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Context-dependency in valuation

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In the last few years, work in the nascent field of neuroeconomics has advanced understanding of the brain systems involved in value-based decision making. An important modulator of valuation processes is the specific context a decision maker is facing during choice. Recently, neuroeconomics has made great progress in understanding, on both the brain and behavioral level, how context-dependent perception affects valuation and choice. Here we describe how context-sensitive value coding accounts for choice set effects, differential perceptions of gains and losses, and expectancy effects of external (economic) signals.

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Introduction

It is not new to neurobiologists that an individual's reaction to stimuli depends on the context in which they are presented. For example, it has been long known and understood how our perception of image brightness depends on how bright other images in our field of vision are and how bright the images we saw previously were. However, until recently, these ideas have not been applied to the neurobiology of valuation, and standard economic theories suggest that valuation should be independent of context. We review here how efforts in decision neuroscience can bridge the gap between theories in economics, psychology and neurobiology.

Neurobiological basis of choice set effects

When considering which alternative to pick from a choice set (e.g. what to pick from a menu in a cafeteria), individuals' valuation of available options is affected by what other alternatives are offered. Marketers long ago realized that they can affect the relative desirability of products by offering additional, irrelevant products that they do not expect to sell. These products, called decoys, should make one of the selling products look better on more dimensions (e.g. taste, price, size) than the other selling product by increasing its perceived attractiveness [1–4]. Economists call decoys *irrelevant alternatives*, and most decision-making models assume that valuation obeys the independence of irrelevant alternatives (IIA) axiom.[4] This runs counter to empirical evidence that the number of alternatives offered affects choice. When selecting from more alternatives, people make worse decisions [5], are more disappointed with their choice [6], and even avoid choice [6–10]. This is surprising, because free choice is usually perceived as desirable. Moreover, people should prefer choosing from bigger choice sets that are more likely to contain preferred alternatives. Nevertheless, when information is costly to encode and process, large choice sets eventually become a liability.

In the 1960s Barlow [11] hypothesized that an organism with limited capacity (a limited number of neurons with limited firing range) would not perceive stimuli objectively but instead should adapt perception to the 'statistics' of the environment. Wainwright and colleagues [12] showed that a form of such adaptation, *divisive normalization* [13] (Box 1), maximizes information about the relative values of stimuli [14]. Divisive normalization has been found in various sensory systems [15–18]. Louie and colleagues [19•] found that neurons in value-coding brain regions follow divisive normalization as well. This naturally implies that valuation is not independent of irrelevant alternatives. To give an example, when choosing between lunch options in a cafeteria the neural signature of the value of lasagna depends on what other food options are available (as explained in the box below).

In the divisive normalization equation (Box 1), the valuation (i.e. firing rate) of each option in the choice set is divided by the same number ($\sigma^\alpha + \sum_j v_j^\alpha$). Hence, the relative ranking of any two alternatives is preserved in *any* choice set. However, as the denominator increases (because the value or number of other alternatives increases),

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[4] The IIA axiom holds that if an individual prefers apples to bananas when considering the choice set {apple, banana}, then he or she also prefers apples to bananas in any other choice set (e.g. {apple, banana, carrot}). Alternatively, one can say that the relative probability of choosing apple to the probability of choosing banana should be the same independent of whether a carrot is available or not [67,68].

Box 1 Divisive normalization model

Firing rate corresponding to reward *i* is given by:

$$SV_i(\mathbf{v}) = r_{\max}\frac{v_i^\alpha+\beta}{\sigma^\alpha+\sum_j v_j^\alpha}+\epsilon_f+\epsilon_S$$

where $\mathbf{v} = [v_1, v_2, \ldots, v_n]$ is the vector of all inputs (rewards in the choice set), σ is the experience-based expectation, β is the baseline firing rate, and r_{max} controls the maximum response rate; α exponentiates all the inputs. $\varepsilon_f \sim N(0, \sigma^2_{fixed})$ is a fixed noise term and $\varepsilon_s \sim N(0, S\mu)$ is mean-scaled noise where S controls how the variance scales with the mean μ. Intuitively, the denominator decorrelates the informational signal of each neuron by removing information common to all inputs ($\sum_j v_j^\alpha$). See [22••] for a recent review.

firing rates decrease[5] and discriminability between options declines. Figure 1 plots a hypothetical distribution of firing rates for two high-value alternatives (solid and dashed black lines) and low-value irrelevant alternatives (distractors) (gray lines). As the number (A) and value (B) of distractors increase, the firing rate distributions of high-value options overlap more, discriminability is reduced, and the chooser picks second-best more often. Thus, context-dependent valuation can explain why and predict when irrelevant alternatives affect choice [20,21].

