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A plausible Decision Heuristics Model: fallibility of human judgment as an endogenous problem

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This study meditates about mental heuristic rules as a representation of bounded rationality in individual decision making. The heuristic process presented here represents simultaneously limited computational capacity, the capacity to determine relevant information in complex contexts around beliefs, and time as an endogenous part of decision. The mathematical model of this heuristic rule correlates to the fallibility of the agent depending on the relative outcome of the alternatives in exogenous terms; the availability of only part of the information regarding the alternatives concert by beliefs; and the amount of time the decision maker is willing to spend on a decision based on previous experience and knowing that there is a tradeoff between time and fallibility. The resulting mathematical model can be applied to many disciplines like such as opinion models, game theory, the comparison of systems of distribution of authority, and fields that utilize the technique of agent-based models (ABM) that use individual behavior to study the macroscopic results of interactions.

Keywords: Bounded rationality, individual decisions making, heuristic, fallibility, modelling decisions, ABM.

JEL classification: A14; C00; D03; Z13

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1. Introduction

Decision theory analyzes how people choose the option that they believe will offer the best results given their preferences. Decisions such as whether to invest in stock, to buy a house, or even to get married are issues that confront us and for which we hope to provide formal explanations. In recent years, the literature on decision theory has had an enormous influence on disciplines such as psychology and economics.

Once an individual has completed the process of searching for viable alternatives and determining a range of possible options, he makes a decision based on a given set of information. If information about the outcomes of the alternatives is complete, the individual faces a situation of certainty. Conversely, if the information is incomplete, the outcomes of the options are unknown, causing a situation of risk (in which the probabilities of outcomes are known according to a state of nature) or uncertainty (outcomes cannot be foreseen in terms of objective possibilities) (Knight 1921).

Ramsey (1931), Von Neumann and Morgenstern (1944) and Savage (1954) demonstrate that in situations of uncertainty, choices between alternatives should satisfy certain conditions so that subjective probabilities and measurable gains can be derived from them. Formal rational choice theory does not attempt to consider either the nature of individual preferences or why people prefer some things to others (Bell, Raiffa and Tversky, 1988). Rather, it assumes those preferences will satisfy basic, logically consistent axioms (transitivity, completeness, asymmetry, …). The method of decision making and inductive inference remains therefore implicit in axioms of consistency.

The economic model of rational choice establishes a system of inference based on the axioms mentioned above, making possible to attribute subjective probabilities to situations of choice, attribute cardinal gains to the consequences of actions, calculate the expected utility of each wager associated with each alternative action, and compare numerically the different actions one another, selecting option maximizes expected utility. One of the primary problems of this model is that it considers its axioms as canons of rationality; that is, a decision maker confronted by a problem of uncertainty will be rational if and only if he or she maximizes the expected subjective utility.

Success in decision making depends on drawing inferences about the subjective probabilities that should be inductively obtained based on uncertain signals. In this manner, something great in size is associated with great effort: a big car is associated with a big fortune, proper appearance is associated with proper upbringing. Many researchers have defended the rational decision making model that establishes that laws of human inference are the laws of probability and statistics. However, it does not seem that this mode of rationality satisfies the assumption of realism necessary for the methodological construction of any scientific theory. To do so would require individuals to possess not only computational capacities but also a capacity to seek and store all information necessary, which is unrealistic (Simon 1947). As demonstrated by Tversky and Kahneman (1981, 2000), Kahneman, Slovic and Tversky (1982), Munier (1988), Cook and Levi (1990) and Hogarth (1990), human intuition regarding probabilities is very poor, producing multiple biases in decision making under conditions of uncertainty. These articles introduce a mental process heuristics and biases that not only facilitate bounded rationality in decision making but also—and above all—illustrate the fallibility of human judgment.

The limits of rationality are a consequence of the limitations inherent in human nature regarding computational capacity, selection of relevant information, and time. Our mental process is a heuristic choice rules and it attempts to bring together simple decision rules employed by the human mind to choose between the available options at a given time. In this context, there is no reference to the search for options, only the search for information in the form of signs, characteristics, consequences, etc., with respect to the current options (Hertwig and Hezog, 2009).

Our rules not only seek at maximizing the combination of result and resources (mainly time) also to demonstrate the possibility of error in decision making. The relationship between time and the viability of human judgment should be considered in behavioral models, given the very real potential for individuals to choose the option that ultimately yields the least. Psychology has studied how decision making is affected under pressure of time. The existence of a trade off between the time required to make a decision and the decision quality seems to be widely accepted[1] (). Shortage of time is a daily circumstance that explains the use of heuristic rules (Payne et al., 1993). The heuristic provides a better yield in terms of speed, albeit at the expense of precision; that is, the heuristic renders us susceptible to errors or biases.

This study describes a mental model based on some heuristic choice rules and their consequences for fallibility in decision making, correlating error and time. The error is endogenous since it results from limited human capacity to collect and manage information, this appearance differs the essence of this work from the traditional vision on economics in which the error is a problem of information and, thus, exogenous to the decision-maker.

[1] De Paola and Gioia, 2016; Kocher and Sutter, 2006; Maule et al., 2000 for a brief review.

The individual must make a dichotomous decision whose outcome is uncertain[2]. It is possible to erroneously choose the alternative that presents a lesser result or utility. Selecting one alternative over another is carried out through a heuristic choice rule used to compare numerous characteristics of both alternatives, such that if all signs favor one alternative, it will be accepted, or if contradictory signs exist, the process is repeated until agreements are found. The decision maker should choose the number of characteristics to be compared according his experience. Thus, it is to be expected that decisions of greater importance with respect to outcome require more time to reduce the risk of making a mistake and vice versa. The more signs needed to make a decision or the more experience, the closer the approximation to hypothetical behavioral rationality. The quality of decisions is measured based on two aspects: the probability of choosing erroneously and the amount of time invested in the process. This proposal is in line with the thinking of Simon (1947) and implicitly with that of Sah (1991) and allows modeling of the incompleteness of the decision-making process. That is, although an agent will not always choose one option against another, it will do so with a certain probability, committing errors of perception that can lead to mistakes.

The proposed heuristic mental model of decision-making mechanism establishes a relationship among the outcome of each alternative and errors made such that when two alternatives have a similar outcome, it is because they have a number of similar unitary characteristics, and therefore, the probability of choosing either alternative is the same. Accordingly, the model takes into account the relative outcome of one alternative versus another, recognizing that it is easier to arrive at a decision when significant differences exist among the alternatives, thus reducing the possibility of error.

[2] It is common to invoke strategies of satisfaction through sequential searches for information through options (for example, apartments, cars, computers, courses of action, or partners) that disappear over time.

