SYDE 556/750

Simulating Neurobiological Systems
Lecture 5: Feed-Forward Transformation

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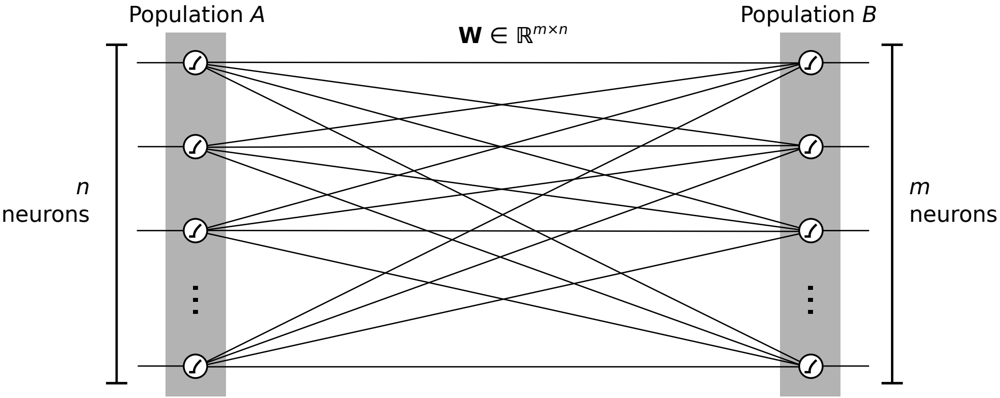
Introduction

- 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

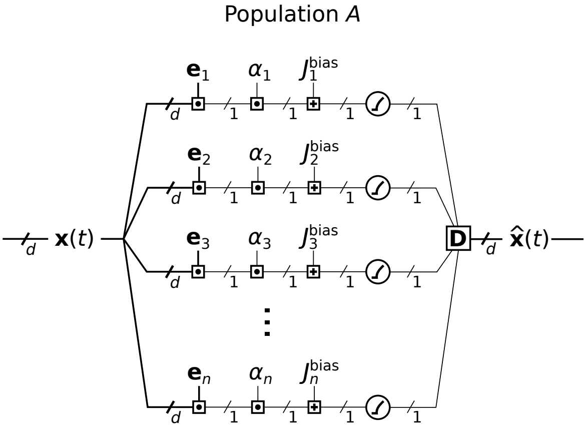
NEF Principle 2: Transformation

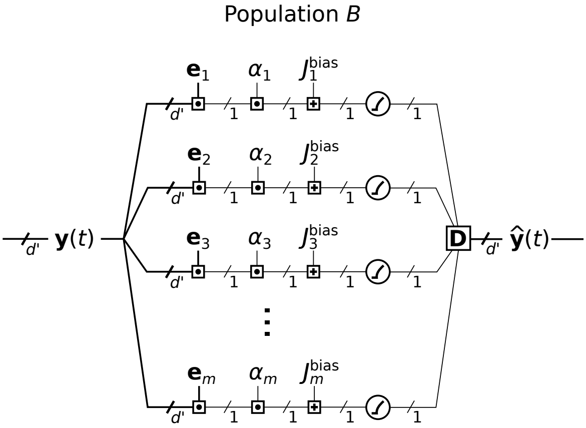


NEF Principle 2 – Transformation

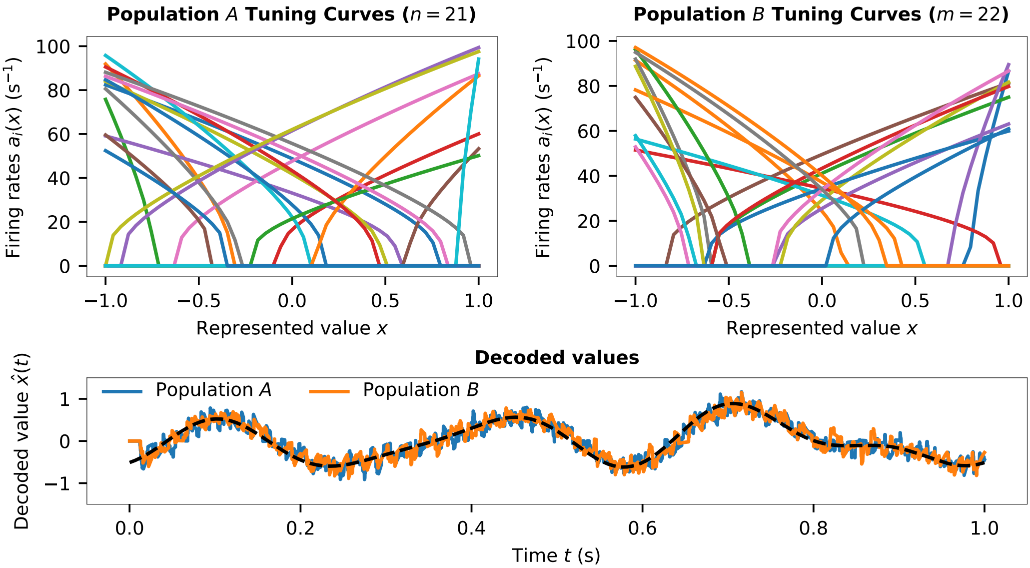
Connections between populations describe *transformations* of neural representations. Transformations are functions of the variables represented by neural populations.