Neurobiological basis of gain-loss asymmetry

Context-dependent valuation can also explain observed asymmetries in valuation of gains and losses [22••,23••,24]. Kahneman and Tversky in hundreds of studies observed that people tend to avoid risks when betting on monetary gains and take risks when betting on losing money. Consider two decision problems from their seminal paper [25]:

Problem 1.

You have been given $1000. You are now asked to choose between (a) a gamble with a 50% chance of winning an additional $1000 and a 50% chance of winning nothing, or (b) winning an additional $500 with certainty.

Problem 2.

You have been given $2000. You are now asked to choose between (a) a gamble with a 50% chance of losing $1000 and a 50% chance of losing nothing, or (b) losing $500 with certainty.

These problems are equivalent in terms of distributions over the final wealth states. Nevertheless, the majority of subjects chose the sure option in Problem 1 and the risky lottery in Problem 2. Kahneman and Tversky hypothesized that people behave in this way because they value rewards relative to a reference point (rather than in absolute terms), and sensitivity to rewards diminishes away from the reference point [25]. Value function in their model is thus S-shaped: concave (convex) over gains (losses) relative to the reference point (see Figure 2a).

Although Kahneman and Tversky proposed the S-shaped value function well before any neural evidence on subjective value coding was available, it is well aligned with recent developments in neuroeconomics. Given a fixed neural activity budget, an efficient neural representation of subjective value should aim to increase discriminability between the most likely inputs. Therefore, it should align the steepest region of the subjective value function with the most likely input values. In the language of neuroeconomics, subjective value function should be the steepest around the reward expectation (see Figure 2b) [23••]. In the normalization model, this is achieved by modulation in σ, the expected reward value, which aligns the subjective value function with the distribution of expected rewards [22••]. Sensory systems construct the distribution of expected stimuli by tracking experienced stimuli statistics [26–28]. In valuation this is a more complex process (reviewed in *Neural systems underlying expectancy effects* section).

The diminishing sensitivity from the reference point, a descriptive property of the subjective value function [25], is essentially equivalent to the normative property of making the subjective value function the steepest around the expectation for better discriminability. The consequence of an S-shaped value function is risk aversion over gains and risk seeking over losses. Although counterintuitive, seemingly contradictory choices in Problems 1 and 2 above can be explained by context-dependent value coding. Kahneman and Tversky suggested that the reference point against which outcomes are evaluated is $1000 in Problem 1 and $2000 in Problem 2 [25].

In the language of context-dependent coding in neuroeconomics, perception is optimally adapted to different distributions of expected rewards. In Problem 1, the probability distribution is centered around $1000 (black lines in Figure 2b); in Problem 2 it is centered around $2000 (gray lines in Figure 2b). It is then straightforward to see from Figure 2b that individuals prefer the sure option in Problem 1 ($SV_1(\text{safe}) > SV_1(\text{lottery})$) and the lottery in Problem 2 ($SV_2(\text{lottery}) > SV_2(\text{safe})$). Hence, the consequence of context-dependent value coding is risk aversion over perceived gains and risk seeking over perceived losses, with rewards classified as gains or losses relative to a reference point. By changing the reference point, we can alter choice.[6]

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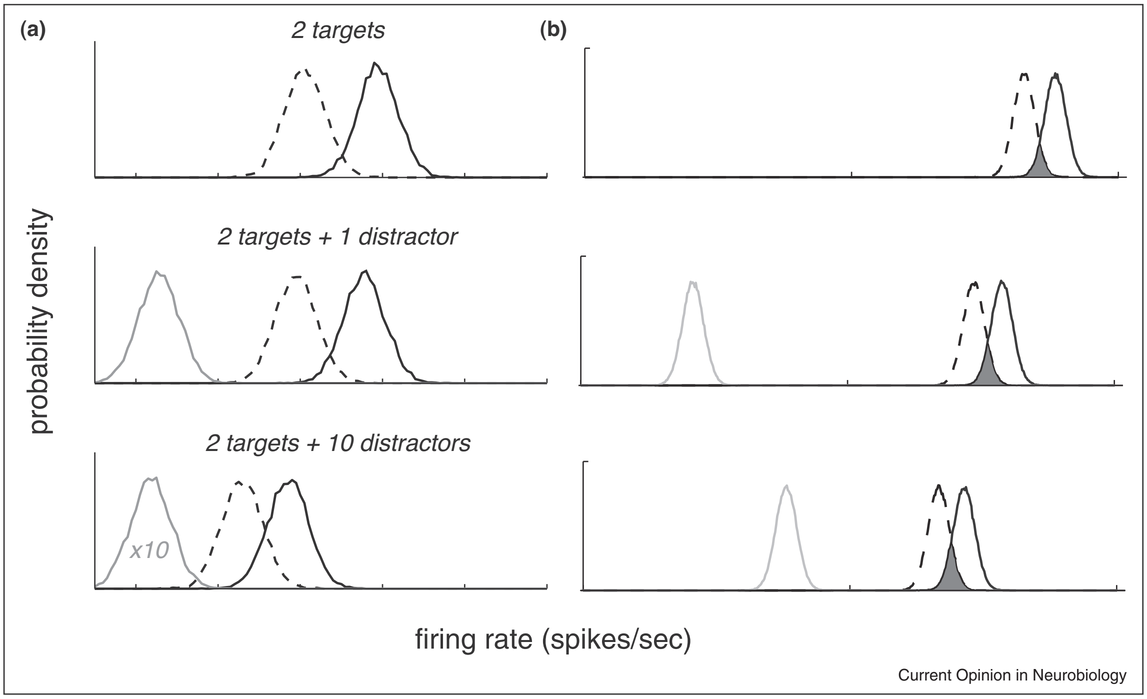
[5] A prediction observed in the neural data [69,70].

