Exploring Biologically Plausible Mechanisms to Induce Noise Correlations for Learning

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INTRODUCTION

Neurons in brain that correspond to the same stimulus tend to show correlated firing patterns across stimulus presentations [1]. Noise correlations introduced above can speed learning by potentially constraining learning to task-relevant dimensions [2]. Yet this advantage depends critically on the correlation pattern, since correlations among similarly-tuned neurons would restrain theoretical encoding limit of the population.

Here we examine potential mechanisms through which a neural network might produce noise correlations that are beneficial for learning.

BACKGROUND

Tuning Curve: a curve representing the average response of a neuron to a set of stimuli.
Noise: trial-to-trial variability of neuron to same stimulus.
Noise correlated: for two neurons, if both mean responses increase/decrease together as the stimulus increases, then they are positively (noise) correlated (Fig1 a), otherwise negatively correlated (Fig 1b).

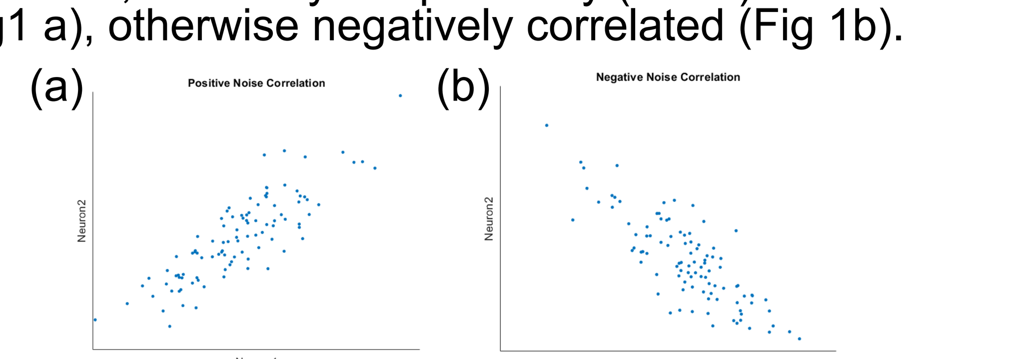

Fig 1: two positively/negatively correlated neurons

Per Averbeck [1], noise correlations can either increase or decrease the amount of information encoded in pairs of simultaneously recorded neurons, which may affect how to learn appropriate readouts of population codes.

MOTIVATION

Consider a task where the subject is presented with a binary stimulus (left/right movements), and the subject is learned to decide whether left or right movements are taking place with the use of a neural network.

We investigate how we can use, or even create, noise correlations that assist subjects to learn the task. Recent work in Nassar Lab [2] has shown that artificially assigning noise correlations to pairs of neurons in the input could push learning into task-relevant dimensions, thus simplifying the learning problem and making the learning process faster and more robust.

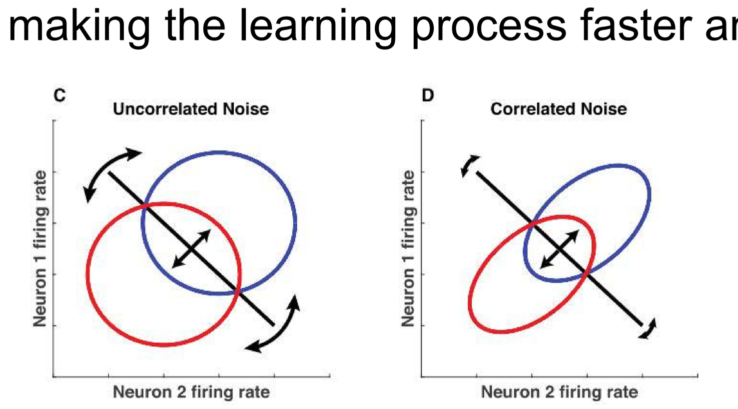

Fig 2: noise correlations facilitate learning

When noise correlations are manipulated in ways that the proportion of overlap of distributions of two classes is fixed, the minor tweaks of the decision boundary during learning hurts little to the expected error rates.

