Statistics in Neuroscience; Robert E. Kass

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Course Presentation: Neuroscience of Learning, Memory, Cognition
Sharif University of Technology

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Overview

Introduction

Robert E. (Rob) Kass
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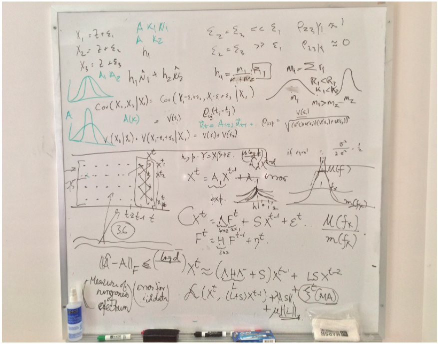
Robert E. (Rob) Kass

- A statistician interested in the analysis of data arising in the brain sciences
- Having studied Bayesian methods and the conceptual foundations of Bayesian inference for the first half of his career, leading to his recognition by the Institute for Scientific Research as one of the most highly cited authors in the field of mathematics, 1995-2005
- Since roughly 2001, concentrated on methods for the analysis of neural data, especially spike train data recorded from electrodes

Robert E. Kass

`https://www.cmu.edu/bme/People/Faculty/profile/rkass.html`

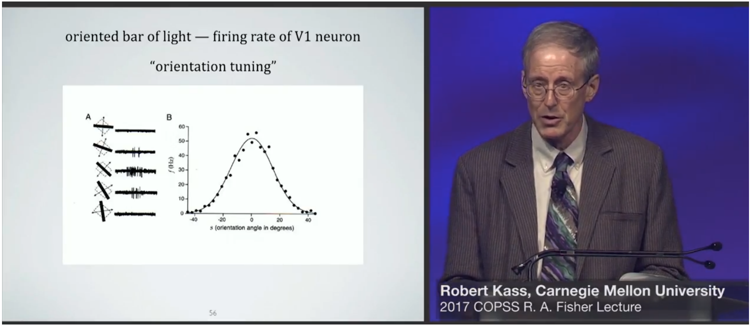
Robert E. Kass; An Image of Work Life



> *...for people like me, such scribbles seem to capture the deepest part of human existence: symbolic thought, made explicit...*

http://www.stat.cmu.edu/~kass/whiteboard/

Brain Research is Underserved by Statistics



https://www.youtube.com/watch?v=_2EyHnua0W4&feature=youtu.be

Brain Research is Underserved by Statistics

Contents of the lecture:

1. Some questions that have generated interesting statistical problems
2. Statistical ideas used to solve those problems
3. Observation: such solutions require appreciation of the statistical paradigm

https://www.youtube.com/watch?v=_2EyHnua0W4&feature=youtu.be

The Statistical Paradigm

The Statistical Paradigm:
the guiding philosophy promoted by advanced statistical training

https://www.youtube.com/watch?v=_2EyHnua0W4&feature=youtu.be

Brain Research is Underserved by Statistics

Examples of neuroscience questions that led to interesting statistical problems, and solutions based on statistical paradigm:

1. How are memories consolidated?
2. How does the reward system function differently in psychiatric disorders?

https://www.youtube.com/watch?v=_2EyHnua0W4&feature=youtu.be

Research Areas of Robert E. Kass

1. Single Neurons: Spike Counts and Trial-Averaged Firing Rate
2. Single Neurons: Within-Trial Analysis
3. Multiple Neurons
4. Decoding and Brain-Machine Interface

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Publications - Single Neurons: Spike Counts and Trial-Averaged Firing Rate

1. **Temporally Segmented Directionality in the Motor Cortex (2017)**
   - a major goal of systems neurophysiology: Understanding and modeling the dynamic activation of neural ensembles
   - detailed examination of the tuning time course in motor cortex suggests that direction coding may be labile