[6] People tend to show greater sensitivity to losses than to gains of equivalent size, a property labeled *loss aversion* [25]. For neural signatures of loss aversion, see for example [71].

Figure 1



Hypothetical distributions of neural activity representing the values of two high-value options (solid and dashed black lines) in the absence or presence of **(a)** different numbers of low-value distractors and **(b)** different distractor values (gray lines).
Source: Adapted from [20,21].

Neural systems underlying expectancy effects

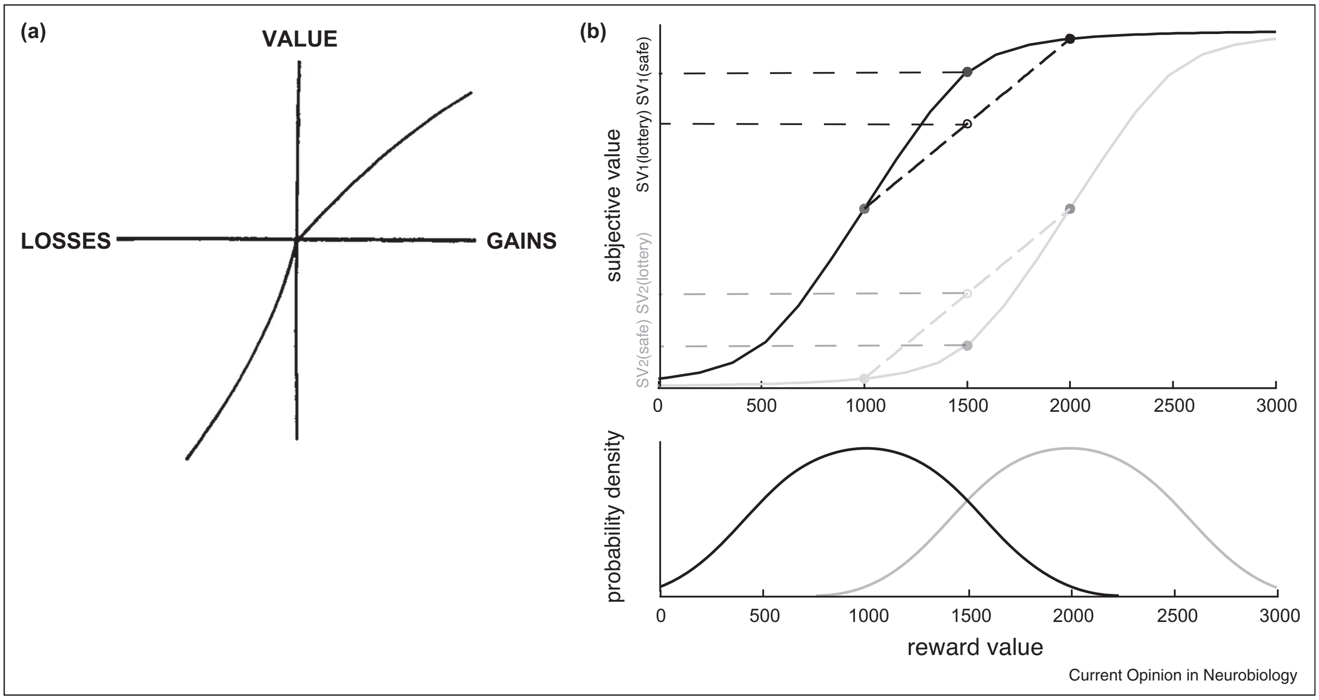
Expectations play an important role in the formation of reference points [29] and thus are central to context-dependent valuation. Expectations are beliefs and predictions about future feelings, events, or outcomes of decisions. They are linked to learning and conditioning [30] and the context-dependent meaning of the option for choice [31,32]. They can be influenced by external (economic) cues that generate quality expectations, such as the price of the good [33,34] and the information on the packaging, among others [35–37]. Such cognitive psychological concepts and learned values lead to expectations that, in turn, influence valuation of goods and services even when the physical properties of consumed goods are kept constant [38–40].

