Representing and Computing with Latent Dynamics

Presented by Hal Rockwell

Classical signal processing view

- Populations of neurons, each with their own independent tuning curve
- Each neuron has a scalar response to a stimulus, which “encodes” (is linearly related to) some feature of the stimulus
- Various problems: not very robust, oversimplified, relies on clean, stable readouts, and highly organized connectivity

New: “Latent” and “Dynamics”

- Latent: map the neural response into a lower-dimensional space, and consider the components of that space
    - could assign them tuning curves, but that tends not to work out
    - Dimensionality reduction means the readout from individual neurons depends on others

- Dynamics: consider response over time, so it’s not scalar

- A concrete example together: PCA on the NxT response matrix giving basis-neurons

Additional note on dynamics

- Can treat the whole evolution through time as representation
  - e.g. an doing linear decoding from the NxT matrix

- Alternatively, can treat activity at each time as representation, and the changes over time as a computation performed on that representation
  - e.g. doing linear decoding on the N vector, improving over T time steps
  - the second paper does this

Long-term stability of cortical population dynamics underlying consistent behavior

Juan A. Gallego, Matthew G. Princh, Raeed H. Chowdhury, Sara A. Solla, and Lee E. Miller

Overview

- Individual neuronal tunings aren’t consistent over long time periods
  - and recording is even less consistent

- They find that latent dynamics are, if they can be linearly realigned to account for the changing recorded neurons

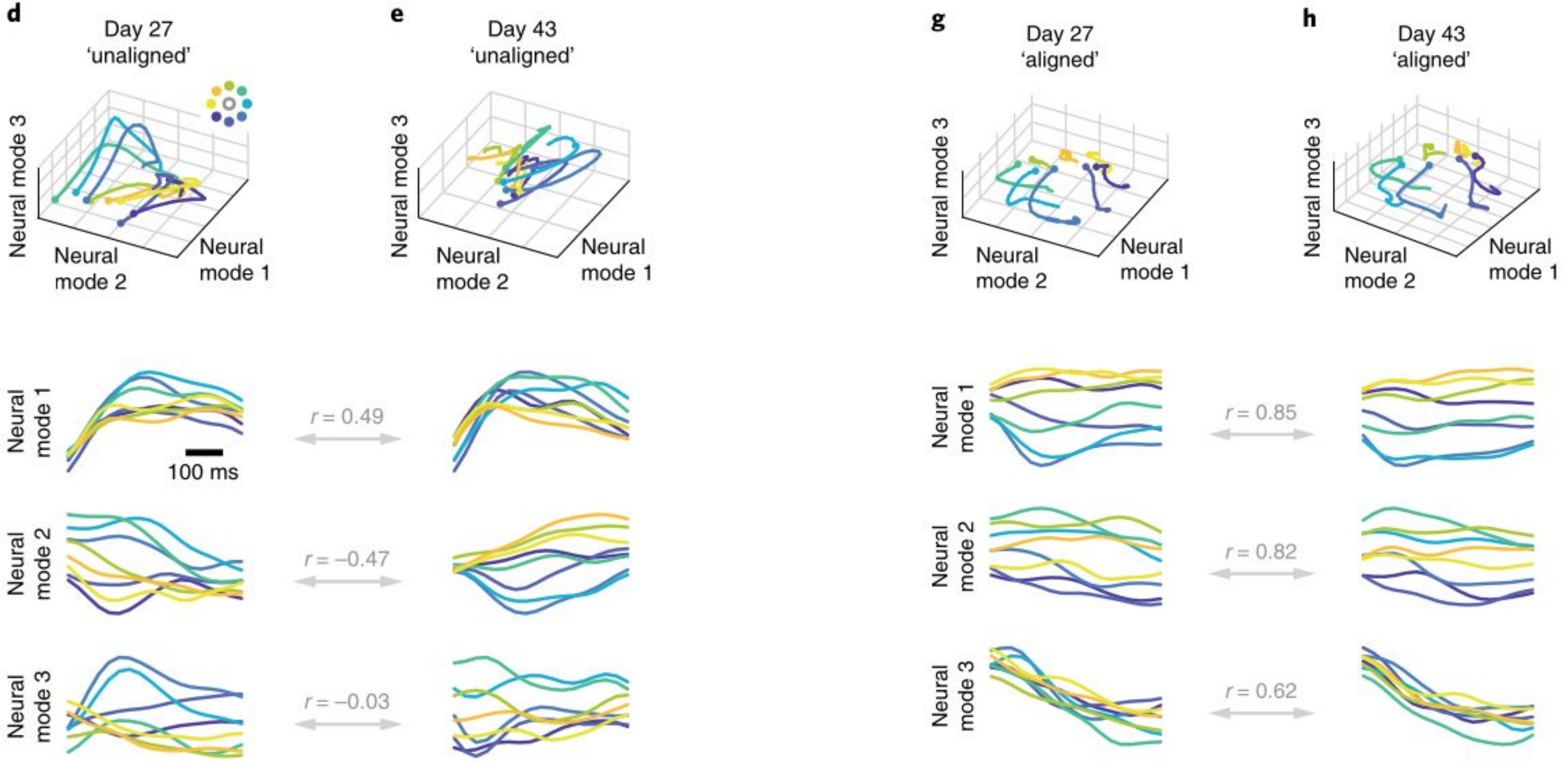
- Dynamics considered because that’s what motor neuroscientists do, but the main takeaway is that this latent space is a better candidate for the “true” neural code

