Dimensionality reduction of large-scale neural recordings

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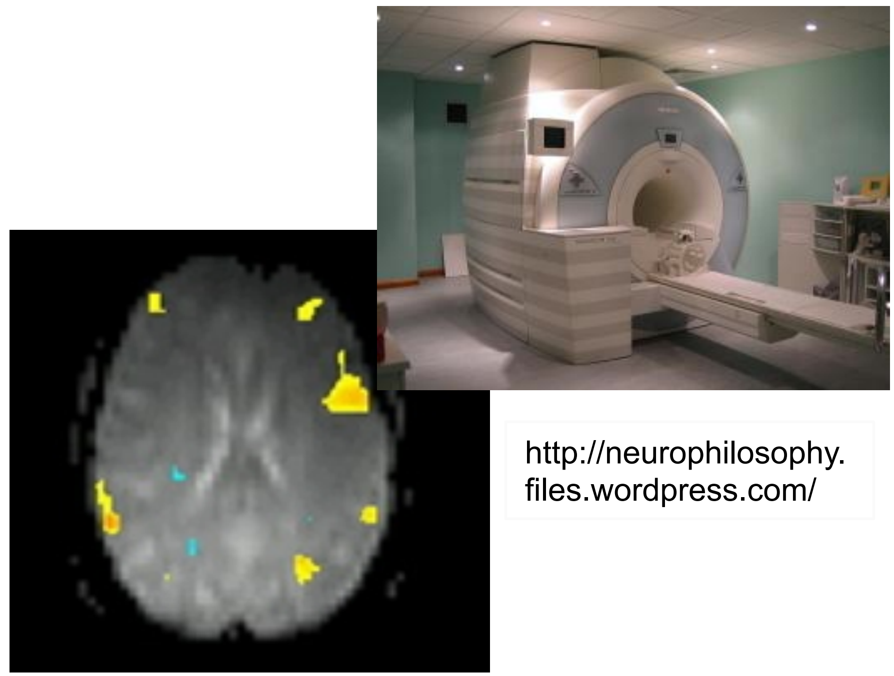
Multi-dimensional neural recordings

Electroencephalography (EEG)

http://people.brandeis.edu/~sekuler

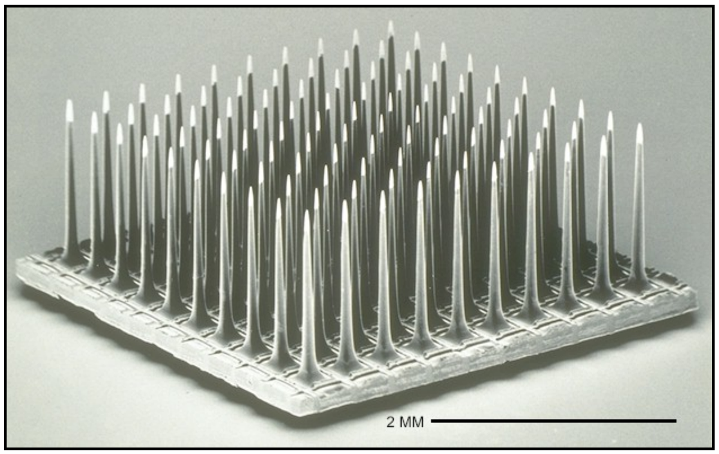
Functional magnetic resonance imaging (fMRI)



