1

Understanding Human Decision Making – A Fundamental Step Towards Effective Intelligent Decision Support

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Summary. As researchers try to accumulate knowledge in artificial intelligence (AI), towards developing better models and artefacts to embody complex decision making processes based on the characteristics of human decision making, we are reminded that at the beginning of this whole endeavour our intellectual ancestors – Newell and Simon (1972) for instance, had warned that a comprehensive understanding of human decision making would be required if AI was to yield substantial benefits. In wondering whether this has been achieved, we trace back the accumulated knowledge in the area of human decision making from the work of Savage through to that of Simon and we critically assess whether we have reached the required critical mass in our understanding of human decisions. Such knowledge development is a requisite benchmark to measure the progress of research in artificial intelligence, as illustrated by the other chapters in this book.

1.1 Introduction: Neurobiology of Human Reasoning and Decision Making

Although decision making is an activity that is almost as exclusively human as language itself[1], its neurobiological components have not been studied until the end of the twentieth century, which is comparatively much later than the investigation of the biology of language (Damasio 1994; Damasio et al. 1996).

Research in this critical area has generated two fundamental results. First of all, it has revealed the existence of a centralised area in the ventromedial prefrontal lobe of the brain where reasoned decision making takes place (Damasio 1994; Fuster 1996; Berthoz 2003). Any destruction or lesion in this area leads to highly irrational behaviour in previously "normal" subjects, as

[1] "Decision making is, in fact, as defining a human trait as language" (Damasio et al. 1996)

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illustrated by the Phineas Gage case in Damasio (1994). One of the striking symptoms characterising subjects who have been injured in this area of the brain is their indifference to risk or at least, their inability to "properly" assess risk (Damasio 1994; Adolphs et al. 1996)[2]. An alternative hypothesis which has been put forward by Pomerol (1997b), but has not (yet) received empirical validation, is that these subjects may have lost their ability to arbitrate between short term and long term benefits or tradeoffs, thereby pursuing immediate satisfaction of their needs rather than future gains. This, of course, would tally up with the symptoms described in Damasio's and Adolphs et al.'s research, where subjects seem to be unable to properly take obvious risk factors into account. Indeed, this inability to anticipate risks has already been observed in other cases of frontotemporal mental deficiency (Schoenbaum et al. 1998; Berthoz 2003, p. 99).

Secondly, this research has shown the crucial role which emotions play in decision making. Damasio for instance, has gone as far as predicting that the role of reasoning in decision making would be found by future researchers to be less than is now thought. This is further discussed in Sect. 1.5 of this chapter, which is concerned with cognitive and decisional biases, in particular the *frame effect*. The reduced role of reasoning in human decision making is not necessarily a cause of concern for AI researchers, however, as although it is beyond debate that the emotional side of human nature has a strong effect on decision making activities, it does not mean that this aspect of human decision making is beyond modelling, as Simon (1995) has illustrated. Different models can be proposed to describe the effect of human emotion on decision making at a cognitive level, in the shape of short circuits or positive reinforcement. For instance, intuition or, intuitive decision making has been defined in previous research as an instantaneous, quasi automatic decision triggered by an affective, visual or sensorial stimulus. Klein (1993) went further when his studies of firemen and emergency response personnel led him to the concept of *recognition-primed decision*, where decisions are based on the recognition of previously known patterns and a solution is designed to match this pattern. Klein's work is crucial because it properly emphasises the importance of the *matching* aspect of decision making (see Berthoz 1996[3]).

These observations justify our belief that there are two key poles in decision making: *reasoning* and *recognition*, which are inextricably linked in the case

[2] "Subjects with VM (ventromedial) frontal lesions [...] invariably lose money on the task as a result of continuously choosing cards from the risky decks, even after they have had substantial experience with the decks, and have lost money on them. Interestingly, the VM frontal patients are quite aware that they are losing money, and some even figure out the fact that the decks from which they are choosing are likely to be more risky. None of this knowledge, however, appears to influence their abnormal behavior, and they continue to choose from risky decks despite continued losses" (Adolphs et al. 1996, p. 162)

[3] "The brain is a matching machine and a simulator of action, not a "representational" machine" (Berthoz 1996, p. 89)

of human decision making. However, one may wonder how specifically human such behaviour really is? It could also be hypothesized that this characteristic of decision making grew throughout natural evolution with the development of the frontal lobe, the most recent portion of the brain. The simple observation of Nature around us provides countless examples of decisions based on the recognition of stimuli with varying states of complexity, from the worm crawling away from a drop of acid to the sheep running away from the shadow of a plane mistakenly identified as a bird of prey. In the first instance, we can identify the increasing complexity of the pattern recognised (Berthoz 1996)[4], then, we move to the learning capacity identified in birds and mammals by Pavlov. Thus, to return to our initial questioning: is the behaviour of the dog fetching its lead when its master puts on his coat evidence of the premise of a reasoning capacity (on a lower level than those displayed by human agents, but reasoning nonetheless)?

It should further be noted that reasoning can only occur on a significant scale in the presence of memory. It is undeniable, as observed by Newell and Simon (1972), that intelligent information processing systems are all built around an apparatus that can capture and interpret stimuli, a number of specific memories and an apparatus for symbolic reasoning; indeed, this is a perfect description of the human brain. Thus, memory, reasoning and decision have evolved in tandem throughout human evolution. Of course, language can be added to this list insofar as it is very similar to decision making: both activities require the chaining of sounds, words and inflexions for language and of images, memories, facts and actions for decision making (Calvin 1991, 1994). The fact that case-based reasoning has been described as a language dedicated to decision making reinforces this point.

In this chapter, we review the two key aspects of decision making: reasoning and recognition. We review the classical models of previous researchers and evoke the arguments of their proponents and opponents. Finally, we examine recognition based decision making, reasoning based decision making and consider the cognitive biases that affect decision making, which takes us back to our discussion of the brain.

1.2 Procedural Rationality and Bounded Rationality

1.2.1 The Savage Model and Expected Utility

Even though Savage's (1954) model has been very well described in previous research, it is useful to go back to its key elements and to pragmatically examine its true meaning for a theory of action. Savage's (1954) model is primarily

[4] "But we have also proposed the idea that, (...) higher central loops that have increasingly gained complexity during evolution operate on another mode that we have called a projective process. In this mode, signals are processed in internal loops having no direct link with sensors" (Berthoz, 1996, p. 84)

important because it provides a formal and coherent framework to think about decision making. Savage rightly insists upon the crucial difference between the elements which the decision maker cannot control (Events, referred to as the set E) and the elements which he can control (Actions, referred to as the set A). Using a simple example, we can illustrate this difference with the story of the man going for a walk and considering whether to take his umbrella. Two actions are possible: (TU) and (NTU). For the sake of argument, we can also assume that only two events can occur during the walk: rain (R) or no rain (NR). We can then use the matrix in Table 1.1 to describe a function of A x E in the set of consequences C. Here the set of results is $\{-2,\ 1,\ 0,\ 2\}$.

Savage says that if the decision maker follows a coherent decision making path towards making a choice, then there is a set of probabilities and a utility function U such that the decision maker can seek to maximise his expected utility for the said probabilities. Savage's theorem is often used in reverse – i.e. to suggest which action maximises the expected utility of the decision maker given a set of known probabilities for possible events.

Savage's model formalises a number of key aspects of decision making even before one considers the theorem itself. Firstly it copper fastens the separation between events and outcomes. It is a fundamental point because most novice researchers of decision making "trip" at this first hurdle and confuse the skill of a decision maker with the lucky occurrence of a positive outcome. Indeed, human nature may push us to claim as evidence of good reasoning the fact that we took no umbrella and it did not rain, even though clouds are everywhere to be seen. Savage's theory, however, makes no mistakes: because you ignored the greater probability of rain and you were simply lucky not to get soaked! The theory appears kinder when considered in reverse: it admits the possibility that a sound decision should turn out to be a disastrous one. This aspect of the theory is closer to typical human understanding as many people are not slow to invoke bad luck in such cases. Thus, Savage's separation between events, actions and outcomes is probably, as humorously stated by Howard (1988), his most important contribution to decision making theory.

On second examination, however, one must wonder whether it is a realistic viewpoint to separate the universe in terms of actions and events. Indeed, some

Table 1.1. Example of a decisional matrix

	R	NR
TU	1	0
NTU	–2	2

actions modify future events. If a manager sets a price change for a product (Action), then the reactions of competitors (events) are clearly the result of the manager's action. Generally speaking, the separation of the decision maker and the environment (including the other actors around him or her) is nothing but a simplification of reality (see Boland 1979 for a well argued criticism). Savage's theory illustrates that such a separation, however simplistic, is a required hypothesis for whoever wants to propose a theory of decision making and of rationality.