They can also change subsequent behavior. For example, hotel room attendants whose daily work was framed as physical exercise (a) perceived themselves to be getting significantly more exercise than before and (b) showed a decrease in blood pressure, body fat, waist-to-hip ratio, and body mass index relative to a control group [41]. These findings suggest that expectations can create ‘self-fulfilling prophecies’ and trigger psychological processes potentially going beyond mere rational expectations about the likelihood of decision outcomes and the setting of reference points.

Understanding the brain processes underlying expectations, value, and learning is critical to understanding why expectations have such a powerful influence on valuation. A few studies have investigated whether expectations alter valuation of positive experiences (see for a review [40]). In one study [42], activity in the mOFC/vmPFC in response to the consumption of wine depended on quality beliefs about its price. Consuming identical wines with high versus low price tags correlated with changes in neural activity in the mOFC/vmPFC, which has been considered a ‘secondary taste cortex’ and responds to value-related signals and conceptual processes outside the gustatory realm [43,44].

These findings parallel the wealth of research on placebo hypoanalgesic effects (see for recent reviews [45••,46•]). Studies in this area have shown placebo hypoanalgesic effects on (a) physiologic and autonomic responses such as skin conductance and pupil diameter (e.g. [47]), (b) a range of neuroendocrine responses such as serotonin and cortisol (e.g. [48]) and gut-level hormones such as ghrelin [49], and (c) distributed neural patterns of pain processing that are both sensitive and specific to pain (e.g. [50]). Neuroimaging studies on placebo hypoanalgesic effects have contributed substantially to the understanding of the underlying neural systems involved in pain placebo effects. They found that pain placebos do not only

Figure 2



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(a) The original value function in prospect theory reprinted from [25]. **(b)** Subjective value functions (above) corresponding to assumed prior probability distributions over rewards (below) centered at different reference points: $1000 (black) and $2000 (gray). Black (gray) curves represent lower (higher) reference point.
Source: Adapted from [22••,23••].

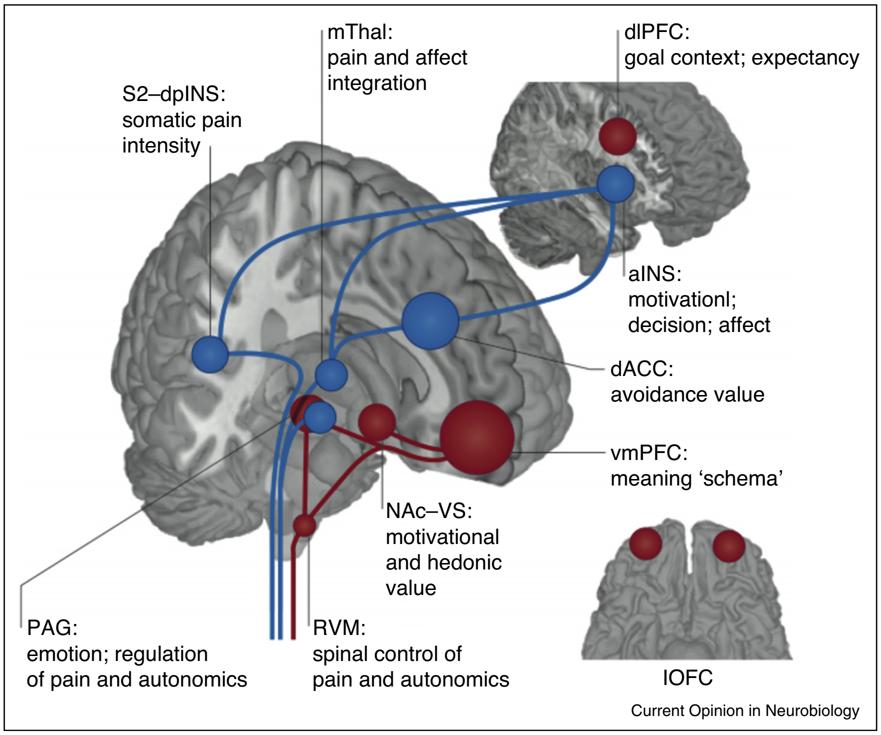
decrease neural activity on pain pathways in the brain (shown in blue in Figure 3), but also alter autonomic nociceptive responses in the spinal cord [46•,51,52].