http://neurophilosophy.files.wordpress.com/

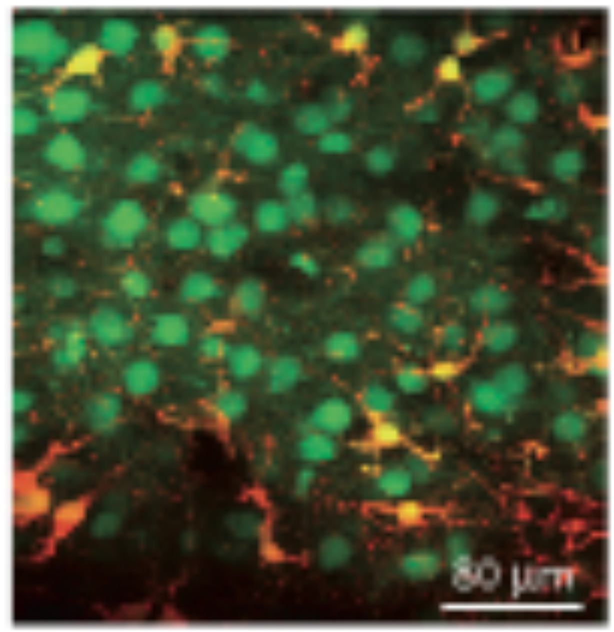
Multi-dimensional neural recordings

Multi-electrode arrays

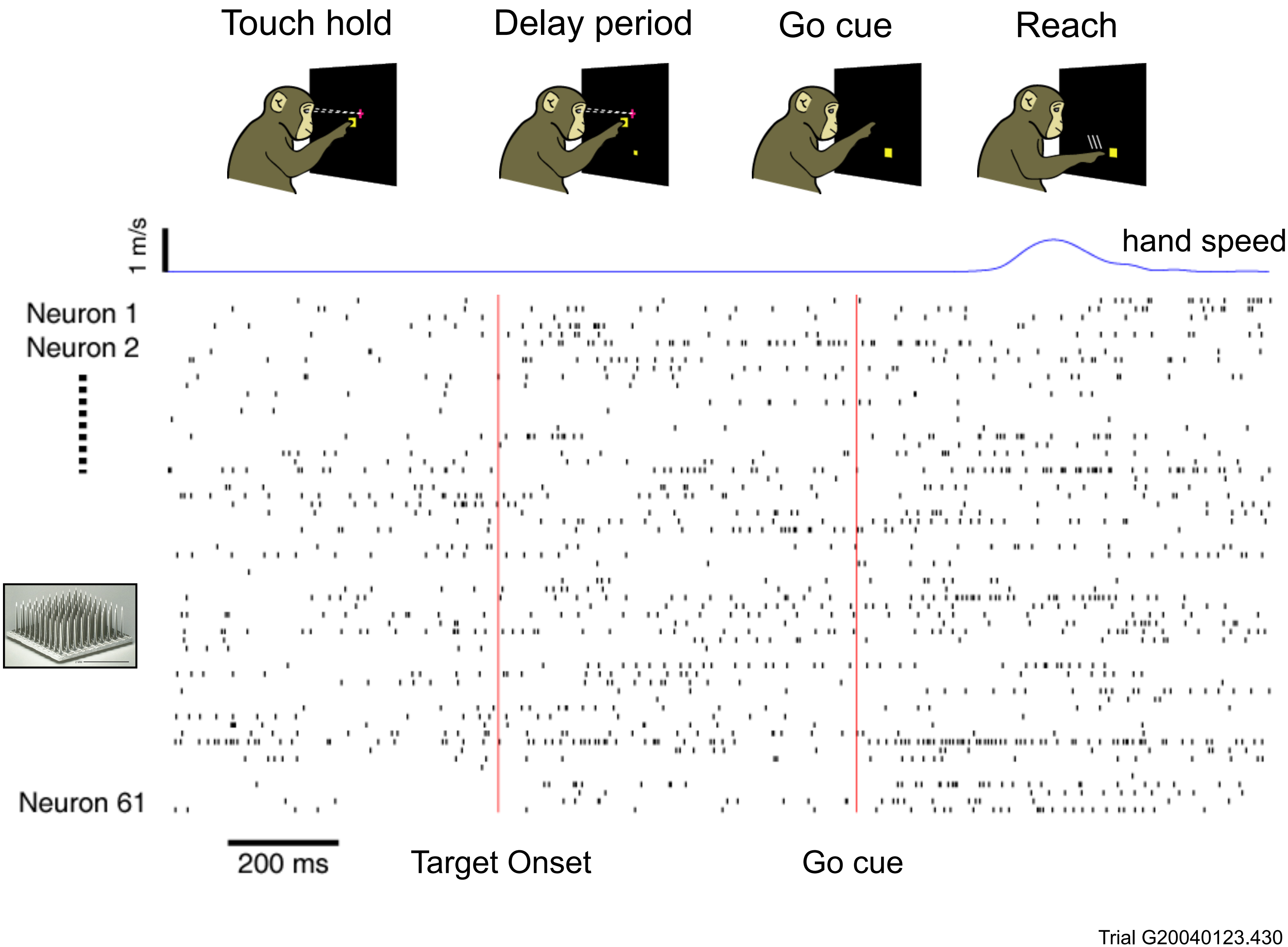


Blackrock Microsystems

Optical imaging



Kerr and Denk, 2008.