The remainder of this article is organized as follows: section two presents a brief summary of the frame of reference for individual decision making based on the concept of bounded rationality and its implications. It also includes an analysis of how heuristic decision making rules offer an approximation to real of decision making and how the concept of human error is introduced. Section three describes the elements, dynamics and formalization of the proposed heuristic decision making rule. Section four presents alternative models that can be derived from this proposal and losses of the axioms of classical economic theory and its implications. Section five summarizes the conclusions and main results.

2. The frame of reference for individual decision making

2.1. Bounded rationality

Traditional rationality theory establishes the process for obtaining a solution to a decision-making problem under uncertainty, assuming that individuals have unlimited computational capacity and information. However, it lacks of procedures for reaching a solution based on an acceptable amount of computational effort (Simon, 1947). Almost no one makes a decision, however important[3], by creating hypothetical situations to which a distribution of subjective probabilities must be attributed. Meanwhile, the mere fact of having to choose causes us focusing the attention on some aspects of the decision (focal points) according our beliefs (basic assumptions) over others, given our inability to compare the total set of options in pairs (completeness). Conversely, most of our decision-making effort is dedicated to gathering information about the available options. Our physiology itself limits the processing of information (Soros 2013). The human brain is incapable of processing the millions of sensory impulses to which it is subjected

[3] Gabaix (2011) shows a model which induced outcomes reflect basic psychological forces governing limited attention.

at any given time and must choose just some of them. Meanwhile, those impulses must be quickly interpreted, leading to mistakes and distortions.

The bounded rationality proposed by Simon (1947) implies a procedural instead of a substantive notion of rationality, replacing the concept of maximization with that of satisfaction (that is, Simon claims that decision makers worry less about choosing an optimal option than about choosing an action whose result will prove satisfying). These transformations led to a descriptive theory of decision making based on the limits of rationality (Simon, 1947; Rubisntein, 1998; Gigerenzer and Selten, 2001; Todd and Gigerenzer, 2003).

Therefore, for example, if I wish to buy a house, I will not necessarily buy the one that maximizes my utility (which may be impossible); instead, I will compare a limited number of houses based on their prices and the characteristics that I find satisfying (although no individual house maximizes my utility in all possible areas such as price, size, location, distribution, etc.) given the available time. What is lost in mathematical precision is undoubtedly gained through the model's realism.

2.2. A mental model based on heuristic choice rules

It seems sufficiently demonstrated by experimental economics and psychology that individuals exhibit limits to rationality in their decisions and attempt to adapt to the circumstances of choice (difficulty, time, importance of returns), using simple decision rules suited to the availability of information and time (Gigerenzer and Seltzen, 2001). Ecological rationality considers that the limits to rationality stem from not only computational capacity, time limitations, and the ability to determine relevant information in complex contexts, but also from the sum of those factors. Ecological rationality models the rules of heuristic decision making employed by the human mind to adapt to its environment. People seek adaptive rules that offer quick, low-cost decision making given an experience, a particular environment and a set of possible outcomes. Heuristic decision rules are simple rules that attempt to maximize agent's returns, considering costs in terms of the time and resources needed to implement aforesaid decisions. Such rules are a collection of cognitive mechanisms constructed in our mind through learning and evolution (Todd and Gigerenzer, 2003). We can distinguish three heuristic processes that typically compose the mode of reasoning under assumed bounded rationality (Gigerenzer and Selten, 2001): simple search rules, simple stopping rules, and simple decision rules. Using search rules, individuals acquire a certain number of units of information about different options, assigning an approximate amount of time to that decision. Stopping rules help an individual decide when to stop searching and incorporate new information; for example, when deciding to repeat the process of searching for information until the decision rule is met. After acquiring a determined quantity of information, a simple decision rule is applied; for example, choose the object that is preferred according to a determined reason without having to evaluate all possible reasons. The term "rapid decision-making heuristic rules" applies to the multiple criteria or decision-making rules that are actually used by people in the most diverse contexts to make low-cost, effective decisions (Todd and Gigerenzer, 2003). There is plenty of literature on the use of heuristics for individual decision making (Gigerenzer and Todd, 1999; Gigerenzer and Selten, 2001; Todd and Gigerenzer, 2003).

The simplification of reality is a necessary process for human beings, proof of which is the fact that substantial computational capacities have been developed based on the binary used by computers. In this way, heuristic processes are a shortcut for formally established statistical processes. This does not imply that such processes are not logical, but instead, indicates that factor like time has an important cost in the deliberation of our cognitive process. In this study, we will focus on modeling "choice," defined as a decision between two alternatives. Individuals normally face a limited number of positions on a specific issue—whether to change or stay the same, go left or right, defend or attack, buy or sell—and if this is not the case, we can always repeat a selection process until arriving at a final choice between two options. Even complex choices between many alternatives can be reduced in a sequential manner to a dichotomous selection.

2.3. Fallibility

The theories of bounded or ecological rationality does not overlook the fact that errors in choice can occur with these heuristic rules, that is, inferential failures can lead to bad results (Bröder, 2000). The key issue, however, lies not in demonstrating that individuals adopt certain types of heuristics to make decisions but instead in seeking out patterns in both correct and incorrect decision making to model reality more precisely. The normative core of the classical vision has been conserved in heuristic processes. A discrepancy between the dictates of traditional rationality and actual reasoning is what defines an error as a process that does not obtain maximum outcome through choice. Error can be an acceptable option when the difference between current outcome and future outcome is insufficient to justify dedicating more time to obtaining that difference. Therefore, error is a tradeoff between outcome and time. In this way, although both points of view, bounded rationality and traditional rationality theory, accept the laws of probability and statistics as normative, they disagree about whether human beings can confront these norms.

3. The model

3.1. Heuristics decision rules

A model of choice between two alternatives *(a, b)* with two outcomes, denoted as *R(a)* and *R(b)* is proposed. The values *R(a)* and *R(b)* do not necessarily represent monetary values; instead, they could also stand for values of utility, returns, etc. To make a better choice the agent have two improve sources, specific information and generic information. The specific information spends time and the generic information may be acquired from personal learning in same problem or it can be obtained through inferences based on other problems with similar resolution mechanisms.

Conditions of limited cognitive and reasoning capacity require a method that is representative, available and adjustable and that can be used to obtain approximate solutions. The heuristic is a very economical and generally effective method, although it leads to systematic and predictable errors (Kahneman, Slovic and Tversky, 1982; Gilovich, Griffin and Kahneman, 2002); thus, we should incorporate error into our analysis as part of the process. What is important is to determine the frequency of error to establish reasonable predictions of individual behavior. A systematic error that appears to break simple probability rules can be justified if there are tiny differences in outcome among different alternatives, given the cost of changing decision-making rules. When the differences in outcome are larger, there should more indicators pointing to the correct response, thus reducing the probability of error.

This study proposes an inductive process that uses limited information to make rapid inferences. The agent trys to get reasoned conjectures about returns of alternatives regarding unknown characteristics of the world based on uncertain indicators. The agent should infer which alternative a or b has the higher *(R)* value. Suppose we build a vector of M characteristics (1, 2, …, i,…, M) in which the agent prefers one alternative to the other, eliminating those elements for which agent is indifferent. Each characteristics has the same level of relevance and is considered an elemental fundamental characteristic.

