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Decision making: How the past guides the future in frontal cortex

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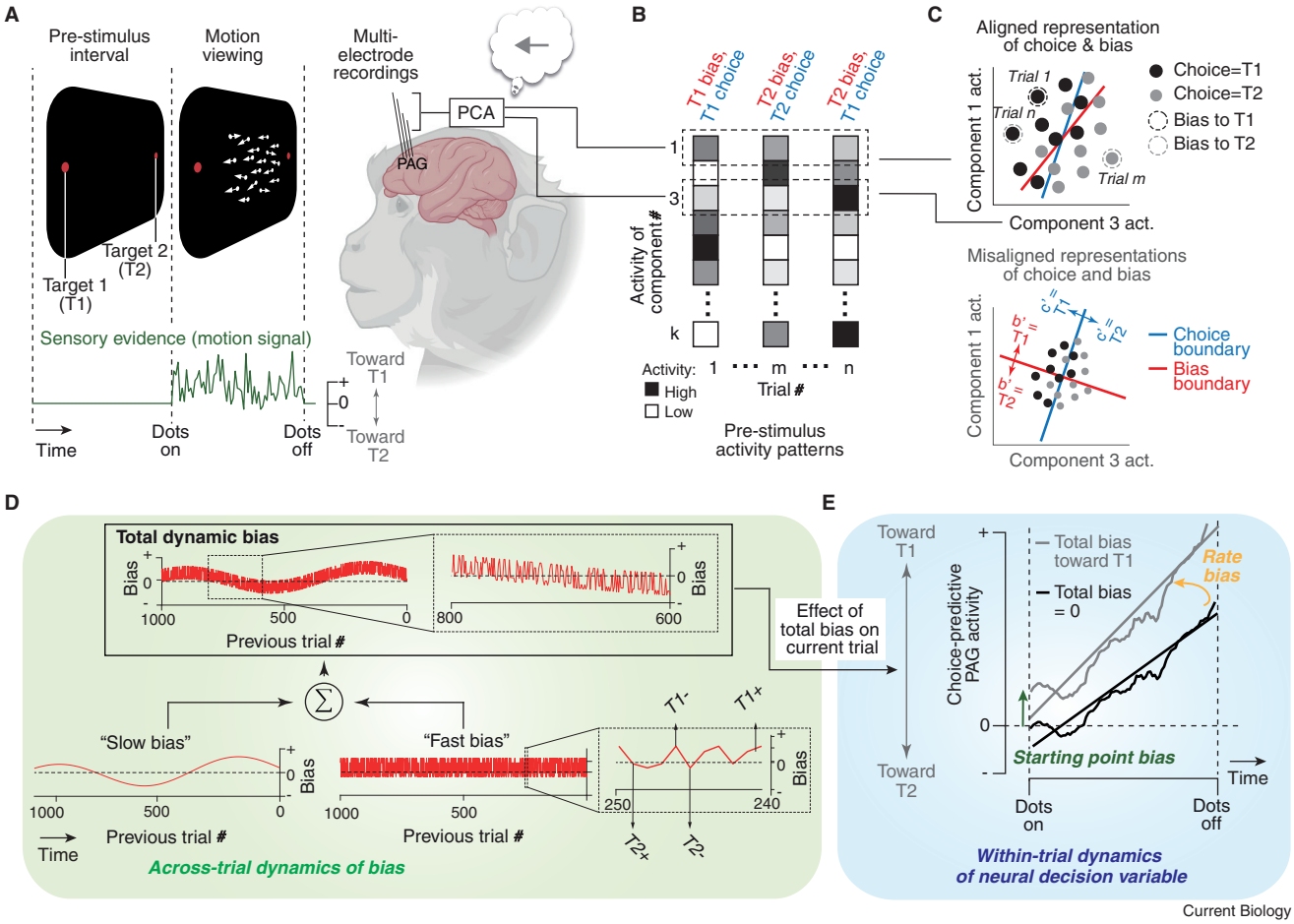
Our judgments of our environment are often shaped by heuristics and prior experience. New research shows that the resulting biases are encoded, and combined with new sensory input, by groups of neurons in the frontal cortex during decisions under uncertainty.