Touch hold
Delay period
Go cue
Reach
1 m/s
hand speed
Neuron 1
Neuron 2
Neuron 61
200 ms
Target Onset
Go cue
Trial G20040123.430

Rationale for dimensionality reduction

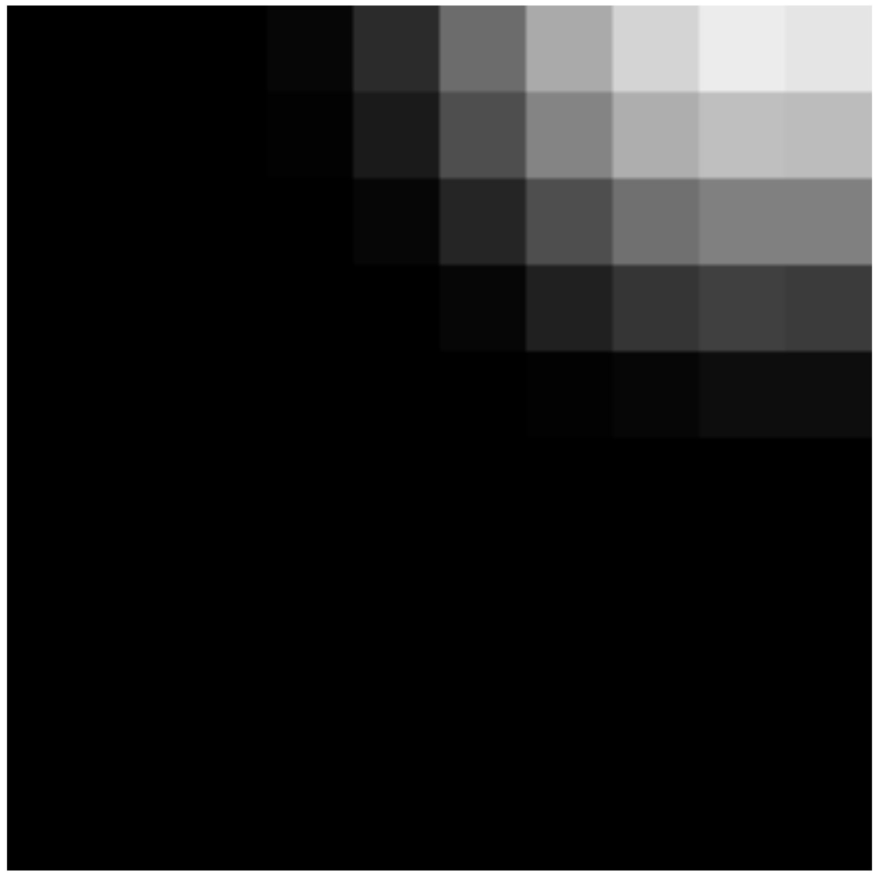
- Because neurons form networks, each neuron cannot act independently
- The brain has fewer degrees of freedom at its disposal than the number of neurons at play

