SYDE 556/750

Simulating Neurobiological Systems Lecture 5: Feed-Forward Transformation

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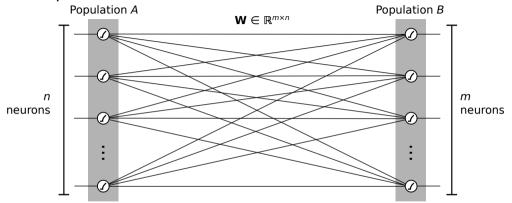
Introduction

- We've only talked about representation til now
 What about computation?
- ► We start by focusing on the state of a network after learning and development
- ► A kind of hypothesis testing and generation



DALL-E AI Generated Art, 2022

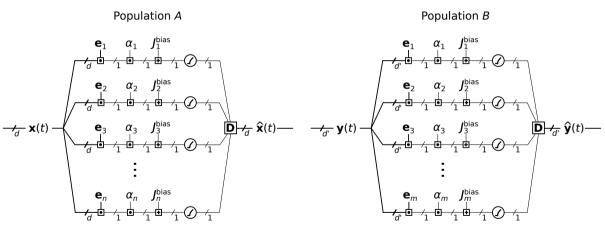
NEF Principle 2: Transformation



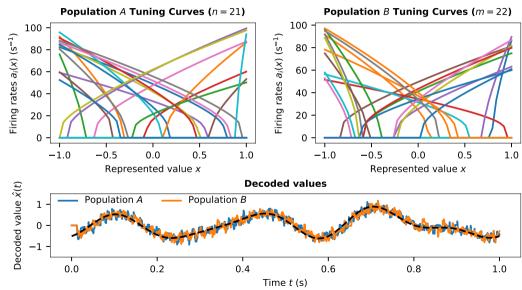
NEF Principle 2 – Transformation

Connections between populations describe *transformations* of neural representations. Transformations are functions of the variables represented by neural populations.

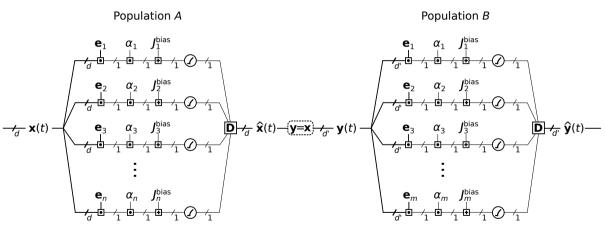
A Tale of Two Populations (I)



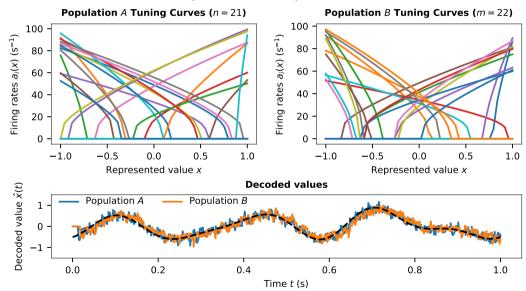
Communication Channel Experiment: Same input signal



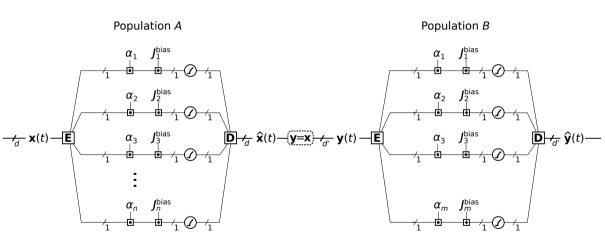
A Tale of Two Populations (II)



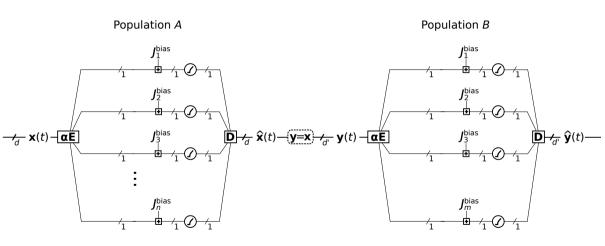
Communication Channel Experiment: Populations in series



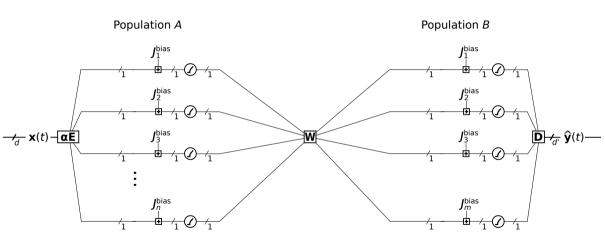
Computing Synaptic Weights: Step 1 – Encoding Matrix



Computing Synaptic Weights: Step 2 – Scaled Encoding Matrix



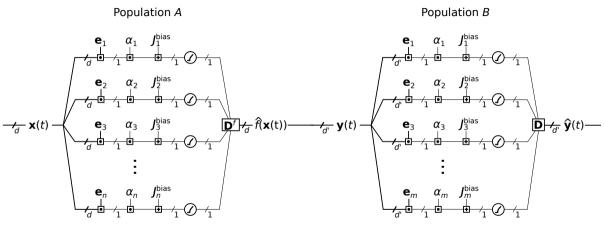
Computing Synaptic Weights: Step 3 - W = ED



