Homework 1

Yilun Kuang

July 10, 2020

1 (Research) Identify an academic paper (in any field) that uses regression methods to fit the data and make some predictions. Please find such a paper with code; preferably, the code is on a public repository like Github. Please summarize the paper below, paying specific attention to the regression methods.

Orhan, A.E., Ma, W.J. A diverse range of factors affect the nature of neural representations underlying short-term memory. Nat Neurosci 22, 275–283 (2019). https://doi.org/10.1038/s41593-018-0314-y

GitHub Code: https://github.com/eminorhan/recurrent-memory

Sequential and persistent activity models are two state-of-the-art models of the neural basis of short-term memory. Sequential models describe short-term memory as encoded in the dynamic neural circuits where individual neurons does not serve the central role in storing memory. Persistent models suggest that individual neurons serve as a fixed point attractor that maintain short-term memory. This paper trains recurrent neural networks (RNN) with similar psychophysical profiles compared to biological brains. RNNs are tested to perform short-term memory task. Researchers conclude that both sequential and persistent models represent part of the short-term memory functions across a spectrum based on different conditions.

To measure the sequentiality of RNNs as opposed to the persistency, a sequentiality index (SI) is developed based on "the sum of the entropy of the peak response time distribution of the recurrent neurons and the mean log ridge-to-background ratio of the neurons" (Orhan and Ma 2019). Several factors can affect the sequentiality of the RNNs, including the temporal complexity of tasks.

Different short-term memory tasks differ in temporal complexity and can generate significant variability of SI in RNNs. Researchers adopt five different tasks (see Fig. 1.b) and perform a linear regression on SI variability (see Fig. 3.a).

Researcher hypothesize that larger temporal frequency leads to increased sequentiality. To test this hypothesis before analyzing the SI of five different short-term memory tasks, researchers train RNNs to output sine functions with different temporal frequency (see Fig.

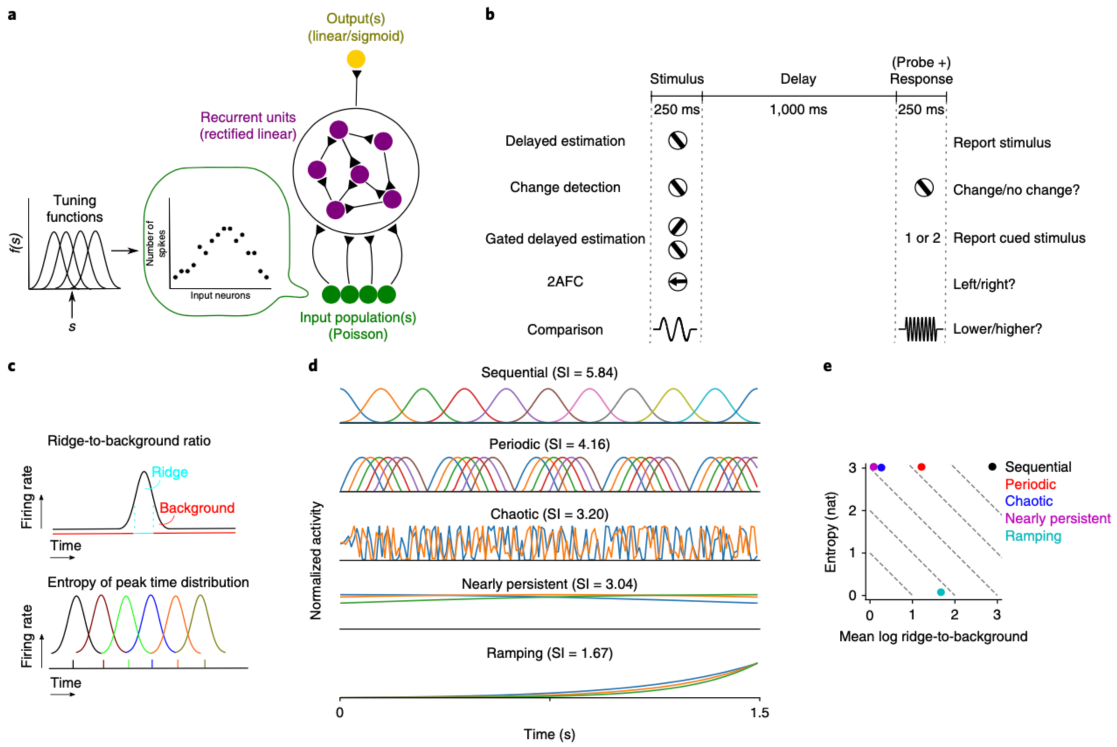

Fig. 1 | Experimental setup. a, Schematic diagram of recurrent networks. The input neurons are Poisson neurons providing noisy information about the stimulus or stimuli. These neurons project onto the recurrent neurons, which are modeled as ReLUs. Recurrent neurons in turn project onto the output unit or units, which are either linear or sigmoidal in different tasks. **b**, The five main experimental tasks and the common trial structure. **c**, Two factors determining the SI: the ridge-to-background ratio[16] measures the temporal localization of the activity of individual units; the entropy of the peak time distribution measures the uniformity of the peak response times of the units in a given trial. The SI for a given trial is then given by the sum of the mean log ridge-to-background ratio of the recurrent units and the entropy of the peak time distribution. **d**, Example idealized single-trial activity patterns with the corresponding SIs indicated at the top of each panel. The different colors represent the temporal activity patterns of a subset of individual units. These example trials were generated with the same number of recurrent units and time steps as in the simulations in the rest of the article. Hence, the SI values shown in the figure are directly comparable to the SI values reported elsewhere in the article. A small amount of noise, independent across neurons and time, was added to the responses of all neurons to break possible ties in determining peak response times. **e**, How the example trials shown in **d** score along each of the two dimensions defining the SI. The dashed lines represent several iso-SI contours. All examples except for the ramping one score close to maximum on the entropy dimension, hence their SIs are largely distinguished by the mean ridge-to-background ratio. Note that the nearly persistent example was generated by broadening the temporal activity profiles in the sequential example. Thus, it has the same peak time entropy as the sequential example, but has a much smaller mean ridge-to-background ratio. The ramping example, on the other hand, has minimal peak time entropy and a medium mean ridge-to-background ratio.

