# Decisions by Inexperienced Agents

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**Abstract**

The neoclassical theory of economics assumes a fully rational agent. Already a well established experimental economics field, however, demonstrates that this is not the case for the common people. Rather, we all exhibit that our minds are bounded. This behavioral stream of literature tries to explain why our decisions are surprisingly quite close to optimal in complex problems despite the fact of bounded rationality. Simple heuristic rules appear to be the explanation when considering experienced agents. I present a model when uncertain future circumstances do not allow the agent to be considered to be experienced. To get an experience, she needs to provide a costly effort of gathering information. Not complexity, but uncertainty makes the agent "inexperienced". The model exhibits how the agent can become more experienced and consequently, how her decision making develops into more precise process.

## Introduction

Almost fifty years after Simon (1955) presented the first behavioral model of decision making the vast majority of economists still stick to the rational agent, although it enjoys rather scarce support by empirical observations. In the rational-agent literature, it is directly assumed that the agent incurs no costs during the decision process, e.g. for obtaining the set of alternatives, for anticipating uncertain future states of nature and options' outcomes, nor for making (usually nontrivial) computations, thus leading to a "Laplacean Demon", as introduced in Gigerenzer (2002).

Fortunately, there is an increasing effort of investigation regarding decision making agents with bounded rationality in recent literature. For the bounded-rational agent, the empirical results suggest and theoretical work analyses that people simply choose an appropriate heuristic from an "adaptive toolbox" they possess, and thus avoid deeper searching, simplify anticipation and substitute computations by acquired choice rules.

However, a common denominator of these two lines of thinking is that there are attempts to have an ideal agent, who is able to perfectly (or almost perfectly) decide about the solution, with no or negligibly small costs. The focus on heuristic thinking is reasonable in some situations and environments, where a decision routine can be implemented. Usually, these routines are imitated from other agents, or based on personal experience. Therefore, they function as if the bounded-rational agent "solved" without any cost the optimization problem, i.e. as if she behaved as the fully rational agent.

It is often mentioned in the literature on bounded rationality that an "experienced agent" (or "skilled agent") differs in the decision making from an "inexperienced agent". The former usually provides remarkably lower deliberation and her final decisions are generally better. Indeed, it has been shown in several experiments that skilled decision makers do better when they trust their intuitions than when they engage in detailed analysis (Kahneman 2003). This is in line with the empirical results (cf. Kahneman et al. 1997, Ofek et al. 2002) showing that, under certain circumstances, the previous experience and past decisions affect and predict fairly well our actual decisions. Furthermore, Betsch et al. (1998) empirically demonstrated that novelty in task presentation provokes routine deviation and increased deliberation.

An interesting question arises: How do people decide when they lack relevant experience or information? Or in other words, how do they decide if a lot of novelty is present in the decision problem? Do they tend to use heuristic tools, which are not so efficient in these situations, or do they prefer to use more deliberation, which leads to additional costs?

I present a model which is somewhere in-between of the two theoretical directions. The model reasonably assumes that some parts of the decision process are costless (or leading to negligible costs) and some subprocesses are costly for the agent, and importantly, it is worth to expose the agent with deliberation there. It will be shown that, oppositely to the rational agent, utility maximization and preference ordering may not be equivalent for agent with bounded rationality. More precisely, using preferences may lead to a decision process which is much less costly than utility maximization.

Up to my knowledge, there is no effort in the behavioral literature to define precisely an experienced agent, mentioned above. I will try to fill this gap by discussing some plausible definitions to point out that *uncertainty* is very the factor that makes the agent inexperienced. I will also argue that very the presence of novelty in the decision process leads to a decision model as the one that is introduced in this paper, because the standard heuristics cannot be used in this setting. We need a decision rule which deals with uncertainty, not with complexity, as the majority of frequently discussed heuristics do. Obviously, some parts of this model may also be called heuristics, as they offer rules for making decisions. However, they are not as simple as the rules the word heuristic is typically assigned to.

## Theoretical Framework

### Decision Process

It is generally agreed in both rational agent and bounded rationality fields that an agent comes to the final decision in a sequence of steps. Also psychologists argue that reasoning is a set of slow, serial and effortful operations (see Kahneman 2003). Suppose the decision process is characterized as follows.

