of a study demonstrating that incorporating clustering into the connectivity can also introduce spontaneous transitions between different firing regimes[14].

As with all computational models the network studied by Ostojic[1] incorporates potentially important simplifications, including the fact that the synapses sum linearly (there is no saturating driving force). But perhaps one of the most important assumptions of the model is that the units are spontaneously active. Thus, in a sense, the burstiness is not an emergent property of the network because each unit in isolation is essentially 'tonically bursting'. Rather, it may be the pattern of inhibition-induced pauses in tonic activity that creates the heterogeneous state. In addition, strictly speaking, the patterns do not arise autonomously from the internal dynamics of the network as with actual cortical networks, in which self-perpetuating patterns of activity can be observed even *in vitro*[15]. Thus, another question for future studies will be to determine whether Ostojic's results[1] hold for excitation-dominated regimes and whether the network can generate heterogeneous patterns of activity that are driven entirely by the internal dynamics.

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Go means green

Joseph T McGuire & Joseph W Kable

A simple cued-approach training procedure can bias economic choices toward specific goods. It appears to work by drawing overt attention toward trained items, scaling up their judged value.

A bottle of Napa Valley Cabernet is probably tasty, but is it worth $70 to me? Is a fancy cup of coffee worth $7? As a would-be purchaser, I need to translate my subjective and intuitive valuation of a good into units of cold, hard cash. Even for nonmonetary choices, such as whether to read a book or watch TV, I need to be able to assess and compare the values of dissimilar options on a common scale.

Schonberg *et al.*[1] describe a simple manipulation that boosts the value people place on individual goods. The goods in their experiments were snack items (for example, a Butterfinger bar) and the manipulation consisted of 'Go' training. Pictures of 60 different foods appeared one by one on a computer screen, 12 times each over the course of 48 min. Most items just had to be viewed passively, but about a quarter were designated by the experimenters as 'Go items'. Every appearance of a Go item was quickly followed by an auditory signal to make a speeded key press.

In the next stage of the study, participants made binary decisions, picking which of two snack items they would rather receive at the end of the experiment. In pairs consisting of a Go item and a control item, matched for their pretraining value to the participant, Go items were selected 60–65% of the time. Similar effects were apparent in a subsequent auction task, in which participants bid an average of about 12 cents more for Go items than for originally equivalent control items.

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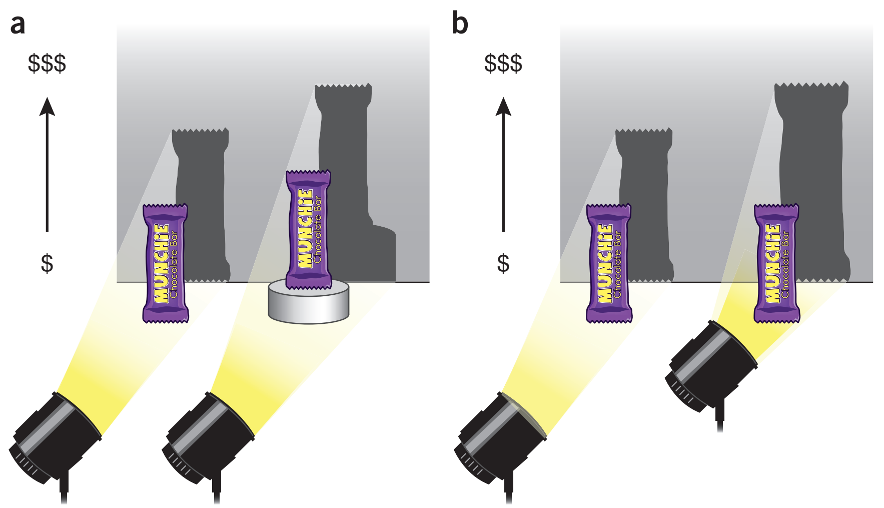
These are surprising results, as the Go-training manipulation differed markedly from other common strategies for modifying people's preferences. Items were not associated with any new incentive, participants received no additional information, and the Go and control items did not differ in their familiarity or duration of exposure[2]. The manipulation does not appear to target habitual responding[3,4], nor does it alter the framing of decisions[5] or the architecture of the choice environment[6]. Given the unexpectedness of the observed effects, it is important and commendable that the researchers present multiple replications[7], documenting the influence of Go training on binary choice in a total of five independent samples.

A potentially revealing wrinkle is that not all snack items were equally susceptible to the effects of Go training. There was a 'rich-get-richer' effect across items, such that an individual's favorite items received the biggest boost. The strongest effects were seen when comparing initially high-valued items assigned to the Go versus control condition. For initially less-favored items, the differential effect of Go training was small to nonexistent.

