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# Why Context Should Matter

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Context effects are traditionally considered among the most canonical violations of economic rationality. However, a growing interdisciplinary narrative asserts that context dependence is integral to adaptive behavior. Here, we expand on this narrative by considering the effect of context through a computational lens. We posit that context should influence judgment because it helps us *interpret* and *represent* the world. Formally, interpretation and representation improve an algorithm's *sample efficiency* and *coding efficiency*. Incorporating contextual information has also led to significant improvements in the state of the art in machine learning, in part because context allows artificial systems to form efficient representations and make better use of limited data. Thus, the computational principles that lead to good artificial intelligence systems also generate context effects in humans. This angle offers an opportunity to reconcile apparently anomalous context effects with the rational framework, leading us to a renewed, more precise understanding of when and why context matters.

*Keywords:* context effects, computational rationality, Bayesian inference, information theory



In the realm of conventional economic theory, our choices are dictated by stable preferences, impervious to the changing nature of context. In this view, any deviation from economic rationality, broadly defined as preference consistency in terms of expected utility maximization, is considered an anomaly. These context effects—the influence of peripheral, "Supposedly Irrelevant Factors" (R. H. Thaler, 2015, p. 9)—are seen as glitches in our decision-making mechanism, interfering with our rational, optimizing behavior. They disrupt the neat trajectory of rational choice theory (Shafir & LeBoeuf, 2002), and so considerable effort has been expended on documenting these deviations (Camerer & Loewenstein, 2004; Slovic, 1995; Spektor et al., 2021; Thomadsen et al., 2018; Tversky & Thaler, 1990; Warren et al., 2011).

But what if these "bugs" are actually features of a well-tuned system calibrated to a complex world? An interdisciplinary narrative has taken shape arguing that context effects are not irrational interlopers but adaptive responses to the intricacies of the world around us (Bhui et al., 2021; Gershman, 2021; Gigerenzer, 2018; Lieder & Griffiths, 2020; Page, 2022; Payne et al., 1993; Rosati & Stevens, 2009; Sher et al., 2022; Summerfield & Parpart, 2022).

In this perspective, we expand on this narrative by discussing the effect of context through the lens of computational rationality, which considers judgment as optimal given constraints on cognitive resources. This viewpoint reveals the integral role of context in adaptive behavior: Context *should* influence judgment because it helps us *interpret* and *represent* the world. These functions correspond to desirable computational properties like *sample efficiency* and *coding efficiency*. Growing evidence from machine learning also indicates that context helps artificial systems learn faster by improving their ability to

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efficiently represent the world (Doersch et al., 2015; Hallak et al., 2015; Johnson, 2014; Zintgraf et al., 2019).

This perspective offers an opportunity to reconcile the anomalies of context effects with the rational framework, ultimately leading us to a renewed, more precise understanding of *why* and *when* context matters. By redefining the role of context, we seek to uncover a deeper kind of rationality. As the adaptive mechanisms we discuss naturally produce what appears on the surface to be inconsistent, this view is closer to the notion of correspondence between behavior and environment as a rational benchmark (Arkes et al., 2016; Sen, 1993). It also echoes and refines the theme of procedural rationality, which posits that rationality should be determined based on the process of decision making within computational limits (Simon, 1978, 1986). Further, this approach could more practically enrich tools from machine learning for estimating context effects, which tend to make few cognitive assumptions (Peterson et al., 2021; Seshadri et al., 2019; Tomlinson & Benson, 2021). By illuminating the cognitive structure that underlies context dependence, we clarify our conception of its key predictors, which can help enhance estimation and avoid model misspecification due to omitted variables.

In what follows, we will outline the many benefits of this computational approach: it refines our understanding of why context matters, sharpens our sense of what context means, suggests when context effects occur and what form they will take, and substantiates the influential analogy between economic and perceptual judgment.

## Questioning Economic Rationality

Classical economic theory has long dominated our analysis of decision making. In this framework, agents hold consistent preferences, unmoved by the influence of peripheral factors. Context effects, with their apparent unpredictability, therefore emerged as anomalies—the exceptions that challenged the rule.

