Accurate estimation of neural population dynamics without spike sorting

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Background

Spike sorting is laborious $\implies$ miserable students / grumpy postdocs.

Manual methods: several hours, different people $\to$ different results.

Automatic methods: promising, but computationally intensive, sensitive to electrode drift, no ground truth.

When studying popn. dynamics (PSTH geometry) or using dim. reduction: doesn't matter if axes are aligned with neurons.

[tedious twitter row re. #manifolds].

We argue that, in such situations, spike sorting may be unnecessary.

[Trautmann et al. 2017]

Random Projections

Neural recordings as projections

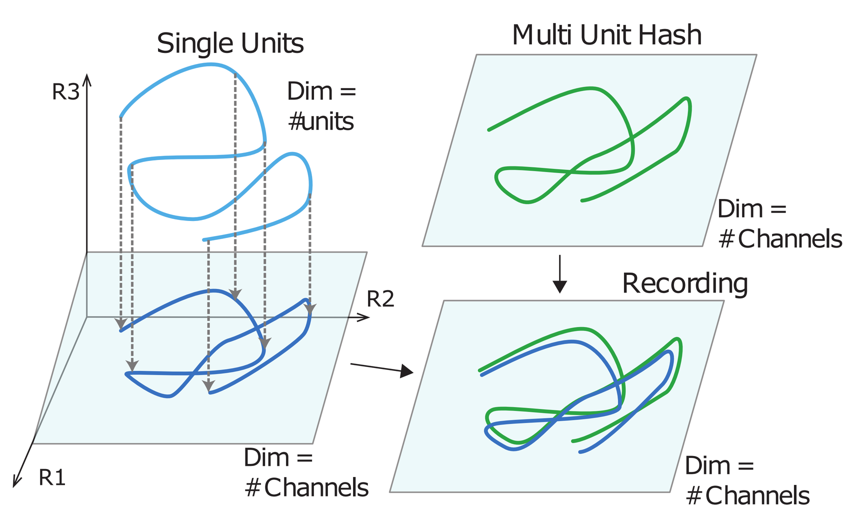
$\boxed{\text{Relevant neurons}} \to \boxed{\text{Recorded neurons}} \to \boxed{\text{Electrodes}}$.

Both steps are projections. Spike sorting $\sim$ "unprojection".

Previous work argued: 1st projection $\implies$ ~~distorted~~ 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 $\mathbf{A}$:

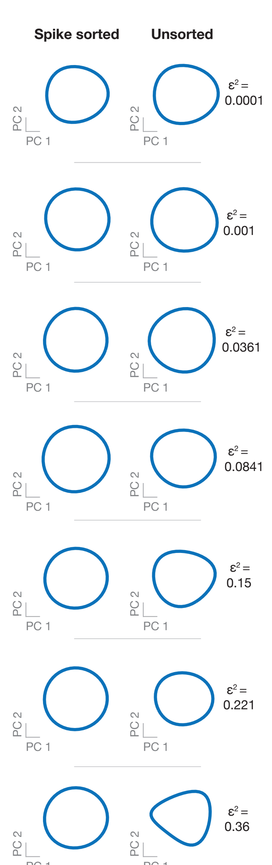
$$\epsilon = \min_{\lambda} \max_{\mathbf{x},\mathbf{y}\in\mathcal{S}} \left| \frac{\lambda \|\mathbf{A}(\mathbf{x}-\mathbf{y})\| - \|\mathbf{x}-\mathbf{y}\|}{\|\mathbf{x}-\mathbf{y}\|} \right|$$

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 variables,
ntc: Neural task complexity $\sim$ Task volume / neural corr. volume.

Potential problems

Projections not random? Special neurons?

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

These projection matrices are of different types to theory.

