Dual-process theories of decision-making: a selective survey *

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Abstract

Brain modularity is a key concept in neuroscience. It challenges the common view of the single coherent self adopted in many disciplines, including economics. Multi-process theories of decision-making rely on the existence of several brain systems interacting with each other to revisit standard paradigms of choice, propose choices that fit the behavioral data better, and offer testable predictions. In this paper, we present a selective review of our recent research in this area. We focus on constrained optimization models rather than the computational models extensively used in neuroscience.

Keywords: neuroeconomic theory, decision-making, dual-process, constrained optimization.

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1 Introduction

1.1 Brain modularity and neuroeconomic theory

The premise of Neuroeconomic Theory is the existence of multiple interacting brain systems. The relationship between brain systems is intricate. Typically, each system performs different functions and each function needs the intervention of several systems. Neuroscientists refer to it as *brain modularity.* Taking a decision, solving a problem or performing a motor task requires the coordination of different functions and therefore the involvement of different systems. Depending on the nature of the function and the degree of the overlap between systems, they will produce a response that is 'as if' they were cooperating with each other or 'as if' they were competing with each other.

The main consequence of such a construct is that an individual is best understood as an *organization of systems.* When a choice must be made, systems performing functions related to that decision are recruited. Those systems independently or jointly contribute to the decision. The final outcome emerges from a complex process and may not be consistent with predictions made by standard economic models of decision-making. Indeed, traditional models presuppose that the individual is a single coherent entity with well defined underlying preferences, a clear understanding of the environment, and an unparalleled ability to learn. Such a normative view is extremely useful because it defines a benchmark for comparison with actual behavior. However, it overly simplifies decision-making and, as a result, does not always represent well the observed behavior.

The idea that standard models do not always represent actual behavior accurately is not new. Researchers in the fields of "bounded rationality" or "behavioral economics" have developed behavioral models that fit data better. Some of these models rely on the intuition that decision-making is not made by a unique coherent entity. Inter-temporal choice offers a good example. For some authors, an individual is best understood as a succession of selves with different preferences and different levels of awareness of such preferences. Hyperbolic discounting is one such model (see e.g., Strotz (1956), Laibson (1997), O'Donoghue and Rabin (1999) and Carrillo and Mariotti (2000)). It explains, in particular, why decision makers prefer a small reward today to a big reward tomorrow and, at the same time, a big reward in one year and one day to a small reward in one year. Still, this type of model is built to account for observed behaviors. As such, the set of variants is large, making it sometimes difficult to determine which assumptions are the most appropriate. A related strand considers the individual as an entity with conflicting objectives. In the next section we briefly review some papers in this "dual-process" approach to decision-making, a well-established branch of the literature which is the central topic of this special issue (we refer to Rustichini (2008) for a critical review of the unitary vs. dual system approach and to Livnat and Pippenger (2006) and Bisin and Iantchev (2010) for evolutionary arguments in favor of duality).

1.2 Dual-process models of decision-making

The earliest accounts of dual-process theories in psychology date back to Schneider and Shiffrin (1977a, 1977b) who used a series of experiments on attention to propose a theory of information processing based on two processing modes: *controlled and automatic*. This type of models has been extended and applied to economic situations. Bernheim and Rangel (2004) study consumption under the assumption that the individual operates either under a 'cold mode' where he selects his preferred alternative or a 'hot mode' where choices may be suboptimal given his preferences, and show that the model accounts for a number of patterns well documented in the addiction literature. Benhabib and Bisin (2004) show that an agent with the ability to invoke either an automatic process susceptible to temptation or a costly but non-tempting control process will follow a simple consumption-savings plan characterized by a cut-off rule for invoking the control process. Loewenstein and O'Donoghue (2005) use this duality to explain, among other things, why people tend to exhibit an S-shaped probability-weighting function.

In another set of models pioneered by Thaler and Shefrin (1981) and Shefrin and Thaler (1988), dual-processes take a *myopic vs. forward-looking* temporal dimension: the individual is split into a long term planner interested in the future effects of choices and a short-sighted doer interested in immediate gratification only. The authors use the model to explain the benefits of commitment devices such as mandatory pension plans and lump-sum bonuses in promoting savings. They have been extended and further developed by Fudenberg and Levine (2006, 2011). The first paper argues that the split-self approach with linear cost of self-control can explain dynamic preference reversals and the paradox of risk-aversion in the large and in the small whereas the second paper can explain the Allais paradox provided that the cost of self-control is convex.