Unfortunately, there are many cases when separating actions and events is not fruitful. Gilboa and Schmeidler (1995) provide two such examples. Their first example is that of a recruiter seeking to hire a sales representative. The actions are represented by the potential candidates that can be hired. Events, on the other hand, do not lend themselves to such modelling: they are represented by the qualities of the candidates, their honesty, their performance, etc. To properly describe such events, one would have to be cognisant of all the present and future capacities of each candidate. Thus, events are characterised by significant uncertainty which managers must reduce by collecting information and interviewing the candidates. This scenario is better analysed in terms of multi-criteria decision making as described in Pomerol and Barba-Romero (1993) for instance.

Gilboa and Schmeidler's second example is that of strategic decision making. In this case, the horizon of the decision maker is so long that events must be seen as long chains of consecutive events. The multiplicity of sub-events leads to a combinatory explosion of the number of events. The famous case study of the Bay of Pigs invasion provides an illustration of the difficulty in arbitrating the short term and long term objectives of such decision making. In such cases, it is simply impossible to consider all conceivable resulting events and the search is limited to a few scenarios some more likely than others. In the case of the Bay of Pigs, it is well understood that the scenario that actually unfolded was never contemplated by the Kennedy administration, or else, they would never have gone ahead! Savage's work is quite applicable to such situations, with the proviso that the complexity and interrelatedness of events over long periods makes it impractical to discuss any notion of expected utility! Using the decision tree model is much more interesting because it facilitates taking into account the sequence of unfolding events (Raiffa 1968). However, the basic problem of assigning conditional probabilities to all conceivable scenarios remains. When the concept of expected utility becomes as complex as in the above example, Gilboa and Schmeidler (1995, 2000a) advocate the use of case-based reasoning instead.

In closing, it is useful to illustrate what paradoxical situations may arise if the model used to describe the decision problem is badly set. The following example shows a gambler attempting to use the theory of to decide on which horse to bet between two possible winners, *Lame runner* and *Ate the wrong stuff*. This example is presented in the shape of a question: which one of the two models presented in Table 1.2 is the correct one? (cf. Poundstone 1990).

Table 1.2. Comparison of the two models

	My horse wins	My horse loses
Bet on *Lame Runner*	50	–5
Bet on *Ate the Wrong Stuff*	45	–6

Model 1

	p Lame Runner wins	(1-p) Ate Wrong Stuff wins
Bet on *Lame Runner*	50	– 5
Bet on *Ate the Wrong Stuff*	– 6	45

Model 2

In the first model, *Lame Runner* is always the good choice because it is always on top. In the second model, the correct bet depends on the probability of a win for either horse and it is a better bet to pick *Ate the wrong stuff* as soon as the probability of it winning the race is above 50/106. Thus, in the first model, actions and events are incorrectly linked, whereas the second model is the correct one.

This example of drastically incorrect modelling shows the theoretical importance of Savage's formal framework for understanding decision making, quite apart from any consideration of expected utility.

1.2.2 Criticisms of Expected Utility

An important component in the debate around Savage's work centres on the way that the probability of occurrence of events is measured. Specific probabilities can of course be assigned to each event, but alternatively, it is also possible to assign a fuzzy measure of probability (see Dubois and Prade 1985; Bouchon-Meunier and Nguyen 1996; Bouchon-Meunier and Marsala 2003). Discriminating between events based on the likelihood of their occurrence is indeed quite tricky. For recurring events, it may be possible to measure their frequency of occurrence over time and to derive probabilities from this data. This would apply for instance to a computation of the probability that a regular train will be on time on a particular day. This is a *recurrent probability.*

This situation can be found in medicine for instance, where it is possible to derive statistics for typical pathologies within specific populations. On the other hand, it is of no use in the case where a manager attempts to predict the price of crude oil in a 6 month forward frame. In this case, probabilities do not apply in a rigorous sense. Savage's contention is that even when there is no way to estimate probabilities, an internally coherent decision making process will automatically imply a de facto assessment of the probability of key events. In other words, the very fact that one is able to properly select one action amongst others reveals one's inner perception of the probabilities at play.

Specific criticisms have also been levelled at Savage's work. Allais (1953) criticised the *sure thing principle* (Savage 1954) because Savage's vision of independence means that the utility function is linear with regards to the probabilities which, although required for the mathematical coherence of the model, is unlikely to be true in practice (at least not all the time). A second criticism centred on the axiomatic aspect of Savage's work refers to the principle of coherence, in situations where the decision maker ignores certain types of actions because they simply aren't "on his radar", and also ignores events that don't really have an impact on the decisions made. Finally, Savage was also criticised because the probabilities described in his work may make good theoretical sense, but mean nothing to real life decision makers. The notion that the decision maker can express the probabilities pertaining to all future events and that he or she can then maximise their expected utility is not realistic. The probabilities assigned by a decision maker can only ever be a priori because they do not follow from observation and subjective because they do not rest on any specific knowledge of future events. Certain researchers have indeed likened such probabilities to guess work lacking any objectivity (de Finetti 1937; Nau 2001). This then amounts to trying to model uncertainty with non-probabilistic models – for instance by using a maximisation principle (e.g.: where the decision is argument of $\mathrm{Max_A}\ \mathrm{Min_E}\ \mathrm{U}(a, e)$). The most sophisticated of these models also consider the influence of the worst possible results as in Jaffray (1988) and Essid (1997).

Even though the concern that the a priori probabilities assigned by managers are very subjective, is a valid criticism of the theory, it is always useful to remember that, in practice, this never prevented managers from making decisions! The observation of actual decision makers in real situations illustrates the two different paths that are typically followed in business: (1) find experts that are supposed to be able to provide reasonable probabilities and (2) forget about pure rationality and make *reasonable* decisions. This case broadly corresponds to Simon's notion of *Limited Rationality.*

To conclude on the work of Savage, it is worth noting that the critique of the role of probabilities can also be levelled at the role of the utility function. In the end, the decision that a manager should take in order to maximise expected utility is dependent on the chosen utility function and this is a fundamental problem from both theoretical and empirical standpoints. Knight's observations (1921, p. 230) on the confusion between risk and uncertainty is relevant here since he defined the former as relating to "the logic of probability" and the latter as "the problem of intuitive estimation". There is scope for applying expected utility theory in situations of risk when probabilities may be assigned, however arrived at (a priori or statistical). Where uncertainty prevails, any data that exists do not lend themselves to statistical analysis and "Business decisions, for example, deal with situations which are far too unique, generally speaking, for any sort of statistical tabulation to have any value for guidance. The conception of an objectively measurable probability or chance is simply inapplicable" (Knight 1921, p. 231).

1.2.3 Bounded Rationality

Based on his observations on the way in which the municipal decision makers of his town of Milwaukee made their decisions, Simon came to realise early on the distance that there was between managerial practice and the model of expected utility. Following this initial experience, he devoted most of his scientific career to trying to understand human decision making (Simon 1991).

He understood that, if the model of expected utility does not offer a complete explanation of human decision making, i.e. where uncertainty is of interest, the Taylorian vision of Dewey (as quoted in Simon 1977) is not much more relevant:

- What is the problem?
- What are the possible actions?
- Which one is the best?

This simplistic vision of the decision problem is hardly operational insofar as:

- "Unfortunately, problems do not come to the administrators carefully wrapped in bundles with the value elements and the factual elements neatly sorted" (Simon 1997); the environment of the decision is primarily ambiguous and depend on the personal interpretation of the decision maker (March and Olsen 1976; Boland 1979);
- Possible actions are not given but must be built from experience (see Keeney 1992; Roy 2000).
- The selection of the best course of action rests on the proper identification of the criterion for choice, which brings us back to our criticism of Savage's work or to multicriterion decision making (see Sect. 1.2.4).

Based on these observations, Simon insists on the diachronic aspect of the decision-making process and introduces his famous normative model of decision making stages, which from the initial three will become four (Simon 1977). Thus, Simon initially presented decision making as comprising three stages:

1. The identification of all the possible actions (or alternatives)
2. The determination of the consequences of all possible actions
3. The evaluation of the consequences of each possible action

Compared to Dewey's three questions, Simon's contribution is obvious. His focus is on the processes and he does not say: "what are the possible actions", but "we must find them all" (difficult question!). Let us note in passing that this presentation also has the merit to avoid the hollow question of "which is the best action". Thereafter, Simon adds several other aspects to the various phases of his decision making process, in particular with regard to problem representation, the way of posing the problem (or "setting the agenda") and the search for information. This leads to his seminal work on the four phases (Simon 1977):

1. Intelligence
2. Design
3. Choice
4. Review

The role of information is fundamental in the first two phases, for one chooses only among the actions which one identified and was able to document. Thus, as Simon indicated: information constrains the decision. Notwithstanding the criticisms levelled at his presentation of the decision process, Simon was perfectly conscious of the connections between the various phases and he provided examples of iterations between phases; even stating that each phase can be recursively regarded as a decision in itself (Simon 1977, p. 43). But undoubtedly the most significant contribution of this seminal normative model is that post-Simon, it has become more difficult to reduce the decision to the moment of the choice: “All the images falsify decision by focusing one the final moment” (Simon 1977, p. 40). This change of attitude will kill off a certain vision of the decision as mythology or epic (Julius Cesar crossing the Rubicon or De Gaulle launching the Concorde) to bring it back in the domain of management and a more scientific and systematic observation of its reality.