A Tale of Two Populations (I)

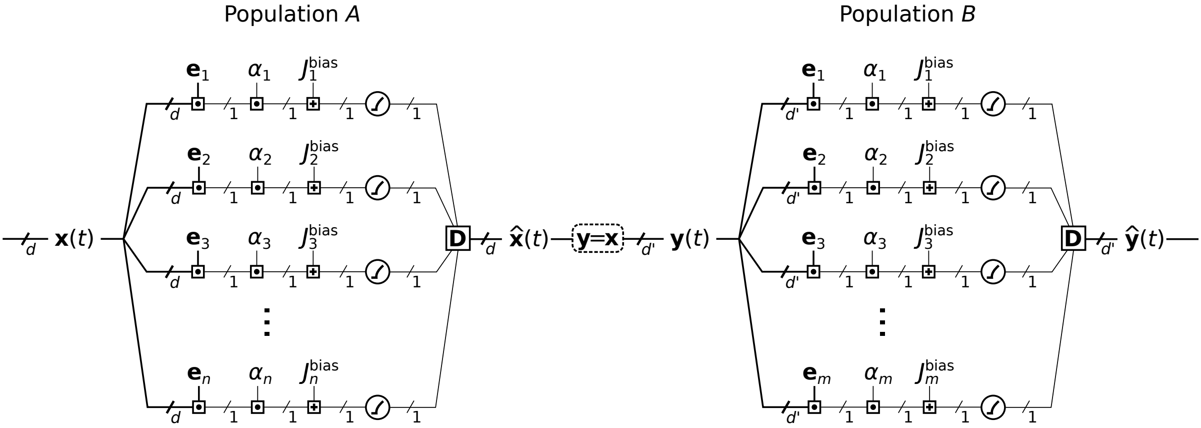




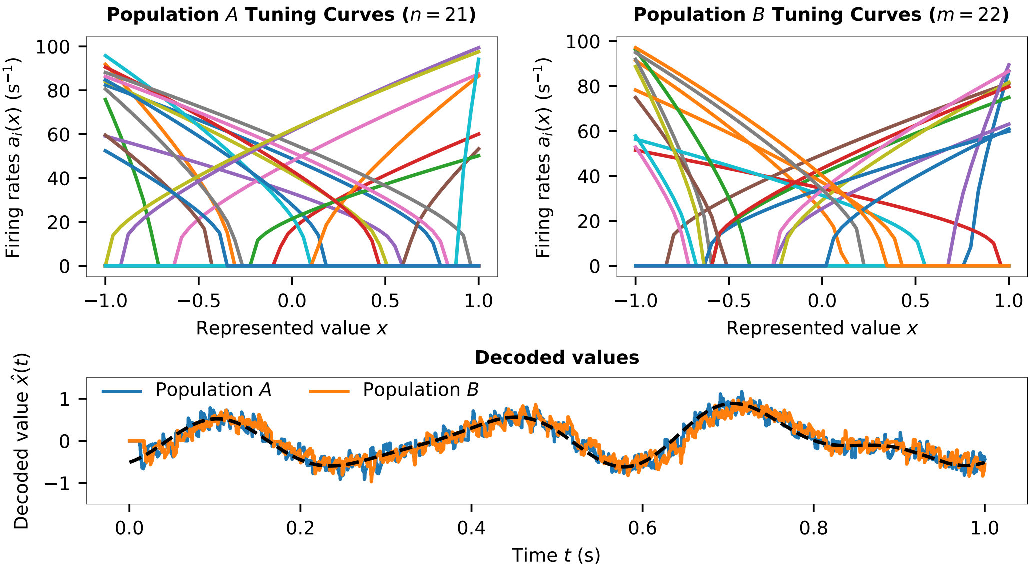
Communication Channel Experiment: Same input signal