(1) The set of decision alternatives is recognized,
(2) For each option, its future outcomes are recognized,
(3) The expected utility of those outcomes is estimated,
(4) The option with the highest expected utility is chosen.

A well-known result from economic theory says that utility maximization is equivalent to preference ordering for a rational agent. That is, the decision process can equivalently be stated in the following way.

(1) The set of decision alternatives is recognized,
(2) For each option, its future outcomes are recognized,
(3') The preference ordering over the alternatives is estimated,
(4') The option which dominates all other alternatives is chosen.

Of course, the rational agent is perfect in all those steps. The set of decision alternatives is fully recognized, the future outcomes are correctly evaluated and respective probabilities are faultlessly anticipated, expected utility is precisely computed, preference ordering is undoubtly done, and finally, the optimal option is decided upon.

However, a bounded agent may fail in any or even in all of these tasks. The decision costs, which may be due to effort for searching information, deliberation, or monetary needs, depend on particular decision problem. There are situations when it is very difficult to search for new alternatives and the agent may prefer to choose from among a restricted set of options, instead of having broader (or full) set of available possibilities. Sometimes, one's information-processing "unit" is not capable to deal with all the accessible information, leading to imprecise expected utility computations or wrong preference ordering. In some cases, disturbing factors, such as regret, may be present leading to imperfect choice in the last step.

I will focus on the problems of the recognition of future outcomes of the alternatives, having a consequence that the expected utility cannot be calculated and preference ordering cannot be done *with certainty*. There are many important decision settings where very this step is the most problematic one, and other actions are rather simple, thus inducing negligible costs to the overall decision process. This is an interesting issue, because simple heuristics cannot be used in this setting. There is usually no simple feature to prevail, some information may be missing or unreliable, it is impossible to imitate the solution etc. (See the examples in the next paragraph.)

Deciding for a Ph.D. thesis supervisor or choosing a house for living, are examples of such problems. The sets of alternatives in these two examples are quite simply accessed, as they are restricted by known factors: the supervisors must be from the agent's department or field and houses must be offered by a real estate agency (assume that the agent does not like to buy it directly from an individual because of very high risk). The list of alternatives may thus be easily accessed for example by the faculty web page and the agency web site, respectively. Once the future outcomes are well predicted (e.g., based on characteristics of each researcher and each house, respectively), one usually does not have any difficulty in making the final choice. The really problematic part is to prognosticate the future outcomes, such as how the agent will enjoy the thesis topic, if the supervisor will pay attention to her investigation and lead her well, what is the possibility to publish in a top journal warranting a good start for professional career, etc. One can easily think of similar attributes for the house case.

### The Model

Many authors from the bounded rationality stream admit that there is a structure of decision making process, depending on particular problem and/or its environment. Bear in mind that we are trying to analyze a problem, where there are typically many (completely known) alternatives and the decision is very important in the sense that it influences significantly our future life (utility). A typical approach to this kind of problems is acquiring information by "batches", in several rounds. First, we tend to obtain some basic and not very costly information about each alternative (e.g. the field of interest and the professional career of researchers; the price and location of houses). Based on that, we narrow (significantly) the set of alternatives, and do the same process of searching for more detailed information. We repeat the process until we are left with a unique option that we accept (if it satisfies our minimum expectations).

We will now specify the model more precisely. Let the set of alternatives be completely known by the agent. Each alternative $a$ leads to a flow of future outcomes, which are assigned to perfectly known states of nature, so that an alternative is completely characterized by a level of expected utility $EU_a$ (for the agent). However, the future outcomes are in general not obvious and the agent can only estimate them. If she puts an effort to search for additional information on a given alternative, her estimate gets better. Her estimation of expected utility from an alternative $a$ providing an effort $p$ may be characterized as a random realization $EU_a(p)$ from a distribution with mean value $EU_a$ and variance decreasing in effort $p$. However, providing an effort is a costly activity for the agent and it is given by an increasing cost function $C_a(p)$.