If we apply context-dependent coding to these findings, an intuitive prediction would be that pain hypoanalgesic expectations change the reference point and hence the distribution of neuronal firing in the neurologic pain signature. A related idea has been suggested recently by Buechel *et al.* [46•], who proposed a Bayesian model where the autonomic and the central pain systems resemble a recurrent system allowing for the implementation of predictive coding. Their framework suggests that the brain is actively making inferences based on prior experiences that account for parts of the placebo response [46•].

Interestingly, existing models built around the idea that valuation depends on expectations [24,29,46•,53] need to be extended to account for an interesting finding in the psychology literature suggesting that learning and updating between expectations and actually experienced value take place only to a limited degree. In other words, these models suggest that with repeated experience expectancy effects would attenuate through the computation of prediction errors and associated learning processes, but none of the pain placebo studies has reported such findings to date [45••]. Strikingly, even if participants are told that they are receiving a placebo pill, they still exhibit a placebo hypoanalgesic response [54], and in some studies the magnitude of placebo effects increased over time [55,56]. This could be partly due to the fact that beyond bottom-up pain processes, affective, motivational, and self-regulatory responses were also found to mediate pain placebos [45••,46•] (areas showing increasing activity, illustrated in red in Figure 3). That means that, in addition to relying mainly on expectations as informational signals, a model that would fully capture expectancy effects also needs to incorporate expectations as motivational signals. Such a motivational component has been demonstrated in analgesia studies, for example by volunteers 'wanting' to terminate pain that contributed significantly to placebo hypoanalgesia [45••,56–60]. Thus, placebo could become self-reinforcing.

Last, it is important to note that placebo responses also have limitations. The predictive coding model from Buechel *et al.* [46•] suggests that if expectations and actual experience are distributed too far apart in their subjective pain perception, then the usual assimilation effects confirming the expectation will turn and result in contrast effects [46•]. This idea was empirically tested by Gneezy *et al.* [61••], who showed that a higher-priced 'bad' wine is liked less than the identical wine with a lower price tag. Interestingly, placebo effects might be a

Figure 3



Brain systems involved and their potential functions in pain placebo analgesia (source [21]). Areas shown in blue show reduced responses to pain after placebo treatment. These are the medial thalamus (mThal), anterior insula (aINS), dorsal anterior cingulate cortex (dACC), periaqueductal gray (PAG) and secondary somatosensory cortex–dorsal posterior insula (S2–dpINS). Areas shown in red are associated with increased activity to placebo treatment. These are the ventromedial prefrontal cortex (vmPFC), dorsolateral PFC (dlPFC), lateral orbitofrontal cortex (lOFC), nucleus accumbens–ventral striatum (NAc–VS), PAG and rostroventral medulla (RVM).

uniquely human primate process: studies in capuchin monkeys could not show evidence for placebo effects of price, although the same lab showed that they exhibit a range of other context-dependent valuation processes similar to those of human primates [62,63].

Conclusions

The goal of neuroeconomics has always been to explain and predict behaviors that traditional economics and psychology models cannot account for. Many behavioral phenomena that were previously unexplained and labeled as 'irrational' errors because they are against axioms of normative rational choice theories in economics (in a sense that they lower individual's payoff from a single decision in all possible circumstances) have now been successfully explained on the level of the nervous system. Neuroeconomists no longer label these behaviors as irrational and instead interpret them as efficient responses of a system that makes a series of decisions and has limited neural resources available for valuation and choice. It is noteworthy that not only functional properties of neurons and systems of neurons (as reviewed above in Neurobiological basis of choice set effects) but also structural properties of the brain seem to be related to individual choices [64•,65] and individual sensitivity to context [66•]. The ongoing challenge is to understand exactly how reference points, central to virtually all modern theories of choice but nonetheless not yet fully specified, are formed on the neural level and then to incorporate this knowledge into theoretical choice models.

Conflict of interest statement

Nothing declared.

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References and recommended reading

Papers of particular interest, published within the period of review, have been highlighted as:

- • of special interest
- •• of outstanding interest

1. Tversky A, Simonson I: **Context-dependent preferences.** *Manage Sci* 1993, **39**:1179-1189.

2. Simonson I, Tversky A: **Choice in context: tradeoff contrast and extremeness aversion.** *J Mark Res* 1992, **29**:281-295.

3. Huber J, Puto C: **Market boundaries and product choice: illustrating attraction and substitution efects**. *J Consum Res* 1983, **10**:31-44.

4. Huber J, Payne JW, Puto C: **Adding asymmetrically dominated alternatives: violations of regularity and the similarity hypothesis**. *J Consum Res* 1982, **9**:90-98.

5. DeShazo JR, Fermo G: **Designing choice sets for stated preference methods: the effects of complexity on choice consistency**. *J Environ Econ Manage* 2002, **44**:123-143.