Finally, Simon was well aware of the fact that the decision, once taken, must still be implemented: “In the foregoing discussion I have ignored the fourth phase of decision making: the task of carrying out decisions. I shall merely observe by the way that seeing that decisions are executed is again decision-making activity” (Simon 1977, p. 43). He added (p. 44): “Executing policy, then, is indistinguishable from making more detailed policy”. In the end, actions and decisions are inseparable for Simon and execution is merely a progression towards increasingly small decisions that can be readily implemented. This fundamental idea has yet to be exploited in management.

The framework defined by Simon makes it possible to connect decision and information but it is not rich enough in terms of understanding choice and analysing the role of future events. It is precisely at the core of the debate on the cognitive limits of human decision makers and their incapacity to predict events far in the future, which is necessary to apply the model of Savage. In other words the limitations of the brain and the nature of business decisions make it impossible to face the combinatory explosion of all the possible scenarios (Pomerol 2001). This led Simon to ask some awkward questions such as: how can a decision maker evaluate all the consequences of an action and compare them between them? We still don’t have answers to these questions.

Simon had an interesting vision of the knowledge of the decision maker and his or her capacity to evaluate consequences (Simon 1997, p. 85). The problem of evaluation of the consequences of an action is central in any decision-making process. In Savage’s work, the evaluation of the consequences supposes the knowledge of all the future events with their probabilities. In theory, it may be enough to maximize a function of utility for a set of choices, but the difficulty is to determine what is, in practice, the role of reason when there are neither clear choices, nor a complete utility function and managers operate with a minimal knowledge of future events.

In his book "Administrative Behaviour" Simon admits that the question we asked in the previous paragraph, in particular, about the evaluation of the consequences in uncertain situations is not solvable by a human mind in the terms of the expected utility model. Simon calls this "absolute" rationality which would require that one chooses, following the model proposed by Dewey, the best possible action (i.e. an optimised choice) having evaluated all possible consequences going 100 years into the future. According to Simon, this *substantive* rationality, as he later called it, is a practical failure because (Simon 1997, p. 93–94):

- Rationality requires a complete knowledge and a total anticipation of the consequences of all choices. In practice knowledge on the consequences is always partial especially in uncertain or ambiguous situations; This question of exhaustiveness is also central in Janis and Mann (1977) and Klein (2002)
- Consequences are a matter of speculations and the mind must fill in the blanks in assigning values to them
- Rationality requires choosing among all the possible actions that have been identified (March and Simon 1993, p. 159). In reality, only a small number of possible actions come to mind
- The decision maker does not hold a complete set of preferences for all possible consequences, i.e. he or she does not have complete utility function (March and Simon 1993, p. 159). There are therefore difficulties inherent in the ranking and comparing of the alternatives (Janis and Mann 1977).

The core criticism levelled by Simon boils down to the fact that, except in very simple cases, using subjective expected utility (SEU) in a correct way is simply impossible. Indeed, his criticisms presented above are aimed squarely at the implicit assumption of the model of expected utility. He said: "When these assumptions are stated explicitly, it becomes obvious that the SEU theory has never been applied and never can be applied – with or without the largest computers – in the real world" (Simon 1983, p. 14). The volume of knowledge necessary to apply the model justifies that Simon should call it the *Olympian* model (Simon 1983, p. 19). In his work, Simon will endeavour to replace these *Olympian* assumptions with realistic assumptions. In 1955, these assumptions will then become the basis of bounded rationality. These can be summarized as follows:

- It is impossible to assign probabilities to all the events and even quite simply to enumerate all the possible events with their permutations.
- The preferences of the decision maker are not rational insofar as there is no possible maximization of a utility function. In fact, they are multi-criterion

and variable, which means it is impossible to have a complete utility function for the choice made.

- Decisions and their consequences are spread out in time and, in organizations, form a temporal process in which all sub-decisions are not independent from other sub-decisions, but can be made at different times and levels based on evolving criteria. In addition, preferences, actions and goals cannot normally be readily separated ("closely related to the idea that actions generate their goals is the fact that action is itself an important goal in the lives of many people" (March and Simon 1993, p. 15)); The articulation of the sub decisions as described above rules out any form of overall optimization (Simon 1983, p. 18).
- Information is fundamental and conditions each decision. This is perfectly illustrated by the small number of actions which an individual is able to study seriously. The limited attention of managers further constraints and limits the analysis of the problems facing them and conditions subsequent decisions. Attention is a rare resource and it tends to be concentrated on the most salient problems.

This means that, since we cannot have complete knowledge of the world, we, as human decision makers must aim at making sub-optimal or satisfactory decisions, which Simon labelled "satisficing". In practice, the decision-making process stops as soon as the decision maker finds a solution which gives satisfaction taking into account the most plausible scenario, and is also unlikely to turn out to be catastrophic. Simon (1984, p. 594) evokes explicitly how "satisficing" operates. He explains that an action is satisfactory as long as it reaches or exceeds a certain level of aspiration for the criteria considered by the decision maker (March and Simon 1993, p. 161). It must also be noted that the level of aspiration evolves during the intelligence phase and is interpreted at a local level depending upon the difficulties of reaching it (Selten 2002). The concept of "satisficing" tends to become increasingly important in Simon's work after 1960 such as Simon (1983). The limited rationality of 1955 is gradually replaced by the "bounded rationality" (Simon 1972). This "bounded rationality" is more and more frequently presented in algorithmic form as was already implicit in 1955 in the form of a "satisficing rule". The algorithmic aspect stresses the sequential and heuristic aspects of decision-making processes. Thus, following Gigerenzer (2002) it is possible to summarize the notion of bounded rationality with a number of fast, rough and robust rules: (1) for the intelligence phase, (2) to stop searching for information and (3) to make a choice (Gigerenzer 2002). This vision justifies the use of the term *procedural rationality* (Simon 1976) which Simon opposed thereafter to substantive rationality. This evolution in Simon's thinking is accompanied by an increasing interest in artificial intelligence ("Alternatives of action and consequences of action are discovered sequentially through search processes" (March and Simon 1993, p. 191)). The heuristic process involved is characterised by the use of procedural rationality, because rationality is used in the search for information, while at the next stage, the manager's thought process or "problem solving" is characterised by substantive rationality (March and Simon 1993, p. 200). In searching for information, managers follow a form of procedural rationality which obeys a program just like a heuristic search. The criterion used to interrupt the search is the satisfaction of the decision maker when a "satisficing" level is achieved taking into consideration his or her aspirations.

The fourth limitation of rationality in our above list, is critical because it presents a dual aspect. Firstly, there is the informational aspect – i.e.: that the quantity of information which an individual can process is limited. In the "information age" where we are plunged, the gap between the information potentially available and what a decision maker can apprehend is widening (it is even truer with the Web). Simon (1955) explained: "Broadly stated, the task is to replaces the total rationality of Economic Man with a kind of rational behaviour that is compatible with the access to information and the computational capacities that are actually possessed by organisms, including man, in the kinds of environments in which such organisms exist". This first aspect leads to a second idea: that the cognitive resources are also limited (Bell et al. 1988). In fact, one already finds in Simon's "administrative behaviour" the first reflections on the role of attention, information and the stress in the decision process (in the chapters devoted to psychology). These considerations will lead Simon to the problem of cognitive load in decision making. He describes attention as a rare resource (especially in view of the limited cognitive capacities of human beings) which plays an important part in the decision process. This topic is pursued in his book with March ("... the ways in which attention is allocated is critical to understanding decision" (March and Simon 1993, p. 4)) and becomes one of the key elements in the garbage can model (Cohen et al. 1972).

As Simon's thinking evolves, cognitive limitations gradually became a major element of limited rationality by reference to the brain as a system for symbolic processing. "In its simplest form, the theory of limited rationality is a theory of "how to live" in an infinite world, while having only very modest means of computation; means which do not depend on the size of the real world, but only of the local environment and what you can do there" (Simon 1984, p. 595). Simon's contention is that managers must make do with their capacities which rules out the exhaustive study of all possible actions and their consequences. Thereafter Simon will often oppose the procedural rationality which is the rationality whereby human beings seek to understand the consequences of actions with their limitations in information, in cognitive capacity and in attention, which is inherently a *satisficing* rationality[5] leading

[5] "The idea of limited, consequential rationality found in the book has become more or less standard in modern theories of decision-making, at least outside the hard core of orthodox neoclassical economic theory" (March and Simon, 1993, p. 9)

to satisfactory decisions, as opposed to the substantive rationality which is the preserve of the Gods and which is inherently an *optimizing* rationality.