Video analogy

- Each pixel is a neuron
- Pixel intensity is activity level of neuron

Video analogy

Video analogy

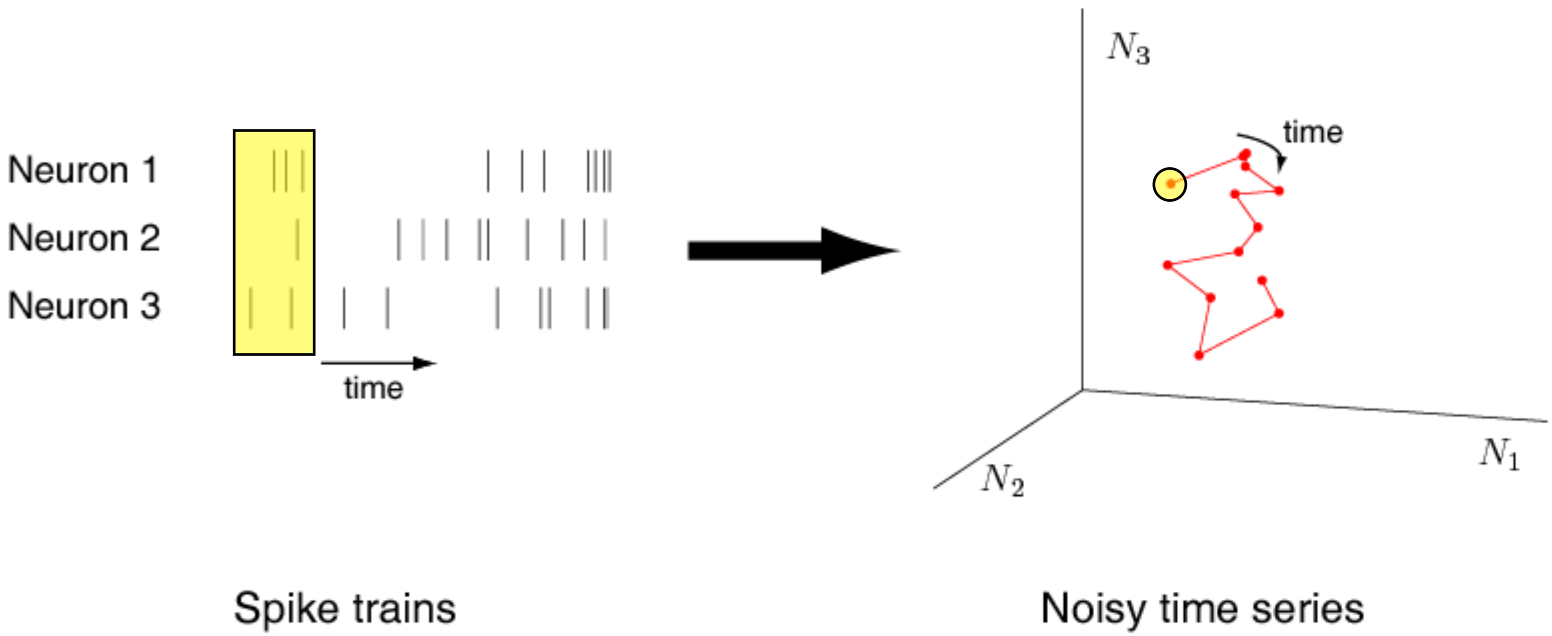


Video analogy

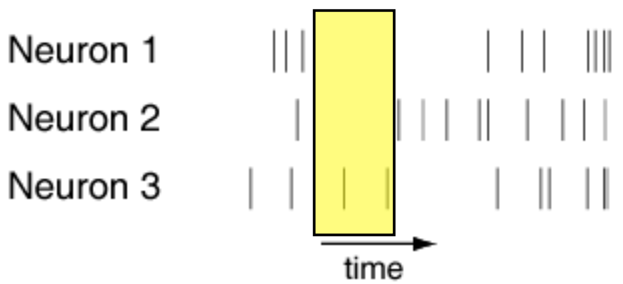
Video analogy

- To fully describe this video, don't need to model each pixel's intensity (high-D)
- Each frame fully specified by location of ball (2D)
- Sequence of frames fully specified by Newton's laws
- Challenge: can we identify low-D state from noisy high-D observations ("**dimensionality reduction**")?

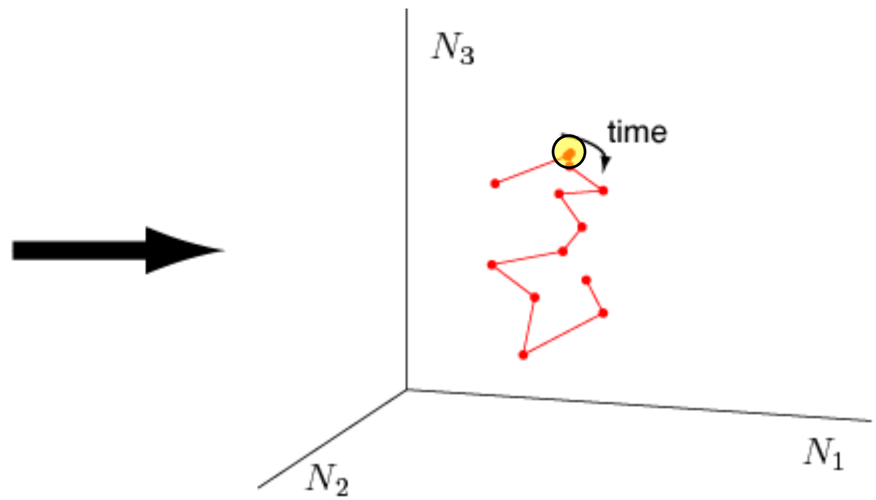
Dimensionality reduction of population activity