We can consider without loss on generality that the effort $p$ is ranging between $0$ and $1$ and can be interpreted as a probability of having a complete information, or the level of "being sure" about given alternative. When the effort $p = 0$, the agent does not have any information about the alternative, so it is reasonable to assume that the realization $EU_a(0)$ has a distribution of infinite variance. On the other hand, when $p = 1$, the agent has perfect information and so $EU_a(1) = EU_a$ (the distribution variance is zero).

The decision maker may possess some prior information about some of the alternatives. Moreover, it has been argued in the literature that the agent usually "has a solution in mind", that is, she already knows, what is a rather good choice (Betsch et al. 1998). This pre-existing solution is in general not optimal, because it has to do with intuition that can be shaped by many factors, including prior choices and behavior, reference-dependence and framing effect. The alternatives that people face arise one at a time, and the principle of passive acceptance suggests that they will be considered as they arise. Their existence can also appear in situations, e.g. when it is easy to imitate the decision made by other agents, when the agent has already faced and solved a similar problem that indicates which alternative should be chosen (having a habit or routine), or when she values much her intuition. Indeed, psychological experiments demonstrate that when a set of objects of the same general kind is presented to an observer – whether simultaneously or successively – a representation (prototype) of the set is computed automatically, which includes quite precise information about the average (cf. Kahneman 2003).

The agent may then rely on such a priori solution, or may decide to put some amount of effort, depending on her beliefs about the possibility to improve the solution. These beliefs usually strongly depend, apart of other factors, on the estimation (or the belief) of the expected utility of the alternative finally chosen. There are various empirical observations confirming this statement, including auctions, when the people often pay for an object much more than what is its objective value. This happens because they overestimate the expected utility of the object, which draws the maximum acceptable price for the buyer up.

To put this prior solution existence into the context of our examples, the decision maker may know some of the possible supervisors from class where she might find a relevant information, or a real estate agent may have very strong intention to sell a particular house to the decision maker, so that the former provides some information without having the decision maker to put any conscious effort. The existence of the ultimate solution is manifestable as well. The supervisor decision maker knows what the typical "very good" course of thesis supervision is: open discussions, interesting and important topic, attending conferences, publications in top journals etc. For the house it is even clearer: everybody has a "dream house" in his mind.

We will denote by $p_a^0$ the level of the prior information for an alternative $a$. It is as if the agent already has incurred the cost of $C_a(p_a^0)$ before she is faced by the current decision problem. This cost cannot be recovered, so it is not included in the cost investment for the current problem. That is, if the agent invests an additional effort of $p_a$ during the decision process, the total deliberation cost she incurs is $C_a(p_a^0 + p_a) - C_a(p_a^0)$.

We can finally achieve the utility function of the agent. If the decision maker ends the decision process with an effort $P_a$ on exploring an alternative $a$ and chooses finally an alternative $A$, we will consider that the total expected utility of the agent is given by

$$TEU = EU_A - \sum_a \left[ C_a(P_a) - C_a(p_a^0) \right]$$

Note that by definition, it is always $P_a \geq p_a^0$ and since the cost function is increasing, the difference $C_a(P_a) - C_a(p_a^0)$ is always nonnegative. Therefore, there is an upper bound on total expected utility $TEU \leq EU_A$. However, there is no lower bound on $TEU$ that would guarantee that total expected utility be positive. It depends on the cost function, on the alternative finally chosen, and on the levels of efforts on *all* alternatives. It may happen that $TEU$ be negative – when the cost of effort is higher than the improvement of the decision, which may simply occur, because at the end of the process there still can be some level of uncertainty in the agent's information.

We will add to the model an assumption that the decision maker has an a priori solution. Let $B$ be the a priori preferred alternative (we require that we have some prior information about it, i.e. $p_B^0 > 0$). If the agent were perfect in predicting the future outcomes (i.e. could anticipate them without uncertainty), she could simply compare the expected utility of the a priori solution $EU_B$ and the expected utility of the finally chosen alternative $EU^*$, and decide to invest any effort of cost lower than or equal to $EU^* - EU_B$. Note that investing precisely the amount of this difference leads to the same utility as effortless accepting the a priori alternative, and investing more than it leads to unfavorable state, since she is better-off taking the a priori preferred alternative.