Naturally, such duality may take other forms. For example, in the self-signalling game of Bodner and Prelec (2003) and Mijovic-Prelec and Prelec (2010) one mechanism selects an action and another mechanism interprets the action selected or, more precisely, draws inferences from the action and generates emotional responses consistent with those inferences.

However, and with few notable exceptions (e.g., Bernheim and Rangel (2004)), the multiple-process models are mostly loosely inspired by biological processes. Given the current knowledge from neuroscience and neurobiology, we believe that it is now possible to build models grounded more directly on the evidence provided by those disciplines. In other words, the multiplicity of systems should not be used as a tool to fit empirical facts but it should rather try to accurately represent the way information is processed and decisions are made in the brain. In this article, we present a selective survey of some of our recent research. We put a special emphasis on examining how modeling the actual processes that lead to choices can illuminate our understanding of economic behavior. The survey is obviously partial and incomplete, with many important contributions to neuroeconomics not being discussed. Our goal is to provide some examples of what a multi-process constrained optimization methodology has to offer to understand individual decision-making. We refer the reader to the original papers for the formal proofs of the results and for an exhaustive review of the literature related to those papers.[1] Before discussing the models, we provide in section 2 a brief description of the methodology we use to map information about neural activity into models of the brain (see also Brocas and Carrillo, 2008a).

2 Building 'as if' models

The methodology used in neuroeconomic theory is in fact quite close to the methodology economists rely on to represent the choices of an individual assuming he is a coherent entity. We are simply taking one step back: the coherent unit is not the individual but rather the cells (and perhaps the systems) that compose him.

When an individual faces a decision, populations of neurons specialized in different functions relevant for that decision are recruited. Neurons fire in response to certain inputs. For instance, consider the case of an individual looking at a picture to determine whether RED is the dominant color. The picture acts as a signal and neurons extract information from this signal and encode its content, resulting in neural activity. Now, the spiking activity of a typical neuron in the visual system represents a small part of the visual environment, as the neuron is sensitive to the presence of a few specific features only. That is, each neuron will detect the color it is tuned to detect but not the other colors. In other words, neurons are interested exclusively in extracting and transmitting information regarding the features they are designed to detect. Interestingly, the intensity of the response is correlated with the intensity of the signal: the spiking activity of neurons tuned to detect RED is as intense as the proportion of RED in the picture is high.

[1] A more exhaustive survey of recent advances in neuroeconomics can be found in Fehr and Rangel (2011), although it focuses mainly on computational models and experimental results and barely mentions dual-process models. Other important contributions left out of the review include for example the axiomatic model of dopaminergic function developed by Caplin and Dean (2008) and tested by Caplin et al. (2010).

Given such a construct, a system performing a function only transmits information detected by its components, that is, information relevant for that function. Therefore, a system can be represented as an entity that cares exclusively about transmitting information to perform its own function.[2] By an argument analogous to the revealed preferences argument, the neural response of a system can then be represented by a performance function and the system acts as if it optimizes the response given the signal received. Tasks are rarely as simple as the one we chose to illustrate our concept. However, the same logic applies when the task is now to identify the author of a painting with many colors and shapes, or to determine whether the painting is legitimate. Populations of neurons tuned to perform part of the task are recruited to extract and transmit the information required. Systems tuned to encode information aim at transmitting a response that captures the content of the signal. Systems tuned to guide a decision given a signal encoded elsewhere aim at generating the neural response triggering the decision that is best suited to the signal.

Notice that the 'as if' representation is paired with the concept of optimization. The activation of neurons in a system in conjunction with a task (their observable behavior) reveals that they are tuned to detect features present in that task. The absence of activation of neurons in conjunction with an orthogonal task reveals that they have a clear objective: to detect some features irrespective of the presence of others. The neural intensity differential across treatments reveals that they are programmed to minimize the distance between their response and the detected features, that is, to optimize the reliability of the information transmitted given their objective. Interestingly, the 'as if' optimization approach is generally not used in the neuroscience literature. Though many mathematical formal models are proposed, notably in computational neuroscience, they are invariably mechanical in nature. That is, they do not work under the assumption that what we observe (neural activity, behavior) is produced as the best possible solution to a decision problem given a certain objective and a set of physiological constraints.

