Do we really have to sort our spikes?

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June 8, 2021

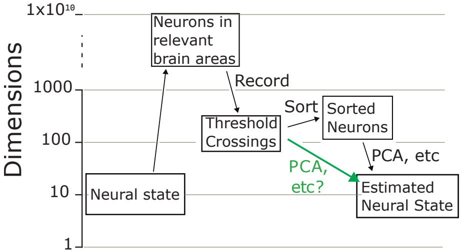
Accurate estimation of neural population dynamics without spike sorting,
Trautmann, Stavisky, Lahiri, Ames, Kaufman, O'Shea, Vyas, Sun, Ryu, Ganguli, and Shenoy,
Neuron, 103(2):292–308.e4, (2019), bioRxiv:229252.

Introduction

Spike sorting is a leading cause of unhappiness in grad students.

We often don't care about single neurons:

- using dimensionality reduction,
- studying geometry of neural manifolds.



Would non-sorting affect scientific results? Why? When?

Outline

Section 1

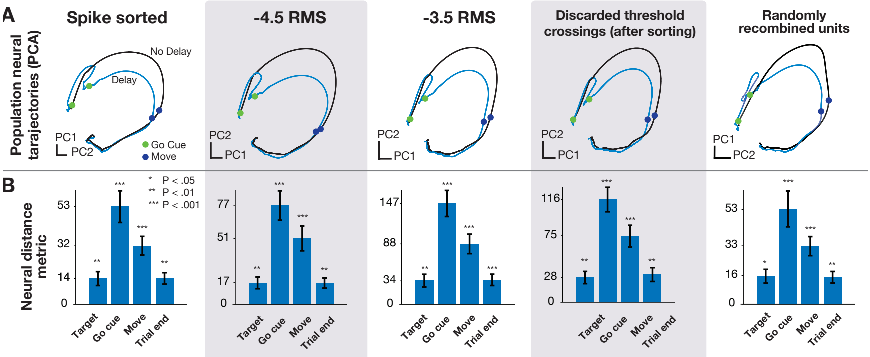
Example datasets

Neural dynamics of reaching following incorrect/absent preparation

Is preparatory neural state necessary for accurate reaches?

No delay period/change target at go-cue → bypass preparatory state.

[Ames et al. 2014]

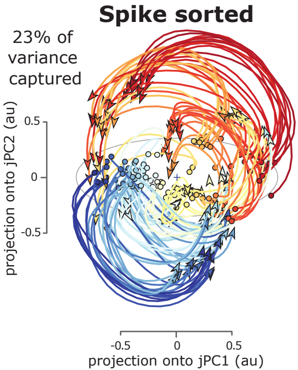


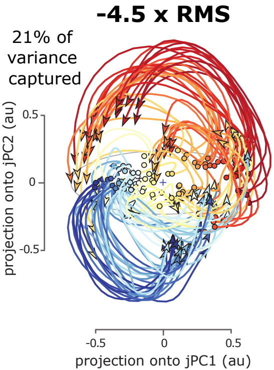
Neural population dynamics during reaching

Churchland et al. argue: motor cortex uses oscillatory basis functions to construct complex time-varying signals to control muscles.
Rotational dynamics: from fast, short patterns in individual firing rates.

[Churchland et al. 2012]

Does summing units wash out precise temporal features?



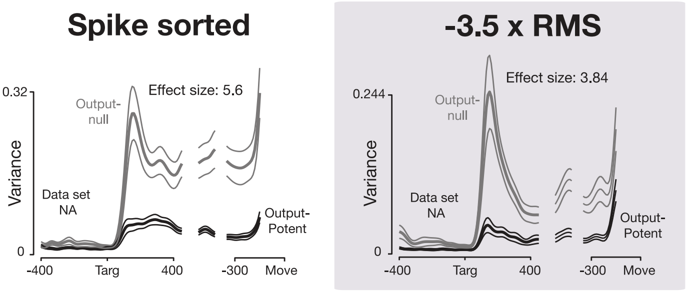


Cortical activity in the null space: preparation without movement

Large firing rate changes in delay period $\rightarrow$ no motion?