METHOD

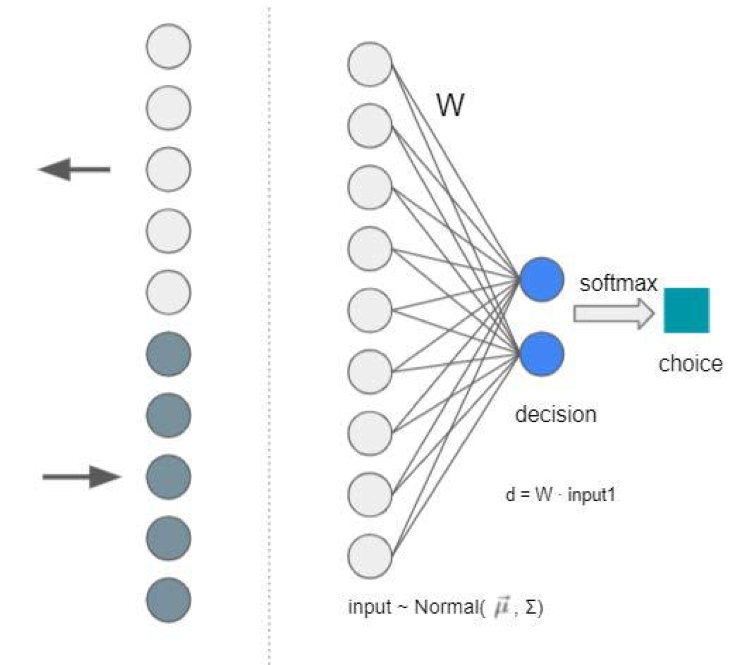

Fig 3: inputs and model architecture

We have two pools of neurons (Fig 3a), each favoring one of the two stimuli (left/right). Given a stimulus, the firing rates are sampled from multivariate Gaussian distribution (each pool has its respective mean firing rate; each pair of neurons are independent). A simple, two-layered neural network is used for this classification task (Fig 3b).

Message Passing

In real life circumstances, a stimulus is often displayed for a period of time. Then, intuitively, it would be reasonable to 'reuse' the activations in the decision layer, incorporating it with firing rates collected at the next instant to form the new input (Fig 4). Note that the model is still two-layered.

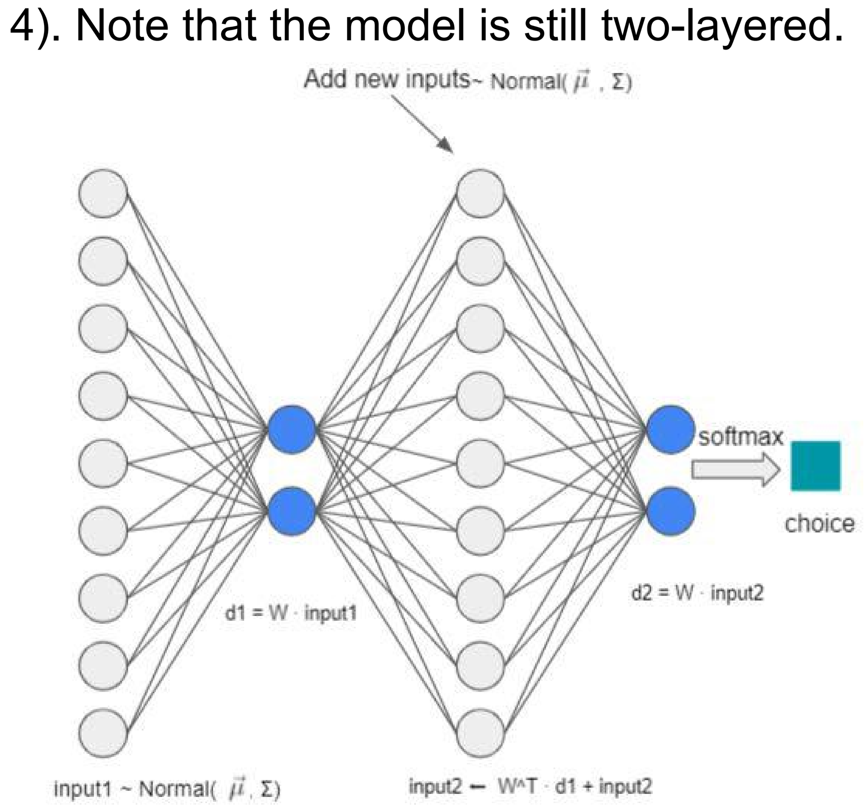

Fig 4: message passing model

Scaling Factor μ

Since we do not usually use pass information to its entirety, we introduce a scaling factor ($0<\mu<1$) to constrain the proportion of past activation.