The model of limited rationality is, according to Simon, a middle of the road model (Simon 1997, p. 331) half way between the point of view of some Economists who tended to believe in pure rationality but some of whom now examine alternative models to the maximization of utility and, on the other side, the point of view of those that the notion of rationality frightens and who argue that managers are purely reactive and intuitive in their behaviour (e.g.: case-based reasoning research). As we see it, bounded rationality was the first attempt to provide a scientific framework for the rigorous and meaningful study of real decisions made by real decision makers in real life organizations. This explains why the concept of limited rationality has had such an impact, even 50 years on.

1.2.4 Multi-Criterion Decision Making

Simon was one of the first researchers to express with a certain scientific authority that real life decisions are characterised by more or less contradictory criteria insofar this observation is one of the components of limited rationality. This observation had obviously already been made by real life decision makers and Benjamin Franklin suggested the "for and against" method where arguments for and against are cancelled out until one of the columns is empty (letter with Joseph Priestly, see Zionts 1992).

The concept of multi-criterion decision making is fundamentally human in the sense that everyone wants to "have their cake and eat it". This problem has of course no solution and yet people carry on making decisions (Keen 1977) unless they elect to stay in a non-decision making scenario (Judge 1997), which is, in itself, a form of decision making. The need to arbitrate between short term and long term is an excellent illustration of inevitable and sometimes painful multi-criterion choice. How can compromises be made? From the neurobiological point of view, we have seen in Sect. 1.1 that the ventromedial part of the frontal cortex is a key centre and that certain aberrant behaviours come from a failure to integrate available information, the dominance of short term gains and uncontrolled sensitivity to certain emotions.

As illustrated by Gilboa et Schmeilder's first example (the manager trying to hire a sales representative), multi-criterion decision places more emphasis on the description of the characteristics of the possible actions than on the events to come. In a certain manner it is better to spend time on a good evaluation of a potential action, rather than to endlessly consider highly uncertainty events. This is why the proponents of multi-criterion decision making appear somewhat indifferent to uncertainty: "Information versus Uncertainty" is indeed a recurring theme. By the same token, fast decisions are better than long studies of hypothetical events to come (Eisenhardt 1990), especially when decisions are not irreversible (Pomerol 1997a). That has been illustrated in experiments such as the "beer game" (Sterman 1989) and in empirical studies of real decisions with delayed feedback (Kleinmuntz 1985, 1993).

Fundamentally, human actors don't like the tension inherent in multi-criterion choices (Kottemann and Davis 1991; Berthoz 2003, p. 286) and very often will seek to rationalize their choice either by the search for dominance (Montgomery 1983, 1987), or by reasoning by analogy, but almost never by having recourse to aggregation, which seems to be an effort to rationalise limited to the scientific community. Thus, the decision maker will often prefer to use heuristics and limited rationality, to proceed by trial and error using interactive methods (see Pomerol and Barba-Romero 1993) and local adaptations fitting their levels of aspiration (Lévine and Pomerol 1986; Selten 2002). These decision making traits are exacerbated in certain models, such as Klein's (1993) recognition-primed decision making where only one scenario is considered in great detail and its implementation monitored against the elements that emerged from a rapid simulation carried out by the decision maker in his or her mind.

1.2.5 Other Models

We considered the problems arising from the use of the probabilities and the concept of expected utility in relation to Savage's model. We have also shown how it is possible to bypass these problems by adopting alternative models, such as MaxMin. In practice, sensitivity to the worst result is a phenomenon well attested (March and Shapira 1987; Tversky and Wakker 1995). Tversky and Simonson (1993) have even coined the term "extremeness aversion" to describe it.

Researchers have tried to construct models that take into account the probabilities and the aversion for overwhelming losses (e.g.: Cohen and Jaffray 1988; Jaffray 1988; Rubinstein 1988; Leland 1994). A more complete attempt consists in taking into account the difference in value between the results versus the difference between their probability of occurring (Shafir et al. 1993). Such models try to recreate a hybrid selection criterion by introducing the aversion to strong losses or great differences in profits. The issues arising from the existence of events with very small probabilities are important ones, because they are one of the main sources of error of judgment in human decision making (March and Shapira 1987; Morel 2002). The use of belief functions as in Dempster (1967) and Shafer (1976) also allows for a mix of beliefs on the probability of future events and some degree of ignorance. In Smets' (1990) model, the belief functions are transformed into probabilities at the time the decision is made in a transformation process known as pignistic transformation (see Dubois et al. 1996).

The alternative perception of probabilities as illusory precision is also a legitimate one and Dubois and Prade (1985) have suggested replacing them with possibilities, which are sub-additive measurements (i.e. the measurement of two independent events can be lower than the sum of the measurements of each event). It is then sufficient to rank the events from the most probable to the least probable and only the rank of each event in the list counts. It is then possible to use a Choquet integral to integrate the results and obtain a probabilistic expected utility as well as other decision criteria within a probabilistic axiomatic framework (Dubois and Prade 1995; Dubois et al. 2001). The result provides a *qualitative* decision because only the relative plausibility of the events is taken into account without an absolute measure of their probability of occurrence intervening. Dubois et al. (2003) provide a good synthesis of the various models and criteria which rest on weaker measures than actual probabilities. Much recent research has shown that models as coherent as that of Savage have been proposed in this way (Dubois et al. 2002). In some cases however, such models lead to an over-focus on the most plausible events in setting up the decision (Dubois et al. 2002, 2003).

1.3 Decision Making, Pattern Recognition and Look Ahead

1.3.1 Diagnosis and Decision

We have already stated that it is impossible to describe human decision making without considering the role of future events. By contrast, a deer's sudden decision to run away is a mere reaction to a stimulus. This flight reaction is built into the animal's genes and does not entail a representation of the future. Naturally, humans may display such automatic behaviours in some cases, such as ducking when an object is thrown in one's direction. In the domain of *reasoning*, (i.e. when the decision maker has enough time to generate a projection of future events in her or her mind), it is useful to distinguish between two key phases: *diagnosis* and *look-ahead*. It is, of course, not always easy to separate these two but, from an engineer's point of view, it facilitates the design of systems aimed at supporting the process of decision making. In Fig. 1.1, we have sketched out what may be regarded as a realistic human decision process, tracking the main components of decision reasoning. In Fig. 1.1 we have drawn a line from the preference box to the actions because many consider that it is possible, to some extent, to define the actions according to preferences. First define what you want, then design the actions that will get you there! This is expressed in current research originated mainly by Keeney (1988, 1992), about value-driven thinking. Here attention is drawn to the fact that the action (or alternative) set is not a given and can be changed during the process of reasoning.

It has been often observed that many real decision makers are over-constrained in their perception of the alternative set and study just a small subset of the possible alternatives. Classical decision theory assumes that the actions are known, even though it has for long been recognised that the design of the actions itself is an important step in the decision process (Simon 1977).

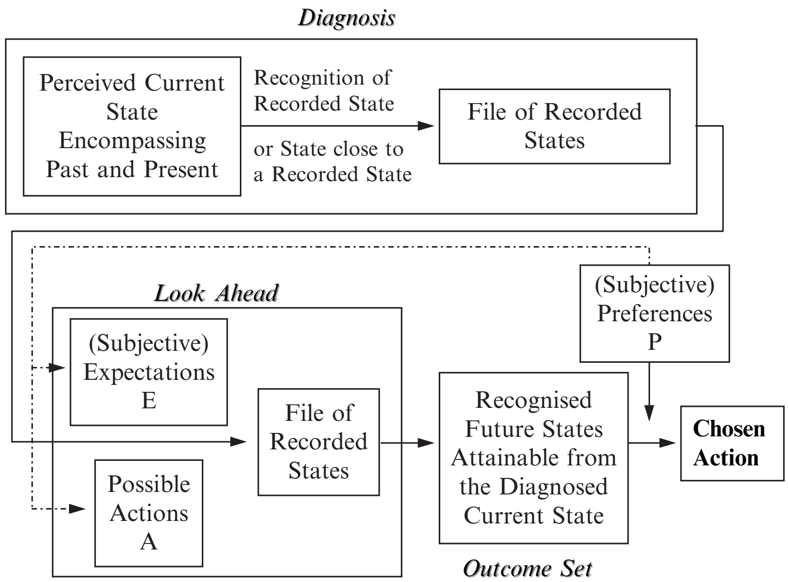


Fig. 1.1. The decision process (adapted from Pomerol 1997a)

In some cases, it is also defensible to draw a line from the preferences to the expectations box. This may be regarded as a psychological bias because it means that the future is considered in terms of the preferences. This probably frequent situation should be avoided in rational decision making, as should the inverse situation where the preferences are influenced by expectations. The latter can be regarded as a kind of framing effect (see e.g. Tversky and Kahneman 1983, 1988 and Humphreys and Berkeley 1985, for a discussion). Indeed, rationally, preferences should be independent from expectations.