We often need to choose actions on the basis of uncertain interpretations of the state of our environment, for example when deciding whether or not to cross the street in busy traffic. Such decisions depend not only on the momentary sensory input, but also on our prior expectations. These expectations may result from similar decisions made in the past or their outcomes — for example, almost being hit by a car when crossing at the same spot the day before — and are often generated through idiosyncratic heuristics. An important goal for neuroscience is to understand how such expectations are formed, and to pinpoint their representation in the neural circuits involved in the control of goal-directed behavior. A new study reported in this issue of *Current Biology* by Mochol *et al.*[1] shows that, when new decisions are made, populations of neurons in prefrontal cortex encode a bias inherited from previous decisions, and combine this bias with current sensory input.

Mochol *et al.*[1] recorded the activity of many neurons from a region in the macaque monkey prefrontal cortex known as the pre-arcuate gyrus (PAG). Two monkeys had to choose one of two targets (T1 and T2) by making a saccadic eye movement. On each trial of the task, the targets were presented first, followed by a cloud of dots, some of which moved jointly in the direction of the correct target (Figure 1A). It was already known that neural population activity in PAG reliably tracks the evolution of the decision while monkeys are processing this motion stimulus[2]. Mochol *et al.*[1] moved beyond this by showing that patterns of PAG activity, measured before the motion stimulus onset, encode a bias inherited from previous trials and predict the upcoming choice (Figure 1B). Using a clever analysis, the authors further showed that the neural representations of history bias and upcoming choice were 'aligned' in the high-dimensional space of neural population activity in PAG (Figure 1C). This indicates that the history bias is the major factor contributing to the choice-predictive PAG-activity before stimulus onset.



Current Biology

Figure 1. Decoding history biases from prefrontal cortical population activity.

(A) Experimental approach. Monkeys judge the net motion direction of dynamic random dot patterns on a computer screen, while neural activity is recorded with multiple electrodes from the PAG region. Green, example trace of the noisy decision-relevant 'evidence' (left *versus* right motion signal contained in the stochastic stimulus). Principal component analysis (PCA) is used to project the multi-electrode recordings onto so-called components that explain at least 50% of the variance in the data. (B) Bias and upcoming choice are encoded in neural activity patterns (strength of component activations) before onset of the motion stimulus. Pattern vectors are shown for three example trials for illustration. (C) Alignment of neural representations of bias and choice in PAG pre-stimulus activity. This is illustrated schematically in a two-dimensional space (the actual analysis operates in an approximately 40-dimensional space). Each data point is the activation of components 1 and 3, on single trials. The authors identify the boundaries that best separate between biases toward T1 vs. T2 (red line) or choices of T1 *versus* T2 (blue line). Predictions of bias or choice based on these classification boundaries are denoted as b' or c', respectively. The two boundaries are largely aligned (top), indicating common neural population codes for bias and choice. The alternative, orthogonal boundaries for bias and choice, is shown below for comparison. Act., activation. (D) Dynamics of bias across trials, as sum of a slow bias (drifting across hundreds of trials) and a fast bias from the preceding choice and outcome (juice reward for correct choice indicated as '+', no reward as '–'). (E) Schematic of within-trial build-up of choice-predictive PAG activity, in an unbiased (black) and biased (gray) trial.

How is this neural bias in PAG combined with new sensory input? The decision in the dot motion task is commonly conceived as a temporal accumulation of the fluctuating sensory evidence[3]. This yields a so-called decision variable that ramps over time, as reflected in the build-up of PAG activity during motion viewing[2] (Figure 1E, black). In this scheme, choices can be biased by shifting the starting point of the decision variable (Figure 1E, green arrow) or altering the rate of evidence accumulation towards a particular direction (Figure 1E, orange arrow). In line with the former scenario (Figure 1E, gray), Mochol *et al.*[1] found that the neural bias in PAG before motion viewing was maintained, as an offset, in PAG ramping activity throughout motion viewing. But they also found a bias in the rate of choice-predictive activity (Figure 1E, gray).