Methods

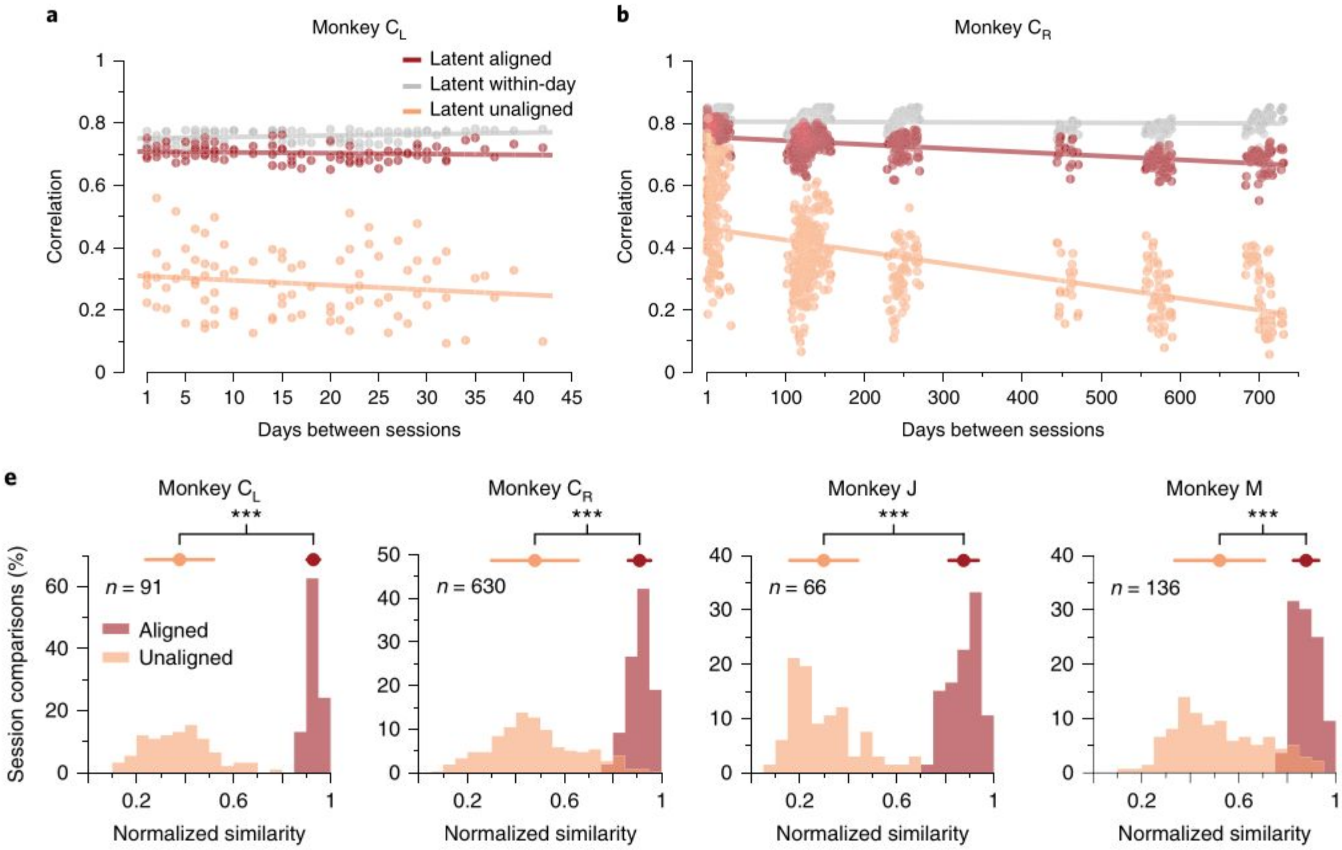
- Monkeys performed a simple reaching task (in different directions), with consistent behavior across 2 years (!)
  - recordings from S1, M1, and PMd (premotor cortex, involved in movement planning)