The same logic can be applied to a system. Going back to the decision of the individual, it can be understood as a multifaceted task requiring the involvement of several systems. As the task becomes complex, more systems may be implicated, each detecting information and passing it along to other systems. The brain is best represented by an organization of systems that interact with each other.

The ultimate decision will result from a process in which systems provide informa-

[2] Neurons active in one function are considered part of the system performing that function. However, they can also be active in another function performed by a different system. In other words, two systems do not need to be two physically different areas of the brain.

tion about the features they perceive and advocate *exclusively* for the expression of those features in the individual's behavior. Even though cells are programmed to produce automatic responses, there exists a variety of mechanisms that can modulate the activity of neurons. For instance, the response of the neurons detecting RED may be suppressed and not reproduced in the decision of the individual. Systems will typically cooperate, compete, or modulate the activity of other systems. In our 'as if' methodology, each system wants to pass reliable information given its objective. However, this information may contradict the information passed by a different system. A third system may then inhibit the activity of one of the systems to distort the decision in favor of the other. Overall, behavior can be represented as the result of an interplay between systems with different objectives, and the particular nature of the interaction will vary across decision problems.

Our methodology consists in building brain-based models of decision-making rooted in the documented evidence on the architecture of the brain. The evidence is used to obtain a representation of what the brain is doing at the time of decision-making. For instance, if systems are found to compete for the expression of their preferred features, the representation will take the form of a strategic interaction between systems with conflicting objectives. If systems are involved in a vertical relationship, the representation will build on a hierarchical model. If systems have the same objectives but receive projections from different sub-systems, the representation will feature optimizing systems with different access to information. These representations can in turn deliver behavioral predictions. In the next sections, we present some dual-process models of constrained optimal decision-making that illustrate the methodology. These models cover several unrelated paradigms and focus on individual choice problems that have received attention in psychology and economics. As already noted, details can be found in the original papers.[3]

3 Time preferences

Consider an individual deciding how much to consume and how much to work in each period of time. Any return from work that is not consumed is saved for the future. Alternatively, the individual can borrow to consume today and will need to work in the future to repay. To make a decision, the individual needs to evaluate his immediate desire to consume, his willingness to work, the effect of these choices on his future welfare and the decisions this might trigger in the future.

Recent studies in Neuroeconomics have investigated some aspects of neural correlates

[3]Section 3 is based on Brocas and Carrillo (2008b) sections II and III. Section 4 is based on Brocas and Carrillo (2008b) section IV. Section 5 is based on Alonso, Brocas and Carrillo (2011). Section 6 is based on Brocas and Carrillo (2011).

in intertemporal decision-making. It has been argued that two different systems, namely some areas of the amygdala and the prefrontal cortex (PFC), are responsible for evaluating information related to immediate and future prospects respectively (Bechara, 2005). This view suggests a temporal evaluation conflict between an impulsive and a reflective system (McClure et al., 2004).[4] The literature in neuroscience also provides evidence of informational asymmetries in the brain. Because neural connectivity is a limited resource, some brain areas are either unlinked or unidirectionally linked to others. These restrictions act as physiological constraints on the flow of information, and result in limited awareness of motivations for decisions (Rauch et al., 1997).

This combined evidence suggests that one system is mostly interested in valuing the current options available to the decision-maker while another system is responsible for evaluating the long-term consequences of potential actions. Roughly speaking, the first system (hereafter "the agent", he) is interested only in representing payoffs at date t. Denoting c_t and n_t the amount of consumption and labor at date t, its objective can be summarized by:

$$U_t = \theta_t \, u(c_t) - n_t$$

where $u' > 0$, $u'' < 0$, and $\theta_t \in [\underline{\theta}, \overline{\theta}]$ represents the privately known marginal value of consumption at t. The second system (hereafter the "principal", she) wants to solve the intertemporal trade-off. She maximizes the expected utility of all agents:

$$S = \sum_{t=1}^{T} E[\theta_t \, u(c_t) - n_t]$$

under the budget constraint that links lifetime consumption with lifetime labor:

$$\sum_{t=1}^{T} c_t(1+r)^{T-t} \leqslant \sum_{t=1}^{T} n_t(1+r)^{T-t}$$

where $r > 0$ is the interest rate and T the last period in which choices are made. The principal is therefore in charge of modulating the signal obtained by the agent and imposes rules to optimize intertemporal decision-making. Given the positive interest rate r, if the principal knew θ_t she would concentrate work in early periods and consume at each date according to the marginal valuation. The consumption and labor decision at a given date would therefore be, to a certain extent, independent.