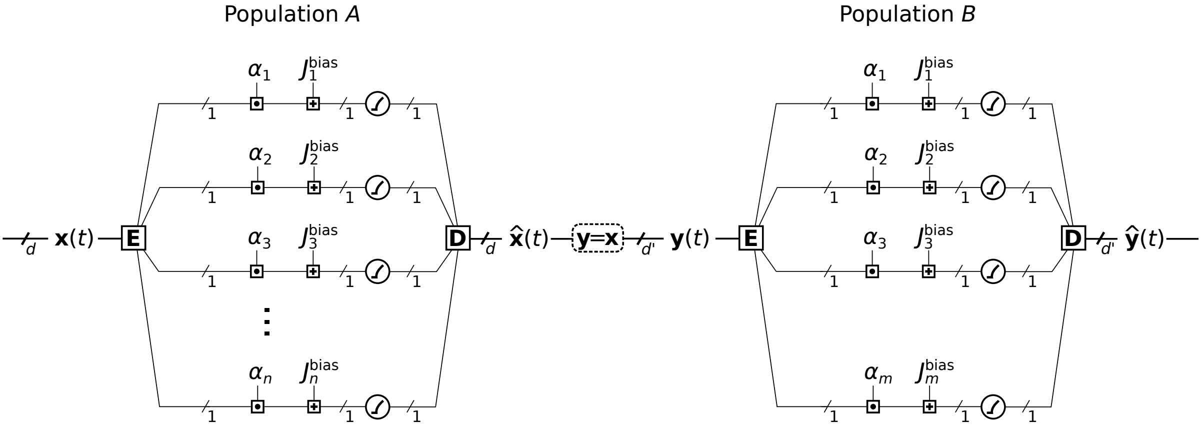
A Tale of Two Populations (II)



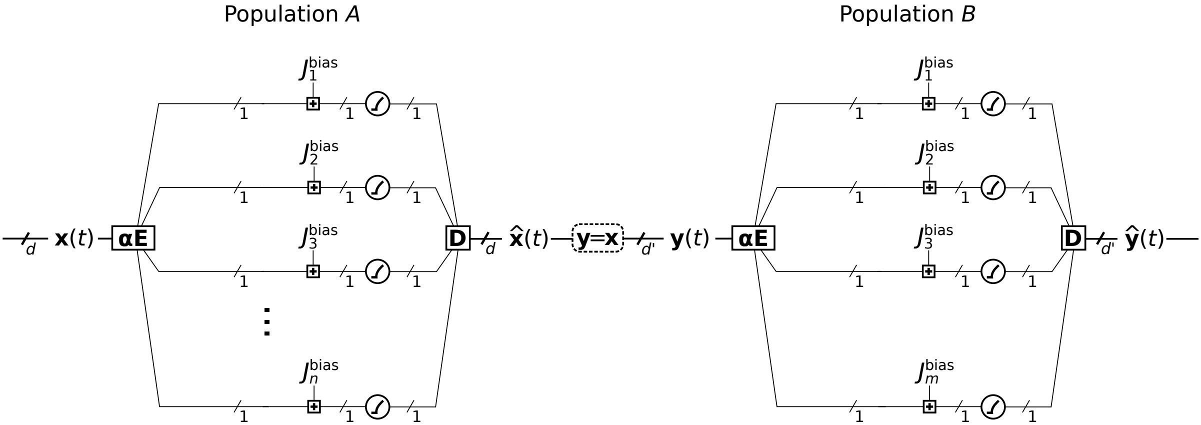
Communication Channel Experiment: Populations in series