- Latent dynamics represented as “neural modes”, 1xT PCs of the NxT response matrix, total latent space uses ~10
  - computed separately for each day, all aligned to one day with CCA (maximizing correlations with that day’s latent space)

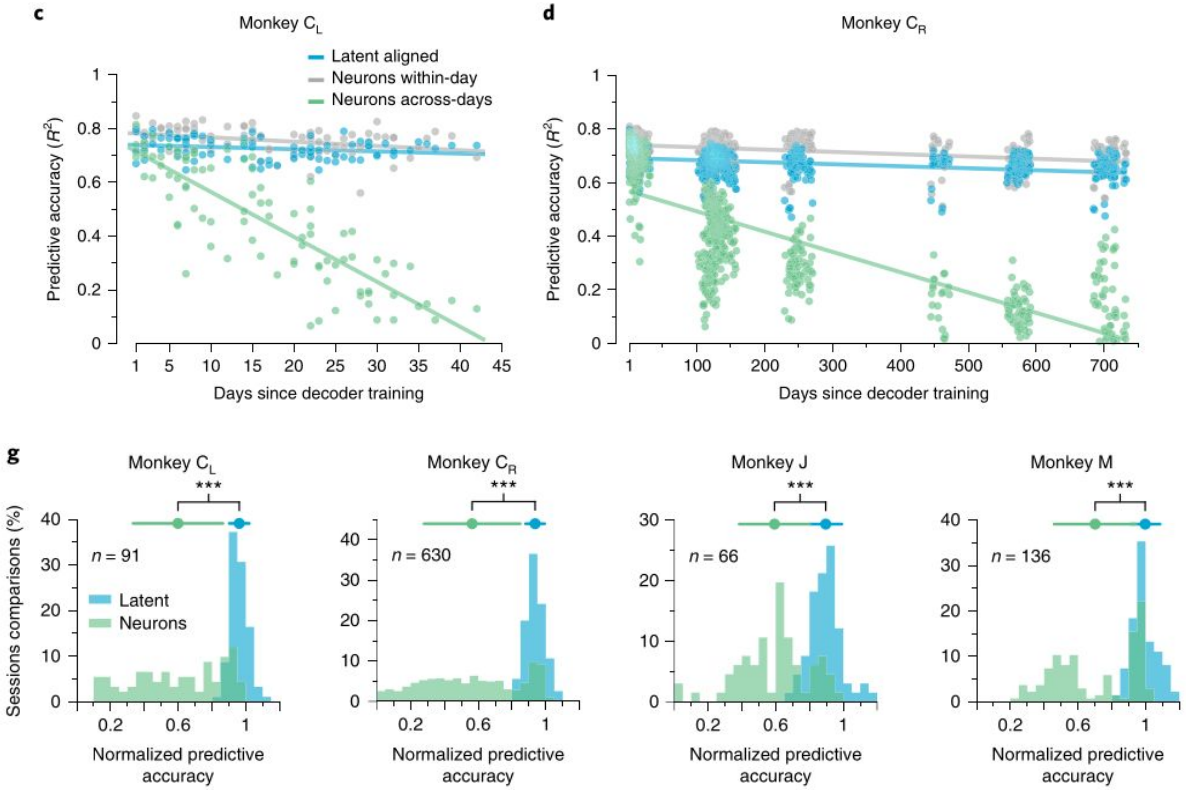
Methods (cont.)