   What paper provides:
   - there are discrete time epochs within single reaches, between which individual neurons change their tuning
   - motor cortical activity patterns may reflect consistent changes in the state of the control system during center-out reaching
   - the task defines changes in the operational structure of the control system

Publications - Single Neurons: Spike Counts and Trial-Averaged Firing Rate

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Publications - Single Neurons: Within-Trial Analysis

2. **Inferring oscillatory modulation in neural spike trains (2017)**
    - Oscillations are observed at various frequency bands in continuous-valued neural recordings like EEG and LFP in bulk brain matter
    - spiking of single neurons often occurs at certain phases of the global oscillation
    - Oscillatory modulation has been examined in relation to continuous-valued oscillatory signals and independently from the spike train alone

Publications - Single Neurons: Within-Trial Analysis

2. **Inferring oscillatory modulation in neural spike trains (2017)**

   What paper provides:

   - describe a flexible point-process framework called the Latent Oscillatory Spike Train (LOST) model
   - decompose the instantaneous firing rate in biologically and behaviorally relevant factors
   - extend the LOST model to accommodate changes in the modulatory structure over the duration of the experiment
   - discover trial-to-trial variability in the spike-field coherence of a rat primary motor cortical neuron to the LFP theta rhythm
   - LOST is able to detect oscillations, when:
     - the firing rate is low
     - the modulation is weak
     - the modulating oscillation has a broad spectral peak

Publications - Multiple Neurons

3. **Separating Spike Count Correlation from Firing Rate Correlation(2016)**
    - Populations of cortical neurons exhibit shared fluctuations in spiking activity over time
    - this phenomenon emerges as correlated trial-to-trial response variability via spike count correlation (SCC)
    - the SCC for a pair of neurons becomes a noisy version of the corresponding firing-rate correlation (FRC)
    - the magnitude of the SCC is generally smaller than that of the FRC, and is likely to be less sensitive to experimental manipulation

Publications - Multiple Neurons

3. **Separating Spike Count Correlation from Firing Rate Correlation(2016)**

   What paper provides:

   - statistical methods for disambiguating time-averaged drive from within-trial noise, thereby separating FRC from SCC
   - studying these methods to document their reliability, showing how the various effects we describe are reflected in the data
   - within-trial effects are largely negligible, while attenuation due to trial-to-trial variation dominates
   - frequently produces comparisons in SCC that, because of noise, do not accurately reflect those based on the underlying FRC

Publications - Decoding and Brain-Machine Interface

4. **Bayesian learning in assisted brain-computer interface tasks (2012)**
    - Successful implementation of a brain-computer interface depends critically on the subject's ability to learn how to modulate the neurons controlling the device
    - How should training be adjusted to facilitate dexterous control of a prosthetic device?
    - An effective training schedule should manipulate the difficulty of the task to provide enough information to guide improvement without overwhelming the subject

Publications - Decoding and Brain-Machine Interface

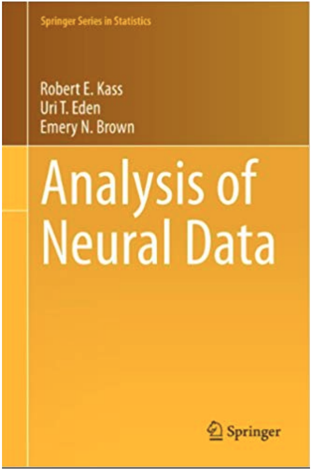
4. **Bayesian learning in assisted brain-computer interface tasks (2012)**

   What paper provides:

   - Introducing a Bayesian framework for modeling the closed-loop BCI learning process that treats the subject as a bandwidth-limited communication channel
   - develop an adaptive algorithm to find the optimal difficulty-schedule for performance improvement
   - This algorithm yields faster learning rates than several other heuristic training schedules, and provides insight into the factors that might affect the learning process

Publications - Textbooks

5. **Analysis of Neural Data**
   Robert E. Kass, Uri T. Eden, Emery N. Brown



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