Also, the subjects' preferences may influence the diagnosis process and the file of the recorded states (i.e.: the memory). Numerous psychological biases are observed in this domain (von Winterfeldt and Edwards 1986; Bell et al. 1988). Another simplification in Fig. 1.1 is that the decision process may appear "linear". This is not the case and many backtracks can occur, especially when the subject becomes aware that the attainable future states are not satisfactory. Moreover, in many actual organisational settings, due to feedback phenomenon, it is not always possible to distinguish an event from an outcome. For example, in an oligopolistic market, are the rise and falls of a price an event (uncontrolled and uninfluenced) or an outcome? In many cases, the decision makers and the modellers do not know, on the one hand, where to set the limit and the time horizon of the model because, depending on the level of analysis, any significant decision may have far-reaching consequences (see Berkeley and Humphreys 1982, for a discussion about the small world assumption), and on the other hand, the line between events and outcomes is rather thin and vague in terms of human agency.

In Fig. 1.1, the diagnosis phase consists in recognizing the current state of the world, i.e. the past and the present. In the next phase, the decision maker must anticipate the consequences of potential decisions, based on his or her perception of the future, it is the projection phase. This is the stage that best distinguishes human decision making from animal decisions. Even though it is logical to imagine that the appearance of an increasingly present projection phase in our decision making occurred gradually during our evolution, there is a stage where this decision making phase became the most important and paleobiology does not allow for a conclusion regarding which of our ancestors had or did not have access to such capability. The evolution also explains why in human behaviour certain situations still involve decisions that are either automatic, or based on the recognition of patterns.

We have argued that decisions made directly on the basis of the recognition of a state of the world, i.e. a diagnosis calling for a standard reaction, was a frequent and even sometimes rational process, in particular for continuous types of decisions such as in industrial process control (Pomerol 1997a). Expert systems were based on such concept: a good diagnosis leads to the decision, whether one represents the states of the world in the form of rules as in the expert systems or in the form of cases (see Riesbeck and Schank 1989 and Kolodner 1993 for an introduction to case-based decision making). The phase of diagnosis consists in recognizing a state of the world. In cases where an exhaustive list of the "diagnosable states" is present, together with a list of decisions such that a one-to-one relation can be built between the two, decision tables can be used as the decision taking device (see Pomerol 1997a).

The situation is often more complicated in particular when the diagnosis does not make it possible to identify a case already recorded in the memory. We will examine the model of Gilboa and Schmeidler (1995, 2000a) which tackles this question of the recognition when not all the "recognizable" states are present in the memory of the decision maker.

1.3.2 Case-Based Reasoning

The principle of case-based decision making is simple. It assumes that there is a set of decisional cases in the mind of the decision maker and that these cases represent all the experience of the "decisional system". Faced with a new situation, the decision maker recognizes one of the cases already encountered and initiates the decision adapted to this case (decision which has also been stored). In the simple case of the decision table scenario, the difficulties which arise are purely "representational", i.e. it is necessary to have an advanced language or a representation scheme which makes it possible to capture the richness of each case and authorizes a rapid pattern matching. These present key questions for ARTIFICIAL INTELLIGENCE researchers which are dealt with in the chapters of this book.

In reality, Case-based reasoning is not only about pattern matching insofar as, as the proponents of CBR have rightly claimed - the learning dimension of

CBR systems is the most important one. For instance, the set of cases must be able to grow to encapsulate any newly encountered case which does not fit existing cases. The system must also be able to deal efficiently with any unrecognisable case that is encountered. The issue of similarity between cases becomes a critical one, with the system having to properly assess the distance between any new case and one or several existing cases. Gilboa and Schmeidler (1995, 2000a) proposed a framework to formalise the relationship between case based reasoning and case-based decision making. They propose that each case is a triplet (p, a, r) where p $\in$ P (the set containing all problems), a $\in$ A (the set of possible actions) and r $\in$ R (the set containing all results). Case-based reasoning is concerned with the problems and how to classify them in comparison with each other. Gilboa and Schmeidler defined a similarity function between problems:

$$\mathrm{S} \ : \ \mathrm{P}^2 \rightarrow [0, 1].$$

This function gives the distance between two problems. The decision maker can also use a utility function on the outcome:

$$\mathrm{U} = \mathrm{R} \rightarrow \mathrm{IR}.$$

Let M be the set containing all cases stored in memory: the relevance of a given action for a given problem is expressed as:

$$U_p(\mathrm{a}) = \sum_{(q,a,r)\in M} s(p, q)u(r).$$

In other words, for a given a and p, all problems q in the memory that satisfy $(q, \ a, \ r) \in M$ taking into account their distance to p (i.e. s $(p, \ q)$) which increases when q gets very close to p. It is then logical to select the action a that maximises U_p (a). Gilboa and Schmeidler (1995) also provide axioms which show the coherence of their model. As in Savage's model, a coherent choice of an action yields a measure of the distance between the problems (instead of the probabilities of the events in Savage's model). This similarity between these two types of model proves – indeed it is one of the great weaknesses of this type of model – that the reasoning on future events (i.e. uncertainty) is contained in the similarity function built in the model. In Gilboa and Schmeidler (2000a), the model is extended to the similarity between the pairs (problem, action) and the triplets (problem, action, result). By contrast with Savage's work, case-based reasoning (as in the previous paragraph) has a significant advantage that instead of knowing all the states of nature and the consequences of the various possible actions, it is enough to have a memory of all previous cases. It remains to be considered whether the set of previous cases has pertinence in understanding future events. It is therefore of great interest that the set of recorded actions is allowed to grow richer by the introduction of new cases, but also by the refinement of the similarity function, as the model is used.

In a recent work Gilboa and Schmeidler (2000b) proposed an axiomatic model to derive probabilities on the basis of a set of recorded cases. The principal element of appreciation is the number of occurrence of the cases, a high number of occurrences resulting in a higher associated subjective probability. It is another way to model the availability, reinforcement (Anderson 1983, 1995) and representation phenomena (Tversky and Kahneman 1982a, b).

1.3.3 Recognition Primed Decision Making

In considering the specificities of human decision making and the importance of the projection phase, especially when the patterns faced by the decision maker is not an exact match for any previously experienced situation, it is useful to discuss in some detail the work of Gary Klein (see Klein 1993) and his associates on recognition primed decision making (RPD) and naturalistic decision making (NDM). NDM is at the same time a body of research on human decision making and a methodological orientation which has focused on the study of certain cognitive functions that emerge in natural settings, often in decision making situations that involve severe time pressures and/or life and death decisions. At the outset, Klein and the adopters of his ideas studied fire fighters, emergency room nurses and paramedical staff with the view to getting direct observations on how this extreme decision making can occur. Their observations reveal that, contrary to the predictions of normative models, these individuals do not design alternative solutions that they compare with one another, but use their diagnosis of the situation to construct very quickly a best case solution, the execution of which they then simulate in their minds to see if it is a good fit for what they imagine is happening: this is what is termed recognition primed decision making. This is radical, because it proposes that RPD is about selecting one solution and running a quick simulation in one's mind to test its robustness. In the following phase, when the solution is implemented, Klein's decision makers use their simulation to validate whether the situation responds in the way they expect and take further decisions as they see an unexpected course of event developing, such as this fire fighter getting his team out of the building seconds before the ceiling collapses on them because he identified that the fire should have been reduced by their attacks and he understand that the fact that it is not abating means a faulty diagnosis (i.e.: the incorrect identification of the location of the fire in the building).

These observations are very interesting, because they illustrate well the importance of experience and why more experienced decision makers are less likely to get themselves and their teams in trouble. As illustrated in Fig. 1.1 in Sect. 1.3.3, the size and variety of the file of recorded states, determines both the likelihood of an accurate diagnosis and the likelihood of an effective solution being implemented. It also allows for a more detailed monitoring of the implementation progress. Thus, RPD suggests a two stage decision process: (1) pattern recognition and (2) mental simulation. Klein concluded from his observations that human beings are active interpreters of everything they see around them and their experience cannot be deconstructed into the kinds of rules that will fit into expert systems. He also noted that experienced decision makers see a different world than novice decision makers see and that what they see tells them what to do. Ultimately, it remains to be seen whether RPD is a specific form of decision making that applies to certain individuals in certain situations or whether it can be considered as a broadly applicable alternative model of human decision making.

1.4 Recognition, Reasoning, Decision-Making Support and the Use of Scenarios in Decision Making

For anyone interested in human decision making, it is enough to read the recent work published in neurobiology to be convinced of complexity of the neuro-processes involved (see Damasio 1994; Damasio et al. 1996; Berthoz 2003) and it is important to repeat that conscious and deliberated reasoning is not the only domain of research that must be considered: recognition, as we have illustrated in the previous sections, is also a critical aspect of decision making. Indeed, even in animals, pattern recognition is moderated by context and training (Berthoz 2003). This has led researchers to conclude that a sound alternative to trying to model such a difficult activity was "to leave the human actor in the loop" and to focus on interactive decision support systems (DSS). DSS aim at assisting rather than replacing, the human decision maker by providing rational models to support his or her reasoning abilities and by extracting relevant patterns in vast volumes of overabundant information to support his or her recognition abilities. There is a vast literature on these systems, including, Keen and Scott Morton (1978), Bonczek et al. (1981), Sprague and Carlsson (1982), Lévine and Pomerol (1989), Burstein (2001), Humphreys and Brézillon (2001), Adam et al. (2002), Mora et al. (2002), Adam et al. (2003). In final analysis, decision making, when the decision maker has time to consider alternatives, boils down to the ability to build representations of the (uncertain) future and to project oneself in it. Consequently, supporting decision-making is initially concerned with the construction of scenarios and the amplification of this specifically human aptitude to project in the future in a conscious way.

