R01EB022864: Toward a Theory for Macroscopic Neural Computation Based on Laplace Transform

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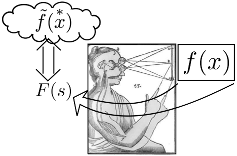
To make a theory of cognition in the brain we need

- Write a set of concise equations that we can understand computagtionally.
- To map smoothly between cognitive models and activity of many neurons.
- To have this theory apply across different “silos” of computational cognitive neuroscience.

Howard & Hasselmo (2020, arXiv)

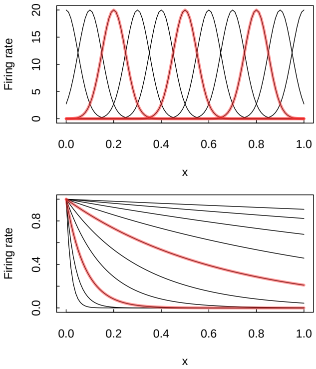
Overview

- Theory for coding information as functions *via* Laplace transform/inverse pairs.
- Neurons are not the atom: Populations are
- Predictions of the theory are confirmed for functions of time in EC/hippocampus
- Can build cognitive models for memory, navigation, evidence accumulation



Representing functions with populations of neurons

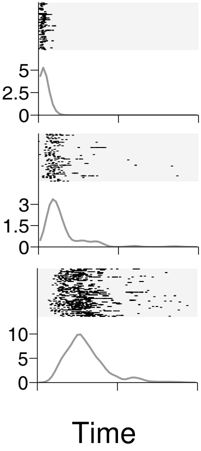
- Continua distributed across neurons
- $\tilde{f}(\overset{*}{x})$ estimates $f(x)$.
- Laplace domain $F(s) = \mathcal{L}f(x)$



Populations of neurons

- Individual neurons in $F(s)$ have exponential receptive fields indexed by their rate constant s.
- Individual neurons in $\tilde{f}(\overset{*}{x})$ are indexed by the center of their receptive field $\overset{*}{x}$
- $F(s)$ is the Laplace transform of f and this has important computational implications.

What would $\tilde{f}(\overset{*}{\tau})$ look like in the brain?

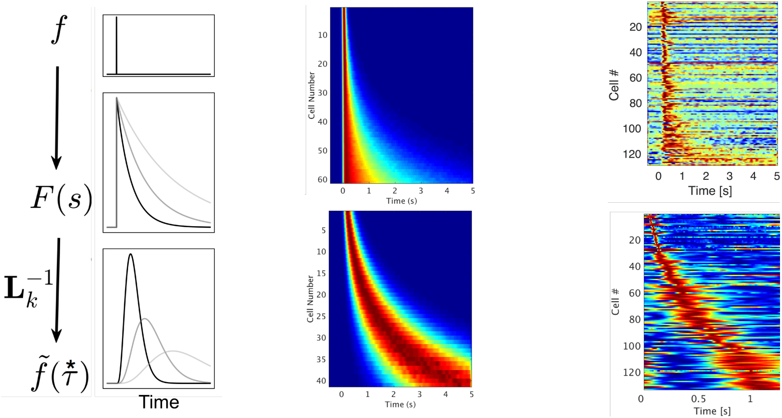


MacDonald, et al., 2011

- “Time cells” are compressed.
- Different stimuli trigger different sequences.
- Hippocampus (CA1, CA3, DG) in rodents
- . . . and monkeys (Cruzado, et al., bioRxiv)

Laplace transform of time in monkey EC

Bright, Meister, Cruzado, Tiganj, Howard and Buffalo, (bioRxiv)



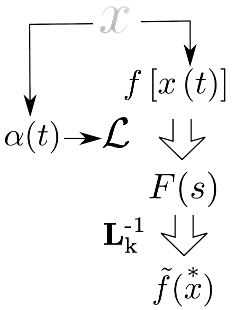
(See also Tsao et al., (2018, *Nature*)

Time in EC and hippocampus

- Populations in entorhinal cortex (LEC) estimate $F(s)$ for functions of time.
- Populations of time cells in hippocampus (CA1,CA3,DG) estimate functions of time
- These populations are one synapse away: $\tilde{f}(\overset{*}{\tau}) = \mathbf{L}_{\mathrm{k}}^{-1} F(s)$
- This frames systems/computational neuroscience questions about this structure.

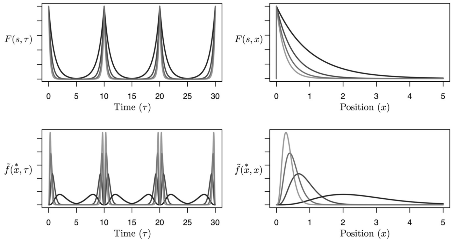
Functions of space in hippocampus and MTL

$$\frac{dF(s)}{dt} = \alpha(t)\left[-sF(s) + f(t)\right]$$



$\alpha(t) = dx/dt$; $f(t)$ is landmark contact

Border cells/place cells

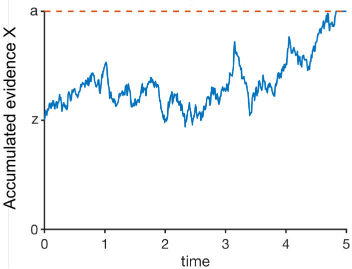


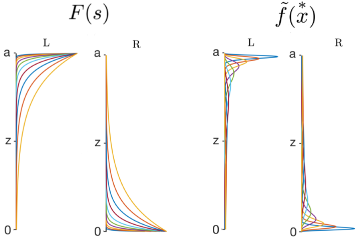
Navigating in a Laplace decision space

Howard, Luzardo & Tiganj (2018, *Comp. Brain & Behav.*)

Diffusion model (Ratcliff 1978) for evidence accumulation:

$$X_t = X_{t-1} + \mathcal{N}(\mu, 1)$$





Populations of leaky integrator neurons with a spectrum of leak rates (Koay, Thiberge, Brody & Tank, 2019; bioRxiv))

Decision spaces

- We can generalize from time to any variable for which we have the time derivative.
- Makes predictions about border/place cells, trajectory/splitter cells, etc in the MTL.
- We can model abstract decision spaces and numerosity
- Theory maps directly onto behavioral diffusion model and also neurophysiology.

Summary

- We can build cognitive models and describe neural populations with the same equations . . .
- . . . across domains of cognitive neuroscience.
- The signature of the theory is heterogeneity in RFs
- We're working to generalize to N-D, unify other domains of computational cognitive neuroscience, and develop AI applications.