Computational Complexity

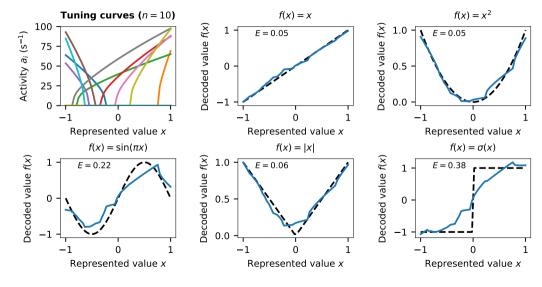
- ▶ Weights multiplying $\mathbf{a} \in \mathbb{R}^n$ with $\mathbf{W} \in \mathbb{R}^{m \times n}$ is $\mathcal{O}(nm)$ i.e., $\approx \mathcal{O}(n^2)$
- ▶ Decoding $\hat{\mathbf{x}} = \mathbf{Da}$ is $\mathcal{O}(dn)$
- ▶ Encoding $\mathbf{J} = \mathbf{E}\hat{\mathbf{x}} + \mathbf{J}_{\mathrm{bias}}$ is $\mathcal{O}(dm)$
- lacktriangledown Encoding/Decoding $\mathcal{O}(d(n+m))$ or $pprox \mathcal{O}(dn)$ for n=m
- ▶ So if *d* is small we get a linear complexity $\mathcal{O}(n)$
- Therefore, sequential decoding and re-encoding saves a lot of time compared to using actual synaptic weights
- One reason why Nengo is so fast compared to other SNN simulators

Computing Functions

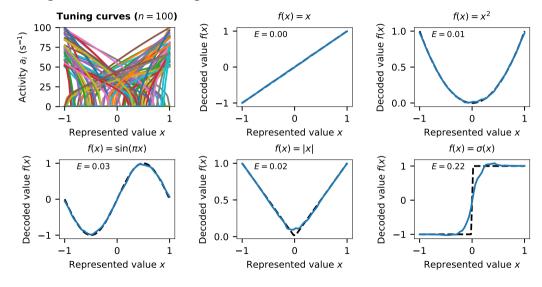


Function Decoder $\mathbf{D}^f = \left((\mathbf{A} \mathbf{A}^\mathsf{T} + \mathcal{N} \sigma^2 \mathbf{I})^{-1} \mathbf{A} \mathbf{Y}^\mathsf{T} \right)^\mathsf{T}$, where $\left(\mathbf{Y} \right)_{ik} = \left(f(\mathbf{x}_k) \right)_i$

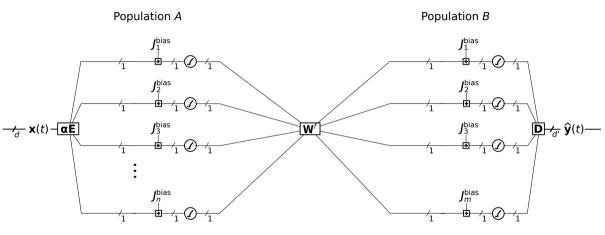
Decoding Functions – Using a Few Neurons



Decoding Functions - Using More Neurons



Computing Functions – Weight Matrix



$$\mathbf{W}^f = \mathbf{E}\mathbf{D}^f$$

Recipe for any feedforward transformation

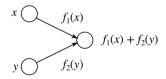
- 1. Define encoding for two populations (input/output)
- 2. Write the transformation with the represented input variables
- 3. Solve for the \mathbf{D}^f for that transformation for the input population
- 4. Sub 3. into the encoding for the output variable

Computing Multivariate Functions

→ Homogenous population
 → Linear connection
 → Inh. connection
 → Exc. connection

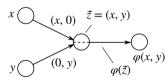
Linear Superposition

$$W^{f_1}\mathbf{a}_1(\mathbf{x}) + W^{f_2}\mathbf{a}_2(\mathbf{y})$$



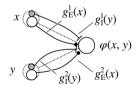
Nonlinear Functions

Multi-dimensional ${f z}$



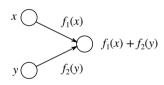
(Dendritic Computation)

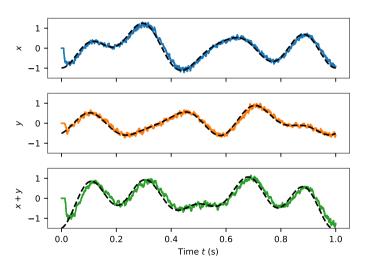
Exploit dendritic nonlinearity



Computing Multivariate Functions – Linear Superposition

Linear Superposition

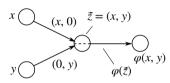




Computing Multivariate Functions – Multiplication

Nonlinear Functions

Multi-dimensional z



Multiplication is useful...

- Gating of signals
- ► Attention effects
- Binding
- Statistical inference

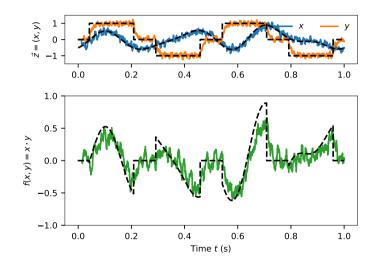


Image sources

Title slide

"Yellow Butterfly"

Author: Albert Bierstadt, circa 1890.

From Wikimedia.