Consistency of latent dynamics



Decoding consistency of latent dynamics



Additional details/remarks/conclusions

- Dynamics are not trial-averaged, but are smoothed
    - so the low-D manifold can be compared to noise correlations
- Latent-dynamics-decoding is compared to decoding with overall firing rates
    - so not entirely clear what part of the benefit is from dynamics, and what part a latent code
- “What are the dynamics doing?” left unanswered
    - presumably generating motor commands in some way, but that’s not considered

Bayesian computation through cortical latent dynamics

Hansem Sohn, Devika Narain, Nicolas Meirhaeghe, and Mehrdad Jazayeri

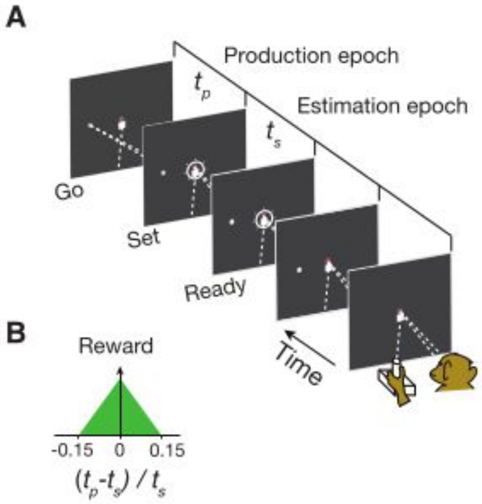
Overview

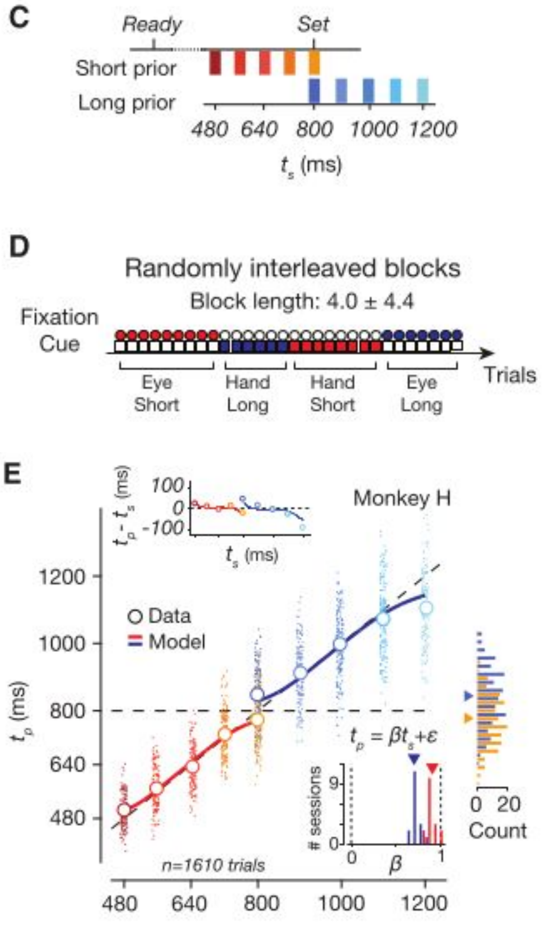
- What is the neural underpinning of Bayesian inference?

- At least for a simple time-estimation task, they convincingly show it’s due to the geometry of the latent dynamics

Methods: task and behavior

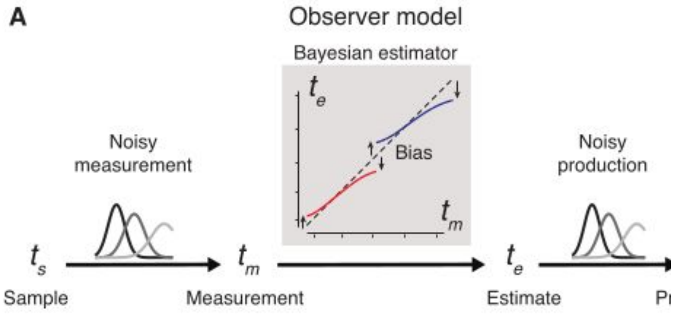
- Reproduce an experienced time interval, with a prior over length
- Biased on the ends of intervals