It is useful to note that despite genuine advances in practice, with countless applications developed and implemented with success in industry, we still lack a strong theoretical basis to integrate the very disparate systems we are aware of into a coherent whole. One promising direction of research consists in regarding the use of DSS applications as performing a heuristic search for a solution. (Bonczek et al. 1981; Lévine and Pomerol 1989, 1995). The DSS then, facilitates this heuristic search by helping the user to explore the future ("what if analysis"). This exploration must be done at two levels: the level of the data and the level of the models (Pomerol and Adam 2003). It is the need for this dual degree of freedom which makes such applications as spreadsheets so popular and so effective (Pomerol et al. 2002, 2003). Obviously the heuristic search stops when a satisfactory solution ("satisficing") is found. This is a perfect illustration of Simon's bounded rationality in action.

Given the unlimited number of possible future states of the world, the human decision maker, helped by his or her decision support artefacts, will develop scenarios, a small number compared to all those possible (Pomerol 2001). These scenarios will be projected against a given timeframe depending on the context of the decision, but which can be quite long for strategic problems, hence the need for a DSS, because the combinatory explosion can grow well over the ability of the human mind, even for a small number of scenarios.

The use of scenarios appears to have been both the most common and the surest way to explore the future. In its most formalized form, it has given rise to the use of decision trees (Raiffa 1968; von Winterfeldt and Edwards 1986; Shafer 1996), decision tables, or other graphical methods described elsewhere. By assigning conditional probabilities to the various successive events that make up the scenario, decision makers enter a mode of reasoning referred to as backward folding, which makes it possible to rigorously determine the scenario with the best expected utility. It is interesting to note that, due to the opposition between the short term and the long term, the best scenario is practically never the chaining of the best scenarios at the intermediate stages.

Many other graphic methods have been derived from decision trees, for instance, towards decreasing the need for independent probabilities between all the events (networks of influence, Bayesian networks, see Oliver and Smith 1990; Shenoy 1994) and so have various qualitative methods (Oliver and Smith 1990), some of which use no probabilities to represent the context of the decision (Brézillon et al. 2002; Pomerol et al. 2002).

One of the important aspects of the practice of decision making which is corroborated by many empirical observations (Pomerol et al. 1995; Brézillon et al. 2002) relates to the simplification of the scenarios in human reasoning. This involves the use of actions that are considered to be robust in the face of large series of events belonging to a common temporal threat, and which make it possible to eliminate a number of problems at the same time (Pomerol 2001). This leads to successions of standard decisions which are quite common in practice.

Another way to reduce the combinatory explosion already discussed consists in delaying as many decisions as possible until the end of the scenario. This has been called action postponement in Pomerol (2001). This can be interpreted as the continuation of the search for information before making a decision (when information is available), or as an illustration of the old saying about not keeping all your eggs in one basket, in this case by delaying the decision point until after as many uncertain elements as possible have disappeared. In dynamic programming, this capacity to keep as many options open for as long as possible is referred to as flexibility (Rosenhead 2001). These very pragmatic ways of thinking, even though they do not add up to substantive rationality, are perfectly "rational" and fit well with the idea of using scenarios for reasoning.

In this perspective, the question which decision support systems must help answer concerns the choice of the most useful scenarios. In many cases, this choice of scenario is a multi-criterion problem, in the sense that the decision maker must make conscious trade offs between possible criteria for success. Although it is uncertain exactly how the human mind processes these cases, neurobiologists (Berthoz 2003) claim that the mind relies more on the elimination of potential solutions than by choice. In other words, through a complicated physiological process bringing into play many parts of the brain, a dominant solution ends up inhibiting all other possible solutions. This is reminiscent of the phenomenon of search for predominance described in Montgomery (1983, 1987) and of the empirical results obtained in Psychology in experiments where an individual convinces themselves a posteriori that they bought the best car or bet on the right horse given existing constraints (Festinger 1957). It can be hypothesised that there are thresholds in the discharge of our brains' neurons which result in a "winner takes all" phenomenon. This type of phenomenon is measurable in multi-criterion decision making but, it is essentially hidden in the stage where weights or relative importance are allocated to each criterion. As Keen (1977) pointed out: the most interesting in human decision making is that even when there is no solution in theory, we go on making decisions in practice – judgement is exercised.

In the selection of scenarios, robustness plays an important part. Robustness may be understood to relate to events, to data and to the parameters built into the models used (see Roy 1998, 2002; Vincke 1999). In considering robustness as it relates to events and their probability of occurrence (or any other measurement as discussed earlier), one is reminded of the comments made about Savage's framework: it is extremely complex to abandon the maximisation criterion, robust "against any move of nature" and to try to establish which events are negligible or not (Lehmann 1996; Monnet et al. 1998). It is all the more difficult given the weakness of the human mind in appreciating small probabilities. This cognitive bias is found in many reported accidents, such as the loss of the space Shuttle Challenger. The designers of the boosters used to propel the craft during take-off were confident of warm weather, based on historical data showing only one or two days of cold per century in Florida. Unfortunately, this particular launch took place during a cold spell which led to the disastrous explosion (Morel 2002). It is noteworthy that the expected rate of failure for such spacecrafts was assumed to be 1% by its designers and 1 per 100,000 launches by the managers of the Space Shuttle project. This difference in probability leads to radically different behaviours: one may perceive a 1% scenario worth considering, whereas a 1 in 100,000 chance scenario can be neglected.[6] Sect. 1.5 concentrates on the limitations of the human mind, such as this problem with assessing small probabilities, and other reported cognitive biases.

1.5 Cognitive Biases

There are unavoidable obstacles which defeat all efforts at rationality in human decision making. The first one concerns small probabilities: should a low probability of disaster (such as total bankruptcy) automatically rule out a possible action? Should one leave the car at home when there are high winds? Decision makers may either take a very pessimistic decision criterion and remain in bed all day, or treat these exceptional situations as exceptions and display basic logical incoherence (Dubois et al. 2003). The sure thing principle is another obstacle because it imposes a "rationality" that nobody accepts: there are good reasons to buy the fastest car even though its petrol consumption is greater than that of other models if you have a large budget for your purchase. On the other hand, if you budget is limited, you are likely to look for an economical model, even if it goes slower. The assumption of linearity of the preferences as they relate to the probabilities (or to the weights in multicriterion decision making) is unavoidable. However, it is purely mathematical and is not particularly rational because it is quite conceivable to change one's mind in relation to one's preferences depending upon the level of satisfaction that can be obtained. The ignorance of other axioms not discuss so far, can also yield severe inconsistencies in human decision making. It is the case for the axiom known as the "irrelevant alternatives" axiom (see Pomerol and Barba-Romero 1993) which, when it is not satisfied, leads to such paradoxes as that exploited in his time by Talleyrand where individuals can be forced to make one particular choice regardless of their own preferences (Woolsey 1991). In this case, very bad or very expensive choices are introduced in order to push decision makers towards a particular choice, for instance the median choice!

These facts are well attested in laboratory experiments, as is the violation of the principle of independence. Following Allais' foundational critic, many experiments have confirmed this phenomenon, notably the work of Kahneman and Tversky. These results are presented in Sect. 1.5.1 as they relate to some of the problems discussed thus far (see also Kahneman et al. 1982; Kahneman and Tversky 2000).

We will not spend undue time on the emotional aspects of certain decisions, such as the "frame effect", or on the effects which the presentation of

[6] "There is a tendency in our planning to confuse the unfamiliar with the improbable. The contingency we have not considered looks strange; what looks strange is thought improbable; what is improbable need not to be considered seriously", T. C. Schelling (1962, p. vii)

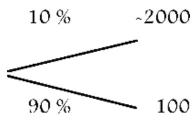
the context of a decision can have on decision makers (Tversky and Kahneman 1988; Slovic et al. 1988). Many experiments have revealed this effect identified a long time ago by Tversky and Kahmeman. Notably, Zickar and Highhouse (1998) have shown that the importance of this effect depended on each individual and Slovic et al. (2002) reported many examples of the sensitivity of human decision makers to the presentation of the facts of a decision. In brief, if one presents the same situation in term of possible death or in term of survivors one often manages to reverse the judgement of the majority of subjects. It is obviously purely irrational as are techniques that have been developed to manipulate public opinion using very small probabilities combined with the so-called principle of precaution (e.g.: invading a country because there is a possibility that it possesses weapons of mass destruction). In the following paragraphs, we will consider cognitive biases relating to probabilities, and those related to the anchoring effect and to the levels of aspiration of decision makers (Kahneman et al. 1982; von Winterfeldt and Edwards 1986; Bell et al. 1988; Kahneman and Tversky 2000).