Examples

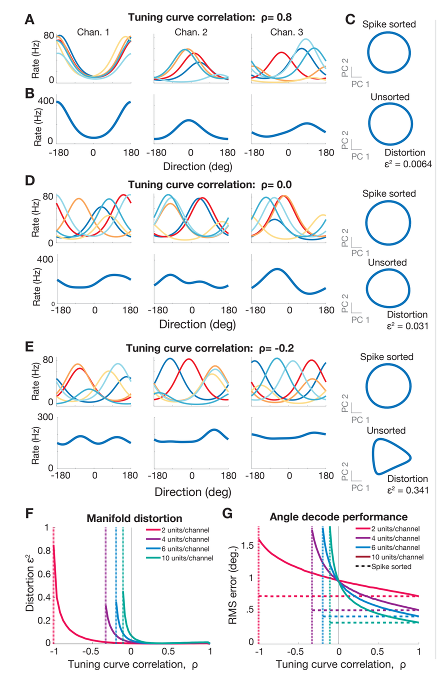
Summing different tuning curves

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.

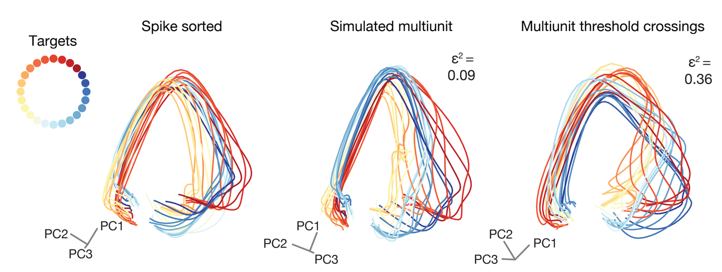


Neural dynamics of reaching from Neuropixels

Instructed delay reaching task.

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

Distortion higher than Utah array cases.

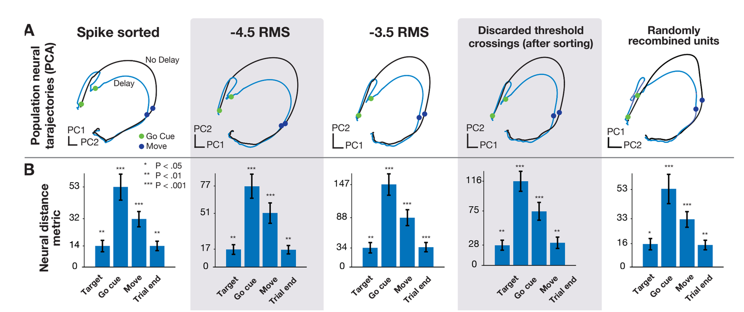


Neural dynamics of reaching following incorrect/absent preparation

Is preparatory neural state necessary for accurate reaches?

No delay period/change target @ go-cue $\to$ bypass preparatory state.

[Ames et al. 2014]



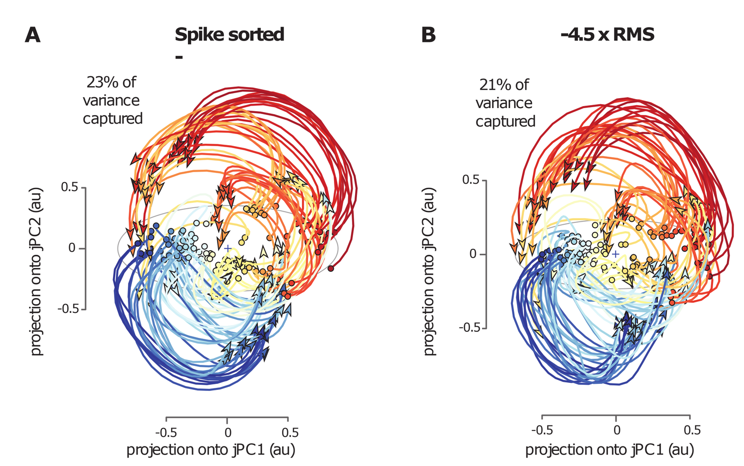
Neural population dynamics during reaching

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?