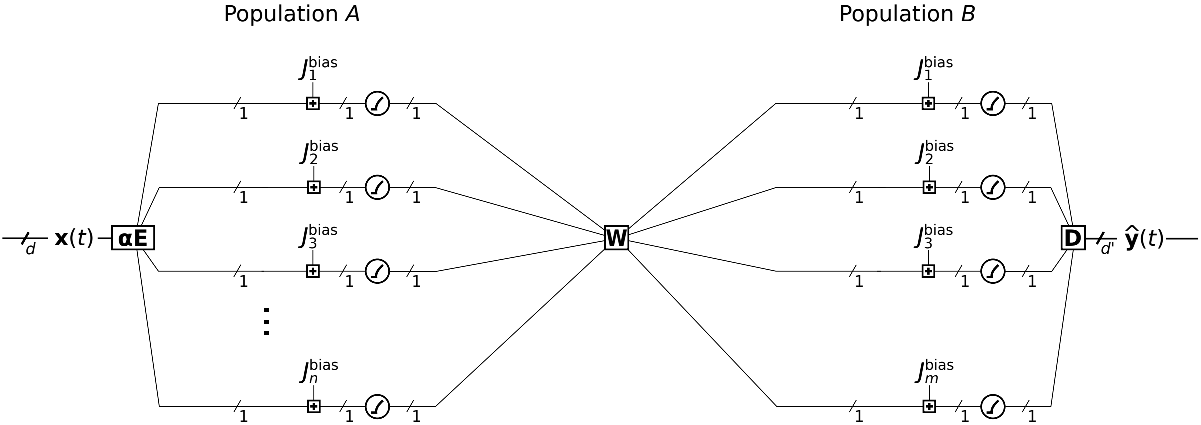
Computing Synaptic Weights: Step 1 – Encoding Matrix



Computing Synaptic Weights: Step 2 – Scaled Encoding Matrix



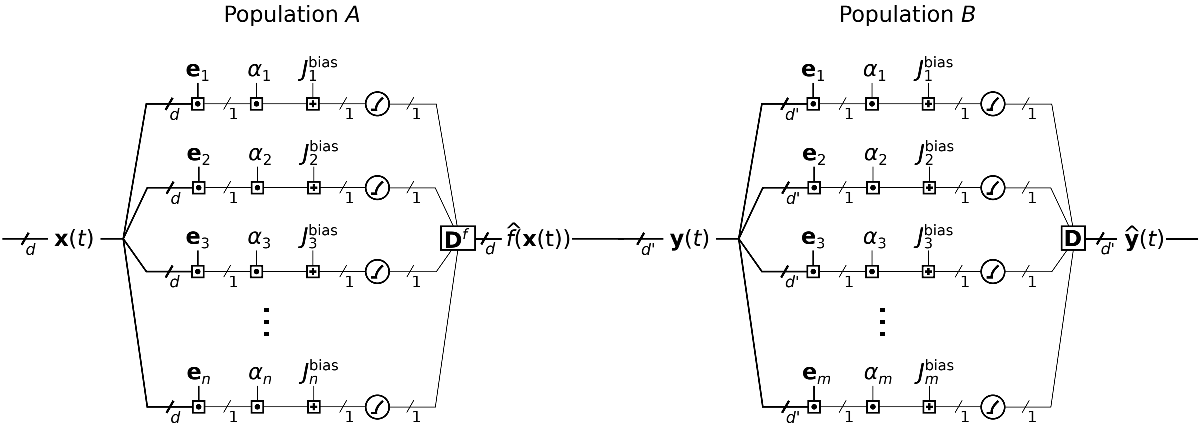
Computing Synaptic Weights: Step 3 – $\mathbf{W} = \mathbf{ED}$



Computational Complexity

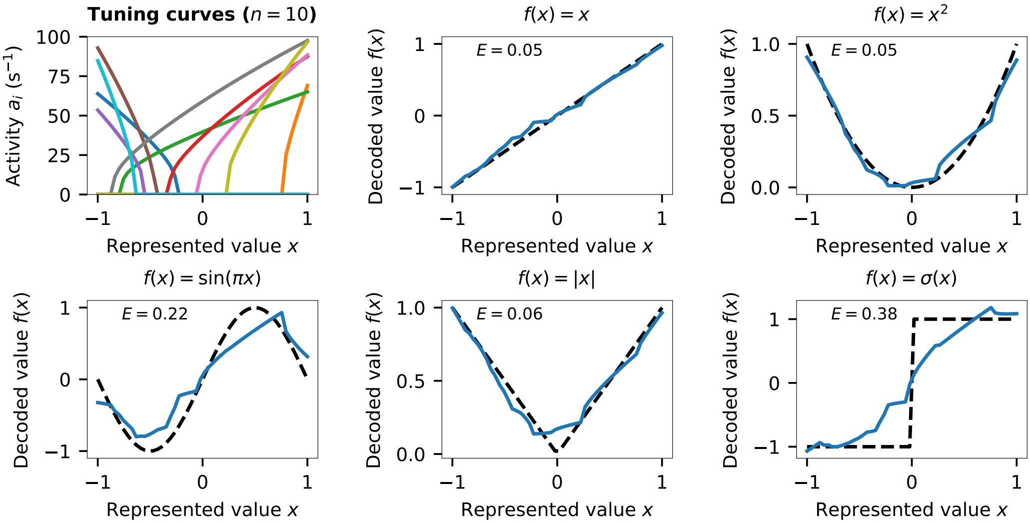
- Weights - multiplying $\mathbf{a} \in \mathbb{R}^n$ with $\mathbf{W} \in \mathbb{R}^{m \times n}$ is $\mathcal{O}(nm)$ i.e., $\approx \mathcal{O}(n^2)$
- Decoding - $\hat{\mathbf{x}} = \mathbf{D}\mathbf{a}$ is $\mathcal{O}(dn)$
- Encoding - $\mathbf{J} = \mathbf{E}\hat{\mathbf{x}} + \mathbf{J}_{\text{bias}}$ is $\mathcal{O}(dm)$
- Encoding/Decoding - $\mathcal{O}(d(n+m))$ or $\approx \mathcal{O}(dn)$ 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