Contrasting with previous work[4], the choice biases in the experiment by Mochol *et al.*[1] were not induced by instruction or any systematic contingency of the environment. Each monkey's biases evolved spontaneously throughout each experimental session. The authors inferred the bias for each trial, by fitting a statistical model that predicted the probability of a T1-choice on each trial, as a function of the current sensory input and a bias. One part of this bias fluctuated dynamically from trial to trial, modeled as a linear combination of two components: first, a 'slow bias' that gradually drifted toward one or the other choice option across a few hundreds of trials (Figure 1D, bottom left); and second, a 'fast bias' that was driven by the monkeys' choice and outcome (liquid reward or not) on previous

trials (Figure 1D, bottom right). Mochol *et al.*[1] determined that the timescale for the generation of the slow bias comprised at least 130 trials, and that only the immediately preceding trial contributed to the generation of the fast bias. Applying this best-fitting model to the data enabled the authors to estimate the total bias (or its components) on each trial, and decode it from the PAG population activity.

The study by Mochol *et al.*[1] showcases the potential of combining detailed behavioral modeling with sophisticated analyses of neural population data. This combination enabled them to 'reverse-engineer' hidden cognitive dynamics at an impressive level of detail. Idiosyncratic choice history biases have been found in the behavior of rodents[5–7], monkeys[8,9], and humans[10] across a range of studies using similar perceptual choice tasks. But it has been challenging to identify neural correlates of these biases with traditional single-cell physiology[8], possibly because these biases are only weakly expressed in the activity of individual neurons. Monitoring the activity of large populations of neurons has enabled the identification of history biases in rodent posterior parietal cortex[5,11,12]. Mochol *et al.*[1] provide the first demonstration of history biases in the neural population activity of the primate prefrontal cortex, and illuminate how this bias is incorporated into subsequent decisions.

Previous work has shown that prior probability[4] and choice-history bias[10] alter the rate of evidence accumulation, rather than instantiating an offset of the decision variable at the start of evidence accumulation. The observation by Mochol *et al.*[1] of a change in the build-up rate of choice-predictive PAG-activity during the accumulation of evidence is consistent with these previous findings. However, the bias also introduced a robust offset of the PAG ramping activity[1], raising the question of how these two manifestations of the neural bias during evidence accumulation are related. One possibility is that the offset in PAG-activity is accumulated within PAG to produce the measured bias in the build-up rate. An alternative possibility is that offset signal in PAG biases the state of sensory cortex via feedback[13,14]. This feedback scheme would resemble selective attention[15] and should translate into a biased rate of evidence accumulation in downstream regions, including PAG. Unraveling the interplay between distinct populations of neurons within the PAG microcircuit as well as the interplay between sensory and downstream brain regions[14,16] in future work may illuminate the mechanisms by which the brain incorporates priors into new decisions.

While the fast bias systematically depended on the choices and outcomes on previous trials (Figure 1D, bottom right), the sources of the slow bias that spontaneously wavered across hundreds of trials (Figure 1D, bottom left) are less clear. It is tempting to relate this to slow drifts that have been observed in neural activity in visual and frontal cortex[9,17]. One study[9] found that slow fluctuations in visual cortical single-unit activity and choice behavior are largely driven by separate processes. Another study[17] showed a similar slow drift in prefrontal and visual population activity synchronized with slow behavioral changes in a go/no-go visual detection task. The slow drift in that study increased the general ('impulsive') tendency to report target detection, possibly due to a non-specific neuromodulatory signal[17]. The asymmetric (go/no-go) task obscures the relation to the slow bias found by Mochol *et al.*[1]. It will be important to dissect the sources and functional consequences of such slow and spontaneous drifts in cortical activity and behavior in future work.