1.5.1 Cognitive Biases Related to Probabilities

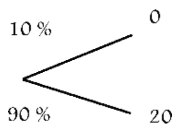
We already noted that small probabilities are not correctly apprehended by the human mind, in that they either are ignored (March and Shapira 1987), or over-estimated (Tversky and Wakker 1995). To tell the truth, between a probability of 10^{-3} and one of 10^{-6}, it is difficult to properly represent what the difference means and, without an emotional content, the mind has no point of reference. However, between catastrophic floods which occur on average every 3 years or every 3,000 years, there is a big difference for the inhabitants of an area. Experimentation has shown that 10^{-3} seems to be an important threshold for the perception of risk in human decision makers. Below 10^{-4} individuals tend to disregard the risk: it is the same probability as getting 12 or 13 consecutive heads when tossing a "regular" coin. Below 10^{-3}, the risk is accepted within certain limits if there is a perception that it can be somewhat controlled – e.g.: the decision maker thinks that if they really pay attention, they will get through safely (Perrow 1984, Chap. 9; McKenna 1993). For an average driver living in France and driving 20,000 km per annum, the risk of personal injury is 1/300 and the risk of a fatal accident is 1/4,300 (1997 statistics). The risk of a fatal accident which mountaineers face if they go out for a serious climb once a year also ranges between 1/500 and 1/1,000. For a "frequent flyer" travelling around 20,000 km per annum the risk of death is 10^{-5}, which is considered negligible. The example of road traffic is very interesting, because it shows that even with a non-negligible probability of serious accident, drivers are happy to undertake difficult journeys on "heavy" days (such as long week ends and holidays) with their families on board because they feel that being careful reduces the probability to within acceptable levels of exposure.

At the other end of the scale of probabilities, the effect of certainty is also well attested. The certainty of winning of smaller amount is always preferred to the possibility of winning a larger amount with a probability $1-\mathrm{e}$, or nothing with a probability of e, even when the expected utility is exactly the same. But in this case the common sense rationality at play is obvious: a bird in the hand is better than two in the bush! This takes us back to our previous discussion: if this behaviour appears rational for $\mathrm{e} = 10^{-3}$, it is more difficult to justify it for $\mathrm{e} = 10^{-6}$ but human nature is inherently risk averse when it comes to gains (see Kahneman and Tversky 2000, part three).

People don't like to lose and this has been amply demonstrated since work by Kahneman and Tversky (1979). Human behaviour faced with uncertainty, is not the same for profits or for losses. We have already noted the impact of possible large losses (e.g.: total bankruptcy) and the aversion they generate in human decision making (March and Shapira 1987; Cohen et al. 1987; Tversky and Simonson 1993; Tversky and Wakker 1995). By contrast, human decision makers are happier to take great risks in situations involving losses. Thus, human decision makes are risk takers when it comes to losses. In experiments, subjects were happy to face the risky odds in the figure below in order to avoid a sure loss of -10:



This means that subjects preferred an expected utility of -110 rather than a sure loss of -10! This type of behaviour may in part explain certain gambling addictions where individuals try to bail themselves out by taking increasingly greater risks. This can be contrasted with subjects preferring a sure gain of 10 to the situation proposed in the figure below, which has an expected utility of 18:



It seems that subjects' perception of the real utilities is somehow altered such that their utility curve looks like the one presented in Fig. 1.2. This preference reversal (PR) between gain and loss perception described by Kahneman and Tversky (1979) is a key notion for anyone hoping to understand human decision making.

We will not discuss here what happens when Bayesian rules are not respected or the incapacity of human decision makers to properly account for conditional probabilities. It is obvious that the human mind is not built like a calculator, so when it comes to computing conditional probabilities, its reliability breaks down. This is not really a weakness if one considers the

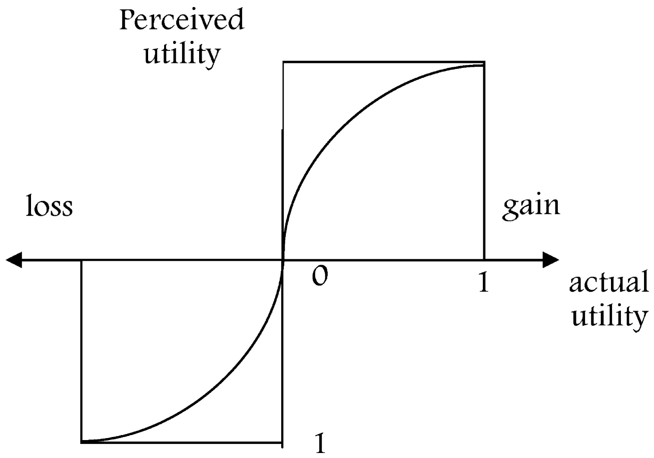


Fig. 1.2. Subjective perceptions of utility

intractable cognitive load involved as soon as 4 or 5 possible events must be considered with their conditional probabilities. This is where scientific reasoning and scientific tools must take over. Thus, in medical decisions (Grenier 1990), the last 50 years have seen unprecedented progress in terms of diagnosis, with the application of Bayesian and conditional probabilities. It is also worth noting that the issue of the coupling of events plays a significant part in the assessment of reliability of systems or machines and the risk of accident can be strongly underestimated if events are wrongly understood to be independent when they are not. Perrow (1984) demonstrates how tight coupling between very complex systems can lead to sequences of seemingly unconnected events which result in serious accidents.

The last effect that we would categorise as relating to probabilities is referred to as the illusion of risk control (Kahneman et al. 1982, part V; Slovic et al. 1982; March and Shapira 1987; Kahneman and Lovallo 1993; McKenna 1993; Barki et al. 1994). The notion of risk control is somewhat irrational and can be regarded as a pre-Savagian regression where a confusion is allowed between what the decision maker does and does not control. It amounts to refusing the principle of separation between actions and events and leads to paradoxes and incoherence as described in Sect. 1.2.1 with the betting example. The only reasonable notion when it comes to controlling risk, is that greater, more systematic information retrieval, and better forecasts, gives a better understanding of what may happen. For instance, using weather forecast for planning one's commute on foot or in a car reduces the risk of getting wet, and, in certain countries, weather experts give their forecasts in terms of probabilities. The search for information also leads to the notion of postponement (as in Sect. 4.2), where decision making is delayed until uncertain aspects of the future have passed. The illusion of control of uncertainty seems to have become a feature in every day life. During the winter 2003, local administrations along the Seine river (in Paris) were asked (in all seriousness) to begin planning for the impact of a flood expected to come approximately every 100 years because the last one had taken place in 1906! This is a perfect illustration of the misuse of statistics and of common misunderstanding of small probabilities (Kahneman and Tversky 1972).

1.5.2 Representation, Satisfaction Levels and Anchorage

We have discussed how human decision makers' attitude to risk seems to reverse around a point which we arbitrarily represented as zero in Fig. 1.2. It seems that each of us has a "neutral" point corresponding to our level of aspiration and that all our preferences are measured in reference to this point: aspiring to anything above it and rejecting anything below it. This idea is not new (Lewin et al. 1944; Siegel 1957) and was exploited by Tversky and Kahneman (1974). There is also ample empirical justification for it as it is clear that to lose or gain one euro is not the same for one of the Rockefellers or for a person sleeping rough.

The concept of level of aspiration is semantically close to that of level of reference which leads to the concept of anchoring. The point of anchoring is the point in relation to which the emotions and the experience of decision makers allow them to form an opinion and evaluate their choices. For example, a happy summer holiday in a Greek island will be used as point of reference to choose any future holiday. This phenomenon of anchoring has been noted to have several interesting dimensions: cognitive and mnesic dimensions, representational dimension and finally narrative dimension.

At the cognitive and mnesic level, certain events are ingrained in the memory and will affect future choices in situations where the decision making is emotionally reminded of them. This is very reminiscent of the "frame effect". A subject who had an unpleasant experience, even resulting from a good decision will hesitate when faced with the same decision. Individuals can be manipulated using their level of reference exactly as with the "frame effect". It even seems to be more effective than manipulating people's perception of context (Kühberger 1998).