[4] This result is not without controversy. Indeed, it has been challenged by Kable and Glimcher (2007) who argue in favor of a single valuation theory where only one system responds to a combination of magnitude and delay of reward. More recently, Hare et al. (2009) propose a hybrid of the two theories, where one system computes goal value and another system modulates this value by incorporating long term considerations.

As developed in section 1.2 this dual-process myopic vs. forward looking formalization was first introduced by Thaler and Shefrin (1981) and Shefrin and Thaler (1988) in the context of a consumption-savings problem. More recently, it has also been used by Fudenberg and Levine (2006, 2011) to explain behavioral anomalies in consumption choices. There are two differences between our setup and the aforementioned papers. First, we consider two actions, consumption and labor, rather than just one. This allows us to explore how the multi-process conflict affects the relative choice of actions and the link between the actions both within periods and between periods. Second and perhaps more importantly, we introduce information asymmetries on this problem. Indeed, in the absence of a full knowledge of θ_t, the principal now needs to intervene to regulate an excessively short-sighted decision-maker. From the mechanism design literature, we know that the best she can do is to propose at each date a menu of incentive compatible consumption-labor pairs $\{(c_t(\theta_t), n_t(\theta_t))\}_{\theta_t \in [\underline{\theta}, \overline{\theta}]}$ and let the agent pick one of them. We obtain the following result.

Result 1 (Brocas and Carrillo, 2008b) *At each date, higher consumption is allowed in exchange of higher labor. Inter-temporal choices exhibit properties consistent with positive discounting, decreasing impatience, and higher impatience for goods where valuation has high variability.*

By definition, principal and agent disagree on the desired levels of consumption and labor so, under incomplete information about the value of consumption, the former cannot impose her preferred choices. It is not optimal to delegate the decision to the agent either: since he is interested exclusively in the present, he will at every date consume the maximum and work the minimum. Yet another option would be to select the levels of consumption and labor that maximize the principal's expected welfare. Result 1 shows that the optimal strategy is different: it consists in offering to the agent at every date several pairs characterized by a positive link between current consumption and current labor, and let him choose among those pairs. Overall, a self-disciplining rule of the form "work more today to consume more today" emerges *in equilibrium* as a response to the temporal and informational conflicts. As the agent 'lobbies' for a higher level of consumption, the principal 'requests' more labor in exchange.

Consumption in this model exhibits properties that are consistent with recent theories of discounting. By construction, the choice when θ is known to the principal is analogous to that of an individual without conflict and no discounting. The choice when θ is unknown is characterized by positive levels of consumption and labor at every date. Interestingly, since the marginal value of labor is greater in earlier than in later periods (due to the positive interest rate on savings) then, other things being equal, the principal is willing to grant more consumption per unit labor at date t to agent t than at $t+1$ to agent $t+1$. The behavior is then observationally equivalent to that of an individual with no conflict and positive discounting. In other words, Result 1 suggests that discounting can be endogenously derived from the primitives of the model (informational asymmetry and temporal conflict) rather than imposed as an ad-hoc feature of preferences. Perhaps more surprisingly, when evaluating the decrease in consumption over time one realizes that it is also consistent with decreasing impatience, that is, with a period-to-period discount rate that falls monotonically as in the hyperbolic discounting case although, once again, such discounting is derived from the model. Finally, the theory has a third implication: individuals are most impatient in activities where the marginal valuation of consumption exhibits highest volatility across periods. Although it is well known in psychology and economics that discount rates are activity-different, we are not aware of any previous theory that would account for such variability.

Finally, note that the individual closely ties consumption to labor within each period at equilibrium. Interestingly, empirical studies have shown an excessive sensitivity of consumption to current income. This empirical regularity cannot be reconciled with existing consumption smoothing theories which postulate that forward-looking individuals should base decisions on the expected income flow. In contrast, such behavior arises naturally in our model.

4 Self discipline

Having determined the dynamic allocation of pleasant (e.g., consumption) and unpleasant (e.g., labor) activities, we now study its static counterpart: the distribution of a fixed budget over a tempting and a non-tempting good. Temptation has received a great deal of attention in economics. It has been modeled as a dynamic conflict of preferences (as for example in the hyperbolic discounting theory of Laibson (1997) and others) and also as a static decision theoretic problem (see e.g., Dekel et al. (2001) or Gul and Pesendorfer (2001)).[5] However, we argue that temptation can be better understood if we incorporate insights from neuroscience.