6. Iyengar SS, Lepper MR: **When choice is demotivating: can one desire too much of a good thing?** *J Pers Soc Psychol* 2000, **79**:995-1006.

7. Tversky A, Shafir E: **Choice under conflict: the dynamics of deferred decision**. *Psychol Sci* 1992, **3**:358-361.

8. Boatwright P, Nunes JC: **Reducing assortment: an attribute-based approach**. *J Mark* 2001, **65**:50-63.

9. Bertrand M, Karlan D, Mullainathan S, Shafir E, Zinman J: **What's advertising content worth? Evidence from a consumer credit marketing field experiment**. *Q J Econ* 2010, **125**:263-305.

10. Iyengar SS, Huberman G, Jiang G: **How much choice is too much? Contributions to 401(k) retirement plans**. In *Pension Design and Structure: New Lessons from Behavioral Finance.* Edited by Mitchell OS, Utkus SP. Oxford University Press; 2004:83-97.

11. Barlow HA: **Possible principles underlying the transformations of sensory messages**. In *Sensory Communication.* Edited by Rosenblith WA. MIT Press; 1961.

12. Wainwright MJ, Schwartz O, Simoncelli EP: **Natural image statistics and divisive normalization: modeling nonlinearity and adaptation in cortical neurons**. In *Probabilistic Models of the Brain: Perception and Neural Function.* Edited by Rao RPN, Olshausen BA. MIT Press; 2002:203-222.

13. Heeger DJ: **Normalization of cell responses in cat striate cortex**. *Vis Neurosci* 1992, **9**:181-197.

14. Simoncelli EP, Olshausen BA: **Natural image statistics and neural representation**. *Annu Rev Neurosci* 2001, **24**:1193-1216.

15. Shapley RM, Victor JD: **The effect of contrast on the transfer properties of cat retinal ganglion cells**. *J Physiol* 1978, **285**:275-298.

16. Barbour DL, Wang X: **Contrast tuning in auditory cortex**. *Science* 2003, **299**:1073-1075.

17. Rabinowitz NC, Willmore BDB, Schnupp JWH, King AJ: **Contrast gain control in auditory cortex**. *Neuron* 2011, **70**:1178-1191.

18. Rieke F, Rudd ME: **The challenges natural images pose for visual adaptation**. *Neuron* 2009, **64**:605-616.

19. • Louie K, Grattan LE, Glimcher PW: **Reward value-based gain control: divisive normalization in parietal cortex**. *J Neurosci* 2011, **31**:10627-10639.

The authors show that neurons in monkey LIP encode value of options relative to the values of other available alternatives. This paper provides evidence suggesting that the standard form of sensory gain control (divisive normalisation) may be a general mechanism for cortical computation.

20. Louie K, Glimcher PW: **Set-size effects and the neural representation of value**. In *Neuroscience of Preference and Choice: Cognitive and Neural Mechanisms.* Edited by Dolan RJ, Sharot T. Academic Press; 2012:143-169.

21. Louie K, Khaw MW, Glimcher PW: **Normalization is a general neural mechanism for context-dependent decision making**. *Proc Natl Acad Sci U S A* 2013, **110**:6139-6144.

22. •• Louie K, Glimcher PW, Webb R: **Adaptive neural coding: from biological to behavioral decision-making**. *Curr Opin Behav Sci* 2015, **5**:91-99.

The authors review the biological, neural and behavioral evidence on the context-dependent neural coding in sensory systems and valuation. They argue the deviations from optimal decision-making occur because of the intrinsic biophisical constraints in value coding such as the cannonical gain control algorithms in sensory systems.

23. •• Woodford M: **Prospect theory as efficient perceptual distortion**. *Am Econ Rev* 2012, **102**:41-46.

In this theoretical paper, the author starts with an assumption that individuals have limited neural information processing capacity while making decisions. He then applies efficient processing hypothesis to show that capacity-constrained individuals will exhibit gain-loss asymmetry in risk attitudes such as in Prospect Theory [25].

24. Louie K, De Martino B: **The neurobiology of context-dependent valuation and choice**. In *Neuroeconomics: Decision Making and the Brain.* Edited by Glimcher PW, Fehr E. Academic Press; 2013:455-476.

25. Kahneman D, Tversky A: **Prospect theory-analysis of decision under risk**. *Econometrica* 1979, **47**:263-292.

26. Symmonds M, Bossaerts P, Dolan RJ: **A behavioral and neural evaluation of prospective decision-making under risk**. *J Neurosci* 2010, **30**:14380-14389.

27. Cheadle S, Wyart V, Tsetsos K, Myers N, de Gardelle V, Herce Castañón S, Summerfield C: **Adaptive gain control during human perceptual choice**. *Neuron* 2014, **81**:1429-1441.