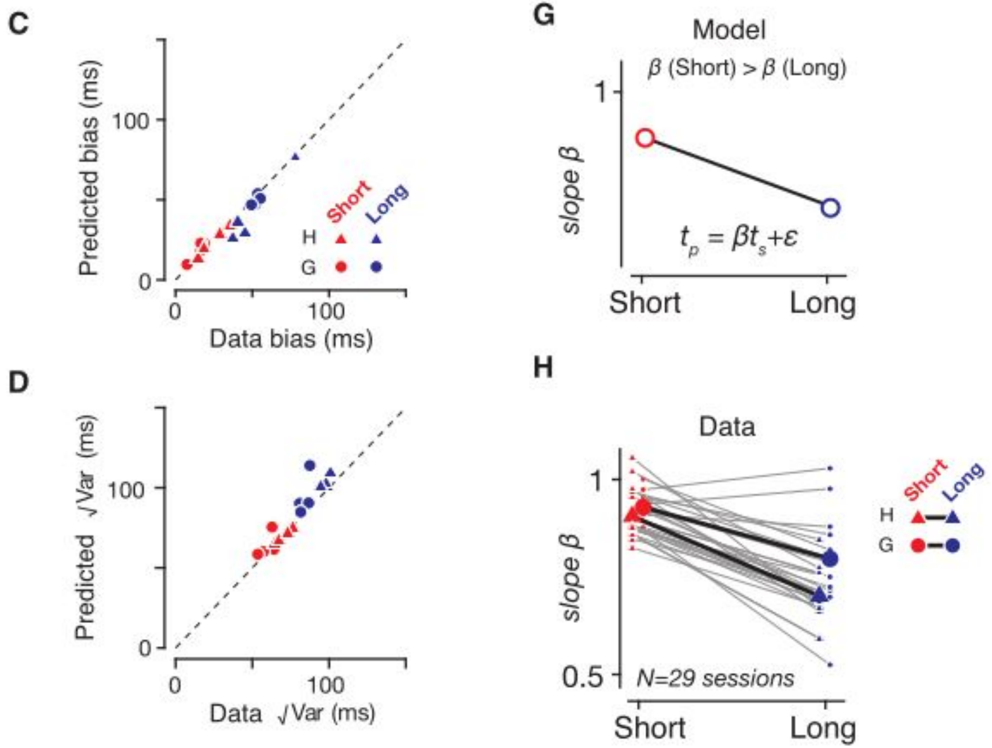




Methods: Bayesian model

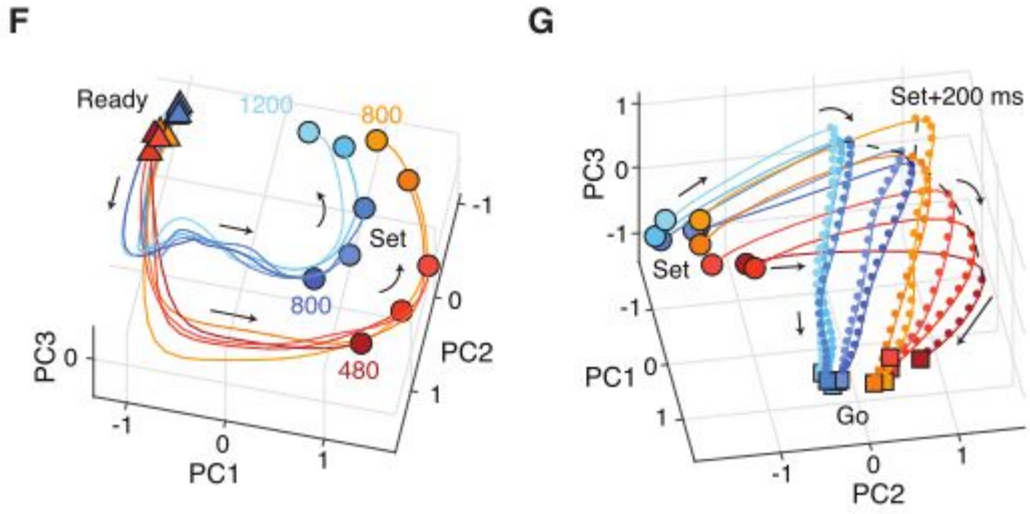
- Reproduces observed behavior