The pioneering work of Kahneman and Tversky set the stage for the modern study of context effects, by arguing that certain elements of economic judgment are intrinsically context-dependent (Kahneman, 2003; Kahneman & Tversky, 1979). Their work and that of others (e.g., Huber et al., 1982) underscored the powerful influence of context on human behavior, cementing its role within decision science (Barberis, 2013). They threw into question the very foundations of economic models, challenging the tenets of rational choice and utility maximization (Shafir & LeBoeuf, 2002; Thaler, 1980). While this approach successfully highlighted the ubiquity of context effects, it fell short of comprehensively explaining *why* context should matter.

## A Computational Perspective on Context Dependence

*Computational rationality* (aka *resource rationality*) offers compelling accounts of context dependence. This framework posits that people are doing as best as possible within the constraints of resources like time, energy, and data (Bhui et al., 2021; Gershman et al., 2015; Griffiths et al., 2015; Lewis et al., 2014; Lieder & Griffiths, 2020). Using this approach, we can appreciate the dual functions that context serves, which we call *interpretation* and *representation*.

First, context helps us to *interpret* the world. Uncertainty is pervasive, and the true properties of stimuli are often unknown. Context can reduce this uncertainty by helping us decipher what is going on under the surface. Intuitively, this is what "putting something into context" means.

Second, context tells us how to efficiently *represent* the world. Given the complexity of daily life, we must take shortcuts to economize on our limited cognitive capacities. This can be done by focusing on stimuli that are expected based on contextual cues.

These two pivotal roles of context can be described in computational terms, as follows.

### Interpretation

Consider a stimulus $S$, which could be characterized as the value of an option or the quality of a percept. The actual stimulus is not directly observable; instead, we receive an imperfect signal of it, which we can denote as $S'$. Our objective then becomes to estimate the true attributes of $S$ based on this imperfect signal. Bayesian inference gives us a way to do this using the posterior probability $P(S|S')$. This probability can be computed using two key components: (a) the likelihood of perceiving $S'$ given the true stimulus $S$, denoted as $P(S'|S)$ and (b) the prior probability of the stimulus $S$, denoted as

$P(S)$, which represents our expectations about $S$ before we actually perceive it.

Suppose the stimulus is found in context $C$, which could be any environmental variables that may impact our beliefs about the likelihood or the prior, such as alternative options in a choice set. In the presence of context $C$, the Bayesian formula adjusts to $P(S|S', C) \propto P(S'|S, C)\, P(S|C)$. Thus, the interpretation of $S'$ and the resulting evaluation of the stimulus $S$ depend on the context $C$, showcasing how it affects our interpretation.

We posit that the function of this context-dependent interpretation is to improve the *sample efficiency* of our learning process. In machine learning, sample efficiency refers to the ability of an algorithm to learn effectively from a relatively small number of data points (Kaelbling, 2020; Yu, 2018). Sample efficiency is a computational virtue as it means that an algorithm can quickly learn useful policies without requiring large amounts of data.

Achieving sample efficiency, however, is a rather challenging task. In the context of reinforcement learning, environments often provide sparse feedback and thus, learning an effective policy requires many interactions (Sutton & Barto, 2018). In recent years, contextual information has been increasingly used to overcome this challenge and improve the state of the art in reinforcement learning (Hallak et al., 2015; Modi et al., 2018; Sodhani et al., 2021). For instance, context-based meta-learning methods allow faster learning of new tasks by efficiently extracting meta-knowledge from previously encountered tasks (Chen et al., 2021; Dubey et al., 2020; He et al., 2019; Zintgraf et al., 2019). Here, context serves as an additional input to the model, allowing the model to use contextual information to adapt to individual tasks while the meta-trained parameters are used to learn task-general properties.

Sample efficiency is not only a virtue for artificial intelligence but also a virtue for any biological intelligence. A hallmark of adaptive behavior is rapid learning from sparse data and being able to quickly adapt and generalize from a small number of samples. In the setting of computational rationality, this can be seen as the ability to make the most of the limited evidence available. Analogous to its role in improving the sample efficiency of reinforcement learning algorithms, context allows us to make inferences and predictions about the world based on a relatively limited set of experiences. Thus, context guides our learning process by reducing uncertainty and helping us become more sample-efficient.

## Representation

In the preceding section, we explored the interpretation of a stimulus, denoted as $S$, and the role of context in mitigating uncertainty during the learning process. However, beyond the interpretation of a stimulus, an organism must also act on a stimulus. Consequently, it becomes crucial to effectively *represent* a stimulus to facilitate appropriate actions. The process of creating this representation can be conceived as an optimization problem: We strive to encode as much useful information as possible about the stimulus while minimizing computational load.