28. Ohzawa I, Sclar G, Freeman RD: **Contrast gain control in the cat's visual system**. *J Neurophysiol* 1985, **54**:651-667.

29. Köszegi B, Rabin M: **A model of reference-dependent preferences**. *Q J Econ* 2006, **121**:1133-1165.

30. Bar M: *Predictions in the Brain: Using Our Past to Generate a Future*. Oxford University Press; 2011.

31. Roy M, Shohamy D, Wager TD: **Ventromedial prefrontal-subcortical systems and the generation of affective meaning**. *Trends Cogn Sci* 2012, **16**:147-156.

32. Barrett LF: **Solving the emotion paradox: categorization and the experience of emotion**. *Personal Soc Psychol Rev* 2006, **10**:20-46.

33. Shiv B, Carmon Z, Ariely D: **Placebo effects of marketing actions: consumers may get what they pay for**. *J Mark Res* 2005, **42**:383-393.

34. Waber RL, Shiv B, Carmon Z, Ariely D: **Commercial features of placebo and therapeutic efficacy**. *J Am Med Assoc* 2008, **299**:1016-1017.

35. Allison RI, Uhl KP: **Influence of beer brand identification on taste perception**. *J Mark Res* 1964. [no volume].

36. Chandon P, Wansink B: **The biasing health halos of fast-food restaurant health claims: lower calorie estimates and higher side-dish consumption intentions**. *J Consum Res* 2007, **34**:301-314.

37. Lee L, Frederick S, Ariely D: **Try it, you'll like it: the influence of expectation, consumption, and revelation on preferences for beer**. *Psychol Sci* 2006, **17**:1054-1058.

38. Ariely D, Norton MI: **Conceptual consumption**. *Annu Rev Psychol* 2009, **60**:475-499.

39. Berdik C: *Mind Over Mind: The Surprising Power Of Expectations*. Current; 2012.

40. Plassmann H, Wager TD: **How expectancies shape consumption experiences**. In *The Interdisciplinary Science of Consumption.* Edited by Preston SD, Kringelbach ML, Knutson B, Whybrow PC. MIT Press; 2014.

41. Crum AJ, Langer EJ: **Mind-set matters: exercise and the placebo effect**. *Psychol Sci* 2007, **18**:165-171.

42. Plassmann H, O'Doherty J, Shiv B, Rangel A: **Marketing actions can modulate neural representations of experienced pleasantness**. *Proc Natl Acad Sci U S A* 2008, **105**:1050-1054.

43. Rangel A, Camerer C, Montague PR: **A framework for studying the neurobiology of value-based decision making**. *Nat Rev Neurosci* 2008, **9**:545-556.

44. Bartra O, McGuire JT, Kable JW: **The valuation system: a coordinate-based meta-analysis of BOLD fMRI experiments examining neural correlates of subjective value**. *Neuroimage* 2013, **76**:412-427.

45. Wager TD, Atlas LY: **The neuroscience of placebo effects:**
•• **connecting context, learning and health**. *Nat Rev Neurosci* 2015, **16**:403-418.
The authors provide a comprehensive review of the underlying brain and neurochemical systems mediating placebo analgesia. They present a conceptual framework suggesting that the neuropsychological processes that mediate placebo effects may be crucial for a wide range of therapeutic approaches, including many drugs.

46. Büchel C, Geuter S, Sprenger C, Eippert F: **Placebo analgesia: a**
• **predictive coding perspective**. *Neuron* 2014, **81**:1223-1239.
The authors provide a conceptual predictive coding account of how expectations and experience can lead to placebo hypoalgesia. Their Bayesian formulation of the predictive coding framework might directly account for differences in the magnitude but also the precision of expectations that are known to influence the strength of placebo hypoalgesia.

47. Nakamura Y, Donaldson GW, Kuhn R, Bradshaw DH, Jacobson RC, Chapman CR: **Investigating dose-dependent effects of placebo analgesia: a psychophysiological approach**. *Pain* 2012, **153**:227-237.

48. Benedetti F, Amanzio M, Vighetti S, Asteggiano G: **The biochemical and neuroendocrine bases of the hyperalgesic nocebo effect**. *J Neurosci* 2006, **26**:12014-12022.

49. Crum AJ, Corbin WR, Brownell KD, Salovey P: **Mind over milkshakes: mindsets, not just nutrients, determine ghrelin response**. *Heal Psychol* 2011, **30**:424-429.

50. Wager TD, Atlas LY, Lindquist MA, Roy M, Woo C-W, Kross E: **An fMRI-based neurologic signature of physical pain**. *N Engl J Med* 2013, **368**:1388-1397.

51. Eippert F, Finsterbusch J, Bingel U, Büchel C: **Direct evidence for spinal cord involvement in placebo analgesia**. *Science (80-)* 2009, **326**:404.