Figure 1: Fig 1

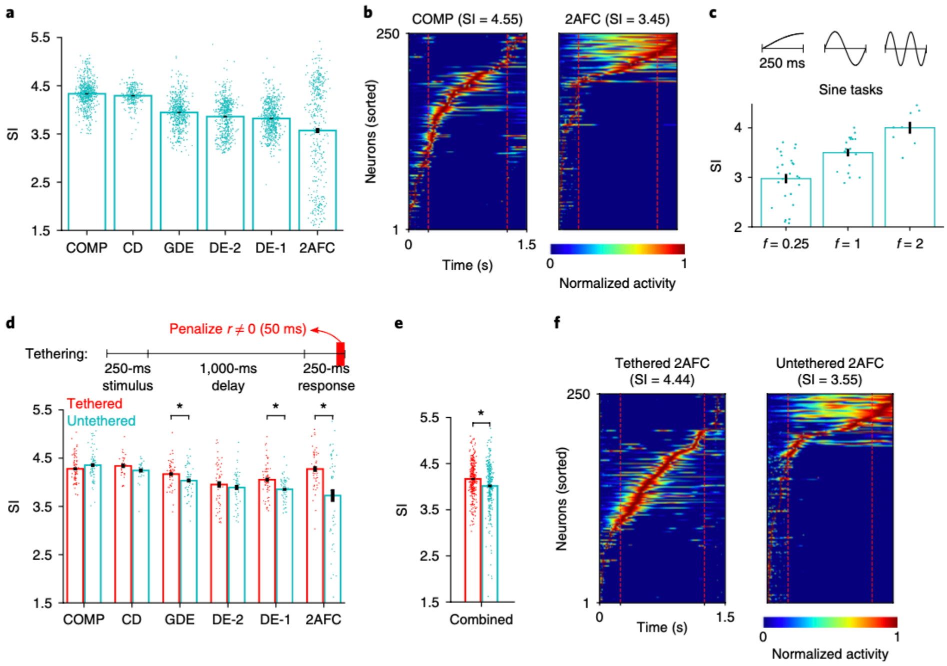

Fig. 3 | The temporal complexity of the task increases the sequentiality of the recurrent activity in trained networks. **a**, SI in different tasks. DE-1 and DE-2 refer to delayed estimation tasks with one and two stimuli, respectively. Each dot corresponds to the mean SI for a particular setting of the hyperparameters. The error bars represent the mean ± s.e.m. across different hyperparameter settings. **b**, Normalized responses of recurrent units in a pair of example trials from the COMP and 2AFC tasks, respectively, trained under the same hyperparameter setting. The SI values of the trials are indicated at the top of the corresponding panels. We chose representative trials with SI values close to the mean SI for the two tasks. Only the responses of the most active 250 units are shown. The actual networks always consisted of 500 recurrent units. The remaining units were mostly or completely silent throughout the trial. **c**, SI in the sine tasks. In these tasks, the network was trained to output a sine function with temporal frequency f during the response period (target functions are shown in the upper panel). Higher frequency target functions (larger f) led to more sequential responses: linear regression of SI on f yielded a slope of 0.60 ± 0.10 ($R^2 = 0.43$, two-sided Wald test, $n = 54$ experimental conditions, $P = 0.000$). The error bars represent the mean ± s.e.m. across different hyperparameter settings. **d**, Tethering manipulation and its effect on the SI of different tasks. The asterisk indicates a significant difference at $P < 0.05$ (two-sided Welch's t test). The error bars represent the mean ± s.e.m. across different hyperparameter settings. **e**, SI in the tethered versus untethered conditions, combined across all tasks in **d**. The error bars represent the mean ± s.e.m. across different hyperparameter settings and different tasks. Exact sample sizes and P values for any statistical test in **a** and **c**–**e** are reported in Supplementary Table 1. **f**, Normalized responses of recurrent units in a pair of example trials from the tethered and untethered versions of the 2AFC task, respectively, trained under the same hyperparameter setting. We again chose representative trials with SI values close to the mean SIs of the two conditions.

Figure 2: Fig 1

3.c). According to the Figure, larger f indeed leads to more sequential responses. Linear regression of SI on f yielded a slope of 0.60 ± 0.10 ($R^2 = 0.43$, two-sided Wald test, n = 54 experimental conditions, P = 0.000). In actual short-term memory task (see Fig 3.a), the SI is measured by the fractal root mean squared error (RMSE), which is

$$\frac{100 * (RMSE_{netw} - RMSE_{opt})}{RMSE_{opt}} \tag{1}$$

, "where $RMSE_{netw}$ is the RMSE of the network and $RMSE_{opt}$ is the RMSE of the ideal observer" (Orhan and Ma 2019).

Another factor that affect sequentiality is the Hebbain short-term synaptic plasticity. It turns out that "symmetric Hebbian short-term plasticity decreased the sequentiality of the recurrent activity in trained network" (Orhan and Ma 2019). Similar linear regression is performed and plotted in Orhan and Ma's paper. Overall, Orhan and Ma's paper has reconciled the ongoing debate between sequential and persistent models by positing them on different positions of a spectrum of the neural representations of short-term memory.