However, a bounded agent does not predict future outcomes perfectly, so in the beginning of the decision process she only possesses an estimation of the expected utility of the prior solution $EU_B(p_B^0)$ and an estimation of the expected utility of the finally chosen alternative $EU^*$. Therefore, she is not going to compare the difference $EU^* - EU_B(p_B^0)$ with zero. For positive, but too low value of this difference, the decision maker will still prefer taking the a priori solution, reflecting the uncertainty of the values $EU_B(p_B^0)$ and $EU^*$.

Looking on the heuristics typically discussed in the literature we can reveal that almost all of them lead to some kind of dominance rule. Because time is scarce, decision makers ignore some elements in decision problems while selectively thinking about others (Gabaix et al. 2003). A bounded agent looks for a rule (heuristic) which would help her to say easily that one alternative somehow dominates another. A list of most common empirically observed heuristics is given in Goldstein et al. (2002). In *Imitation*, an alternative dominates another if it is preferred by other agents. In *Take the Best*, the dominance is defined as the dominance in most important factor. In *Take the First*, an alternative is accepted if it dominates an aspiration level. In *Recognition Heuristic*, the domination is based on recognition (what the agent does not recognize, it is considered to be dominated). Therefore, it seems that we may conclude that the only real decision rule is "dominance", in whichever sense. This is also suggested by empirical observations of dominance violations as there appear to be two distinct modes of choice: choosing by dominance rule and choosing by liking, if the former is not accessible or easily applied (Kahneman 2003).

I am about to propose a dominance rule which will be useful in our model, because it deals with uncertainty. To show the idea of the rule, we will assume that the realizations $EU_a(p)$ are drawn from the normal distribution (of mean value $EU_a$ and variance decreasing in effort $p$). Suppose we have the estimations $E_1=EU_1(p_1)$ (from the normal distribution function $P_1 \sim N(EU_1, V_1)$) and $E_2 = EU_2(p_2)$ (from the normal distribution function $P_2 \sim N(EU_2, V_2)$) for two of the alternatives, where $E_1 > E_2$. Based on this information, we are asking whether in the true expected utilities holds that $EU_1 > EU_2$ under a probability level of error $\alpha$.

We define that the value $E_1$ $\alpha$-dominates the value $E_2$, if $E_1 - E_2 > z_2(\alpha) - z_1(\alpha)$, where $z_1(\alpha)$ is the value such that $P_1(X \leq z_1(\alpha)) = \alpha$ if the mean $EU_1 = 0$, and $z_2(\alpha)$ is the value such that $P_2(X \geq z_2(\alpha)) = \alpha$ if the mean $EU_2 = 0$. Since the distributions are normal, we can write the dominance rule as $E_1 - E_2 > z(\alpha)(\sqrt{V_2} + \sqrt{V_1})$, where $z(\alpha)$ is the critical value that comes from the normal $N(0,1)$ distribution.

It is possible to shed light on this definition using simple geometrics. As $E_1$ is expected to be equal to $EU_1$ (because $E[E_1] = EU_1$), then $E_1 + z_1(\alpha)$ represents the point such that $EU_1 > E_1 + z_1(\alpha)$ with probability $1 - \alpha$. So, there is a one-tail $(1-\alpha)$-confidence interval $(E_1 + z_1(\alpha); \infty)$ for $EU_1$. Similarly, $(-\infty; E_2 + z_2(\alpha))$ is a one-tail $(1-\alpha)$-confidence interval for $EU_2$. If the two intervals do not intersect, we say that $E_1$ $\alpha$-dominates $E_2$.