52. Matre D, Casey KL, Knardahl S: **Placebo-induced changes in spinal cord pain processing**. *J Neurosci* 2006, **26**:559-563.

53. Daw ND, Tobler PN: **Value learning through reinforcement: the basics of dopamine and reinformcement learning**. In *Neuroeconomics.* Edited by Glimcher P, Fehr E. Academic Press; 2014:283-317.

54. Kaptchuk TJ, Friedlander E, Kelley JM, Sanchez MN, Kokkotou E, Singer JP, Kowalczykowski M, Miller FG, Kirsch I, Lembo AJ: **Placebos without deception: a randomized controlled trial in irritable bowel syndrome**. *PLoS One* 2010, **5**:e15591.

55. Montgomery GH, Kirsch I: **Classical conditioning and the placebo effect**. *Pain* 1997, **72**:107-113.

56. Vase L, Robinson ME, Verne GN, Price DD: **Increased placebo analgesia over time in irritable bowel syndrome (IBS) patients is associated with desire and expectation but not endogenous opioid mechanisms**. *Pain* 2005, **115**:338-347.

57. Bingel U, Lorenz J, Schoell E, Weiller C, Büchel C: **Mechanisms of placebo analgesia: rACC recruitment of a subcortical antinociceptive network**. *Pain* 2006, **120**:8-15.

58. Wager TD, Atlas LY, Leotti LA, Rilling JK: **Predicting individual differences in placebo analgesia: contributions of brain activity during anticipation and pain experience**. *J Neurosci* 2011, **31**:439-452.

59. Price DD, Finniss DG, Benedetti F: **A comprehensive review of the placebo effect: recent advances and current thought**. *Annu Rev Psychol* 2008, **59**:565-590.

60. Vase L, Robinson ME, Verne GN, Price DD: **The contributions of suggestion, desire, and expectation to placebo effects in irritable bowel syndrome patients. An empirical investigation**. *Pain* 2003, **105**:17-25.

61. Gneezy A, Gneezy U, Lauga DO: **A reference-dependent model**
•• **of the price–quality heuristic**. *J Mark Res* 2014, **51**:153-164.
Using data from three field experiments the authors develop a reference-dependent model proposing that higher prices set higher expectations, which serve as reference points. When expectations are met or exceeded, they observe the familiar positive correlation with price and subjective quality. However, people evaluate a low-quality product with a high price more negatively than a low-quality product with a low price.

62. Catapano R, Buttrick N, Widness J, Goldstein R, Santos LR: **Capuchin monkeys do not show human-like pricing effects**. *Front Psychol* 2014, **5**:1330.

63. Santos LR, Platt ML: **Evolutionary anthropological insights into neuroeconomics**. In *Neuroeconomics.* Edited by Glimcher PW, Fehr E. Elsevier; 2014:109-122.

64. Kable JW, Levy I: **Neural markers of individual differences in**
• **decision-making**. *Curr Opin Behav Sci* 2015, **5**:100-107.
The authors review evidence on associations between individual decision traits and neuroanatomy and neurophysiology, including morphometry, structural connectivity, functional connectivity and positron emission tomography. They conclude in priciple neurobiological markers of decision traits are identifiable and may improve the ability of neuroeconomic models to predict behavior.

65. Gilaie-Dotan S, Tymula A, Cooper N, Kable J, Glimcher P, Levy I: **Neuroanatomy predicts individual risk attitudes**. *J Neurosci* 2014:34.

66. Plassmann H, Weber B: **Individual differences in marketing**
• **placebo effects: evidence from brain imaging and behavioral experiments**. *J Mark Res* 2015, **52**:493-510.
Using structural brain imaging (i.e. voxel-based morphometry, VBM) this study found that grey matter volume in the striatum and the dorsalmedial prefrontal cortex positively and grey mater volume (GMV) in the posterior insul negatively correlate with the occurrence of price placebo effects. Using reverse-inference posterior probability maps and behavioral lab and online studies the authors link GMV to three different personality traits and show that they moderate price placebo effects.

67. Luce RD: *Individual Choice Behavior: A Theoretical Analysis*. Wiley; 1959.

68. Ray P: **Independence of irrelevant alternatives**. *Econometrica* 1973, **41**:987-991.

69. Roitman JD, Brannon EM, Platt ML: **Monotonic coding of numerosity in macaque lateral intraparietal area**. *PLoS Biol* 2007, **5**:e208.

70. Churchland AK, Kiani R, Shadlen MN: **Decision-making with multiple alternatives**. *Nat Neurosci* 2008, **11**:693-702.

71. Tom SM, Fox CR, Trepel C, Poldrack RA: **The neural basis of loss aversion in decision-making under risk**. *Science (80-)* 2007, **315**:515-518.