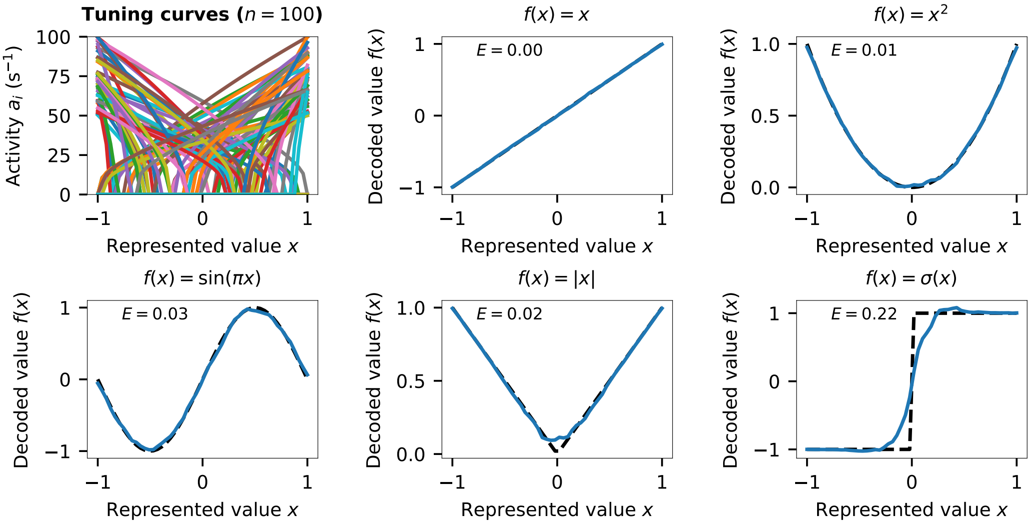


Function Decoder $\mathbf{D}^f = \left((\mathbf{A}\mathbf{A}^\mathsf{T} + N\sigma^2\mathbf{I})^{-1}\mathbf{A}\mathbf{Y}^\mathsf{T} \right)^\mathsf{T}$, where $(\mathbf{Y})_{ik} = \left(f(\mathbf{x}_k) \right)_i$

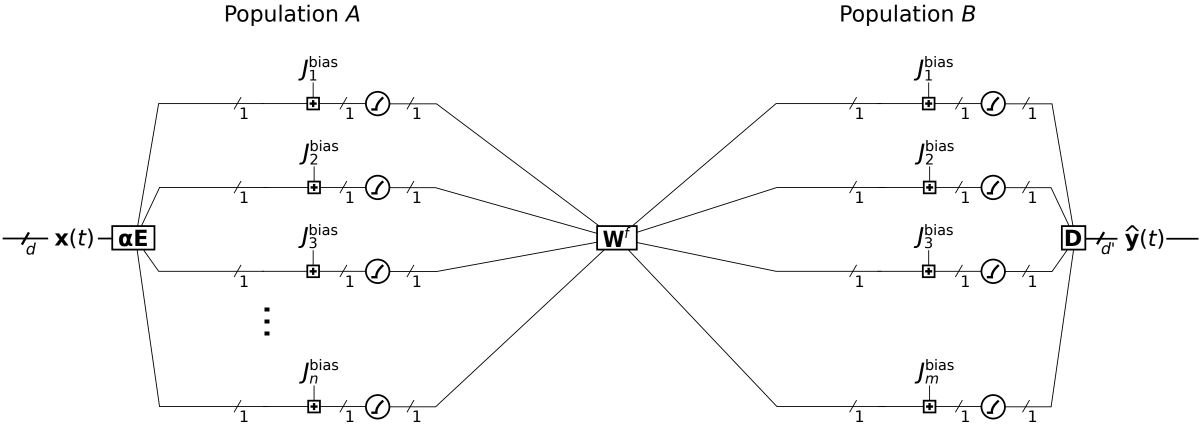
Decoding Functions – Using a Few Neurons



