DECISION-MAKING

Same lesson, varied choices by frontal cortex

In an unfamiliar situation, animals display variable choice behavior. Based on computational modeling and empirical data, a new study suggests that the variability in decision-making across individuals is driven by differences in internal neural dynamics in the medial frontal cortex.

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The goal of many neural circuits is to perform a behavioral function. To achieve this goal, a myriad of circuit configurations may be possible and equally up to task. For example, in the stomatogastric ganglion, a simple circuit of about thirty neurons, it was estimated that hundreds of thousands of disparate implementations of the network, each with distinct values for synapse strengths and neuron properties, are capable of generating the same desired motor output[1]. While the many implementations are seemingly indistinguishable in terms of learned outputs, what if they have to face an unfamiliar situation and perform a behavioral function beyond the initial goal? A new study in this issue of *Nature Neuroscience* asks this question in the context of decision-making. The authors show that rats and computational models displayed diverse choice behavior when tested on unfamiliar stimuli and that this behavioral variability across individuals relates to the neural activity dynamics in the medial frontal cortex[2].

In rodents, decision-related signals are prevalent in the frontal cortex. Specifically, in the medial frontal cortex (including the medial agranular cortex in rats and secondary motor cortex in mice), many neurons show differential firing activity for one choice over another[3,4]. This neural signal for choice emerges early in decisions. In a dynamic foraging task in which rats select between two paths for probabilistic rewards, choice signals arise in medial agranular cortex before the rat physically indicates its decision[3]. The choice-related signal is also task-specific. When mice need to switch between multiple auditory–motor mappings, choice-related neural signals in secondary motor cortex are modulated by the behavioral context[4]. The prominent, early, and task-specific nature of the choice-selective activity in the medial frontal cortex suggests a central role for this region in mediating action selection. However, so far most prior studies have relied on over-trained stimuli and well-defined behavioral
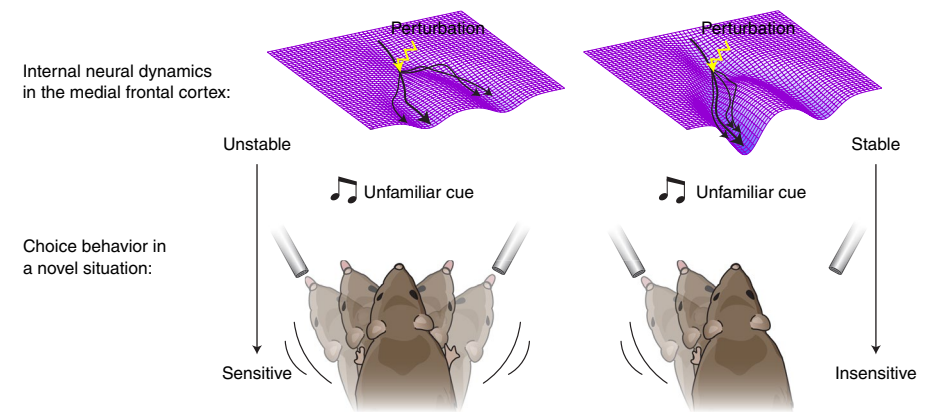

Fig. 1 | Internal neural dynamics in the medial frontal cortex as a determinant of choice behavior. The time-varying population activity in the medial frontal cortex can be visualized in a high-dimensional space as a trajectory (black line). In response to random perturbations (yellow arrow), the population activity may be pushed to divergent locations or remain adherent to the same path, indicative of the stability of the internal neural dynamics. In rats, this internal property of the frontal cortical network is shaped by task learning and correlates with an animal's choice behavior in a novel situation in terms of sensitivity to unfamiliar stimuli. For the purpose of illustration, the rat's choices were drawn to include orienting movements.

situations. It is still unclear to what extent the medial frontal cortex may help animals decide in novel situations, when stimuli are unfamiliar.

By recording from an ensemble of neurons in the medial frontal cortex, we can obtain a precise account of the time-varying neural activity in single trials, which provides a glimpse into the decision-making process. In monkeys performing a two-choice discrimination task, there are moment-by-moment fluctuations in the population activity, perhaps reflecting animals weighing between alternative options, with large vacillations indicative of a 'change of mind'[5]. Trial-by-trial fluctuations in the population activity can also be detected in the frontal cortex of rodents that are learning or switching between sensorimotor rules[4,6]. These moment-by-moment and trial-by-trial variations and, more broadly, the overall temporal dynamics of ensemble activity, must be underpinned by the recurrent

architecture of the frontal cortex[7]. However, mechanisms for how a recurrently connected network could support, guide, and constrain a variety of neural dynamics remain to be elaborated.