Two new vectors of basic characteristics can be constructed: $a(a_1, ..., a_i, ..., a_M)$ and $b(b_1, ..., b_i, ..., b_M)$, one for each alternative, where values that a_i and b_i can adopt 1 if alternative is preferred in that characteristic and 0 if it is not. Both vectors are complementary in the sense that when a_i=1, then b_i=0, and when b_j=1, then a_j=0. To predict which alternative is preferable, the agent chooses whether to focus on one or various of these characteristics, according to the stopping rule. The outcome of each alternative (a and b) is the sum of the fundamental characteristics (a_i and b_i, respectively) represented in their respective vectors of quality. This measure is relative; that is, it is only valid for the purpose of the comparison described. The individual does not wish to know the totality of the attributes of the object but instead wishes to know enough to make a decision, accepting his or her limited knowledge capacity.

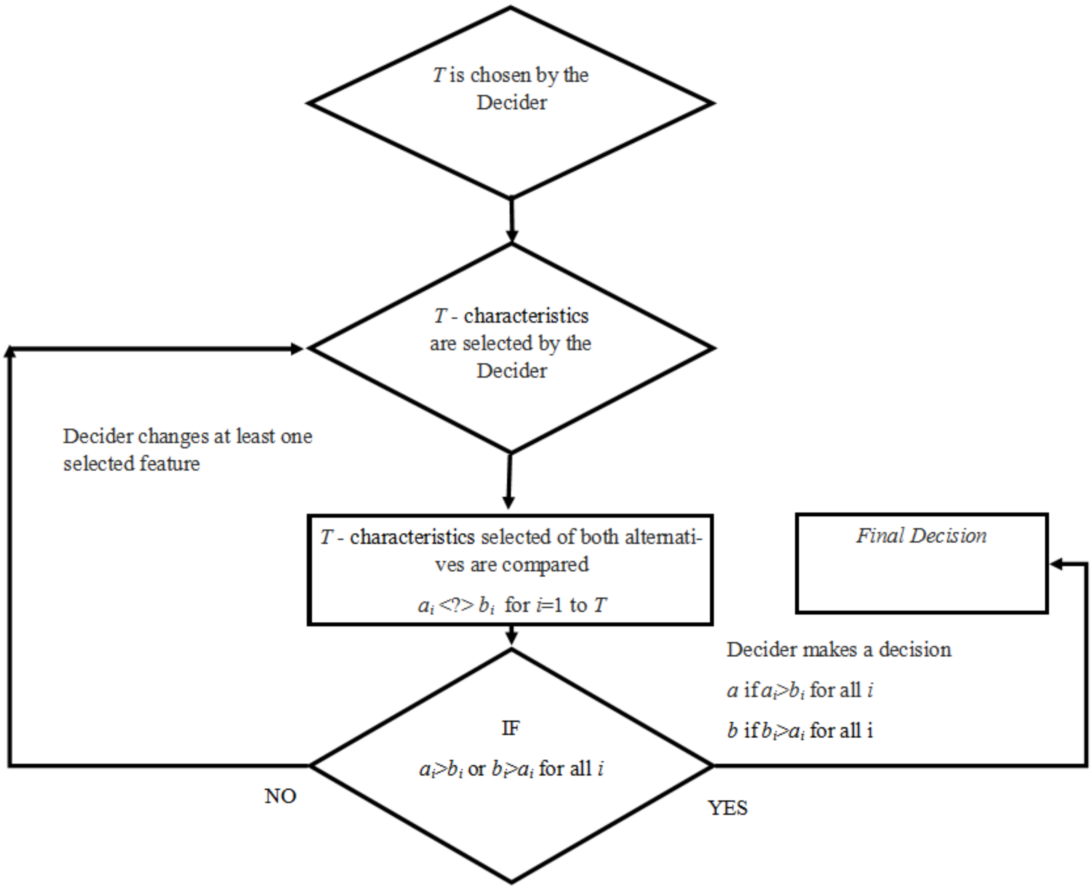
In modeling, the probability of an error is directly related to the number of characteristics that the individual believes sufficient for making a decision. The individual will focus on known characteristics to generate a prediction, which represents the recognition heuristic (Goldstein and Gigerenzer, 2002). The smaller the number of attributes is used, the faster the decision-making takes place, although there is a higher error likelihood. If we assume that it is sufficient to obtain a single, unitary characteristic, this component of the outcome vector being known, a decision can be made. However, if the selection process is more demanding in terms of the information required (for example, if two unitary characteristics are needed), the individual should compare the information about the characteristics of the two alternatives until the decision-making condition is met. The recovery of a memory register occurs automatically and instantaneously in the mental scenario and, therefore, it can always enter into inferential processes when other information needs to be processed (Pachur and Hertwig, 2006). The recognition heuristic is assumed to be a non-compensatory strategy (a highly controversial aspect noted by Bröder and Eichler, 2006; Newell and Fernandez, 2006; Oppenheimer, 2003; Pohl, 2006; Richter and Spath, 2006; Pachur and Hertwig, 2006, and Pachur, Bröder, and Marewski, 2008). That is, once an object is recognized as better than other, the search concludes. For a heuristic to function, it should achieve a certain level of predictive success. The selection of information should be systematic, producing a correlation between recognition and the chosen characteristic or characteristics. Such correlations exist for example, in academic excellence (Hertwig and Todd, 2003), athletic ability (Pachur and Biele, 2007; Serwe and Frings, 2006) and city size (Goldstein and Gigerenzer, 2002; Hertwig et al., 2008), and are collected and internalized as beliefs by a learning process.

The proposed cognitive algorithms are found in probabilistic mental models (PMM theory) (see Gigerenzer, 1993; Gigerenzer, Hoffrage and Kleinbölting, 1991). PMM theory assumes that inferences about unknowns in the world are based on probability cues (Brunswik, 1955). The theory, proposed by Reichenbach and other frequentist statisticians, connects three perspectives: (a) inductive inference should be studied with respect to natural environments; (b) inductive inference is carried out through satisfaction algorithms; and (c) inductive inferences are based on the frequency of events. PMM theory presents a reasonable framework for learning process. The agent heat accumulates experience improves her score in two ways: focusing its attention on characteristics indicative of a higher overall performance and fixing the demand for quality of choice that the agent will establish in advance when deciding on the number of characteristics that must be compared in order to make a choice.

The mechanism proposed here allows us to connect classical probability with simple and plausible mechanisms of psychological inference, that is, rules allowing agents to save time in decision making. Neural networks regression models attempt to achieve the optimal integration of all available information; each bit of information is both considered and combined in a computationally demanding manner. However, the search for relevant information (a characteristic taken from among *M* possibilities) in memory is reduced to the greatest extent possible, and there is no integration of the distinct pieces of information. These satisfaction algorithms require that all known information be managed completely because there are limits with regard to time and the understanding of the weights and covariances of each piece of information. The association between of characteristics and yields, driven by the learning, is a simplification necessary, given the limits own of the nature human.