Berridge (2003) and Berridge and Robinson (2003) document a discrepancy in the relative importance that different brain systems attach to these goods. More precisely, they argue that one system (what they call the "liking" system and is identified in some areas of the prefrontal cortex) mediates the sensation of pleasure and pain, whereas a

[5] There is also a large literature on consumption of addictive substances (starting with Becker and Murphy (1988)), which can be considered as a special class of tempting goods.

different system (the "wanting" system, which is identified in the nucleus accumbens and amygdala among other areas) mediates the motivation to seek pleasure and avoid pain. In their experiments, the authors first determine through a training phase the extent to which rats will work for food as a function of the type of food, difficulty of the task, etc. Then, using pharmacological manipulations in the mesolimbic dopamine system, they are able to increase the willingness of rats to work for the same amount of food. One way of capturing this effect is by assuming that the "wanting" system overemphasize the pleasure of tempting goods, while the "liking" system is responsible for overriding ill-motivated impulses.[6]

To capture this tension between systems, consider a static model where an individual allocates a fixed amount of resources k between a tempting good x and a non-tempting good y. The reflective or liking system is interested in optimizing consumption given how much each good is actually enjoyed. Her objective can be represented by the function:

$$W(x, y; \theta) = \theta\, a(x) + b(y)$$

with $a' > 0$, $a'' < 0$, $b' > 0$, $b'' < 0$, and θ represents the current desire for the tempting good. The impulsive or wanting system has a biased motivation, that is, a willingness to engage in excessive consumption of the tempting good compared to how much it is really enjoyed. His objective is to push behavior towards the tempting good. Formally, it can be captured by the function:

$$V(x, y; \theta) = \alpha\, \theta\, a(x) + b(y) \quad \text{with} \quad \alpha > 1$$

where α represents the extra emphasis. As in section 3, suppose now that the impulsive system has a superior knowledge of θ while the reflective system can impose any decision rule. The impulsive system may use his private information to misrepresent his desires and the rule imposed by the reflective system must therefore be incentive compatible. We obtain the following result.

Result 2 (Brocas and Carrillo, 2008b) *The reflective system sets a consumption cap for the tempting good but, apart from that, she delegates choices to the impulsive system.*

The intuition behind this result is simple. First, full delegation implies excessive consumption of the tempting good. However, even though the interests of the reflective and impulsive systems are not aligned, they are not opposed either. Therefore, increasing the consumption of the tempting good does not reduce the welfare of the reflective system, it

[6] Using fMRI studies with humans, Hare et al. (2009) find a related multi-system interaction, with one system encoding value and another system modulating this value by exerting self-control.

simply does not increase it at the same rate. Second, if the reflective system resorts to sophisticated mechanisms to impose her choices (a menu of pairs that satisfy the incentive compatibility constraint as in the previous section for example), she will generically not fulfill the budget constraint: $x + y < k$. Because of the first argument, this option of wasting some resources is always suboptimal. Combining the two elements, the optimal policy consists in setting a consumption cap for the tempting good, anticipating that the agent will incur some moderate excesses. The impulsive system obtains his preferred choice as long as his current desires are sufficiently small (low θ). As the desires increase, so does the cost of inefficient overconsumption, resulting in strict intervention to cap the consumption of the tempting good.

The individual will appear as if he indulges himself in small pleasures and, at the same time, exerts self-control when the desire for the tempting good is strong. The individual may also appear to avoid large quantities of a highly desirable good. This implies that the utility representation one could deduce from behavior may not be as well behaved as those generally used in economics. It is important to realize that the types of goods for which our analysis applies does not require addiction in the traditional economics sense of complementarity between past levels of consumption and current marginal values of consumption. One should also notice that this static model with value discrepancy and two goods is formally similar to the dynamic model of Amador et al. (2006), where the conflict is due to hyperbolic discounting and the goods are consumption at different dates. It would be interesting to further explore the similarities and differences (regarding both the techniques and the interpretations) in models of inter-period vs. intra-period conflicts of preferences.