#Neurons > #Muscles $\implies$ some neural directions $\nrightarrow$ movement.

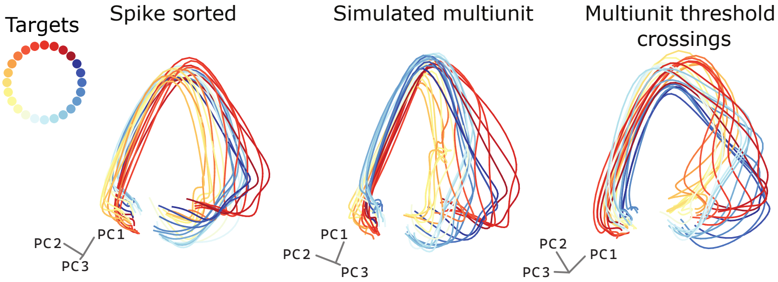
Use output-null directions during delay, output-potent during motion.
Note: different directions, not different neurons. [Kaufman et al. 2014]



Neural dynamics of reaching from Neuropixels

Instructed delay reaching task.

Recording: Neuropixel probes in PMd. $\Longrightarrow$ excellent spike sorting.



Distortion higher than Utah array cases.

Section 2

Explanation from random projections

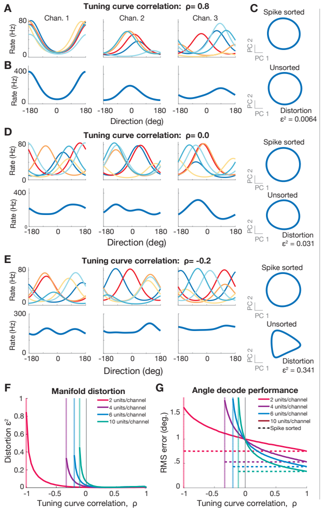
Intuition: summing different tuning curves

Simulation: 200 channels,
each sums 2-10 neurons.
Tuning curves on same channel correlated
$\rho = -\frac{2M}{N}, \ldots, 1$.

Amplitude-angle vectors $\sim N\left(0, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}\right)$.

$\rho = 0$: each channel has poor, but nonzero, tuning. Across 200 channels – still enough tuning to see structure and decode angle. Because PCA / linear decoder care about directions, not units.

Has to get very anti-correlated to see much distortion.



Neural recordings as projections

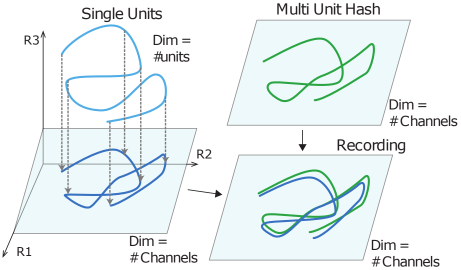
$\boxed{\text{Relevant neurons}} \rightarrow \boxed{\text{Recorded neurons}} \rightarrow \boxed{\text{Electrodes}}$.

Both steps are projections. Spike sorting ~ "unprojection".

Previous work argued: 1st projection $\implies$ undistorted popn. dynamics.

[Gao et al. 2017]

Does the same logic apply to the 2nd projection?



Theory of random projections

Distortion of $\mathcal{S}$ under a projection $\mathbf{A}$:

$$\epsilon = \min_{\lambda} \max_{\mathbf{x},\mathbf{y} \in \mathcal{S}} \left| \frac{\lambda \left\|\mathbf{A}(\mathbf{x}-\mathbf{y})\right\| - \left\|\mathbf{x}-\mathbf{y}\right\|}{\left\|\mathbf{x}-\mathbf{y}\right\|} \right|$$

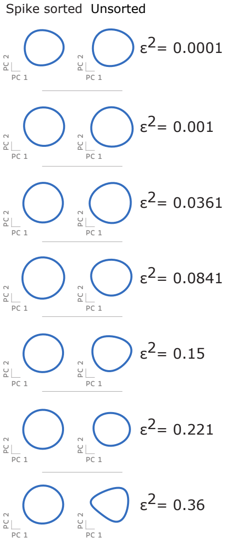
λ: don't care about overall scale.