The heuristic proposed here works as follows: the agent chooses decision rule to adopt according his experience, this rule establishes the number *"T"* of elemental attributes that must be favorable for one of the options. In this way, the agent decides whether to dedicate more time (greater *T*) or less time (less *T*), establishing a rule that becomes more or less strict. With increased strictness in decision making, the time required increases because the agent will continue to seek sets of elemental *T* characteristics until one is obtained that satisfies the decision rule, following the flow chart described in Figure 1.

Figure 1. Decision-making process for the selection of one of two alternatives



This process continues as long as no decision has been made in favor of *a* or *b*. When just one part of the *T* characteristics is favorable to one of the alternatives, the process is inconclusive and requires more information, and the process is repeated as many times as needed to reach a decision.

Search rule. Establish the set of fundamental characteristics (*T*) that will be sought for each alternative to carry out a comparison. This quantity (*T*) is fixed in advance based on the evaluation of the problem according to the agent and his previous experience. Individuals with lower failure rates may find the number of fundamental signs more relevant and require fewer signs in their decision-making processes to achieve reasonable success rates. A tradeoff exists between the number of signs and the time needed to make a decision.

Stopping rule. If all the signs obtained favor one alternative, the search is halted. Otherwise, this is not the case the search for characteristics is repeated.

Decision making. It is predicted that an alternative has greater outcome when the fundamental characteristics obtained favor that alternative.

This heuristic is a simple rule for carrying out inductive inference: it does not needs all available information and allows violations of transitivity of preferences because it accepts errors in choice. That is, when the agent decides *ex ante* that T=1, the algorithm implies that any multidimensional object a (a_1, a_2,..., a_n) is preferable to b (b_1, b_2,..., b_n), if in the chosen characteristic (i), a_i surpasses $b_{i.}$. This preference can be reversed, increasing the number of characteristics required to make a decision (increase T) or choosing another sign j (a_j versus b_j). Meanwhile, outcome $R(a)$ and $R(b)$ can be visible or not visible and can change over time because of the incorporation and/or elimination of characteristics that affect the final result. Occasionally, the outcome is an extraordinarily complex variable about which the decision maker knows only a small amount.

This algorithm has the following properties: 1) the search extends to only one part of the total knowledge (certain characteristics, at least T) and ends immediately when a set of conclusive characteristics is found (all are favorable to one option); 2) it is very simple; 3) each individual decides the level of information processed in accordance with the amount of time he wishes to dedicate to the process. Each individual establishes T to achieve a certain outcome per unit of time. This algorithm mathematically represents the behavior of an agent with bounded rationality, drawing on Simon's concept of "satisfaction." In this context simplified and static, the agent does not attempt to optimize his decision based on previous experience but rather establishes the time that will be used to make a decision, both knowing that less time implies a greater possibility for error and seeking a satisfactory option given the time cost.

Mathematical modeling of the process described allows us to establish the probability of deciding correctly as a function of the relative outcome of the alternatives and the level of information required by the agent.

$$\frac{p}{q} = \frac{R^{+T}}{R^{T}} \qquad (1)$$

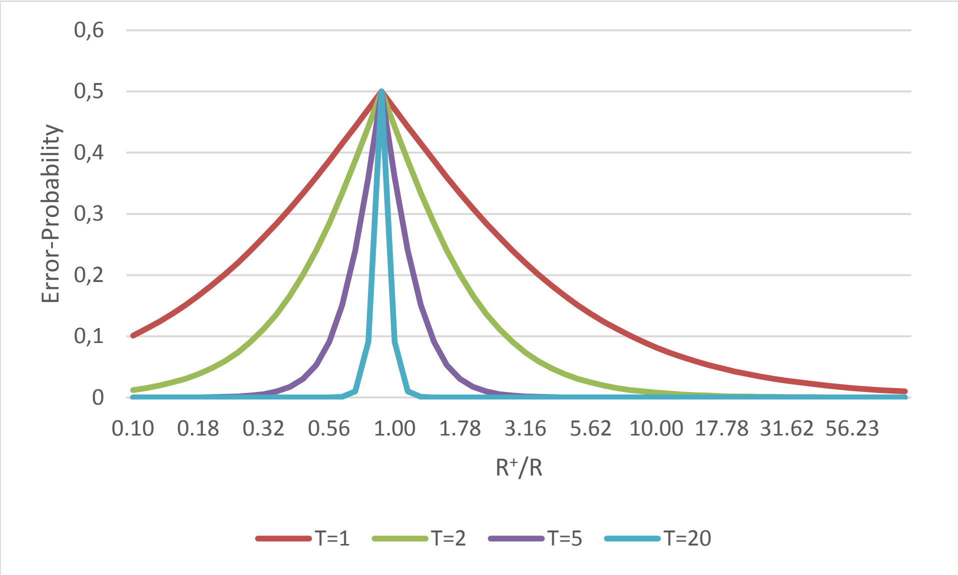
Where, p is the probability of a correct choice, and q is the probability of error, whereas R^{+} is the option with higher outcome, and R the option with lower outcome. T represents the level of information required by the agent and gives us an estimation of the amount of time used.

Ruling out the possibility of a correct choice in (1), we obtain:

$$p = \frac{R^{+T}}{R^{T} + R^{+T}} \qquad (2)$$

In this formula, it is easy to deduce that if T=1, the probability of a correct choice depends exclusively on the relative yield of both alternatives. When there is a greater difference between the alternatives, the probability of a correct choice increases; when there is a smaller difference, it decreases. The distribution of the probability of making an error can be seen in Graph 1, which illustrates that it is more likely to make an error when the outcome of the two alternatives are similar, as well as when T decreases.

Graph 1. Distribution of the probability of error as a function of relative yield



This probability summarizes the heuristic process described above in which the agent opts for one alternative or another simply by comparing the two alternatives' characteristics. Supposing that the agent considers just one characteristic in the decision-making process to save time and that the outcome of *a* is *R*(100) and the outcome of *b* is $R^+(120)$, this would imply that there are 100 elemental characteristics in which *a* is preferable to *b* and 120 elemental characteristics in which *b* is preferable to *a*, so the probability of choosing *b* (*p*) with the heuristic process described is 120/(100+120). If the agent increases the amount of information required and decides to establish a more rigorous decision-making process (for example, obtaining 5 favorable characteristics for one of the options) in this case, the probability of choosing *b* would be $120^5/(100^5+120^5)$.

3.2. Functional form

The model described allows to predict individual behavior assuming a percentage of error as part of the decision-making process.