The study also suggests that the capacity to refrain from succumbing to tempting choices is tied to the ability of the PFC to impose a consumption limit. In fact, its involvement is needed only when the impulsive system recommends a consumption level at or above the cap. This result is consistent with Hare et al. (2009) which shows that the dorsolateral PFC modulates the value signals. The authors find that its activity increases when the value signal increases and self control is exerted. In Brocas and Carrillo (2012b) we provide a formal model of this experimental finding and derive further implications.

5 Multi-tasking

Our ability to handle several tasks at the same time depends on the coordination of multiple brain mechanisms. Research in the brain sciences has established that decision-making requires the allocation of scarce metabolic resources (oxygen and glucose) and attentional resources to the brain systems involved in understanding tasks, planning responses and implementing actions (Fox et al., 1988). Metabolic and attentional resources are scarce and there is a limit on the number and difficulty of tasks that can be completed flawlessly at the same time (Knudsen, 2007).

As noted in the previous sections, different brain systems are recruited to perform different tasks and neurons in a given system respond exclusively to features of that particular task. Systems therefore compete for the available resources.[7] Neurons in a system remain active as long as they receive resources and the task is not completed. Their behavior is therefore consistent with the maximization of performance in the task they are designed to complete. The consumption of resources in a brain system triggers a signal which results in more resources being allocated to that system. This dynamic process can be construed as a 'message game' in which systems communicate needs to complete a task by depleting the resources present in the local bloodstream. There is also evidence that the resource allocation process is centralized. In particular, some areas of the lateral prefrontal cortex play an active role when attention is divided, for instance when two tasks have to be completed at the same time. This points to the existence of what has been called a 'Central Executive System' (CES) whose role is to coordinate the systems involved in the different tasks (D'Esposito et al. (1995), Szameitat et al. (2002)).

Following this evidence, we model the brain as an organization in which a coordinator allocates limited resources to brain systems responsible for different tasks. Some systems are privately informed about the amount of resources necessary to perform their task while the needs of other systems are known. The coordinator arbitrates the demands while satisfying the resource constraint. Formally, we assume there are three tasks. System l ($\in \{0, 1, 2\}$) is responsible for task l. The needs of system l are drawn from a known distribution $F_l(\cdot)$. If system l needs θ_l ($\in [0, \overline{\theta}_l]$) resources to carry out task l flawlessly and it is granted x_l resources, then the performance of that system is:

$$\Pi_l(x_l; \theta_l) = -(x_l - \theta_l)^2.$$

Notice that performance deteriorates as the absolute difference between needs and resources $|\theta_l - x_l|$ increases. Also, tasks that are more complex require more resources. The objective of the CES is to maximize the overall performance in the tasks. It can be represented by:

$$\Pi_0(x_0; \theta_0) + \Pi_1(x_1; \theta_1) + \Pi_2(x_2; \theta_2).$$

[7] See Livnat and Pippenger (2006) and Bisin and Iantchev (2010) for evolutionary rationales for competition between systems.

The CES must distribute a fixed amount of resources k among the three systems so as to maximize its objective. It therefore faces the budget constraint:

$$x_0 + x_1 + x_2 \leq k$$

Last but crucially, we assume that the CES does not know the realized needs θ_1 and θ_2 of systems 1 and 2 while the needs θ_0 of system 0 are common knowledge. Therefore, the CES maximizes the expected performance and resorts to an incentive compatible revelation mechanism to obtain information from systems 1 and 2. The solution to this problem has the following properties.

Result 3 (Alonso, Brocas and Carrillo, 2011) *In the optimal allocation, each system is guaranteed a minimum amount of resources. A system obtains resources above that minimum if and only if the other systems choose not to exhaust their allocation.*

Resource is the sole 'currency' in the brain. Given its scarcity, the CES must decide which system will make a better use of those resources knowing that systems consume them exclusively to perform their own task. Under full information about θ_1 and θ_2, marginal benefits are equalized resulting in under-performance in all tasks. Under asymmetric information, CES imposes to each system with privately known needs a consumption cap. This cap depends negatively on the resources requested by the other system. As result, systems have minimum guaranteed levels of consumption. If one or both needs are below those levels, the unused resources are passed to the other system and/or to the system with known needs. If they are both above, the constraint is hit. This means that, as long as both systems with private needs turn out to necessitate few resources (easy tasks), they obtain the full amount at the expense of the system with known needs but when at least one system faces a complicated task, it receives extra resources only if the other task is really simple. In sum and contrary to the full information case, the theory now predicts that performance will be flawless if the task is sufficiently simple. Interestingly, the optimal mechanism can be implemented using a simple and physiologically plausible rule: (i) systems receive resources at different rates according to their expected needs, (ii) they choose whether to deplete them, and (iii) depending on the depletion decision, the CES decides whether to provide more resources.