When μ=0, the model is equivalent to the model in Fig 4; when μ=1, it is equivalent to accumulating two samples, where in each sample, all pairs of neurons are independent, so there would be no noise correlations induced.

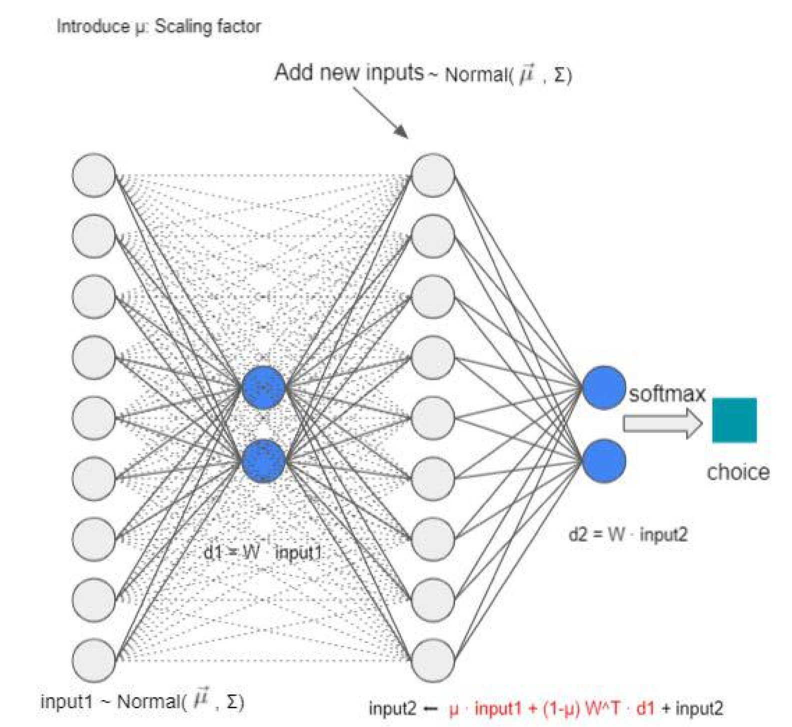

Fig 5: scaling factor

RESULTS

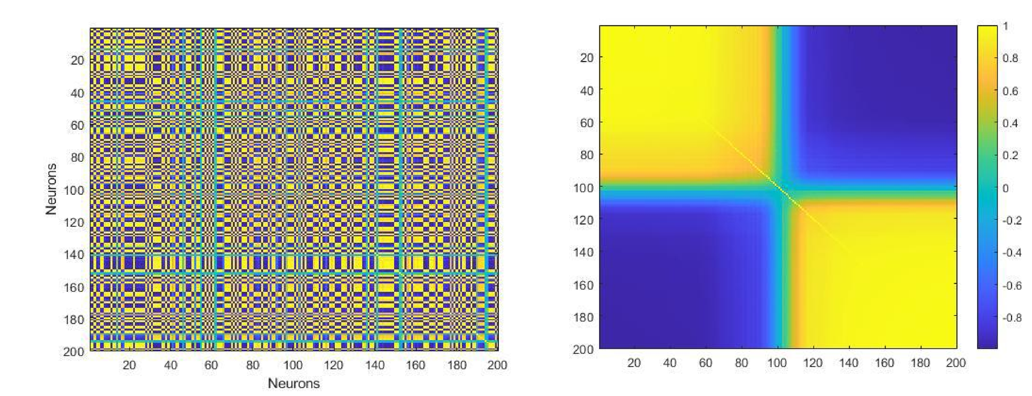

Fig 6: message passing with no signal

When there is no signal, all the neurons are sampled from a distribution with zero mean.
After sorting firing rates by their relative weights: inputs with greater significance tend to positively correlate with each other while negatively with others.