So far we have seen a static model with high level of abstraction. To include a certain degree of dynamism must include the result of a possible process of learning of the decision-maker and his representation in the model. Learning literature has been classified as cognitive and reinforcement learning, both seek to anticipate the performance of alternatives from characteristics. The difference between the two is that reinforcement learning is an unconscious process of association between characteristics and performance (pain or satisfaction) while the cognitive learning is the result of a conscious process. We will not make a distinction in the origin, and we focus on the result produced by the learning process in the decision. When the agent learns improving their ability to hit (to discern between alternatives) due to the association between performance and characteristics, i.e., experience has a result similar to the increase in the requirement for the number of characteristics to make a decision. Both processes increase the decision-maker information and require time. As most important differences is that learning is general and does not require time consumption for each decision making, against the increase in characteristics is a specific information and requires time in the decision making. We identify ecological validation as outcome of learning procedure, we will call "beliefs", giving an improvement in success capacity without to spend time. The mathematical representation of this new, more complex scenario, would be written as:

$$p = \frac{R^{+\,\alpha+\beta t}}{R^{\alpha+\beta t} + R^{+\,\alpha+\beta t}} = \frac{1}{(\frac{R}{R^{+}})^{\alpha+\beta t} + 1} = \frac{1}{e^{-r(\alpha+\beta t)} + 1} \tag{3}$$

where replaced R^{+}/R for e^{-r}, r is the rate, in continuous time, which multiply R for R^{+}, α represents "beliefs" of the decision-maker, β represents the ability to manage specific information and t is the time spent on particular decision.

3.3. Implications

When α and β = 1 concerns in the formulation (2). High values of α implies "beliefs" help significantly to discern ex ante alternative return, whereas α values less than unity indicates that beliefs are bad and reduce the ability to ascertain given by difference in alternatives return, and whereas α values are negatives, beliefs are wrong and increase probability to choose worse alternative. Increases in β imply better performance of time in obtaining specific information. Finally, increase in spending time decision making improves its quality, as we have seen in simple scenario. The function is increasing in *r*, α, β and *t*.

$$\frac{dp}{dx} = \frac{e^{-x}}{(1+e^{-x})^2}$$

α, β and *t* always be positive while *r* can adopt values negative or positive. When *r* is negative R^+/R is less than unity and therefore the alternative considered by the decision-maker has a return lower than the status quo.

The decision-maker will have incentives to improve their level of specific information when he expects a positive balance. Therefore, given a R^+ and R, the agent will try to maximize its outcome $y(t)$:

$$y(t) = R^+ p + R\,(1-p) - c\,(t)$$

assuming that the function $c(t)$ is linear and equal to Ct.

$$\frac{dy}{dt} = (R^+ - R)\frac{r\beta e^{-r\beta t}}{(1+e^{-r\beta t})^2} - C$$

For $\beta > 0$, time profitability increases with the difference among alternatives returns and decreases with unit cost time.

Time that maximizes the performance of the decision will be:

$$t^* = \frac{\ln\left\{r\beta(R^+ - R) - 2C + [r^2\beta^2(R^+ - R)^2 + 2C(R^+ - R)]^{1/2}\right\} - \ln\left\{2C\right\}}{r\beta}$$

The value chosen for t will be one that exceeds the level of satisfaction established by the decision-maker. This establishes a relationship between spent time and expected result.

The search for elemental or complex characteristics in decision making is a product of a learning process. Agents constantly interact with their environment, deeming various characteristics relevant based on their experiences of success and failure. In this way, an individual experiences a problem with an initial perception, considers and chooses certain behavior that produces an outcome and if this is satisfactory, the behavior is repeated, generating a habit and reinforcing beliefs that can become values. These values and beliefs (mentality) are the product of repetition both in interactions with the environment (learning) and in the capacities of individual. The impossibility of experimenting obligates actors to transfer beliefs and values from one problem to another, limiting the apparent rationality of both the problem and (to a large extent) the final result (Berg and Hoffrage, 2008).

The rational model has underestimated the role of values and beliefs in the construction of models. Errors of judgment or prejudices determine subsequent logical processes of treatment of information to make a decision. There have been studies on the effects of distortions in perception including not only the “halo effect” (an outstanding quality that causes others to be overestimated) and the “contrast effect” (the characteristics of a problem are overvalued or undervalued due to confrontation with another recent problem), both of which involve stereotyping or assigning characteristics to a person simply because they belong to a given group, but also the “Pygmalion effect” (self-fulfilling prophecy).

Intuition is a rapid response based on beliefs. This type of response puts a great quantity of information in play, and the results will not necessarily be erroneous; however, it lacks consideration of specific information for this problem and thus requires a logical process of ordering and choice as established by the rational model to obtain a rapid response. All decision-making agents experience time restrictions. Thus, in a process of rational decision making, one should choose the information relevant to resolving the problem, a process that requires individuals to seek recourse to their mentality; given a person’s limited capacity to process information, individuals might be prevented from reaching an optimal solution and instead make do with an acceptable solution. The tradeoff between obtaining information and the time required affects both the quality of the decision and the probability of error.

The algorithm presented also explains surprising empirical choices such as those in which “more is less” (agents possessing more information make worse decisions than those with less information). This is because individuals with positive experiences that take a known characteristic of choice are unlikely to spend time obtaining and considering additional information; instead, they base their choices on a simple rule derived from previous success. Meanwhile, individuals lacking experience establish more demanding choice rules given their lack of knowledge of the material and therefore draw better inferences than those who would seem to know more. This surprising prediction has been confirmed in practice. For example, Gigerenzer (1993) demonstrates that students in the United States make slightly more correct inferences regarding the populations of German cities (about which they know little) compared to U.S. cities, and vice versa for German students.

The information obtained by learning can be employed in different decisions and grouped and stored in memory as a single characteristic or sign. The process can become complicated, resulting in the formation of grouped characteristics that behave as objects composed of fundamental characteristics. This grouping process occurs through learning and enables the simplification of choice rules and the establishing of links with sources of information that facilitate comparison. This process has traditionally been known as validity associated with a characteristic and is indicative of its predictive power. The beliefs (ecological validity) of a complex characteristic is the relative frequency with which the complex characteristic correctly predicts the objective, which is defined with respect to the form of reference. However, this probability can be associated with the probability of choosing correctly (or making a mistake), which returns us to the initial problem. Now we have $a(1, 0, 0, 1,\dots, R^a_j, 1, 0)$, where R^a_j is the outcome associated with the set of j unitary characteristics comparable with alternative b $(0, 1, 1, 0,\dots, R^b_j, 0, 1)$. In this way, we can associate the probability that $R^a_j > R^b_j$ with the probability that $R(a) > R(b)$. The process of obtaining these values has been termed ecological validation (Gigerenzer and Goldstein 1996). At the same time that this approach facilitates choice, it can result in errors in judgment. If it is erroneously deduced that $R^a_j > R^b_j$, one could be led to think that $R(a) > R(b)$, weakening the correlation with success.