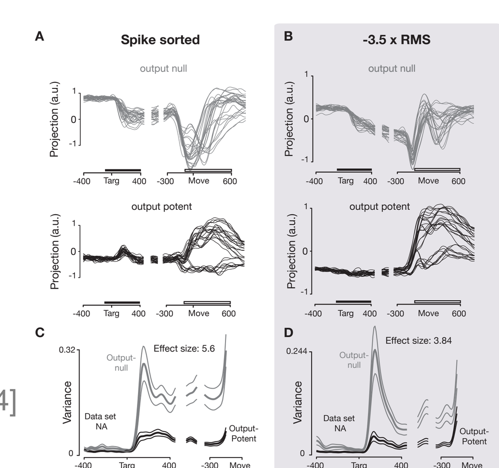
Cortical activity in the null space: preparation without movement

Large firing rate changes in delay period $\to$ ~~motion~~?

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

Use output-null directions during delay,
output-potent during motion.
Note: different directions, not different neurons.

[Kaufman et al. 2014]



Simulations

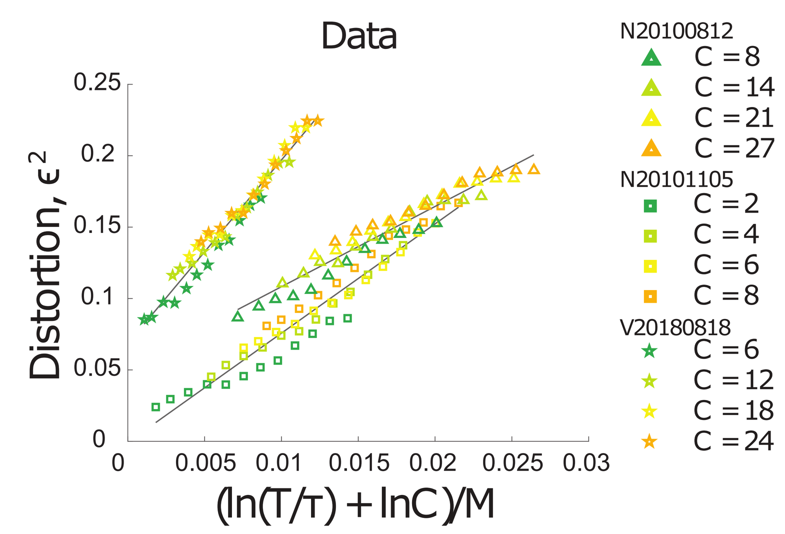
Truly random projections: simulated PSTHs

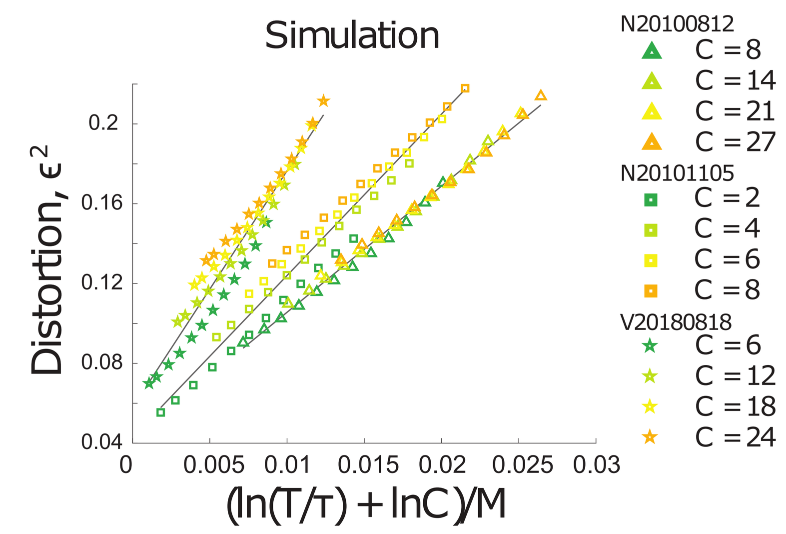
See if random projection theory applies.
Simulate randomly oriented PSTHs to compare with data

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

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





Discussion

Conclusions

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

Place electrodes further apart?

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

We need a theory of noisy random projections.

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