These findings are important for two reasons. First, they establish that it is not necessary to assume ad-hoc limitations to predict some observed characteristics of performance in multi-tasking. The latter emerge as the optimal solution to a constrained optimization problem. Second, our study also shows that a resource allocation problem that looks a priori very complicated can be decentralized at no loss using a simple procedure. In other words, the brain is physiologically equipped to optimize decision-making under a resource constraint.

6 Memory

Memory limitations is a challenging but well understood phenomenon in neuroscience. Although some economists have been attracted to this problem (see e.g. Mullainathan (2002), Benabou and Tirole (2002) and Kocer (2011)), the evidence about the neurobiology of bounded memory has not been exploited in economic models. This section summarizes our research on the existence and functionality of different memory systems and the implications for decision-making (Brocas and Carrillo, 2011). As in the previous sections, we present a model based on constrained optimization that relies on the coexistence of multiple interacting systems. Unlike previously, however, there is no hierarchical relation, no information asymmetry and no conflict of objectives between the systems. Instead, there are just systems (in this case memory systems) with different characteristics and the brain uses the system which is most appropriate depending on the properties of the task at hand.

Memory refers both to the conscious recollection of facts and historic events and to the unconscious and automatic retrieval of information necessary to perform everyday simple tasks. However, the processes involved in storing, learning and retrieving different types of information differ largely. Memory is broadly classified into two main categories (with further subcategories): declarative and non-declarative. In a nutshell, the different memory systems can be seen as tools to solve different problems. The declarative system helps find a solution to problems like "where did I park this morning?" while the non-declarative system solves best problems like "where do I usually park?".

More precisely, declarative memory refers to the capacity to recollect information about facts and events in a conscious way. Learning is fast and effortful but tends to erode. Declarative memory engages the hippocampus and surrounding structures (Eichenbaum, 2001). By contrast, non-declarative memory refers to learnt skills and habits and also to perceptual learning or conditioning. Learning is effortless, gradual and slow but also durable. It engages a variety of structures depending on the finer sub-classification of memories. For example, skills and habits are placed under the umbrella of procedural memory and engage structures like the striatum (Kreitzer, 2009). Conditioning is linked to the amygdala and the cerebellum (see Squire (2004) for a detailed classification).

Two elements have been emphasized in neuroscience, especially with regards to the declarative and procedural memory systems. First, memory systems are *substitutable*:

when one memory system is impaired another may be used to perform the retrieval task (Bayley et al., 2005). Second, there exist neurobiological mechanisms which make sure that behavior is *optimized*: information is retrieved with the system most adequate given the type of experience involved (Poldrack et al. (2001), Foerde et al. (2006)).

Following this evidence, we build a four-stage model of *optimal memory management*. In stage 1, an individual learns with full precision the state of the world x, which for simplicity is assumed to be drawn from the following distribution:

$$x \sim \mathcal{N}\left(\mu, \frac{1}{p}\right)$$

In stage 2, a memory about the state is formed by the individual using either the declarative memory system ($i = D$) or the procedural memory system ($i = P$). This choice affects future recollections.

In stage 3, the state is noisily recollected using the memory system selected in stage 2. Formally, if memory system i ($\in \{D, P\}$) is invoked, the individual pays a cost c_i to retrieve a signal s_i which is correlated with the true state x:

$$s_i = x + u_i \qquad \text{with} \quad u_i \sim \mathcal{N}\left(0, \frac{1}{h_i}\right).$$

In this equation, u_i is the noise. In expectation, the signal is unbiased: $E(s_i) = x$. Following the neuroscience evidence, we assume that $h_D > h_P$ (> 0) and $c_D > c_P$ (≥ 0). The former inequality captures the greater accuracy of information retrieval under the declarative system than under the procedural system whereas the latter inequality captures its higher cost in terms of effort or attentional resources.

In stage 4 and based on the recollected memory about the state, the individual takes an action a and obtains a payoff that depends negatively on the distance between the action and the true state: $l(a, x) = -(a - x)^2$.

