# **Supporting Information**

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#### **SI Results**

Effect of Neural Variability on Model Context Dependence. To examine the role of variability, we examined choice across a range of fixed and mean-scaled noise levels and quantified the decrease in efficiency mediated by increasing distracter value ( $-\Delta E$ ; decrease in optimal choice between  $V_3 = 0$  and  $V_3 = 100$ ). These simulations revealed three properties governing the influence of variability on context dependence (Fig. S1). First, noise of either kind is critical to context-dependent behavior: Without trial-to-trial variability in the representation of value, discriminability between options is unaffected by the shift in mean firing rates produced by divisive scaling. This effect is unsurprising given that stochastic choice behavior in the model depends on neural noise, but it emphasizes the importance of understanding the role of variability in neural coding. Second, context dependence occurs across a broad range of both fixed and mean-scaled noise levels. To orient the reader, we point out that an ideal Poisson neuron is represented by S = 1.0 and  $\sigma_{fixed} = 0$ . Finally, distributional noise characteristics are important: Context dependence consistently decreases with the strength of the mean-scaled noise relationship (S). With mean-scaled variance, the widths of the firing-rate distributions decrease as rates are reduced by divisive scaling, partially compensating for decreases in mean rate differences driven by normalization.

### Effect of the Semisaturation Constant on Model Context Dependence.

In addition to divisive scaling, the behavior of the normalization algorithm is governed by the semisaturation term  $\sigma_H$ , which controls the effective response range and saturation behavior. With a single option,  $\sigma_H$  determines the value  $V_i$  that produces the half-maximal response. With more than one option,  $\sigma_H$  functions in an additional manner, controlling the degree of context dependence in value representation (Fig. S2A). At low  $\sigma_H$  (relative to V), the denominator in Eq. 2 is dominated by the value terms and the model shows strong context dependence: The activity representing the value of option 1 depends markedly on the value of the other alternatives (Fig. S2A Left). At higher  $\sigma_H$ , the denominator is increasingly dominated by the semisaturation constant itself and the response approaches an absolute value representation (Fig. S2A Center and Right).

Given its modulatory control of contextual value coding, we hypothesized that the semisaturation constant would also affect the extent of behavioral context dependence. Fig. S2B shows simulated choice behavior at three different magnitudes of  $\sigma_H$ (10, 100, or 1,000). In these simulations, the gain parameter was adjusted to keep mean firing rates approximately equivalent; all other model parameters were fixed. As evident in the decreasing range of choice curves, a larger semisaturation constant decreases the effect of context on behavior. Examined across a broad range of  $\sigma_H$  magnitudes, context dependence decreases exponentially as a function of the semisaturation parameter (Fig. S2C); this exponential decrease suggests that context-dependent effects persist for a broad range of semisaturation values.

Thus, context dependence does not require the specific parameters of the normalization algorithm observed in parietal cortex; in particular, contextual effects are driven by the value summation term in the normalization denominator. However, inclusion of  $\sigma_H$  in the model allows a parametric examination of the effects of normalization terms. These results show that the extent of context dependence depends on the precise parameters of normalization and thus may be modifiable. For example, changes in  $\sigma_H$  have been proposed to mediate the effects of adaptation in

visual responses, suggesting that the normalization mechanism (and context dependence) may vary with temporal history. In the sensory and decision-making literature, the semisaturation constant is primarily treated as an empirical constant fit to neural data; identifying the biophysical source of this term and mechanisms by which it may be modulated in neural circuits is a key area of future research.

#### **SI Materials and Methods**

**Monkey Trinary-Choice Experiment.** Two male rhesus monkeys (*Macaca mulatta*) were used as subjects (monkey W, ~6.0 kg; monkey B, ~14.0 kg). All experimental procedures were performed in accordance with the US Public Health Service's *Guide for the Care and Use of Laboratory Animals* and approved by the New York University Institutional Use and Care Committee.

Experiments were conducted in a dimly lit, sound-attenuated room using standard techniques. Visual stimuli were generated using an array of tristate light-emitting diodes situated on a tangent screen 145 cm from the eyes of the monkey. Eye movements were monitored using the scleral search coil technique, with horizontal and vertical eye position sampled at 500 Hz using a quadrature phase detector (Riverbend Electronics). Presentation of visual stimuli and water reinforcement delivery were controlled with an integrated software and hardware system (Gramalkn; Ryklin Software).

Each session was conducted in blocks consisting of a series of instructed trials followed by choice trials. In a given block, reward magnitudes were randomly assigned to three target locations situated 16° from fixation and equidistant from one another. To encourage the animals to learn new reward-location associations each block, one of four different location triplets was randomly selected for each block. Reward magnitudes (in microliters) were drawn in a pseudorandom fashion from the sets  $V_1 = \{130, 143, 156, 169, 182\}, V_2 = 156$ , and  $V_3 = \{26, 104\}$ .