This idea aligns with the concept of *coding efficiency* from information theory, which describes the ability of a communication channel to represent or transmit information (Cover & Thomas, 1991; Shannon, 1948). This efficiency can be formally characterized in various ways such as the mutual information between the mental representation and the actual stimulus (Bhui et al., 2021). A natural consequence of coding efficiency is that the system harnesses the statistical structure of the context to adaptively encode incoming stimuli, minimizing redundancy and maximizing the amount of information conveyed.

Context also helps artificial systems to efficiently represent the world (Sodhani et al., 2021). In machine learning, being able to learn high-level representations in an unsupervised manner is a long-standing goal (Bengio et al., 2013). This challenge often hinges on striking the right balance between compression and performance (Abel et al., 2019; Higgins et al., 2017; Tishby et al., 2000; Tishby & Zaslavsky, 2015). Recently, ideas related to coding efficiency have been used to leverage contextual information and make significant strides in extracting useful representations from high-dimensional data (Doersch et al., 2015; Oord et al., 2018).

Together, converging evidence from information theory and machine learning suggests that context allows a system to efficiently represent the world, which places fewer demands on processing capacity and in some cases may even improve the ability to learn. Thus, context is crucial to the optimization process of creating a useful mental representation—it helps to inform the prior distribution $P(S)$ and hence the representation of $S$, indicating the types of stimuli we are likely to encounter and therefore should be prepared to represent. From the perspective of computational rationality, context enables the economical use of our limited cognitive resources.

## Examples of Context Dependence

Let us delve into two classic examples of how context impacts decision making—choice set effects and relative thinking—and mechanisms that can give rise to them: contextual inference and efficient coding.

### Interpretation: Choice Set Effects

Choice set effects occur when a specific option is evaluated differently depending on the presence of additional options, apparently at odds with the notion of stable preferences. A classic example of this phenomenon is the compromise effect, where a focal option becomes more desirable if the addition of the third option makes it a compromise between two extremes (Simonson, 1989). Another seminal example is the attraction effect (also known as the decoy effect): When choosing between two options, the addition of a third option that is inferior to the focal option makes the latter more attractive (Huber et al., 1982).

Why might these phenomena happen? The presence of other options in the set can provide information that influences our beliefs about the focal option. This mechanism, referred to as "contextual inference," has been formally developed in several models of probabilistic reasoning (Kamenica, 2008; Shenoy & Yu, 2013; Wernerfelt, 1995; see Fischhoff et al., 1978; Luce & Raiffa, 1957, for earlier informal mentions of how context can convey information). In other words, choice set effects are an example of how context helps us to *interpret* the world and helps reduce uncertainty. For instance, the compromise effect may occur when one is aware of their relative preferences compared to the population but not their absolute preferences. The choice set then provides information about the distribution of tastes in the population and implies that the best option for the average person is the compromise option. The attraction effect may occur when the importance of each attribute is uncertain. The inferior option provides information on the "fair market value" and signals that the focal option is even better. Experimental testing finds that people draw information from the choice set and this inference affects their preferences in line with these theories. Prelec et al. (1997) presented participants with sets of two or three products in scenarios designed to assess the compromise and attraction effects. They found that perceptions of what was considered an average product in the market were significantly affected by the choice set. Moreover, shifts in participant preferences could be largely predicted from these context-induced shifts in beliefs.

Intriguingly, similar principles applied to different variables in this setup can explain not only the attraction effect but also its opposite (known as the repulsion effect), in which the inferior decoy makes the focal option less appealing (Brendl et al., 2023; Frederick et al., 2014; Spektor et al., 2018). If the overall value of the focal option is uncertain (as opposed to the relative value of its constituent attributes), the decoy can provide information that it is worse than it appears to be if they are linked together (Bhui & Xiang, 2022). Bhui and Xiang (2022) found that participants' preferences for focal consumer options dropped only when they were explicitly said to be from the same group as the decoy, such as two restaurants managed by the same group of people.