Dimensionality reduction of population activity

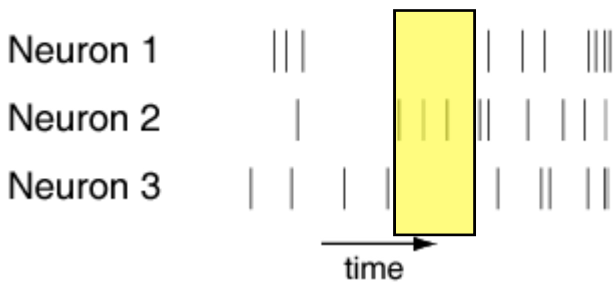


Spike trains

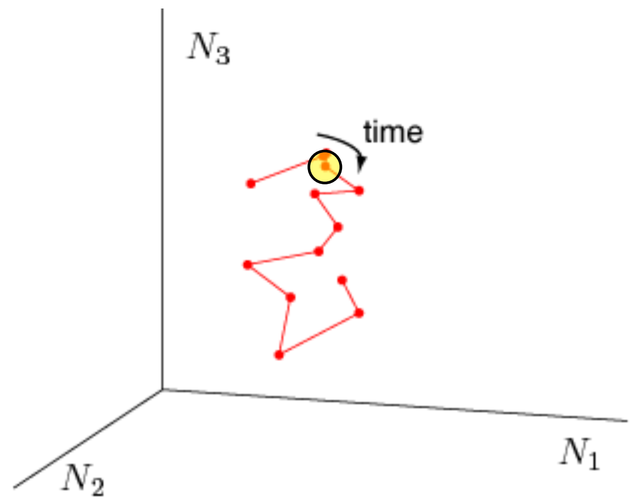


Noisy time series

Dimensionality reduction of population activity

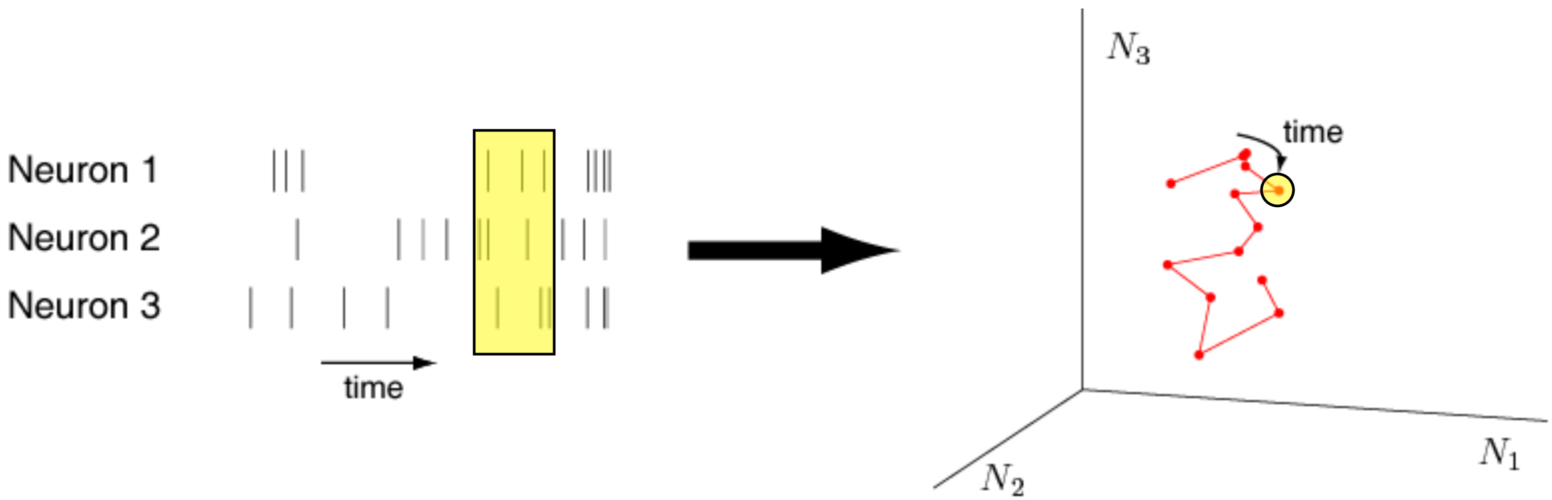


Spike trains



Noisy time series

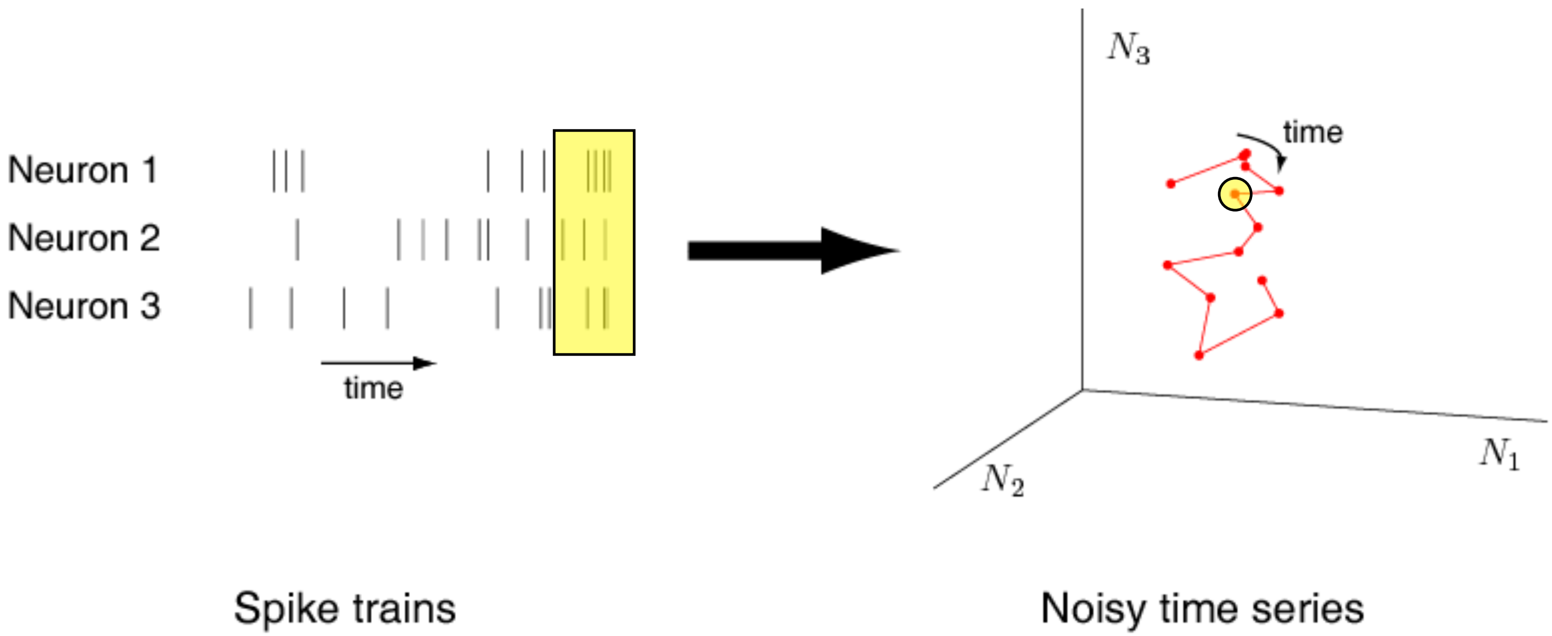
Dimensionality reduction of population activity