Theory of random projections:

$$\epsilon^2 \sim \frac{\cdot \log ntc}{M} + \frac{K}{M} \cdots$$

[Clarkson 2008; Eftekhari and Wakin 2015; Lahiri et al. 2016]

N: #Neurons, M: #Electrodes, K: #Task params,
ntc: Neural task complexity ~ Task vol./corr. vol..



Potential problems

Projections not random? Special neurons?

These projection matrices are of different types to theory.

Theory doesn't account for noise (multi-unit hash).

Section 3

Simulations of random projections

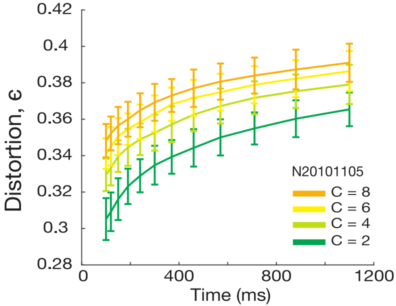
Truly random projections: simulated PSTHs

See if random projection theory applies.
Simulate randomly oriented PSTHs to compare with data

$$
\begin{aligned}
e_\mu(t,c) &= \sum_n A_{\mu n} r_n(t,c) + h_\mu(t,c), \\
r_n(t,c) &= R(t,c) + \beta_r \left[z_n(t,c) + k_r z(t,c) \right], \\
h_\mu(t,c) &= H(t,c) + \beta_h \left[\epsilon_\mu(t,c) + k_h \epsilon(t,c) \right] + \frac{1}{N} \sum_n \left[M k_s A_{\mu n} + k_d \right] r_n(t,c),
\end{aligned}
$$

e_μ, r_n, h_μ: PSTHs of electrodes, neurons, multiunit hash.
R, H: means across t, c.
$z_n, z, \epsilon_\mu, \epsilon$: independent Gaussian processes with covariance across t, c fit.
$A_{\mu n}$: projection matrix.
$\beta_r, \beta_h, k_r, k_h, k_s, k_d$: constants fit to 2nd order stats across units.

Comparing data, simulation and theory



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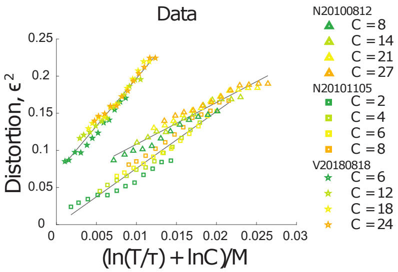

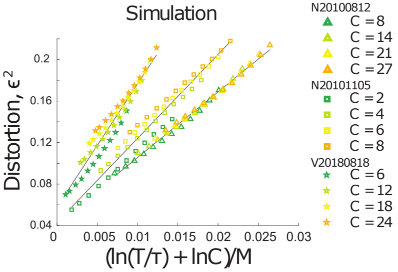

Same type of trend as theory.

Different slopes & intercepts for different datasets
- different type of projection? - different SNR?

Section 4

Discussion

Conclusions

Don't need to spike sort if you're studying (simple) manifolds.

Future probes: place electrodes further apart?

Theory of random projections $\Longrightarrow$ domain of validity?

We need a theory of noisy random projections.

Acknowledgments

Collaborators: Eric Trautmann, Sergey Stavisky, Katherine Ames, Matthew Kaufman, Daniel O'Shea, Saurabh Vyas, Xulu Sun, Stephen Ryu, Surya Ganguli, and Krishna Shenoy.

Ganguli and Shenoy lab members, past & present.

Tim Harris (Janelia), Barun Dutta (IMEC), Wei-lung Sun (Janelia), Nick Steinmetz (UCL), Bill Karsch (Janelia), and Will Allen for assistance with Neuropixels.
M. Risch, M. Wechsler, J. Aguayo, C. Sherman, E. Morgan, R. Reeder, B. Davis, E. Castaneda, and B. Oskotsky for administrative and technical support.

Funding: Burroughs Wellcome, Sloan, Simons, McKnight, and James S. McDonell foundations, the Howard Hughes Medical Institute, and the Office of Naval Research.

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