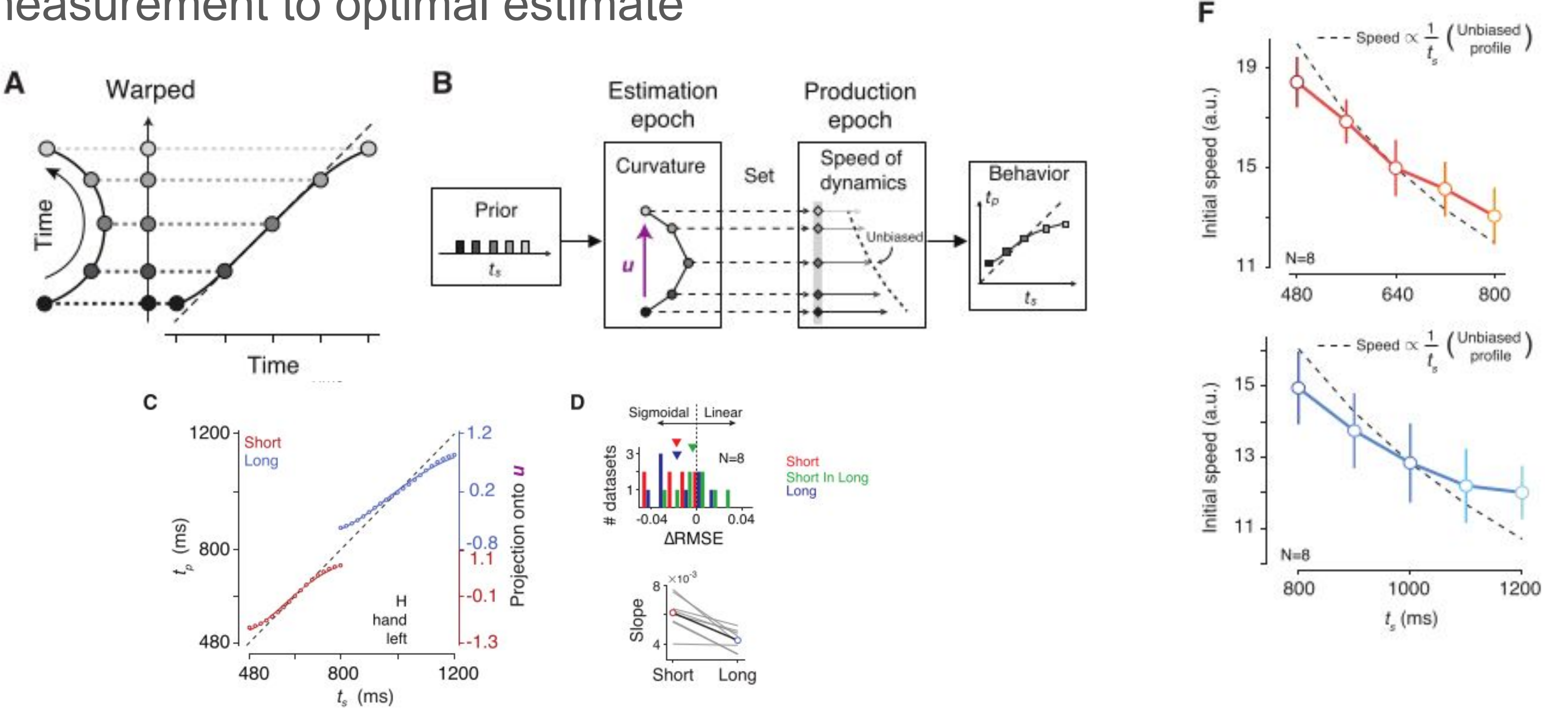
Methods/Results: latent dynamics analysis

- PCA on the averaged neural firing rates
  - but (I think) with basis-times, yielding Nx1 PCs