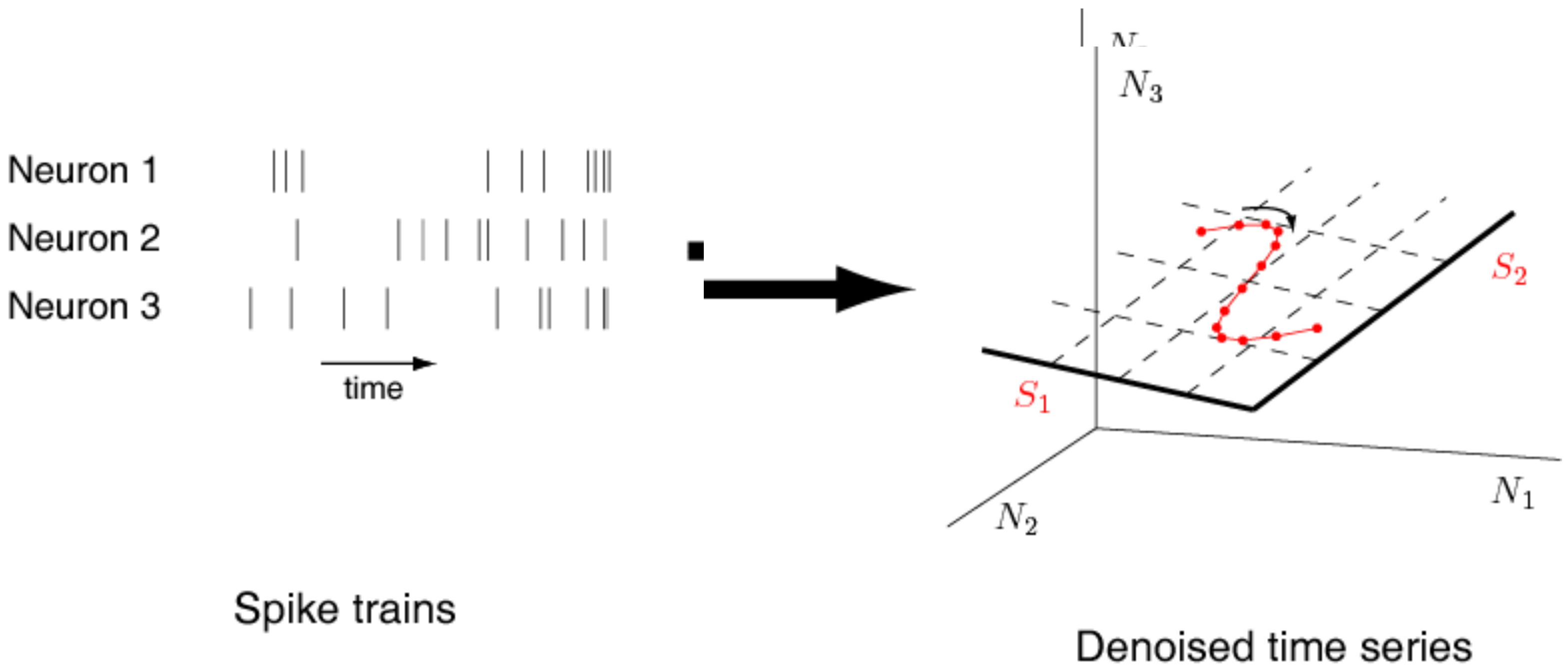
Spike trains

Noisy time series

Dimensionality reduction of population activity



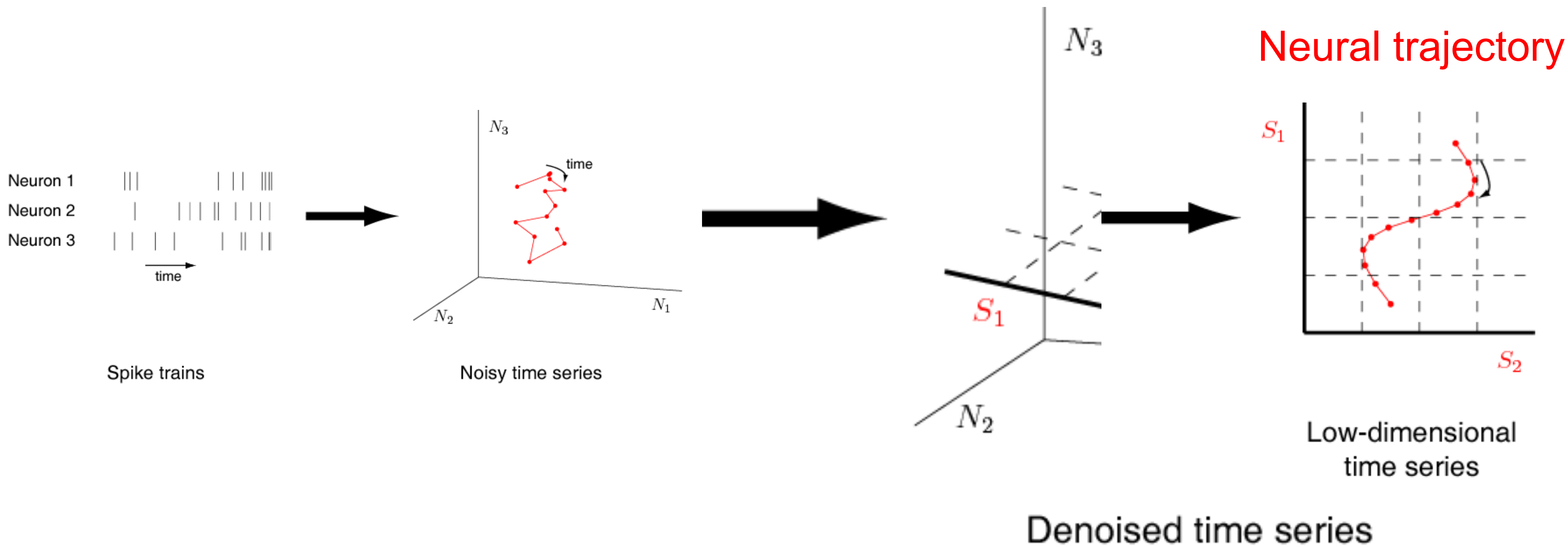
Dimensionality reduction of population activity



Key operations:

- Temporal smoothing
- Dimensionality reduction

Dimensionality reduction of population activity



Example studies using dimensionality reduction

Decision making: Harvey et al., *Nature* 2013; Mante et al., *Nature* 2013

Learning: Durstewitz et al., *Neuron*, 2010; Sadtler et al., *Nature* 2014

Motor control: Churchland et al., *Nature* 2012; Kaufman et al., *Nat Neurosci* 2014

Olfaction: Mazor & Laurent, *Neuron* 2005

Working memory: Machens et al., *J Neurosci* 2010; Rigotti et al., *Nature* 2013

Visual attention: Cohen & Maunsell, *J Neurosci* 2010

Audition: Luczak et al., *Neuron* 2009

Cunningham & Yu, *Nat Neurosci*, 2014.

Reasons to use dimensionality reduction

1) Single-trial analyses of neural population activity

(e.g., Afshar et al., *Neuron* 2011; Harvey et al., *Nature*, 2012;
Kiani et al., *Curr Biol* 2014; Kaufman et al., *eLife* 2015)

2) Hypotheses about population activity structure

(e.g., Mante et al., *Nature* 2013; Sadtler et al., *Nature* 2014;
Kaufman et al., *Nat Neurosci* 2014)

3) Exploratory analyses of large datasets

(e.g., Ahrens et al., *Nature*, 2012)

Cunningham & Yu, *Nat Neurosci*, 2014.

Dimensionality reduction methods

- Principal components analysis (PCA):
  Good for trial-averaged analyses; no concept of "noise"
- Factor analysis (FA):
  Good for single-trial analyses; no temporal smoothing
- Gaussian-process factor analysis (GPFA):
  Good for single-trial analyses; has temporal smoothing

Cunningham & Yu, *Nat Neurosci*, 2014.