Why were the monkeys of Mochol *et al.*[1] biased at all? By design, categories were uncorrelated across trials in the task that they performed over thousands of trials. So, the past held no information about which stimulus category was to come next. Thus, maximizing reward required only processing current evidence. Natural environments, by contrast, tend to be stable over timescales longer than a single, rapid perceptual decision, so that history biases may be adaptive in a general setting. The tendency to produce sequential biases even in the face of random stimulus sequences may reflect the brain's adjustment to the stability of the natural world[18]. The new findings of Mochol *et al.*[1] provide a tantalizing example for the pervasive nature of this tendency even after extensive training. They also raise the question of whether, and under which conditions, humans and animals can abandon such maladaptive biases in random environments.

It is long established that human judgments under uncertainty, including low-level perceptual decisions[19], are prone to heuristics and biases[20]. But how those biases are generated and shape the neural processing of new decisions has remained elusive. The new findings of Mochol *et al.*[1] provide a glimpse of the generation, and active use, of idiosyncratic biases within a key brain region for the control of goal-directed behavior. The study sets the stage for tracking the hidden, idiosyncratic dynamics of cognitive biases in other settings and brain regions.

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Plant biology: Positive feedback between auxin and cell wall mechanics during apical hook formation

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Apical hook formation protects fragile tissues of the hypocotyl in soil during seedling emergence. A new study reveals a positive feedback loop between asymmetric distribution of the hormone auxin and the cell wall pectin conformations underpinning cell elongation and tissue bending.

Plant growth largely depends on the formation and growth of cells. Both processes depend on the generation of large amounts of novel material and require energy. This energy primarily comes from photosynthesis, the process by which light energy is used to capture air-borne CO_2-carbon into energy-rich organic compounds. When germination starts within the soil, seedlings are characterized by a quickly growing and etiolated embryonic stem, the hypocotyl[1]. To protect the fragile shoot apical meristem from mechanical damage when being pushed upwards through the soil, dicotyledonous plants have evolved two folded cotyledons and the formation of a hook-like structure of the hypocotyl. Three consecutive phases take place during this so-called apical hook formation — formation, maintenance and opening[2].

Many molecular insights into the gene regulatory networks of apical hook formation and hypocotyl elongation come from the model plant *Arabidopsis thaliana*[3–5]. An apical hook is formed by differential cell elongation on the opposite sides of the hypocotyl[4]. When cell growth rates are lower at the inner side than at the outer side of the hypocotyl, bending and hook formation are initiated and maintained. Upon emergence from the soil and light perception, opening of the hook is initiated with growth rates of cells at the inner side exceeding those of cells located at the outer side[5,6].

Differential cell elongation and apical hook development are tightly controlled by a complex hormonal network. It has been known for many years that auxin modulates curvature of the apical hook[7], yet it was shown rather recently that an asymmetric auxin gradient towards the inner side of the hook lies at the basis of hook formation[8]. Genetic and cell biological evidence identified the auxin transport machinery as a key role player in the development of the auxin asymmetry. Mutants in both auxin import carriers, AUX1 and LAX3[9], and efflux-carriers of the PIN family show hook developmental defects[10]. Downstream of auxin, many studies have confirmed the involvement of several components of the auxin signaling pathway in apical hook formation[10,11]. A major question that remains is the link between auxin and cell wall mechanics controlling cell growth.

A new study in this issue of *Current Biology* by Jonsson, Lathe *et al.*[12] shows the existence of a positive feedback loop between auxin, cell wall pectin conformations and cell wall mechanics. Plant cells are encapsulated in a 'wooden box' — the cell wall, made up by cellulose microfibrils and hemicelluloses that are embedded in a hydrated pectin matrix[13]. Although cell walls act as rigid structures surrounding and protecting the plant protoplast, they need to be flexible to