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

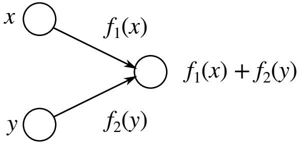
Computing Multivariate Functions

Homogenous population Heterogenous population

Linear connection Inh. connection Exc. connection

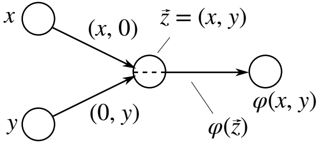
Linear Superposition

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



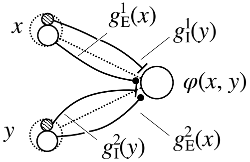
Nonlinear Functions

Multi-dimensional $\mathbf{z}$



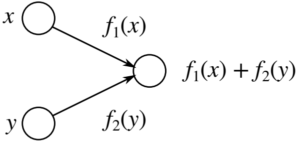
(Dendritic Computation)

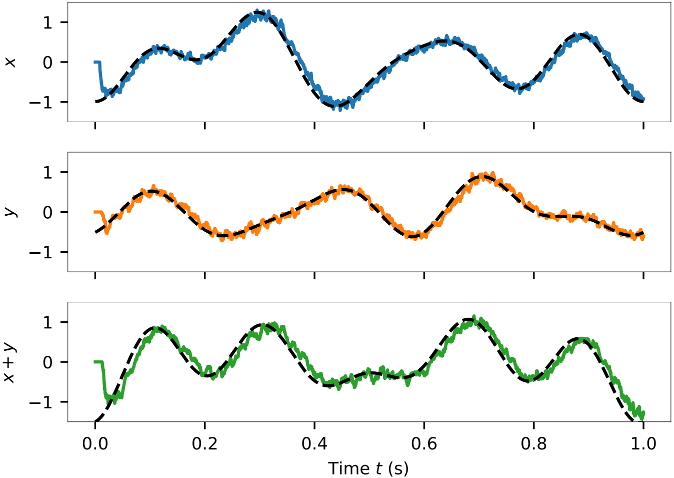
Exploit dendritic nonlinearity



Computing Multivariate Functions – Linear Superposition

Linear Superposition

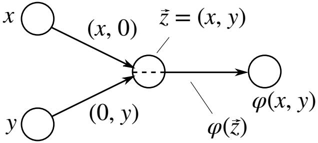




Computing Multivariate Functions – Multiplication

Nonlinear Functions

Multi-dimensional $\mathbf{z}$



Multiplication is useful…

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

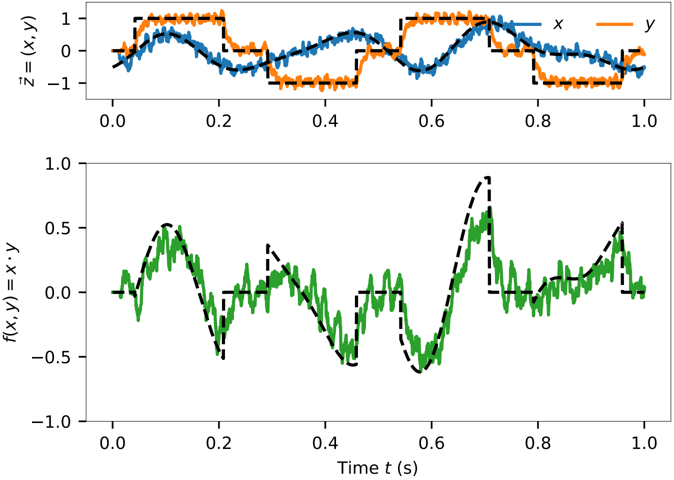


Image sources

Title slide
"Yellow Butterfly"
Author: Albert Bierstadt, circa 1890.
From Wikimedia.