Dimensionality reduction methods

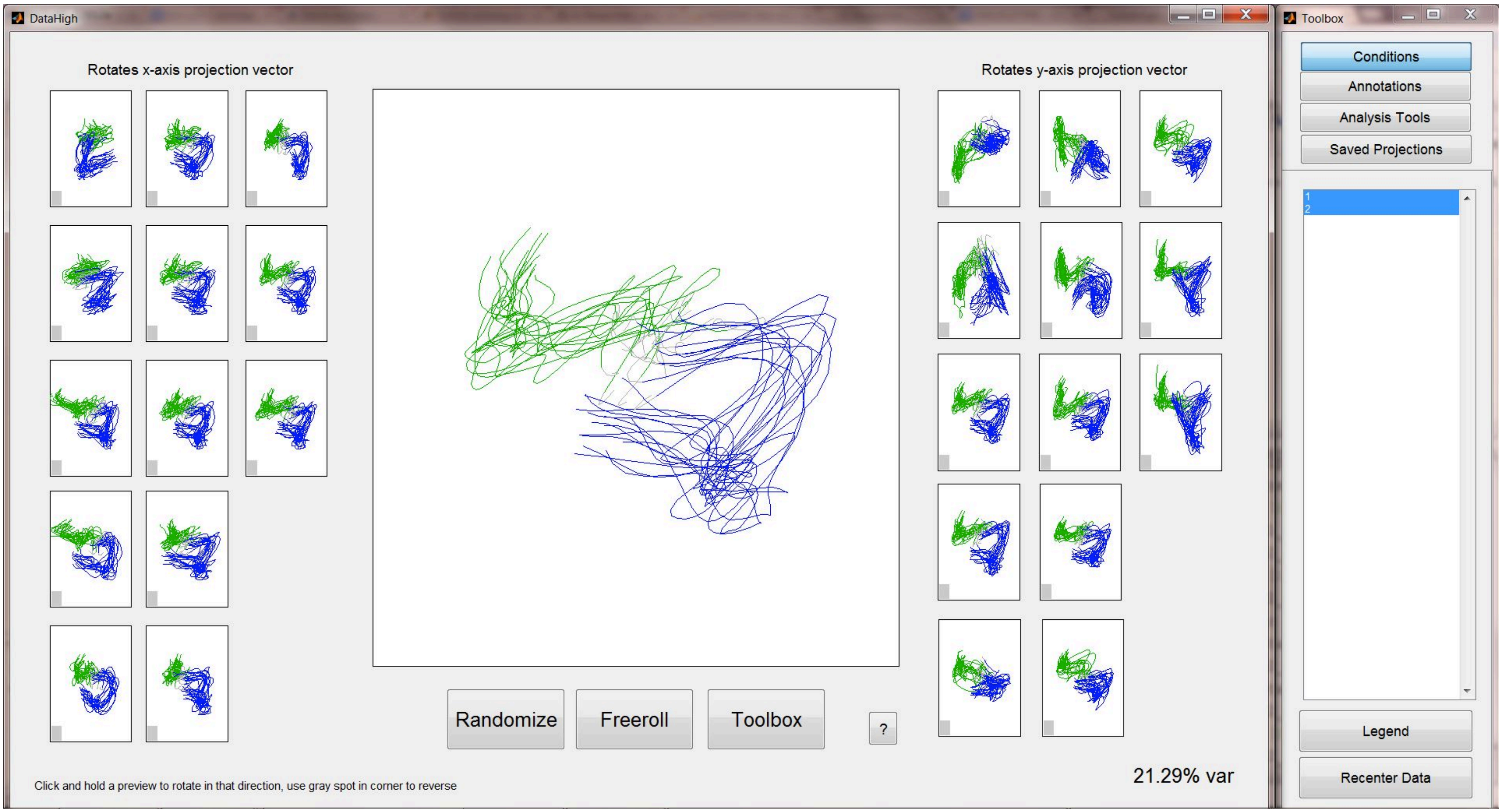
- Latent dynamical systems (e.g., LDS, LFADS):
  Use if want to incorporate dynamical rules governing time-evolution of neural activity

- Non-linear methods (e.g., Isomap, LLE):
  Generally not recommended; typically don't deal well with noisy data

- Supervised methods (e.g., LDA, dPCA):
  Good for identifying dimensions that represent stimulus, behavior, and/or time.

Cunningham & Yu, *Nat Neurosci*, 2014.

DataHigh



Software: http://users.ece.cmu.edu/~byronyu/software

Cowley et al., *J Neural Eng*, 2013.