**A diagram of a function

AI-generated content may be incorrect.**

**Figure 2. Alignment of stimulus information with the axis of correlated variability makes the “noise axis’’ the optimal read-out direction.**

**A.** Recurrently connected network with rank-one feed-forward weights (blue), recurrent weights (grey), and linear read-out weights (orange). A stimulus enters through (; independent private noise is injected at each neuron and is shaped only by .

**B.** In a generic rank-one network the *stimulus axis* (blue arrow) can lie at an arbitrary angle to the principal component of baseline activity (PC1, grey dots). However, theory and data show that learning tunes the recurrent weights ​so that their slowest dynamical mode aligns with the feed-forward drive conveyed by (Chadwick et al., 2023). After this tuning, stimulus-evoked activity rotates onto PC1, making the *noise axis* and *coding axis* one and the same.

**C.** Once this alignment is achieved, fluctuations along PC1 decay much more slowly than along any orthogonal mode: power on the slow mode (black curve) persists, whereas power on PC2 (light grey) vanishes rapidly. Assigning the task-relevant input to the slowest decaying eigen-direction enables the circuit to integrate information over time, providing a normative rationale for the recurrent tuning described in B.

**D.** We examine a linear read-out whose axis (orange) forms an angle with the recurrent / noise axis (blue).

**E.** Normalized signal (blue) and noise (grey) variances delivered to the read-out as a function of . Signal power decreases more steeply than noise variance as the read-out is rotated away from the noise axis.

**F.** Fisher discriminability peaks at demonstrating that, once stimulus and noise axes are aligned by tuning, the optimal linear decoder is to read out along the noise axis.