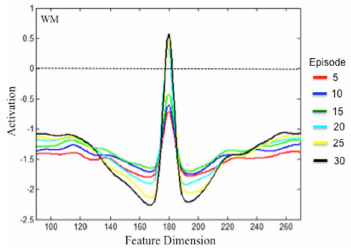
The SPH Emerges from Experience









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Summary: Learning & Development

- Memory traces open up DFT to neural processes that extend over a *learning* timescale
- We can also capture *developmental* change by increasing the strength of excitatory and inhibitory neural interactions
- Recent work suggests a link between the accumulation of memory traces distributed over metric dimensions and developmental changes in neural interaction strength
  - Learning and development might be mechanistically related

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