For example, we suppose that an agent who wants to increase his or her productivity at work must choose between two computers (*a* and *b*) whose characteristics include screen size, hard drive speed, and the presence or lack of a USB 3 port. The agent does not need to know the totality of the characteristics of each option. In our example, the speed of the coprocessor would be a component of the vector because greater speed in this element generates a better outcome from the computer, being a potential sign. In other words, it is probable but not certain that a computer with a better coprocessor will obtain a better outcome than one with a worse coprocessor. Suppose the agent knows that computer *a* has a better coprocessor than computer *b*. This can be sufficient to make a decision if it is assumed that the comparison of one quality is sufficient for decision making. This heuristic, given the complexity of a computer's outcome, offers a greater possibility of choosing correctly in terms of outcome, although it is far from a guarantee of avoiding an error, even though obtaining and processing the information did not require much time. Perhaps the agent did not need to seek out this information and just happened to recall this fact about the computers. A computer with a better coprocessor has a reasonable likelihood of success.

The formation of complex characteristics and their transference from one problem to others offers criteria for making predictions. This relationship is shown empirically in Scheibehenne and Bröder (2007), Boulier and Stekler (2003) and Forrest, Goddard, and Simmons (2005), where individuals are seen as capable of delivering high percentages of correct choice regarding sports outcomes using only simple information about the protagonists. For example, Scheibehenne and Bröder (2007) analyze the capacity of correctly predicting the results of Wimbledon tennis matches in 2005 based exclusively on player name recognition, obtaining a 70% success rate in predictions. Curiously, this success rate was similar to that achieved by Association of Tennis Professionals (ATP) rankings or predictions by Wimbledon experts; only online betting had a better success rate in predicting the results. The proposed heuristic process establishes a correlation between an object's characteristics and the capacity to correctly determine its outcome. In this sense, this study examines predictions based on an ecologically rational heuristic; that is, time should be allotted for the reception of adequate, not always conscious, information.

Probabilistic representations of decision is based on the recognition of error as a real and daily possibility in decision making. Each alternative is assigned an outcome, and choice requires adopting one of them according to known characteristics. Choosing becomes more difficult when the outcome of both alternatives are alike because the number of fundamental characteristics in favor of one alternative is very similar to the number of fundamental characteristics in favor of the other. Many times, these heuristic rules are not visible. We cannot know the criteria obtained by each person, only the amount of time dedicated to the decision-making process and the percentage of correct choices given the value of the decision (i.e., the difficulty of the problem).

3.4. Literature Previous

Literature has used the probabilistic representations of behavior to account for the myopia of agents in the learning model by Ellison (1993); bounded rationality has been considered in the model of selection of providers by Valluri and Crosson (2005); the adoption of an innovation in game theory has been considered by Montanari and Saberi (2010); and noise has been introduced as bounded rationality in the diffusion of social innovations by Young (2011).

Highlights learning models present very similar to (3) functional shapes to represent the probability of adoption of an alternative to the other. These models have concentrated their efforts to represent empirical or experimental evidence. In these models, probability is not assigned an economic value, and therefore, the concept of absolute rationality is not applied. Between them stands out the model of Arthur (1991) that generalizes the model Bush-Mosteller introducing different speed of learning, in a try of model the choice given the bounded rationality. His proposed was present an algorithm of decision parameterized and calibrated to behavior coincides with the real human conduct. Roth and Erev (1995) and Erev and Roth (1998) go further the study of the problem of individual selection of Arthur and examine what reinforcement learning algorithms paint experimental data from various multiplayer games that have been studied by experimental economists. The model of reinforcement that Roth and Erev (1995) is similar to Arthur, but there are some differences and important modifications that allowed achieve to fit model to the experimental data. Camerer and Ho (1999) combine different learning models based on routine (Herrnstein, 1970 and Herrnstein and Prelec, 1991) with the argument that every one of the previous models (routine learning) reflected the different types of learning (reinforcement and cognitive). In the EWA (Experience-Weighted Atraction) model of Camerer and Ho is argues that there are two types fundamental learning processes: reinforcement learning and cognitive learning. The model is designed to describe these two learning processes as parameters borderline cases.

In these models the probability that agent plays the strategy *j* in the period *t* is according to:

- Lineal decision rule $p_t^j = \frac{s_t^j}{\sum_{j=1}^{n} s_t^j}$ where s^j_t represents the performance assigned by agent to each alternative, given his information,
- Exponential decision rule $p_t^j = \frac{e^{\lambda s_t^j}}{\sum_{j=1}^{n} e^{\lambda s_t^j}}$ where λ is a reinforcement learning parameter.

Cheung and Friedman (1997) used a logistic function as a stochastic approach to the rational learning (Bayesian) Cournot type "fictitious play" (model about how players build their beliefs about other players behaviour to choose the best answer based on them, in a zero-sum game with two people):

$$p_t^j = \frac{1}{1 + e^{\alpha + \beta r_t^j}}$$

where α is an fixed specific effect individual that indicates the decision-maker bias by action j and β that represents decision-maker sensitivity of profitability differential concerning rest of alternative (r_t^j).

Saenz et al. (2015) about innovations diffusion in complex networks and Salas et al. (2016) about ideas diffusion into organization used "ad hoc" this representation of bounded rationality to added social pressure:

$$p = \frac{bR^+}{aR + bR^+}$$

where a and b represent people number supporting each alternative in a network environment, in this way ideas of environment affect the likelihood of individual acceptance.

These representations show as form mathematical obtained here (as representation of a mental model where decision-maker tries to simplify looking for reference characteristics that he allows make a fast decision) can paint the reality in learning processes and can serve to perform simulations at laboratory level.

4. Implications of the models

The proposed mental model of bounded rationality connects the likelihood of error in decision making with the relative outcome of the alternatives, the beliefs and the amount of time used by the decision maker. The proposed approach has important implications in the agents' behavior and brokenness classical axioms. The agent can assume error as part of its decision. When the implications of a possible error are not appreciable, additional information (time spent on the decision) is reduced, assuming that when the performance difference between the alternatives is not very large, being wrong is not excessively burdensome and it may be acceptable. Our model includes loss aversion by agents (Tversky and Kahneman (1981, 2000), Kahneman, Slovic and Tversky (1982)). As an example, suppose the bounded rationality expressed in (2), i.e. a situation in which the probability only depends on the yields of the alternatives, the probability of accepting an alternative 50% superior to the status quo is 0.6 while the probability of rejecting an alternative 50% less than the status quo is 0.67 illustrating the asymmetry that penalizes the losses.