Coming back to our model, the agent now has a rule for deciding whether to stick to the a priori decision or to put some effort and try to improve it. She will invest an effort only if $EU^* - EU_B(p_B^0) > z_B(\alpha) - z^*(\alpha)$, where $z_B(\alpha)$ comes from the distribution of $EU_B(p_B^0)$ and $z^*(\alpha)$ comes from the distribution of $EU^*$. Moreover, the maximum cost of effort she may provide is given by the difference $EU^* - EU_B(p_B^0) - (z_B(\alpha) - z^*(\alpha))$ and the appropriate amount of effort leads to no improvement comparing to the effortlessly choosing the a priori preferred alternative. Hence, the decision maker will choose just a fraction $\beta$ $(0 \leq \beta \leq 1)$ of this difference to be spent on deliberation (information seeking), which may be inferred for example from her aspiration level, from the minimum improvement she is willing to put an effort for, or from the past experience about the preciseness of her estimations. Therefore, we will denote by *TEC* the total expected costs spent over the decision process, which is given by the expression

$$TEC = \beta\left(EU^* - EU_B(p_B^0) - (z_B(\alpha) - z^*(\alpha))\right).$$

In the next step, the agent will provide the effort. However, before doing that, she will allocate the cost she is willing to spend (*TEC*) among alternatives. It is argued in the literature that decision makers have an idea about the structure of decision process before engaging in the decision making itself. We will suppose that the decision process is done in rounds, which is a common approach in the cases as we are focusing on. In each round, the decision maker has a set of alternatives, on which she allocates the effort according to the cost planned to be "spent" in this round. After providing the effort, she checks for $\alpha$-dominance and discards all alternatives which are $\alpha$-dominated by some other alternative available. This procedure is repeated until the agent is left with a unique alternative that she chooses as the final solution.

Put formally, the agent estimates the number of rounds $n$, based on her past or obtained experience of the decision process in this particular situation. Then, she allocates the total expected cost *TEC* among those $n$ rounds, denoted $(C^1, C^2,\ldots, C^n)$. In the beginning of a round $i$, if $N_i$ is the number of alternatives considered in this round, she also needs to distribute the cost $C^i$ among those alternatives: $(C_1^i, C_2^i,\ldots, C_{N_i}^i)$. Then, the appropriate levels of effort for all alternatives is figured out and provided. Thus, the estimations of expected utilities are updated (together with the distributions) and a comparison of those estimates is made. This comparison is more precise in every subsequent round, because providing an effort decreases the variance of the distributions the estimates are taken from, and so, the threshold value $z_2(\alpha) - z_1(\alpha)$ gets smaller.

## Additional Comments

The model described in the previous section was tried to be presented in a very general and at the same time in a precise way. Several aspects may be simplified or made more complex. Although it may seem now to be very complicated model and our assumption that the agent does not incur any cost when doing all the deliberation steps discussed earlier may sound like unrealistic, it is not the case much of the time. People simplify and we will do the same with the model and present in the next section a particular case of it.

The complexity of the model can be increased and, if done intelligently, it will lead to lower costs. For example, the agent may adapt her behavior to the actual information after each round. Typically, the agent gets closer to the optimal solution after each round and so, she may change her preferred alternative. Then, she may reconsider all the information and use it as the a priori information for a new decision making process with the same structure. Therefore, it is likely that she will decrease the expected number of rounds and that she will reestimate the *TEC*, which altogether should lead to a more precise decision.

However, it seems that people usually do not actualize the information so often and they follow the strategy that came to their mind when they were faced by the problem, as this strategy came usually to their mind unconsciously and without any cost. A similar argument applies to the possible actualizations of the information after effort on each alternative is put, or even in a continuous way, as it is often done in theoretical discussions.

It is not difficult to see that our agent may be called "experienced", if her prior information is relatively high, so that coming to a decision does not require much effort and the outcome is fairly precise. Clearly, the more prior information, the more experienced the agent is. However, it seems to me that it would be better to consider a bit more complicated rule, because this one does not capture an important issue of how precise her information is. For example, the higher number of alternatives with relatively low variance, the more experienced agent, or considering higher weight for the "better" alternatives than for the "worse" ones, since the information about relevant alternatives is more important than about the rest.

We can learn from the model that if an agent is experienced enough, she will not invest much effort into the decision process. For example, if she is familiar enough with all alternatives (all $p_a^0 > p > 0$), she may discard many alternatives even before the first round of effort. Or more interestingly, if her a priori solution is good enough, her *TEC* may be negative, recommending not entering into decision process at all. Opposingly, this does not happen for an agent who is not familiar much with the problem. Such an agent has a strong incentive to engage in the decision making as it is very likely that she improve her a priori solution.