In the model, the individual invokes a memory system anticipating the imperfect and costly recollection of information which will lead to a second-best decision. The key question is to determine which system, the accurate but costly declarative ($i = D$) or the vague but costless procedural ($i = P$) should be used depending on the experience. Our result is as follows.

Result 4 (Brocas and Carrillo, 2011) *It is optimal to retrieve information with the declarative memory system when the state is extreme (striking events) and with the procedural memory system when the state is intermediate (ordinary events).*

Under either system, the posterior belief about the state, and therefore about the optimal action to take, is a convex combination of the prior μ and the signal s_i. As the precision of the memory increases (that is, as we move from procedural to declarative), the signal s_i becomes more informative and reliable. The individual is then inclined to put a higher weight on the signal and a lower weight on the prior. Anticipating this logic, there is an efficient way of memorizing the state. When the state is close to the prior μ, the utility loss of remembering it imperfectly is, on average, smaller the higher the weight put on the prior in forming the posterior. Hence, it is optimal to resort to the procedural system. Conversely, when the state is far away from μ, it is on average better to put a low weight on the prior and a high weight on the signal, so using the declarative system is now desirable. Stated differently, because the information retrieved is more accurate but also more costly when the declarative system is used, the loss under that channel relative to the other is smaller if the state departs substantially from the prior belief. As a consequence, it is worth spending the extra cost of memory only for extreme states. Overall, an *optimal memory management policy* requires striking events to be retrieved with the declarative system and non striking events to be retrieved with the procedural system.

Our theory can help organize better the data obtained in the literature. In particular and according to standard results in neuroscience, the declarative memory system is typically associated with effortful but accurate memories regarding "how much I like this exceptional product" while the procedural memory system is typically associated with effortless but imprecise memories regarding "how much I like this average product." According to our model, the fact that exceptional and average experiences are encoded in different memory systems is not an exogenous characteristic of these two systems, that is, it is not because the procedural cannot encode exceptional memories and the declarative cannot encode average memories. Instead, this choice emerges as the result of an optimal memory management solving trade-offs between the costs and the precision of remembering an experience. The theory therefore unveils *causal* relationships between systems and the characteristics of the information retrieved.

7 Conclusion

In this paper we have selectively summarized some of our recent studies on decision-making based on a dual-process approach. These models provide examples of anomalies that can be explained with a careful modeling of the evidence about brain functions. They illustrate that it is possible to unveil causes for bounded rational behavior, identify mechanisms that lead to choices and, importantly for economics, predict choices in other related environments.

In the interest of brevity, we have left out all areas of recent theoretical research in neuroeconomics that are not based on the dual-process paradigm. Of special interest to us are the studies on the processes that map sensory perceptions into actions. Indeed, the well-known decision field theory and drift diffusion models have been very successful in fitting a wide variety of decision-making processes and anomalies in choices related to bounded memory and other perceptual imperfections.[8] The authors propose a set of dynamic equations for the stochastic information accumulation process, compute the likelihood of making one decision or another, and find the parameters that fit best the experimental data. In Brocas and Carrillo (2012a) we argue that such a behavior can be also derived from an optimization approach where neurons respond to changes in the value of making one correct decision vs. another by modulating the knowledge necessary to stop the information accumulation process. In other words, the paper shows that the properties of the computational models developed in neuroscience emerge *endogenously* from the result of a constrained optimization process. Moreover, the optimization model provides new predictions and comparative statics that can be taken to the data (see Brocas (2012) for an extension and an in-depth comparison of both types of models).

We would like to conclude with a comment regarding the methodology that guides our research. Experimental neuroeconomics, neuroscience and neurobiology provide a tremendous amount of data supporting the idea that an individual is not a single, coherent entity. Instead, decision-making is the result of complicated interactions between systems tuned to perform subtasks. This evidence should serve as a *precise guide* for new behavioral theories. Many paradigms are still under study and the evidence is not always as sharp as we would like. Theoretical models can help refine the paradigms and generate new predictions that can be further tested, which in turn will help produce new data to identify correct models. More generally, we believe that behavioral theories should not be based on inspiration or casual observation. Instead, they should be tightly connected to evidence from the brain sciences, the former and the latter helping each other to unveil the motivations for decision-making.

[8] See Busemeyer and Diederich (2002) for a survey and Ratcliff (1978) for the first of a long list of applications to neuroscience.

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