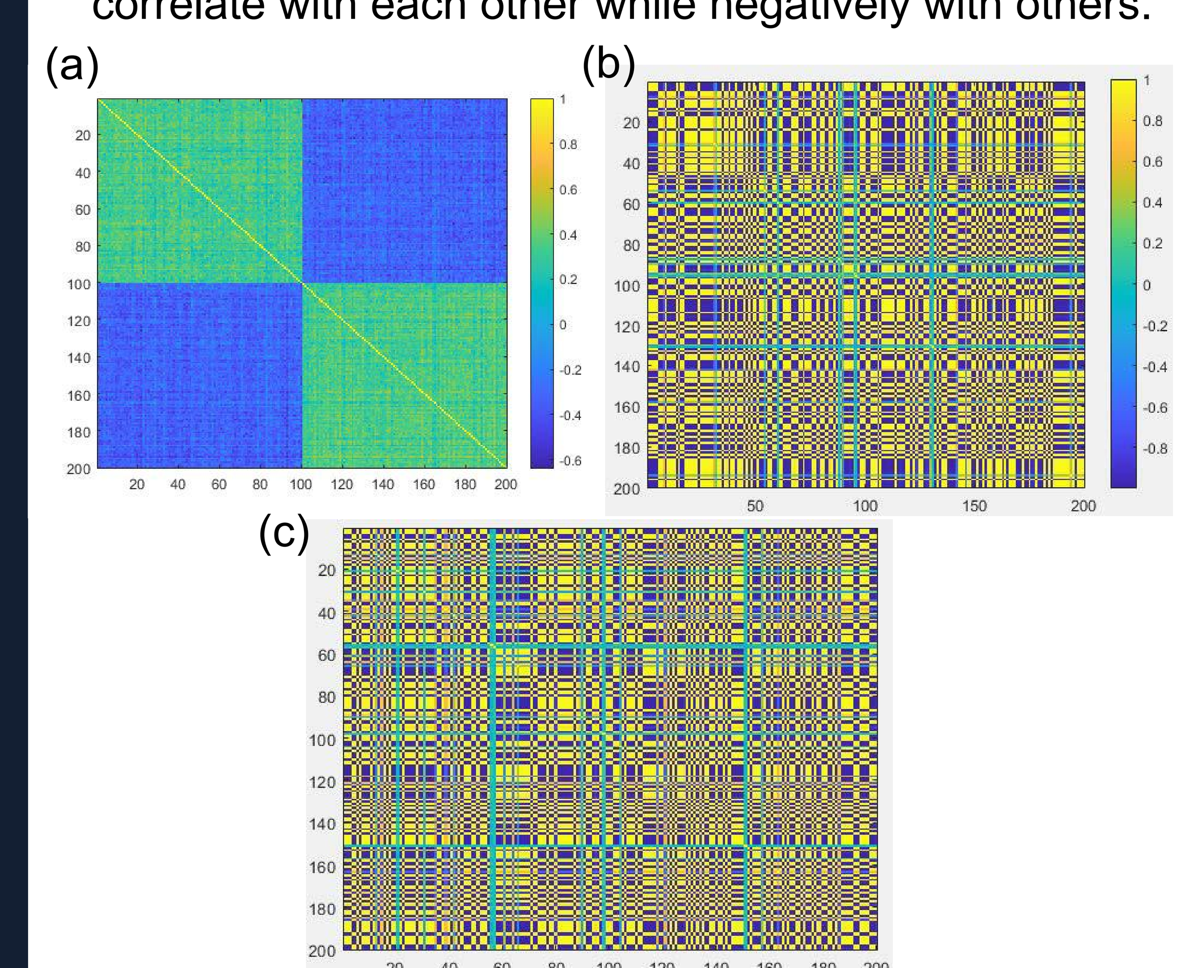

Fig 7: message passing with signal

In Fig 7a, there exists positive noise correlations among neurons in the same pool, and negative correlations among neurons in different pools before message passing. The correlations of message passing are also messy (Fig 7b). After regression, the residuals still show a messy pattern (Fig 7c).