4.1. New vision about behavior of economic agents.

4.1.1. Information as an endogenous problem

The economists have been forced to acknowledge the fact that individuals act in a manner substantially different from the predicted by the rational model, and we should approach our theories of cognition processes to reality. For the most of decisions, people uses a automatic mode, intuitive and associative of thought (based in beliefs), rather than a mode deliberative, reflective and strong effort (based in the search of information specific). This paper has shown a mental model of fast thinking based on a small part of the relevant information, conditioned by beliefs, along with a deliberative thought by searching for specific information. We are modelling how decisions making is affected by the learning process and the amount of information chosen (time dedicated to taking the decision). This approach breaks the traditional transitive preference ordering in the economy. The classical paradigm does not represent beliefs about the world, but establishes a level of information given in exogenous form (agent Bayesian), through a distribution of underlying States probability, so a rational agent chooses an option that maximizes the expected value given her information. The classic axioms prevent making mistakes since the choice is always the same for information level does not change.

This approach breaks with the traditional view since internalizes in the agent the assignment of probabilities. Therefore, there are no objective probabilities, but there are simple situations in which the schedule has much relevant information, anticipating good returns of the alternatives, almost as if he was rational. The classic vision materialized the noise in the information given in exogenous form, while here we recognize that the bias or error is generated by agent with her interpretation of reality. For each agent, the world is not the world but simply what she thinks about it.

Therefore, an important contribution is that the level of information is endogenous, is the decision-maker who takes the amount of information needed to make a decision, given the perceived performance of the alternatives and their beliefs about them, conscious of his bounded rationality. The problem of the agent is internal in the sense of limitation on processing the reality, a problem in how to manage the information. The agent tries to anticipate the real performance of alternatives attending to simple indicators (characteristics chosen according to her beliefs) and choosing the amount of information that she thinks is enough according to her experience and knowledge.

4.1.2. Beliefs

Decisions in situations under risk or uncertainty depend of decision-maker inferences. The information is obtained in inductive form from signals (characteristics) and this allows the agent to assign probabilities to alternatives. The learning process allows tie elementary or complex signals from alternative with its performance. When behaviour (taking a decision) provides success, it is repeated, generating habit, reinforcing beliefs about tie between characteristics and returns and, finally, those beliefs may become unquestionable values. Beliefs establish links between performance superiority and superiority in certain characteristics, simplifying the problem and allowing fast improving the probability of success. Values and beliefs (mentality) are product of learning process. Learning, in final, improves the ability to process the information and its result is an improve in the capacity of recognize the true performance of two alternative with a given performance differential (R^+-R). The impossibility to experience (due to lack of time or resources) forces to use beliefs and values from other problems, limiting the apparent rationality of decision and the return. Performance of human experimentation is very limited due to a high number of repetitions are necessary to get outcome. In this sense the observation and the socialization allows putting in common group experiences (culture), crucial in saving learning time. Individual beliefs are subject to two important social influences that are: socially some characteristics are perceived as permissible aspects and others as not admissible, limiting ability of individual choice and simplifying the problem; socially is establishes what are the characteristics relevant (helping to choose the vision of the world) that the person uses to process the information. These factors are part of the decision since they affect the assessment of alternatives and form characteristics filters through which individuals pay attention on a part of their perception, categorize and interpret situations and bias the decision in favour of the more acceptable according to the culture[4]. This social influence usually ends by internalize, becoming indisputable for individual. Culture influences deeply in beliefs and therefore in human cognition, this is due to habits of thought and of behavior can culturally transmitted through generations (Algan and Cahuc 2010; Alesina, Giuliano and Nunn 2013). The rational model has underestimated the values and beliefs for the construction of models. However, beliefs restrict information searches and bias the subsequent logical process.

Beliefs are especially important in complex decisions. When an individual is faced with a problem it has a perception, he reason taking into account not only their experience but also group lessons learned and confirmed by their way of abstracting, finally decides to obtain a performance, if this is satisfactory reinforcing beliefs that will be less questioned in future decisions, representing a significant time savings.

There are errors of judgment that can be based on beliefs (biases). Beliefs determine the search and subsequent treatment of the information to make a decision. The result is that

[4] Hoff and Stigliz (2016) show how plausible are these situations.

can generate is rigidities in the choice difficult of change. This explains situations in which a person is locked in a wrong option whose origin is in a belief (the representation is made through a very low α (less than the unit) which makes very unlikely to choose R^{+} option). This "bias confirmatory" has been well documented in the literature of the psychology (see are, for example, Rabin and Schrag (l999)). Situations in which one tends to interpret any new evidence as favourable to existing belief, although it is not really so. This is favored by the learning process that deteriorates naturally not chosen action. When the agent has chosen several times the same option (given the low probability of the alternative) avoids that she can see any evidence favorable to the alternative. So the probability of being locked in the initial choice is growing. In this work a change in beliefs changes the focus of the characteristics sought, being able to change the manifestation of apparent references, this is consistent with the work of Rabin (1998) and DellaVigna (2007). These beliefs can evolve and can be questioned since they seek correlations between performance and characteristics. However, the logical deduction is unquestionable and its construction not gives place to disagreements, the error only can be in the beliefs initial of split. The fact beliefs can change in a situation given, will result behavior that can violate the consistency. The traditional approach does not account the mistake or mental behind the election processes, since it simply indicates the path of the person towards the solution with greater performance.

According to our model, Scheibehenne and Broder (2007) compares the capacity to predict correctly some results due to people beliefs (based in a small part of the information) with the prediction capacity based on specific information provided by experts.

4.1.3. Time decision and information

Beliefs are sometimes not sufficient to make a concrete decision and it is necessary to collect information (inevitably biased by our beliefs), process the information in a logical way and get a predictor of performance. The agent decodes, conscious of its bounded rationality, how much additional information requires to make a decision, valuing the losses or gains of it. For this agent will decide how much time is willing to sacrifice to make that decision. To increase the time of decision is closely linked to a rational decision-making process with increase in information.

This process improves the rationality of the agent. Increasing the time of decision making by the search of relevant information means that not all decisions are made according to intuition or beliefs, but some decisions are rooted in deliberative decision processes. The question is how long and how much information the agent is willing to use in order to improve her decision. This aspect has been treated in the literature (Maule et al., 2000, for a brief review). According to our argument the agent employed more time when his play-off is positive in the time, i.e., decisions that have an important economic impact are made spending more time than decisions whose impact is low.

The amount of time spend in making decision is decided by the agent base on her experience, in a learning process similar to create beliefs. Individuals vary the time amount (information) to make a decision in a type of problem whenever she gets a net positive performance. Increases in information improve rationality but, since time is costly, there is a trade-off between increases in *t* and the performance improvements that provides.

4.2. Screening

The learning literature is focused in how individuals evolve towards greater performance alternative, without pay attention on what part of this learning is coming from yields real difference of alternatives. Our approach takes the difference between performance of alternative as a variable exogenous, paying attention on evaluation and not in identification of alternatives.