The dependence on initial item value helps to argue against the uninteresting possibility that participants might, for some reason, have selected the Go items on purpose instead of expressing their true preferences. It also helps shed light on how Go training works. One way to make sense of this pattern of effects is to suppose that, instead of adding a fixed increment to an item's subjective value, Go training had an effect more akin to scaling item value by a multiplicative factor (**Fig. 1**). A differential scaling or amplification of subjective value would have the biggest effect if both items were highly valued to begin with.

Amplification-like influences on subjective valuation have been discussed before in characterizing the effects of overt visual attention. A recent theoretical proposal by Krajbich *et al.*[8] holds that choice alternatives loom larger in moment-by-moment value comparisons if they are being visually fixated. Schonberg *et al.*[1] present evidence for a direct connection between Go training and visual fixation. Eye-tracking data revealed that participants spent more time fixating Go items than control items during binary choices, even controlling for the fact that Go items were more frequently selected. This raises the possibility that overt attentional capture may have mediated the effect of Go training on expressed preferences.

In situations in which preferences shift, it is potentially instructive to investigate whether there is a corresponding shift in preference-related brain activity. A natural target for such an investigation is ventromedial prefrontal cortex (VMPFC). VMPFC is one in a small



Marina Corral Spence

Figure 1 An analogy in which a decision maker's subjective evaluation of an item is represented by the size of the shadow the item casts. (**a**) One way to increase an item's value would be to prop it up (right), raising its value by an additive increment. (**b**) A second way would be to light it from closer up (right), scaling up its value multiplicatively. The reported effect of Go training on item valuation looks more like a scaling effect (**b**) than an additive effect (**a**). The subjective value of Go-trained items appears to be amplified, making these items loom larger in value-based decisions.

collection of brain regions whose activity in fMRI experiments consistently shows a correlation with the subjective value of choice stimuli[9–11].

Given that participants valued Go items more highly, one possible hypothesis is that Go items would evoke higher VMPFC activity than control items. This is not, however, what the researchers observed. Instead, VMPFC activity showed stronger modulation by value across Go items, even when only considering items that all had high subjective value initially. That is, there was a bigger difference in VMPFC activity between more- and less-preferred Go items than between more- and less-preferred control items. These neuroimaging findings lend further credence to the idea that value signals were amplified, not merely shifted, as a result of Go training.

The significance of these findings stems in part from the potential for translational extensions. This work could hold relevance for people who are interested in altering their own future choices. For example, individuals wishing to lose weight might be interested in a training exercise that could help increase the future appeal of healthy foods. This type of extension would fall in the same broad family as previous efforts to devise a training exercise for alcohol-dependent individuals to increase their future probability of selecting nonalcoholic beverages[12]. Naturally, there are many steps remaining on the road toward a clinical intervention. One outstanding question is how Go training would generalize to different pictures of the trained items, different items in the trained category and items outside the laboratory. A second important step is to extend the effect to choice items with more complex attribute structure. A bucket of fries and a future lithe figure might both be high-value outcomes, but the choice between them involves starker tradeoffs than a choice between Snickers and Kit Kats. Third, although there is already evidence that the effect can sometimes last a month or more, further research is merited on the factors that govern its durability.

Of more immediate importance, the work by Schonberg *et al.*[1] stands to inform our theoretical understanding of how preferences are constructed even when no one is trying to alter them. There are several potential mechanisms that might account for the efficacy of Go training in altering valuation, and future work is needed to tease them apart. One possibility is that subjective value is enhanced for items with some kind of motor association or affordance (that is, items with which one could physically interact). If this is the case, the present effect might be related to the previous finding that people place higher monetary valuations on snack items that are presented as real, graspable objects rather than as pictures[13]. A second possibility would draw links to the literature on embodied approach/avoidance training[12,14]. If the training were altered so that Go cues required a response connoting avoidance, such as pushing the item away, an embodied-cognition perspective might predict a reversal of the observed effect on later choices. A third potential hypothesis would place importance on the predictive relationship between Go items and the imperative cue (the visual onset of the snack item reliably anticipated the cue by about 750 ms). Perhaps participants learn to pay closer attention to Go items because these items furnish information about the timing of a motivationally relevant stimulus. If this hypothesis is correct, then blocking that predictive relationship—say, by adding a generic predictive cue before every Go item—should diminish the efficacy of Go training. Conversely, the effect might still be obtained if an imperative cue followed the visual offset of the Go item.

In sum, Schonberg *et al.*[1] have reported a new and thought-provoking influence on economic choice and explicit valuation. Their work opens many avenues for future research and lays the groundwork for new insights regarding the fundamental mechanisms of value-based decision making. That's a hard thing to put a price on.

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