Individual blocks began with 40 instructed trials. Each trial began with the monkey fixating a central fixation target (500 ms). A target was then presented in one of the three locations assigned to the block (1,500 ms). Finally, the fixation target was extinguished, and the monkey was rewarded with the designated amount for a saccade to the peripheral target within 500 ms. Instructed trials were followed by a series of choice trials (range 15–30 trials), which were identical to instructed trials except the three targets were simultaneously presented and the monkey was rewarded with the selected target. All blocks of length 30 or fewer were included in the analysis; similar results were obtained with data restricted to smaller datasets.

**Human Trinary-Choice Experiment.** Each behavioral session began with 60 bid trials. In each bid trial, subjects viewed an image of a snack-food item on a computer display and reported how much they would be willing to bid for that item using a mouse-controlled slider bar; possible bid prices ranged from \$0–4 in \$0.01 increments. Stimuli depicted 30 different food items (common salty and sweet snack foods), presented as high-resolution color images (110 pixels per inch). Items were presented in randomized order, and each individual good was presented twice.

Following the bid trials, the items were automatically sorted by their mean bid values into a target group (10 highest-ranked) and a distracter group (20 lowest-ranked). Subjects then performed 250 choice trials; in each trial, subjects viewed three options (two targets and one distracter) and indicated their choice by pressing a mouse button. Distracters comprised a subset of 10 items chosen to sample widely from the identified distracter group [items ranked 1, 3, ..., 19 in mean Becker–DeGroot–Marschak (BDM) bid]. Target item pairs were chosen to sample widely from the possible pairwise target value differences. Each distracter was presented with 25 different target pairs, and each trinary-choice set was presented only once. The location of each item on the screen (left, middle, or right) was randomly assigned in each trial. Following the completion of the session, one of the 310 trials was randomly selected for realization.

If a bid trial was selected, the outcome was determined via a BDM auction; the BDM procedure is widely used in laboratory economic studies because it is easy to explain and implement, and the optimal strategy for subjects is to report their exact subjective valuation. To realize a bid trial, subjects drew a chip from a bag containing chips numbered from 0-4 in 0.10 increments; the drawn number determined the price *p* of the item in that trial and was compared with the bid *b*. If  $b \ge p$ , subjects received the item for the price *p*; if b < p, the subjects paid nothing and did not receive the item. Thus, the best strategy for subjects is to report the maximal price they would be willing to pay, because this has no effect on the price itself but rather on whether or not the subjects will purchase the item. Subjects were carefully informed of this property of the BDM auction in the initial instructions and practiced it before the actual experiment. If a choice trial was selected, subjects received the food item they selected in that trial.



**Fig. S1.** Effect of variability on context dependence. Color indicates the normalization-driven decrease in choice efficiency ( $-\Delta E$ ) as a function of two sources of noise: rate-dependent and rate-independent variability. Trinary-choice simulations were conducted and efficiency quantified as shown in Fig. 2. Data are plotted as a function of the relevant noise parameters (rate-dependent, scaling parameter *S*; rate-independent, fixed noise SD  $\sigma_{fixed}$ ). Noise of either form is critical for context dependence: At minimal levels of both types of variability, changes in context do not affect choice efficiency (lower left).



**Fig. 52.** Context dependence governed by the form of normalization. (*A*) Normalization model response representing option 1 as a function of its value ( $V_1$ ) and the summed value of alternative targets ( $V_2 + V_3$ ) for low, medium, and high semisaturation parameters ( $\sigma_{H}$ ). Color map indicates model neuron firing rate (min = 0 sp/s, max = 75 sp/s). As  $\sigma$  increases, the value representation grows increasingly independent of alternative options, evident as vertical shading. (*B*) Relative target-choice curves at different semisaturation parameters, as in *A*. At higher  $\sigma_{H}$ , distracter value has a smaller effect on choice behavior. Colors indicate different distracter values as in Fig. 2; for legibility, data are shown for distracter values from 0 to 100 and positive target-value differences. (*C*) Context-driven decrease in choice efficiency ( $-\Delta E$ ) decreases exponentially as a function of semisaturation parameter magnitude. Error bars indicate bootstrap 95% confidence intervals.



**Fig. S3.** Normalization model and set-size effects. (*A*) Example set size-dependent choice behavior. The value of two target options ( $V_1$  and  $V_2$ ) were varied as in the trinary-choice simulations; the number of additional, fixed-value ( $V_3 = 20$ ) distracter items varied from 1 to 64. Each point in the simplex plot represents average choice behavior in a given set size for a particular value condition, color-coded by the number of distracters. Choice behavior under fixed target-value pairs ( $V_1$  and  $V_2$ ) are connected with blue lines and deviate markedly from the linear constant relative ratio lines predicted by rational-choice theory (gray lines). Example simulation parameters: K = 100,  $\sigma_H = 50$ , w = 1,  $\sigma_{fixed} = 8$ , S = 0. (*B*) Context-dependent relative target choice functions. Lines are color-coded by distracter number, as in *A*. (*C*) Relative target choice efficiency plotted as a function of distracter number.