To ask how neural variability may relate to behavioral variability, Kurikawa and colleagues tasked well-trained rats with classifying unfamiliar sensory stimuli[2]. Initially, rats were trained to respond with a left or right lick for a low- or high-frequency tone, respectively. After rats reached a performance criterion, they were tested on five unfamiliar tones with frequencies in the intermediate range, in addition to the two familiar tones. Rats displayed variability in their choice behavior for unfamiliar tones. Some rats were sensitive to tone frequency, responding to the intermediate tones by calibrating the proportion of left and right choices. Other rats were insensitive, choosing with a strong bias for one of the sides irrespective of the tone frequency.

To gain insights into how the behavioral variability emerges, the authors constructed a computational model. This model is based on reservoir computing, a class of models known to generate rich activity dynamics that parallel firing patterns measured in the frontal cortex[8]. Briefly, the model consists of a reservoir of spiking neurons that are randomly connected, with a distribution of synapse strengths. The reservoir receives stimulus-tuned inputs and is read out by a pair of output neurons that also provide feedback to the reservoir. Only synapse strengths from the reservoir to readout neurons are modifiable through a reward-based learning rule. When Kurikawa and colleagues trained this model on the task with only two stimuli, many networks with different initial configurations could learn to solve the task and achieve high performance. More interestingly, when these networks were tested subsequently on the full task, they displayed a variety of sensitivity to unfamiliar stimuli, much like what was observed in animals. The modeling approach thus enabled in silico tests of hypotheses regarding the neural mechanisms that are difficult to test with experiments.

What features of the neural dynamics may underlie the variability in choice behavior? The authors surmised that a key parameter might be the stability of the population activity dynamics at the time when the stimulus is presented. To test this idea in silico, they determined stability in model networks by applying a perturbation and then simulating how the network activity would evolve. By repeating and randomizing the perturbation, they quantified the divergence of the perturbed network activity. Essentially, they were evaluating the landscape in neural activity space around the time of cue onset. They found that in model networks, a large spread in response to perturbations, which indicates a shallow local landscape and low stability, correlates with greater variability in the network's choice selection to unfamiliar stimuli (Fig. 1).

Experimentally, measuring the local landscape in neural activity space is difficult. To test whether this relation between neural stability and behavioral variability holds for rats, Kurikawa and colleagues decided instead to measure a surrogate of neural stability in their data: the trial-by-trial variability in neural activity. Here they found empirical support, albeit in a modest number of animals, that this proxy of neural activity stability correlates with the variability of choice behavior for rats. Further empirical evidence would be desirable and may be possible in the future by perturbing neural dynamics with more precision, for example using cellular-resolution optogenetics[9] or through a brain–machine interface[10].

Overall, the framework of training animals and model networks on a particular task and then examining how they generalize in a novel condition is a fascinating problem. The current study highlights a neural substrate for this process. Specifically, traces of prior learning may be detected in the internal neural dynamics, which manifest as important determinants for current decisions. This conclusion made by Kurikawa and colleagues builds upon a couple of prior findings. The idea that variability in the neural dynamics at present may be attributed to past experience is consistent with results in the mouse posterior parietal cortex during evidence accumulation[11], although the timescale for this earlier work was much shorter and on the order of individual trials. Moreover, there is strong evidence that trial-by-trial variability in neural activity is quenched during preparatory periods, such as before the onset of a movement[12]. The reduced neural variability had been taken as evidence that the network is optimizing for the impending behavior. The current study agrees with this view and suggests that the amount of neural variability depends on prior training.

The study illustrates the power of going from experiments to computational models and then back to experiments. However, the study has a few limitations as well. Choice behavior for animals likely involves brain systems beyond the frontal cortex. Behavioral variability could originate from sources such as motivation and arousal, independent of the frontal cortex. For model networks, neural and choice variability presumably arise from how reservoir networks with different initial settings respond to reward-driven learning. However, only several dozen networks were tested, whereas the parameter space is extremely large and is therefore underexplored. Finally, the generalization task relies on interpolation. By contrast, one may try a task requiring extrapolation, by testing tones beyond the initial frequency range or stimuli in a different auditory dimension. Extrapolation is a more difficult challenge that is relevant to the transfer-learning problem in machine learning.

To conclude, the finding that variability in decision-making across individuals relates to an underlying feature of the internal neural dynamics, which is imparted by prior learning, is an intriguing proposition. Studies that can link neural ensemble dynamics with behavior are crucially needed if we want to test the previously proposed functions for the rodent medial frontal cortex in decision-making[13,14]. Behavioral variability across individuals is expressed in unfamiliar situations, but can also be exacerbated by neuropsychiatric disorders. One could speculate that altered landscape in the neural activity space, as reported for mouse models of schizophrenia[15], may explain the abnormal range of behaviors. Therefore understanding how normal and maladaptive learning modify neural dynamics may carry significance for both basic science and translational research. ❐

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Competing interests
The authors declare no competing interests.