Another less well-known effect, which is nonetheless well illustrated empirically and commonly used in AI, is the proximity effect whereby recent events (or freshly memorized) have a greater weight than older events. These recent events will greatly influence choices in looking for solutions to current problems. Anderson (1983) and Newell (1990) modelled this effect in an attempt to make their systems more credible. It has also been observed that the human mind is able to invent false correlations on the basis of completely independent events (Chapman and Chapman 1969). Thus, a simple experiment where certain figures are impressed on subjects before asking them the number of nations in the UN, will reveal that their cognition is influenced by the figures given to them, even though these bear no relationship whatever with the UN (Piattelli-Palmarini 1995). This phenomenon has also been interpreted as an anchoring effect (Tversky and Kahneman 1974). The proximity effect is a significant cognitive bias and it is particularly strong in the estimation of very small probabilities. Faced with a probability around $10^{-2}/10^{-4}$, a decision maker will be very likely to be overly influenced by recent events or salient events that are absolutely not related.

The second component of the anchoring effect is representational. It results in events with which one can easily relate being assigned a greater probability than those which are difficult to assimilate (Tversky and Kahneman 1982b; Slovic et al. 1982, 1988; March 1994, pp. 82–83). This is the representativeness effect. Morel (2002) has reported the case of an aircraft pilot who was so extremely anchored in considering the implication of his landing gear not deploying (which is not an uncommon situation) that he forgot the risk of running out of fuel until this eventually brought the plane down. This representativeness effect is very strong in terms of diagnosis as subjects' assessment of the current state of the world is unavoidably very dependent on their representations of it, which has lead to many reported accidents as in the case of the Three Mile Island near disaster so masterfully recalled in Perrow (1984). Other cases have been reported by Boy (1991) and Morel (2002).

The third component of the anchoring effect – undoubtedly the least known, is the narrative aspect. It is useful here to go back to our section on scenarios. To some extent, a scenario is a story. We have seen how, making a decision consists in inhibiting all possible scenarios except one, which will dominate and that this domination is established before the action (constructing a rationale for action see Pomerol and Adam 2003) or after the action (rationalization a posteriori). In any case, there is always a rationalization process, predominantly connected to the contextual elements of the decision (Brézillon et al. 2002). The more credible a story is, the more likely it is that the decision will be adopted. It is generally believed that the narrative mode is a fundamental mode of cognition going back thousands of years (Bruner 1986, 1990; Borland and Tenkasi 1995). It has therefore been written that, in order to "sell" a decision to organisational actors, one has to tell a story that everyone believes in (Weinberger 2001). The narrative side of decision making is a very distant relative of rationality but it brings us closer to language with which, as we said at the very beginning of this chapter rationality has many common features. As Vico (1744) indicated, before any theory of reasoning, mythologies and lyric poetry played a similar role, in the form of stories, as the first modes of structuring the world and accumulating knowledge. In the scientific era at any rate, Tversky and Kahneman (1982a) have shown how the easier to remember the stories the more likely the decision is to be successful (see also Kahneman and Lovallo 1993; Boland 1979).

This discussion begins to show the linkage between human decision modelling and artificial intelligence, in that it shows the importance of being able to represent cases of decision making (Anderson 1983; Newell 1990; Simon 1995). These three references illustrate that this topic has been of primary interest to the pioneers of artificial intelligence and the question remains open, on the one hand, whether one must approach "human reasoning" to the detriment of rationality and, on the other hand, what role the cognitive biases we have described here have played in the success of our species. Indeed, it is impossible to evaluate whether these biases and heuristic idiosyncrasies have conferred advantages or impediments to human beings in their fight for survival. Answering this question requires a multicriterion evaluation. Undoubtedly, decisions by heuristics have the advantage of speed and robustness, even if they do not have theoretical qualities (see Gigerenzer and Selten, Sect. 1.2.3). Speed is obviously an important factor for the survival of an individual as illustrated in very practical terms by Klein's "recognition-primed decision making" (see Sect. 1.3.3).

Other cognitive biases may no be so useful, even though cognitive psychology tends to view them in a positive light. At the end of the day, one must also realise that the rationality of the species as a whole is not necessarily the same as that of a given individual (the notion of survival of the fittest and the elimination of lesser males by the dominant males comes to mind here). Thus, it may be more difficult to justify the frame effect and the anchoring effects which allow the manipulation of other individuals in strict evolutionary terms. On the other hand, risk aversion for gains is certainly a useful behavioural aspect (prudence is a sound principle), but how can risk taking for the losses be useful? It may be that this cognitive anomaly is the strongest driver of cultural and technical change insofar as risk takers who throw caution to the wind are needed for innovation and great discoveries. Finally, it is possibly wise for a species to be able to neglect small probabilities and be able to find intellectual certainty in areas where there is none.

The most ambivalent cognitive bias is that of "risk control", because it leads to reckless behaviour in human activities (stock exchange, driving a car, etc...). But the other side of the coin is that, without this blindness to risk, there would probably have been no landing on the moon in 1969 (in an era where computers looked like fridges and had less computational power than the calculators today's school children use for their additions).

1.6 Conclusion

This chapter provides a historical tour of the link between decision theory and human decision making. The first observation we wish to make is that, contrary to the contentions of certain researchers in biology, psychology and sociology, these linkages run deep and are inherently useful.

These linkages run deep because for instance, if one ignored the principles put forwards by Savage's work, their limits, and their critical examination in light of today's understanding of qualitative decision making, it would simply be impossible to conceptualise the role of rationality in human decisions involving very uncertain situations. It is Savage's model that makes it possible to identify chance and bad luck in rational decisions. One could debate, as we did in this chapter, whether the assumptions of the model are realistic or rational, but one cannot deny that, apart from the game theories put forward in the 18th century, Savage's framework is the only quantitative or qualitative framework that provides the theoretical basis for distinguishing between a bad but lucky decision maker and a good but unlucky decision maker. Furthermore, it is the extension of this model by the psychologists Tversky and Kahneman that made it possible to understand the reversal of preferences in human decision makers facing uncertainty when they deal with losses or when they deal with gains.

The biological side of decision making is also a very interesting viewpoint from which to reflect on the specificities of human decision making, and therefore on the targets set for artificial intelligence. From an evolutionary point of view, even though it is clearly legitimate to consider language and decision making as specifically human activities, it is undeniable that there is a continuum between the neurons of the cockroach which make it "decide" to flee or to "play" dead, and our own neurons. Several millions of years of unfinished evolution explains the great complexity of the circuitry involved in decision making – as far as we can see, a seamless combination of different areas of the brain. Amongst the key areas, are the most primitive part of the brain and the prefrontal cortex, the most recently developed of all areas (see Berthoz 2003). Thus, human decision making is a team effort coupling the ancestral part of the brain, that most closely related to the body and the emotions, and the "reasoning" part with the frontal cortex acting as an integrating agent centralising all the information involved in the decision making process. The "reasoning" part gives us the capacity to project in the future, and by complex and, as yet, badly identified processes, to allow an action to eliminate all others within what amounts to a multi-criterion decision framework. Crucially, this domination sometimes requires a form of validation a posteriori, post-decision, because emotions and intuition can combine to allow for a quasi-instantaneous diagnosis of a situation or more complex pattern recognition guided by experience, followed by an immediate decision, which means that reason can only play catch up. Case-based reasoning and decision making and recognition primed decision making have allowed researchers to model this specificity of human decision making to a degree. In the end, it is elegant to conclude that the notion of expected utility, even though it applies in a strict sense in reality only in situations of risk, and then depends on the soundness of measured probabilities, is still the best way to represent rational decision making, in the same way that supply and demand in pure and perfect competition are the best way to represent the dynamics of markets, even though, in reality, no market behaves in the way these theories stipulate in the strict sense.

The limits of the notion of expected utility were pointed out with great clarity when Simon introduced his "counter-model" of bounded rationality. Bounded rationality offers, if not a complete model in the traditional sense of the term, a framework for understanding human reasoning, supporting the conception of and experimentation with many reasoning and problem solving systems, on the basis of existing models of decision making (Newell and Simon 1972; Anderson 1983, 1995; Newell 1990 inter alia). Simon's framework also provided the language and terminology to discuss heuristic searches and "what if" analysis. The simplicity of this framework and its explanatory power are certainly enough to explain its popularity and longevity.

Without revisiting our earlier observations on cognitive biases, we would urge that they be systematically taken into account in a rigorous way for any decision involving high stakes. And for anyone inclined to dismiss the normative models of decision making presented for instance by Simon (1977) and masterfully summarised by Mintzberg et al. (1976), it is useful to recall that without normative model, it is impossible to identify these biases. Consequently even when Savage is no great help, because probabilities are unknown and the utility function is not clearly defined, the theory can still act as a fortress against the ill effects of mis-representation of events, the illusion of risk control or the weakness of our minds when it comes to appreciating small probabilities.

Finally, we could not conclude this chapter without a warning for all the every-day decision makers and AI researchers: when all "i"s are dotted and all "t"s are crossed, and all possibility of bias have been pushed aside, one must still remember that a "decision is good only if it sounds good and tells a convincing story" (Sfez 1980, translated rather freely by the authors). This quote quite appropriately reminds us that the narrative and social dimensions of human decision making are the binds that tie decision and language, and make *Homo sapiens sapiens* a rather unique creature.

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