It was not discussed in the previous section, besides some very basic features, how the cost functions and the variance of the estimates depend on the effort provided. However, they are closely tied to each other. The typical case is that the cost functions are increasing and convex, whereas the variance (or standard deviation) of the estimates is decreasing and convex. Moreover, they are problem-dependent, that is, they must be scaled according to the values appearing in the considered problem.

For a rational decision maker, it is costless to consider preferences instead of utilities. However, for a bounded-rational individual, it is not so, because she can avoid some deliberation costs when making the decision wisely. Very this result will be shown in the example that is presented in the final section.

## A Typical Case of the Model

Let $\{1, 2, \ldots, N\}$ be the set of alternatives, having the true expected utilities $EU_a$ for each $a$. Let the distribution of the estimations $EU_a(p)$ when providing an effort $p$ be normal with mean $EU_a$ and standard deviation (the square root of variance) $K_1(1 - p)/p$, where $K_1$ is a problem-related scaling factor (the same are the factors $K_2$ and $K_3$ introduced later). Furthermore, let the cost function be the same for all alternatives and given by $C(p) = K_2p^2/2$. As the cost function we have here is invertible, we have that the effort associated with its cost is $p(C) = \sqrt{(2C/K_2)}$.

Consider that the effort represents gathering information and that the cost is the time spent. The function $p(C)$ is easily interpretable: The amount of information depends on the time spent by gathering it. We can see that this function $P(C)$ is concave. Indeed, the gathering of information is usually more efficient in the beginning of the process; once the agent knows quite a lot, it is more difficult to find more relevant information about an alternative. This also explains why the cost function should be convex.

Let the alternative *1* be the a priori solution ($B = 1$) with $p_1^0 > 0$ and estimation of its expected utility $EU_1(p_1^0)$ and let $EU^*$ be the estimation (belief, expectation, etc.) of the finally chosen alternative's expected utility. The value $EU^*$ can be assumed to be a realization from a normal distribution with the mean $\max_a\{EU_a\}$ (which is again unknown to the agent) and standard deviation $K_3$ (inferred by the agent from her previous or acquired experience).

Finally, let $\beta = 1$ and the confidence level be $\alpha = 0.05$, so we can approximate $z(\alpha) = 2$. Hence we have $TEC = EU^* - EU_1(p_1^0) - 2(K_1(1 - p_1^0)/p_1^0 + K_3)$. The decision process is divided into $n$ rounds (as $\beta$ takes the maximum possible value, $n$ should be an estimation of the worst case), where for each round we allocate the same amount of cost $TEC/n$. Similarly, in each round we distribute the cost among alternatives evenly.

Note that, as we obtained a closed formula for the information level (or effort) $p$ depending on the time $C$ spent by gathering information, we can rewrite everything in the terms of the costs. Our model can then represent a problem of time allocation among several alternatives, without any need to deal with the effort variable at all. We will present it in the example that follows.

## An Example

We will apply the model from the previous section to a problem of choosing a house. Suppose there are $N = 10$ alternatives, with the vector of the true expected values $EU = (6, 1, 2, 3, 4, 5, 7, 8, 9, 10)$. To make the example a bit simpler, we will assume that the estimations are always correct (i.e. $EU_a(p) = EU_a$ for all $p > 0$) and the level of effort affects only the level of "being sure" about the value. Nevertheless, let the agent's estimation of the best alternative be overvalued (as it is often the case in practice): $EU^* = 11$. Let $K_1 = K_3 = 0.5$ and $K_2 = 2$. Let $p_1^0 = 0.5$ (so the standard deviation of the alternative *1* is *0.5*) and $p_a^0 = 0$ for all $a > 1$ (thus implying infinite variance). Finally, the agent will expect to make the decision in $n = 3$ rounds.