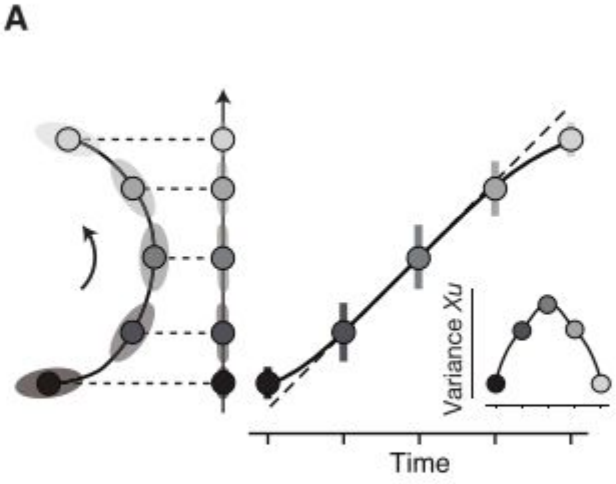
Results

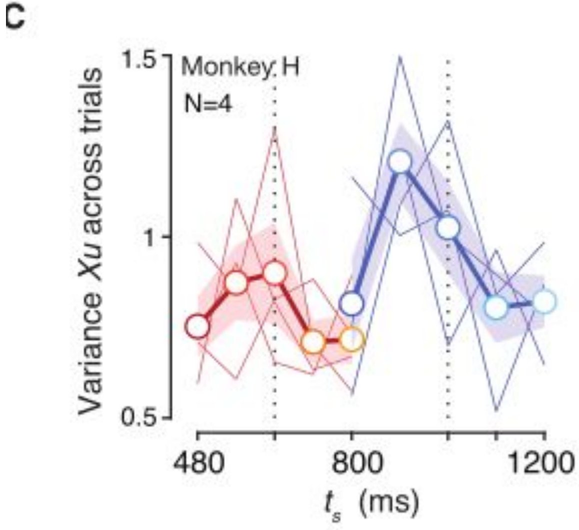
- Curvature of latent dynamics can perform the mapping from noisy measurement to optimal estimate



Results: variance

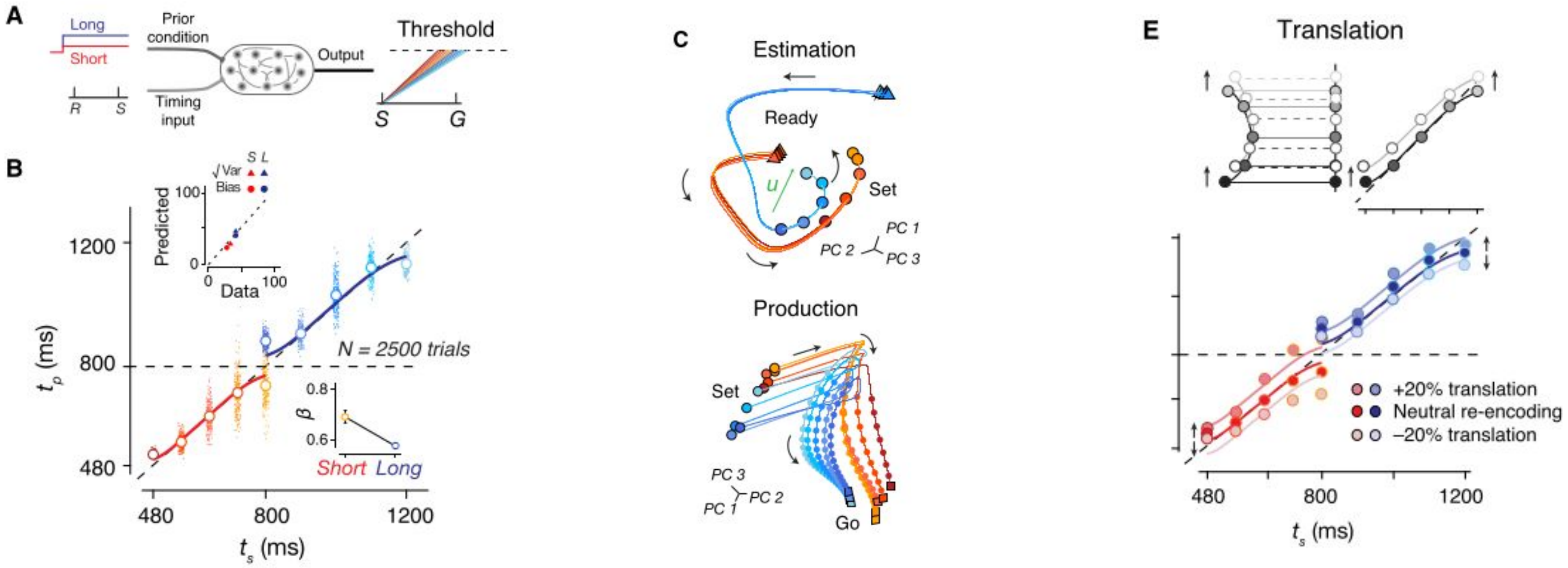
- Variance of estimates also predicted by using the curvature of latent dynamics





Results: RNN

- So far just correlational, and can't make causal experimental interventions in the brain, but *can* in an RNN model
  - necessary because a given representation may not be what the brain actually uses



Conclusions

- Fairly convincing evidence that latent codes are relevant, and that their dynamics are used by the brain to do useful computation
    - albeit not shown directly in sensory areas (except S1, kind of)

- Leaves some questions about how to model latent dynamics, and how to think about them

- Relating latent codes to computation is much easier if they're very low-dimensional, but that's probably not true for vision