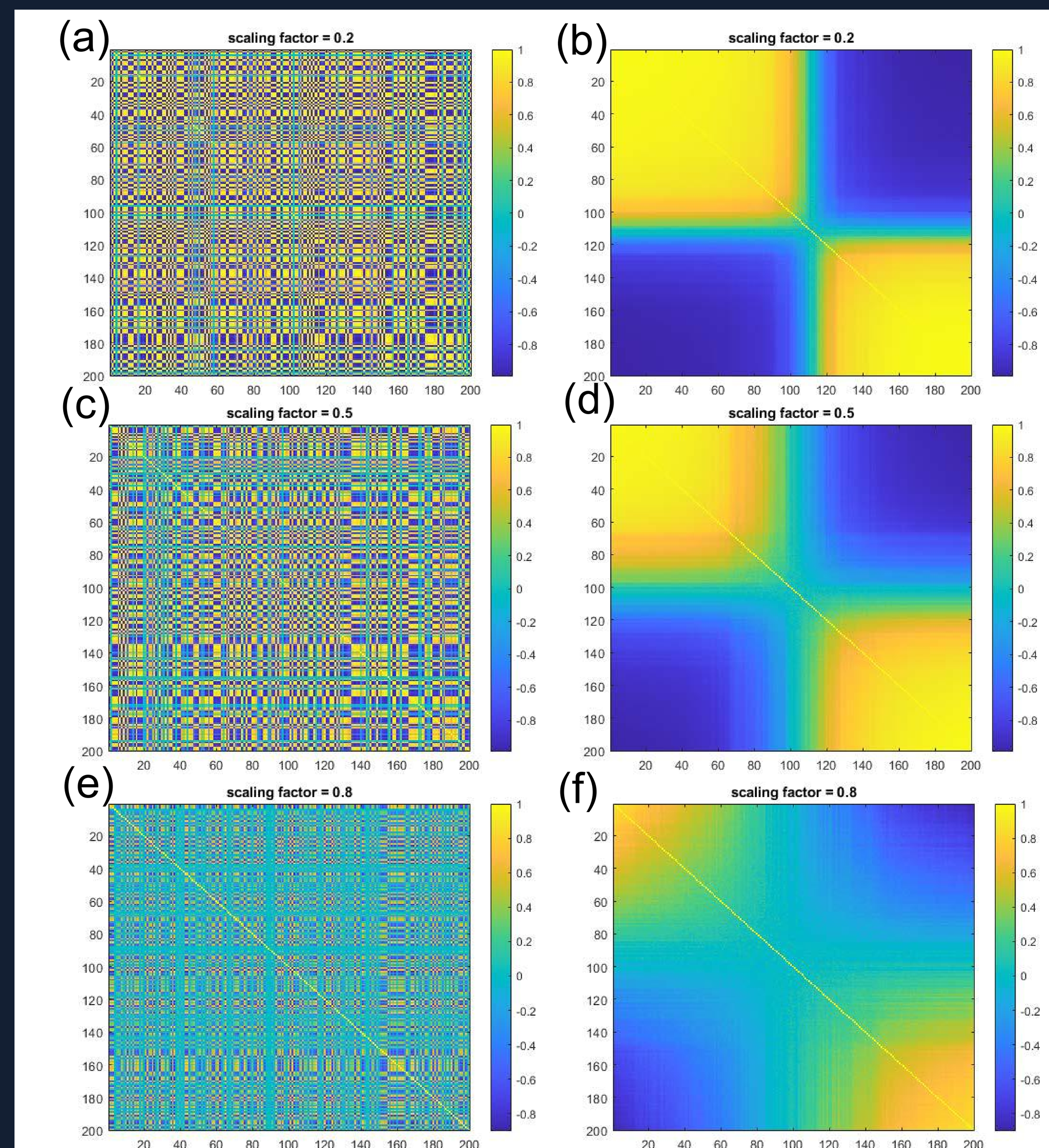

Fig 8: varying scaling factor with zero signal

The correlation matrix becomes more like an identity matrix as the scaling factor increases, which supports our intuition. Cases with signals are under work.

NEXT STEPS

We set out to take advantage of correlations in the noisy brain to simplify perception tasks and introduced ideas that are biologically plausible. However, they do not demonstrate clear patterns of noise correlations (Fig 6a, 7b,c, 8a,c,e). Even if they do, we need to be cautious about how to utilize them, since some patterns may impair the accuracy of the model. We also need to test how rapidly the models are learning when the proposed schemes are implemented as well as recording their accuracies. It would also be worth examining cases where optimal weights are not readily available prior to training.

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[2] Matthew R. Nassar, Daniel Scott, and Apoorva Bhandari. Noise correlations for faster and more robustlearning.Journal of Neuroscience, 2021