Choice set effects are thus consistent with the idea of context playing the role of helping us to interpret the world and can be consistent with Bayesian principles. Forms of contextual inference have been applied to understand other phenomena like framing effects (Leong et al., 2017; McKenzie & Nelson, 2003; Sher & McKenzie, 2006) and joint–separate reversals (Sher & McKenzie, 2014), based on the notion that frames or options leak choice-relevant information. For example, participants in McKenzie and Nelson (2003) were more likely to describe a cup as "half-full" when it was originally empty compared to when it was originally full, and more likely to infer that it was originally empty when it was described as "half-full." Similarly, Sher and McKenzie (2014) presented participants with job candidates to evaluate, showing either two candidates together (joint evaluation) or each one alone (separate evaluation). Beliefs about the distribution of typical job candidate attributes were substantially shaped by the mode of presentation. When the candidate with more programming experience was shown alone, typical candidates were thought to have more programming experience in general. Furthermore, when these context-specific distributions were given to new participants, their resulting evaluations recapitulated the joint–separate reversal, indicating the crucial role of inference.

These computational theories suggest novel variables that can shape context effects. In particular, the statistical properties of the environment play a key role because the interpretation of the choice set depends on beliefs about how it came to be. Bayesian reasoning inverts this generative model: it takes the visible surface-level information and infers the likely hidden mechanisms at play based on these statistics.

### Representation: Relative Thinking

The proposal that outcomes should be evaluated relative to a reference point is a key tenet of behavioral economics (O'Donoghue & Sprenger, 2018) and has been formalized within prospect theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). Even absolute differences are evaluated with respect to a reference frame and can be perceived as big or small relative to the range of comparators (Mellers & Cooke, 1994; Parducci, 1995; Soltani et al., 2012; Tversky & Kahneman, 1981).

Here, context serves the important role of providing information about which stimulus values are most important to *represent*. This follows the "principle of efficient coding," according to which brains are designed to represent information as cost-effectively as possible and do so by adapting neural representations based on environmental statistics (Attneave, 1954; Barlow, 1961; Bhui et al., 2021; Louie et al., 2015; Summerfield & Tsetsos, 2015). Real brains cannot be sensitive to all possible value gradations at the same time. Our cognitive resources must thus prioritize sensitivity in the region of stimulus values that are most likely to be encountered according to the prior distribution. Information theoretic models have been used to specify what efficient encodings look like (Bhui & Gershman, 2018; Bucher & Brandenburger, 2022; Woodford, 2012). Such models generally produce forms of reference dependence with value functions matching the contours of the prior cumulative distribution function: the value function is steepest (i.e., most sensitive) in the range of the most likely stimuli.

These models support more refined properties of relative thinking compared to previous mechanistic theories. For example, rather than the traditional single reference point, stimuli may be evaluated relative to the entire reference distribution (Heng et al., 2020; Parducci, 1995; Rigoli, 2019; Stewart et al., 2006). They also indicate different kinds of data which can substantiate theories. Recordings of neural activity corroborate the fundamental nature of context dependence in value representations across multiple species (Cox & Kable, 2014; Kobayashi et al., 2010; Padoa-Schioppa, 2009; Rangel & Clithero, 2012; Tobler et al., 2005). Moreover, these foundational principles shed light on the link between perceptual and economic judgment, underscoring the unifying thread that context-dependence presents across these seemingly disparate domains.

## The Link Between Economic and Perceptual Judgment

The work of Kahneman and Tversky was guided by the idea that elements of economic judgment share notable similarities with perception—a process inherently influenced by context (Kahneman, 2003). Contextual inference can not only explain choice set effects but has long been used to elucidate properties of sensation such as visual illusions (Knill & Richards, 1996). Relatedly, the principle of efficient coding originally emerged in the analysis of sensory perception (Attneave, 1954; Barlow, 1961; Wark et al., 2007) and continues to motivate parallel investigations in value-based judgment. Similarly, motivated by studies in perception, context sensitivity also has a rich history in computer vision (Biederman, 1981; Carbonetto et al., 2004; Divvala et al., 2009) and has played a key role in driving modern-day advancements in computer vision (Gkioxari et al., 2015; Hu et al., 2018).

What's less discussed is why this analogy makes sense. Why should judgment parallel perception? One answer is that both systems are subject to the same fundamental neurocomputational principles. The human brain expends a huge amount of energy, totaling 20% of resting oxygen consumption in adults (Laughlin, 2001). Efficient information processing is crucial for an organism's survival, as the substantial metabolic costs associated with neural activity and infrastructure emphasize the necessity of avoiding unnecessary waste. Natural selection, therefore, places strong pressure on organisms to develop streamlined cognitive mechanisms that maximize information utility while minimizing energy expenditure (Bassett & Bullmore, 2006; Bassett et al., 2009;

He et al., 2022). This argument applies to both economic and perceptual judgment across modalities and species (Santos & Rosati, 2015). It is worth noting, however, that our current understanding of the intricate processes by which the brain achieves this efficiency remains limited, underscoring the complexity of biological systems.