As the time function is $C(p) = p^2$, the inverse function for computing the level of effort for given time is $p(C) = \sqrt{C}$. Let $C^0$ be the vector of time units a priori allocated to the alternatives, that is, reached from the a priori information levels: $C_1^0 = 0.25$ and $C_a^0 = 0$ for all the other alternatives. The standard deviation for the estimate of an alternative $a$ is then given in terms of time by $0.5(1/\sqrt{C} - 1)$.

Therefore, we get that the total time expected to be spent by the decision process is $TEC = 11 - 6 - 2(0.5(1 - 0.5)/0.5 + 0.5) = 3$ units. The agent will allocate the time (cost) of *1* unit in each round. That is, the time of *1/10* for each alternative in the first round, leading to the overall time of $1/4 + 1/10 = 7/20$ spent on the alternative *1* and *1/10* for the rest of the alternatives. The standard deviations will become *0.345* for the first alternative and *1.082* for all the rest.

The dominance rule is $x - y > 2(\sqrt{V_X} + \sqrt{V_Y})$. Hence, for any pair not including the alternative *1*, the minimal difference for $\alpha$-dominance is *4.328*, that is, alternatives number *2, 3, 4, 5, 6* are $\alpha$-dominated by the alternative *10*. For comparing the alternative *1* with any other, the critical value is *2.854*, so it is also $\alpha$-dominated by the last alternative.

In the second round, there are only four alternatives (*7, 8, 9, 10*) left, so the agent divides the planned time of *1* unit into four parts, that is, *1/4* time units for each alternative. This leads to $1/10 + 1/4 = 7/20$ time units for each alternative. Thus, we obtain the standard deviation of *0.345* for each alternative, implying the critical value of *1.380*, so the alternative *10* $\alpha$-dominates the alternatives *7* and *8*.

In the third round she allocates a cost of *1/2* time units to each alternative, i.e., the overall time spent on each of the two alternatives will be $7/20 + 1/2 = 17/20$ leading to the standard deviation of *0.042* which implies the critical value of *0.168*. Hence, the alternative number *10* clearly α-dominates the alternative *9*.

The agent has decided correctly and her total time spent during the decision process was *3* time units. If she wants to find out all the expected values with certainty (as the rational agent does) she would incur the total of *10 - 1/4* of time units, which is far greater than following the sequential decision process. This shows that for an agent, for who the deliberation (information seeking) is costly, is more beneficial to use preference ordering than utility maximization.

## Conclusion

The model presented here has strong limitations. It is appropriate for a class of decision problems, but does not reflect their features perfectly. The cost of deliberation may not always be negative, any of us would agree that, in some situations, we like thinking, we like challenging! We undergo deliberation when the utility of final choice is low, or even when there is no final choice to be done. Similarly, time spent by searching for information may bring us an overseen and unexpected benefit, or we may prefer to explore an alternative when we expect to learn more about utilities of all alternatives. There may simply exist relevant characteristics that the decision maker does not know about. (Consider the information that it is better to have a house build on the south side of a hill because of energy savings.)

Although it is important to create pure fields of interests in order to make clear what a particular theory is and what is not, closing ourselves myopically in a restricted and perfect world has never been a great idea for creating a comprehensive understanding of the things around us. I have presented a compelling model for non-ideal agent – either in terms of perfect rationality or bounded rationality. It is now up to empirical studies to show its relevance for common decision makers.

I believe that the model is appropriate for a significant class of situations. For example, I and many other students have used a very similar way of deciding for our Ph.D. thesis supervisor. Therefore, the model designs a realistic decision process which is not uncommon in our lives.

The discussion done in the paper implies several, basically empirical, questions. First, one should test the preciseness of decision maker's a priori estimates of the final solution and the existence of the a priori preferred alternative. Second, it should be confirmed that there are situations, when agents use the probabilistic α-dominance heuristic, which is expected to be particularly exhibited in the decision processes bearing high uncertainty. Third, it is necessary to demonstrate that people do their decisions in sequences, and observe how and to what extend they update their information between single steps of the decision process. Fourth, it should be documented how the expected costs are allocated through the course of decision, for example, if the alternatives which are more likely to be optimal are being explored more than the other alternatives.

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