Evaluation of alternatives from their performance has barely been studied (Gavetti and Levinthal, 2000) specifically. The assessment is characterized by the degree of reliability in which is get distinguish between the performance of an alternative and the status quo. An evaluation perfect, would distinguish between alternative without importing performance differences between the two proposed. Knudsen and Levinthal (2007), Christensen and Knuden (2010), Császár and Eggers (2013) and Császár (2013) pose agents are not always good classified. The quality of each alternative is seen through a set of signals (in our case characteristics) and each agent's ability to perceive the true performance of each alternative is characterized by a "screening" function that takes into account the difference in performance between alternatives. It is more common agents are able to perform a misclassification of alternatives when difference in alternatives reward is small. On the contrary, if value difference is high, it is harder to go wrong. That recognizes classification or evaluation is not a random process, although its functional form is not defined. For these authors source of the error is in information bias received by the agent for us alternatives performance is part of reality and bias is caused by bounded rationality of agent.

In short, when economists use the term "rational actor" do not mean a high level of thought, but only to seek a certain level of consistency in behavior. For us, three are the fundamental factors affect our rationality in decision making, the difference in returns between the alternatives as an exogenous element, as evolutionary beliefs, and specific information or time of deliberation as an endogenous elements.

The limits of rationality are a consequence of the limitations inherent in human nature with respect to computational capacity, selection of relevant information and time. Our model based on heuristic decision rules tries to describe a process employed by the human mind to choose among the options available at any given time. In this context, we do not mean to search for options, but only to find information in the form of signs, characteristics, consequences, etc., with respect to the current options, as a necessary simplification system. This quest for improvement requires time to learn or to search for specific information and therefore has a cost.

This model allows us to introduce bounded rationality behavior in different areas of study such as opinion models, innovation diffusion models, marketing models, learning models, etc.

5. Conclusions

This study proposes a mental model based on heuristic decision rules for two alternatives using a mathematical model that has into account the fallibility of the agent and the relative outcome (odds) of the alternatives. The agent has beliefs that help her to make a fast decision and he establishes ex ante the amount of time to sacrifice to make a decision based on previous experiences. This translates into a relatively strict search rule, knowing that a tradeoff exists between time and fallibility. The probability of error is greater when there is a smaller difference in outcome between the alternatives. The agent adopts a position without having all of the information about the alternatives, focusing on unitary or complex characteristics considered more correlated with the outcome of the alternatives, what we call beliefs. This correlation can be either the result of previous experience and/or the observation of a given (or a similar) problem and/or an output of socialization. The alternatives are not recognized randomly—instead, they are recognized systematically, and correct predictions are made according to the difficulty of choice.

This paper is an attempt to broaden the standard economic speech through the incorporation of a mental model that reflects everyday aspects of human behavior. Although rationality is a central part of classic economic theory we need another kind of model to describe the actual decisions. Our model reflects the essence concept of bounded rationality Simon, accepted the error as a possibility and internalize the origin of the error in the person being a consequence of the limited ability to perceive and process information. The classic economy has located the source of the error in the information received by the agent and the costs of improving the processes of information in limited resources. This approach focuses the problem in external elements to the decision-maker. For us, the modelling of the decision should focus is in internal elements, so in a context temporary keep in mind two aspects essential of behavior, people learn and are adapted to environment. This not implies that never will produce errors, but with time, through experimentation and observation, people arrive to processes of decision with reasonable yields. From a procedural interpretation of rationality, we will say that an agent is more rational as best results get given a performance difference between alternatives.

Our mental model describes a procedure of choice that is made up with three elements: a description of the environment external (difference between the performance of the alternative); a set of internal factors (beliefs and time dedicated to the decision) that they set the procedures of decision that restricts the result of the decisions; and a criterion for assessing the factors (success or error). Given the time constraints that affect both the problem specific reasoning process, and the formation of beliefs, it is assumed that how to choose is satisfactory to the decision-maker at that point in time.

From a positive point of view, the model expresses the measure in which the behavior is adapted to the environment of the decision (estimate of the level of rationality). From a normative point of view, factors that improve performance information and beliefs should be specifically studied. Any improvement of the sources of information acts on beliefs and, therefore, also acts indirectly on the outcome. A regulatory model must include the main factors that affect the performance of the decision-maker, failure percentages suggest that important factors have been ignored. Our model lays the foundations of the positive and normative part of a vision of bounded rationality whose outcome is adaptation.

Technological development has allowed improving simulation systems like social laboratories. Many works have focused on the understanding of basic processes of diffusion and games coordination networks giving ideas on how individual behaviour are transformed into various group behaviors, how the network structure has an impact on the aggregated results, and how the position in the network is important. These works may provide information relevant on questions related with the design of organizations and markets or with those forms of intervention.

But this development will be impossible without the implementation of a realistic individual behavior, which is supported by the idea of bounded rationality and to define the results of individual action. A model of simple decision can help the subsequent complex grouping and interaction process. Our model allows establish an individual basic behavior depending on the performance of the alternatives. Over this it can build interactions that allow see macroscopic behaviors of systems depending on rationality level of agents. On the other hand, we found important similarities with the main learning models. It may be interesting future research develop learning models whose basis is on the concept of bounded rationality picks up in this work.

The mathematical model resulting from the heuristic rule described here in represents a model of agentic behavior with bounded rationality that can be incorporated into various spheres of knowledge such as opinion models, models of group behavior, game theory, the comparison of systems of distribution of authority, the adoption of innovations, and the approval of projects, particularly in fields that utilize ABMs.

Agent-based models (ABMs) are among the most frequently used methods for evaluating outcome in decision making (Macy and Willer, 2002; Carley, 2002; Chang and Harrington, 2005; Harrison et al., 2007; Fioretti, 2013). ABMs have been used to model the incorporation of individual behavior into organizational or market designs. This method enables us to examine how individual decision-making processes, mutual influence and the exchange of information influence a group result. Fioretti (2013) defines ABMs as a virtual reality where actors interact, eventually repeating certain interactions along recurring patterns that constitute a sort of collective decision making. They are representations of complex realities expressed through algorithms.

ABMs were developed amid growing interest in calculating the values of the variables represented by interactions between objects. Each object (or social agent, in organizational and market research applications) implies a sequence of instructions about how to make decisions and interact with others. The resulting interactions can be as large or complex as the simulation in finding a meaningful solution.

This paper has presented a heuristic choice model that allows for the incorporation of error and thus the bounded rationality of ABMs. It sets out the probability of choosing correctly or incorrectly for each agent, which is easily programmable in future simulations. This behavior by agents can be introduced into sequences of random mutual interaction with neighbors within a network, describing opinions or making decisions. Bounded rationality (Simon, 1947; March and Simon, 1958) and social influences (Friedkin and Johnsen, 1990; Flache and Macy, 2011), as conditions of individual behavior that mark final group decisions, are the basis of organizational research and market research. What we propose here is an instrument for representing bounded rationality that will facilitate the study of organizations and markets in which individuals with bounded rationality act as blocks of information processing.

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