This line of thinking also raises some potential differences in both interpretation and representation. Contextual inference varies depending on assumptions about the environment which differ across systems and situations. For instance, the set of goods available in a marketplace results from the choices of other people, in contrast to the set of stimuli faced in nature, shaping the information content of the choice set (Kamenica, 2008). Taking this into account changes the inference drawn from the choice set and the magnitude of context effects (Colantonio et al., 2021; Shafto & Bonawitz, 2015). In terms of representation, the plasticity of processing may vary across different systems. In high-level cognition like economic judgment, there might be more room for flexibility given the complexity and variability of the economic environments we navigate. Flexible aspects of our cognition might be more susceptible to adjustment based on context, experience, or other variables. This might include learned priors that we develop over short timescales. Indeed, many apparent violations of economic rationality are limited to one-shot vignettes and tend to diminish when feedback is introduced (see Lejarraga & Hertwig, 2021, for an extensive review).

By contrast, in lower level perceptual processing, there might be less room for such flexibility due to the constraints imposed by our sensory systems and the immediacy of perceptual decision making. Some neurobiological constraints could rigidly restrict our mental computations (Sadtler et al., 2014). For instance, we are not generally capable of learning to "unsee" visual illusions no matter how much feedback we are given. However, even such rigidity may be the result of adaptive processes on longer timescales. Perfect, metalevel rationality is impossible (Russell, 2016), but evolution and development might move towards optimizing the depth of metareasoning given our life history and that of our ancestors (Conlisk, 1996; Cosmides & Tooby, 1994; Frankenhuis & Walasek, 2020; Fusco & Minelli, 2010; Kenrick et al., 2009; Snell-Rood, 2013; Zador, 2019).

## Conclusion

Richard Thaler opened his famous "Anomalies" column in the Journal of Economic Perspectives (R. H. Thaler, 1987) with a quote from Thomas Kuhn, the esteemed philosopher of science: "Discovery commences with the awareness of anomaly, i.e., with the recognition that nature has somehow violated the paradigm-induced expectations that govern normal science."

Discovery may *begin* with anomalies, but it does not *end* there. New paradigms must be developed that bring these anomalies into the fold, transforming them into the foundations of a more complete worldview. Computational rationality offers the hope of reconciling both the rational and irrational sides of our nature in a way that is both psychologically realistic and theoretically tractable, and holds significant implications for policymaking (Hertwig & Grüne-Yanoff, 2017; Krijnen et al., 2017; McKenzie et al., 2018; Sher et al., 2022).

Possibly the most fundamental implication of this approach is that it offers a profound shift in addressing seemingly irrational behavior. Instead of simply labeling apparent anomalies as flaws, it recognizes them as manifestations of intelligent judgment within the limits of being human. This perspective offers a unified lens for understanding the diverse domains of the mind, spanning perception, attention, memory, reasoning, planning, and decision making. It also alters our view on policies meant to improve individual and societal well-being. For instance, rather than a traditional approach to choice architecture which "nudges" people towards a given decision, architects may instead aim to improve the relevance and salience of information or the way in which this information is put together—facilitating the process of a decision as opposed to the outcome (McKenzie et al., 2018; Sher et al., 2022).

Overall, a number of outstanding questions at the intersection of the cognitive, social, and computational sciences are raised, such as:

- How might the adaptive nature of context effects impact the welfare outcomes of policy interventions meant to address or harness them?
- When does the analogy between economic and perceptual judgment apply most strongly and when does it break down?

- What cognitive algorithms implement the adaptive computations that may produce context dependence?
- How might neural data help disentangle various mechanisms behind, or properties of, context effects?
- Which contextual biases found in human judgment can be observed in algorithmic judgment, and vice versa?

This discussion has aimed to shed light on how these principles can inform our understanding of context dependence in economic judgment and beyond. The ultimate ambition is to fortify the connections across modalities, theories, and disciplines, and in doing so, develop a deeper vision of judgment and decision making.

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